



A Characterization of Land-use Changes in the Proximity of Mining Sites in India

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For a growing economy like India, most of its energy resources are obtained through extractive processes such as mining of coal and other minerals. Mining can however have many negative social and ecological impacts if it is not well regulated. Illegal mining or inadequate reclamation of abandoned mines can amplify these impacts, emphasizing the need to develop methods that can monitor changes in the land-use patterns in and around mining sites. We develop a method using machine learning on freely available satellite data to monitor the extent of mines, and augment it with outputs from land use and land cover classification, deforestation detection, and PM2.5 particulate matter estimation from remote sensing data to track land-use and ecological changes taking place in the proximity of mining sites. We provide evaluation results of our mining delineation classifier, a feasibility check of this suite of tools to monitor mining areas over a period of four years, and a temporal characterization study over 628 mines in India that were granted a clearance for operations during the period 2006 to 2012. We further use this suite of monitoring tools to compare socio-economic development and health indicators across mining and non-mining areas, across various states in India, to study whether extractive processes of mining benefit the immediate population in their neighbourhood.

CCS Concepts: • **Applied computing** → **Environmental sciences**; • **Computing methodologies** → **Machine learning**.

Additional Key Words and Phrases: Surface mining, remote sensing, deep learning, socio-economic development, pollution, ecology, land use and land cover classification, deforestation

1 INTRODUCTION

Mining of minerals is an essential activity for socio-economic development, especially for developing countries where new infrastructure of roads, housing, electricity, and manufacturing is coming up rapidly with urbanization and economic growth. Mining, however, can create severe environmental damage such as land degradation, deforestation, water pollution, and air pollution [11, 33, 35, 40, 60, 74, 81, 90]. Despite greater awareness of the need for strict environmental regulations for mining, incidents are common of evasion of regulations by mining companies, such as to bring excess land under mining, or flaunt pollution norms, and illegal mining in nearby areas by land mafias [50]. According to the Ministry of Environment, Forest and Climate Change (MoEFCC) of India, after a mining site has been exhausted, the land should be reclaimed by ground levelling, tree plantations, water storage structures, farming, etc [62], but this too may not be pursued rigorously. It is therefore important to develop methods to monitor mining sites in terms of their extent, expansion, land reclamation, and wider land-use and environmental changes influenced by mining [50].

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Monitoring mines exclusively through physical inspection may not be scalable, and also stands the risk of not being able to catch associated corruption where rent-seeking public inspectors may be aligned with legal and illegal mining operations. We therefore examine the feasibility of using freely available remote sensing data from satellite systems to monitor land-use changes in and around mining sites.

Prior work has shown that supervised machine learning methods can be used to identify mining areas [55]. These areas have visible features such as contour cuts, tailing dams, water storage structures, roads, and buildings [88]. We develop deep-learning based classifiers that use openly available optical spectral data provided by the Sentinel-2A satellite system to identify such surface mining areas. We then use this classifier to delineate mining areas of 628 mining sites from across the states of Orissa, Jharkhand, Chhattisgarh, Tamil Nadu, Gujarat, and Karnataka, and examine the land-use changes that have happened over time at these locations. These mines were granted a clearance during the period of 2011 and 2012, and we find that in general the operational area of mines expanded during this time, along with an increase in built-up area. This came at the expense of loss in tree cover, croplands, shrubs and scrubs, and bare land, with different kinds of land-use conversions prevalent in different states. Despite considerable land use changes in mining areas, we observed only a marginal improvement in the overall socio-economic development of the area, with increasing levels of PM2.5 particulate matter concentration.

We make three key contributions in this paper:

- We develop a machine learning based method to delineate surface mines in India by using publicly available satellite imagery.
- We provide a temporal characterization of land-use changes in the proximity of 628 surface mines across India with respect to their operational area, tree cover, built-up area, croplands, shrub and scrubs, and bare lands conversion.
- We compare sub-districts having mining activities with agricultural led sub-districts on indicators related to socio-economic development and health (PM2.5 concentration), and are able to uncover different kinds of patterns in different states.

The paper is organized as follows. We present related work in Section 2. Section 3 describes the dataset and pre-processing steps we undertook to build a supervised deep learning classifier. Section 4 outlines the architecture and evaluation results for our classifier. Finally, in Section 5 we present a temporal characterization of land use changes in mining areas, and a comparison between mining and non-mining areas based on socio-economic development and health indicators.

2 RELATED WORK

2.1 Use of remote sensing to identify mining areas

Satellite data has been actively used to identify changes in the spatial extent of mining areas, to study if it exceeds the permitted area [52, 66] due to illegal mining activities [87]. In India, maps were used to manually delineate coal mining areas in the Ledo-Margherita region in the Tinsukia district of Assam, between 1996 to 2016 [10]. Similarly, spatial changes in surface mines were mapped in the Singrauli district of India [2] by visualizing Landsat images on false colour composites (FCC) in 2002, 2010, 2015.

To automate the process of identifying mining areas, a spectral index called the Coal Mine Index (CMI) was designed [58], but such spectral indices are known to require local thresholding that varies with season and are hence not straightforward to automate [73].

Machine learning methods have been shown to hold stronger promise [48]. Early methods that have been used extensively in the Indian context include unsupervised pixel-level segmentation using ISODATA [82] and K-Means clustering. Open cast mines were classified from Landsat and Cartosat-I images using the ISODATA cluster algorithm for the Ballarpur and Rajura talukas of Chandrapur district in the state of Maharashtra [21]. Coal mining areas in the Godavari Valley Coalfield of Telangana were similarly identified from Landsat 5 and

8 imagery using ISODATA [6, 32]. Evolution of Opencast Mines in the Raniganj Coalfield [65] was similarly assessed from Landsat imagery over 1991, 2001, and 2014. Opencast coal mining regions were detected using K-means clustering on Landsat 8 satellite data in the Jharia coal field [59] by developing a clay mineral ratio defined as the ratio of SWIR-I to SWIR-II spectral bands. Coal mines in the central Salt Range of the Indus River Basin of Pakistan were monitored using tasseled cap transformation and surface temperature derived from spectral bands of Landsat images [4] using K-means clustering.

With the availability of labelled data, supervised machine learning methods such as maximum likelihood classifiers, support vector machines (SVM), and random forests (RF) have been used for pixel-level classification. Derived spectral indices of Landsat-8 such as the normalized difference vegetation index (NDVI), normalized burning ratio index (NBRI), normalized difference moisture index (NDMI), shortwave infrared, and red reflectance were used to fit a multivariate normal distribution to detect mining areas and their expansion over time in Myanmar [51]. Landsat imagery was used to learn 11 land use land cover (LULC) classes, including a mine class, using a maximum likelihood classifier in the Dhanbad district of India [49, 77]. Limestone mining areas were mapped in the Kadapa district of Andhra Pradesh using Sentinel-2A images [85] and a random forests classifier. Surface mining activities in the Goynuk open cast mine in Turkey were identified using an SVM classifier on high resolution satellite imagery (1m) from the Ikonos and Quickbird systems [23]. High resolution satellite imagery of Quickbird-2 was also used to train an SVM classifier to map active mines in Milos island, Greece, over a period of 23 years (1987–2010) [68]. Multi-modal remote sensing data including both synthetic aperture radar (SAR) data from Sentinel-1 and optical data from Sentinel-2 were used to detect coal mines in the Asansol and Jharia regions of India [7] using an SVM classifier. Active surface mines were mapped in the Jiu valley, Romania [86] using an SVM classifier operating on derived spectral indices such as NDVI, Soil-Adjusted Vegetation Index (SAVI), and Modified Soil-Adjusted Vegetation Index-2 (MSAVI-2).

