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Landscape Analysis of Cobalt Mining Activities from 2009 to 2021 Using Very High Resolution Satellite Data (Democratic Republic of the Congo)

Chloe Brown [1,2], Doreen S. Boyd [1,2,*] and Siddharth Kara [2,3]

[1] School of Geography, University of Nottingham, Nottingham NG7 2RD, UK; chloebrown.rs@gmail.com
[2] Rights Lab, University of Nottingham, Nottingham NG7 2RD, UK; siddharth.kara@nottingham.ac.uk
[3] School of Sociology and Social Policy, University of Nottingham, Nottingham NG7 2RD, UK
* Correspondence: doreen.boyd@nottingham.ac.uk

Abstract: The cobalt mining sector is well positioned to be a key contributor in determining the success of the Democratic Republic of the Congo (DRC) in meeting the Sustainable Development Goals (SDGs) by 2030. Despite the important contribution to the DRC's economy, the rapid expansion of mining operations has resulted in major social, health, and environmental impacts. The objective of this study was to quantitatively assess the cumulative impact of mining activities on the landscape of a prominent cobalt mining area in the DRC. To achieve this, an object-based method, employing a support vector machine (SVM) classifier, was used to map land cover across the city of Kolwezi and the surrounding mining areas, where long-term mining activity has dramatically altered the landscape. The research used very high resolution (VHR) satellite imagery (2009, 2014, 2019, 2021) to map the spatial distribution of land cover and land cover change, as well as analyse the spatial relationship between land cover classes and visually identified mine features, from 2009 to 2021. Results from the object-based SVM land cover classification produced an overall accuracy of 85.2–90.4% across the time series. Between 2009 and 2021, land cover change accounted to: rooftops increasing by 147.2% (+7.7 km^2); impervious surface increasing by 104.7% (+3.35 km^2); bare land increasing by 85.4% (+33.81 km^2); exposed rock increasing by 56.2% (+27.46 km^2); trees decreasing by 4.5% (-0.34 km^2); shrub decreasing by 38.4% (-26.04 km^2); grass and cultivated land decreasing by 27.1% (-45.65 km^2); and water decreasing by 34.6% (-3.28 km^2). The co-location of key land cover classes and visually identified mine features exposed areas of potential environmental pollution, with 91.6% of identified water situated within a 1 km radius of a mine feature, and vulnerable populations, with 71.6% of built-up areas (rooftop and impervious surface class combined) situated within a 1 km radius of a mine feature. Assessing land cover patterns over time and the interplay between mine features and the landscape structure allowed the study to amplify the findings of localised on-the-ground research, presenting an alternative viewpoint to quantify the true scale and impact of cobalt mining in the DRC. Filling geospatial data gaps and examining the present and past trends in cobalt mining is critical for informing and managing the sustainable growth and development of the DRC's mining sector.

Keywords: cobalt; Copperbelt; sustainable mining; land cover; child labour

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1. Introduction

Tackling the climate crisis is a global priority [1–5] recognised, in particular, by the Sustainable Development Goals (SDGs) in SDG 7: Affordable and Clean Energy, and SDG 13: Climate Action. Securing access to responsibly sourced raw minerals is essential to ensure that international climate agreements can be met. Cobalt is a key element in the green economy and innovation of battery technology—as a component in rechargeable lithium-ion batteries, cobalt is used to power electronic devices such as smartphones, laptops, and electric cars. Demand for cobalt is set to skyrocket, with the World Bank projecting global cobalt production to mushroom to 585% by 2050 [6], yet cobalt has a distinct geography with respect to source and supply.

The Democratic Republic of the Congo (DRC) is the largest producer and exporter of cobalt, accounting for 74% of mined cobalt in 2021 [7]. The DRC is widely recognised as one of the wealthiest countries in the world regarding natural resources [8–10]. Despite this extraordinary mineral wealth, 73% of the DRC's population lives in extreme poverty [11], surviving on less than USD 1.90 per day (the international poverty rate). The mining sector is essential to the country's economy, representing 30% of the DRC's gross domestic product (GDP) in 2019 [12] and 95.3% of total exports in 2020 [13], the majority of which are made up of copper and cobalt export. On a regional scale, cobalt mining in the "Copperbelt", an area of concentrated copper/cobalt deposits that extends from Southeastern DRC to northern Zambia, serves as a source of livelihood for an estimated 60% of households [14]. Despite the important contribution to the DRC's economy, the rapid expansion of mining operations has resulted in major social, health, and environmental impacts. Child labour, abusive working conditions, racism, the violent displacement of local communities, and the prostitution of women and young girls have been routinely observed at cobalt mines [15,16]. A lack of proper safety gear and industry regulations pose serious health impacts for adult and child miners, including respiratory and skin problems, heavy metal poisoning, cancers, as well as life-threatening mining accidents, such as mine collapse, underground explosions, and suffocation due to poor ventilation [17–19]. Outside of the industrial mines, widespread environmental pollution from acid, dust, and tailings [20,21] has led to increasing public health concerns over the local population's exposure to toxic substances [22–25].

Cobalt mining is divided into two district groups: large-scale mining (LSM) and artisanal small-scale mining (ASM). Although there are no reliable figures due to cross-contamination between LSM and ASM, LSM is estimated to comprise between 70 and 80% of cobalt production in the DRC, while ASM is estimated to represent the remaining 20–30% [26]. A lack of credible material traceability and extensive commercial and physical interaction between ASM and LSM, via an informal ecosystem of traders, buying houses, and ASM cooperatives, has left the exact percentage breakdown of LSM and ASM output a topic of debate. In 2016 and 2017, Amnesty International published reports [27,28] 'naming and shaming' several high-profile consumer brands for the high prevalence of human rights abuse, in particular child labour, linked to their cobalt suppliers and sub-suppliers in the DRC. Major media outlets have echoed this message [29–35], placing considerable emphasis on tying child labour in the DRC's ASM cobalt sector to the supply chains of global brands, including Apple, Google, Microsoft, Dell, and Tesla. Customer awareness of child labour exploitation, coupled with regulatory obligations and increased shareholder focus on responsible business practices, has applied pressure on businesses to prove ethical and sustainable activity throughout their cobalt supply chains. Sourcing cobalt from LSM in the DRC is often presented as a way to avoid the serious human rights abuses considered to be more prevalent in ASM [36], with industrial-mined cobalt being branded as the more traceable, 'cleaner', and accepted resource in the global green energy revolution. However, a joint investigation carried out by the corporate watchdog Rights and Accountability in Development (RAID) and Centre d'Aide Juridico-Judiciaire (CAJJ) [37] found that workers employed by subcontractors in LSM earned substantially less than those hired directly by the LSM companies, with most not earning the minimum living wage. Workers interviewed also described a "colonial-era" level of discrimination, reporting excessive working hours, unsafe working conditions, racism, and violence. An investigation by the Guardian [38] described a comparable account on the experience of subcontractor workers in LSM, with an interviewee quoted as, *"The relationship between us and the [mine] is like a slave and a master"*, [38].

