Seeing the Gallery Forest for the Savanna Chimpanzees

Remote Sensing for Great Ape Conservation in Kedougou, Senegal

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GEOG 596B: **Capstone Project Report**

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Spring, 2024

The Pennsylvania State University

Master of Geographic Information Systems Program

CONTENTS

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my best friend for the past 24 years and loving husband for 17 of those years, David Green, for his support, patience, and unceasing encouragement during this 3-year academic adventure. I am also very grateful to my advisor, Jitendra Bal (JB) Sharma at Pennsylvania State University for his professional feedback and encouragement, and for his inspiring insight and advice on the big picture. Also, thank you greatly to my colleagues Brian Gelder and David James at Iowa State University for their professional support, and last, but not least, a special thank you to Jill Pruetz at Texas State University for very generously allowing me into her savanna chimpanzee field journals ten years ago to support my GIS and remote sensing endeavors —and she has always been uniquely accessible since then. Thank you, Jill, I hope this project can help current and future primatologists working to protect savanna chimpanzees.

ABSTRACT

Gallery forests are ecosystems unique to the Sudanian Zone of southeast Senegal, providing vital habitat for the critically endangered Savanna Chimpanzee *(Pan troglodytes verus)*. These forests provide savanna chimpanzees with refuge during the hot months of the dry season, and tall evergreen trees for nesting, shade, and protection from predators year-round. However, these ecosystems are under increasing anthropogenic pressures, primarily from mining, agriculture, and settlement development, and their preservation is becoming a critical need for savanna chimpanzee conservation. To facilitate efforts to preserve these unique ecosystems, their current and historical extent needs to be better understood. To help meet this need, this study developed a remote sensing method for tracking and mapping gallery forests in Kedougou, Senegal, using Trimble eCognition 10.3 software to apply an unsupervised classification with data fusion and object-based image analysis and segmentation. Closed-vegetation, ecotone, and open-vegetation were defined in the classifications as recommended in recent scientific literature by biological anthropologists in the field. The developed method was successful at locating gallery forests in 1988, 2000, 2010, and 2023. Classification results for a single focal month show a marked shift from 2010 to 2023 to predominately open-vegetation. These dates correspond to the gold mining boom in Kedougou, Senegal. This project supports the effort to protect gallery forests and savanna chimpanzees simultaneously, because they are inextricably linked to each other. All chimpanzees need trees to survive.

1. INTRODUCTION

1.1. Senegal

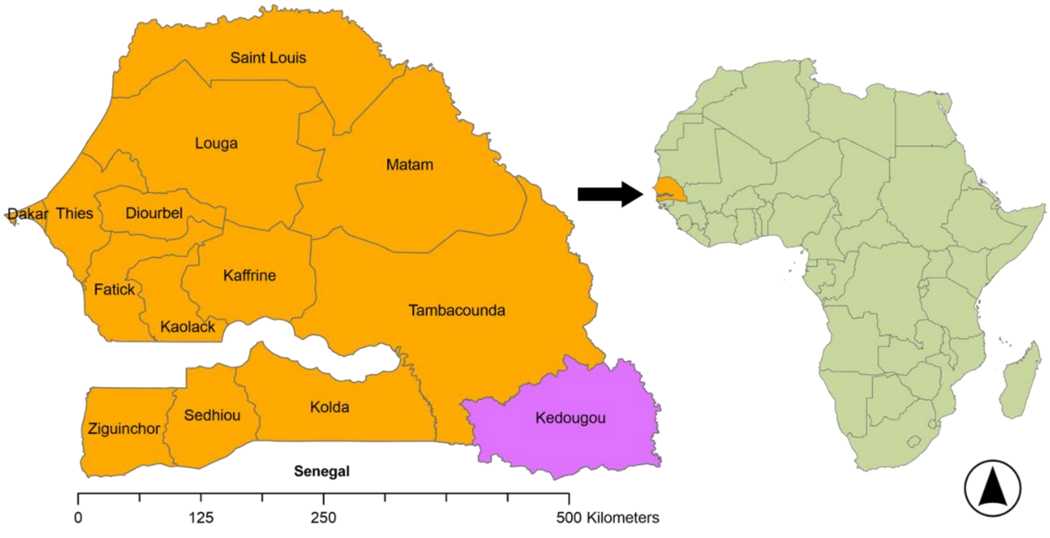


Figure 1. Senegal is the westernmost country in the continent of Africa. Kedougou is the southeastern most region in Senegal. The region of Kedougou is in the Sudanian Zone and it is characterized as the domain of the savannas.

The Republic of Senegal is the westernmost country on the continent of Africa (centroid: 14° 30′ 56.22″ N, 14° 26′ 41.41″ W), located between the borders of Guinea-Bissau in the southwest, Guinea in the southeast, Mali in the east, Mauritania in the north/northeast and the North Atlantic Ocean on its western border (Figure 1) (Central Intelligence Agency, 2023). The Gambia is the smallest country in mainland Africa and lies within Senegal between the Casamance region to the south and the capital of Senegal, Dakar, to the north, and straddles between the Gambia River. The Port of Dakar, also known as the "Gateway to West Africa," is one of the most important ports in Africa. The economy is centered mainly on extractive industries, such as, mining gold, iron ore, zircon, phosphate and limestone, in addition to petroleum refining and offshore oil extraction, building and ship construction, tourism, fish processing and agricultural products, such as, millet, peanuts, corn, sorghum, rice, cotton, tomatoes, green vegetables, cattle, poultry, pigs and fisheries (Central Intelligence Agency, 2023).

Senegal is 196, 722 km^2 or roughly slightly smaller than the state of South Dakota and has a population of 18,384,660 million people (2023 est.) (Central Intelligence Agency, 2023). Comparatively, the population of South Dakota is 886,667 in the 2020 Census (United States Census Bureau, 2020). The landscape in Senegal is largely considered to be flat, as 75% of the country has a maximum elevation of 50 meters (164.04 ft.) above sea level (Carter, Ndiaye, Pruetz, & McGrew, 2003). It is estimated that the highest point is located at the foothills of the Fouta Djallon mountains in the furthest southeast corner of Senegal at 358-meters (1263 ft) above sea level (Carter, Ndiaye, Pruetz, & McGrew, 2003).

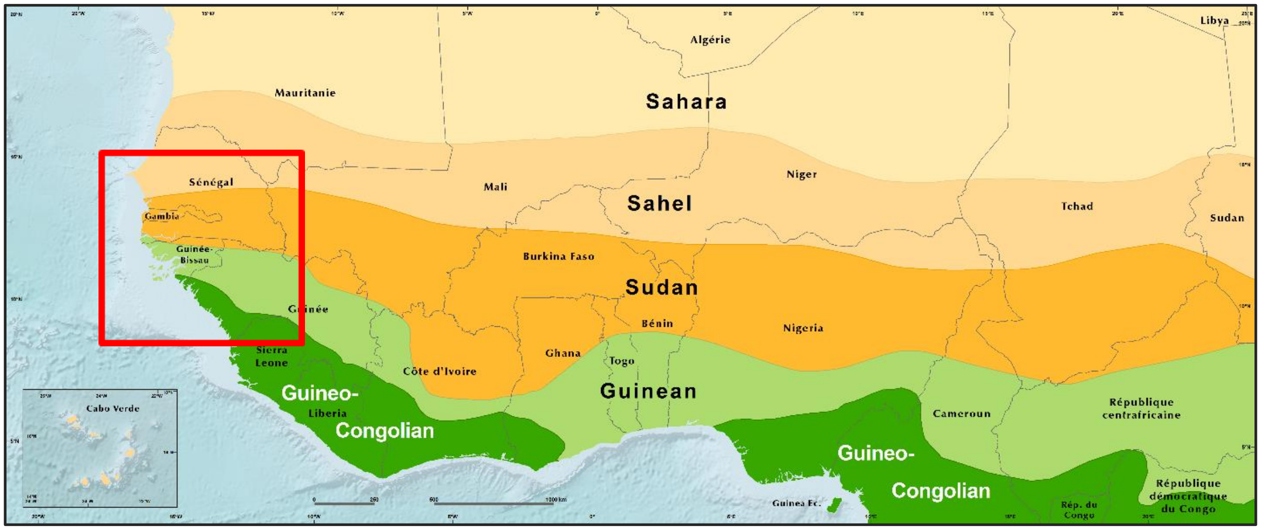


Figure 2. The Bioclimatic Zones of West Africa, the Sahara, Sahel, Sudan, Guinean, and Guineo-Congolian (CILSS, USGS, & USAID, 2016).