Pixel-level classification is known to not pick up semantic and contextual features; deep learning methods based on convolutional neural networks (CNNs) are seen to perform better for this reason [8]. Open-pit mining areas were mapped in Yuzhou city, China using high spatial resolution satellite imagery from Gaofen-2 (GF-2) [18, 89] with CNNs used for the segmentation task. A DUSegNet model inspired from SegNet, UNet, and DeconvNet, was used here. Sentinel-2 satellite data was used to identify surface coal mines in Australia, Germany, India, Poland and China [54] using pre-trained deep networks such as VGG, ResNet, and DenseNet for patch wise classification. Open-pit mining areas in the Ordos city, China were identified using a semantic segmentation network based on the attention mechanism [27]. Artisanal and small-scale mining areas were detected in West Africa using Sentinel-2 satellite imagery on a modified U-Net architecture [19, 22].

In our study, we also use a UNet architecture to identify mining areas using remote sensing. U-Net was originally developed for the segmentation of neuronal features that appear as discolourations in biomedical images, and was found to work well with imbalanced classes where the damaged neuronal areas were much smaller in extent than other areas [71]. UNet is known to give a good performance on small training datasets [71], and hence seemed suitable for our purpose where we too have a limited set of mining polygons. UNet has been heavily used even in the remote sensing context for applications such as road network extraction [64], mapping of mangroves [53], tree species classification [46], segmentation of deciduous and evergreen trees [47], mapping of burnt regions [83], tree health classification [41], and detection of mines [19, 89].

2.2 Impact of mining

The construction and operation of mines alters the natural flow of groundwater and leads to dewatering of the aquifers and diversion of surface runoff, which may further result in the depletion and pollution of groundwater [11, 60]. Surface mining regions such as in the West Bokaro coalfield in Jharkhand faces acute shortage of portable water extracted from the ground [81]. Household interviews of residents staying near mining sites indicate

that people living closer to iron-ore mines have more respiratory illnesses [74]. This arises from dust and fuel burning [90], and heavy metal contamination of the soil, air, and water [40]. Surface mining activities also lead to deforestation. Forests are home to diverse flora and fauna, and the livelihood of tribal communities also depend upon forest produce [35]. In the Dakra mining area in Jharkhand, 4% out of the 10% deforestation noticed in the district of Ranchi was primarily due to mining activities [33]. Post the mining operations once the mines are exhausted, the contaminated water and degraded land interferes with vegetation growth. Although the Ministry of Coal (MoC) and the Ministry of Environment, Forest and Climate Change (MoEFCC) in India have imposed stringent regulations to carry out land reclamation on overburden sites [45], reclamation in the Jharia coalfields between 2000-2015 was observed to have happened in only 21% of the overburden area.

Mining also results in substantial socio-economic changes in surrounding areas. An operational mining site is often accompanied with improved rail and road infrastructure to transport the mined material. Inbound migration of workers to work in the mines can result in diversion of agricultural and forest land to residential areas [24]. Corporate social responsibility (CSR) rules imposed on mining corporations are supposed to provide for wider community welfare through schools, hospitals, food security, gender equality, and ensure environmental sustainability [31]. However, it has been observed that CSR funds earmarked for community development often go under-utilized [76]. Illegal mining areas also tend to mushroom around abandoned mines or by scavenging at operational mines [50]. Significant ecological damage therefore tends to result from these illegal mines and poor adherence to environmental norms even by registered mines, despite an improvement in infrastructure and urbanization around the mining sites.

In our study, we develop automated methods to monitor similar impacts of mining such as the extent of mining area, deforestation, built-up activity, agricultural land conversion, socio-economic development, and increase in particulate matter concentration. We present a characterization study of these changes having taken place in the proximity of 628 mining sites in India.

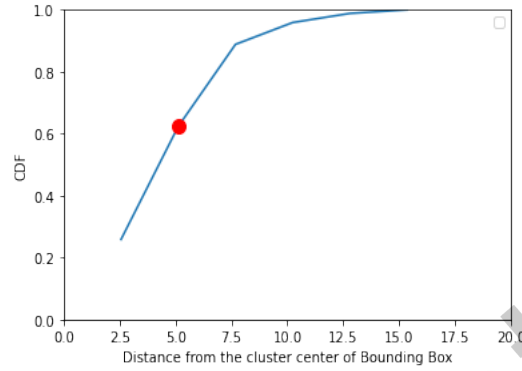
3 DATASET

To build a supervised classifier for mining delineation, we use a global dataset of more than 6,000 mines that was created through visual inspection of high resolution Bing and Sentinel-2 imagery as of 2019 [55]. The dataset provides 21,060 polygons of global surface mining sites which were operational between 2000-2017, and covers a total area of $57,277 \text{ km}^2$ under mines. The dataset has been used in several innovative ways by researchers: to obtain deforestation trends due to expansion of industrial mining [34], ecological impacts in the Belt and Road countries since 2013 [20], links between local conflicts and water scarcity created due to mining in Africa and central America between 2002-2017 [84], biodiversity loss in global supply chains of mining products [14], and the impact of these mines in Africa on urban growth and material wealth [69].

For our study, we used 781 polygons of Indian surface mining sites in the dataset and refer to it as the Indian surface mines dataset in subsequent sections. The average size of each polygon was 2.41 km^2 . Polygons belonging to the same mining area were clustered together, and we identified 170 mining areas by grouping nearby polygons together. This was done by using k-means clustering on the (latitude, longitude) of the centroid of each polygon, and we found that a choice of $k = 170$ was able to produce distinct mining area clusters. A square of $10.24 \text{ km} \times 10.24 \text{ km}$ was able to entirely encompass 63% of the mining area clusters, as shown in figure 1, and we chose this value as the image size over which to develop the mining delineation classifier. We use Sentinel-2 optical data as the source of satellite imagery, which at a resolution of $10 \text{ m} \times 10 \text{ m}$ corresponding to a single pixel, results in an image size of 1024×1024 for the mining area classifier. Mining area clusters larger than this image size were analyzed using multiple image tiles.

