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A historical and future impact assessment of mining activities on surface biophysical characteristics change: A remote sensing-based approach

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A R T I C L E I N F O

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A B S T R A C T

Mining activities and associated actions cause land-use/land-cover (LULC) changes across the world. The objective of this study were to evaluate the historical impacts of mining activities on surface biophysical characteristics, and for the first time, to predict the future changes in pattern of vegetation cover and land surface temperature (LST). In terms of the utilized data, satellite images of Landsat, and meteorological data of Sungun mine in Iran, Athabasca oil sands in Canada, Singrauli coalfield in India and Hambach mine in Germany, were used over the period of 1989–2019. In the first step, the spectral bands of Landsat images were employed to extract historical LULC changes in the study areas based on the homogeneity distance classification algorithm (HDCA). Thereafter, a CA-Markov model was used to predict the future of LULC changes based on the historical changes. In addition, LST and vegetation cover maps were calculated using the single channel algorithm, and the normalized difference vegetation index (NDVI), respectively. In the second step, the trends of LST and NDVI variations in different LULC change types and over different time periods were investigated. Finally, a CA-Markov model was used to predict the LST and NDVI maps and the trend of their variations in future. The results indicated that the forest and green space cover was reduced from 9.95 in 1989 to 5.9 Km^2 in 2019 for Sungun mine, from 42.14 in 1999 to 33.09 Km^2 in 2019 for Athabasca oil sands, from 231.46 in 1996 to 263.95 Km^2 in 2016 for Singrauli coalfield, and from 180.38 in 1989 to 133.99 Km^2 in 2017 for Hambach mine, as a result of expansion and development of of mineral activities. Our findings about Sungun revealed that the areal coverage of forest and green space will decrease to 15% of the total study area by 2039, resulting in reduction of the mean NDVI by almost 0.06 and increase of mean standardized LST from 0.52 in 2019 to 0.61 in 2039. our results further indicate that for Athabasca oil sands (Singrauli coalfield, Hambach mine), the mean values of standardized LST and NDVI will change from 0.5 (0.44 and 0.4) and 0.38 (0.38, 0.35) in 2019 (2016, 2017) to 0.57 (0.5, 0.47) and 0.33 (0.32, 0.28), in 2039 (2036, 2035), respectively. This can be mainly attributed to the increasing mining activities in the past as well as future years. The discussion and conclusions presented in this study can be of interest to local planners, policy makers, and environmentalists in order to observe the damages brought to the environment and the society in a larger picture.

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1. Introduction

Over the last three centuries, the Earth's surface has changed significantly due to the human activities (Hurtt et al., 2011; Crutzen, 2016). Several ecological, socioeconomic and political factors, such as environmental crises, government decisions and local management, affect land-use/land-cover (LULC) changes (Mayes et al., 2014). LULC changes might have positive or negative effects on natural resources at local and global scales (Mialhe et al., 2015; Symeonakis, 2016; Mousivand and Arsanjani, 2019).

A major negative impact of LULC changes is a deforestation (Jaimes et al., 2010; Li et al., 2016). Deforestation has caused a series of environmental effects, including CO2 emissions, climate change, environmental quality, biodiversity decline, surface ecological status, and surface biophysical characteristics (Harris et al., 2012; Peralta-Rivero et al., 2014; Mahmood et al., 2016). All these suggest that LULC change studies are highly important to understand their negative impacts (e.g., on past and future deforestations) and their key driving factors. Thus, several investigations have been conducted under both local and global scales (Hansen et al., 2008, 2013; Ernst et al., 2013).

One of the most important and basic foundations of any country's economy is its mineral resources (Wright and Czelusta, 2003; Sekerin et al., 2019). The role of mines in economic growth is very serious and strategic, and the exploitation of the country's mines is an undeniable necessity in economic development. Many people in every country are working in this industry and it can be acknowledged that the mining industry in every country has a significant impact on social welfare in that country (Sonderegger et al., 2020). However, the adverse effects of this industry on our environment is not hidden from anyone. Therefore, in order to balance these three sectors, namely economic growth, social welfare and reducing environmental disorders, we are required to enter sustainable development in this industry (Farjana et al., 2019; Berger et al., 2020).

Mining activity is such that it has externality effects (Hemalatha et al., 2005; Papagiannis et al., 2014). These effects will occur when a firm or individual engages in an activity that directly affects others (firm or individual) (positively or negatively) but does not pay or receive money for it. This means that the individual or firm creating the externality effect does not include the costs or benefits of doing so in its cost-benefit calculations.

The operation of a mine, in addition to the costs faced in the production process, imposes another cost on the environment, which is called social costs (Ajith and Ghosh, 2019; Spitz and Trudinger, 2019). Normally, the mine does not pay for this cost to the environment. As a result, this environmental cost is not included in the cost-benefit function of the enterprise. This causes the level of production of the enterprise to be higher than the optimal social level and the pressure of mining activities excessive and uncontrollable on the environment. The social planner should try to make the level of activity of the enterprise at the optimal level of society (Sonderegger et al., 2020). The first step in solving this challenge is to identify and model the adverse effects of mining activities on environmental conditions in a region.

Mining and related operations are parts of activities that have a potential to harm the surface biophysical characteristics. In some cases, mining directly affects natural resources with serious consequences (Lin et al., 2005). The negative impacts of mining operations on the surface biophysical characteristics may appear in different mining stages including exploration, extraction, and processing (Woldai, 2001). The impacts of mining activities on LULC change and surface biophysical properties depend on types of minerals, location, extraction methods, and other parameters (Azcue, 2012; Padmanaban et al., 2017). Surface biophysical properties that might be affected by mineral activities include surface temperature, albedo, water content and vegetation. Changes in these properties can influence the ecological and climatic conditions of an environment at different scales. Therefore, it is vital to assess environmental impacts of mining activities.

In recent studies, satellite images have been employed to monitor and assess the effects of anthropogenic activities on surface biophysical characteristics state (Fu and Weng, 2016; Estoque and Murayama, 2017; Moghaddam et al., 2018; Fu et al., 2019). Satellite data offer several advantages, such as being multi-temporal and multi-spectral, and cover extensive areas, that make them suitable to study and explore dynamic phenomena (Firozjaei et al., 2018). These data can be used to determine the type, amount and location of LULC and surface biophysical properties changes (Butt et al., 2015; Zhang and Zhou, 2016; Tong et al., 2017; Wang et al., 2017).

Over the past few years, studies have been conducted to explore the effects of mineral activities on the surrounding surface biophysical characteristics using remote sensing technology (Sarma and Kushwaha, 2005; Joshi et al., 2006; Charou et al., 2010; Borana et al., 2014; Vasuki et al., 2019). For example, Townsend et al. (2009) showed that the intensity of mining activities caused extensive degradation before the surface reclamation in 1977 in the Central Appalachian Mountains in the United States, while the degradation and LULC pattern changes were significantly reduced after the reclamation until 2006. In another study, Obodai et al. (2019) identified mining activities as the key driver of deforestation in Ankobra river basin, Ghana between 2008 and 2016. Cano Londoño (2018) evaluated the negative effects of mining activities on three sections life cycle assessment, exergy analysis, and emergy accounting. Life cycle assessment evaluates process sustainability based on the environmental impacts generated by waste and emissions released to the environment, emergy based on the use of the necessary resources to carry out the process, and Exergy based on process efficiency based on this.

Previous studies on the effects of mining activities on the surface biophysical characteristics have several limitations including (a) The focus of studies was on the effects of mineral activities on LULC changes of mines' surrounding areas. (b) These studies were only employed optical remote sensing images to investigate the effects of mineral activities on the surface biophysical characteristics (Padmanaban et al., 2017; Guo et al., 2019; Obodai et al., 2019). (c) These studies have been focused on examining the trend of mine land area changes and LULC changes resulting from it in the past.

Due to these counted limitations and challenges in previous studies, considering the following actions are important: (a) To more accurately assess the negative effects of mining activities on the surface biophysical characteristics, using satellite imagery based quantitative indices such as land surface temperature (LST) and normalized difference vegetation index (NDVI) can be very useful. Both LST and NDVI are the most important and applicable indicators in modeling the surface biophysical characteristics (Weng et al., 2004; Karnieli et al., 2010). (b) Due to the complexity of interactions in surface biophysical characteristics, combining remotely sensed information recorded in the optical and thermal ranges of the electromagnetic spectrum from surface can increase the accuracy in modeling the surface biophysical characteristics (Li et al., 2018; Meng et al., 2018). (c) Modeling the changes in surface biophysical characteristics caused by anthropogenic activities in the past is of great importance. However, predicting the future trends of these changes is critical and useful for management and planning in controlling the negative effects of these changes (Ahmed et al., 2013; Mushore et al., 2017; Firozjaei et al., 2018).

The main objective of this study was to evaluate and predict the impacts of mining activities on the surface biophysical characteristics. The main contribution and innovations of this study is multifold by: a) a quantitative investigation of the effects of mineral activities on LST and NDVI changes, b) integration of optical and thermal information obtained from remote sensing to investigate the effects of mineral activities on the surface biophysical characteristics, c) predicting mining activities' impacts on the surrounding surface biophysical characteristics through application of multi-temporal satellite images.

2. Materials and methods

2.1. Study area

To select the study areas, diversity criteria were considered in (1) geographical location and (2) the type of extractive materials and (3) the type of surface cover of the surrounding areas. In this study, four mines from four different countries (Sungun mine in Iran, Athabasca oil sands in Canada, Singrauli coalfield in India, and Hambach mine in Germany) were selected in order to investigate the effects of mineral activities on surface biophysical characteristics change (Fig. 1).

Areas around these mines include green space and forests. From these mines, copper, Oil sands, coal and lignite are extracted, respectively.

2.1.1. Sungun mine

Arasbaran biosphere reserve is a unique and key biosphere reserve that serves as a representative case study for biogeography, ecology, wildlife, cultural resources and landscapes-related studies. This study area is located between 38°, 41´ and 38°, 43´ N latitude and 46°, 39´ and 46°, 43´ E longitude covering about 24,754 ha (Fig. 2). The Sungun copper mine is placed on the Qaradagh Mountains and parts of Dezmar and Arasbaran protected areas, which is surrounded by pastures and forests. The mine is located in a mountainous area with an average height of 2000 m above sea level ranging from 1700 to 2460 m, which indicates a high variation of elevation within a short distance along with steep slopes. It was declared as a biosphere reserve by the United Nations Educational, Scientific and Cultural Organization (UNESCO) in 1976 (Rasuly et al., 2010; UNESCO, 2015). The most important and valuable natural habitat of Arasbaran biosphere reserve is the Dezmar protected area, which is the main habitat of Arasbaran forest species. While being a national biosphere reserve, a large mining project of copper, so-called Sungun copper mine development plan, has started to evolve and even host some related factories and infrastructure plans such as electricity supply and accommodation for staff. To the best of our knowledge, no study has investigated the development of mining activities and its impacts on the surface biophysical characteristics.