As an Alliance 8.7 Pathfinder country, the DRC has committed to accelerating efforts to achieve the objectives of SDG Target 8.7:

> *"Take immediate and effective measures to eradicate forced labour, end modern slavery and human trafficking and secure the prohibition and elimination of the worst forms of child labour, including recruitment and use of child soldiers, and by 2025 end child labour in all its forms"*. [39]

At the time of this study's publication, a roadmap with specific priorities for achieving SDG Target 8.7 for the DRC has not been published [40], however, combatting child labour in the ASM cobalt industry is set to be a major priority [41,42]. For the DRC, addressing challenges in the mining sector has significant implications for achieving a number of UN SDGs by 2030. The cumulative effect of cobalt mining has the potential to impact: SDG 1: End Poverty; SDG 3: Good Health and Well-Being; SDG 8: Decent Work and Economic Growth; SDG 12: Responsible Consumption and Production; SDG 15: Life on Land; and SDG 16: Peace, Justice, and Strong Institutions. Furthermore, commitments set by the 26th UN Climate Change Conference of the Parties (COP26) also require the social, health, and environmental impacts associated with the extraction of cobalt to be addressed. Green transition commitments, for example, the UK government ban on the sale of petrol and diesel cars from 2030 [43], are set to apply more demand and pressure on the DRC's mining sector. The regulation of both the ASM and LSM sectors is the responsibility of the DRC's government, however, the necessary data on the present and past distribution and extent of mining sites in the Copperbelt are critically missing. Such information is required to assist the DRC in demonstrating its commitment to meeting SDGs and establishing 'clean' cobalt supply chains.

Satellite Earth Observation (EO) has been extensively applied to map structurally complex mining environments [44–47]. For example, Dupin et al. [48] combined ancillary data and satellite EO imagery to assess land cover fragmentation dynamics over a 30-year time period (1979–2011) in the Katanga province, DRC. Three case study areas were established, located in the surrounding areas of Kolwezi and Tenke-Fungurume copper–cobalt mining sites and the Basse-Kando Natural Reserve. In general, the results showed the most dominant fragmentation processes were gains in the barren soil and cities' surface class and a reduction in the burned area class. Specifically, the Kolwezi case study results presented a close relationship between the growth and regression of the barren soil and city class over vegetation. Departing from the Copperbelt, Kranz et al. [49] used very high resolution optical stereo satellite data to assess land cover change in a cassiterite (tin) ASM area in Bisie in North Kivu, DRC. The study combined an object-based change detection classification approach with detailed digital surface models to assess land cover change between 2010 and 2015, marking a time period of conflict and suspension of ASM activities in North Kivu. Results revealed an increase in the bare soil area (interpreted as the mining area) by a rate of 47% from April 2010 to September 2010, followed by a significant decrease of 47.5% until March 2015 (related to the 2014 mining ban). The study concluded that EO data can deliver detailed insight into complex ASM surface dynamics, supporting the surveillance of mineral traceability systems and informing the development of conflict mitigation and peace-building recommendations and strategies.

Monitoring land cover and land use changes can allow stakeholders to examine the interplay between cobalt mining activities and the wider landscape structure and function, providing critical information to manage and protect sustainable growth and development in the DRC's mining sector. The objective of this study was to quantitatively assess the cumulative impact of mining activities on the landscape of a prominent cobalt mining area in the DRC (focused on Kolwezi). To achieve this, the study proposes the implementation of a support vector machine algorithm (SVM) using very high resolution (VHR) EO data and an object-based method to assess land cover change in Kolwezi over a +10-year time period (2009–2021). Multiple studies applying EO data to assess mining locations have noted the limitations of using medium spatial scale EO imagery, such as Landsat or SPOT, as the footprint of ASM activities can be relatively small and spectrally similar to other land cover classes [50,51]. As ASM land cover features at the study site vary dramatically in size, VHR satellite imagery was required to ensure features could be visually registered. Past research has demonstrated that object-based classification methods perform better than more traditional pixel-based approaches when applied to VHR EO data in complex landscapes [52,53]. Object-based classifications consider the spectral, spatial, and textural information in the data modelling approach. To classify an EO image, the method extracts homogenous groups of pixels, known as 'objects', which share similar properties to classify the scene, as opposed to single pixels in a pixel-based approach. The SVM classifier was selected as the algorithm as it has been proven to produce superior accuracy results compared to other machine learning classifications, such as a decision tree, random forest, k-nearest neighbour, and Bayesian [53,54]. Additionally, the study also merges the SVM object-based classification outputs with data derived from the manual interpretation of VHR EO imagery to explore land use change in relation to cobalt mining features, specifically, changes in the cobalt mine type and structure. Filling geospatial data gaps and examining the present and past trends in cobalt mining will help secure a sustainable balance between the positive economic benefits and the negative social, health, and environmental impacts of the DRC's mining sector.

2. Materials and Methods

2.1. Study Area

The study focuses on Kolwezi, capital of Lualaba province (ex-Katanga region) in the southeastern corner of the DRC (Figure 1). Situated on the Manika plateau at an average altitude of 1500 m above sea level, Kolwezi is the largest and most important copper and cobalt mining centre in the world. The city was founded in 1938 by the Union Minière du Haut Katanga as the headquarters of its newly-created western division. Kolwezi's population has grown fast, with a continual influx of people looking for employment, primarily in the mining sector. Current estimates set the population figure at 453,000 inhabitants [55], although ground observation suggests a population of closer to one million. Kolwezi and the surrounding mining areas have a complex landscape structure. The city has been previously described as an agglomeration of mini-urban areas, shaped by colonial planning [56]. Townships and surrounding slums have sprawled from the city centre, creating a scattered and poorly-serviced urban environment. The dominant natural vegetation in the region is open deciduous Miombo woodland, with herbaceous vegetation covering the prominent steep copper/cobalt hill outcrops [57] (Figure 2). However, deforestation and environmental degradation directed by mining activities have altered the natural landscape of the study's AOI (Figure 3).