There are three main bioclimatic zones that are generally categorized by different occurrences of vegetation and climate coupled with temporal and spatial seasonality: the Sahel, the Sudan, and the Guinean (Figure 2). The Sahelian Zone is in the north of the country, and it is the transitional region between the Sahara Desert in the far north and the savanna woodlands to the south in the Sudanian Zone. The Sudanian Zone is characterized as the 'domain of the savannas,' identified by their tall grass and woody structure, ranging from open tree to wooded to open woodland savannas and grasslands (CILSS, USGS, & USAID, 2016; Carter, Ndiaye, Pruetz, & McGrew, 2003).

The southern regions of the Sudanian Zone are more densely wooded, making this region susceptible to natural and human induced brush fires. Natural brush fires have been a part of the ecology of this region for millennia; however, human induced brush fires are relatively new by comparison (CILSS, USGS, & USAID, 2016).

Unique to the Sudanian and Guinean Zones are the gallery forests that occur along the seasonally flooded arterial watercourses. These features are generally not affected by fires, and can serve as natural fire breaks and refugia for wildlife (Baldwin, 1979; Boyer Ontl & Pruetz, 2020; Ndiaye, Ndiaye, Lindshield, & Pruetz, 2024).

In the Sudanian Zone, the Kedougou regions annual rainfall was 900-1800 mm from 1995 to 2015, with a long-term mean of approximately 1200 mm (Sylla, Ndiaye, Lindshield, Bogart, & Pruetz, 2022). The dry season is from November to April, and May is a transitional month into the wet season from June to September and October is a transitional month into the dry season (Lindshied, Danielson, Rothman, & Pruetz, 2017; Sylla, Ndiaye, Lindshield, Bogart, & Pruetz, 2022).

The temperature varies by wet and dry seasons — but in general it is hot. In the Kedougou region the average daily temperature range has been recorded as high as 40°C to 44°C (104°F to 111°F) and as low as 16°C (61°F) (Carter, Ndiaye, Pruetz, & McGrew, 2003; McGrew, Baldwin, & Tutin, 1981; Pruetz J. D., 2007; Pruetz & Bertolani, 2009). The land use can be described in general terms as agriculture, plantations, mining operations, rural settlements and urban development, and transportation infrastructure.

There are four major rivers in Senegal that flow westward toward the Atlantic Ocean: the Senegal River, Saloum River, the Casamance River and the Gambia River (Mulroy, 2008). The Senegal River defines the border between Mauritania and Senegal, stretching 1,642 km (1,020 miles). Its major tributaries are the Bafing, Bakoye and Faleme Rivers which arise in Guinea and passing through Mali (Mulroy, 2008).

There are 14 political administrative regions in Senegal that are subdivided into 45 administrative departments, and 133 arrondissements, and these boundaries are further grouped by 46 communes d'arrondissement that include 113 communes de ville, and 370 communautés rurales (Senegal - Subnational Administrative Boundaries, 2018).

Senegal is considered one of the most stable democracies in Africa, and has a well-known reputation for international peacekeeping, mediation, and statesmen's diplomacy. It is also recognized for its integrated and peaceful cohabitation of a dozen different ethnic groups comprised of 94% Sunni Muslim, 5% Roman Catholic, and 1% Animist or Indigenous beliefs (Central Intelligence Agency, 2014). Its multicultural population speaks 36 different languages; however, the official language is French, but the most common language is Wolof (Central Intelligence Agency, 2014).

Presently, Senegal has a rapidly growing population. In 2014, the population was estimated at 13.97 million and in 2023 the population grew to an estimated 18,384,660 million people (Data Commons: Place Explorer, n.d.; Central Intelligence Agency, 2023). This is primarily due to outside investors who are interested in exploiting finite resources and the immigration flow that comes from surrounding countries when these investors attract new employment opportunities. Growing anthropogenic pressures derived from rapid population growth are driving deforestation, soil erosion, desertification, water and soil contamination, air pollution, over-grazing, overhunting, and overfishing — all of which overlap in areas of habitation for humans and wildlife.

Consequently, these extremely complex interactions between finite natural resources, local communities and cultures, government, and foreign corporate industries have led to compounding social inequality, injustice, and economic and political strife in vulnerable and poor regions of Senegal, such as Kedougou (Boyer Ontl K. M., 2017; Edwards, et al., 2014).

Furthermore, rare, and critically endangered wildlife populations are also in peril due to these anthropogenic pressures in the form of overhunting, illegal poaching, illegal logging, zoonotic disease transmission, and habitat destruction and degradation, all of which has intensified at a rapid rate as people immigrate into the country seeking financial opportunities.

Senegal does have a large number of protected natural areas; although, enforcement of laws and protections of these areas can be weak. Senegal is considered to be a forward-thinking Democratic country, and a model leader in African conservation. They participate in numerous international environmental agreements on issues that promote awareness and action for climate change, endangered species, biodiversity, desertification, hazardous waste, marine life conservation, ozone layer protection, whaling, wetlands, and ship pollution — but these treaties are only signed, and not yet ratified, but nevertheless the intention is significantly notable. (Central Intelligence Agency, 2023).

1.2. Gold Mining in Kedougou, Senegal

Mining can be described as the practice of exploiting virgin land by excavating into the earth to extract specific naturally occurring minerals (Down & Stocks, 1978). Worldwide, mining is second only to agriculture as the oldest and most important industry, and trading minerals between and within nations has been common since prehistoric times as demonstrated in the increasing mining complexity in these three prehistoric periods: the Stone Age, Bronze Age, and the Iron Age (Down & Stocks, 1978).

Today, nearly every material item is a mined product or produced indirectly with the assistance of mining byproducts such as steel, fertilizer, or energy (Down & Stocks, 1978). Mining can be significantly important to a country's economic development, it can generate income and foreign exchange through exports, provide employment to local citizens who in turn purchase local goods and services. Governments receive tax revenues from mineral productions that can then be used to raise up poverty-stricken areas by providing roads, electricity, access to education, and health care (Amponsah-Tawiah & Dartey-Baah, 2011). As long as there is a demand for a greater variety of minerals to accommodate a greater range of purposes, and the methods to extract become more efficient and technologically advanced – there will always be mining (Down & Stocks, 1978).

The continent of Africa alone contains 30% of the world's mineral resources; however, less than 5% of the global exploration has occurred in Africa (Edwards, et al., 2014). Africa also has the largest known reserve of strategically important minerals, such as, phosphate, platinum-group metals, gold, diamonds, chromite, cobalt, manganese, vanadium, and large deposits of aluminum, uranium, iron ore, and coal (Edwards, et al., 2014; Taylor, et al., 2009).

West Africa, which is comprised of thirteen countries: Benin, Burkina Faso, Cape Verde, The Gambia, Ghana, Guinea, Guinea-Bissau, Côte D'Ivoire, Liberia, Nigeria, Senegal, Sierra Leone, and Togo, is known for having been the world's most important gold supplier between 400 BCE to 1500 CE (Geward, 2010; Robertson & Peters, 2016). During this time placer deposits were widespread and accessible across West Africa to the local agricultural communities who prospected and mined these placers to supplement their income during the off-season or dry season of farming (Boyer Ontl K. M., 2017; Geward, 2010). Placer mines are described as shallow-pocked mining locales usually near a water source where mineral extractions are mined from surface sand or gravel with little need for sophisticated tools (Allan, 2015). Placers are also known as “dijouras,” referring to traditional West African gold panning sites. This system of informal gold mining as a means to supplement incomes remained in place as the only mining method until the introduction of large-scale industrial mining projects in the 20th century (Robertson & Peters, 2016). Today, placer mining in Africa is referred to as artisanal and small-scale gold mining (ASGM) or artisanal and small-scale mining (ASM) (Hruschka & Echavarria, 2011).

In Kedougou, Senegal there are three types of gold mines: (1) the large-scale mine which is an industrial mine with trained employees using large-scale mechanized tools to extract the gold quickly, and the investors are foreign and West African; (2) the intermediate-scale gold mine that is not as expansive as a large-scale mine but also not as small as a small-scale mine either; and (3) the small-scale artisanal gold mine is cultural subsistence mining that has been present in the region for millennia. The intermediate-scale mine has more infrastructure, is typically adjacent to a village, and usually has communal rules. The investors are generally traditional local people, but people also travel from neighboring countries to exploit the dijouras as well.

For more than 10 years, Senegal has been experiencing a gold mining boom. This presents an immense challenge for primate conservation because mining development brings new levels of anthropogenic disturbances and ecological pressures, such as, loss of group connectivity, loss of connectivity to habitat preference and protected areas due to road construction, mining pits, pond tailings, fencing, development, poaching, hunting, and forest degradation (Boyer Ontl K. M., 2017; Micheletti, 2018). Furthermore, gold mining brings mercury (Hg) contaminated soils, sediment, and water (Figure 3) (Birane, et al., 2014; Gerson, Driscoll, Hsu-Kim, & Bernhardt, 2018; Lindshield, et al., 2021). Mercury is amplified in higher trophic levels (i.e., up the food chain), also known as biological magnification. This creates a significant health risk to aquatic and terrestrial life.