2.1.2. Athabasca oil sands

This study area is located between 56°, 50´ and 57°, 24´ N latitude and 112°, 20´ and 110°, 45´ W longitude covering about 4608 Km2 (Fig. 1). Boreal ecosystems contain more than half of the carbon in forested areas of the earth and more than half of the earth's surface freshwater. Boreal ecosystems have recently been recognized as the most important ecosystems in our planet that provide services such as carbon storage, flood control and water filtrations, with a total value many times greater than current resource exploitations (Schindler and Lee, 2010). In this valuable ecosystem in Canada, large mining activities of oil, the so-called Athabasca oil sands, have developed. The Athabasca oil sands (Athabasca tar sands) are large reservoirs of bitumen (heavy crude oil), located in northeastern Alberta, Canada (mostly near the Fort McMurray town). The Athabasca reservoir is the largest known reservoir of bitumen in the world and the largest of three major oil sands reservoirs in Alberta (Atkins and MacFadyen, 2008; Giesy et al., 2010). The oil sands in some references called as tar sands (Gailus, 2012; Smandych and Kueneman, 2013). Broadly, Athabasca oil sand reservoirs located under 141,000 km^2 of boreal forest and muskeg. The boreal forest is habitat for many wildlife species who are sensitive to industrial activities (Schneider and Dyer, 2006).

2.1.3. Singrauli Coalfield

Singrauli Coalfield is located in the central part of India that is divided into two parts by the Kachni River. The Singruali coalfield covers an area of almost 300 km^2. The major part of the coalfield (about 220 km^2) is located in Singrauli district of Madhya Pradesh and a small part (almost 80 km^2) located in Sonbhadra district of Uttar Pradesh (Majumder and Sarkar, 1994). The study area is located between 24°, 05´ and 24°, 14´ N latitude and 82°, 30´ and 82°, 47´E longitude covering about 469 Km^2 (Fig. 1). Major coal mines in this part of Singrauli colfield are: Amlohri, Nigahi, Jayant, Dudhichua, Khadia, Krishnashila and Bina mines. The study area is a hilly region in the northern part of Singrauli colfield with elevation ranges from 270 to 620 m above mean sea level (Javed and Khan, 2012). Indeed, Singrauli coalfield is a typical erosional landscape with plain and plateau topography. The area in the south-eastern has a mild slope towards the reservoir of Rihand Dam (also known as Govind Ballabh Pant Sagar reservoir) (Singh et al., 1997). The

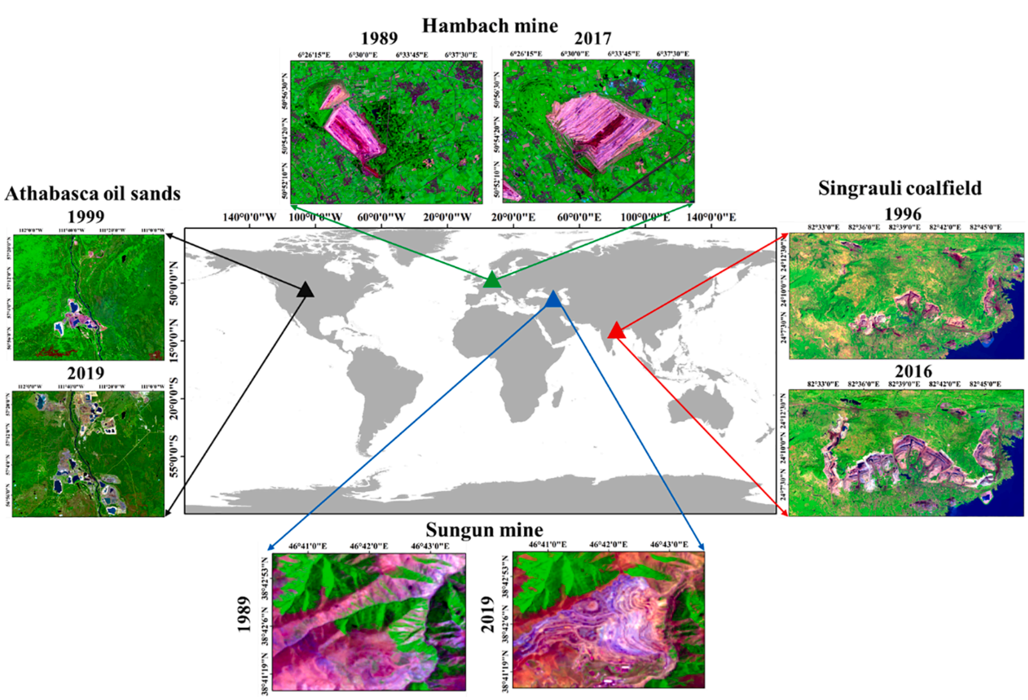

Fig. 1. Location of the study areas.

Fig. 2. Views of Mining activities in Sungun mine (Iran).

nearest cities to Singrauli coalfield are Waidhan (25 km) and Renukoot (50 km) (Javed and Khan, 2012). The climate type of Singrauli district between November and June is tropical monsoonal dry and during other months (rainy season) is very humid (Khan and Javed, 2012).

2.1.4. Hambach mine

This study area is located between 50°, 51´ and 50°, 58´ N latitude and 06°, 24´ and 06°, 39´ E longitude (Fig. 1). Hambach forest, a highly biodiverse old-growth forest, is one of Europe's oldest forests with a unique ecology. The forest is located next to one of the largest lignite mine fields in western Europe as so-called Hambach mine. Decades of mining activities and forest degradation caused the rapid decrease of this uniqueness and now just 10% (almost 200 ha) of oak and hornbeam vegetation remain from what had been the largest forest in the Rhineland, west of Cologne, Germany.

The Hambach mine is a large open pit mine located between Düren and Rhine-Erft districts, in the Rhenish coalfields. The mining activity has been started near the town of Niederzier and developed in areas that once belonged to the Hambach forest. Mining activities in this area is predicted to continue until 2040. The Hambach mine alongside Garzweiler and Inden mines provide almost 40% of the power needs of the populous state of North Rhine-Westphalia (NRW) (Heumann and Litt, 2002; Hempel and Kulik, 2004) (https://www.group.rwe/en/our-portfolio/our-sites/hambach-mine-site). Started in 1970s, the mine's area has a size of 43.8 km2 in end of 2017, with the maximum area of the Hambach mine has been calculated around 85 km^2. With overall coal deposits in the Hambach Mine of 2.5 billion tonnes of lignite, the extraction capacity is 40–45 million tonnes per year. The lignite was created from dense forests, which have existed in the Lower Rhine Bay between 30 and 5 million years ago. The total coal extracted from all mines in NRW is almost 100 million tonnes per year and is employed to generate 12% of Germany's power need (Schmitz, 2006; Fehres, 2010; Imboden and Moczek, 2015).

2.2. Data and pre-processing

The satellite images of Landsat 4, 5, 7 and 8 were used in this study for LULC and LST mapping. The acquired images in GeoTiff format were geo-referenced in the World Geodetic System (WGS84) datum, and projected in the Universal Transverse Mercator (UTM, zone 38 N, 12 N, 44 N, and 31 N for Songon mine, Athabasca oil sands, Singrauli coalfield and Hambach mine, respectively). While selecting satellite images within 1989–2019, the absence of cloud cover and having no precipitation two days prior the satellite's passage was considered (Table 1). In order to provide the training and test data for image classification and accuracy assessment of extracted LULC maps, Landsat false color composite, and Google Earth Images for each data were used.

To complete the input parameters of the LST estimation algorithms, water vapor product (MOD07L2) of the MODIS sensor and the air temperature data measured at the weather stations at Landsat overpass time were used.

Table 1
The used Landsat imagery for study areas.

Study area	Satellite (sensor)	Row/ Path	Date
Sungun mine	Landsat4-TM/ TIR	166/33	16/07/1989
	Landsat5-TM/ TIR		04/08/1993, 19/07/1998 and 28/07/2007
	Landsat7-ETM$^+$/ TIRS		08/08/2003
	Landsat8-OLI/ TIRS		10/07/2013 and 11/07/2019
Athabasca oil sands	Landsat5-TM/ TIR	042/ 020	16/05/1999
	Landsat8-OLI/ TIRS		21/05/2019
Singrauli coalfield	Landsat5-TM/ TIR	142/ 043	09/10/1996
	Landsat8-OLI/ TIRS		16/10/2016
Hambach mine	Landsat5-TM/ TIR	197/ 025	17/06/1989
	Landsat8-OLI/ TIRS		14/06/2017

2.3. Methods

In order to achieve the designated objectives of this study, a set of tasks, as presented in Fig. 3, were followed: a) the optical bands of Landsat images were employed to extract LULC changes from 1989 to 2019 based on the homogeneity distance classification algorithm (HDCA); b) the LULC changes by future were predicted using the CA-Markov model; c) the LST and vegetation cover maps were calculated based on single channel algorithm and NDVI, respectively for different dates; d) the LST and NDVI variations trend caused by each LULC changes type in different time periods were investigated; e) the CA-Markov model was employed to predict the future maps of LST and NDVI.

2.3.1. LULC changes in past and future

The LULC types in the tree study areas include forest and green space, pasture, mine, bare land built-up and water for the time period 1989–2019. HDCA was used to classify satellite images. Prior to the supervised classification of images, training dataset was carefully selected, so that, it could provide a representative pattern of the LULC types. The incorrect definition of classes by training data affects the entire process of supervised classification and leads to the inaccurate classification (Otukei and Blaschke 2010). In order to avoid that, 450 sample points per class were selected, which were geographically distributed over the entire study areas.

The HDCA is inspired by the gravity law is a supervised classification method for satellite images. HDCA used merging, traveling and escaping operators for image classification based on spatial and spectral information. HDCA runs in two supplementary computing stages. The weighted Manhattan distance (WMD) was used in HDCA. Feature selection in HDCA was applied by an improved gravitational search algorithm (IGSA) optimization to determine the optimal feature space scale. More details about HDCA can be found in Firozjaei et al. (2019a). After LULC classification, the overall accuracy and kappa index were calculated for accuracy assessment (Foody 2002). Finally, LULC maps and areal coverage of each class was extracted for different timestamps. Additionally, the CA-Markov model was used to predict future LULC. More details on CA-Markov model are presented by (Arsanjani et al., 2013; Firozjaei et al., 2019b). The LULC map of future was produced using LULC maps of past years and LULC changes in different years was compared using Cross-Tab model (Shalaby and Tateishi, 2007).