The landscape is dominated by LSM installations, with three-quarters of developed space in Kolwezi taken up by mining sites [37]. Mineral extraction is the main source of employment and income for the city, with both LSM and ASM activities intertwined (Figure 4). Commercial agricultural production is weak. The region produces crops such as maize, cassava, and groundnuts, however, the farmed produce is insufficient to meet local needs. Lack of access to agricultural credit and the rural exodus of young people to more profitable ASM activities has resulted in a poorly developed agricultural sector.

2.2. Satellite EO Time Series

To investigate land cover change and the interplay between mining features and the wider landscape in Kolwezi, VHR satellite EO imagery were required over the +10-year time period of interest. The study is focused on 2009 to 2021; this time series marks a dynamic period in Kolwezi's cobalt mining sector, characterised by political change, the rapid development of the LSM and ASM sectors, and fluctuating market prices. VHR satellite image was acquired for the years 2009, 2014, 2019, and 2021. Table 1 provides full details on the satellite data used in this study. To reduce the risk of error introduced by seasonal variations in the spectral characteristics of different land-cover classes, the imagery was only sourced for dry season months only, specifically, May–July.

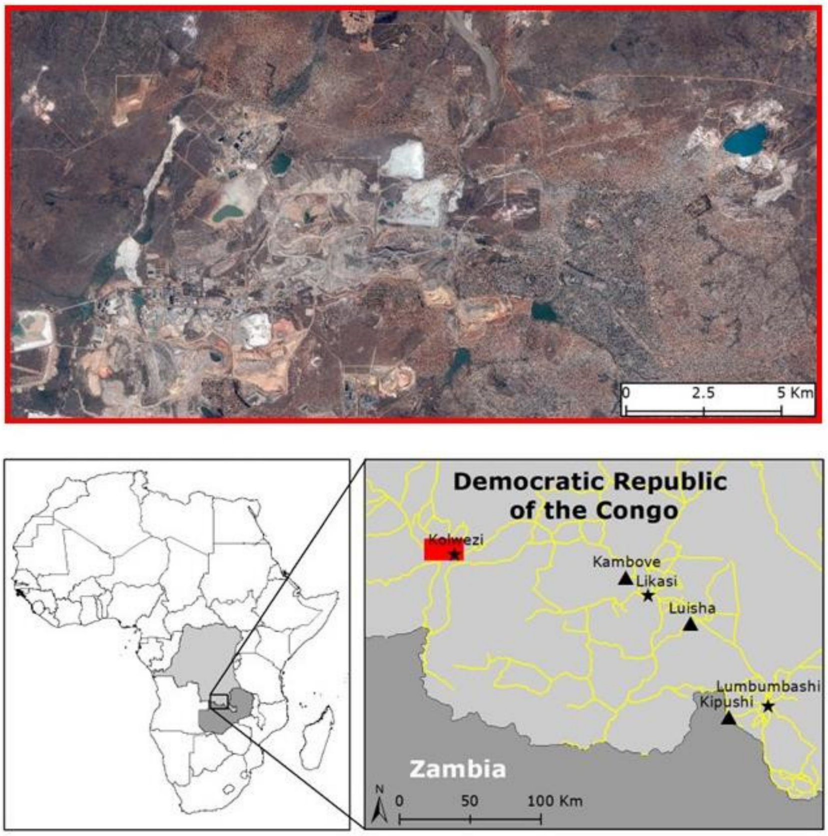

Figure 1. The black outline (larger extent) indicates an area of the Copperbelt" with the location of the major cities (star marker) and townships (triangle marker). Yellow line represents the road network. The red outline (smaller extent) indicates the extent of the study's area of interest visualised in very high resolution satellite imagery (2021 Pléiades data).

Figure 2. Field photography of Copperbelt countryside. Photograph: Siddharth Kara.

Figure 3. Field photography of a mine wall and surrounding area degraded vegetation in Kolwezi. Photograph: Siddharth Kara.

Figure 4. Cobalt artisanal small-scale mining (ASM) sites. Left: surface ASM site. Right: Cobalt tunnel mine. Photograph: Siddharth Kara.

To ensure that the multi-sensor satellite imagery time series was as comparable as possible, the following basic pre-processing steps were performed: mosaicking, resampling (0.5 m), radiometric calibration, and image-to-image registration. Each of the VHR satellite images was clipped to an area that overlapped every image in the time series. This clipped area will hereby be referred to as the study area of interest (AOI) (Figure 1). The AOI covers an area of over 350 km^2, capturing the entire city of Kolwezi, as well as the surrounding areas, featuring large-scale industrial mine complexes and undeveloped vegetated land. All pre-processing steps were performed in ITTVIS ENVI 5.4. (Broomfield, CO, USA).

In addition to the satellite spectral bands of blue, green, red, and near-infrared (for the 2019 WorldView-2 image, the near-infrared band used was Near-Infrared 1), the Normalised Difference Vegetation Index (NDVI) and Normalised Difference Water Index (NDWI) were calculated for each year in the time series and added to the image band stack for further analysis.

NDVI proposed by Rouse et al. [58], expressed as the following:

$$\mathrm{NDVI} = \frac{(NIR - R)}{(NIR + R)}$$

NDWI proposed by McFeeter [59], expressed as the following:

$$\text{NDWI} = \frac{(G - NIR)}{(G + NIR)}$$

Vegetation indices bands, NDVI and NDWI, were calculated using the 'raster' package [60] for R (version 3.6.1; RStudio PBC; Boston, MA, USA).

Table 1. Summary of satellite data used in the time series.

Satellite	Acquisition Date	Spatial Resolution	Spectral Bands
GeoEye-1	7 July 2009	0.46 m (Panchromatic)	Panchromatic: 450–800 nm Blue: 450–510 nm Green: 510–580 nm Red: 655–690 nm Near Infrared: 780–920 nm
Pléiades	16 May 2014	0.5 m (Panchromatic)	Panchromatic: 480–830 nm Blue: 430–550 nm Green: 490–610 nm Red: 600–720 nm Near Infrared: 750–950 nm
WorldView-2	25 June 2019	0.46 m (Panchromatic)	Coastal blue: 400–450 nm Blue: 450–510 nm Green: 510–580 nm Yellow: 585–625 nm Red: 630–690 nm Red-edge:705–745 nm Near Infrared 1: 770–895 nm Near Infrared 2: 860–1040 nm
Pléiades	30 July 2021	0.5 m (Panchromatic)	Panchromatic: 480–830 nm Blue: 430–550 nm Green: 490–610 nm Red: 600–720 nm Near Infrared: 750–950 nm

2.3. Land Cover Classification

In this study, the ENVI Feature Extraction workflow (ENVI 5.4) was used to perform the object-based classification. This workflow includes: segmentation, square kernel sizing, training data selection and attribute assignment (spectral, spatial, and textural), and classifier algorithm selection. The segmentation approach involved two scaled parameters: segmentation level and merge level. An edge-based segmentation algorithm was used to group image pixels into image 'objects' based on similar spectral, spatial, and textural attributes. The segmentation level can be set from 0–100. A low segmentation level may result in over-segmentation with large numbers of small segments (increasing the size and complexity of the file), while a high segmentation level may result in under-segmentation with few large segments (grouping more than one class in one object). Determining segmentation level is a crucial step in object-based classification [61]. An optimal segmentation scale should be defined relative to the shape and size of the target features or classes in the classification scenario in order to prevent mixed-object errors in the final outputs [62]. After trial-and-error tests and visual analysis, the segmentation level in this study was set to 40.5. To reduce over- or under-segmentation, merging of objects was performed using the Full Lambda-Schedule algorithm. In this study, a merge level of 19.7 was set to aggregate the image objects.

