CHAPTER-2

LITERATURE SURVEY

2. General Statement

Coal mining supports local communities by providing raw materials for thermal power plants as well as coal-based industries. However, the mining impacts to the surrounding environment in general, and water in particular. The impacts of extensive coal mining activities on nearby water bodies hold considerable significance at the global scale. The global water pollution caused by coal mining has been the subject of extensive research. However, a limited study has been made in India, to assess coal mining impact on water quality in terms of physicochemical parameters, heavy metals, LULC changes, and impacts on LST, NDVI and NDWI. The significant results and contributions of all of these noteworthy research studies globally have been carefully noted, and described below.

2.1 Mining and Water resource

Tijani, 1994 assessed the quality and suitability of groundwaters in the Moro area of Kwara, Nigeria. The extensive assessment of the chemical analysis of several groundwater samples was carried out. The findings of the chemical analysis shows that Ca^{2+}, Mg^{2+}, and HCO_3^- presented in more concentrations than Na^+, K^+, Cl^-, and SO_4^{2-}. All the aforementioned ions concentrations fall within acceptable norms based on domestic and agricultural guidelines, except the few sites where Fe is substantially higher. The prevailing hydrogeochemical composition of the groundwater in the region is classified as Ca-Mg-HCO3 type. The presence of Ca-Mg-Na-HCO3 facies in water of particular regions can be attributed to cation exchange mechanisms. The scatter plot between TDS and horizon thickness in the boreholes suggests that precipitation contributes to ionic inputs in groundwater along with weathering and dissolving activities.

Anbazhagan S. & Nair A. 2004 analysed about the study area for mapping the groundwater quality by using a GIS in Panvel Raigarh Maharashtra, India. Even though receiving an extensive amount of rain, the basin frequently experiences water shortages as well as poor water quality in some areas. Therefore, this research focused on the analysis of groundwater quality mapping utilising a GIS and water sample data. Some of the parameters, including Cl^-, hardness, TDS, and salinity concentrations, were exceeded the standard limits in groundwater samples. The groundwater quality map was generated by the utilization of Idrisi 32 GIS software. This software was also employed to produce various other thematic maps and conduct spatial analysis. The groundwater quality map demonstrates that groundwater is safe for human consumption and can be used for irrigation. The basin of this area has high-salinity issues therefore the areas need to be handled carefully.

Singh et al. 2010 collected 77 mine water samples and thereafter subjected to analysis in order to assess their appropriateness for various applications, including drinking, industrial, and irrigational reasons. The nature of the mine water samples ranges from being slightly acidic to slightly alkaline. The TDS value varied from 171 to 1626 mg/l, which suggests that there were Changes in the activities of the lithology as well as the predominant hydrological regime. The primary dominating anions in the mine water of the Barakar formation were sulphate (SO42-) and bicarbonate (HCO3-), whereas the major dominant cations were Ca^{2+} and Mg^{2+}. In contrast, the dominant cation in the mine water of the Raniganj formation was Na^+. The total hardness and total dissolved solids levels in the mine water of the Barakar deposit were quite high. The concentrations of a few trace elements such as iron (Fe), nickel (Ni), and chromium (Cr) exceeded the acceptable thresholds for residential use. Therefore, the water samples can be used for irrigation purposes, with the exception of some locations within the Raniganj formation, where there is an observed increase in SAR value, %Na, RSC, Mg ratio, and salinity.

Singh et al. 2016 have collected total 44 mine water samples from Korba Coalfield for the purpose of the study. These samples were tested for several parameters including pH, TDS, EC, major anions like K^+, Ca^{2+}, Mg^{2+}, Na^+, major cations like NO_3^-, SO_4^{2-}, Cl^-, HCO_3^-, dissolved silica (H_4SiO_4) and the few trace metals. The collected samples were mildly acidic to alkaline in nature based on pH values (6.7-8.5). The observed TDS values ranged from 97 to 785 mg/L, suggesting significant lithological variation. The present analysis revealed that the primary anions identified were SO_4^{2-} and HCO_3^-, while the predominant cations detected were Ca^{2+} and Mg^{2+}. The primary facies identified in mine water include Ca-Mg-SO4-Cl and Ca-Mg-HCO3. On the basis of saturation indices, calcite, dolomite, and aragonite were oversaturated, whereas gypsum, anhydrite, and halite were undersaturated. The quality of the mine water was evaluated, and the results showed that a few elements found in the water were beyond the permitted level. As a result, the mine water could not be used in its natural state; instead, it needed to be treated. In general, it has been observed that the mine water quality comes under good to permissible limit. Thus, it may be consumed for domestic and irrigate purposes.