Satellite images of 2019 for Sentinel-2 were downloaded from the Google Earth Engine, and is referred to as the D1_2019 dataset henceforth in the paper. Our choice of using Sentinel-2 was guided based on two reasons. First,

Fig. 1. CDF (x-axis denotes the horizontal and vertical distance from the cluster center of a mining area to the square boundary of the image tile; y-axis denotes the cumulative percentage of clusters that entirely fit within this boundary; the marked red point denotes a boundary of twice 5.12km (10485.76 hectares) on all sides of the cluster center; 63% of the clusters fit within this boundary)



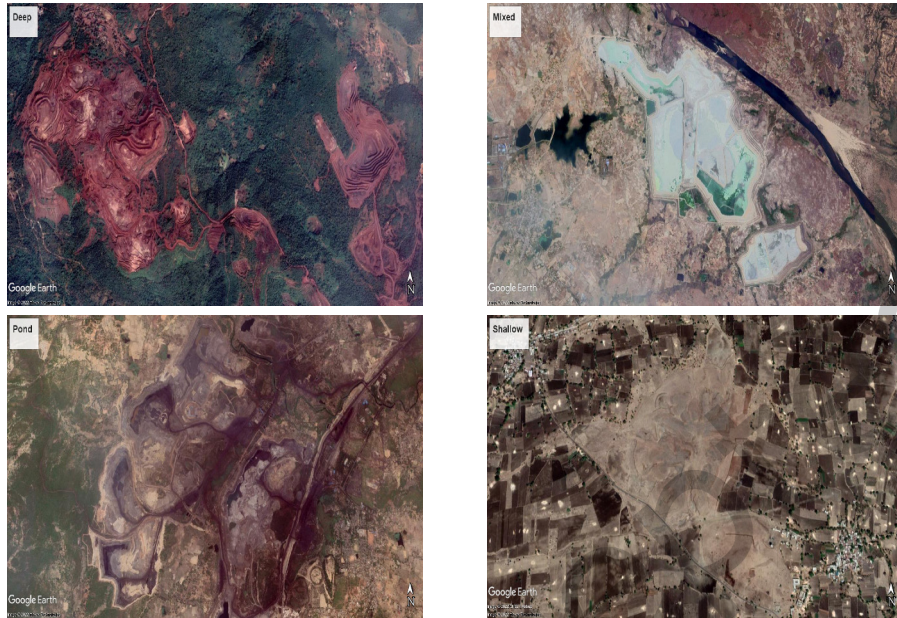
its revisit frequency is 7-10 days and it has been operational since 2017, therefore it can help analyze changes in the extent of mining areas over these years. Second, it is an open datasource and provides the highest spatial resolution amongst open satellite datasources. This would help in the reproducibility of our results and methods at a low cost. Many others papers have used the Landsat satellite data which stretches even further back in time, but provides a spatial resolution of only 30m, which we found to be inadequate to observe the kind of features we found distinctive to mining areas [51, 78, 79].

We further inspected these 170 mining areas in our dataset using high resolution imagery from Google Earth Pro, and found that 5 marked mining areas consisted only of dense vegetation, likely post reclamation; we decided to drop these mines from our dataset since they would not give any distinctive features for mining sites. The rest of the mining areas were categorized into one of the following four types of unique mining characteristics, also shown in table 1 and table 2: (a) areas with mines that have visible deep contours and which do not result in the formation of water bodies at the bottom, (b) areas with mining strips that do not have such deep contours and we refer to them as shallow contour mines, (c) areas which result in large water bodies at the bottom, which we refer to as ponded mines, and (d) mixed mining areas that seem to consist of multiple types of these mines. We then divided this data into a train-val-test split evenly for all the four types of mining areas, and learned a UNet based classifier. The architecture and results are described in the forthcoming sections.

Table 1. Categories of surface mines in the D1_2019 dataset

Category	No. of mines
Mixed mines	113
Deep contours	12
Shallow contours	21
Ponded mines	19

Table 2. Categories of mines



In addition to the Indian surface mines dataset described above for training a classifier, we also obtained a dataset of 628 (latitude, longitude) coordinates of mines that were granted clearance by the Ministry of Environment, Forest and Climate Change (MoEFCC) and the Indian Bureau of Mines (IBM) between 2006 and 2012 [62]. We refer to this dataset as the Indian mine clearance dataset in subsequent sections. We run our mine delineation classifier on areas around these coordinates to detect the expansion of mines from 2018 to 2022. We also observe other changes in their proximate area, such as deforestation, increase in built-up area, and changes in the socio-economic profile of areas close to the mining sites.

4 MINING DELINEATION CLASSIFIER: MODEL AND RESULTS

After removing the mining areas that were found to be covered in vegetation, we were left with 165 images in the Indian surface mines dataset. This was divided into a train-val-test split in a 70:15:15 ratio, in a category-wise manner. Data augmentation through random rotation (clockwise, anti-clockwise, or up-side-down) and flipping (horizontally and vertically) was also performed. Further augmentation was performed by also downloading Sentinel-2 images for 2021, so that the classifier could be resilient to variations caused by satellite sensors across the years. This dataset is called the D1_2021 dataset. Through manual visual inspection on Google Earth Pro, we checked to ensure that there were no significant changes in the groundtruth between 2021 and 2019.

4.1 Classifiers

A random forest pixel-wise classifier was trained to serve as a baseline by sampling pixels randomly from the mining areas and adjacent non-mining areas. The classifier performed with an accuracy of 84.82% and F1 score of 35.3%.

Based on the results reported in related work, a UNet architecture with 7 encoder and decoder layers was chosen as the main classifier for the delineation of mining areas, and several variants were tried [71]. UNet is a

semantic segmentation architecture originally developed in the medical image analysis domain [71] but has been found to work well for geo-spatial studies as well, especially when classes are imbalanced and the supervised training data is less in quantity [64, 71, 89]. In our case too, the training dataset consists of only 165 images and the non-mining to mining pixels ratio is heavily imbalanced, at 8.83 [13]. UNet is a fully convolutional network that consists of three components: an encoder portion built as a series of convolution layers followed by max-pooling, a bottleneck portion with two convolution layers, and a decoder portion which through a series of up-samplings produces a segmentation map by assigning an output label to each pixel. The Sentinel images we use provide a multi-spectral input with each band as a channel, and the model is thus architected to take a $1024 \times 1024 \times (\text{number of channels})$ image as input and output a $1024 \times 1024 \times 1$ prediction map.

We experimented with taking all twelve Sentinel-2 bands as features (channels), and also include nine additional derived bands such as NDVI, Mine index, etc. as mentioned in table 3 [15, 58, 73]. Some of these derived bands were proposed in related work specifically to help identify mining areas [57]. Initial tests however showed that these derived bands did not help improve the UNet model performance, and therefore we only used the twelve bands to provide 12-channel images to the model.

