International Journal of Applied Science and Engineering Review

ISSN: 2582-6271

Vol. 6, Issue.3, May-June 2025, page no. 143-161

To cite this article: Kombozi Yaya Dieu-Merci, Amosi Kikwata Guld, Kakule Lwanga, Bolekaleka Singa Valentin, Basandja Longembe Eugène, Tagoto Tungipame Alliance, Panda Lukongo Kitronza Jean and Losimba Likwela Joris (2025). LANDSCAPE ECOLOGY AND SPATIAL DISTRIBUTION OF MPOX IN ISANGI TERRITORY, DRC, International Journal of Applied Science and Engineering Review (IJASER) 6 (3): 143-161 Article No. 234 Sub Id 361

LANDSCAPE ECOLOGY AND SPATIAL DISTRIBUTION OF MPOX IN ISANGI TERRITORY, DRC

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DOI: https://doi.org/10.52267/IJASER.2025.6310

ABSTRACT

Introduction: Mpox is a viral zoonosis caused by the Mpox virus. The rise in cases in endemic regions since 2005 is strongly correlated with environmental changes such as climate change, deforestation, and human migration.

Isangi Territory has experienced repeated Mpox over the past three years. This situation coincides with recurrent floods and significant anthropogenic pressure on the environment, leading to substantial changes in land use.

Methods: This descriptive study aimed to describe the ecological profile of health areas affected by the Mpox epidemic in Isangi Territory, using remote sensing data and field surveys. We analyzed land-use changes between 2010 and 2024 using Landsat 5 (2010) and Landsat 8 (2024) satellite imagery, mapping the forest cover of the Yabaondo, Yakusu, and Yahisuli reserves.

Results: Health areas reporting suspected cases were characterized by deforested primary forests, oil palm plantations, experienced seasonal flooding and Areas with fallow land and secondary forest reported

Our results reveal a possible link between Mpox and the Isangi landscape.

Conclusion: Cases predominantly occur in oil palm plantations and deforested areas, suggesting that ecosystem modifications favor transmission. Flood-prone areas also play a role, confirming the importance of landscape ecology for public health strategies.

KEYWORDS: Mpox, Ecology, Landscape, Isangi

INTRODUCTION

Mpox is a viral zoonosis that has long remained a neglected tropical disease in Sub-Saharan Africa [1]. The Mpox virus (MPXV) is an endemic zoonotic virus in West and Central Africa, belonging to the Orthopoxvirus genus. In humans, MPXV infection can lead to a smallpox-like illness characterized by fever, lymphadenopathy, and a rash. Initially, lesions are macular but eventually transform into papules, vesicles, pustules, and finally, scabs [2].

As of October 5, 2022, over 68,000 laboratory-confirmed cases were reported in 100 non-endemic countries [3]. Cases during this epidemic primarily occurred among MSM [4]. The emergence of this disease was characterized by rapid international spread with a growing number of cases in new geographical areas, a preponderance of the disease among members of a distinct social group, and a somewhat atypical clinical presentation, collectively shaped in part by increased international travel, human behavior, and viral pathogenicity [5].

In Africa, Mpox epidemics are common. Between 2017 and 2019, Nigeria reported a record 424 suspected MPXV cases and 155 confirmed cases. The highest number of confirmed cases was recorded during the 2017 epidemic for ages ranging from 21 to 40, whereas historically the disease was more frequent in those under 15 [6].

The DRC alone has reported nearly 85% of known human Mpox cases in recent years, across several epidemics [7]. From October 2021 to the end of 2022, 6032 suspected Mpox cases, including 233 deaths, were reported in 23 of the country's 26 provinces [8].

In West and Central African regions where Mpox is endemic, the increase in human cases since 2005 has been fueled by climate change, deforestation, war, human migration, and decreased collective immunity due to remote smallpox vaccination [9], [10], [11]. Specifically, regarding deforestation, several studies have shown that its acceleration means an increase in interactions between wildlife, reservoirs of unknown viruses, and human activities, particularly agriculture. Nearly 50% of zoonoses emerging since the 1940s are associated with agriculture [12].

Ecological niche models have been used to better define the geographical extent of areas that are ecologically suitable for monkeypox [13], [14], [15], [16]. These models were based on developing an understanding of the ecological factors at the location of human cases (using remote sensing data in conjunction with human MPX occurrence data), and then identifying the extent of other areas that met the same conditions. At the continental scale, models revealed that monkeypox transmission was primarily associated with the sub-Saharan African rainforest [15], [17]. At the regional scale, models built from historical data and projected into contemporary environmental data in the Congo Basin showed changes in the distribution of suitable conditions with a potential expansion of at-risk areas [13]. In recent years, several human cases have been reported in these predicted areas [13]. At the local level, models confirmed a higher risk of monkeypox in heavily forested areas [18].

In the Tshopo province, the Isangi Territory has experienced repeated outbreaks of Mpox epidemics over the past three years, primarily in the health zones of Yakusu, Yabaondo, and Yahisuli. Concurrently, this territory has faced recurrent floods and significant anthropogenic pressure on the environment, leading to important changes in land use. Indeed, Isangi is the most populated territory in Tshopo province and the smallest in terms of area. The population of this territory is also confined between large expanses of plantations and industrial timber concessions, making it one of the deforestation hotspots in the DRC.