Singh et al. 2017 examined the impact of coal mining activities on surface and groundwater resources within the Korba Coalfield region, Chhattisgarh. They simply collected a few water samples from a variety of sources, but they analysed those samples for major ions, mining effluent parameters, and trace metals. The surface and groundwater samples were slightly acidic to mildly alkaline. According to molar ratios, silicate weathering and ion exchange is the major solute acquisition process affecting groundwater chemistry in the Korba Coalfield mine. The hydrogeochemical composition of the water samples exhibited a prevalence of two different facies, namely Ca-Cl-SO4- and Ca-HCO3. The analysis of the groundwater and river water quality indices (GRWQI) revealed that around 82% of the water samples were classified as excellent to good category, while the remaining 18% were categorized as poor. Meanwhile, it was observed that the effluent water quality indices (EWQI) indicated that 6/8 samples were classified as the excellent category. The concentration of trace elements, specifically Fe, Pb, and Mn, exceeded the permissible limit, while the remaining elements remained within the acceptable range. The majority of the samples, fall into the good to permitted category used for irrigational purposes as per Wilcox and USSL diagrams. The result of this study is that mine effluent water must be treated before use.

Chourasia, 2018 analysed the different types of mixture of untreated/ partially treated/ treated industrial waste being discharged through the different kinds of pipe line in the Korba district. This study aims to evaluate the quality of groundwater for drinking purposes using the water quality index (WQI) method. The assessment includes the analysis of pre and post monsoon data from a two-year period of 2013 and 2014. A total of 15 parameters such as TDS, K^+, Ca^{2+}, Mg^{2+}, Na^+, NO_3^-, SO_4^{2-}, Cl^-, HCO_3^-, Pb, Fe, Mn, Ni, Cd and Cr were measured for the calculation of WQI. The groundwater quality during the pre-monsoon season of 2013 was seen to be poor, mostly attributed to elevated levels of certain parameters such as (Ca^{2+}, Na^+, HCO_3^-, Cl^-). However, a noticeable improvement in water quality was observed during the post-monsoon season of 2014 in the vicinity of Korba City, in comparison to the previous year.

Numanbakth et al. 2019 evaluated the hydro-chemical properties of water and its suitability for irrigation applications in hard rock mining locations. The hydro-chemical examination revealed that several indices, including pH, Sp. electrical conductivity, turbidity, Cl^-, Na^+, Fe^{3+}, Cd^{2+}, soluble silica and other elements were exceeded the permissible limits for both drinking and irrigation purposes. The concentration of SiO_2 was very high as compared to standard limit indicating, the direct impacts of granite rocks (such rock contains 50.17%-74.7% by weight) from mine. The study of the groundwater samples revealed excellent water quality, as indicated by the WQI. In contrast, the surface water exhibited a good water quality suitable for irrigation purposes. According to the Piper trilinear plot, it is observed that 77.24% of the groundwater samples and 85.7% of the surface water exhibit the CaHCO3 facies. The Durov diagram illustrates the dissolution of ions in a water system including reverse ion exchange. The water in the mining zone has been determined to fall within the acceptable range for irrigation purposes based on measurements of SAR, %Na, salinity, and TDS.

Singha et al. 2020 analysed 56 water samples for physicochemical analysis. The analysis of pH values revealed that the majority of the groundwater samples had alkaline characteristics. Approximately 17% of the samples were classified as hard to extremely hard, 9% were categorised as posing a moderate hazard, and 4% were classified as having significant salinity categories. Water indices, including SAR, %Na, KI, PI, RSC, and magnesium absorption ratio, have been employed to assess the suitability of water samples for irrigation purposes. Based on the computation of water indices, it was determined that the groundwater samples obtained from particular locations are suitable for irrigation purposes. According to the analysis of USSL plots, it has been shown that 54% of water samples obtained within the C1-S1 and C2-S1 class exhibit low to medium saline levels, together with a low alkali hazard. These findings suggest that such water can be utilised for irrigation purposes for all types of soils. The study region was predominantly impacted by rock-water interaction phenomena, as indicated by the hydrogeochemical model. The hydrogeological composition of the research area predominantly exhibited a Ca-Mg-HCO3 composition, as seen by the Piper plots and Chadha diagrams.