Table 3. Derived spectral indices

Name	Formula
Clay Minerals	$\frac{SWIR1}{SWIR2}$
Ferrous Minerals	$\frac{SWIR1}{NIR}$
Iron oxide (Ferric Minerals)	$\frac{RED}{BLUE}$
Transformed NDVI	$\sqrt{\frac{NIR-RED}{NIR+RED}} + 0.5$
NDVI	$\frac{NIR-RED}{NIR+RED}$
Difference vegetation index	$NIR-RED$
Simple Ratio	$\frac{NIR}{RED}$
SQRT simple ratio	$\sqrt{\frac{NIR}{RED}}$
Mine Index	$\frac{SWIR1-SWIR2}{SWIR1+SWIR2}$

We also experimented with changing the number of encoder and decoder layers from 7 to 4, tried various optimizers including SGD, RMSProp, Adamax, Adam, Adadelta and Adagrad [72], and variations in loss functions of binary cross entropy (BCE) loss, focal loss to be more sensitive to class imbalance, dice loss to focus on an IOU goal, and combinations of these different loss functions [43].

We further experimented with a MultiResUNet architecture variation wherein feature maps are extracted at various scales (with 3 successive convolutions of 3×3 filters) and residual connections were incorporated to make learning easier [30, 42]. In another variation, we incorporated attention gates to enhance the weights placed on specific pixels of interest [1], and similarly experimented with deep supervision which allows the feature maps at each scale to be trained in a supervised manner [1]. Further, we experimented with and without transfer learning from a VGG-19 network [54]. The transfer learning models used only the RGB bands instead of the full range of 12 Sentinel bands.

4.2 Evaluation

Table 4 shows the results. Our final choice was the 7-layered UNet architecture with batch normalization, RMSProp as optimizer, a combination of BCE and focal loss as the loss function, trained for 600 epochs. Early stopping was used with convergence on minimum validation loss. This provides an IOU of 50.4%, and precision and recall of 69.1% and 76.3% respectively. Out of the best performing models, we chose the one that gave higher IoU and recall score to be able to spot more mining areas. The performance is much better than the baseline random forest model and comparable with the performance reported by other papers using Landsat or Sentinel satellite data [7, 22, 49, 51, 54, 77, 85, 86]. Research works that have used higher resolution imagery such as Gaofen-2, OM-DeepLab, Ikonos, and Quickbird report better performance, but such imagery is not freely available or for a longer past [18, 19, 27, 89].

Table 4. Experiments

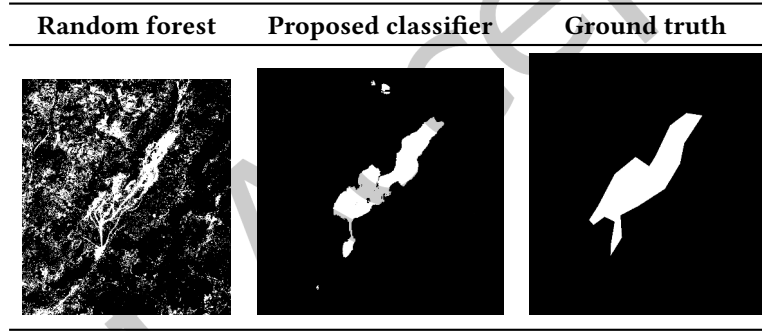
Data Augmentation			
	Precision	Recall	Mean IOU
D1_2019 + D1_2021	0.78066	0.499905	0.35659
D1_2019	0.800012	0.584270	0.448768
Feature Addition			
21 Band Data	0.80425	0.56929	0.43005
12 Band Data	0.800012	0.584270	0.448768
Architectural Variations			
4 Layered (4L)	0.783648	0.542847	0.407554
Multiresunet (4L)	0.528483	0.068396	0.037821
Multiscale Input (4L)	0.852071	0.525453	0.381543
Attention Model (4L)	0.77919	0.610458	0.417647
Deep Supervision (4L)	0.735892	0.675445	0.4702
VGG19(4L)	0.711208	0.511309	0.359607
Deep Supervision (7L)	0.640273	0.744395	0.433609
Dropout (7L)	0.804792	0.480026	0.364324
Batch Norm. (BN) (7L)	0.782488	0.67778	0.504973
Loss Function Variations			
BCE	0.782488	0.67778	0.504973
Focal+BCE	0.691768	0.76362	0.50448
Optimizer Variations			
Adadelta	0.57175	0.55767	0.40857
SGD	0.741178	0.60209	0.42717
Adagrad	0.697987	0.678439	0.453046
Adam	0.722042	0.68413	0.483329
Adamax	0.74969	0.67848	0.48371
RMSProp	0.691768	0.76362	0.50448

Table 5 also shows the disaggregated performance for the four types of mine categories. The classifier is able to perform reasonably well across all the categories. Corresponding prediction maps generated by the baseline and UNet classifier are also shown in tables 6 and 7. The UNet classifier seems to perform best on pond mines, followed by deep, mixed, and shallow contour mines, in that order.

Table 5. Comparison of the UNet classifier with random forest (RF) as baseline, analyzed on four different categories (deep, pond, mixed and shallow) of surface mines.

	Precision	Recall	Mean IoU
Baseline(RF)	0.234	0.721	0.217
Proposed classifier	0.69	0.76	0.50
Deep contours	0.73	0.61	0.49
Mixed mines	0.66	0.77	0.49
Ponded mines	0.76	0.72	0.62
Shallow contours	0.81	0.77	0.45

Table 6. Comparison of the baseline prediction map and the UNet classifier prediction map against ground truth



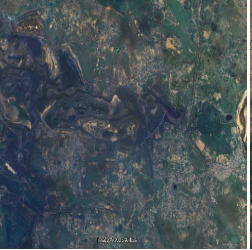
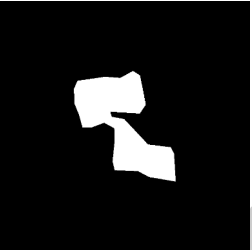
5 LAND-USE, SOCIO-ECONOMIC DEVELOPMENT, AND PM2.5 CONCENTRATION CHANGES AROUND MINING AREAS IN INDIA

5.1 Validation and feasibility testing

We further used a small sample of mines from the Indian clearance dataset of 628 mines to evaluate the performance of the UNet trained model on an out of sample dataset. We randomly selected 10 mines from across different states, spanning Orissa, Jharkhand, Chhattisgarh, Tamil Nadu, Gujarat, and Karnataka. For each mine, we created groundtruth manually through visualization on Google Earth Pro of a 10.24km x 10.24km buffer around the reported (latitude, longitude) of the mining site. Table 8 shows the performance of the UNet classifier trained on the surface mining dataset as explained in the previous section. The performance is seen to be satisfactory for all the 10 mines.

We next ran the classifier for the years of 2018 and 2022, to detect expansion of these mines during this interval. As shown in table 9, the identified mining area increased across all the 10 mines, except one mine in the state of Karnataka. An increase in mining area is expected since clearances for these set of mines were granted

Table 7. Comparison of the UNet classifier against ground truth on different spectral signatures of surface mines

	Deep	Mixed	Ponded	Shallow
Google earth imagery				
Ground Truth				
Prediction map				

between 2011 and 2012. We further verified through Google Earth Pro imagery that the Karnataka mine which showed a decrease in mining area according to our classifier indeed saw an increase in tree cover, perhaps due to reclamation of some areas.