Once segmented, the Feature Extraction workflow next computed the spatial, spectral, and textual attributes for each of the defined image objects [63]. Training data were then manually collected for each of the land cover classes (Table 2) in order to provide spectral, spatial, and textural signatures for the land cover classifier. The number of samples (objects) collected for each class was dependent on the occurrence of the class in the AOI scene.

Table 2. Description of the land cover classes.

Class	Description
Rooftop	Includes: metal, clay, concreate building materials
Impervious surface	Includes: asphalt, low-albedo surfaces
Bare land	Includes: dirt track, construction sites, sediment deposits, bare soil
Exposed rock	Includes: mine pits, rock piles, tailings, smelt waste, natural rockslides
Trees	Includes: mature tree growth
Shrub	Includes: woody shrub species
Grass and Cultivated land	Includes: mixed grassland, cultivate land, low-cover herbaceous species
Water	Includes: rivers, lakes, ponds, water retention areas, streams
Shadow	Includes: shadowed areas
Glare	Includes: bright solar reflection

Independent land cover classifications were performed on the segmented AOI 2009, 2014, 2019, and 2021 image scenes employing an SVM classifier. SVM is a linear model for classification and regression. It is designed to find the optimal solution for classification problems by using hyperplane fitting to provide the 'best' separation between two classes in multidimensional feature space [64]. SVM was performed with a Radial Basis Kernel Function within the ENVI Feature Extraction workflow.

Access to the study area was limited, therefore, ground reference information was not available to assess the accuracy of the land cover classification outputs. The overall accuracy of the four classification map outputs was determined by an individual visual analysis of 500 randomly selected points for each land cover output in the time series. Visual analysis was conducted using VHR imagery and image interpretation guided by expert knowledge gained from extensive prior fieldwork in Kolwezi.

2.4. Visual Assessment

Areas identified as exposed rock by the land cover classification model for the years 2009 and 2021 were further categorised by mining landscape feature: open pit, surface, and tunnel (Table 3). In this study, mining was not simply categorised as LSM or ASM as ASM, in particular surface mining, can occur in both natural and artificial deposits created by industrial mining waste or tailings. Additionally, the reported complex system through which artisanal miners 'illegally' access LSM sites [16] may pose a challenge when interpreting the dynamic spatial patterns of mining at a landscape scale.

Table 3. Summary of the visual descriptions used to identify the mining landscape features from the exposed rock land cover class.

Feature	Description
Open-pit	Includes: uniform, terraced platform structures
Surface	Includes: artisanal surface mines (irregular lunar surface texture); storage areas of excavated minerals or earth, for example: ore, tailings, smelt waste, or gangue material from mineral processing
Tunnel	Includes: locations with tunnel mine entrances (1–2 m in diameter) and/or pink tarp tents (covering tunnel mine entrances)

The mining features were visually identified in the 2009 and 2021 VHR AOI imagery and corresponding land cover classification output guided by expert knowledge gained from extensive prior fieldwork in the DRC Copperbelt. Each feature identified was digitised and stored in a database. Areas where multiple mine features were located in the same site were noted and categorised according to the dominant feature present. The categorised mining features were analysed in terms of the changes in spatial statistics from the start and end of the studied time interval. The spatial relationship between identified features and land cover classes, in particular classes related to built-up, urban areas (classes: rooftop and impervious surface) and water were also assessed.

3. Results

3.1. Land Cover

Analysis of the spatial distribution and expansion of land cover classes over the study's time period of interest was based on the presentation of the 2009, 2014, 2019, and 2021 object-based SVM classification outputs (Figure 5) and respective spatial statistics (Table 4) in terms of the total area (km^2) of each class in each study year.

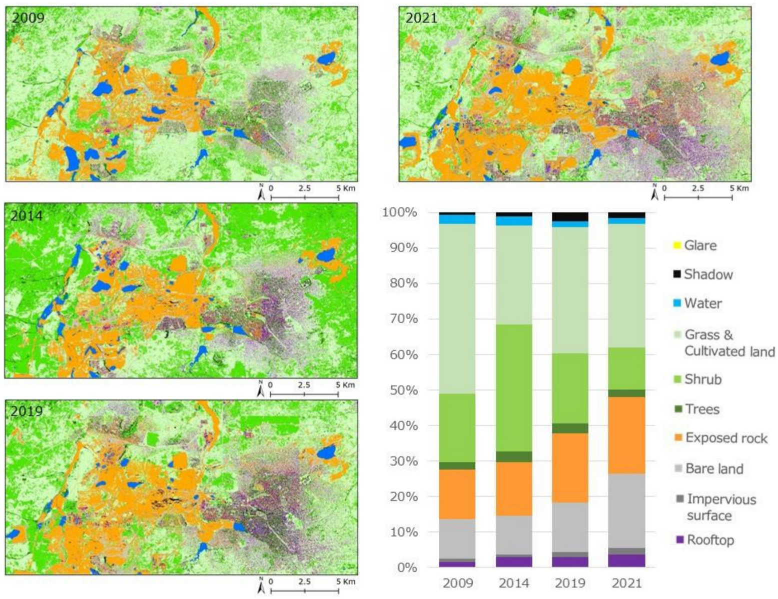

Figure 5. Land cover classification outputs for 2009, 2014, 2019, and 2021, alongside percentage area breakdown for each land cover class.

Table 4. Area (km^2) and percentage area (%) for each land cover class in the AOI during 2009–2021.