Due to the resurgence of monkeypox outbreaks in the Isangi territory, which appears to present an environment conducive to the occurrence of this disease, we deemed it appropriate to conduct the present study. Its objective is to describe the ecological profile of the areas affected by the Mpox epidemic using remote sensing data and field surveys.

2. MATERIAL AND METHODS

2.1. Material

2.1.1. Study Setting

This multicenter study was conducted in three out of four health zones in the Isangi territory: Yakusu, Yahisuli, and Yabaondo, which had reported suspected Mpox cases during our study period.

Located in the center of Tshopo province (24° 15’ 56’’ E and 0° 46’ 48’’ N), Isangi territory is the smallest in the province (15,770 km²) but the most populous (estimated population of 701,548 inhabitants). It is entirely situated within the central Congolese basin at an altitude of 376 m and does not border any other province. The prevailing climate is equatorial, and the vegetation is primarily evergreen forest [19]. The territory hosts one of the largest forest reserves, the Yangambi Biosphere Reserve (225,000 km²), as well as several logging concessions and agro-industrial plantations.

This territory boasts significant hydrography, with numerous waterways crisscrossing almost its entire extent. This abundance of waterways, while a source of wealth, also contributes to recurrent floods observed in recent years across a large part of the territory. Conflicts related to non-compliance with social clauses by industrial timber operators and issues concerning the delimitation of protected areas exacerbate tensions with the growing population, who are seeking space for agriculture and forest resource exploitation. This makes Isangi territory one of the deforestation hotspots in the DRC.

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IJASER

ISSN: 2582-6271

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Health Zones in Isangi Territory

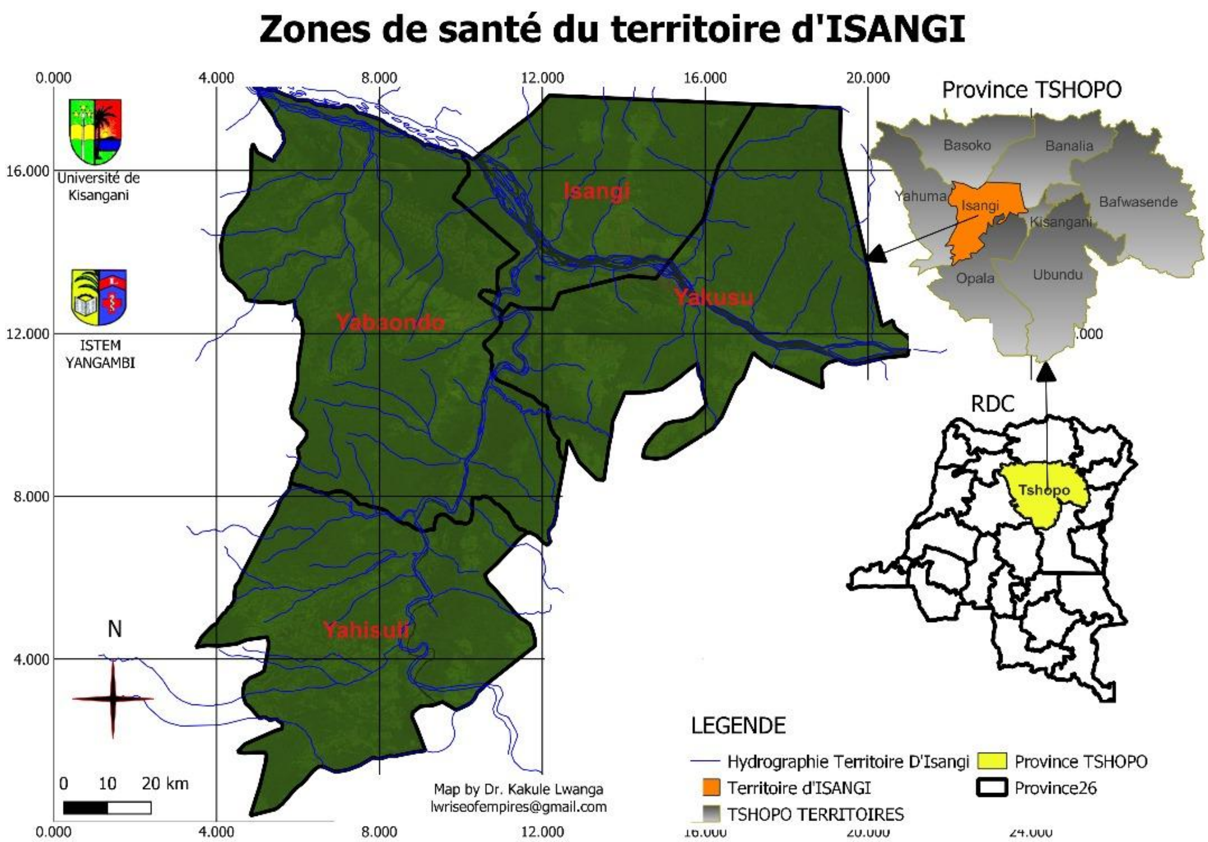

Fig 1: Map of Health Zones in Isangi Territory

2.2. Methods

2.2.1. Study Type and Period

This was a descriptive study. Data related to land-use change covered the period from 2010 to 2024. Data on notified suspected cases concerned the period from January 2023 to January 2024. Satellite images for remote sensing were acquired during February 2024.

