Spatial dynamics and sustainable management of territories around mining sites: analysis of transformations and future perspectives in Kawama village in Haut-Katanga, DR Congo

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ABSTRACT

This study aims to analyze land use changes in Kawama, Democratic Republic of the Congo, between 1992 and 2022, assessing the impacts of mining and considering the use of a Multi-Agent System (MAS) to model these dynamics and the challenges they may introduce. The methodology includes selecting Landsat satellite images from 1992 to 2022, processed using ENVI 4.5 and ArcGIS 10.4 software, georeferencing the images to the UTM Zone 35S reference frame, performing supervised classification based on the maximum likelihood algorithm with verification through confusion matrices and Kappa coefficient, and analyzing land cover dynamics by calculating class proportions and examining spatial transformations. Quantified results indicate overall classification accuracy ranging from 89.5% (1992) to 84.5% (2022), Kappa coefficient from 87.4% (1992) to 83.8% (2022), an increase in built-up areas from 2% (1992) to 30% (2022), rapid growth of bare soil by 40% (1992-2022), and a 50% decrease in vegetation cover (1992-2022). Key conclusions highlight rapid urbanization and vegetation degradation driven by economic and political changes, particularly the liberalization of the mining sector, emphasizing the need for sustainable land use management to preserve the local environment. The use of MAS is proposed to model and manage the complex interactions between mining activities, urbanization, and environmental impacts, incorporating various stakeholders and their interactions.

Keywords: Land use changes – Mining – Multi-Agent Systems (MAS) – Urbanization –Sustainable management – Satellite imagery – Kawama.

1. INTRODUCTION

Mining is an economic activity that has major impacts on the territories where it takes place. It is leading to profound transformations of landscapes, natural resources and populations. It can be a source of development, but also of conflict, pollution, environmental degradation and social vulnerability (Chuhan-Pole et al., 2019 ; De Dieu et al., 2021 ; Sikuzani et al., 2020). Villages around mining sites often face complex challenges related to spatial transformation, such as natural resource management, environmental impact, and socio-economic development (Hilson, 2002 ; Larmer et al., 2021 ; Worlanyo et Jiangfeng, 2021). Kawama has seen rapid urbanization and infrastructure growth due to mining since 2002, intensified by sector liberalization in 2012. This has led to significant environmental degradation, including water

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pollution, deforestation, and soil contamination. Residents face health risks from pollution and precarious living conditions. Rapid, unplanned urbanization strains local infrastructure and can cause land conflicts and community displacement. Social impacts include dangerous conditions for artisanal miners and pressure on infrastructure due to population growth.

The participatory management of these transformations requires advanced tools to facilitate collective decision-making and the integration of the perspectives of different stakeholders (Raynor et al., 2017). Most research on MAS focuses on urban or industrial environments (Daniell et al., 2005 ; Parker et coll., 2003 ; Parygin et al., 2020).

The majority of scientific research on the development of cities around mining sites focuses mainly on socio-economic development and urbanization from a policy perspective (Büscher et al., 2014). Ndaw et al. (2020) studied the integration of mining companies by analyzing their socio-economic involvement and the impact of their social and environmental responsibility. In his thesis (Ndaw et al., 2020), Diallo examines the economic, social, environmental and political development of mining towns, as well as the impact of extractive activities (Diallo, 2015). Many authors, as mentioned earlier, highlight the economic, social, spatial and cultural aspects of mining areas, which are often perceived as places of transformation. In the recent literature, Bryceson and Mackinnon (2012) explored the impact of mining on urbanization in Africa, while Sikuzani et all investigated the Land use dynamics around mining sites along the urban-rural gradient of the city of Lubumbashi, DR Congo (Sikuzani et al., 2020).

However, these spaces, which are at the heart of urban development dynamics, are little studied. They often face complex challenges related to spatial transformation. Mining activities trigger very complex processes of change, affecting social, economic, and environmental dimensions. Understanding and anticipating the dynamics of the territories around mining sites, whether they are urban, industrial, rural, ecological, economic, social, cultural, or even political, is therefore a crucial issue for the sustainable management of these areas.