	2009		2014		2019		2021	
Classes	**Area (km^2)**	**% Area**	**Area (km^2)**	**% Area**	**Area (km^2)**	**% Area**	**Area (km^2)**	**% Area**
Rooftop	5.23	1.49	9.82	2.85	10.19	2.89	12.93	3.66
Impervious surface	3.20	0.91	2.20	0.64	4.78	1.36	6.55	1.86
Bare land	39.60	11.23	38.03	11.05	49.55	14.06	73.41	20.8
Exposed rock	48.86	13.86	51.60	14.99	68.38	19.4	76.32	21.63
Trees	7.61	2.16	10.53	3.06	10.05	2.85	7.27	2.06
Shrub	67.75	19.22	123.12	35.76	69.80	19.8	41.71	11.82
Grass and Cultivated land	168.59	47.82	96.33	27.99	124.79	35.41	122.94	34.84
Water	9.49	2.69	8.53	2.48	5.76	1.64	6.21	1.76
Shadow	2.16	0.61	4.05	1.18	8.83	2.51	5.43	1.54
Glare	0.04	0.01	0.00	0	0.30	0.08	0.10	0.03

In 2009, the land cover of the study area was largely dominated by areas of vegetation (trees = 7.61 km^2; shrub = 67.75 km^2; grass and cultivated land = 168.59 km^2), the exposed rock class also had a significant footprint (48.86 km^2, 13.86%), significantly in the left half of the AOI. Areas of rooftop (5.23 km^2, 1.49%), impervious surface (3.20 km^2, 0.91%), and bare land classes (39.60 km^2, 11.23%) were predominantly co-located in the right half of the AOI, focused around the urban centre of the Kolwezi.

In 2014, the study area was still dominated by areas of vegetation (trees = 10.53 km^2; shrub = 123.12 km^2; grass and cultivated land = 96.33 km^2). Between 2009 and 2014, the rooftop class increased by 87.8% (2014 = 9.82 km^2, 2.85%), interpreted as a result of the expansion of industrial complexes and buildings, and residential development. In 2019, the bare land (49.55 km^2, 14.06%) and exposed rock (68.38 km^2, 19.4%) classes continued to expand. As a result, the vegetation classes shrub (69.80 km^2, 19.8%) and grass and cultivated land (124.79 km^2, 35.41%) decreased in combined area.

In 2021, the land cover of the study area was no longer dominated by vegetation classes, as the expansion of both the mining sector and urban development in Kolwezi between 2009 and 2021 had dramatically altered the landscape structure of the AOI. Between 2009 and 2021, land cover change was accounted to: rooftops increasing by 147.2% (+7.7 km^2); impervious surface increasing by 104.7% (+3.35 km^2); bare land increasing by 85.4% (+33.81 km^2); exposed rock increasing by 56.2% (+27.46 km^2); trees decreasing by 4.5% ($-$0.34 km^2); shrub decreasing by 38.4% ($-$26.04 km^2); grass and cultivated land decreasing by 27.1% ($-$45.65 km^2); and water decreasing by 34.6% ($-$3.28 km^2).

The time series has an overall accuracy of 85.2–90.4% (Table 5) for classifying land cover in the AOI. Across the different years, the highest confusion occurred between the grass and cultivated land class and shrub class and between the bare land and exposed rock class. Both pairs of classes share similar spectral signatures, where often these classes were mixed/both featured to some degree in the object segmented by the object-based approach. Additionally, the rooftop class was at times incorrectly selected by the SVM classification model across a wide variety of land cover classes. This may be due to the high reflectivity and variety of building materials that were featured in this spectrally complex land cover class.

Table 5. Overall accuracy scores for object-based SVM land cover classification outputs.

Year	Overall Accuracy Score (%)
2009	90.4
2014	85.2
2019	89.4
2021	90.2

3.2. Mining Features

Mining feature categories were interpreted for the 2009 and 2021 exposed rock class outputs and VHR EO data based on expert knowledge gained from extensive prior fieldwork in the DRC Copperbelt. Table 6 outlines the number of mining features identified for each category, over the time period 2009–2021. Open-pit increased from 3 to 7, Surface decreased from 183 to 177, and Tunnel increased from 24 to 41. The size of mining features varied considerably (Figure 6), although the average size (km^2) for all mine feature categories increased from 2009 to 2021. The percentage increase for each mining feature category was 181.13% for Open-Pit, 16.67% for Surface, and 200% for Tunnel.

Table 6. Descriptive statistics for the mining features digitised.

Year	Mine Type	Number	Mean Area (km^2)	Minimum Area (km^2)	Maximum Area (km^2)
2009	Open-Pit	3	0.53	0.02	1.39
	Surface	183	0.18	0.0002	3.97
	Tunnel	24	0.03	0.00005	0.12
2021	Open-Pit	7	1.49	0.05	4.12
	Surface	177	0.21	0.001	3.03
	Tunnel	41	0.09	0.00009	1.32

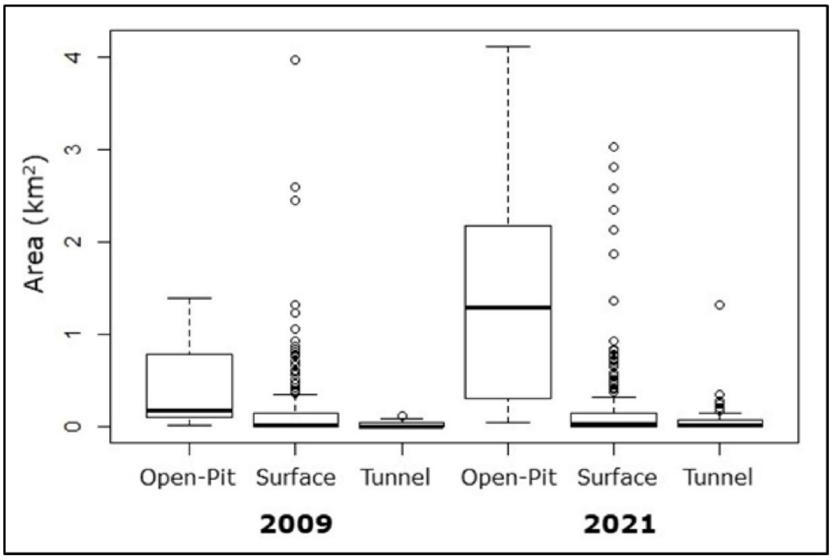

Figure 6. Boxplots of area (km^2) for the identified mining feature area for the years 2009 and 2021.