2.2.2. Data Collection

2.2.2.1. Tools

Satellite Images

We used Landsat satellite images (freely downloaded from the U.S. government website http://earthexplorer.usgs.gov/) to map the dynamics of land use in the three health zones. Two dates (years)

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were selected: 2010 and 2024, corresponding to the TM (Landsat 5) and OLI-TIRS (Landsat 8) sensors, respectively. In addition to these satellite images, other data were used, including: Google Earth images, printed and scanned land-use maps of the DRC and the Yabaondo, Yakusu, and Yahisuli territories to facilitate photo-interpretation. These vector data helped us precisely delimit our study area.

Table I. Materials and Application.

Tools	Applications
Landsat 8 and Landsat 5 Satellite Images	Color composite using bands 3,4,5 for Landsat 5 images and 4,5,6 for Landsat 8.
GPS Receiver	Collection of ground truth points in test areas, geolocation of land cover classes.
QGIS 2.8 and QGIS 3.16	GIS analysis and map layout.
ENVI 4.4	Image processing (supervised classification).
Google Earth	Photo-interpretation.
Microsoft Office Word, PowerPoint, Excel 2013	Text entry, data processing.

2.2.2.2. Data Collection Techniques

We conducted a field survey in the three health zones of Isangi territory that reported suspected Mpox cases from January 2023 to January 2024. Biological samples were collected from suspected cases during a physical examination, where scabs, vesicular fluid, and blood were obtained and sent to the National Institute of Biomedical Research (INRB) in Kinshasa. Subsequently, a comprehensive questionnaire was used to gather clinical and epidemiological data (not presented in this study), as well as information on the presence of palm groves in the community and seasonally flooded health areas.

We employed a methodological approach based on the spatio-temporal analysis of forest cover in the Yabaondo, Yakusu, and Yahisuli Reserves, utilizing remote sensing. To achieve this, we acquired data via LANDSAT satellite imagery for land cover mapping (forest cover). Landsat 5 (TM sensor, 2010) and Landsat 8 (OLI-TIRS sensor, 2024) images were processed for this purpose.

2.2.2.2.1. Image Acquisition and Selection

Landsat images from 2010 and 2024 (all with a 30 x 30-meter resolution) were used for the spatio-temporal analysis of land use dynamics. These Landsat images from scenes 176-059 and 176-060 were freely obtained from the United States Geological Survey (USGS) website: "http://earthexplorer.usgs.gov/".

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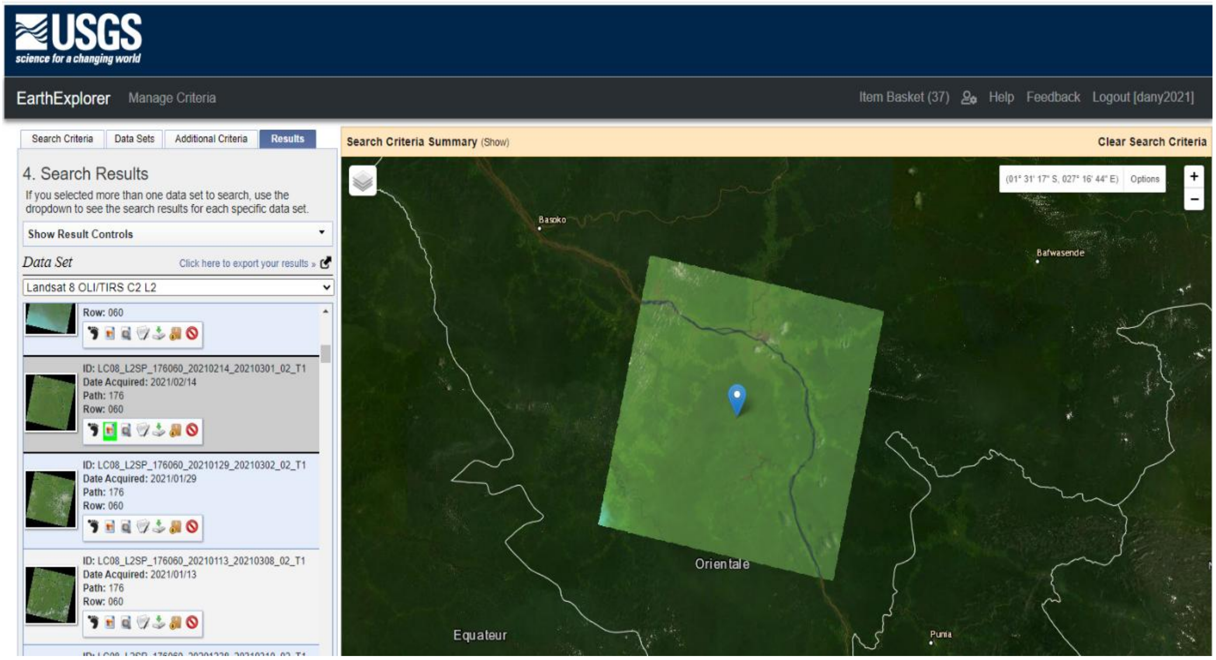

Figure 2. Presentation of the USGS Earth Explorer interface with the Yakusu scene (Path 170 and Row 060)

2.2.2.2.2. Visualization and Color Composite

After downloading and saving the LANDSAT satellite imagery data, a sequence of operations, including visualization of the downloaded images, was performed to verify image quality and enhance object visibility.