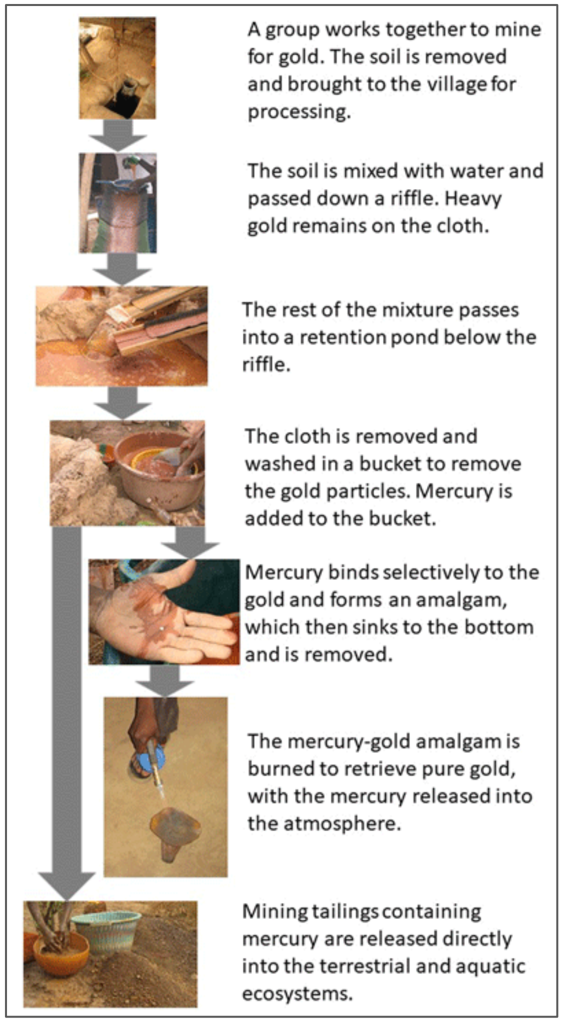


Figure 3. The Small-scale Artisanal Gold Mining Process in Kedougou, Senegal (Gerson, Driscoll, Hsu-Kim, & Bernhardt, 2018).

1.3. Savanna Chimpanzee

The Savanna Chimpanzee or Western Chimpanzee *(Pan troglodytes verus)* was listed as critically endangered in 2016 by the International Union for Conservation of Nature and Natural Resources (IUCN) Red List. Their total population is estimated to be between 18,000 and 65,000 (Humle, et al., 2016) a decline of 80% from 1990 to 2014 (Kuhl, et al., 2017). Their population in Senegal is modeled at 2,642 and surveyed as between 1,077 – 13,293 (Heinicke, Mundry, Boesch, Amarasekaran, & Barrie, 2019; Wessling, et al., 2020). Their total distribution extends from Senegal to Ghana as seen in the red box in Figure 4, and may include parts of western Nigeria (Humle, et al., 2016).

They are considered extinct in Benin, Burkina Faso, and Togo (Humle, et al., 2016). Savanna chimpanzees have been observed at elevation as high as 1200 to 1300 meters in Senegal, with a maximum observed elevation of 1600 meters in other countries (Humle, et al., 2016; Koops, McGrew, de Vries, & Matsuzawa, 2012). However, again, they have not been observed in areas where the average annual rainfall is less than 750 mm (Lindshield, et al., 2021; McGrew W. , 2010).

Rural communities in Kedougou, Senegal have been living side-by-side in balance with the great apes for generations. In this region, local traditional beliefs or taboos prohibit the hunting of savanna chimpanzees (Boyer Ontl K. M., 2017; Lindshield, et al., 2021; Ndiaye, Badji, Lindshield, & Pruetz, 2018; Wessling, et al., 2020). However, their belief systems are not always followed by non-local people who come to work at the mines (Kuhl, et al., 2017).

Senegal provides chimpanzees with complete protection under Article 67-28 of May 23, 1967, and Decree 67–610 of May 30, 1967, of the Code for Hunting and the Protection of Fauna (Kormos, Boech, Bakarr, & Butynski, 2003). It is illegal to hunt or capture protected species throughout the entire range of their territory in Senegal (Kormos, Boech, Bakarr, & Butynski, 2003).

Furthermore, forest resources which include chimpanzee habitat are protected under Article 093-06 of February 4, 1993, and Decree 95-357 of April 11, 1995, of the Forest Code (Kormos, Boech, Bakarr, & Butynski, 2003).

The chimpanzees survive in a savanna habitat that is the northernmost and westernmost limit for the chimpanzee geographical range and it is also the hottest climate range (Boyer Ontl & Pruetz, 2020). Most chimpanzee studies have been conducted in the forested areas of Central Africa (Lindshield, et al., 2021), but in Senegal only 2% of the savanna chimpanzee habitat is made up of forested areas or gallery forests (Wessling, et al., 2020), and savanna chimpanzees would prefer to be there in the dry season during the hottest and harshest time of the year because this is where water, food, shade and tall evergreen trees are for nesting and protection (Lindshield, et al., 2021; Ndiaye, Ndiaye, Lindshield, & Pruetz, 2024). All chimpanzees need trees to survive — even the savanna chimpanzee.

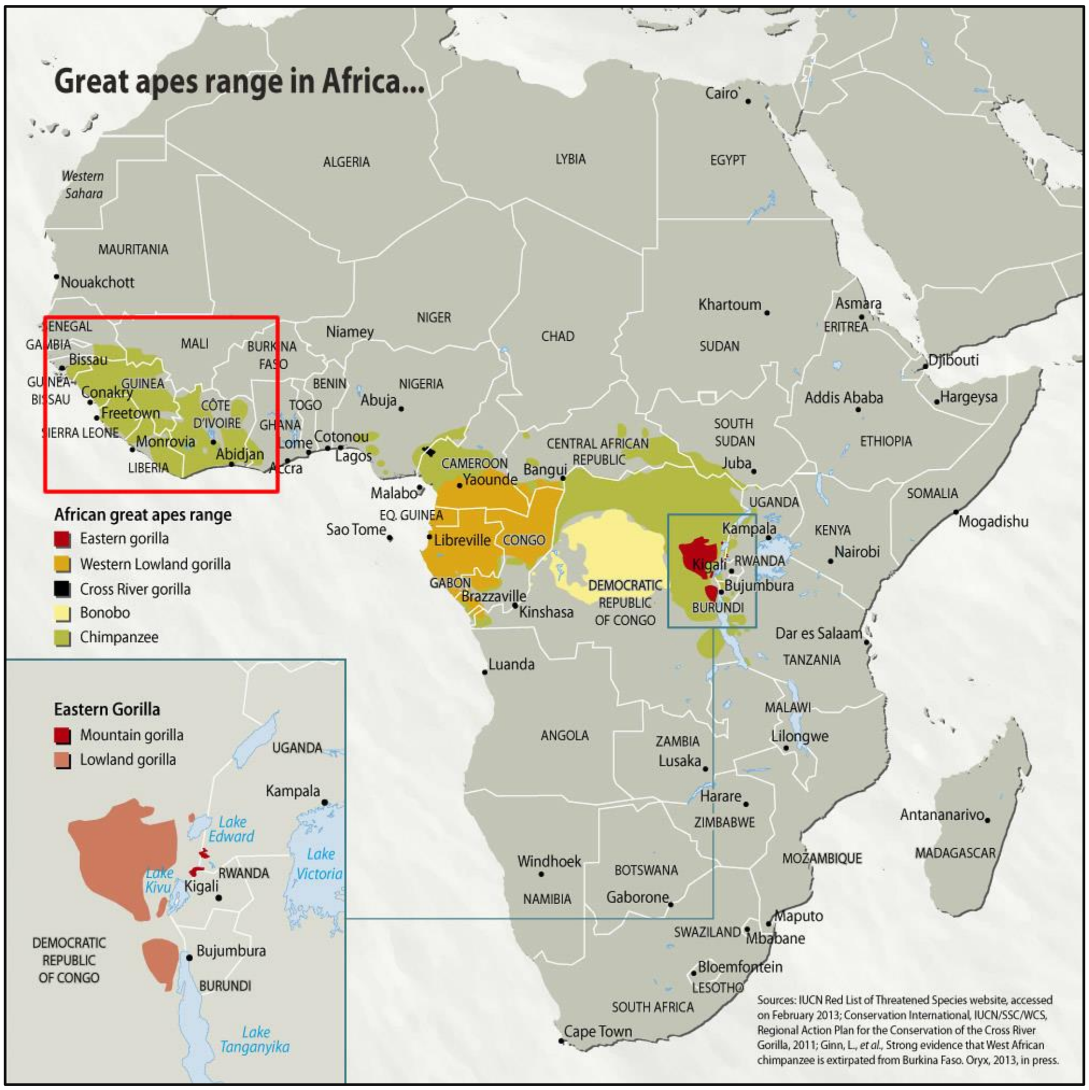


Figure 4. Depicts the range of great apes in Africa with a focus on Savanna Chimpanzees in the red box (Humle, et al., 2016)