Karangoda, R. and Nanayakkara K. 2023 employed various statistical and graphical approaches to assess groundwater quality. A total of 10 water quality parameters were selected for 50 groundwater sources. The assessment of water quality and identification of potential causes for changes across the region were conducted through the use of different scientific methods, including WQI, and geostatistical modelling (HCA, PCA, and correlation analysis). The findings indicated a notable decline in the quality of groundwater in the eastern and southeastern regions of the district. The results of the multivariate analysis indicated significant variations between the groundwater of wet and dry zones of the district, suggesting higher groundwater mineralization in the dry zone. The results also demonstrate that variations in groundwater quality within the region are highly influenced by both soil and climate variables. The outcomes of this study will provide valuable insights for future hydrogeological investigations in the region.

In the literature review, it has been observed that Temporal variations are often inadequately addressed, with studies typically comparing only a few time points (e.g., pre- and post-monsoon). The work is done with simple WQI technique. The major gap has been fulfilled by using advance CCME WQI technique.

2.2 Mining and Heavy metals

Mohan et al., 1996 used DPASV Technique to monitor the presence of heavy metals in drinking water at twelve significant sites in residential areas. The weighted arithmetic mean method was used to calculate the HPI from the measured data. The findings indicate that the water does not exhibit contamination by heavy metals. The suggested pollution Index (HPI) appears to be useful for evaluating overall water quality in terms of heavy metals. Furthermore, the pollution index serves as a tool for comparing qualitative characteristics across different locations and gaining information about the standards for a specific area.

Stamatis et al. 2001 carried out this study in the Lavrio region to examine the effects of previous mining operations as well as inadequate water resource management on groundwater quality. A total of 33 water samples were taken and then analysed for the presence of nine major ions, eight trace elements, and five physical qualities in March 1998. The elevated concentrations of heavy metals, including Pb, Cd, Zn, and Ni, have been detected in groundwater samples obtained from the Lavrio region. The decline of groundwater quality is also occurring, primarily attributed to the infiltration of nitrates from agricultural activities and the intrusion of seawater. A basic correlation analysis was performed on the dataset to ascertain the relationships between various factors. This study identified a strong correlation between the elements Ni and Cr. The PCA analysis indicates the presence of four factors that collectively account for 72.5% of the total variance. Spatial distribution maps are used to identify the regions with high levels of heavy metals.

Begum et al. 2009 reported that the downstream of Cauvery River water has been polluted with particular heavy metals, based on water and sediments analysis. The water samples with a high carbonate hardness are seen, whereas the concentration of element and ions increases in the downstream side of the river. The order of the major ions is $Na^+ > HCO_3^- > Mg^{2+} > K^+ > Ca^{2+} > Cl^- > SO_4^{2-}$ whereas order of heavy metal content in water is Cr > Cu Mn > Co > Ni > Pb > Zn. The concentration of a few elements such as Zn, Pb, and Cr exceeded the standard limits. However, the irrigation suitability of the Cauvery River may be regarded as highly favourable owing to its low levels of salt and sodium. The presence of heavy metals in the downstream side indicates an increase in contaminants generated by fertilizers, industrial effluents, and anthropogenic wastes.

Prasad et al. 2014 considered that the infiltration of leachates originating from various industrial waste and overburden dumps into groundwater, resulting in the deterioration of its quality, has been identified as an important issue in mining regions. A comprehensive analysis was conducted on a total of seven heavy metals. The water samples were collected from twenty distinct significant places in the Dhanbad municipality, which is relatively close to the Jharia coalfield. The heavy metal concentrations were measured to be within the allowable limit, while iron and manganese concentrations exceeded the permissible limits at some locations. The HPI was calculated based on measured concentrations of heavy metals. The computed HPI value was determined to be 6.886, which falls below the established critical limit of 100. Consequently, with the fast expansion of mining and other industrial activities in the vicinity of the town, the groundwater remained free from heavy metal contamination.