We created a false-color composite using ENVI 4.6.1 software. In this false-color composite, we assigned spectral bands 6, 7, and 5 to the RGB (Red, Green, Blue) channels (representing Infrared, Near-Infrared, and Red, respectively) for the 1976 MSS sensor image. For the 2022 OLI sensor image, we assigned bands 6, 5, and 4 (representing Infrared, Near-Infrared, and Red, respectively).

This is considered a false-color composite because the wavelengths we assigned to the three RGB channels do not correspond to these three colors. The colors displayed on screen did not match the real colors of the observed scene but helped highlight certain land cover classes of high importance for this study, such as forests, built-up areas, and water bodies. False-color composites offer the advantage of visualizing data not belonging to the visible spectrum, such as infrared, as well as radar, hyperspectral, elevation data, etc. In other words, they "transform" non-visible data (but recorded by a sensor) into visible data [20].

2.2.2.2.3 Image Classification

Satellite image classification is performed using two methods: unsupervised classification methods and supervised classification methods [21]. For this study, we used supervised classification methods with ENVI 4.4 software. Within this software, the study area on the images was divided into the following classes: Primary Forest, Secondary Forest, Fields and Fallows, Bare Soil and Built-up Areas, Plantation, Water.

2.2.2.2.3.1. Classification of the 2024 Image

Based on the examination of the color composite of the area to be classified, we identified different spectral signatures corresponding to each legend taxon. Furthermore, a land cover type such as "Primary Forest" might exhibit different spectral signatures at the time of image acquisition, depending on, for example, the dominant species and canopy density. Therefore, the task was to define as many spectral classes as there were spectrally distinct situations for each land cover type.

In the context of this work, the Maximum Likelihood classification algorithm was applied to all pixels in the images based on the statistical parameters describing each spectral signature obtained (the means and standard deviations between the green, red, and infrared channels).

2.2.2.2.3.2. Classification of the 2010 Images

While the classification of the 2024 images was based on field measurements, the classification of the 2010 images was performed retrospectively and deductively, given that we did not have field measurements for that period. Thus, the 2024 images served as a reference for processing the older images. The samples defined for each class therefore correspond to areas that were assumed not to have changed land cover between 2010 and 2024 [J1].

2.2.3. Definition of Training Areas or ROI: Region of Interest

This part of the work involved selecting a minimum of 90 to 100 pixels that were spectrally representative of each previously identified spectral signature. These samples, or "training areas," were used for the "calibration" and "validation" of our classification. This operation was carried out using ENVI 4.4 software.

2.2.4. Image Preprocessing

The downloaded satellite images require a certain number of preprocessing operations. This is an indispensable step in the satellite image processing workflow that guides the entire methodological approach. Image preprocessing, or preliminary analyses, is a set of operations aimed at increasing data readability to facilitate interpretation. When properly executed, these operations contribute to a better extraction of useful information [22]. Thus, in this study, the following preprocessing steps were performed:

- Spectral Band Stacking: We combined different spectral bands into a single composite image (a multispectral image) to make manipulation easier, allowing processing to occur simultaneously across all grouped bands. The ENVI 4.4 remote sensing software was used, and the combination was done using the "Layer Stacking" tool.
- Image Cropping: The downloaded satellite images covered large areas that were not necessary for our work. Cropping allowed us to reduce the image size to retain only the area of interest. This facilitated and accelerated operations when running algorithms.
- Mask Creation: To eliminate pixels outside our study area, we created masks. The cropped images still contained areas outside the domain of interest. Therefore, a mask was created to display only the part of the images corresponding to our study area. The masking layer was the shapefile (".shp") of the study area converted to ".evf". This operation was performed in ENVI using the "Basic Tools => Masking => Build Mask" tool.

2.2.5. Calculation of Land Cover Class Separability

The definition of training areas for calibration and validation focused on five predefined land cover classes: dense forest, secondary forest, fields and fallows, built-up/bare soil, and water bodies. For each image to be classified, a separability measure was performed to avoid confusion between classes and to assess the adequacy of the training area selection. This provided insight into the possibility of distinguishing these classes and, therefore, producing an accurate classification. Two separability indices were calculated in ENVI: "Jeffries-Matusita" and "Transformed Divergence."

2.2.6. Post-processing of Classified Images to Improve Visual Render

Several post-processing operations can be applied to a classified image to improve its visual render [22]. In the context of this study, three post-processing operations were performed to enhance visual quality:

2.2.6.1. Post-classification Filtering

Post-classification filtering aimed to reduce the salt-and-pepper effect typical of pixel-based classifications, with the goal of reorganizing misclassified pixels. To do this, we proceeded as follows: performed a majority analysis via the menu "Classification > Post Classification > Majority/Minority Analysis."