To check the feasibility of monitoring land-use changes around the mining sites, we built two additional indicators. First, we used the Global Forest Watch (GFW) global annual tree cover loss output at a 30m resolution to report deforestation in the 10.24km x 10.24km area around the mining sites [38, 39]. GFW provides a facility for real-time monitoring of forest cover within a defined area, anywhere in the world. Table 9 shows that the tree cover change around mining sites ranged from -95.2 to 0 hectares (negative value indicates tree cover loss), with a mean and median of -33.9 and -22.8 hectares respectively, between 2018 to 2022. Second, we used the Dynamic World Land Use and Land Cover (LULC) classification tool to detect changes in built-up, shrubs and scrubs, cropland, and bare land area within the same region around each mining site [17]. Dynamic world is a near real-time LULC classification product that provides probabilities of nine classes: water, trees, grass, flooded vegetation, crops, shrub and scrub, built-up, snow and ice, and bare land [12] at each pixel. It relies on

semi-supervised deep learning to produce pixel-level classification over Sentinel-2 imagery at a 10m resolution. The output is openly licensed by the World Resources Institute and is freely available on Google Earth Engine [28]. Mining is often accompanied with the rise of informal settlements of migrant workers who move to the area in search of work, and also new housing, office infrastructure, roads, power plants, etc. Analyzing the Dynamic World output showed a built-up area increase between 2018 to 2022 of 67.7 hectares on average. Shrubs and scrubs, croplands and bare lands decreased during the same study period with a net decrease of 3156.8, 2514.4, 268.4 hectares respectively, across these mines, and is shown in table 9. Table 13 show the land use changes in the proximity of a few mining sites during this period.

We next built two indicators to monitor socio-economic development and health outcomes at mining sites. To track socio-economic development changes in the area, we used a poverty mapping approach, similar to [44, 63, 67, 80]. Researchers have developed machine learning methods that use a combination of daytime satellite imagery from sources such as Landsat and Sentinel, and nightlights data of DMSP and VIIRS nighttime lights time series for the intensity of lights at night, to predict socio-economic indicators such as the wealth index. We use a similar method to obtain a socio-economic development index called the Aggregate Development Index (ADI) [9], which is composed of indicators related to asset ownership, primary source of drinking water, primary source of lights, access to bathroom facilities, and literacy rate [36] at a village level. ADI ranges from 5 to 15, with a higher ADI indicating better socio-economic development. We obtained changes in ADI between the years 2011 to 2019, calculated as a weighted average of all villages in a sub-district in which the mine is located, to reflect the development of villages in the immediate proximity of the mine. We found that during these years, ADI at the sub-district level changed from a mean base of 7.03 to between -0.1 to 0.44 as shown in table 9, with a mean and median change of 0.16 and 0.2 respectively. The change thus does not appear to be significant.

To track health outcomes, we used data of particulate matter concentration (PM_{2.5}) changes between 1998-2020 in the sub-district of each mining site [37]. Mining areas are known to emit various pollutants such as sulphur dioxide, nitrogen oxides, particulates and other emissions harmful to human health [29]. These arise from blasting and drilling operations, transportation of rocks, and the warehousing and processing of extracted raw materials [75]. Particulate matter of PM_{2.5} and PM₁₀ dimensions lead to chronic respiratory diseases [5, 25, 70]. According to World Health Organization guidelines [61], the recommended annual concentration of PM_{2.5} and PM₁₀ should not exceed 10 and 20 $\mu\text{g}/\text{m}^3$ respectively. As per India's National Ambient Air Quality Standards, the annual concentration of PM_{2.5} should not exceed 40 $\mu\text{g}/\text{m}^3$ for residential, industrial, and ecologically sensitive areas [16]. We obtained changes in the PM_{2.5} concentration between 2006-2020 using a gridded dataset estimated from Nasa's MODIS, MISR, and SeaWiFS instruments [3], and found that PM_{2.5} concentration had increased around mining sites from a mean base of 34.43 by 6.89 $\mu\text{g}/\text{m}^3$ on average. This is shown in table 9.

5.2 Characterization study across all of India

Encouraged by the feasibility to monitor temporal change in the extent of mining area and land use, we next attempted to repeat the exercise at a larger scale of 628 mines from across multiple states of India. These mines were granted clearance during 2006 to 2012 and therefore our analysis helps understand land-use, socio-economic, and health changes during the initial decade or so of the start of mining operations. We are in the process of also similarly monitoring changes around mines that have been abandoned, to examine if land reclamation processes are working as intended. We conduct two sets of analysis. We first study state-wise patterns in the land-use, socio-economic development, and health related indicators of mining sites. Next, we compare these changes in the proximity of mining sites with changes in areas which predominantly have an agricultural economy.

5.2.1 Changes at mining sites. We studied 628 mines and report in table 10 the changes in various indicators. We also conduct paired sample t-tests on the mines in each state for the specified study period, to test whether changes in the indicators during this period were non-zero. The null hypothesis for each state is defined as the

difference between the means in 2018 and 2022 as being zero. The alternative hypothesis is for the difference in means being non-zero.

For changes in the extent of mining area, we found that the null hypothesis could be rejected in all states except Karnataka (KA), indicating that the changes were statistically significant. This is shown in table 10. The mean change in mining area ranged between 228.7 to 1820.3 hectares. Across all states, this increase in mining area is accompanied with an increase in built-up area. The increase in mining and built-up area came at the expense of a reduction in area under shrubs and scrubs, croplands, and bare lands. The states of Andhra Pradesh (AP), Tamil Nadu (TN), and Rajasthan (RJ) mostly converted their croplands and bare lands into the expansion of mines. This seems to tally with metadata published as part of the Indian mine clearance dataset which provides for each mine the primary land-cover class that is being diverted to mining areas. According to these statistics, 69.6% of the mining sites in these states included some extent of wasteland. On the other hand, the states of Jharkhand (JH), Goa (GA), Orissa (OR), Madhya Pradesh (MP), and Maharashtra (MH) converted their shrubs and scrubs and tree cover are for the expansion of mines. According to statistics published in the clearance data, 45.7% of mines had a mix of wasteland or forests, and 20.5% were to come up on mostly forest areas. Gujarat (GJ) converted most of its bare lands for mining expansion according to our assessment, and clearance data indicated that 31.2% of mines had a mix of wasteland and forests. Chhattisgarh (CG) converted most of its tree cover for mining expansion; clearance statistics similarly indicated that 75% of the mines in Chattisgarh were coming up on forest areas.