Tiwari, et al. 2015 collected 28 surface water samples were obtained from 14 distinct sites throughout the West Bokaro Coalfield region. The study employed inductively coupled plasma mass spectrometry (ICP-MS) to assess the seasonal fluctuations and heavy metal pollution index. This was achieved by assessing the concentrations of Mn, Cu, Zn, Ni, As, Se, Al, Cr, Ba, and Fe. The computed HPI value was within the critical limit of 100. The study revealed that there was a significant increase in metal concentrations during the pre-monsoon period compared to the post-monsoon season. In either season, the levels of Zn, Ni, Mn, As, Se, Al, Ba, Cu, and Cr found in the water did not exceed the maximum safe levels permitted for consumption. whereas, Fe content exceeded WHO (2006) and BIS (2003) acceptable limits at a few sites in both seasons. Thus, water with a high Fe concentration must be treated before being used in the household.

Singh et al. 2017 studied the chemistry of water. While opencast coal mining, pollutants from mine drainage can seep into the groundwater. This activity often endangers the water chemistry. The water samples obtained from the Korba Coalfield were subjected to analysis in order to assess the presence of potentially toxic trace elements (PTEs) based on in-situ factors. Thus, HPI, HEI, Cd, and statistical methods were applied to assess heavy metal pollution. Pre-monsoon samples had greater PTE concentrations than post-monsoon samples as per paired-sample t-tests. Several areas exceeded Indian drinking regulations for Fe, As, Al, and Mn pre-monsoon and Mn, Ni, Ba, and Pb post-monsoon. Despite an abundance of these elements, The HPI values were found to be lower than the crucial pollution index value of 100 in both seasons. According to the multiple of mean values approach used to interpret the pollution index results, the majority of groundwater samples fall within low to medium group.

Kwaya et al. 2019 investigated 29 groundwater samples collected from various sites for analysis of pH, temperature and different heavy metals. Three elements such as Cr, Fe, and Mn, values exceeding WHO recommended limits. The metals based on their concentrations is as follows Cr>Fe>Zn>Cu>Ni. The calculated pollution indices revealed that the area had low Cd and HEI values. Whereas, HPI values was high which is signifying that the area was in high contaminated zones. Further, correction analysis was done and observed that there were no any significant relations between heavy metals however, Cd, HEI, and HPI were found to have a strong positive correlation with Cr. This study also incorporated PCA and HCA analysis, both of which are comparable and exhibit concurrence. Chromium pollution in the area was identified based on the concentration of Cr in groundwater samples.

Shylla et al. 2020 used pollution indices approach to evaluate the impact of metal contamination on water sourced from both underground and opencast mines during two distinct seasons. The water is acidic in nature caused by the low pH value (2.4-3.65). The TDS concentration was higher in opencast mine samples than in underground mines samples. The heavy metal concentrations followed the order: Cu< Pb< Cr< Zn< Fe, arranged from lowest to highest concentration. The groundwater bodies were contaminated with heavy metal leaching from mining operations, as per calculated HPI and HEI level. It was found that the pre-monsoon season had a metal content that was significantly higher than that of the post-monsoon season. The samples from underground mines shows a lower concentration than samples from opencast mines. A feasible and efficient technology must be integrated into coal mining methods to manage and avoid metal leaching into the groundwater.

Dheeraj et al. 2023 examined groundwater for drinking and domestic uses during pre-monsoon season around Korba coalfield area. The concentrations of a few metals such as Al, Ba, Cd, Fe, Mn, Pb, Ni, and Zn were calculated using ICP-MS instruments. The concentrations of few metals exceeded allowable limits at a few of the sites. The HPI value, calculated using the average concentration, was found to be 21.64, much lower than the critical limit of 100. The HPI calculation revealed that 73.33 % of samples had a low HPI, 6.67 % of medium, and the rest 20 % of high. The data were also put through a cluster analysis, which split them into two groups. Cluster-1 had 14 members (93.33%), and Cluster-II had one member (6.67%). According to the spatial distribution map, the eastern part of the region has high HPI values. The findings indicate that the eastern region of the area exhibits groundwater contamination resulting from the leaching of heavy metals deriving from opencast mining activities.

In the literature review, it has been observed that most studies rely on a limited number of sampling points which may not capture the full spatial variability of water quality. In the present work, the combination of three indices HPI, HEI and MI are used to fulfilled the major gap.

2.3 Mining and Land use/ Land cover

Soulard et al. 2000 used dataset of land use/land cover for the conterminous United States, covering the period from 1973 to 2000, has been made available by the U.S. Geological Survey Land Cover Trends Project. The land-use/land-cover mapping was conducted using Landsat data obtained from the Multispectral Scanner, TM, and ETM+ imagery for the years 1973, 1980, 1986, 1992, and 2000. The categorization was performed using a modified Anderson Level I classification scheme. The North American Datum of 1983 is utilized for the projection of Albers Equal-Area Conic, employing the derived LULC data, which possesses a resolution of 60 meters. The many categories have been systematically classified in this research to effectively assess this field of study.