In addition to gallery forests, the savanna chimpanzees also utilize other microclimates for refugia, such as caves and pools of water to cool off (Boyer Ontl & Pruetz, 2020; Lindshield, et al., 2021; Pruetz J. D., 2007). The savanna chimpanzees also fish for termites like their counterparts in the jungles forests of Central Africa (McGrew, Pruetz, & Fulton, 2005) and they hunt galago *(Galago senegalensis)*, a small nocturnal primate, with a spear shaped tool that they fashion themselves (Pruetz & Bertolani, 2007). Additionally, they have been observed to patrol their home range in groups that are 10 times larger than Central African chimpanzees, with home ranges that are also 3 times larger (Lindshield, et al., 2021).

Last, the savanna chimpanzees' flexible adaptations also help us to understand how our last common ancestor (LCA) may have survived in an open, hot, dry, and mosaic environment (Lindshield, et al., 2021; Pruetz & Bertolani, 2009; Wessling, et al., 2020).

1.4. Goals and Objectives

The body of work on wild chimpanzees is “forest bias” (Lindshield, et al., 2021). This means that most studies are conducted in Central Africa in places such as the famed Jane Goodall chimpanzees at Gombe. By comparison, very little has been conducted in savanna habitats. Additionally, remote sensing studies for the savanna chimpanzee are even more scarce.

Therefore, it is no surprise that few have looked at the health of the gallery forests since the expansion of gold mining in Kedougou, Senegal. The trees within this unique forest structure are critical habitat for the survival of savanna chimpanzees (Ndiaye, Ndiaye, Lindshield, & Pruetz, 2024). Furthermore, the preservation of nesting sites of chimpanzees is crucial for the conservation of savanna chimpanzees (Ndiaye, Ndiaye, Lindshield, & Pruetz, 2024). The gallery forests are high quality habitat for the critically endangered savanna chimpanzee and perhaps even more so as climate change shifts habitats and animal behaviors.

The objective of this study is to demonstrate a method for tracking and mapping gallery forests or closed-vegetation in the Kedougou region of Senegal, where many of the savanna chimpanzee population of the country resides. It also evaluates the use and consistency in defining savanna land cover classifications, in one format, recommended in Lindshield et al. (2021). This study also reveals what is possible when you harness remote sensing, data fusion and object-based image analysis using Trimble’s state of the art eCognition software.

These results will show a viable technique to survey the health of forest galleries to assist local and non-local primatologists with great ape conservation, forest monitoring, and forest preservation and restoration.

2. METHODOLOGY

2.1. Area of Interest

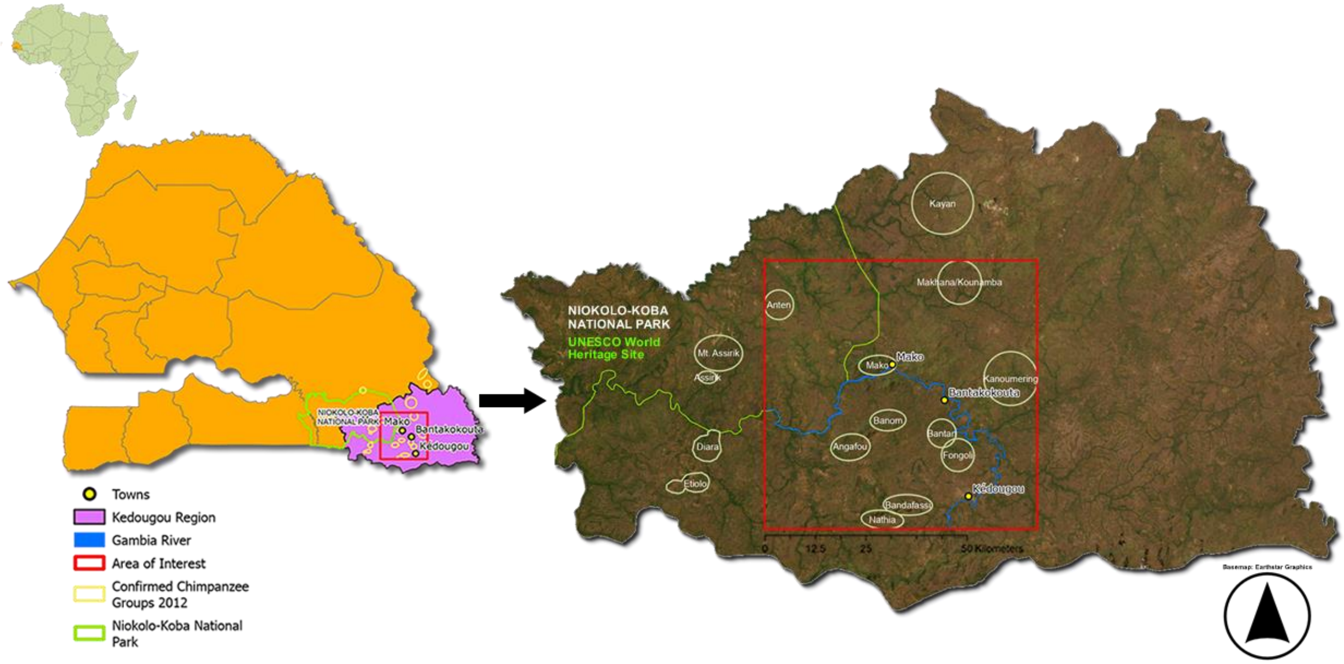


Figure 5. The area of interest (red box) in the region of Kedougou, Senegal.

The area of interest is in the region of Kedougou, Senegal (12° 44′ 36″ N, 12° 13′ 34″ W) (Figure 5). It is 4409 km^2 and it overlaps with the border of the Niokolo-Koba National Park which has been a protected UNESCO World Heritage Site since 1981. The Gambia River runs through the center of the site along which three major towns have been designated, Mako, Bantakokouta, and Kedougou. The site also encompasses ten confirmed savanna chimpanzee groups: Angafou, Anten, Bandafassi, Banom, Bantan, Fongoli, Kanoumering, Makhana/Kounamba, Mako, and Nathia (J. Pruetz, digitized from personal map collection, 2012) (Ndiaye, et al., 2018).

2.2. Data Collection

2.2.1. Workflow

STAGE 1

Data Acquisition

- SRTM DEM (NASA EarthData), PlanetScope (Planet NICFI Program), Sentinel 2A (ESA Copernicus), Landsat 8, 7, 5 (EarthExplorer).

Pre-processing

- Composite Landsat and Sentinel 2A.
- Mosaic Sentinel 2A, PlanetScope, and SRTM DEM.
- Subset all to the Area of Interest (AOI) and adjust the spatial reference to WGS 1984 UTM Zone 28N.
- Data Exploration

STAGE 2

Build Layers

- Create stream network vector and raster and local and subregional watershed boundaries using ArcGIS Pro and Arc Hydro Toolbox.
- Create soils vector, raster, tables and maps from World Soil Information.
- Create Principal Component Analysis for the AOI in 2023, 2010, 2000, and 1988.
- Create indices for NDWI, NDVI, and SAVI for the AOI for all 4 years in eCognition and export out to save and import back into eCognition.

Build Remotely Sensed Meteorological Data

- Create CHIRPS monthly mean rainfall esitmates from 1988 to 2023 specifically for the AOI using Google Earth Engine.
- Create MODIS Land Surface Temperature estimates from 2000 to 2023 specifically for the AOI using Google Earth Engine.

STAGE 3

Classification

- Using Trimble eCognition to classify the AOI for 2023, 2010, 2000, and 1988.
- Ruleset refinement for unsupervised classification and multi-threshold segmentation.
- Classification for: Closed-vegetation, Ecotone, Open-vegetation, Bare Soil, Vegetation Degradation, Development, Large-scale Mine, Mine Tailing Pond, Intermediate-scale Artisanal Mine, Small-scale Artisanal Mine, Water Body, Roads, and NoData.
- Export eCognition vector output to ArcGIS Pro to process and create tables, charts, and maps for the AOI, subregional watershed, and local watershed.