This study aims to contribute by providing a detailed analysis of land use changes in Kawama, DR Congo, between 1992 and 2022, and by proposing the use of a multi-agent system (MAS) to model these dynamics and address the challenges they introduce. How can the participatory management of spatial transformations around mining sites in Kawama village contribute to sustainable development?
In this context, there is a need for modelling tools that can represent and simulate the spatial changes that occur in villages around rapidly urbanizing mining sites, taking into account the diversity and interdependence of the factors that affect it. An agent-based modeling tool could indeed be one of the responses to these challenges.

Multi-agent systems (MAS) are modeling tools that make it possible to design and implement complex systems composed of autonomous entities, called agents, that interact with each other according to defined rules (Devisch et al., 2013 ; Julian et Botti, 2019). The MASs make it possible to model the interactions between the different local actors (citizens, companies, authorities) to facilitate collective decision-making and the management of spatial transformations (Tian et al., 2011). By integrating digital tools, they offer the possibility of simulating various development scenarios and optimizing decisions based on environmental, social and economic impacts.

This work is structured into several key sections, apart from the introduction and conclusion. It addresses the spatial dynamics and management challenges in Kawama. The theoretical framework covers the key concepts of spatial dynamics, main studies, and management challenges for a Multi-Agent System (MAS). The Materials and Methods section details the study area, the selection of satellite images, preprocessing, classification, and analysis of land use dynamics. The results include classification accuracy, land use trends, and mapping of spatial transformations. The discussion explores the implications of the MAS model and proposes a reflection on the use of these models, specifying what will be modeled, the level of detail, the actors involved, their interactions, and the expected dynamics.

2. THEORETICAL FRAMEWORK

2.1. Key concepts of spatial dynamics

The key concepts of spatial dynamics concern the study of changes and evolutions in the organization of geographical space. First, land cover transformation refers to changes in land use and land cover over time. These transformations can be caused by various factors such as urbanization, agriculture, deforestation, and environmental policies (Geri et al., 2011; Roy, 2016). Second, spatial mobility encompasses the mobility of people, goods, and services across geographical space, including migration, commuting, and trade flows (Le Roux & Sierra-Paycha, 2021). In addition, spatial fragmentation refers to the division of space into smaller, often less connected units, resulting from urban expansion, infrastructure construction, or socio-economic segregation (Bret, 2005). This phenomenon can manifest itself at different scales and in various contexts, such as urban, rural or even state-wide. In addition, spatial networks represent the connecting structures between different places, such as transport, communication, and economic networks. These networks play a crucial role in spatial dynamics by facilitating interactions and exchanges (Guillaume Guex, 2016). Spatial network analysis helps to understand how elements are connected and how flows move through those connections, helping to optimize infrastructure, improve urban planning, and manage resources more efficiently. In addition, the analysis of phenomena at different scales, from local to global, is essential because spatial dynamics can vary considerably depending on the scale of analysis. In addition, spatial interactions, which include the reciprocal relationships and influences between different places, are crucial. Spatial interaction models, such as the gravity model, help to understand how these flows are influenced by distance and other factors (Coffey, 2002). These interactions can include economic, social, and environmental interactions, playing a key role in the structuring of geographical spaces and the formation of spatial networks (Pumain, 2023). Finally, spatial modeling uses models to represent and analyze spatial dynamics, including statistical models, computer simulations, and geographic information systems (GIS) (Grataloup, 1996). Spatial modeling is used in various fields, such as urban planning, natural resource management, and environmental analysis, to simulate scenarios, predict future trends, and assist in decision-making. These concepts are essential to understanding how geographical spaces evolve and transform over time.

2.3. Main studies on spatial dynamics

While our study aims to provide a new perspective on the spatial dynamics of villages around mine sites, it is important to recognize that a lot of research has already explored this question, providing a solid basis for our analysis. The dynamics of land use around mining sites along the urban-rural gradient of the city of Lubumbashi is analyzed by Yannick Useni