2.3.2. NDVI and LST

To investigate the surface changes caused by mineral activities for the period of 1989–2019, NDVI and LST were calculated. The NDVI is the most used remotely sensed vegetation index in remote sensing studies (Herrmann et al., 2005). NDVI is calculated by the reflectance of the Red and NIR bands. NDVI extract useful information about surface biophysical parameters including greenness and vegetation (Tucker, 1979).

The Single Channel (SC) algorithm (Jiménez-Muñoz and Sobrino, 2003; Jiménez-Muñoz et al., 2014; Yu et al., 2014) was applied to calculate LST from thermal bands of Landsat 4, 5, 7 and 8. The NDVI threshold method (Sobrino et al., 2008; Jimenez-Munoz et al., 2014) was used to retrieve the land surface emissivity (LSE) for each timestamp.

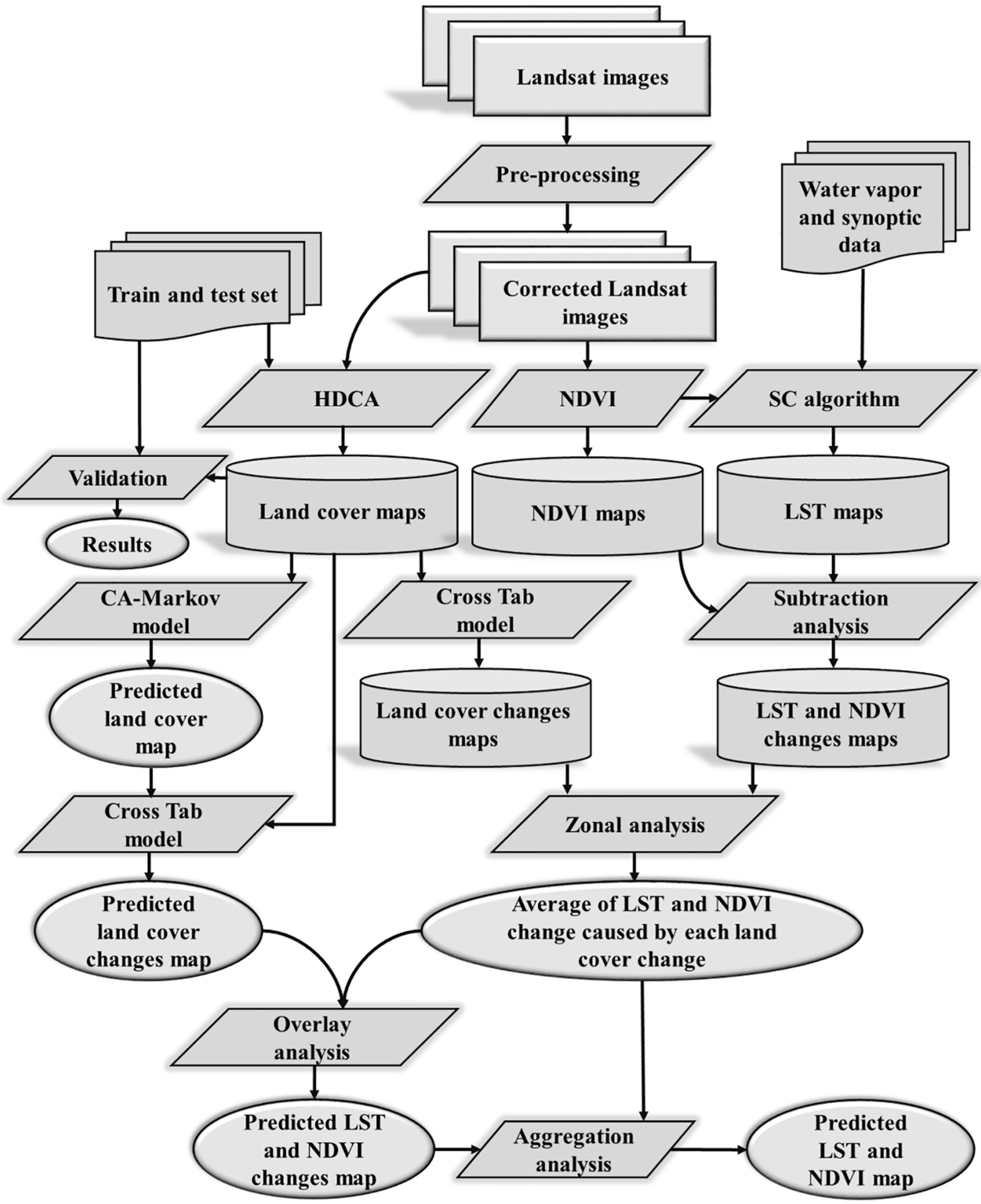

Fig. 3. The flowchart of the study.

2.3.3. Investigating the effects of multi-temporal LULC changes on LST and NDVI

2.3.3.1. Relative prediction of LST and NDVI. To make the relative prediction of LST and NDVI, we used a model proposed by (Firozjaei et al., 2018) as follows:

1. Maps of LST, NDVI, and LULC changes for different time periods were obtained using subtraction and crosstab methods. If n years are considered in the study, then the number $\binom{n}{2}$ of the LST, NDVI, and LULC changes maps for the study period were obtained.
2. The variation in LST and NDVI due to the LULC changes for different time periods was investigated.
3. The average changes in LST and NDVI resulting from LULC change were calculated.
4. The LULC map using the CA-Markov model was predicted for 2039 (For Sungun mine).
5. The map of land cover changes between 2019 and 2039 was obtained using the crosstab model (For Sungun mine).
6. A map of the predicted changes in LST and NDVI resulting from the LULC changes between 2019 and 2039 was obtained (For Sungun mine).
7. Finally, the LST and NDVI maps of 2039 were predicted by combining the LST of the year 2019 and the prediction maps of the LST and NDVI changes due to the LULC changes within 2019–2039 (For Sungun mine).

3. Results and discussions

3.1. The historical and future LULC changes

Broadly, in view of the favorable ecological and climatic conditions of the study area, in addition to bare land class, there are also pasture lands and forests in the studied area. In 1993, due to the development of the Sungun mine activities, the mine class was added to other classes in the region. Over the past two decades, with increasing the activities of Sungun mine, the area of mine land use has also increased. The LULC maps over different years obtained from HDCA classifier are presented in Fig. 4. The mean values of kappa coefficient and the overall accuracy parameters of LULC maps of Athabasca oil sands (Singrauli Coalfield, Hambach mine) based on the test dataset were 0.92 (0.89, 0.91) and 93 (90, 92), respectively.

The visual examination of LULC maps for the period of 1989–2019 confirms the physical development of the mine areas. In the waste disposal of the Sungun copper mine, waste materials accumulated in the surrounding valleys and vegetation covers in the valleys were buried under waste materials. Hence, the landscape view of this area turned into an unpleasant scene as several hectares of vegetations were destroyed due to road constructions. The most important effects of LULC changes in forest and mine classes are evident. According to the LULC map of 2039, the physical expansion of the mine and degradation of vegetation will continue as presented in Fig. 5.

According to Fig. 5, the area of the mine class has been increased from 13.41 ha in 1993 to 621.54 ha in 2019. Similarly, the forest area was decreased from 929.70 to 594.27 ha corresponding to a net area of 115.34 ha. The high rate of natural resource degradation in the region indicates the expansion of human activities, which have been recognized as the main causes of forest degradation all over the world (Wang, 2004; Glantz, 2019; Koglo et al., 2019; Nichols et al., 2019). Based on the results obtained with the CA-Markov model, the area of the mine and forest classes in 2039 will change to 1109.3, and 381.1 ha, respectively. The LULC changes during the period of 1993–2019 and 2019–2039 are presented in Fig. 6.

Our obtained results indicated that more than 229.50 ha of pasture lands were converted to mine land use. Additionally, up to 2039 it is expected that more than 344 ha of forests and pastures in the study area will be converted to mine land use. Conversion of natural resources into mine has negative impacts on the surface biophysical characteristics as well as to the ecosystem (Sarma and Kushwaha, 2005; Joshi et al., 2006; Charou et al., 2010; Borana et al., 2014; Vasuki et al., 2019).

3.2. NDVI and LST

To investigate the negative effects of increasing mineral activities on the biophysical parameters, NDVI values for various dates were calculated as shown in Fig. 7.

The mean NDVI for 1989, 1993, 1998, 2003, 2008, 2013, and 2019 were obtained to be 0.345, 0.340, 0.325, 0.312, 0.289, 0.260 and 0.244, respectively. The results demonstrated that the mean NDVI was