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2.2.6.2. Improving Class Colors

This operation involved applying intuitive colors to each land cover class. To do this, we proceeded as follows: selected the menu "Tools > Color Mapping > Class Color Mapping."

2.2.6.3. Conversion of Post-Classification Filtering Output to Multiple Formats

The output of the post-classification filtering was converted in two steps: first, from the classification to an ENVI vector format ("Classification > Post classification > Classification to vector"); then, from the ENVI vector to a Shapefile ("Availablevectorlayers > File > Export layers to shapefile") to populate the QGIS 3.16 attribute table for cartographic layout.

2.3. Annual Deforestation Rate in the Study Area

The deforestation rate (Td) is expressed as the percentage of forest area lost per year (%/year). The variable considered is area (S). Several formulas currently exist to estimate the deforestation rate. In this study, we used the Catalan formula (1991). The rate was calculated as follows:

$$Td\% = \frac{A_1 - A_2}{A_1 \times n} \times 100$$

Where:

- A1 = Forest area in the initial year (ha)
- A2 = Forest area in the final year of the analyzed period (ha)
- n = Time between A1 and A2

2.4. Change Detection Analysis with Transition Matrix

The analysis of land-use change involves presenting the 2010 and 2024 maps within the scope of this study. A crossing of the two land-use maps yielded a change map and a matrix that reflected the evolution of different classes between these two dates.

We recorded Geographic Information System (GIS) data on the latitude and longitude of health areas that reported suspected cases and proceeded with the distribution of suspected cases, where each point corresponded to one percent of suspected cases in the health zone.

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3. RESULTAT

3.2.1. Yabaondo Health Zone

Table II. Land Use Dynamics and Suspected Case Notification in Yabaondo

. LAND USE DYNAMICS					NOTIFICATION		
Class	Area (ha)		Balance (ha)	Deforestation rate (%)	Health area	Suspected case	%
					Yabetuta	33	12.4
					Logoge	22	8.2
	2010	2024			Imbolo	44	16.5
Water	4533.48	6587.1	+2053.62		Botumanya	50	18.7
PF	380653.92	263499.21	-117154.71	2.198	Itenge haut	41	15. 4
SF	32794.2	54788.58	+21994.38		Yaboila	41	15.4
FL	38030.04	77836.23	+39806.19		Mumba losuna	20	7.4
BS	21612.96	73268.82	+51655.86		Yanguba	16	6
Total	**477624.6**	**475979.94**	-1644.66		**Total**	**267**	100

*PF= primary forest, SF= secondary forest, FL= fallow land, BS= bare soil

The annual deforestation rate (loss of primary forests) was 2.19% in the Yabaondo health zone, representing a loss of 117,154.71 ha between the two study periods. This decrease in primary forest area was reflected by dramatic increases in the surface areas of other land use types. The health areas of Botumanya, Imbolo, Itenge-haut, and Yaboila collectively reported the majority of suspected Mpox cases.

In the Yabaondo health zone, four Mpox hotspots were observed: Health areas with palm groves (red dot): 66% of suspected cases, Health areas with deforested primary forest (purple dot): 20.6% of suspected cases, health areas with fallow land, secondary forest (blue dot): 13.4% of suspected cases and Flood-prone health area (black dot): 12.4% of suspected cases.

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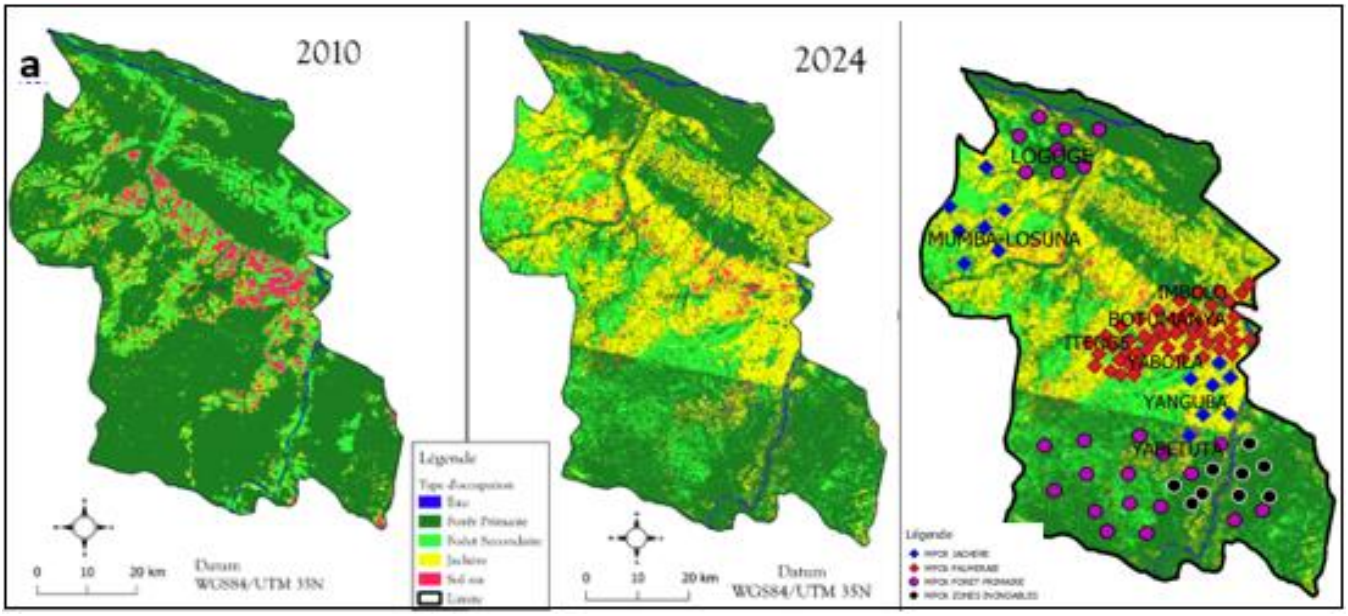