STAGE 4

Accuracy Assessment

- For 2023 classification using ArcGIS Pro and PlanetScope as the reference data.

Change Detection

- Using ArcGIS Pro Change Detection Wizard for 1988 to 2023.

Presence-only Prediction

- Using ArcGIS Pro Presence-only Prediction Tool to predict where the savanna chimpanzee habitat was suitable in 2023.
- Based on savanna chimpanzee nesting data, the classified 2023 AOI, stream network, dominate soils, parent soils, land forms, elevation, aspect, and OpenStreetMap roads.

Extra

- eCognition classification of 2023 PlanetScope AOI.

Analysis of Results and Discussion

Figure 6. Workflow to classify and analyze the area of interest for 1988, 2000, 2010, and 2023.

Data Acquisition

Data were collected from EarthExplorer (Landsat), ESA Copernicus (Sentinel), NASA EarthData (SRTM DEM), and Planet (PlanetScope) through participation in Norway's International Climate and Forests Initiative Satellite Data Program (NICFI). NICFI gives free access to high-resolution imagery for researchers who are working to reduce and reverse the loss of tropical forests, combat climate change, conserve biodiversity, and facilitate sustainable development for non-commercial use, and the region of Kedougou, Senegal just made the extent of their satellite imagery range!

Table 1 shows the specific satellite imagery, date, and layer products used in each data fusion and object-based analysis for each year (i.e., 1988, 2000, 2010, and 2023) in the month of December using eCognition 10.3 software.

Table 1. These data were used to create the unsupervised classification output in eCognition for each year, and to assist with identifying the final classification designations

eCognition Data for 1988	eCognition Data for 2000	eCognition Data for 2010	eCognition Data for 2023
Landsat 5 TM, C2L2 Tier 1, 16 Bit, **30 m**, Date: 12/10/1988 PCA of Landsat 5	Landsat 7 ETM C2L1,**15 m**, Date: 12/19/2000 Panchromatic PCA of Landsat 7 C2L2 Pansharpened Landsat 7 ETM C2L2 Tier 1, 16 Bit, 30 m, Date: 12/19/2000 PCA of Landsat 7 C2L2	Landsat 5 TM, C2L2 Tier 1, 16 Bit, **30 m**, Date: 12/23/2010 PCA of Landsat 5	Sentinel2A, **10 m** Date: 12/27/23 PCA of Sentinel2A
DEM, 30 m, Date: 2/11/2000	DEM, 30 m, Date: 2/11/2000	DEM, 30 m, Date: 2/11/2000	DEM, 30 m, Date: 2/11/2000
Constructed in eCognition with Landsat SAVI_1988.tif NDVI_1988.tif NDWI_1988.tif	Constructed in eCognition with Landsat SAVI_2000.tif NDVI_2000.tif NDWI_2000.tif	Constructed in eCognition with Landsat SAVI_2010.tif NDVI_2010.tif NDWI_2010.tif	Constructed in eCognition with Sentinel SAVI_2023.tif NDVI_2023.tif NDWI_2023.tif
Overlays in eCognition for Classifying Soils, Vector, Date: 2008 Stream Network, Vector, Date: 2/11/2000 Artisanal Mines, Vector, 2014 OpenStreetMap Roads Fishnet Guide	**Overlays in eCognition for Classifying** Soils, Vector, Date: 2008 Stream Network, Vector, Date: 2/11/2000 Artisanal Mines, Vector, 2014 OpenStreetMap Roads Fishnet Guide	**Overlays in eCognition for Classifying** Soils, Vector, Date: 2008 Stream Network, Vector, Date: 2/11/2000 Artisanal Mines, Vector, 2014 OpenStreetMap Roads Fishnet Guide	**Overlays in eCognition for Classifying** Soils, Vector, Date: 2008 Stream Network, Vector, Date: 2/11/2000 Artisanal Mines, Vector, 2014 OpenStreetMap Roads Fishnet Guide
Reference Data: N/A	**Reference Data: N/A**	**Reference Data: N/A**	**Reference Data:** PlanetScope 4.47 m Date: 12/27/23

Figure 7 shows the primary satellite imagery used to set the resolution for each eCognition project for each year. These images are using infrared spectral bands to display healthy vegetation in red.

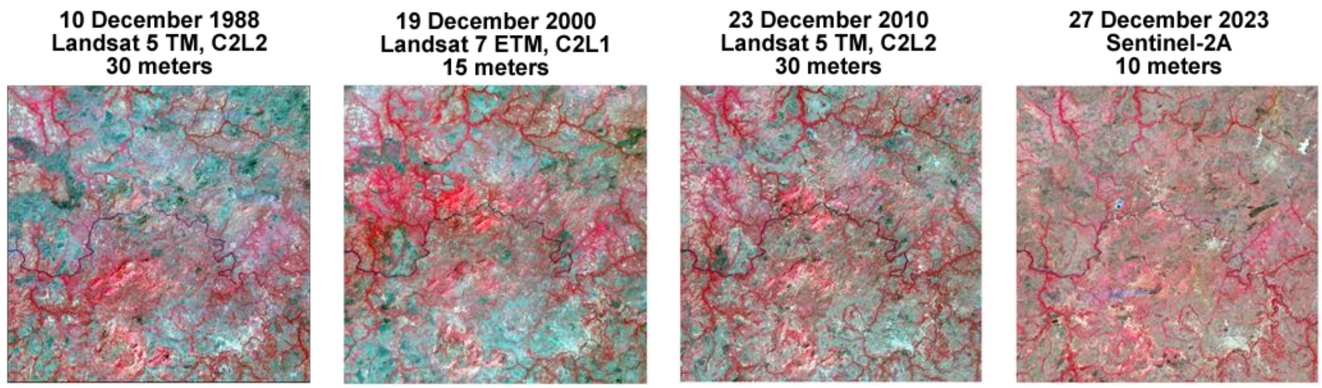


Figure 7. The primary satellite imagery was used to set the resolution for each eCognition project. Landsat 7 ETM and Landsat 5 TM used B4, B3, B2 , and Sentinel 2A used B8, B4, B3 (RGB) to display healthy vegetation in infrared.

The satellite imagery were first composited using bands B1, B2, B3, B4, B5, and B7 for Landsat 5 TM and Landsat 7 ETM, and bands B2, B3, B4, and B8 for Sentinel 2A . Sentinel 2A, PlanetScope and the SRTM required mosaicking before each was subset to the area of interest and the spatial reference adjusted to WGS 1984 UTM Zone 28N. All preprocessing steps were performed in ArcGIS Pro 3.2.2.

2.2.2. Build Layers

Kedougou Stream Network, Watersheds and Elevation

The stream network and watersheds were built using a 30-meter Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM) acquired on February 11th, 2000, and Arc Hydro Toolbox for ArcGIS Pro 3.2.2 (Figure 8). The stream network was vital to the project to visually locate the gallery forests along the watercourses.

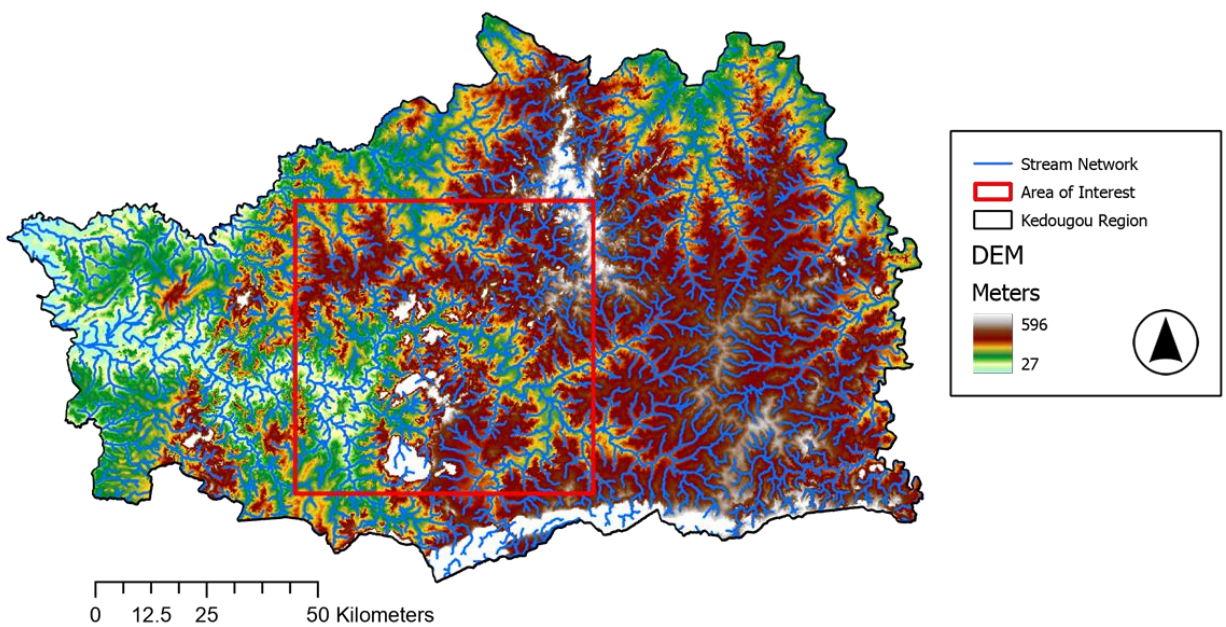


Figure 8. The DEM and stream network for the region of Kedougou, Senegal.