Sikuzani et al. between 1989 and 2014. The study highlights a rapid expansion of built-up areas and a decline in bare soil and vegetation, particularly after the liberalization of the mining sector in 2002 (Bonaventur et al., 2016; Sikuzani et al., 2020) Similarly, the study on the dynamics of land use and the trajectory of vegetation cover around three mining sites in southern Mali between 1988 and 2019 by Traore et al. analyzes the impact of mining on land use and vegetation cover. Using Landsat imagery and maximum likelihood classification, the results show significant degradation of vegetation cover, with a conversion of dense vegetation to bare and agricultural soils (Traore et al., 2022). Furthermore, the research conducted by Galli et al., titled "Impact of Mining Activities on Land Use Dynamics in the Democratic Republic of Congo," examines how mining activities influence land use dynamics in different regions of the DRC. Using satellite data and spatial analyses, it shows that diamond mining in the DRC leads to significant deforestation, excessive water consumption, exacerbates the food crisis, and is associated with local conflicts and unsafe working conditions (Galli et al., 2022). In addition, the paper "Exploring Land Use and Land Cover Change in the Mining Areas of Wa East District, Ghana Using Satellite Imagery" looks at land use change in mining areas in Ghana, focusing on environmental impacts and landscape transformations. The study reveals significant degradation of vegetation cover in Ghana, with a decrease in savannahs and an increase in bare land, resulting in a decrease in vegetation health as measured by the NDVI (Basommi et al., 2015). Finally, the spatial assessment of land use dynamics in a gold mining area, conducted by I. R. Orimoloye and O. O. Ololade, uses remote sensing and GIS techniques. Analysis of Landsat imagery over several decades reveals an increase in built-up areas and water bodies, as well as fluctuations in vegetation, indicating partial regeneration (Orimoloye & Ololade, 2020).

In conclusion, these studies show the significant impact of mining activity on the environment and the need for sustainable management strategies to mitigate the negative effects.

2.4. Management Challenges and Constraints for a Multi-Agent System

Managing mining-related transformations presents several major challenges. First, water pollution is a major problem, as toxic chemical discharges from mines contaminate rivers and groundwater, affecting the health of local people and aquatic wildlife (De Dieu et al., 2021). In addition, mining requires large amounts of water, which can lead to overexploitation of water resources (Cabanes, 2016). Secondly, the degradation of soil and biodiversity is another consequence of mining. Deforestation caused by these activities destroys natural habitats and threatens the survival of many animal and plant species (Becker & Vanclay, 2003; De Dieu et al., 2021). Mine tailings also contaminated soils, preventing vegetation regeneration and contributing to biodiversity loss (Kaleba et al., 2022). In addition, the social impacts of mining are significant, including the displacement of local communities, land conflicts, and the often dangerous working conditions for artisanal miners. Local infrastructure, such as roads and schools, can also be affected by mining activities (De Dieu et al., 2021). In addition, public health is at serious risk, as people living near mining sites are exposed to increased health risks due to air and water pollution, as well as precarious living conditions (Banza et al., 2009). To mitigate these impacts, it is essential that mining companies comply with international environmental standards and adopt sustainable practices. Governments and non-governmental organizations also play a crucial role in monitoring and regulating mining activities to protect the environment and local communities.

These challenges are the constraints for the development of a Multi-Agent System (MAS), which must be able to address these complex dynamics to provide sustainable and effective solutions. The MAS offer an integrated and dynamic approach to managing the complex challenges of mining, combining environmental monitoring, resource optimization, conflict management, regulatory planning, and site remediation.

2.5. Key concepts of multi-agent systems (MAS) applied to spatial dynamics management

Multi-agent systems (MAS) play a crucial role in the management of spatial dynamics by enabling efficient modeling and simulation of complex interactions between different actors and elements of the environment. Indeed, these systems are used to design, model, analyze and simulate complex systems involving multiple interacting entities. The coordination of these entities makes it possible to achieve a collective objective or to promote the stability of the system (Amblard et al., 2021). In addition, an agent is an autonomous entity capable of perceiving its environment, making decisions and acting accordingly (Garijo & Boman, 1999). In the context of spatial dynamics, agents can represent individuals, groups, vehicles, businesses, or even natural entities like rivers or forests. In addition, the environment is the space in which agents evolve and interact. It can include geographical features, infrastructure, natural resources, and urban or rural areas. The environment provides the context and constraints in which agents operate (Amblard et al., 2021). In addition, agents interact with each other and their environment. These interactions can include communication, cooperation, competition, and negotiation. For example, in a traffic simulation, vehicles (agents) interact to avoid collisions and optimize their routes. In addition, the social dimension of SMAs concerns the relationships and social structures between agents (Bouzoubaa & Moulin, 1997). Group formation, hierarchies, roles, and social norms are part of the social dimension. In the management of spatial dynamics, this dimension makes it possible to model collective behaviours and participatory decision-making processes. In addition, agents must be able to adapt to changes in their environment (Tranier, 2007). This includes the ability to adapt to new data, modify their plans, and learn from previous experiences. Finally, coordination is essential to ensure that agents' actions are harmonised and contribute to the overall objective of the system (Tranier, 2007). In the management of spatial dynamics, this may involve the synchronization of actions for natural resource management or urban planning. These concepts provide an understanding of how MAS can be used to model and manage spatial dynamics in an efficient and participatory manner.

