How Cobalt Mining Drives Deforestation in Congo

Author: Olufemi Olamijulo, MPP & MUP 2024[1]

The Democratic Republic of Congo contributes 70% of the world's cobalt, a critical mineral in the global transition to clean energy. At the same time, the country's forest captures 600 million metric tons of carbon annually, making it the only forest in the world that is a net carbon sink. Combined, this makes the DRC the lodestar for averting global climate catastrophe. But advanced data analytics tell a worrying story about the connection between cobalt mining and deforestation in Congo. Using machine learning, AI-driven geospatial analysis, and Geographic Information Systems (GIS), this study's visual analysis provides a clearer understanding of how artisanal mining interacts with deforestation and labor rights violations in the DRC.

Key Findings

1. **Deforestation continues:** Yearly land use change in the DRC shows that deforestation alone accounts for 60% of all land use change yearly. Our analysis reveals that despite global efforts towards environmental sustainability, deforestation rates in the DRC have not significantly decreased over the last 20 years. Mapping data indicates extensive forest change, primarily in regions with high artisanal mining activity.

2. **Deforestation decreases when income from critical minerals is higher:** We found that fewer forests were cut down to farmland when mineral exports were good, and higher deforestation rates tend to occur in tough years when the income from mineral rents was low. This trend points to a local overdependence on an unpredictable mining sector; when demand for critical minerals decreases or the price drops, DRC laborers turn to deforestation to make farmland. This analysis reveals the precarious nature of forest preservation or afforestation.

3. **High labor for mines:** Across all models, the number of mines is a highly significant predictor of the number of workers in mining areas, underscoring the intensive labor required for artisanal mining. The land type (classified as Disturbance, Healthy forest, or Recovery) does not significantly impact worker distribution when controlling for the number of mines; or, alternatively put, worker distribution is influenced more by the number of mines present than by the condition or classification of the land.

Methodology: Analysis with GIS & R

This study employed a mixed-methods research design, integrating quantitative analysis with spatial analysis (GIS) and qualitative insights from expert interviews.

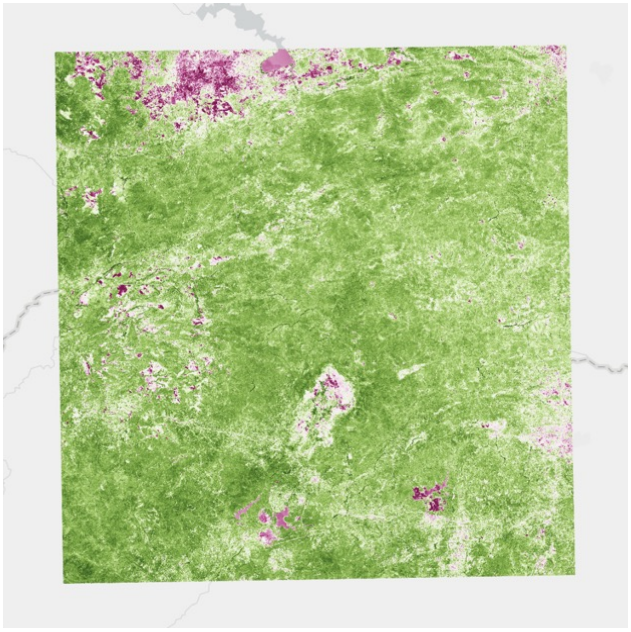
1 This article is a synopsis of the author's Policy Analysis Exercise (PAE). The PAE is the capstone experience to the Masters in Public Policy (MPP) curriculum, providing an opportunity to integrate the skills and knowledge MPP candidates have gained during their time at HKS. An applied thesis, the PAE is different from a traditional research paper in that students are required to engage with a client organization and to develop a series of recommendations to solve a policy or management problem or question for that organization. This PAE's client was the United Nations Office of the Special Adviser on Africa. Augmenting analysis and additional GIS insights are available on this StoryMap.

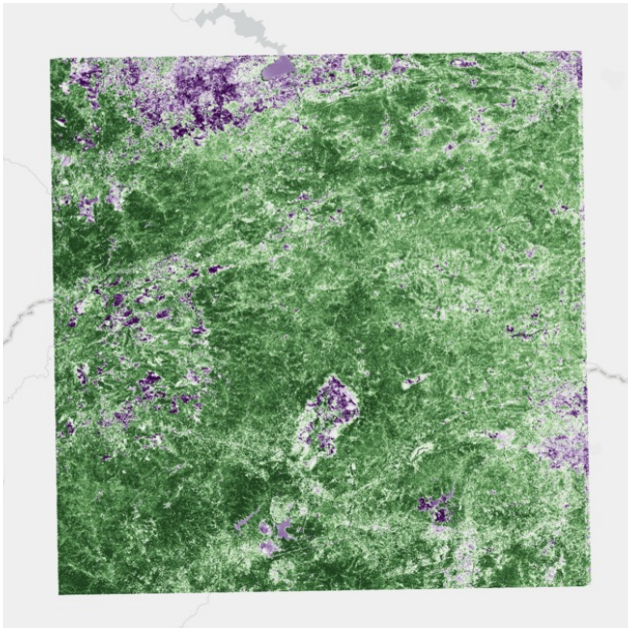
Step 1: Define the Sample Area

Imagery from US Geological Survey (USGS) satellite images from 2019 to 2024 were organized into a multi-dimensional raster format, ideal for time-series analysis. The dataset for the study focused on South Katanga, DRC, chosen because it had a good number of artisanal mines in the north and a lot of free land with no mining activity.