Wu et. al. 2008 used only two temporal TM satellite data sets from 1995 and 2001 to obtain information about the coal mining area. The classification of LULC was carried out using the supervised method in the IRDAS software. The five designated land use and land cover (LULC) classes consisted of water bodies, agricultural land, construction land, mining areas, and other land. This study found significant changes based on the LULC map. According to the LULC change matrix, coal mining areas, water bodies, and agricultural land have consistently followed increasing trends, whereas construction land and other land have consistently followed decreasing trends. Only construction land has seen a high rate of growth (1.08 %). The certain operations, such as coal extraction, have resulted in alterations of different landforms, including agricultural land and land reclamation.

Chitade and Katyar 2010 opined that every part of the world experiences growth and development caused by industrialization. The development exhibits adverse impacts on the local environment, including the contamination of air and water resources etc. The high-quality coal deposits are available in the Wardha basin of the Chandrapur district of (M.S). The region has undergone significant changes in LULC due to the extraction of coal deposit and the subsequent adverse impacts on the surrounding environment. The significant methods, including remote sensing, GPS, and GIS, have been utilized in the process of LULC change detection. The satellite data over the period from 1990 to 2010, namely from Landsat TM to Cartosat-I, were employed for the purpose of identifying changes in LULC. The vegetation and agricultural land, in particular, saw major changes throughout this time period. The dense vegetation experienced conversion into either mining overburden or mining land. The water body increased from 151.898 hectare to 321.568 hectare, however considerable mineral extraction below the surface polluted the study area. In contrast, the findings of this study indicate a significant rise in pollution levels in the surrounding region, primarily attributed to changes in flora. This increase has reached a crucial limit.

Demirel et. al. 2011 observed that the extraction of ore, the process of tripping, surface mining activities, and the disposal of overburden contribute to land use and land cover (LULC) changes in mining regions. Opencast mining has the potential to result in significant land disturbance due to the coal extraction process. The findings revealed that the LULC classes such as forest area reduced by 192.5 hectares and 172 hectares between 2004 and 2008. The primary cause of this phenomenon can be attributed to the depletion of reserves and production in that particular region. In addition to that, several satellite images were utilized, such as those from IKONOS and QUICKBIRD. The accuracy of image classification provided by IKONOS is 97.70% higher than that provided by QUICKBIRD, which is just 93.86%. This resource provides essential information for the strategic planning of mine closure and reclamation operations.

Areendran et. al. 2013 examined the dynamics of LULC in the mining region of Singrauli district, located in Madhya Pradesh, India, during the period ranging from 1978 to 2010. The rapid industrial growth in district has only been facilitated by the presence of a large coal deposit and Govind Ballabh Pant Sagar reservoir on the Rihand river. The multiple satellite data sets were employed to delineate the LULC transformation through the utilization of remote sensing and GIS approaches. The evaluation of spatiotemporal changes in LULC was conducted using landscape metrics. In addition, Markov transition matrix and change rate has been calculated for each LULC map. The change matrix was used to represent the transition from one class to another. The LULC category, specifically vegetation cover, is currently experiencing continuous adverse changes in comparison to other categories. The expansion of built-up areas and mining activities has exhibited a consistently increasing trend, accompanied by a corresponding rise in deforestation rates and forest fragmentation.

Samanta, 2015 focused on examining the impacts of an opencast coal mine on many environmental aspects, such as land, water, and air quality. Additionally, the study investigated the potential effects on worker health, biodiversity, and the social well-being of individuals residing in towns and cities surrounding the Raniganj coal field. This study provides a comprehensive overview of significant evaluations of LULC studies that have examined the environmental impacts of coal mining and associated LULC changes through the utilization of satellite data. The present study reveals a significant change in LULC within this region, primarily attributed to the extraction of coal and minerals. Consequently, the surrounding environment has experienced negative effects as a result.