5.2.2 Comparison of mining areas with non-mining areas. We next attempted to understand how changes in socio-economic development and health indicators differ between mining and non-mining areas. We conduct this analysis at the sub-district level. A mining sub-district is one that contained at least one mine out of the 628 mines in our dataset. We compared these with agriculture led sub-districts obtained through the following process. We used a dataset jointly produced by ICRISAT (International Crops Research Institute for the Semi-Arid Tropics), International Food Policy Research Institute (IFPRI), and TCI (Tata-Cornell Institute) which provides in one place several useful variables related to agriculture and allied sectors, irrigation, infrastructure, GDP, and others, curated from multiple census and survey data sources [26]. We first identified districts for which the agriculture State Gross Domestic Product (SGDP) was greater than their manufacturing SGDP, for each year during 1990 to 2011. We eliminated from this any districts which had mines according to our mining clearance dataset in subsequent years. We then chose one sub-district each from the identified agricultural districts, which had the least built-up area to be able to focus on more rural sub-districts.

In table 11, we show the changes in socio-economic development and of PM2.5 concentration, between mining sub-districts (columns 3, 8) and agri-led sub-districts (columns 5, 10), for each state. We also conduct a t-test to assess the statistical significance of changes between mining and agri-led sub-districts. The null hypothesis is that the mean change is zero. Results are shown in columns 6 and 11. We find that sub-districts with the presence of mines saw a positive change in socio-economic development only in the states of Jharkhand, Orissa, Madhya Pradesh, and Rajasthan, during 2011 to 2019. This change was however modest, of less than 1 unit of ADI, on a mean base of 8.5, despite these states being among the top seven states that contributed 97.04% value of the total mineral production of India [56]. When compared with agri-led sub-districts, no clear pattern emerged. These agri-led sub-districts had a mean ADI base of 9.3, and among those that showed a positive change, the change was only slightly greater than that in mining sub-districts. In terms of socio-economic development therefore, we did not see mining activities as contributing more positive change than other pathways. In fact, mining sub-districts were typically less developed than non-mining areas. Rajasthan and Andhra Pradesh were the only states where mining sub-districts seemed to do marginally better than agri-led districts.

In a similar manner, we compared changes in PM2.5 concentrations between mining and agri-led sub-districts. Mining sub-districts in general had a higher PM2.5 concentration than agri-led sub-districts, as expected. All

states also showed a statistically significant and positive change in PM2.5 concentrations during 2006-2020, for both mining and agri-led sub-districts, indicating that particulate matter pollution is increasing everywhere. Interestingly though, only in Orissa did mining sub-districts have a greater increase in PM2.5 concentration than agri-led sub-districts. This shows that agri-led sub-districts are becoming polluted more rapidly than mining sub-districts (which have anyway had poorer air-quality historically). This is likely to be a consequence of rapid urbanization.

It is unfortunate though, that mining sub-districts in general are less socio-economically developed and more polluted than other sub-districts, but do not seem to enjoy any significant benefits such as more rapid socio-economic development. Despite the relevance of mining activities for the economic growth of the rest of the country, mining areas often suffer at the cost of this broader development elsewhere, as has long been argued by many researchers [24, 31, 76].

We next compare mining and agri-led sub-districts in aggregate in table 12, and also compare them with means of all sub-districts in India. Both mining and agri-led sub-districts saw a significant increase in built-up and PM2.5 concentration, and a significant decrease in croplands and tree cover, during 2018-22. The relative difference with changes in indicators between mining and agri-led sub-districts seem to be significant only for built-up area, with mining sub-districts showing a more rapid increase than agri-led sub-districts. Otherwise, despite contributing towards the economic growth of the country at the cost of significant ecological damage, mining areas do not see any significant benefits in terms of socio-economic development.

Table 8. Performance of trained UNet classifier on an out-of-sample dataset, in the year 2022. The name of sampled mining sites as per the Indian clearance dataset are listed under the state in which it operates.

State	Latitude, Longitude	Granted year	Precision	Recall	IoU
Orissa					
1. Khond Bond Iron and Manganese Ore Mine	21.9, 85.3	2011	0.586	0.943	0.566
2. Bolani Iron Ore Mine	22.1, 85.2	2012	0.631	0.874	0.578
3. Talangi-B Chromite Ore Mine	21.06, 85.8	2012	0.770	0.586	0.499
4. Joruri Iron Ore Mines	21.9, 85.4	2012	0.504	0.956	0.492
Jharkhand					
1. Mclellan Iron Ore Mine	22.2, 85.2	2011	0.901	0.809	0.743
2. Hisri(New) Bauxite Mine	23.4, 84.5	2011	0.792	0.682	0.579
Chhattisgarh					
1. Bailadila Iron Ore Mine	18.6, 81.2	2011	0.579	0.836	0.520
Karnataka					
1. Thimmappanagudi Iron Ore Mine	15.1, 76.5	2011	0.589	0.835	0.528
Gujarat					
1. Rampara, Kukras, Bhetali & Anandpura Limestone Mine	20.9, 70.5	2011	0.631	0.790	0.541
Tamil Nadu					
1. Aminabad and Khairulabad Limestone Mine	11.1, 79.1	2011	0.622	0.829	0.552

Table 9: Monitoring of area under mining, land cover changes (built-up, cropland, shrubs and scrubs, tree cover), and outcomes (ADI, PM_{2.5} concentration), for the sampled mining sites.

Mining site	Change in mining area in hectares (2018-2022)	Change in built-up area in hectares (2018-2022)	Change in cropland area in hectares (2018-2022)	Change in shrub and scrub area in hectares (2018-2022)	Change in bare area in hectares (2018-2022)	Tree cover loss in hectares (2018-2022)	Change in ADI (2011-19)	Change in PM _{2.5} concentration in $\mu\text{g}/\text{m}^3$ (2006-20)
Khond Bond Iron and Manganese Ore Mine	1111.4	48.3	-34.9	-92.8	-28.2	-74.5	0.37	8.6
Bolani Iron Ore Mine	376.79	46.9	17.5	-147.6	-0.68	-37.7	0.17	12.2
Talangi-B Chromite Ore Mine	689.56	181.5	91.0	-40.3	26.1	-41.8	-0.03	8
Joruri Iron Ore Mines	2443.15	31.4	12.1	81.4	72.9	-95.2	0.44	10
McLellan Iron Ore Mine	11.28	12.3	-4.8	-128.2	-0.61	-8.04	0.31	11.5
Hisri(New) Bauxite Mine	99.89	46.5	-115.5	-130.1	-8.7	-8.05	-0.07	9.4
Bailadila Iron Ore Mine	817.02	109.7	-6.3	-217.0	-9.8	-60.8	-0.1	2.9
Thimmappanagudi Iron Ore Mine	-1769.21	79.9	-657.4	-2615.3	-34.5	0	-	2.8
Rampara, Kukras, Bhetali & Anandpura Limestone Mine	450.69	107.4	-1009.1	62.0	-9.6	0	0.23	5.6
Aminabad and Khairulabad Limestone Mine	819.72	13.6	-807.0	71.1	-275.4	-7.81	-	-2.1