Step 2: Calculating the Normalized Burn Ratio (NBR) Index

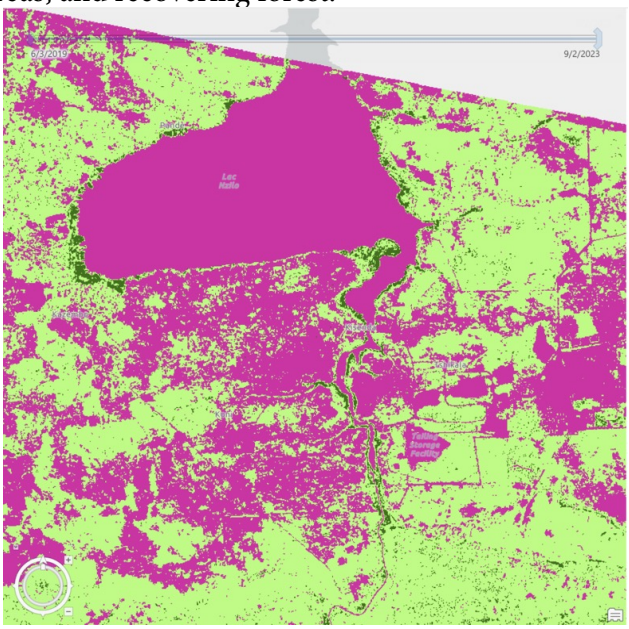
We estimate the NBR index by mathematically comparing the near-infrared and shortwave infrared bands on our image to differentiate between healthy vegetation and deforested areas:

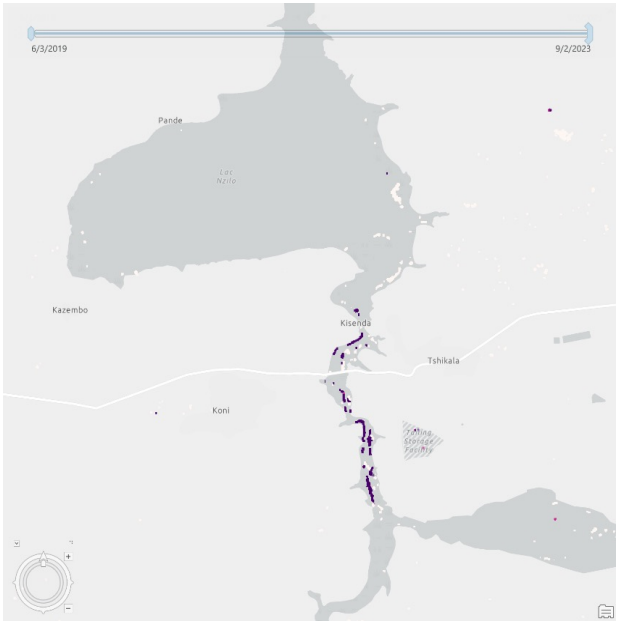




Step 3: Change Detection with LandTrendr

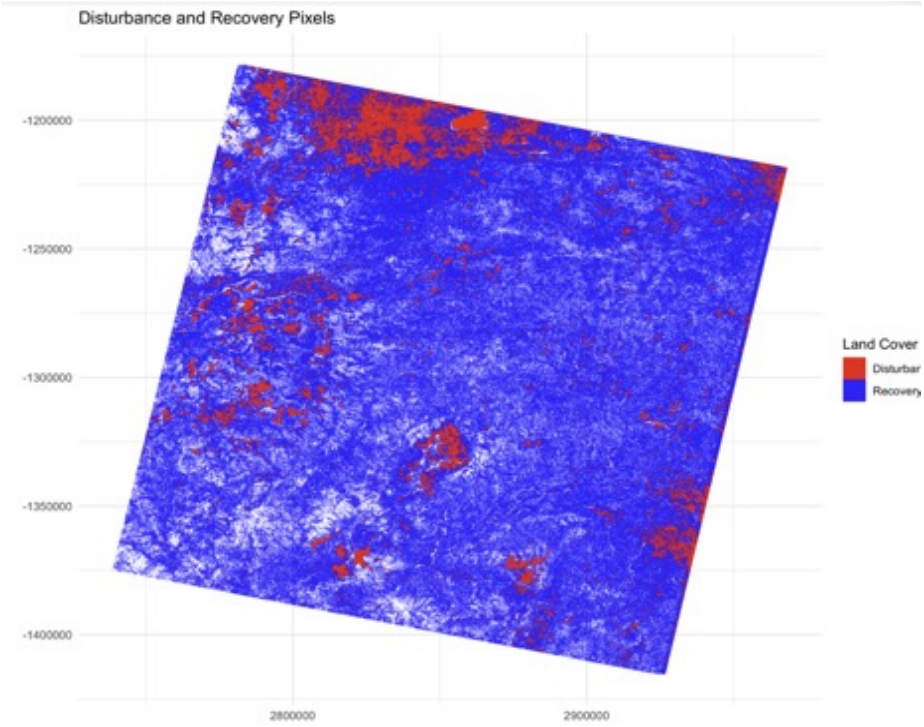
We employed the LandTrendr algorithm to detect changes in pixel values over time (dimensions), indicating disturbances and subsequent recovery. We configured the algorithm to analyze the prepared time series, detecting and characterizing significant changes in forest cover, from tree cutting and natural regrowth. Next, we classified the time series to delineate areas by their change status: healthy forest, disturbed areas, and recovering forest.