Baruah et al. 2016 worked in the coal mining region in the state of Assam (Ledo-Margherita area, Tinsukia District). The study shows that opencast mining significantly changes the geomorphology of the area. According to remote sensing and GIS techniques, the LULC changes from 1996 to 2016 were prepared. A total of twelve LULC classes were determined to be required in order to carry out a complete exploration of this region. While forest land, wetlands, sandbars, and water body all showed declining patterns over the course of the study period. The classes of settlement, mining, cultivation, and grassland experienced increasing trends. The region also experiences an indirect impact of opencast mining on the shifting of agricultural activities, mostly resulting from its influence on soil fertility.

Garai and Narayana 2018 looked into how coal mining affects LULC changes in the Godavari coal area in southern India. A limited number of land use categories, including mining areas, water bodies, built-up areas, forested areas, barren land, and agricultural land, were identified and analysed in terms of their environmental effects. The examination of LULC was carried out at five-year intervals over the course of the past 24 years, from 1990 to 2014. The change analysis and spatiotemporal quantification of the LULC change pattern were also highlighted. It was observed that the water body and mining area were slightly increased from 2.77% to 3.29% and 0.04% to 0.23% from 1990 to 2014 respectively. Furthermore, there was an observed increase in the proportions of built-up area and barren land, which increased from 0.34% to 0.89% and 1% to 1.69% respectively, during the period covering from 1990 to 2014. From 1990 to 2014, the percentage of land covered by forests decreased from 36.38% to 31.67%, while the percentage of land used for agricultural progressively increased from 59.46% to 62.22%.

Azeez and Mukhitdinov 2020 This study assessed the impacts of coal mining activities on changes in LULC in the vicinity, as well as the underlying mechanisms driving these changes in LULC. In the V. D. Yalevsky coal field, Russia, LULC classifications such as mining area, road, water body, woodland, grass, and agriculture land were classified. The analysis of LULC change in the coal mining sector has been conducted over a period of

27 years, covering from 1992 to 2019. The process of change identification was carried out over a span of 13 years utilizing data obtained from the Landsat-4 TM and Landsat-8 OLI. The LULC data was generated on ENVI 5.1 software through the implementation of the maximum likelihood technique for supervised classification. The post-classification change detection estimation was also made. The mining areas and grass cover followed increasing trends whereas the forests, agricultural land, water bodies, and roads followed decreasing trends respectively. The overall accuracy and Kappa coefficient for 1992, 2006, and 2019 are 90.18 %, 0.87 %, and 93.41 % & 0.91, 88.69 % and 0.85 % respectively.

Arifeen et al. 2021 employed remote sensing and GIS methodologies to evaluate the LULC changes within the vicinity of the Barapukuria coal mine located in Bangladesh. In this study, A time series satellite data sets were utilized, including Landsat 7 ETM+ data spanning from 1999 to 2009, as well as Landsat 8 OLI/TIRS data specifically from 2019. ERDAS 2018 software was used to evaluate the LULC map using the maximum likelihood classifier matrix of supervised classification. The four major LULC classes such as settlement, agricultural land, forest area, and water body were identified in the area. The analytical results indicate that the settlement followed an increasing trend with more than 50% to earlier whereas, agricultural land followed a decreasing trend. The overall accuracy of prepared LULC map was 70% and kappa coefficient was more than 0.60. As a consequence of land subsidence resulting from mining activities, an area measuring 1.003 km^2 underwent depression, leading to structural damage in around 1500 residential properties. The results are highly helpful for creating a comprehensive, sustainable development strategy for the area by land use planning and management professionals.

Siddiqui and Jain 2022 mentioned that mining and reclamation are the main factors influencing changes in LULC in the Jharia coalfield. The study involved the analysis of percentage changes in the mining region and their subsequent impacts on the local ecology. The assessment of land cover change at the Jharia mine was conducted by analysing the Landsat data acquired in 1999, 2009, and 2015. An unsupervised ISODATA clustering algorithm with matrix union function was used to prepare the LULC map and track LULC changes in the region. The research findings indicate that over a span of ten years, specifically from 1999 to 2009, the mining industry experienced a notable growth rate of 81.72%. Concurrently, about 8.46% of the surveyed region underwent a transformation from mining sites to vegetative areas. The mining industry experienced an increase of 14.20%, with around 8.92% of the mining sites successfully reclaimed and transformed into vegetative areas. It also demonstrates that five-year interval images better describe classes and reveal changes than ten-year interval images. This study will help in identify changes and build a mining environmental management plan decision-making framework.