After presenting the theoretical framework of our study in the previous section, where we presented our case study and described the key features, context and main dynamics of the study area, we now turn to the practical aspects of our research. In this section, we describe the tools and methods used to analyze land cover change in this region.

3. MATERIALS AND METHODS

3.1. Presentation of the study area

The village of Kawama is located at 11° 31'10.21 S latitude and 27°27'20.52 E longitude (Figure 1) 16 km from the city of Lubumbashi in an area where mining activity has developed since 2000, leading to rapid infrastructure growth and accelerated urbanization. From 2006 to 2022, the village of Kawama showed signs of development and moved closer to the city of Lubumbashi, despite demolitions in 2014 following a mining dispute between the Compagnie minière du Sud Katanga (CMSK) and the diggers living in the village (Amnesty, 2014). Kawama is an administrative entity of the territory of Kipushi, in 1982 this village had 229 inhabitants, since 2014 it has 17,000 inhabitants, their main activities are agriculture and petty trade, mainly by women, the majority of men are in charcoal making and artisanal mining (The Observers - France 24, 2014 ; Lootens-De Muynck et al., 1982).

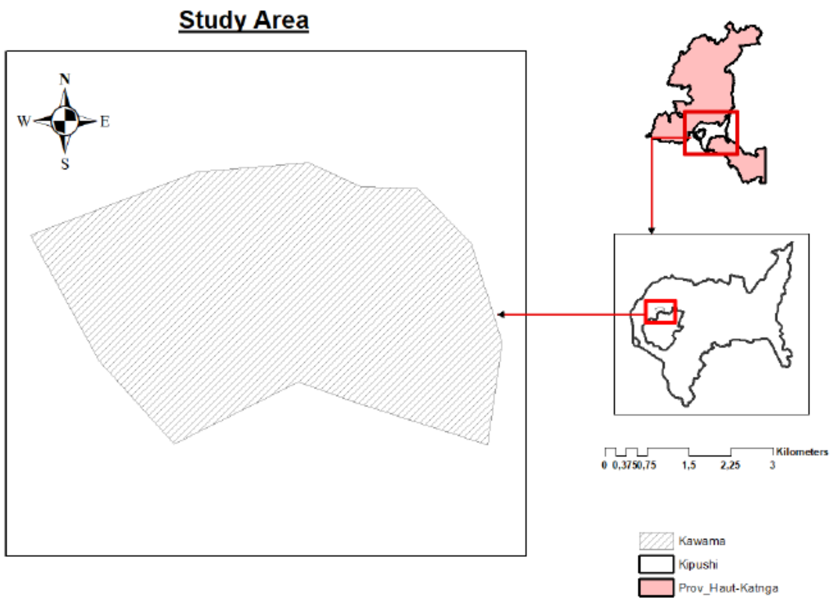

Figure 1. Location of the village of Kawama in the province of Haut-Katanga, in the south-east of the DR Congo.

The figure 2 illustrates the multifaceted challenges and problems faced by the village of Kawama due to mining activities. The images highlight the severe water pollution affecting local sources (A & B), the impact on infrastructure such as National Road No. 1 (C), the presence of small businesses (D), residential houses near mining sites (E), and the conditions of artisanal mining (F). These elements collectively depict the environmental, health, urban, and social issues stemming from both industrial and artisanal mining in the area.

Figure 2: Illustration of the challenges and problems at Kawama.

3.2. Choice of satellite images

The study area was extracted from Landsat imagery taken over the period from 1992 to 2022, on four different dates and with a time interval of 10 years. These images, from the OLI sensor, were chosen based on their availability and processed with ENVI 4.5 software, which specializes in multispectral and hyperspectral image processing, extracting accurate information from Landsat data, which is essential for analyzing changes over a 30-year period, and ArcGIS 10.4 a powerful tool for geospatial analysis and mapping. It allows spatial data to be visualized, analyzed, and interpreted, making it easier to understand changes in the study area. It should be remembered that these Landsat OLI images cover the period before the liberalization of the mining sector in 2002 (1992) and after (2012 and 2022). Ground control points and training areas were collected using GPS (Garmin GPSMAP 64SX, accuracy ± 3).