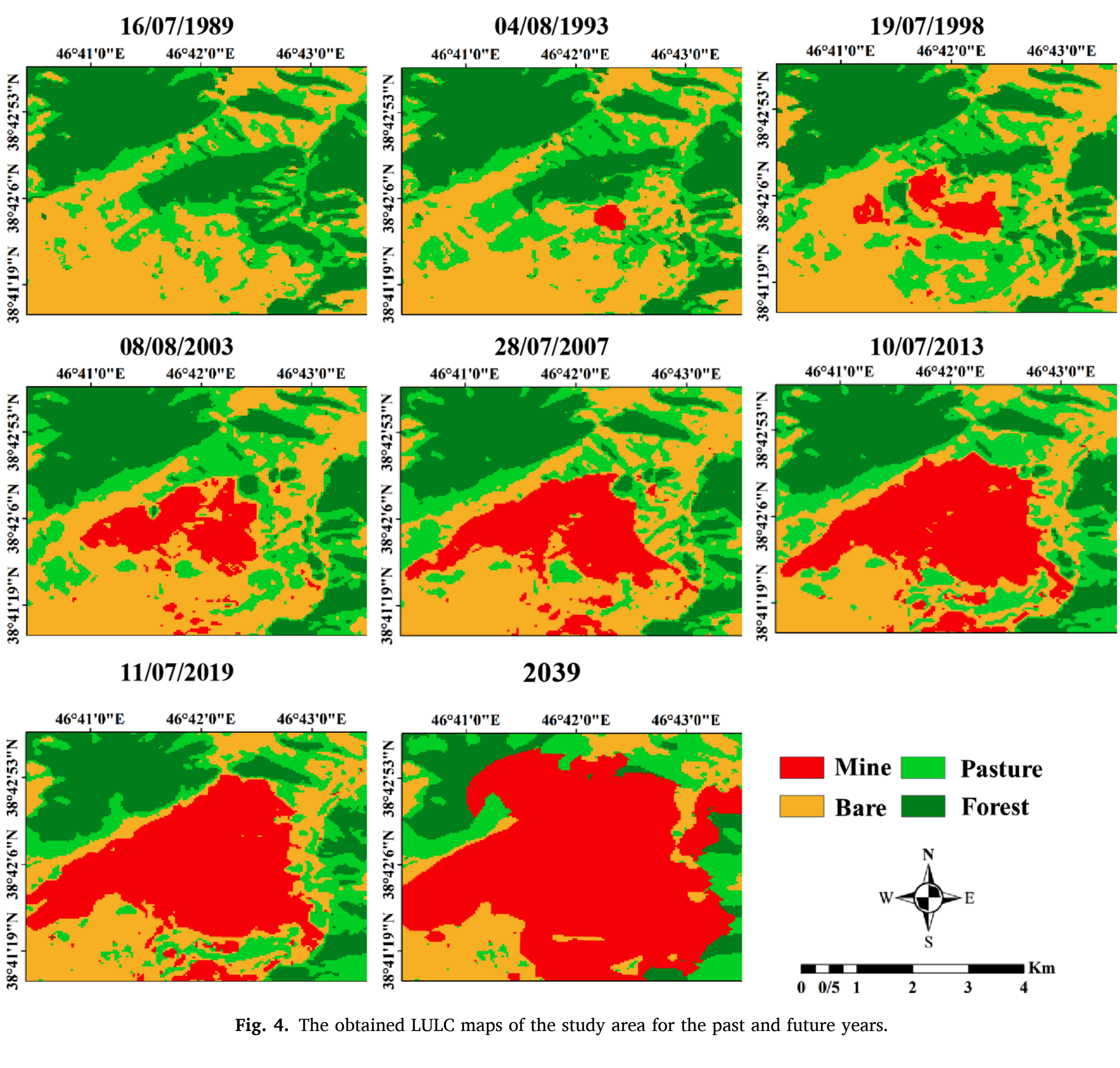

Fig. 4. The obtained LULC maps of the study area for the past and future years.

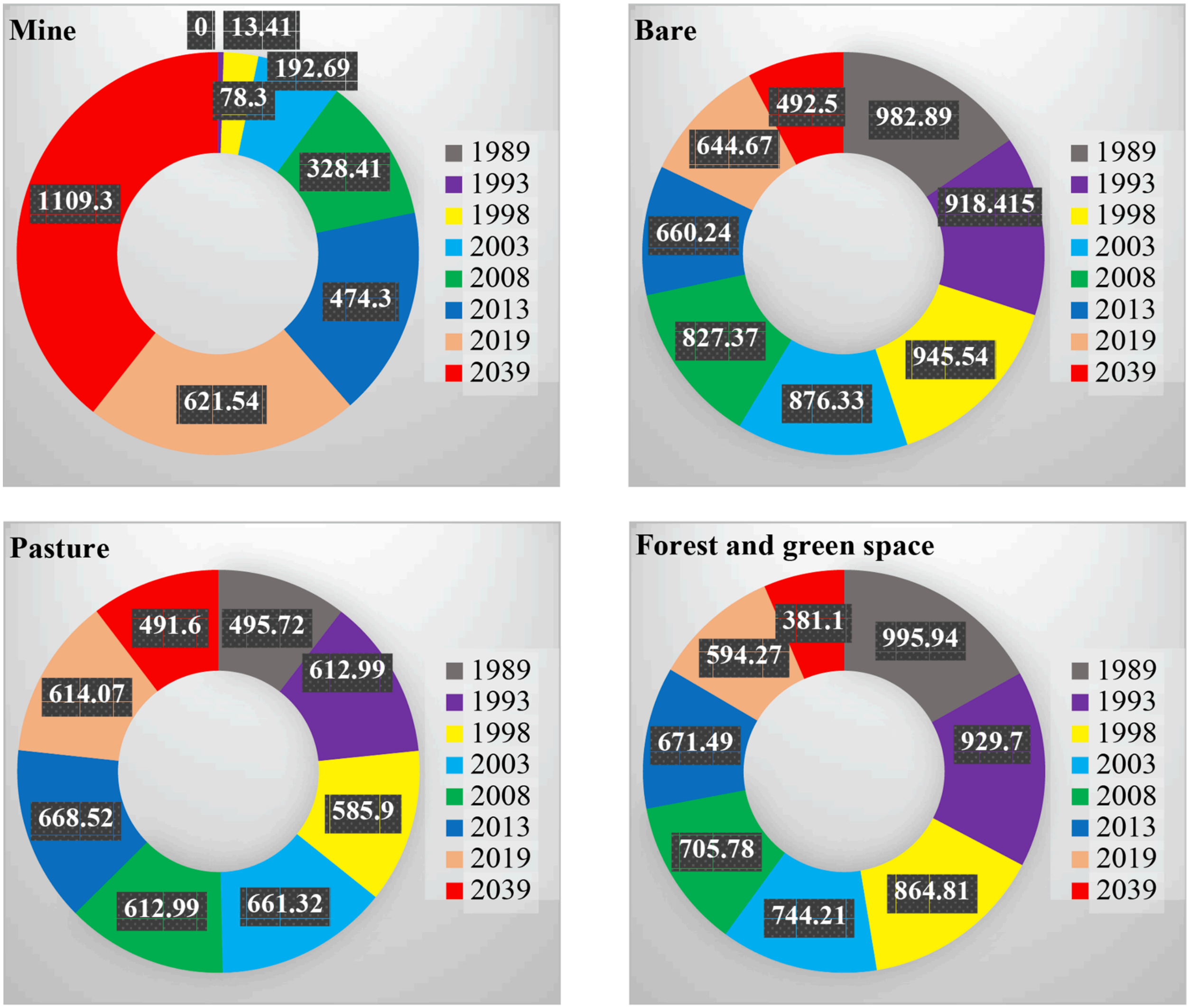

Fig. 5. The areal coverage (ha) of each LULC class within 1989–2039.

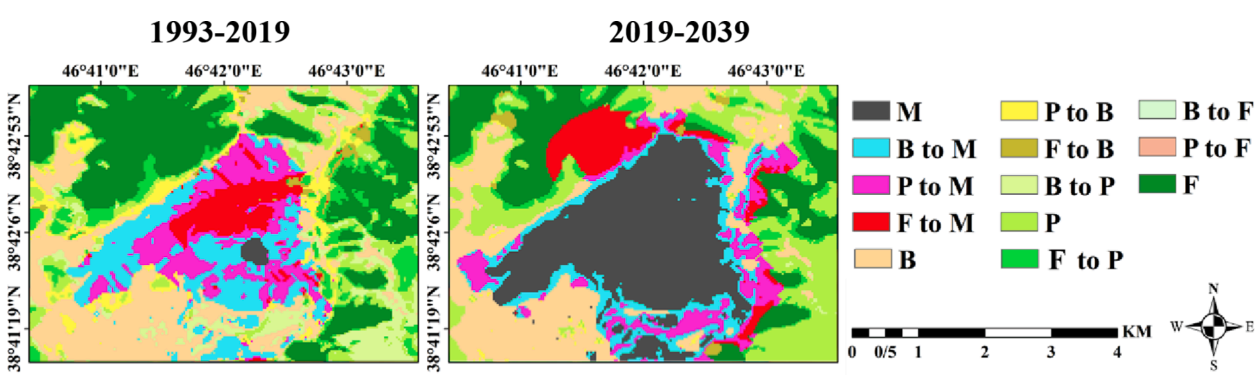

Fig. 6. The LULC changes maps for the time period of 1993–2019 and 2019–2039.

decreased by almost 0.1 during the time period of 1989–2019. The major reason for this decrease can be attributed to reduction of the forests and their conversion into mine and pasture lands. At all dates, forest and mine classes had the highest and lowest NDVI values, respectively. The most important negative effect of LULC changes on surface biophysical parameters is LST variations (Fig. 8).

According to Fig. 8, the spatial distribution of LST values was changed over the time period of 1989–2019. The mean standardized LST values were increased from 1989 to 2019. With increasing mineral activities over the past two decades, the thermal cluster with a low temperature in the center of the study area was changed to cluster with a moderate temperature.

3.3. *Effect of LULC changes on LST and NDVI variations*

The difference operator was applied on the LST and NDVI maps of

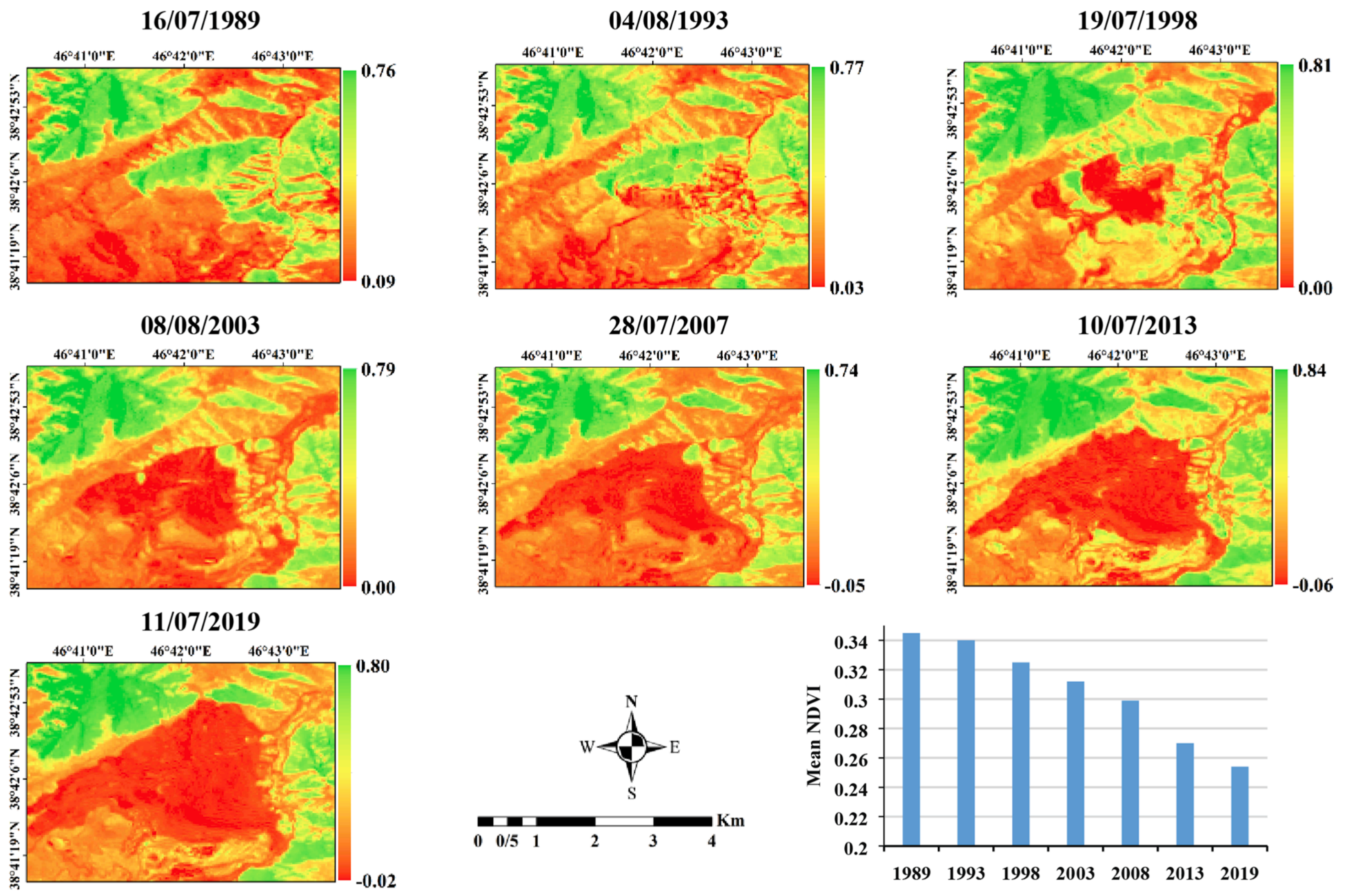

Fig. 7. NDVI maps of the study area across different timestamps.