In the literature review, it has been observed that there is a lack of integration between water quality data and other environmental factors, such as land use changes and climate variability. This work has been done by the earlier researcher using supervised technique. But, the analysis with unsupervised technique with accuracy assessment was lacking hence, unsupervised technique has been used in the present study.

2.4 Mining with LST, NDVI and NDWI

Saini et al. 1998 used Landsat data from 1998 to 2017 for spatiotemporal pattern analysis of NDVI and LST in Dehradun. LST was calculated using emissivity from NDVI imagery as well as Landsat TM/TIRS thermal data. The built-up area has expanded over the previous 20 years and experiences warmer temperatures than the neighbouring vegetative areas, as per the spatiotemporal LST trends. Based on LST statistics, the minimum temperature has increased by 3.5℃ and the maximum temperature has increased by 4.9℃ over the last 19 years. Increased built-up areas resulting from urbanization enhance ambient temperatures and lead to the urban heat island effect. Additionally, an attempt to correlate NDVI and LST have also been made. The results clearly show that there is a negative correlation between these two indices. Thus, this type of research can be used to track urban sprawl and other vegetation-related issues.

Yue et al. 2007 investigated the association between LST and NDVI in the context of urban land use characteristics and patterns in Shanghai, China. The data for the present study was obtained using the ETM+ and remote sensing devices. The findings shows that the correlation between LST and NDVI was calculated by regressive coefficient analysis which shows the negative correlation. The analysis of visual representations of LST and NDVI reveals a correlation between these variables. However, it is important to note that the strength of this correlation varies across different land use categories. Furthermore, the calculation of the association between LST, NDVI, and SHDI was performed. The findings of this study indicate an inverse correlation between the NDVI and SHDI, while a positive correlation was observed between LST and NDVI. The urban ecological environment can be assessed using the three main indices, namely LST, SHDI, and NDVI, based on the provided data. The evaluation of the environmental effects of urban land function zoning can be conducted using moderate-resolution satellite data. This study employs remote sensing and GIS techniques to offer an essential tool for evaluating the environmental impacts of zoning in urban environments.

Lei and Bian 2010 focused on employing time series analysis as a method for examining changes in vegetation index by utilising data from the TM and MODIS sensors. Additionally, the relationship of vegetation, climatic variables, coal mines, etc, was also studied. The study location is quite close to an arid mine region where mining and other eco-restoration activities are occurring. The NDVI from MODIS data and the produced NDVI from atmospheric adjusted TM imagery have extremely similar results. Time series study shows that the impact of coal mining constantly exposes to the monthly NDVI, rainfall, and temperature to an annual periodic rhythm. MODIS-NDVI, which has a spatial resolution of 1 km, is not as useful for spatial information over a 3200 Km2 area as NDVI-TM, which has a spatial resolution of 30 m. This is because MODIS-NDVI has a coarser spatial resolution. A higher NDVI value is associated with higher NDVI spatial variation of a squared correlation coefficient (R^2 =0.6983). It is only happening because anthropogenic activity like industrialization, has damaged natural landforms.

Tian et al. 2013 opined that the more intensive and extensive coal mining operation is going to have serious negative influence on the local sensitive ecosystem. In this study, a spatial and temporal adaptive reflectance fusion model (STARFM) to create the NDVI from 2000 to 2011 utilising several satellite data sets, including Landsat and MODIS with 30 m resolution. Furthermore, examine its capacity for detecting vegetative patterns near an ordinary coalfield on the Loss Plateau. The synthetic NDVI map was developed by employing two different approaches. The first scheme involved utilizing NIR and red band reflectance data obtained by STARFM. The second scheme involved directly inputting Landsat and MODIS NDVI images into STARFM. Compared to scheme 1 ($0.56 < R2 < 0.70$), scheme 2 ($0.70 < R2 < 0.76$) regularly generates better results. Additionally, two separate input data sets like annual maximum NDVI ($NDVI_{max}$) time series and synthetic dense NDVI time series used in the trend analysis. The consistency of both trends was seen to be remarkably high when evaluating accuracy through the utilisation of MODIS time series data.