The footprint of the mining feature categories was analysed in terms of their spatial relationship with land cover classes associated with built-up areas (classes: rooftop and impervious surface) and water (Table 7). In 2009, 46.2% of built-up areas in the AOI fell within a 500 m radius of an area of mining activity and 64.4% within 1 km. For areas of water, 79.2% of the water class in the AOI fell within a 500 m radius of an area of mining activity and 88.2% within 1 km. In 2021, 45.7% of built-up areas in the AOI fell within a 500 m radius of an area of mining activity and 71.6% within 1 km. For areas of water, 68.3% of the water class in the AOI fell within a 500 m radius of an area of mining activity and 91.6% within 1 km.

Table 7. Percentage area of land cover class that fell within a 500 m and 1 km radius of an identified mining feature (open-pit, surface, and tunnel).

Year	Land Cover Class	500 m	1 km
2009	Built-up	46.2%	64.4%
	Water	79.2%	88.2%
2021	Built-up	45.7%	71.6%
	Water	68.3%	91.6%

4. Discussion

The achievement of the UN SDGs will require collaboration and cooperation between governments, non-governmental organisations, development partners, the private sector, and local communities. The cobalt mining sector is well positioned to be a key contributor in determining the success of the DRC in meeting the SDGs by 2030 [65,66]. To varying extents, cobalt mining activities relate to all 17 goals, the most relevant include: SDG 1, SDG 3, SDG 8, SDG 12, SDG 15, and SDG 16. Over the last decade, a surge in on-the-ground narrative reporting and academic research has exposed the destructive social, health, and environmental impacts of mining in the Copperbelt. This study presented an alternative viewpoint to quantify the true scale and impact of cobalt mining in the DRC. Assessing land cover and land use patterns over time, and the interplay between mining features and the landscape structure, allows us to amplify the findings of localised on-the-ground research. Understanding the past and present landscape dynamics of cobalt mining provides a reliable medium to inform sustainability strategies, management, and reporting. In the past, geospatial records of the Copperbelt have been often outdated or inconsistent, making it difficult to inform important policy or decisions-making processes, for example, guiding SDG-related priorities and commitments. The adoption of modern technologies, for example, satellite EO data, will be critical to enhance the DRC's sustainability performance and, as an Alliance 8.7 pathfinder country, meet SDG commitments.

4.1. Land Cover vs. Cobalt Price

Cobalt mining represents a key driver in the DRC's economic performance. The political and economic impact of changes in the mining sector has a significant bearing on past and present land cover dynamics, and future resource management for the Copperbelt. Grouped into classes of interest, the land cover classification outputs have been presented alongside economic data to analyse the links between mining activity in the study AOI and the cobalt market price (Figure 7). The time period of interest in this study was marked by significant price fluctuations in the cobalt market. According to the land cover models, the largest increase in the exposed rock class, interpreted to be mining-related, occurred between 2014 and 2019, with an increase of 32.5% (2014 = 51.60 km^2; 2019 = 68.38 km^2). Increased demand and value for cobalt during this period saw the price of cobalt triple to an annual average of USD 73,000/t in 2018 from USD 28,000/t in 2015. This unprecedented rise in cobalt price correlates with the conversion of land cover from vegetation to exposed rock, and the expansion of urban areas (built-up and bare land classes). After trading at an average of USD 85,000/t in early 2018, the price fell by 70% from the March peak as mining operations resumed at the Glencore PLC Katanga site [67]. Following 2019, the cobalt price began to decline in the first half of 2020 as COVID-19 impacted the global economy. Cobalt prices began to recover after July 2020, motivated by supply-chain disruptions and news of reserve stockpiling by the Chinese government [68]. The ongoing demand for cobalt is visible in the land cover outputs, with the exposed rock class continuing to increase by 11.6% (2019 = 68.38 km^2; 2021 = 76.32 km^2) in just two years (2019–2021). It is important to note here that simply analysing the spatial changes of land cover features cannot provide conducive proof of the extent of mining activity, for example, areas of abandoned mines or areas of rocky outcrop that are not associated with mining could be interpreted as mining activity if classified as exposed rock. However, it does serve as an important indicator of landscape structure and dynamics. The bare land class could also be included in the analysis of mining activities at landscape scales, indicating the potential extension of mining sites or intensification of mining-related activity. Looking ahead, cobalt demand is expected to continue to rise, however, the economy of the DRC remains vulnerable to commodity price movements. Resource management, informed by landscape-scale monitoring and assessment, is necessary to ensure the sustainable development of the Copperbelt region.

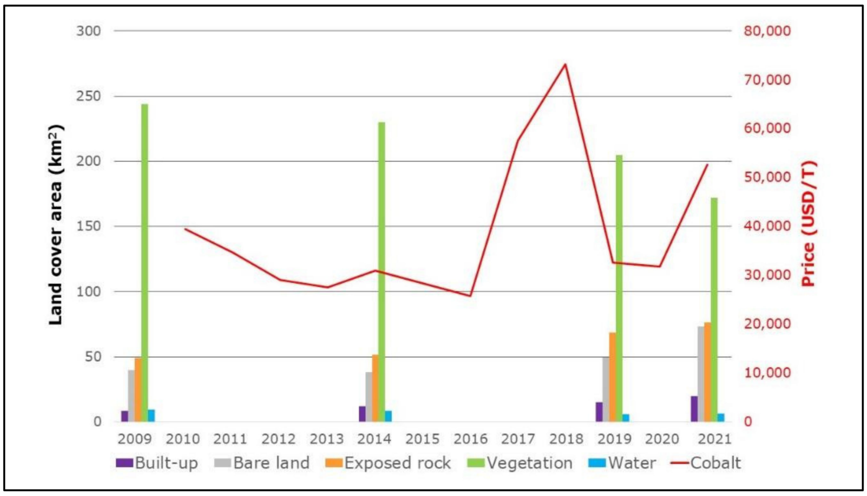

Figure 7. Area of land cover classes of interest (km^2) (columns) and global price of cobalt (USD/T) (line) from 2009 to 2021. Source: Trading Economics [69].

4.2. Spatial Analysis of the Social, Health, and Environmental Impacts

Decades of mining in the Copperbelt have caused considerable environmental degradation, with the region listed in the “10 most polluted sites” worldwide [70], based on soil pollution data from Zambia. The World Bank [71] has listed the multiple pollution sources and pathways for ASM activity in the DRC (Table 8).

Table 8. World Bank list of DRC ASM activity pollution sources and pathways. Source: World Bank [71].