different dates to calculate LST and NDVI variations caused by LULC changes at different time periods. The LST and NDVI variations map and conversion of the other classes to the mine class for the time period of 1989–2019 are shown in Fig. 9.

According to the results presented in Fig. 9, the study area experienced the highest variations of LST (indicated with red color) during the time period of 1989–2019, which spatially coincident with those areas that were converted from forest to mine class. After analyzing all possible LST variations maps (15 different modes) and the corresponding LULC maps (for instance: LST variations map and LULC map for the time period of 1989–2019), the mean values of LST variations caused by LULC changes were calculated. The obtained results revealed that LULC changes from forest to mine, pasture to mine, forest to pasture, forest to bare land and pasture to bare land were changed the LST 5.8, −0.1, −1.4, 1.6, 3.3, and 0.9 °C, respectively. Also, LULC changes resulted in a decrease in NDVI values in the study area (blue-colored). Most of the changes in NDVI values were due to the conversion of forests to mine lands in the center of the study area. The NDVI values of those areas that were converted from pasture class to mine class also decreased considerably.

3.4. Relative prediction of LST and NDVI

The LULC changes caused variations in surface biophysical parameters including LST and NDVI. Based on LST and NDVI variations caused by LULC changes in the past, maps of LST and NDVI for 2039 were produced as presented in Fig. 10a and 10b, respectively. Combining LST and NDVI maps for 2019 with LST and NDVI changes maps derived from LULC changes between 2019 and 2039, the prediction maps of relative LST and NDVI for 2039 were produced and shown in Fig. 10c and 10d, respectively.

Due to the prediction of forest and pasture land degradation as a consequence of the physical expansion of the mine over the future years, the LST and NDVI of the study area will increase and decrease in the further years, respectively. The Area of lands with high LST and low NDVI (red-colored) will increase. For this reason, the current trend of mineral activities will have negative impacts on the surface biophysical characteristics of the study area. According to the prediction results, the mean values of the standardized LST and NDVI will change from 0.52 and 0.25 in 2016 to 0.61 and 0.19 in 2036, respectively.

3.5. Results of other three studied mines

The LULC maps of Athabasca oil sands (Singrauli Coalfield, Hambach mine) in different years obtained from HDCA classifier are presented in Fig. 11. The mean values of kappa coefficient and the overall accuracy parameters of LULC maps of Athabasca oil sands (Singrauli Coalfield, Hambach mine) based on the test dataset were 0.92 (0.89, 0.91) and 93 (90, 92) persents, respectively. The visual examination of LULC maps indicates a significant increase in mine areas and consequently a decrease in green spaces and forest in all three study areas.

According to the obtained results, the area of the mining lands in Athabasca oil sands was increased from 197.67 km^2 in 1999 to 662.67 km^2 in 2019. Similarly, the area of the green spaces was decreased by almost 21%. The results of prediction indicated that up to 2039, the area of mining lands and green spaces will be reached to 1192.8 and 2774.2 km^2, respectively In Singrauli coalfield, mine land use has been increased by 128% from 1996 to 2016. The results of LULC prediction show that the area of each mine, built-up, bare, green space and water class will be 130.44, 39.52, 74.25, 186.79 and 38.27 km^2 in 2039, respectively.

From 1989 to 2017, a significant portion of the green spaces and

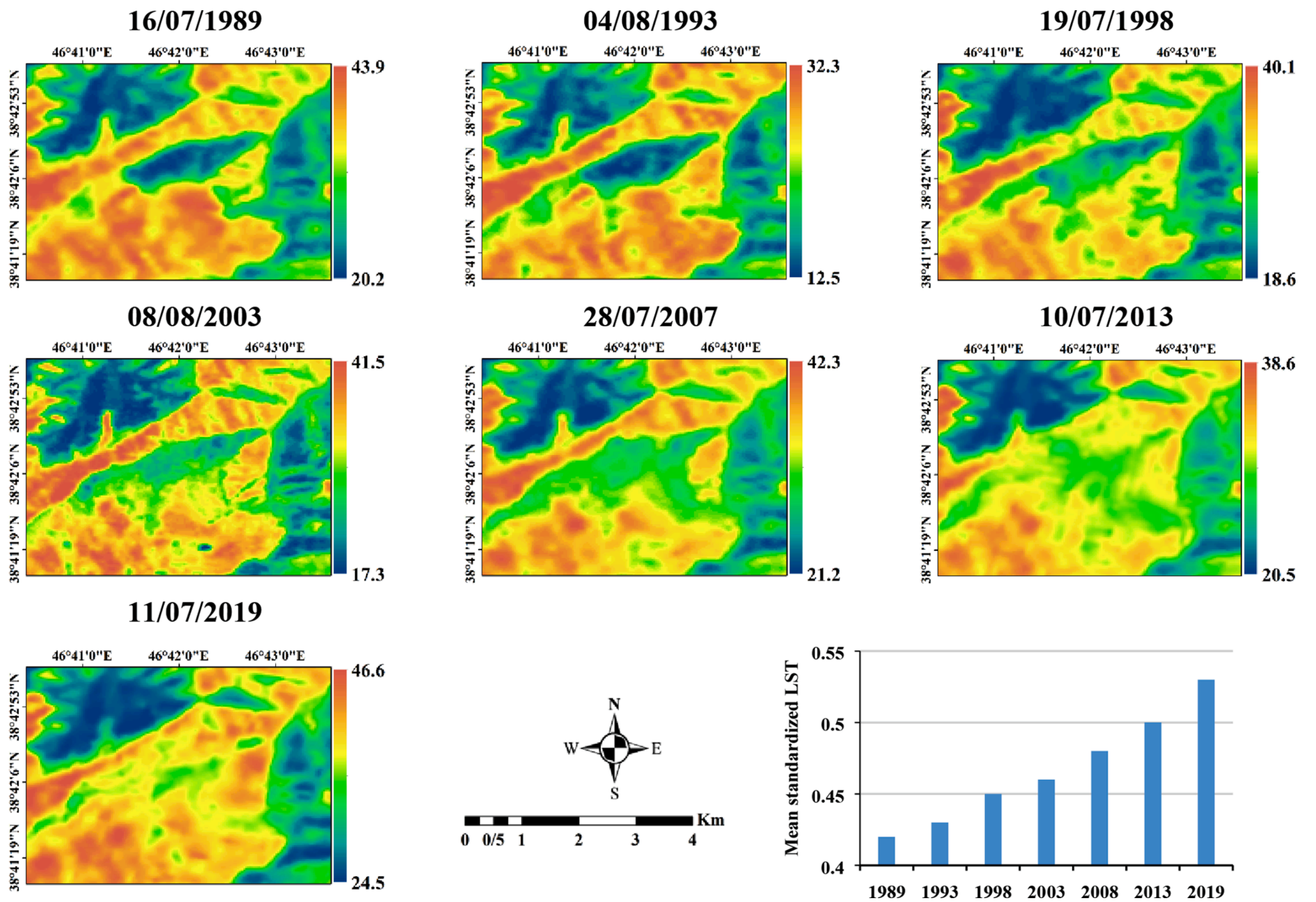

Fig. 8. LST maps (°C) and mean standardized LST (rescale LST range to 0–1 based on maximum and minimum LST of region for each date) of case study in different dates.

forests in Hambach mine region has been converted into mine land use. Indeed, the area of the mine class has increased from 18.45 km^2 to 47.58 km^2. The results show that during the period 1989 to 2017, 6.32 km^2 of mine land use have been converted to re-cultivated area (agricultural use and forest). However, the area of green space class has decreased by 25%. The results of LULC prediction indicate that the area of mine and green space classes will reached to 55.45 and 122.13 km^2 in 2035, respectively. The areal coverage of each LULC class of the study areas in past and future are given in Table 2.

Our obtained results revealed that LULC changes from green spaces and forests to mine land use in past and future have led to the expansion of high-temperature areas (indicated with red color tones) and low NDVI (indicated with white color tone) in the three study areas (Fig. 12).

The changes trend of the mean standardized LST and NDVI of the study areas are presented in Fig. 13. For Athabasca oil sands, the mean standardized LST was increased from 0.45 in 1999 to 0.5 in 2019, which is predicted to be 0.57 in 2039 due to physical expansion of the mine and the LULC changes. The mean standardized NDVI for 1999, 2019 and 2039 was also calculated to be 0.42, 0.38 and 0.33, respectively. Tailings ponds are large areas created when extract bitumen products from the oil sands. The used water in extraction process which tainted with toxic metals, stored in tailings ponds. These tailings is one of the most important environmental challenges in the oil sands industry (Purdy et al., 2005).

For Singrauli coalfield from 1996 to 2016, the mean standardized LST was increased by 0.06 and the mean standardized NDVI decreased by 0.07. According to the prediction results, the mean values of standardized LST and NDVI will reach from 0.44 and 0.38 in 2016 to 0.51 and 0.32 in 2036, respectively. The mean standardized LST and NDVI for Hambach mine in 1989 and 2017 were 0.34 and 0.4, and 0.41 and 0.35, respectively. Our prediction results show that these parameters will be 0.47 and 0.28 in 2035, respectively.