3.3. Image Preprocessing

Using the reference ellipsoid WGS-84, the Landsat images used were georeferenced in the UTM Zone 35S reference frame which corresponds to the city of Lubumbashi. The geometric accuracy of the timing between scenes was less than 1 pixel, the minimum required for a change analysis (Mas, 2000) .

3.4. Classification of Landsat satellite images

To perform the color composition of all these images, bands 4 (near-infrared), 3 (red) and 1 (green) were associated for the Landsat 5 (TM) images, bands 4 (near infrared), 3 (red) and 2 (green) were associated for the Landsat 7 (TM) images and bands 5 (mid-infrared) applied to red, 4 (near-infrared) applied to green and 3 (red) applied to blue for the Landsat 8 (OLI) image. The R and PIR channels are the most commonly used for vegetation studies because they allow the best way to discriminate vegetation (Barima et al., 2009). Four land cover classes were created following an automatic classification (Barima et al., 2009) from the OLI Landsat image. This high number of classes offered the possibility of later merging classes that were similar radiometrically and thematically. A grouping was carried out visually on the basis of in situ knowledge, acquired during field visits, and old land cover maps. The training areas were chosen to carry out the supervised classification based on the maximum likelihood algorithm(Caloz & Collet, 2001). Baseline data were obtained from in situ surveys. The verification sites were chosen to be in homogeneous areas with a surface area greater than 20 pixels (Barima et al., 2009). The visual field inspection was intended to verify categories other than vegetation.

The validity of the classifications was verified by making confusion matrices comparing the thematic classes obtained by numerical means and the ground truth data (Mama et al., 2013).

These confusion matrices made it possible to highlight two indices, namely the overall precision which characterizes the proportion of well-classified pixels, and the Kappa coefficient, which corresponds to the ratio between the correctly classified pixels and the set of pixels considered (Havyarimana et al., 2018). Acceptable values of the Kappa coefficient are those that exceed 60% (Landis, 1977). In the case of a value below 61%, the choice of training areas must be renewed, the land cover classes merged or the algorithm changed (Lagabrielle et al., 2005; Mama et al., 2013). The classified images were vectorized using the ENVI 4.5 software and four land cover maps, for each of the dates retained, were generated using the ArcGIS 10.4 software.

3.5. Analysis of land cover dynamics

In order to establish the relationships between landscape configuration and ecological processes, it is useful to describe these structures in quantifiable terms through a series of indices (Bogaert & Mahamane, 2005). It is the proportion of classes in the landscape that was retained in the framework of this study. The area of each land cover class was calculated at the scale of the study area. The method we propose consists in exploiting the combination of geographic information and a thematic segmentation technique by spectral-textural cooperation of Landsat images, developed by(Anys & He, 1995), as part of a GIS Geographic Information System.

4. RESULTS

4.1. Accuracy of supervised classification and mapping

The classification evaluation uses a confusion matrix and the Kappa coefficient (equations I and II), recommended by (Rosenfield & Fitzpatrick-Lins, 1986), in addition to full accuracy and errors of omission. A Kappa coefficient between 61% and 80% indicates a good agreement, while a value below 61% requires a review of the training zones (Landis & Koch, 1977). This coefficient allows for an overall and category-based evaluation, with a normal distribution facilitating precision comparison between two categories.

Kappa coefficient
$$\widehat{K} = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} X\, x_{+x})}{N^2 - \sum_{i=1}^{r} (x_{i+} X\, x_{+x})} \quad \text{(I)}$$

Overall accuracy
$$MPPCC = \frac{\sum_{i=1}^{r} x_{ii}}{N} x100 \quad \text{(II)}$$

The supervised classification resulted in overall precision values between 89.5% and 84.5%, and Kappa coefficients from 87.4% to 83.8%. Overall, the discrimination between land cover classes was statistically significant (Table 1).

Table 1. Summary of the indices illustrating the reliability of the accuracy of Landsat images classified on the basis of the maximum likelihood algorithm and from points taken on the ground (built-up, bare ground, vegetation).