Kedougou Soils and Terrain

The soils data was acquired from the Soil and Terrain Database (SOTER) for Senegal and the Gambia. The vector data was created with the 2008 version 1.0 at a scale of 1:1 million. The primary soil and terrain data for Senegal was obtained from the Institut National de Pédologie Dakar; and the digital soil map from the Centre de Suivi Ecologique (Soil and Terrain Database (SOTER) for Senegal and the Gambia , 2022). See the Appendix for the download URL and documentation. The soils data were used to locate the gallery forests in fluvial, eutric gleysols, pinthic acrisols, dystic regosols, and the valley floor (Figure 9, 10 and 11).

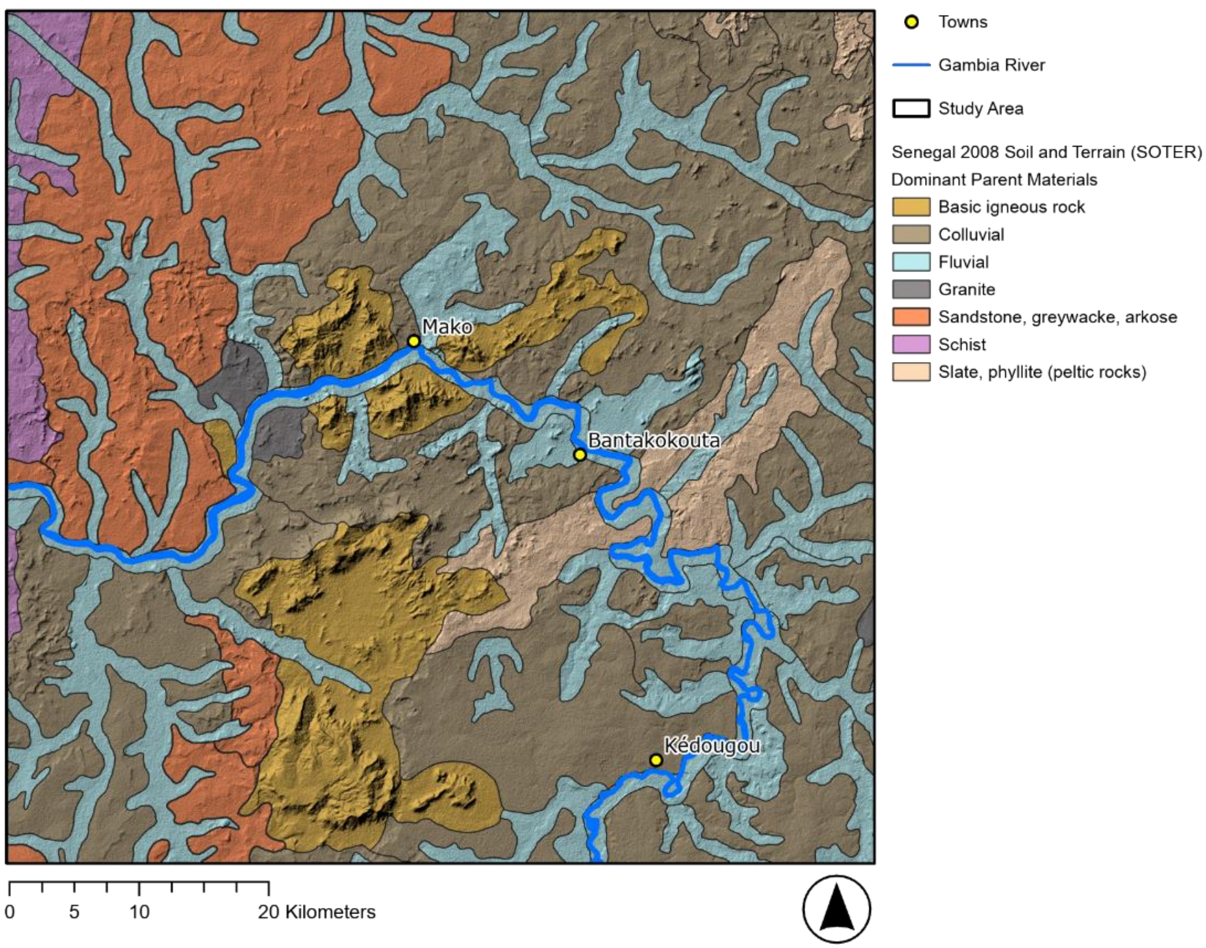


Figure 9. Kedougou, Senegal 2008 Soil and Terrain data for Dominant Parent Materials.

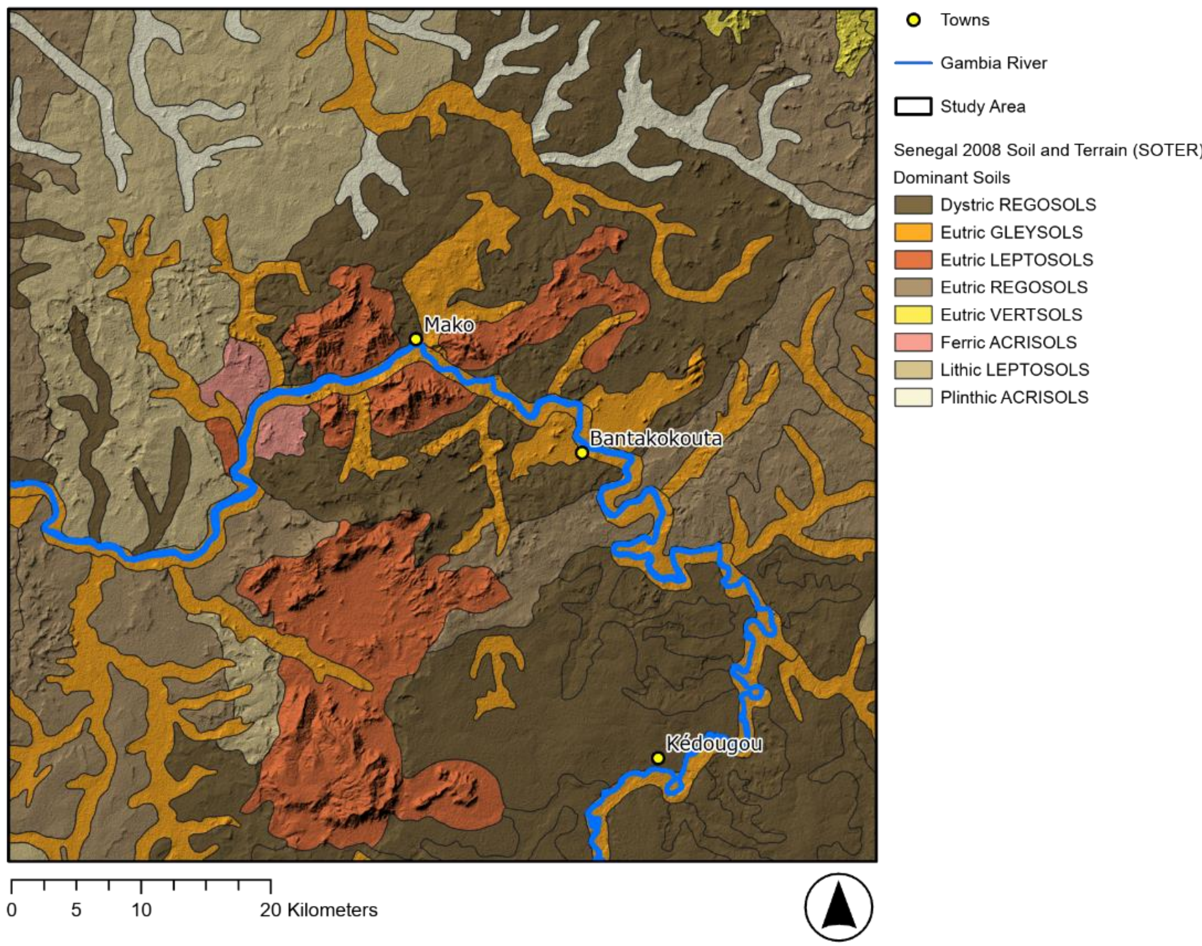


Figure 10. Kedougou, Senegal 2008 Soil and Terrain (SOTER) for Dominant Soils.