Changes analyses of LULC, LST and NDVI for the past years show that the most changes in LST and NDVI in all three regions are due to the conversion of green space to mine land use (Fig. 14).

The results indicated that for Athabasca oil sands, the mean NDVI decreased by almost 0.4 and increase of mean standardized LST by almost 12 °C, as a result of reduction of the green spaces and the conversion of them into mine land use. In Singrauli coalfield with increasing mineral activities over the past two decades, the mean changes of LST and NDVI were 7 °C and 0.35, respectively. Additionally, the results demonstrated that for Hambach mine, the mean NDVI decreased by almost 0.42 and the mean standardized LST increased by almost 15 °C during the time period from 1989 to 2017. On the other hand, part of the mine in 1989 converted to recultivated area (agricultural use and forest) in 2016 (Red Oval). Mine land reclamation in the area has resulted in a mean 13 °C decrease of LST and an increase of 0.61% of mean NDVI, indicating a significant and positive impact of mine reclamation and a decrease in the physical expansion of the mine lands on the surface biophysical characteristics. One of the re-cultivation programs of the Hambach mine was the development of the Sophienhöhe hill in northern area. From 1990, the creation of the Sophienhöhe started in parts of the mining area where lignite deposits had already been removed (Imboden and Moczek, 2015). Although the creation of the Sophienhöhe can be considered as a considerable achievement, but can be not completely compensate other adverse impacts of mining activities on the surface biophysical characteristics.

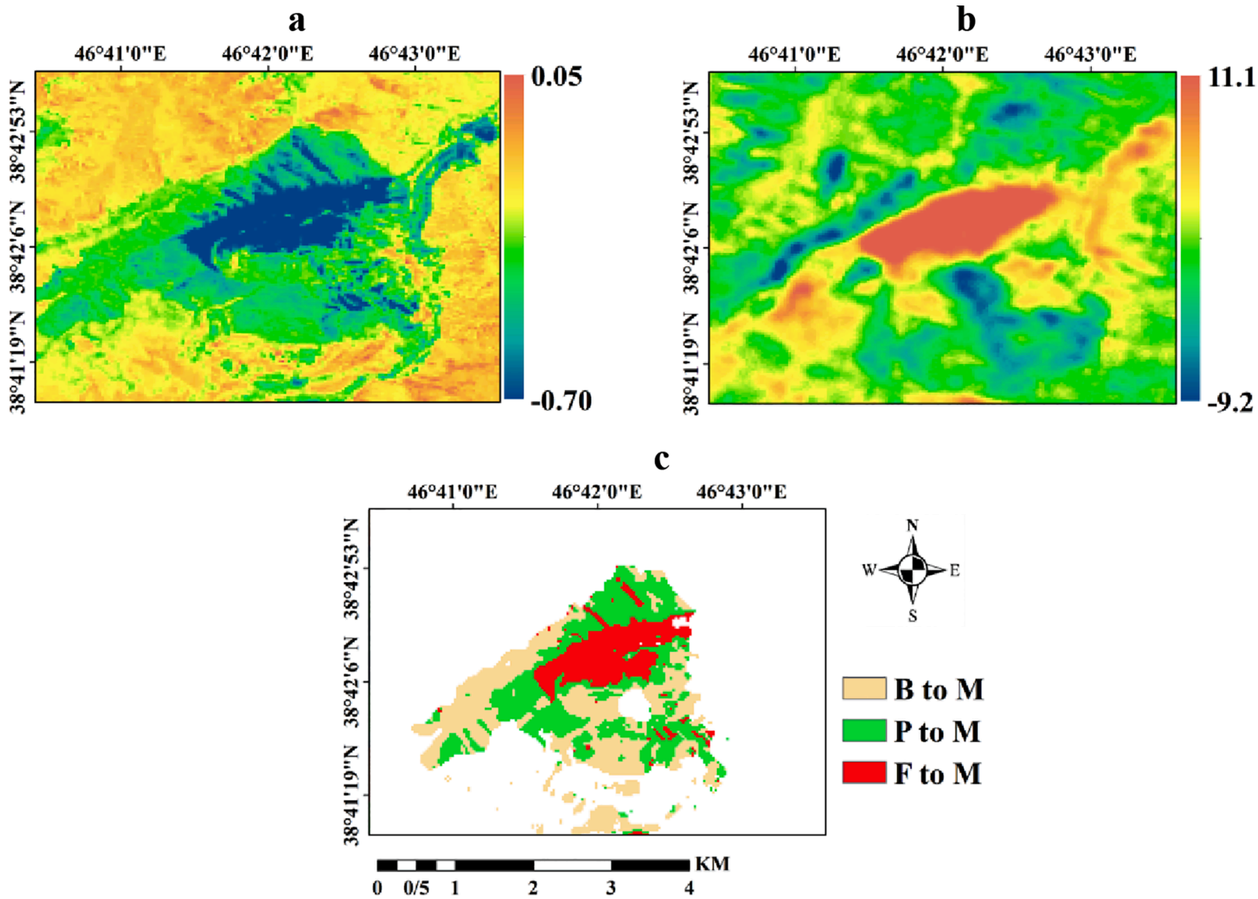

Fig. 9. The NDVI changes map (a), LST variations map (unit: °C) (b), and LULC changes map (c) for the time period of 1989–2019. M: Mine B: Bare land, P: Pasture, and F: Forest.

4. Discussion

The Sungun mine is a large porphyry copper mine with an extraction method of open pit mining (Yari et al., 2013), which causes major impacts on the surface biophysical characteristics such as land and landscape degradation, mass production of waste mineral extraction and loss of vegetation (Xiang et al., 2018). In the waste disposal of the Sungun copper mine, waste materials accumulated in the surrounding valleys and vegetation cover in the valleys were buried under these materials resulting in a sustain change of landscape. During the mine tailing phase, several million tons of tailings were displaced and accumulated in the valleys and adjacent regions. Several hectares of lands were destroyed due to road damaging (Akbari et al., 2006; Alavi and Alinejad-Rokny, 2011). As a result, the natural surfaces of the study area changed significantly over the past two decades from the mining activities. Mining activities in the Sungun Copper mine caused significant changes in the area of forest, pasture, bare soil and mine lands (Figs. 4–6). Increased mining activities and consequently LULC changes resulted in direct and indirect changes in the surface biophysical characteristics of the study area. The direct effects were related to the conversion of natural lands to mine land due to increased mining activities. On the other hand, minerals extracted from the mine also contain Arsenic, Cobalt, Mercury and Nickel in addition to Copper. The soils at the mine neighborhoods were affected by the acidic mine drainage and leakage of pollutants affecting the natural functioning of large parts of the area. The existence of numerous waterways including Sungun-Chay Rivers in the east and Pekhir in the north of the mine and their flow paths in close proximity to the forest exacerbate the indirect negative effects of mining activities on the natural lands (Nasrabadi et al., 2009). Environmentalists have warned the respective stakeholders about the negative consequences of Sungun mine in Arasbaran and Dezmar protected areas (Bidhendi et al., 2007).

In Athabasca oil sands two extraction methods have employed, one of them is surface or open pit mining. Only 20 percent of bitumen extracted through open pit mining (Burrowes et al., 2008; Mech, 2011), which includes large scale excavation using Heavy mining machinery (Center, 2014). Open pit mining in the study area destroyed the boreal forest and muskeg, as well as, built toxic tailings ponds (Rooney et al., 2012). Oil sands activities contributes arsenic, cadmium, chromium, mercury, nickel and other metal elements toxic at low concentrations in streams and rivers of the Athabasca (Kelly et al., 2010). However, oil sands corporations have reclaimed small parts of mined lands (Hildebrand, 2008).

Most of the extracted coal from Singrauli coalfield sent to thermal power plants in the area. The area is suitable for thermal power production and is anticipated to produce Quarter of thermal power need of India (Jamal et al., 1991). over last two decades, Large scale mining activities and operation of thermal power plants have caused major impacts on the surface biophysical characteristics not only on the LULC pattern but also on various ecosystems in this area. Forest and green spaces degradation on a significant scale has occurred due to huge mining activities in this area. forests and green spaces replaced with waste materials from coal mining (Singh et al., 1997).

The resettlements of local villages and towns, air pollution, landscape change and forest degradation were major negative impacts on the surface biophysical characteristics for the expansion of Hambach mine. Half of the landscape that converted to the mine area was forested and rich in biodiversity. 50% of the previously forested areas included deciduous forests with the highest structural diversity and biodiversity composition in the region (Imboden and Moczek, 2015; Brock and