Index	1992	2002	2012	2022
Overall accuracy (%)	89,5	88,2	87,3	84,5
Kappa coefficient (%)	87,4	86,4	85,6	83,8

4.2. Land use trends in the study area

The analysis of the maps revealed considerable changes in the study area, marked by a gradual or regressive spatial evolution of the land cover classes from 1992 to 2022. Generally speaking, the evolution of land use was characterized, between 1992 and 2022, by a rapid expansion of built-up areas and bare ground and a regression of vegetation (Table 2). The spatial evolution of the enthronization of the landscape has been particularly strong between 2012 and 2022 after the liberalization of the mining sector in 2002. Indeed, this liberalization has led to a revitalization of mining activity which has thus strengthened the attractiveness of the village, whose sphere of influence has exceeded its administrative limits stricto sensu. The proportion of built-up in the landscape increased from 2% to 30% between 1992 and 2022 (Figure 1). The expansion of the built-up area and bare ground is observed in the north-east direction of the village, leading to a significant degradation of the vegetation. The vegetation class, the matrix of the landscape, over the four dates studied, has recorded a regression of 83.51 % in 30 years, especially since its share in the landscape has fallen to 16% in 2022, compared to an initial value of 97% in 1992.

Table 2. Land cover composition in 1992, 2002, 2012 and 2022 in the study area in km²

Year	Land cover type		
	Forrest	**built-up**	**Bare soil**
1992	27,86 (97)	0,67(2)	0,32(1)
2002	24,40 (85)	1,46 (5)	2,98 (10)
2012	6,86 (24)	4,55 (16)	17,43 (60)
2022	4,66 (16)	8,65 (30)	15,52 (54)

Values in parentheses correspond to the proportion in the study area. The sum of the areas for each date corresponds to the total area of the landscape (28.85 km²).

4.3. Mapping of observed spatial transformations

This section presents a detailed analysis of the observed spatial transformations, illustrated by accurate and informative maps, in order to better understand the geographical dynamics at play.

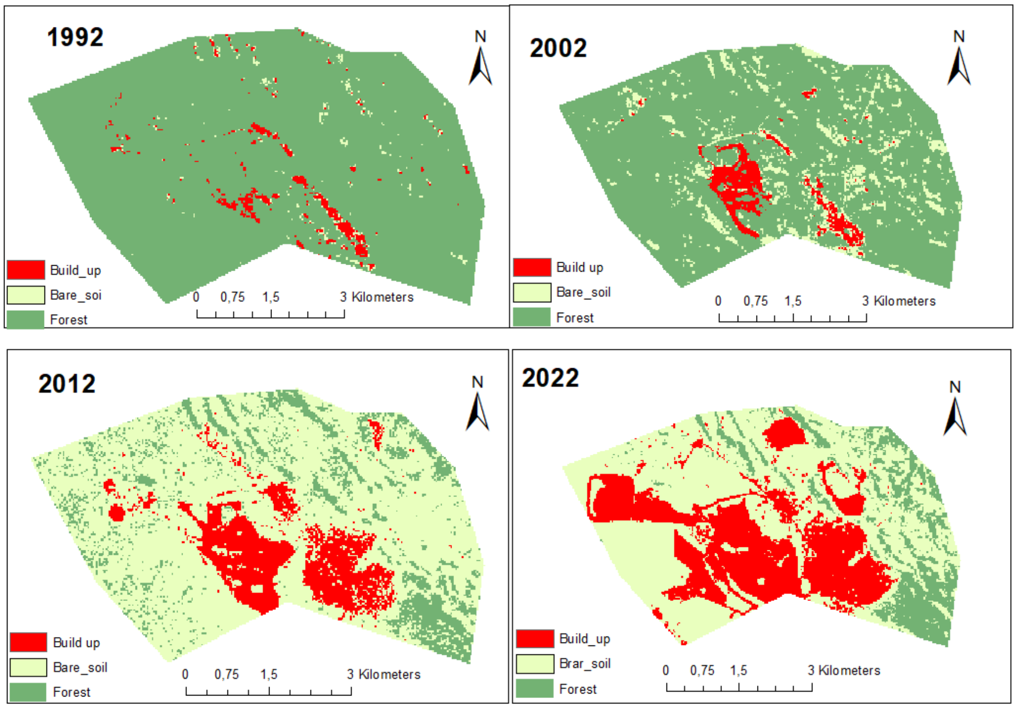

Figure 2. Land cover maps of the study area in 1992, 2002, 2012 and 2022 based on supervised classification of Landsat imagery.