Table 10. State-wise mining area and land cover (built-up, cropland, shrub and scrub, bare, tree cover) changes. The values indicate the mean difference $\pm$ standard deviation, with statistical significance (* for p -value < 0.05 , ** for p -value < 0.01 and *** for p -value < 0.001). Statistically significant and positive mean differences signify an increase the indicator from 2018 to 2022,

State	Change in mining area in hectares (2018-2022)	Change in built-up area in hectares (2018-2022)	Change in land area in hectares (2018-2022)	Change in shrub and scrub area in hectares (2018-2022)	Change in bare area in hectares (2018-2022)	Tree cover loss in hectares (2018-2022)
AP	1686.9 ± 1198.7***	53.2 ± 115.2***	-536.0 ± 462.4***	-7.8 ± 478.9	-136.2 ± 271.3***	-2.1 ± 8.7
JH	400.3 ± 357.9***	47.6 ± 56.0***	-137.8 ± 503.9	-119.8 ± 280.9*	-10.1 ± 24.8*	-17.1 ± 22.7***
GA	519.4 ± 422.7***	39.2 ± 48.6***	-8.7 ± 15.6***	-196.9 ± 187.9***	0.18 ± 3.03	-11.6 ± 6.6***
OR	894.6 ± 849.4***	61.3 ± 57.7***	-27.6 ± 199.5	-278.4 ± 330.7***	7.61 ± 39.3*	-53.0 ± 73.6***
KA	143.1 ± 1269.7	77.5 ± 87.8***	-514.4 ± 401.4***	-1948.8 ± 1467.3***	-38.0 ± 88.7***	-0.3 ± 1.9
TN	400.6 ± 856.5*	99.1 ± 145.5***	-431.5 ± 500.5***	-213.0 ± 654.1	-319.5 ± 261.2***	-6.2 ± 6.2***
GJ	1820.3 ± 1674.3***	105.7 ± 109.7***	86.4 ± 820.1	129.8 ± 1046.2	-1039.9 ± 1713.1**	0 ± -
MP	228.7 ± 252.4***	123.3 ± 50.9***	-60.2 ± 299.1	-424.1 ± 352.7***	-38.8 ± 170.5	-10.5 ± 23.7*
CG	1247.0 ± 1332.6***	115.3 ± 95.2***	-85.5 ± 488.6	-146.0 ± 528.1	-35.5 ± 65.5*	-17.7 ± 30.8**
MH	1085.9 ± 1476.1***	72.1 ± 53.7***	-142.8 ± 441.9	-205.5 ± 409.0*	9.1 ± 20.6*	-10.8 ± 21.3*
RJ	770.5 ± 775.7***	190.5 ± 130.5***	-366.7 ± 430.4***	11.2 ± 424.6	-59.8 ± 260.5*	0 ± -

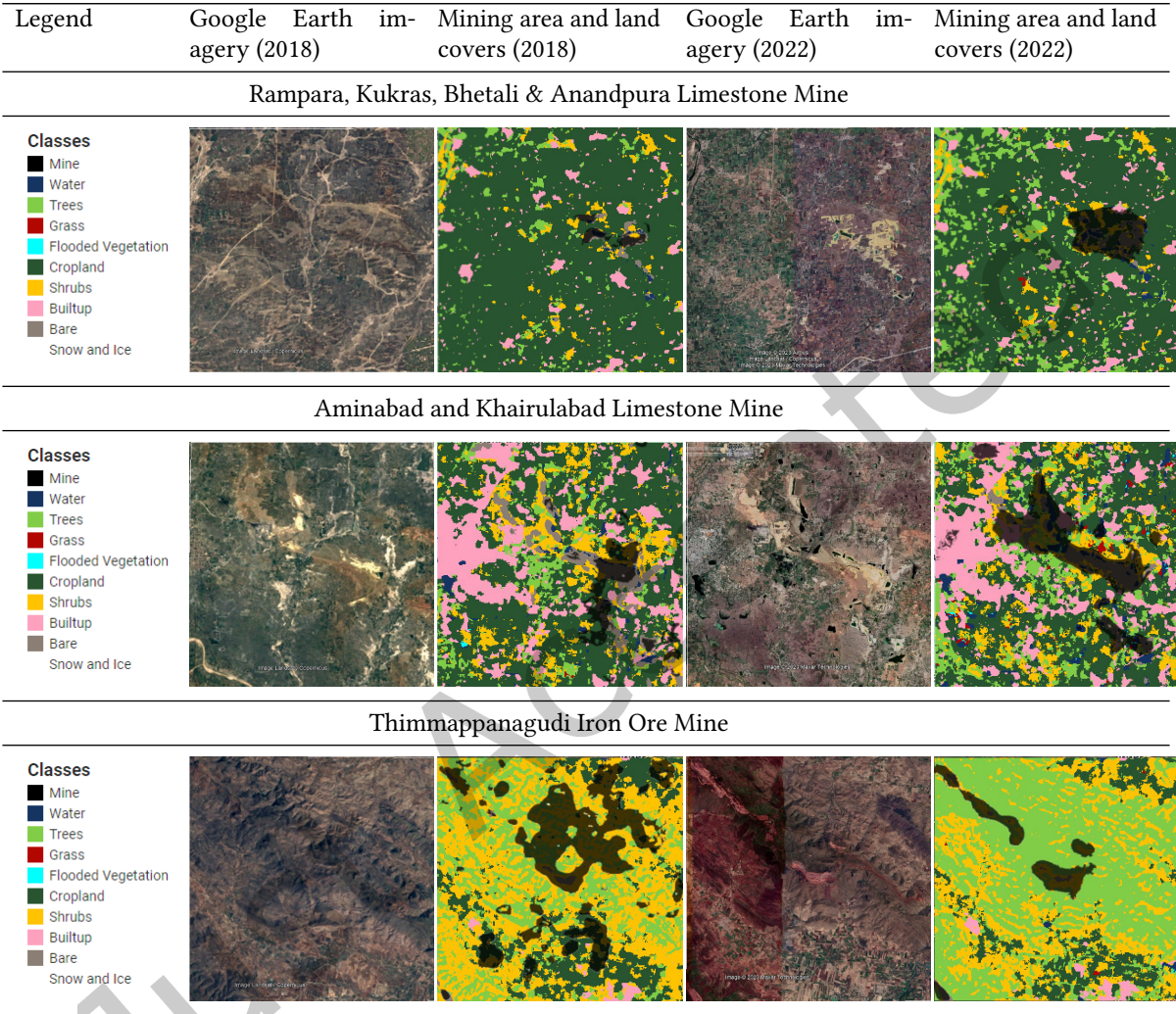
Table 11. State-wise temporal (column 3, 5, 8, 10) and cross-sectional (column 6, 11) statistical significance of change in socio-economic development and PM2.5 concentration, across mining and agri-led sub-districts, along with initial values of development and PM2.5 concentration in the base year (2, 4, 7, 9). We define $H_{0,ADI}$: mean change in ADI across mining sub-districts - mean change in ADI across agri-led sub-districts = 0; and $H_{0,PM2.5}$: mean change in PM2.5 across mining sub-districts - mean change in PM2.5 across agri-led sub-districts = 0.