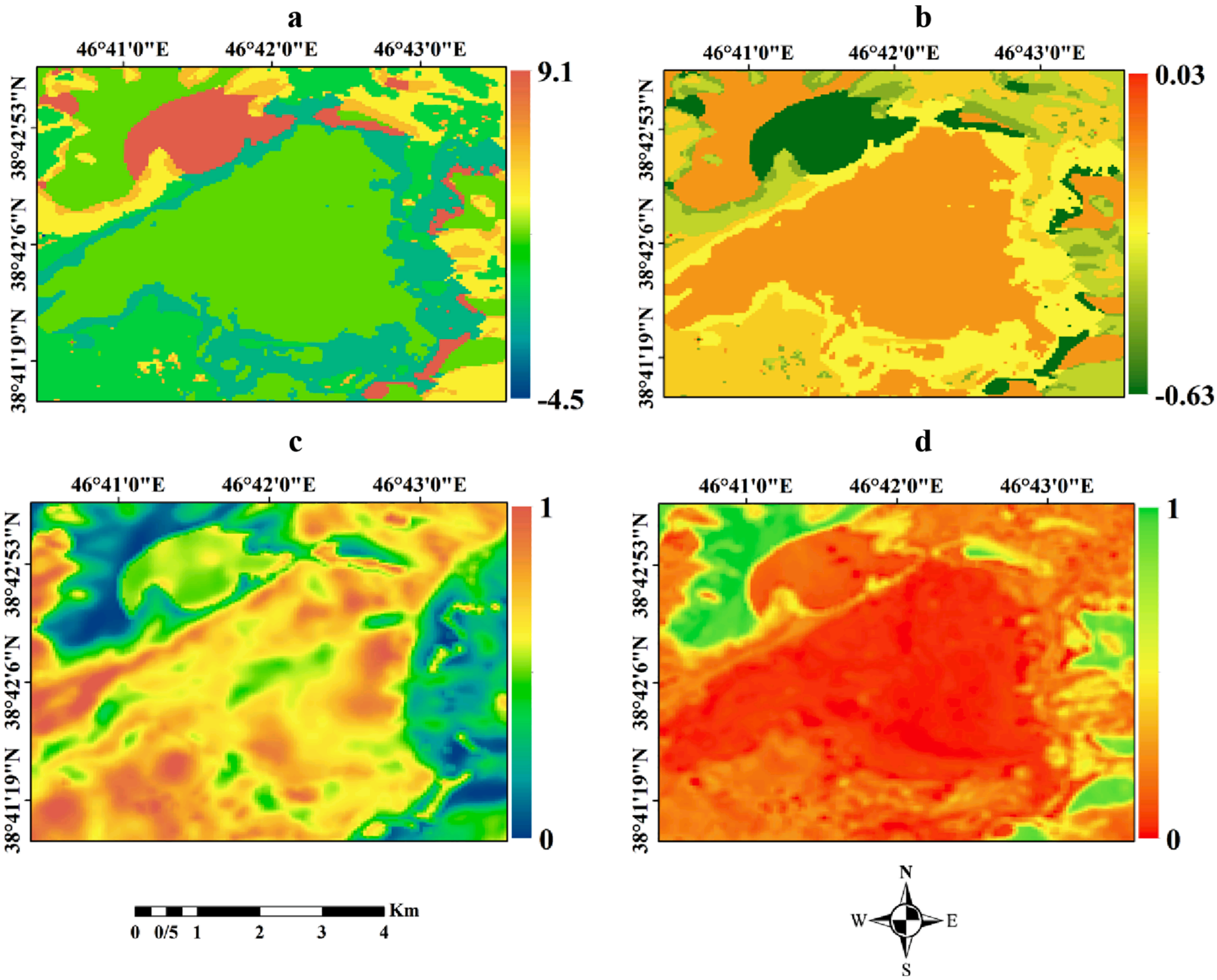

Fig. 10. The maps of: (a) predicted LST changes, (b) predicted NDVI changes, (c) predicted relative LST, and (d) predicted relative NDVI.

Dunlap, 2018). Besides the direct effects on the surface biophysical characteristics, there are also significant social effects on local inhabitants. The most important effect was the resettlement of local villages and towns, which lead to critical public debates in Germany. Around 2,500 inhabitants were relocated in past years. Additionally, the villages Morschenich and Manheim must be relocated (Imboden and Moczek, 2015). Environment activists have protested that if the forest is removed, the species that live there will be killed, including red-list species. Also, the local people concern for climate change (Bringezu, 2019). Since 2010, Environment activists initiated mass-protests and campaigns against RWE's mines in the Rhineland (Brock and Dunlap, 2018).

With the increase of mining activities in previous years, the conversion of natural surfaces to impervious surfaces was increased (Xian et al., 2011; Weng, 2012; Xu et al., 2018). This conversion changed the intrinsic properties of the natural surfaces, resulting in inappropriate surface ecological states (Weng, 2012) and posed negative impacts on the natural processes (Peng et al., 2016; Zhang et al., 2016). The trend of LULC changes was in a way that reduced surface greenness and increased surface heat (Figs. 7, 8 and 13). Surface greenness, and heat are the two primary and important factors affecting surface ecological states (Hu and Xu, 2018; Xu et al., 2018, 2019). The surface ecological states of the study areas was spatially and temporally heterogeneous due to the heterogeneous surface biophysical characteristics.

In general, forest and green space lands had the highest degree of greenness and the lowest degree of heat. For this reason, surface ecological states in forest and green space lands was better than other lands. On the other hand, mine lands had the lowest degree of greenness, and the highest degree of heat. For this reason, the mine land had the worst surface ecological states in the study area. The increased mine land area, significant reduction of forest and green space lands area and changes in surface biophysical characteristics (decreasing degree of Greenness, and increasing degree of heat) (Figs. 9 and 14). The most negative and positive change in modeled SES of the study area was related to the conversion of "forest and green space to mine" and "mine to forest and green space" lands, respectively.

The operation of a mine, in addition to the costs faced in the production process, imposes another cost on the environment, which is called the effects of externality or social costs. The important point is that normally the mining industry does not pay for this cost to the environment, so this environmental cost is not included in the cost-benefit function of the firm, which causes the production level of the firm to be higher than be the optimal social level. To solve this challenge, methods of (1) Pigounian Taxation, (2) No intervention (direct negotiation between parties), and (3) Firm limits, have been proposed by experts in the field of environmental economics.

The Pigounian Taxation method states that by imposing a tax on activities with external influences, the amount of these activities should be placed at the optimal social level. This means that the tax internalizes the unforeseen costs of the activities with side effects for the producer so that his decision to optimize his private interests leads to a socially optimal result. The No intervention method is to form an agreement between the mining investors and the custodians of the environment and natural resources, so that if the negative effects of the mining activities

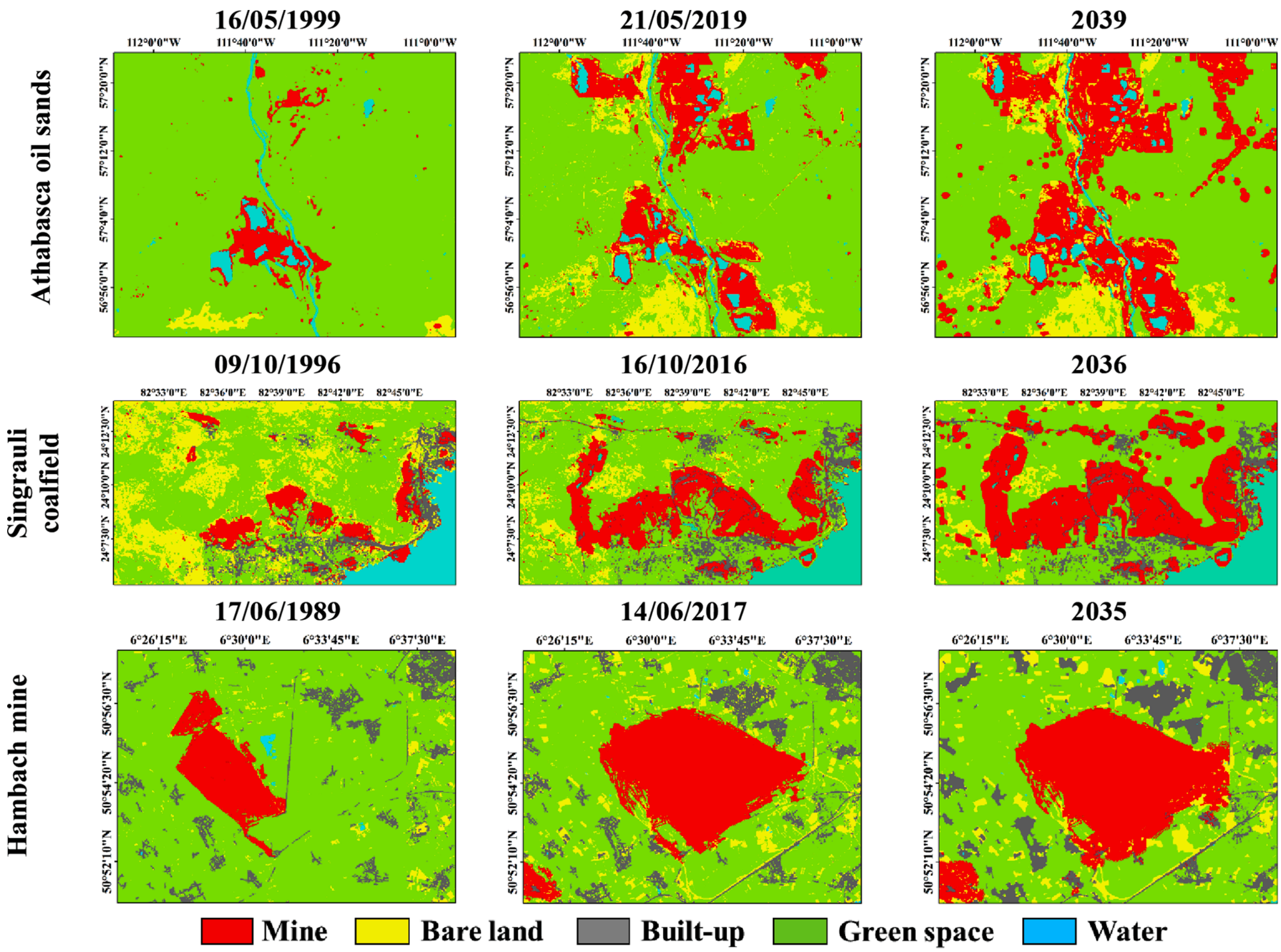

Fig. 11. LULC maps of the study areas for past and future years.

Table 2
The areal coverage (km^2) of each LULC class in the past and future years.

Athabasca oil sands	Mine	Built-up	Bare	Green space	Water
16/05/1999	197.67	–	72.24	4214.67	123.72
21/05/2019	662.67	–	484.96	3309.44	151.23
2039	1192.81	–	494.30	2774.2	147.00
Singrauli coalfield					
09/10/1996	39.36	37.18	123.40	231.46	3787
16/10/2016	89.72	36.49	40.98	263.95	38.13
2036	130.44	39.52	74.25	186.79	38.27
Hambach mine					
17/06/1989	18.45	18.32	5.89	180.38	0.62
14/06/2017	47.58	23.27	18.44	133.99	0.38
2035	55.19	27.34	18.48	122.13	0.52

increase from a certain limit, a cost will be paid by the mining investors to the custodians of the environment and resources. This revenue can be spent by environmentalists and natural resources to improve environmental conditions such as afforestation in the same area or other areas. Implementing the No intervention method costs less than the Pigounian Taxation method. However, the enforceability of property rights is a precondition for using a No intervention method to resolve the mining externality effects of mining activities. Another idea for the issue of externalities is the Firm limits method. In this way, the government has set a ceiling for external effects that cannot be exceeded by the producer of the external work. The amount of limits is determined according to social preferences in such a way that production is at the optimal social level.