Figure 3. Land Use Change and Distribution of Suspected Mpox Cases in Yabaondo Health Zone: A Vegetation Profile in 2010, B Vegetation Profile in 2024, and C Distribution of Mpox Cases Superimposed on Vegetation Profile in 2024.

3.2.2. Yahisuli Health Zone

Table III. Land Use Dynamics and Suspected Case Notification in Yahisuli

LAND USE DYNAMICS					NOTIFICATION		
	Area (ha)		**Balance (ha)**	**Deforestation rate (%)**	**Health area**	**Suspected case**	**%**
Class					Mokombe	30	21.1
	2010	2024			Yaeme	48	33.8
Water	2048.4	3219.93	+1171.53		Likoli	5	3.5
PF	227698.56	164829.33	-62869.23	1.972	Yauta	29	20.4
SF	38105.28	62674.29	+24569.01		Yaolenga	10	7
FL	18366.48	65753.64	+47387.16		Yahisuli	15	10.6
BS	40584.6	29198.25	-11386.35		Yaokoli	5	3.5
Total	**326803.32**	**325675.44**	**-1 127.88**		**Total**	**142**	100

*PF= primary forest, SF= secondary forest, FL= fallow land, BS= bare soil

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ISSN: 2582-6271

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The annual deforestation rate (loss of primary forests) was 1.97% in the Yahisuli health zone, representing a loss of 62,869.23 ha between these two study periods. This decrease in primary forest area was reflected by increases in the surface areas of other land use types, with the exception of bare soil. The health areas of Mokombe, Yaeme, and Yauta collectively reported the majority of suspected Mpox cases in the zone.

Health areas with deforested primary forest (Yaeme, Yahisuli, and Yauta) reported the majority (64.8%) of suspected Mpox cases in this zone, followed by the health area with palm groves (Mokombe: 21.1%) and flood-prone health areas (Yahisuli and Yaolenga: 17.6%). The remaining cases occurred in health areas with fallow land and secondary forest (Lokoli, Yaokoli, and Yaolenga: 14%).

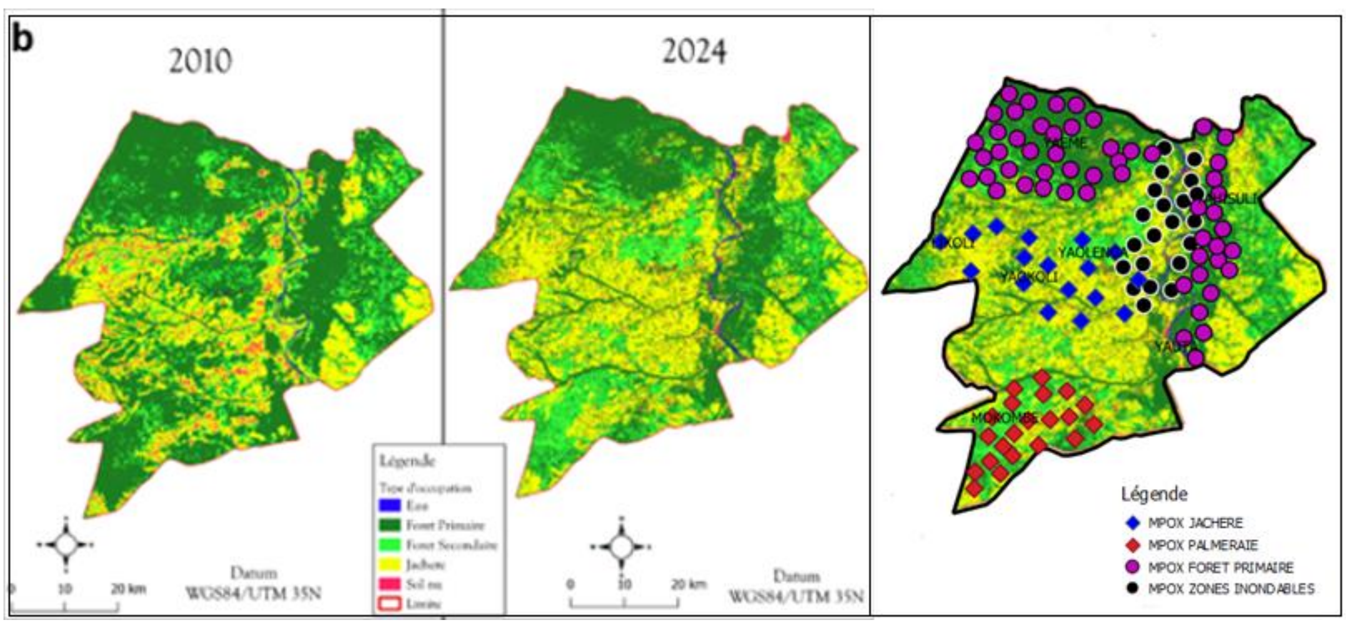

Fig 4. Land Use Change and Distribution of Suspected Mpox Cases in Yahisuli Health Zone: A Vegetation Profile in 2010, B Vegetation Profile in 2024, and C Distribution of Mpox Cases Superimposed on Vegetation Profile in 2024.