Pollution Source
• Drainage from mining sites, including processing water discharge and the breaching of LSM tailings impoundments • Direct dumping of mine/domestic waste • Sediment runoff from ASM sites • Pollution resulting from ASM ‘dredging’ operations in river beds • Anthropogenic mercury pollution (orpaillage) of terrestrial and aquatic ecosystems • Effluents from mineral processing operations • Sewage effluent from the ASM site • Leaching of pollutants from tailings residues, disposal areas, and contaminated soils • Air emissions from minerals processing diesel equipment • Dust emissions from sites close to villages and habitats

Water pollution by trace metals in the Copperbelt has been regularly measured in past research. Muimba-Kankolongo et al. [72] found that a high proportion of drinking water samples collected in the vicinity of mining sites (between 100 m and a few kilometres) in the DRC exceeded the WHO limits for drinking water [73], with the most toxic elements (arsenic (As), cadmium (Cd), and lead (Pb)) present in samples. Extremely high concentrations (above 1000 µg/L for Manganese (Mn), cobalt (Co), Nickel (Ni), Copper (Cu), Zinc (Zn), and Pb; around or above 100 µg/L for As, Cd, and uranium (U)) were also measured at river water sampling sites in the DRC. These sites were positioned close to where effluents from the Likasi hydro-metallurgic industry had been discharged. Cheyns et al.’s [24] investigation concluded, using human exposure biomonitoring methods, that trace metal concentrations of cobalt were highly present in the drinking water samples collected at village sites near industrial or mining activities (mines and metal smelters), and lakeside areas exposed to industrial effluents, as well as uncooked food items (maize flour, washed vegetables, fish, and meat) sweet potatoes leaves, cereals, and fish samples. It is clear that the co-location of mining operations with major waterways has significant implications for the water quality. Spatial analysis of the 2021 land cover outputs and identified mining features revealed that 68.3% of areas classified as water in the AOI fell within a 500 m radius of an area of mining activity and 91.6% within 1 km. Guided by the past research discussed above, a distance proximity of 1 km from an area of mining activity is determined here to be of high risk for water pollution. Thus, 91.6% of water identified in the AOI could be categorised as having a high risk of pollution. It is important to note that the water class in the object-based SVM classification outputs includes areas of industrial water usage (for example, water retention areas and mine ponds) that may not directly impact the local population or environment. However, as listed above, mining run-off and leaching can pollute the wider landscape and pose a serious public health risk.

The reduction of illness and death caused by hazardous chemicals and air, water, and soil pollution and contamination is a target of SDG 3: Good health and well-being. Epidemiologic studies in the Copperbelt have investigated the health effects of cobalt mining and the local population [22,25,74]. With the 2021 land cover classification outputs registering 45.7% of built-up areas to be situated within a 500 m radius of mining activity and 71.6% within 1 km, understanding the spatial relationship between potential residential areas and exposure to hazardous mine pollution and contamination is important for meeting SDG 3 targets. Exposure to high concentrations of cobalt has been linked to plausible lung, thyroid, blood, and heart damage [25,75]. Combined with the toxicity of the other multiple metals (for example: As, Cd, and Pb) associated with mining in the Copperbelt, the long-term impacts on the health of miners and the local population is an issue of great concern. Van Brusselen et al.'s [76] case-control study in Lubumbashi (Copperbelt, DRC) found that mothers who had paid jobs outside the home and fathers who had mining-related jobs were associated with a higher risk of babies being born with visible birth defects. Another study in Lubumbashi associated pre-eclampsia cases with blood lead levels in parturient women [77], although the source of lead contamination was unknown. Moreover, substantial links in the study were formed between poorly regulated mining and smelting activities and dust pollution. Another important aspect to consider is the socio-economic impacts of living in close proximity to a mine. Malpede [78] investigated the educational attainments of individuals who grew up in mining areas at the time of a cobalt mining boom in 2007. The study reported a loss in education attainment, with individuals aged between 6 and 14 at the time achieving 0.5 years of education less compared to their peers who were not exposed to cobalt mining (control population situated over 10 km from a cobalt mine). It was concluded that the loss in education was driven by exposure to illegal cobalt mining during childhood and the household wealth gains due to child labour rather than attending school. Additionally, the analysis uncovered that the initial improvement in household wealth for residents in cobalt mining areas receded after seven years of mining activity.

Previous work exploring the impact of mining, forest management, and livelihoods in the Copperbelt (in both Zambia and the DRC) found, via a combination of semi-structured questionnaires and interviews, that local residents living in close proximity to mines often expressed suffering and anxiety associated with industrial mine exploitation [79]. Distress from local residents was often associated with environmental degradation, examples of interest included: dust accumulation from open-pit mines, waste rock piling, tailings, and stock pilled crusher and mineral processing plant outputs. The disposal of tailings is commonly recognised as one of the most environmentally impactful operations in mining [80]. The volume of tailings that require storage can often exceed the total volume of ore that is mined and processed. Cobalt mining in the DRC has produced large wastelands of tailings, from both LSM and ASM activities. Neighbourhoods in Kolwezi have been regularly documented as having large areas of unregulated and unsafe piles of mine tailings at the entrance to tunnel mines or spilling out of residential properties [23]. A lack of safety precautions and inadequate tailings management pose an enormous risk to mining communities in the Copperbelt. Formal spatial analysis, such as the work carried out in this study, is required to monitor the behaviour and risks associated with LSM and ASM tailings to the local population and wider landscape, as well as to determine final storage locations.

4.3. Case Study: Kasulo

The extent of mining features and the associated land cover change was highly variable across the AOI (Table 6 and Figure 6), from large-scale industrial open-pit structures to subtle small-scale exploratory clusters of tunnels in structurally complex residential neighbourhoods. To capture the spatial footprint of cobalt mining in Kolwezi and the surrounding mining areas, VHR EO imagery was required to analyse land cover change and obtain a more detailed insight into mining dynamics over the study's time period of interest. Visual inspection of the land cover outputs at the AOI boundary scale does not reveal the subtle, localised features recorded through the highly detailed object-based SVM classification. Figure 8 illustrates the VHR land cover classification outputs over a case study area in the AOI. Between 2009 and 2021, Kasulo, the case study area, transformed from a popular urban neighbourhood into an unliveable environment.