5. Conclusions

Anthropogenic activities have caused LULC changes with direct and indirect negative impacts on our ecosystems and surface biophysical parameters. This study represents an example of a mining activity in a precious national biosphere where its impacts on the surrounding surface biophysical characteristics, in terms of changes in vegetation cover and LST, were investigated quantitatively. Our findings indicate a significant and negative impact of the mine activities up to the present time and how it will continue in future. In recent years, significant parts of natural areas were converted to mine lands and mining activities that have significantly increased LST and reduced vegetation cover. Our results show that LST and NDVI have high potential to quantify the effects of human activities on the surface biophysical characteristics. Also, the combination of reflection and thermal information obtained from satellite images increases the accuracy of modeling the surface biophysical characteristics and the impact of mining activities on the surface biophysical characteristics. In the other hand, predicting the effects of mining activities on the surface biophysical characteristics in the future based on CA-Markov and multi-temporal satellite images indicates the worrying results. In the coming years, mining activities can significantly alter the surface biophysical characteristics including LULC, LST and NDVI. Our results and discussions can alarm local planners, stakeholders and environmentalists to consider solutions for protecting natural reserves while continuing mining activities, if necessary. As per potential

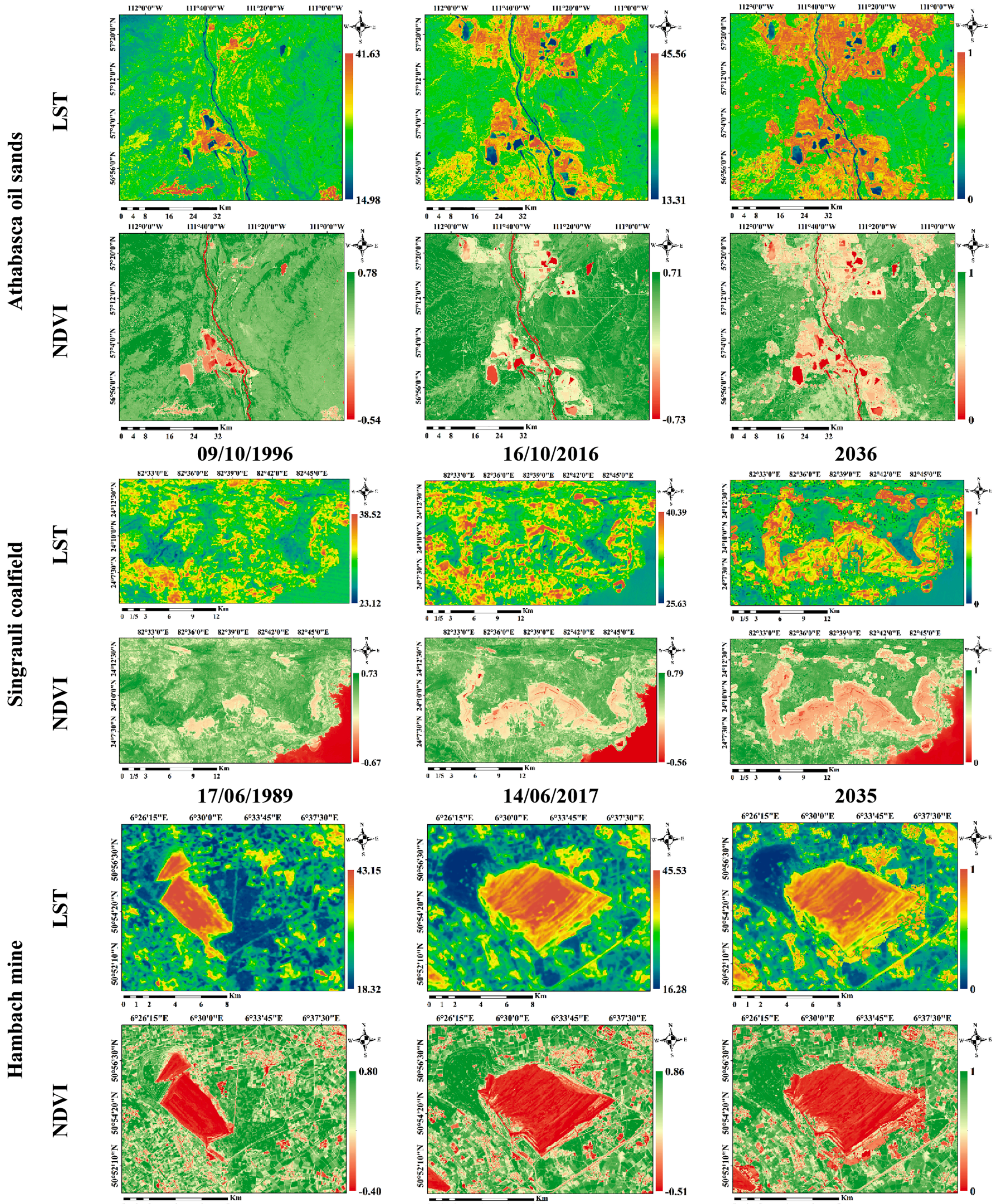

Fig. 12. LST and NDVI within past years, and relative LST and NDVI maps for future years.

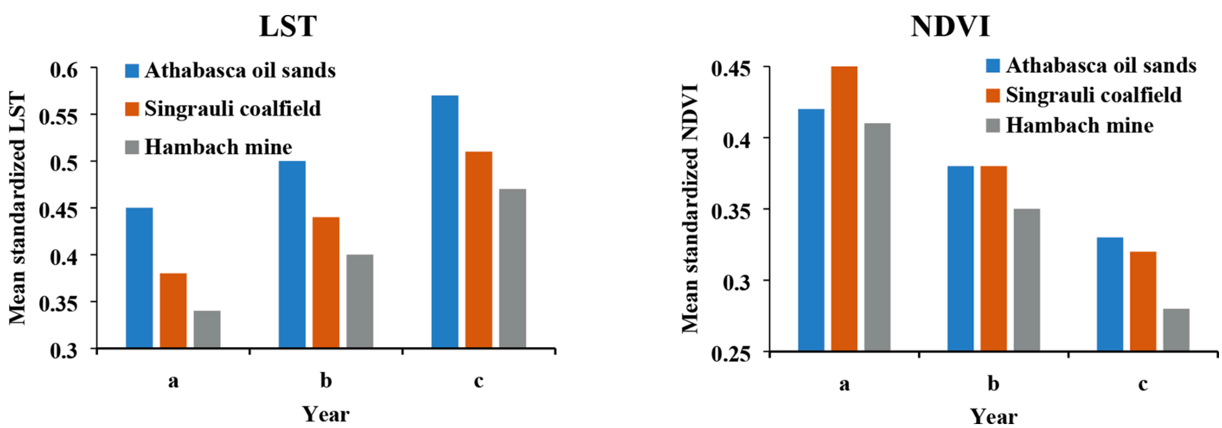

Fig. 13. The mean values of standardized LST and NDVI maps for past and future years (a: 1999, b: 2019, and c: 2039 for Athabasca oil sands, a: 1996, b: 2016, and c: 2036 for Athabasca oil sands, and a: 1989, b: 2017, and c: 2035 for Hambach mine).

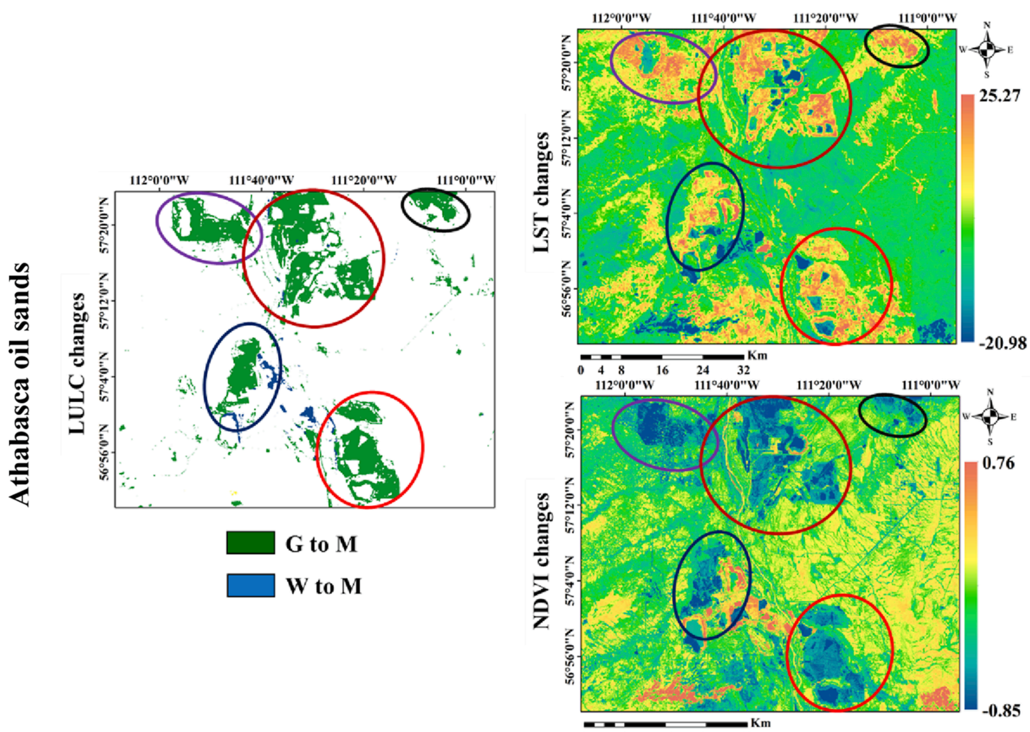

Fig. 14. LULC, LST and NDVI changes maps within past years. M: Mine B: Bare land, G: Green space, and W: Water. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

solutions, consideration of a spatial decision support system for multi-objective land allocation i.e., co-existence of conflicting objectives is recommended. Developing a suitable structure and system for disposal and recycling of mineral waste can be very useful to improve the surface biophysical characteristics of the area around the mine. The results of the Hambach mine showed that the conversion of unused mining areas into forests could improve the surface biophysical characteristics. Also, the management of waterways and streams in these areas will be very useful to reduce the indirect negative effects of mining activities. The cooperation of economic and environmental experts in the development of detailed plans including Pigounian Taxation, No intervention and Firm limits methods in order to balance the economic advantages and environmental disadvantages of mining activities in a region is very important and useful. Moreover, this study proved the usefulness of long-term archive of optical and thermal remote sensing data for monitoring surface biophysical characteristics and anthropogenic-based changes. The application of predictive models is worthwhile gaining insights about the future changes in the ecosystem and taking protective measure against the undesired situations. CA-Markov is a straightforward and user-friendly model for prediction of future changes based on historical changes. As per future directions, studies aiming at environmental impact assessment and changes in the living quality of the surrounding inhabitants are recommended.

CRediT authorship contribution statement

Mohammad Karimi Firozjaei: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing - original draft. **Amir Sedighi:** Conceptualization, Data curation, Formal analysis, Investigation, Validation, Writing - original draft. **Hamzeh Karimi Firozjaei:** Conceptualization, Investigation, Writing - original draft. **Majid Kiavarz:** Conceptualization, Supervision, Writing -

review & editing. **Mehdi Homaee:** Writing - review & editing. **Jamal Jokar Arsanjani:** Writing - review & editing. **Mohsen Makki:** Writing - review & editing. **Babak Naimi:** Writing - review & editing. **Seyed Kazem Alavipanah:** Conceptualization, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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