Step 4: Forest Disturbance Analysis and Classification

This classification used the change information derived from the LandTrendr outputs, combined with additional spectral data from Landsat 8 images, to categorize each pixel accurately throughout the entire study period.

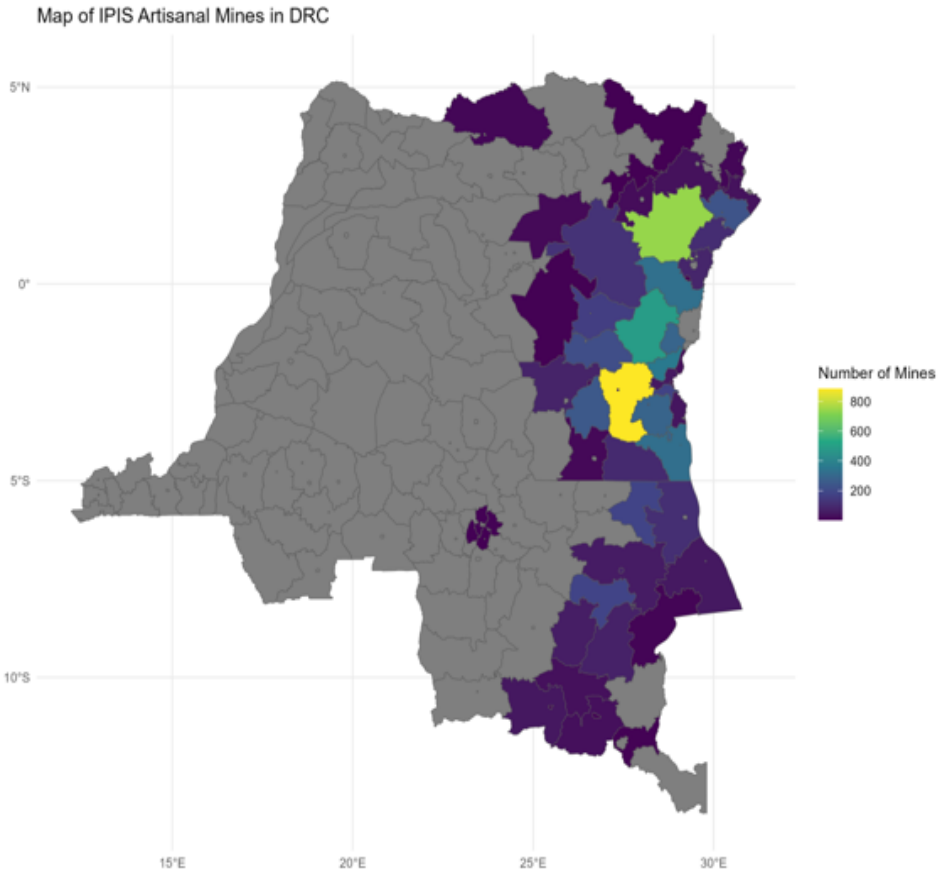


This study highlights the significant human and environmental impacts of artisanal mining in the DRC, driven largely by the demand for cobalt essential for the green energy transition.

Step 5: Analysis with R

Further analysis was then carried out using R Studio to check for correlation between artisanal mines reported by International Peace Information Service (IPIS) and land use change.

The map to the right shows artisanal mines in each city observed in the DRC from 2009 - 2023.



Recommendations

Based on our findings, below are several of the key recommendations offered to the United Nations Office of the Special Adviser on Africa (OSAA):

1. **Expand Geographic Coverage of Studies and Data Collection:** Our study is based on data from a limited area in the southern part of the DRC. This limits the generalizability of our findings; the OSAA should support expanded geographic coverage for future studies and data collection efforts. This should include diverse terrain types such as rocky areas, urban regions, water bodies, and mountainous areas to gain a comprehensive understanding of the impacts of mining.

2. **Enhance Regulatory Frameworks:** The study highlights significant environmental degradation associated with artisanal mining. The OSAA could implement stricter regulations to protect forests and other critical ecosystems from deforestation and degradation due to mining activities.

3. **Support Capacity Building and Skill Development:** Local communities often lack the skills and resources to engage in more sustainable and higher-value economic activities. Invest in capacity building and skill development programs for local communities. This can help diversify the local economy, reduce dependency on artisanal mining, and promote sustainable development.