Anbazhagan and Paramasivam 2016 found that a large number of remote sensing satellites in space which supply the thermal data to estimate the LST these days. In this study, LST in the mining region was estimated using Landsat satellite TM data from three time periods, including 1992, 2001, and 2010. The major goal is to examine LST as determined by the thermal band of Landsat TM data and compare it to the corresponding reference condition. The different Landsat satellite data from different time periods were used, including Landsat 5 TM for the years 1992, 2010 and Landsat 7 for the year 2001, respectively. The ENVI 4.7 software was used to image processing in this study. The evaluation of the emissivity and vegetation index findings for the specified time period reveals that when emissivity rises, the vegetation index exhibits a negative trend. By using statistical programme SPSS, the standardisation of the error coefficient was established, which boosted the study's approach. For both NDVI and LST, a standard regression analysis was performed, and the regression coefficients (B) for the years 1992, 2001, and 2010 are -0.209, -0.143, and -0.190, respectively.

Kumari and Sarma 2017 opined that the Singrauli district is having numerous active coal mines and thermal power stations, as a result it was considered as energy centre of India. Previously, this region was highly forested, had a diverse range of tribal cultures, and was rich in wildlife. The private organizations made extensive use of this land to build massive power producing stations. The Sasan ultra mega thermal power plant encompassed approximately 10 km^2 of land, of which the LULC and LST were estimated for the years 2005, 2010, and 2015, respectively. In this research, multiple remotely sensed satellite data sets such as Landsat ETM and Landsat 8 were used. The LULC analysis was employed to evaluate changes in land classification, specifically observing a decline in forested areas and barren lands, while observing an increase in vegetation and wastelands. These LULC changes has increased the LST by 6.69°C while decreasing the NDVI values from 2005 to 2015. The analysis conducted using Pearson's correlation coefficient indicated a negative correlation between LST and NDVI within the studied region. As a result, the two important factors LST and NDVI can be employed as an excellent tool for evaluating environmental effect on ecosystems.

Pattanayak and Diwakar 2018 attempted to identify and map the NDVI, NDBI, and NDWI in Hyderabad, Telangana, India. This study employed IRS-LISS III satellite data from four different years such as 2009, 2011, 2012, and 2013. High NDVI readings were concentrated in Hyderabad city in 2011. In four different years, the difference between the maximum and minimum NDVI measurements was 1.198, 0.977, 1.984, and 1.065, respectively. The NDWI measurements on four different dates were 0.452, 0.603, 0.996, and 0.666 respectively which declined continuously.

Ramdhani and Sulistyawati 2019 employed Landsat 8 satellite data to assess the correlation between land use and LST in the coal-mining area of South Kalimantan. This study examined how different reclaimed forest planting years and dominating tree species affected LST. The thermal band 10 of Landsat 8 data was utilised as the source to produce the LST in the selected years of 2014 and 2018, respectively. Furthermore, a field study was conducted to evaluate the stand characteristics of restored forests. The study demonstrates that reclaimed forests with a different planting year have equivalent capacity of lowering temperatures. This is shown by the fact that the average LST of rebuilt forests from 1997, 2014, 2015, and 2016 was about 27°C in 2018. The reclaimed forest stands with different dominant tree species and total basal area lower temperature by 4.7-5.7°C after 3-4 years of planting. The findings indicate that the present approaches employed by PT Adaro Indonesia for the decrease of LST are effective.

Azeez, 2022 noticed that LULC and LST play an important role in a number of domains, including hydrology, geophysics, and biophysics. The primary objective of this study is to assess the present situation of the V. D. Yelevsky coal mine region in Russia, while also evaluating LST for this specific area during the years 2006, 2010, and 2019, respectively. It also calculated the correlation between LST and NDVI using Landsat 5 and 8 satellite data. The LULC result demonstrates that the mining area followed increasing trends from 43.89 Km^2 to 111.40 Km^2 from 2006 to 2019. Additionally, LST recorded for three time periods in the mining region was high, reaching 32.05°C, 31.24°C, and 32.18°C, in the years 2006, 2010, and 2019 respectively. The minimum temperature was recorded in case of water bodies i.e., 12.36°C and 18.41℃ in year 2006 and 2019 whereas 12.36℃ for forest area in 2006 respectively. The result shows that the correlation was also done between LST and NDVI for three time period which have strong negative correlation with R^2=0.93, R^2=0.99 and R^2=0.87 in year 2006, 2010 and 2019 respectively.

In the literature review, it has been observed that Insufficient spatial coverage in many studies limit the ability to detect fine-scale variability. A very few works have been done on correlation between LST and NDVI as well as NDWI. The spatial temporal data analysis is lacking. Hence, it has been carried out in the present study by using Landsat satellite data.