3.2.2. Yakusu Health Zone

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Table III. Land Use Dynamics and Suspected Case Notification in Yakusu

LAND USE DYNAMICS					NOTIFICATION		
Class	Area (ha)		Balance (ha)	Deforestation rate (%)	Health area	Suspected case	%
					Yelenge	36	12.7
					Yaoseko	58	20.4
					Yalongosa	22	7.7
					Yaselia	42	14.8
	2010	2024			Bolongo	38	13.4
Water	11143.08	11111.4	-31.68		Yalanga	10	3.5
PF	247392.36	245306.16	-2 086.2	0.16865517	Yaotike	32	11.3
SF	53091	60045.84	+6 954.84		Yasendo	26	9.2
FL	46503.36	42560.28	-3 943.08		Ilota	10	3.5
BS	3552.12	2654.28	-897.84		Ikongo	10	3.5
Total	361681.92	361677.96	**− 3.96**		**Total**	**284**	100

*PF= primary forest, SF= secondary forest, FL= fallow land, BS= bare soil

The Yakusu health zone experienced an annual deforestation rate of 0.16%, equivalent to a loss of **2,086.2 ha** between the two study periods. The health areas of Yaoseko, Yalongosa, Bolongo, and Yelenge collectively reported the majority of suspected cases in the zone.

Health areas with deforested primary forests reported the majority of suspected cases in the zone (Yelenge, Yaoseko, Yalongosa, Yaselia, Yasendo: 64.8%), followed by flood-prone health areas (Yelenge, Yaoseko, Yalongosa, Bolongo: 54.2%), and health areas with palm groves (Bolongo, Yaotike, Yalanga: 28.2%). Other health areas (fallow land, secondary forest) reported 7% of the suspected cases in the zone.

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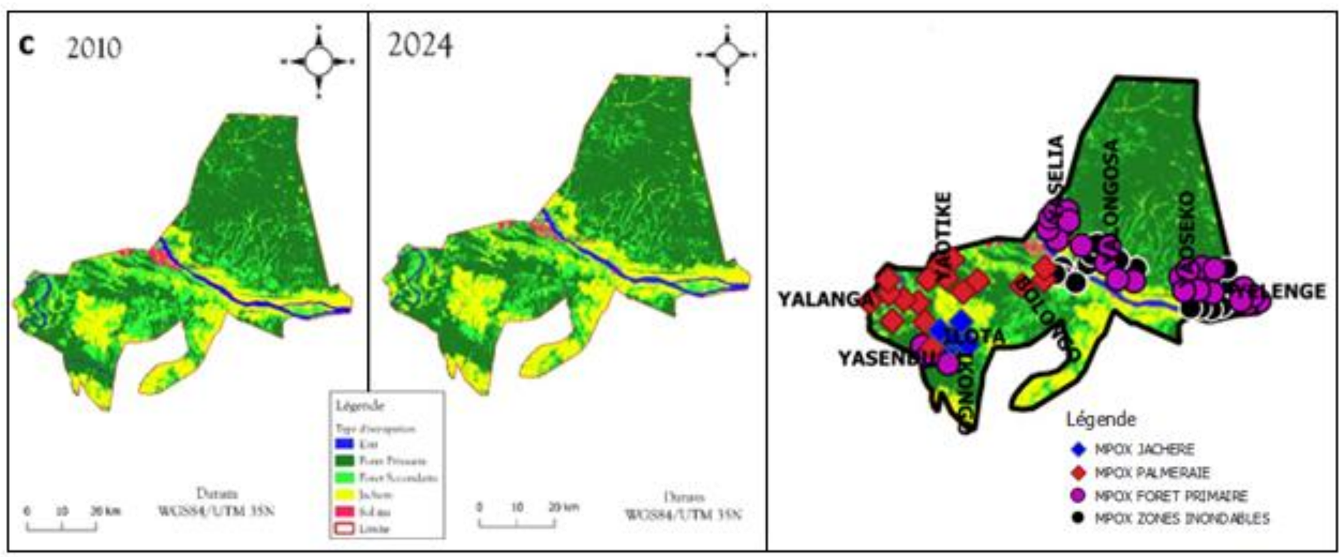

Fig 5. Land Use Change and Distribution of Suspected Mpox Cases in Yakusu Health Zone: A Vegetation Profile in 2010, B Vegetation Profile in 2024, and C Distribution of Mpox Cases Superimposed on Vegetation Profile in 2024.