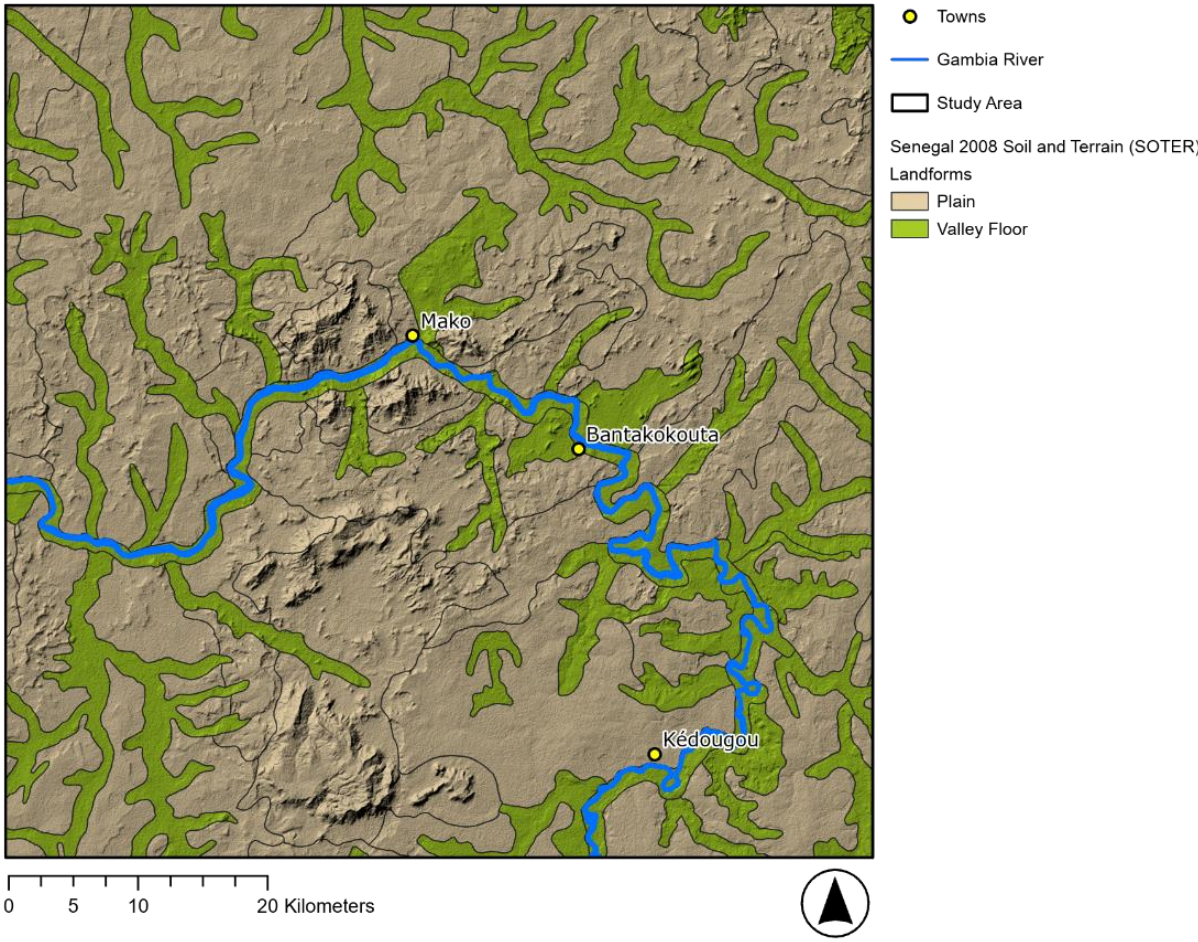


Figure 11. Kedougou, Senegal 2008 Soil and Terrain (SOTER) for Landforms.

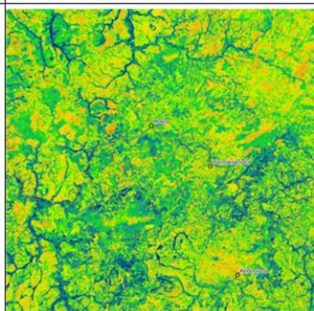
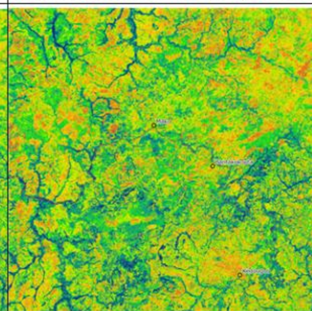
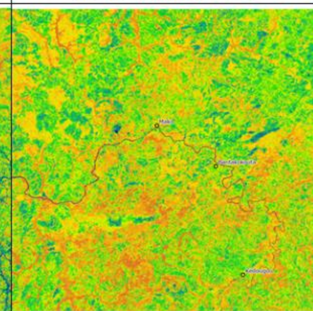
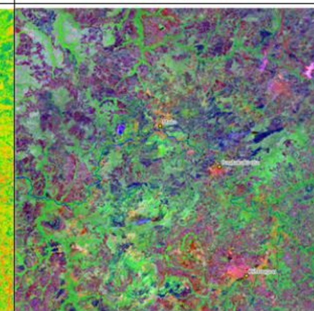
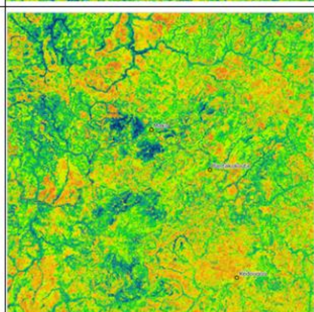
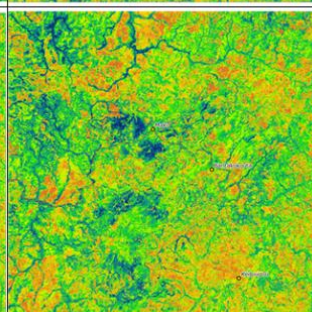
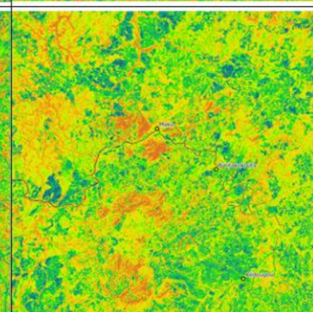
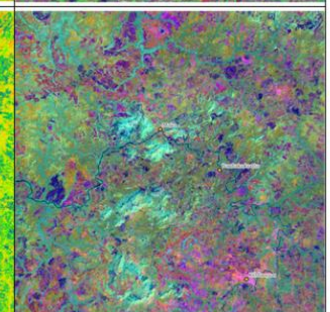
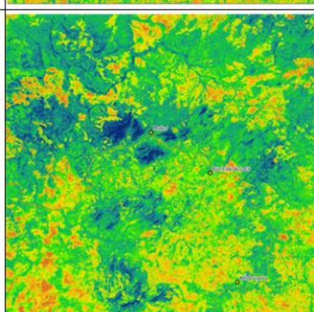
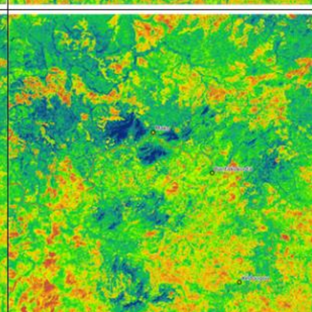
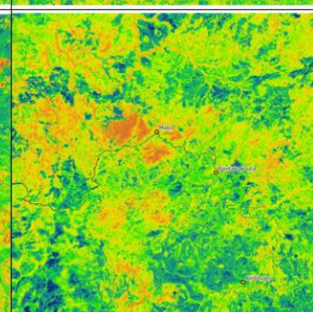
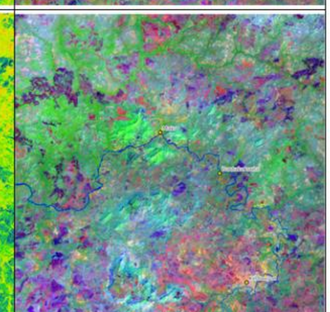
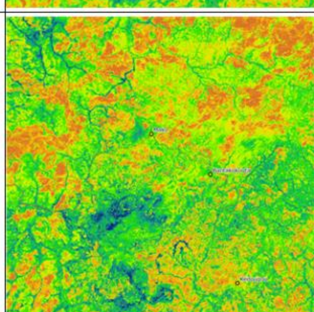
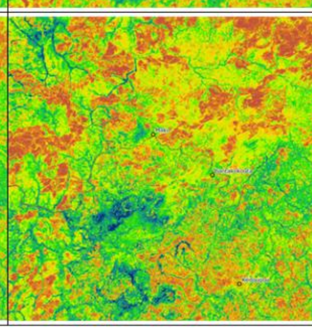
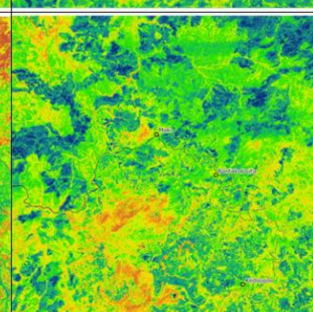
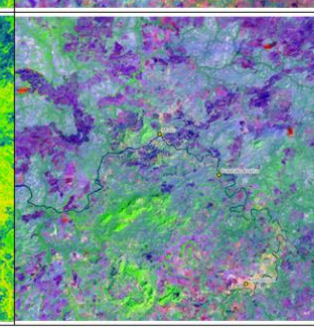
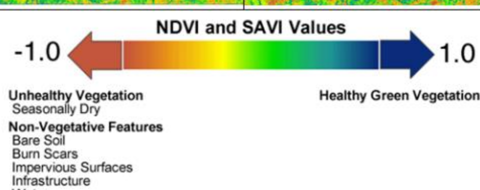
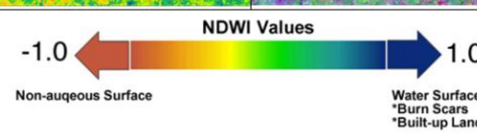
Kedougou Indices and Principal Component Analysis