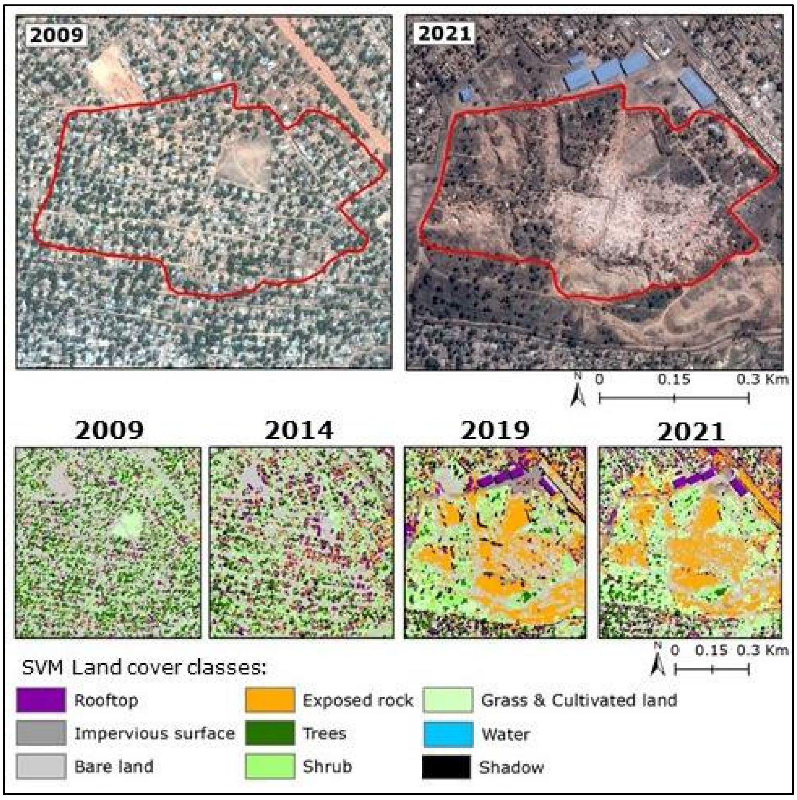

Figure 8. Kasulo case study. Top: very high resolution satellite imagery, 2009 GeoEye-1 and 2021 Pléiades. Bottom: land cover classification outputs for 2009, 2014, 2019, and 2021.

A narrative visible in the land cover classification outputs. In 2014, according to local lore, a resident discovered a rich seam of heterogenite ore running under his house while reportedly digging a new pit latrine. From that discovery, residents started to dig throughout the area, rapidly transforming the urban neighbourhood into an ASM site. Operating unregulated, the site became highly dangerous. Hundreds of open tunnel pits lead to an unsafe underground network of mineshafts, while at the surface, piles of mine tailings degraded local properties and land [27]. In 2014 and 2015, Banza et al. [23] undertook two field sampling campaigns in Kasulo to assess the health of local residents. The study reported noticeable social disruptions linked to the rapid influx of ASM activity, including high alcohol and drug use, prostitution, and violence. In April 2017, the then governor of the Lualaba province, Richard Muyej, awarded a purchasing monopoly to Congo DongFang Mining (CDM) for all the cobalt in Kasulo. CDM was also awarded rights to set up an artisanal mining zone inside the neighbourhood. As part of the deal, CDM was obliged to pay resettlement compensation to the households living in the concession zone. A total of 554 households were identified as being inside the future concession. The inhabitants were given two options—receive a fixed payment of between USD 400 and USD 2000 depending on the value of their homes or move into one of the new homes being built in a village called Samukinda. Based on ground interviews conducted in 2018 and 2019 by Kara with numerous families that used to live in the CDM concession zone in Kasulo, it appears that only a handful of families ever received their payments, and those who moved to Samukinda found their new homes to be unfinished and substandard. The area was then reclassified as a formal ASM site. A wall was built around the concession boundary to prevent non-registered ASM miners from entering the site or any mineral products from leaving. Since 2019, ASM has remained operational at the site (Figure 9). Kara's investigations inside the CDM site revealed that artisanal miners have dug more than 1000 tunnels, some of which are up to 60 m deep. The diggers are not provided safety gear, the tunnels do not have supports, rock bolts, or ventilation shafts, and children under the age of 18 work at the site. Most of the artisanal miners at the CDM concession also work under a system of debt bondage.

Figure 9. Congo DongFang Mining artisanal site in Kasulo. Photograph: Siddharth Kara.

Although more than 14,000 artisanal miners are registered to work at the CDM artisanal site in Kasulo, the number of miners and volume of ore produced have fluctuated over the years driven by the global cobalt price and demand. Integrating localised VHR case study outputs, contextualised via on-the-ground accounts, interviews, and NGO reports, with landscape-scale spatial analysis of land cover patterns provides a richer and more comprehensive understanding of mining dynamics in the Copperbelt. Combining landscape-scale and fine-scale analysis is recommended for future work addressing long-term spatial and temporal trends in cobalt mining in the DRC.

4.4. Future Sustainable Resource Management

Despite its connection with renewable green energy solutions, cobalt, by nature, is a finite resource. Ultimately, after a period of production and profit, the resource will deplete, revenue will drop, and mining operations will cease in the DRC Copperbelt. Without sustainable land management and preparation for this inevitability, mining communities, such as those in Kolwezi, may fall into a worse state of poverty than before mining activities began. Aligning mine action with the SDGs will contribute to building more inclusive, fair, and participatory societies [81]. To achieve this, the consolidation of data from ground-based investigations and EO data analysis is required to inform sustainable decision making and good governance. This study considers only the AOI, yet the object-based SVM classification approach could be applied to map land cover across the entire Copperbelt region. Greater access and reductions in cost from new innovative commercial satellite data providers, for example, the Planet satellite constellation, could be utilised to track the annual change in mining patterns and the wider landscape, as well as predict areas of vulnerability, for example, at-risk neighbourhoods or environmental degradation, to future mining operations. Fusion with alternative EO technologies, for example, the application of novel interferometric synthetic aperture radar (InSAR) satellite data methods, as outlined by Brown et al. [82], for assessing patterns of surface motion related to cobalt mining, is advocated to provide the best insights for building sustainable resource management solutions that will benefit all.

5. Conclusions

The objective of this study was to quantitatively assess the cumulative impact of mining activities on the landscape of a prominent cobalt mining area in the DRC. The results of this study reveal that cobalt mining has had an overwhelming influence on the landscape structure of Kolwezi and the surrounding areas between 2009 and 2021. With global cobalt demand ever-growing, the impacts of the mining sector on land cover and land use are set to intensify in the coming decades. Key trends identified by the study were the expansion of the exposed rock, bare land, and rooftop classes over areas previously covered by vegetation classes (grass and cultivated land, shrub, and trees), marking significant areas of mine investment and urban development. Spatial analysis of the co-location of key land cover classes and identified mine features provided a solution to build objective knowledge on the potential social, health, and environmental impacts of past, present, and future mining activities in the AOI. The map outputs and geo-spatial information generated in this study further complement narrative accounts and reports from NGOs, civil society, and media outlets. The sustainable management of mineral resources is essential to meet the SDGs by 2030. Data-driven informed discussions, monitoring, and decision making on the future of cobalt mining in the DRC is fundamental to safeguarding the sustainable development of the country.

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