4. DISCUSSION

The majority of suspected Mpox cases originated from health areas with deforested primary forests (64.8% in Yakusu, 64.8% in Yahisuli, and 20.6% in Yabaondo). In the DRC, Mandja B et al. found that primary forest (IRR 1.034, 95% CI 1.029–1.040) was positively associated with the annual incidence of Mpox [7]. Furthermore, Thomassen HA et al. observed that deforestation was a significant determinant of Mpox transmission in Sankuru and that land-use changes could influence the distribution and abundance of reservoir species. The majority of areas where an increase in Mpox was predicted were covered by forests, where presumed reservoir species were naturally present. Land conversion in these areas was rampant, with primary forest being transformed into secondary forest due to timber extraction or into agricultural fields [14]. The works of Singh A and Shaikh B [23], as well as K. Brown and P. Leggat [24], noted that deforestation could also have played a role in the resurgence of the disease or its ability to spread. Studies by J. Thornhill et al. [25] and E. Whitehouse et al. [26] confirm that human activities such as deforestation, agricultural expansion, and urbanization have increased contact between humans and wildlife, which raises the risk of transmitting diseases like monkeypox. The increased proximity between human populations and virus-carrying animals, particularly rodents and primates, favors the spread of the disease. This phenomenon is particularly visible in Central Africa, where the destruction of natural habitats has intensified these interactions. To address this situation, appropriate measures such as educating and raising awareness among populations living near deforested areas about the increased risks of contact with wild animals that are potential Mpox virus carriers are therefore essential. Messages should focus on risky practices (hunting, handling dead animals) and preventive measures (hygiene, proper cooking of bushmeat). Furthermore, promoting sustainable economic alternatives that can support alternative economic initiatives to deforestation for local communities, such as sustainable agroforestry, ecotourism, or the production of non-timber forest products, is indispensable. This could reduce pressure on primary forests and thus reduce contact between humans and wildlife.

In this study, health areas with palm groves or oil palm plantations also reported suspected cases of the disease (66% in Yabaondo, an area hosting an agro-industrial oil palm plantation; 28.2% in Yakusu; and 21.1% in Yahisuli, two health zones with oil palm plantations belonging to family farmers). In the DRC, Fuller T et al., in their study on using remote sensing to map the risk of Mpox virus spread in the Congo Basin [18], suggested that the best predictors of human Mpox cases were proximity to dense forests and the associated habitat preferred by rope squirrels (oil palm plantations). The risk of contracting Mpox was significantly higher near sites considered habitable for squirrels (oil palm plantations) (OR = 1.32; 95% CI 1.08-1.63). Thus, they recommended that semi-deciduous tropical forests with oil palm, the primary food source for rope squirrels, be prioritized for Mpox surveillance. Indeed, squirrels of the genus Funisciurus are known to be hosts for the Mpox virus, and oil palm plantations provide them with an abundant food source and a favorable environment for their proliferation. Furthermore, as game, they constitute an important protein source in rural areas, which increases their contact with humans who hunt and consume them.

Health areas prone to flooding reported some suspected Mpox cases in our study (Yakusu: 54.2%, Yahisuli: 17.6%, Yabaondo: 12.4%). In Nigeria, Alakunle E et al. noted that floods bringing humans and MPXV-infected animal hosts into closer proximity were a significant factor in Mpox emergence [6]. A multi-year study of small terrestrial animals sampled in a highly Mpox-endemic region of the DRC, conducted by Doty JB et al., revealed a relative scarcity of orthopoxvirus-seropositive animals in edaphic forest areas (seasonally flooded) [27]. This suggests the displacement of these animals to drier areas, thereby facilitating contact with humans seeking dry locations during or after floods.

5. LIMITATIONS OF THE STUDY

This study has a few key limitations to consider:

- No Causal Link Established: As a descriptive study, it can't determine if environmental factors directly cause Mpox cases in the Isangi territory. To understand causality, correlation studies would be needed.

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- Limited Environmental Factors Explored: The study primarily focused on physical and biogeographical environmental factors like dense forests, deforestation, palm oil plantations, and flood-prone areas. This means other potentially important environmental factors, such as climatic variables (temperature, precipitation), were not investigated.
- Subjectivity in Flood-Prone Area Assessment: The characterization of flood-prone health zones relied on field surveys.
- This method can introduce subjective bias. Using techniques like remote sensing or
- other spatial mapping methods could have provided more objective and precise data, but this wasn't feasible due to budget constraints.
- Spatial Analysis Precision: The study used the geolocation of health zones as its unit for spatial analysis, rather than the individual geolocation of Mpox cases. This approach limits the precision of the spatial analysis and might hide significant local variations in case distribution and their link to environmental factors. A more granular geolocation of individual cases would have allowed for a more detailed spatial analysis and a better understanding of local risk factors.

6. CONCLUSION

This descriptive study, conducted in three health zones within the Isangi territory, allowed for the development of an ecological profile of health areas that reported suspected Mpox cases. Our observations reveal that the health areas where suspected cases were reported exhibit certain notable ecological characteristics, specifically the presence of deforested primary forests, palm groves/oil palm plantations, and to a lesser extent, flood-prone areas. These findings describe the environmental context in which the occurrence of suspected Mpox cases was observed in the studied zones. Correlation studies are therefore essential to elucidate potential associations between these environmental variables and the occurrence of Mpox in this territory.

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