State	Mean ADI (2011) of all mining sub-districts	Mean change in ADI of all mining sub-districts between 2011-2019	Mean ADI (2011) of all agri-led sub-districts	Mean change in ADI of all agri-led sub-districts between 2011-2019	$H_{0,ADI}$	Mean PM2.5 concentration in 2006 of all mining sub-districts	Mean change in PM2.5 concentration of all mining sub-districts between 2006-2020	Mean PM2.5 concentration in 2006 of all agri-led sub-districts	Mean change in PM2.5 concentration of all agri-led sub-districts between 2006-2020	$H_{0,PM2.5}$
AP	10.21	-0.1 ± 1.2	10.12	$-1.2 \pm 2.06^{***}$	Reject H_0	30.23	$2.7 \pm 1.6^{***}$	26.9	1.2 ± 2.2	Cannot reject H_0
JH	7.03	$0.5 \pm 0.5^{**}$	6.87	$0.64 \pm 0.92^{***}$	Cannot reject H_0	43.7	$11.9 \pm 3.0^{***}$	50.8	$10.9 \pm 2.8^{***}$	Cannot reject H_0
GA	-	-	-	-	-	27.61	$5.4 \pm 0.4^{***}$	-	-	-
OR	6.51	$0.6 \pm 0.8^{***}$	5.6	$0.97 \pm 0.33^{***}$	Cannot rej. H_0	39.14	$9.6 \pm 1.9^{***}$	24.3	$3.8 \pm 0.8^*$	Reject H_0
KA	10.55	-0.5 ± 1.4	10.15	-0.28 ± 1.5	Cannot rej. H_0	27	$2.4 \pm 1.5^{***}$	18.7	$1.7 \pm 0.8^*$	Cannot reject H_0
TN	11.85	$-1.4 \pm 1.5^*$	12.52	-0.5 ± 1.9	Cannot rej. H_0	27.3	$-0.9 \pm 0.9^{***}$	19.6	-1.1 ± 1.7	Cannot reject H_0
GJ	10.21	$-1.5 \pm 2.0^{**}$	-	-	-	35.9	$4.8 \pm 1.7^{***}$	-	-	-
MP	7.38	$0.6 \pm 0.7^{***}$	7.77	$0.46 \pm 0.72^{***}$	Cannot rej. H_0	43	$9.9 \pm 4.4^{***}$	49.4	$12.3 \pm 5.7^{***}$	Cannot rej. H_0
CG	7.22	0.2 ± 0.7	6.74	$1.44 \pm 0.35^*$	Cannot rej. H_0	47	$12.6 \pm 6.3^{***}$	37	9.1 ± 4.1	Cannot reject H_0
MH	10.75	$-1.8 \pm 1.7^{***}$	10.37	$-2.04 \pm 0.78^{***}$	Cannot rej. H_0	29.6	$6.6 \pm 2.5^{***}$	36.4	$7.3 \pm -$	-
RJ	8.08	$0.5 \pm 0.9^{***}$	9.41	-0.36 ± 1.31	Reject H_0	56.27	$2.9 \pm 5.9^{***}$	60.32	$6.8 \pm 1.6^{***}$	Cannot reject H_0
National	8.5	-0.005 ± 1.39	9.3	$-0.1 \pm 1.4^{**}$	Cannot rej. H_0	40.1	$5.9 \pm 5.4^{***}$	58.9	$8.9 \pm 5.9^{***}$	Cannot reject H_0

Table 12. Comparison across mining, agri-led, and all sub-districts across India. We define $H_{0,temporal}$: mean in 2022 - mean in 2018 = 0, $H_{0,agrilied}$: mean change across mining sub-districts - mean change across agri-led sub-districts = 0 and $H_{0,all}$: mean change across mining sub-districts - mean change across all sub-districts = 0.

	$H_{0,temporal}$ for mining sub-districts (n = 199)	$H_{0,temporal}$ for agri-led sub-districts (n = 204)	$H_{0,temporal}$ for all sub-districts (n = 3415)	$H_{0,agrilied}$	$H_{0,all}$
Change in built-up (2018-22)	651.2 ± 783.4 ***	212.2 ± 364.7 ***	425.9 ± 634.9 ***	Reject H_0	Reject H_0
Tree cover loss (2018-22)	-49.3 ± 313.5 *	-84.9 ± 459.9 **	54.1 ± 275.5 ***	Cannot rej. H_0	Cannot rej. H_0
Change in cropping area (2018-22)	-1234.5 ± 6538.0 **	-221.6 ± 1594.8 *	-822.6 ± 4038.0 ***	Cannot rej. H_0	Cannot rej. H_0
Change in development (2011-19)	-0.005 ± 1.39	-0.1 ± 1.4 **	-0.56 ± 1.79 ***	Cannot rej. H_0	Reject H_0
Change in PM2.5 concentration (2006-20)	5.9 ± 5.4 ***	8.9 ± 5.9 ***	5.8 ± 5.2 ***	Cannot rej. H_0	Cannot rej. H_0

Table 13. Visualizing mining area and land covers on some sampled mines during the study period, referred in table 8 .



6 DISCUSSION AND CONCLUSIONS

Mining is an extractive activity but essential for economic growth. Our goal in this study was to examine land-use changes in areas in the proximity of mining sites to characterize ecological dynamics, and compare them with areas which are predominantly agricultural to characterize socio-economic development and health indicator changes across these areas with distinct economic development pathways. We developed a mining delineation classifier that can help monitor changes in the extent of mining area, and especially help track illegal mining that might be happening beyond the permitted areas, or reclamation of abandoned mines where reforestation and other treatment measures are normally prescribed. We also used the Global Forest Watch and Dynamic World products to monitor tree cover loss and land use changes taking place in the neighbourhood of mining sites.

We then used a poverty mapping classifier and a dataset of particulate matter (PM_{2.5}) concentration to track socio-economic and health indicator changes taking place in sub-districts with mining activities, and compared them with changes in agricultural sub-districts. We plan to augment this suite of tools with similar remote sensing based methods to track other ecological variables such as groundwater access and biodiversity across mining and non-mining areas. This allows us to compare our results with studies and reports that discuss the socio-economic and environmental damage caused by extensive mining [40, 74, 81], especially in the lives of communities dependent upon forests for their livelihood and welfare [35]. Overall, our analysis so far reveals that mining areas are in general more polluted and less developed than non-mining areas, and do not develop as fast as other areas. This shows that populations in the proximity of mining sites do not benefit proportionally from mining activity despite having to bear the brunt of ecological and health damage due to mining.

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