5. DISCUSSION: IMPLICATIONS FOR A MAS MODEL

The results of the supervised classification show an overall accuracy and a Kappa coefficient varying over the years, with an overall accuracy ranging from 89.5% in 1992 to 84.5% in 2022, and a Kappa coefficient ranging from 87.4% in 1992 to 83.8% in 2022 , which is encouraging since a Kappa coefficient of 61% to 80% indicates good agreement; below 61%, a review is needed (Landis & Koch, 1977). The analysis of the maps reveals significant changes in land use between 1992 and 2022, with an expansion of built-up from 2% in 1992 to 30% in 2022, there was also a rapid growth of bare soil of 53% between 1992 and 2022 and a regression of vegetation of 84 % between 1992 and 2022, this analysis aligns with that of Sikuzani et al., which observed a rapid expansion of built-up areas, followed by a regression of bare soil and vegetation around urban mining sites, particularly after the liberalization of the mining sector in 2002 (Sikuzani et al., 2020). These observed trends will be used to validate the model, ensuring that it accurately reflects the spatial dynamics and land use changes over the study period. The liberalization of the mining sector between 2012 and 2022 has boosted mining activity, increasing the attractiveness of the village and extending its influence beyond administrative boundaries. In summary, our results confirm the environmental and socio-economic impacts of mining activities documented by previous studies, underlining the importance of sustainable management strategies and participatory management models to promote sustainable development around mining sites.

To address these challenges, it is crucial to explore how Multi-Agent Systems (MAS) can model and manage the complex interactions between mining activities, urbanization, and environmental impacts in Kawama. Bousquet and

Le Page have shown that MAS are useful for social and spatial issues, such as land-use change (Bousquet & Le Page, 2004). Problem-solving is accomplished by breaking down the issue into smaller tasks and assigning them to specific agents within the system (Gjikopulli, 2020), the level of detail should include the spatial distribution of mining and residential infrastructures, the flows of water and air pollution, changes in vegetation cover and biodiversity, as well as population movements and land conflicts. The actors in this model will include industrial mining companies responsible for large-scale mining operations, artisanal miners operating on a smaller scale often in precarious conditions, local residents affected by the environmental and social impacts of mining activities, local authorities responsible for regulation and urban planning, and non-governmental organizations (NGOs) involved in environmental monitoring and defending the rights of local communities.

The aim of multi-agent systems (MAS) is to analyze the interactions between autonomous agents and their organization (Bousquet & Le Page, 2004), the interactions between these actors will include negotiations between mining companies and local authorities on mining permits and compliance with environmental standards, potential conflicts between artisanal miners and local residents over land and resource use, collaboration between local residents and NGOs to monitor environmental and social impacts and advocate for better living conditions, as well as cooperation between local authorities and NGOs to implement sustainable development and environmental protection policies.

An agent-based model is a system made up of multiple autonomous entities evolving in a specific environment where they are located (Treuil et al., 2008). By using MAS models, it will be possible to observe the evolution of urbanization, the effects of mining activities on water quality, vegetation cover, and biodiversity, the development and resolution of land conflicts and social tensions, as well as the impact of policies and NGO interventions on reducing the negative impacts of mining. By modeling these dynamics, it will be possible to better understand the complex interactions at play in Kawama and develop more effective strategies to manage the challenges related to mining and promote sustainable development.

6. CONCLUSION

Mining, while offering opportunities for economic development, leads to significant transformations of landscapes and ecosystems, as well as complex social impacts. In the context of the study of the Kawama region in the Democratic Republic of Congo, analyses of land cover changes between 1992 and 2022 reveal rapid urbanization and alarming environmental degradation, highlighting the need for sustainable resource management and urban planning.

The use of multi-agent systems (MAS) proves promising for modeling these spatial dynamics, allowing for a participatory approach that incorporates the perspectives of local communities in decision-making. By combining geographic data from satellite images with advanced analytical techniques, it is possible to obtain precise information on land cover evolution, thereby facilitating the planning and management of territories affected by mining activities.

To ensure a sustainable future, it is crucial to adopt integrated management strategies that consider the interactions between environmental, economic, and social dimensions, while actively involving local stakeholders in the decision-making process. In doing so, we can hope to mitigate the negative impacts of mining while promoting harmonious and sustainable development for the affected communities.

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