Table 2 shows all indices and PCA products created. eCognition's ready-made index for Soil Adjusted Vegetation Index (SAVI) was created using an L factor of 0.75. This corrects for soil brightness where L= 0 for high vegetation cover, and L=0.50 for intermediate vegetation cover, and L=1 for low vegetation cover. The layers for Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) were also processed in eCognition and exported out as .tif files, and then imported back into each eCognition project. eCognition builds virtual layers for the indices that duplicate each time a project is saved; to avoid computer memory consumption export to a .tif file and delete the virtual layer.

The NDVI and SAVI are very similar, but the SAVI is thought to be superior to the NDVI because it shows more detail. The NDWI uses the NIR and Green band, a feature of eCognition for all sensors. This can be problematic as the NIR and Green bands are also sensitive to built-up land which may cause an overestimation of water bodies.

The Principal Component Analysis (PCA) was performed in ArcGIS Pro 3.2.2, and it shows the clusters with the most dominant features. These layers were all chosen to support the data fusion to locate the gallery forests.

Table 2. The SAVI and NDVI show unhealthy vegetation in red and healthy vegetation in blue and the NDWI shows waterbodies and burn scars due to the sensitivity of the green and NIR bands. The PCA colors are random, and display feature information that is clustered and extruded to show the most dominant features in the scene.

Year	Res.	NDVI (NIR-Red)/(NIR+Red)	SAVI ((NIR-Red)/(NIR+Red+L)) * (1+L) **L=0.75**	NDWI (Green-NIR)/(Green+NIR)	Principal Component Analysis (PCA)
Dec 2023 Sentinel 2A	10 meters				
Dec 2010 Landsat 5 TM	30 meters				
Dec 2000 Landsat 7 ETM	15 meters				
Dec 1988 Landsat 5 TM	30 meters				
				 *NDWI that use Green and NIR bands to highlight water bodies are also sensitive to built-up land and can result in an overestimation of water bodies.	

2.2.3. Build Remotely Sensed Meteorological Data

It is hard to track the variation in vegetation using a scene from one month, but the Kedougou region is unique in its predictable seasonal patterns, and rainfall and vegetation growth are tightly correlated. Therefore, it is possible to infer some seasonality patterns using precipitation and land surface temperatures for several decades, and these data can assist with selecting the best month for optimal observations (Figure 12).

For this project, the goal was to get a snapshot of the gallery forests when the highest and lowest vegetation growth would not interfere with capturing the classification. The gallery forests are evergreen, meaning they have some greening all year round; however, they do degrade during harsh seasons and drought.

The meteorological products were constructed using Google Earth Engine's satellite imagery database, its Code Editor platform, and YouTube videos by Spatial eLearning. The data was specifically extracted from the boundary of the area of interest for this project. For more information see the Appendix.

January	February	March	April	May	June	July	August	September	October	November	December
Dry	Dry	Dry	Dry	Transitional	Wet	Wet	Wet	Wet	Transitional	Dry	Dry

Figure 12. Dry and wet seasons in Kedougou, Senegal.

CHIRPS Monthly Mean Rainfall Estimates

The Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) is a 30-year quasi-global rainfall dataset that incorporates 0.05° resolution satellite imagery with in situ station data to create gridded rainfall time series from 1988 to 2023 (Funk, et al., 2015). Figures 13 to 17 show different interpretations of CHIRPS for this project's area of interest.

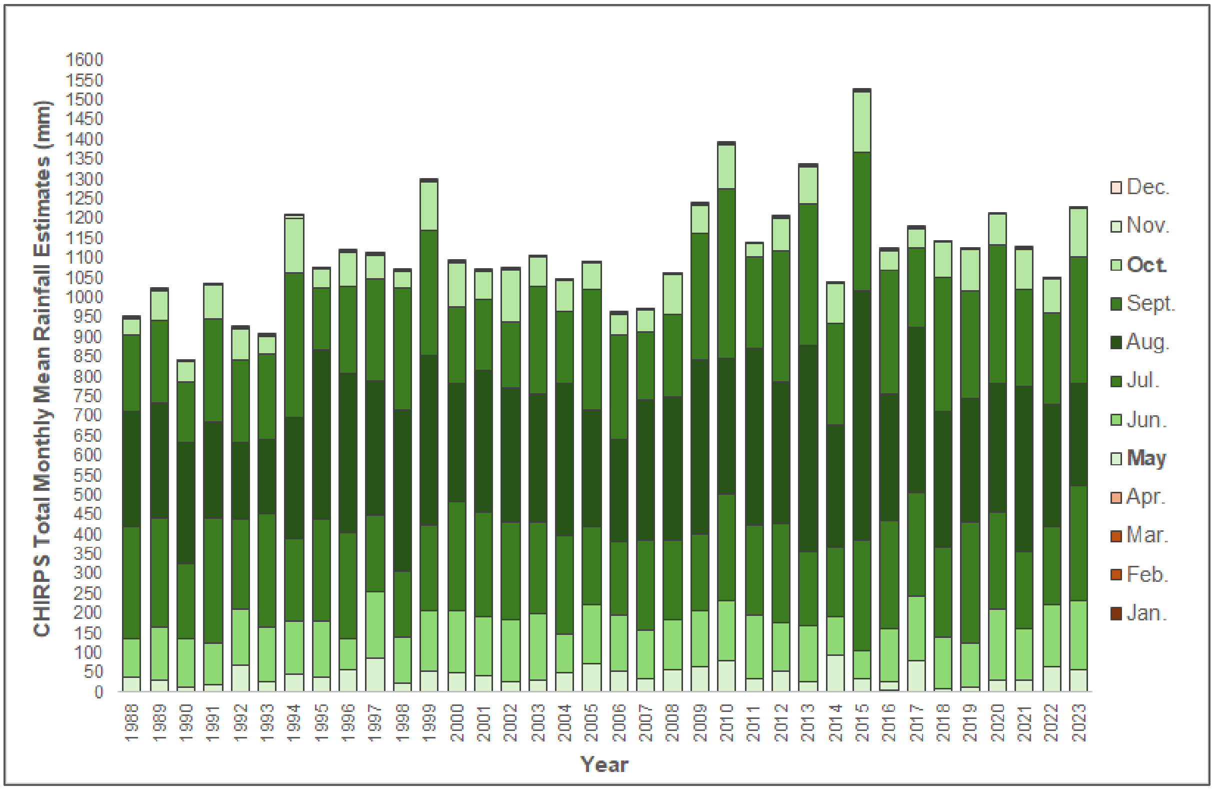


Figure 13. CHIRPS total monthly mean rainfall estimates in millimeters tied to vegetation growth or greening as the peak of growing season is the month with the peak rainfall. This is for the area of interest in Kedougou, Senegal for this project.

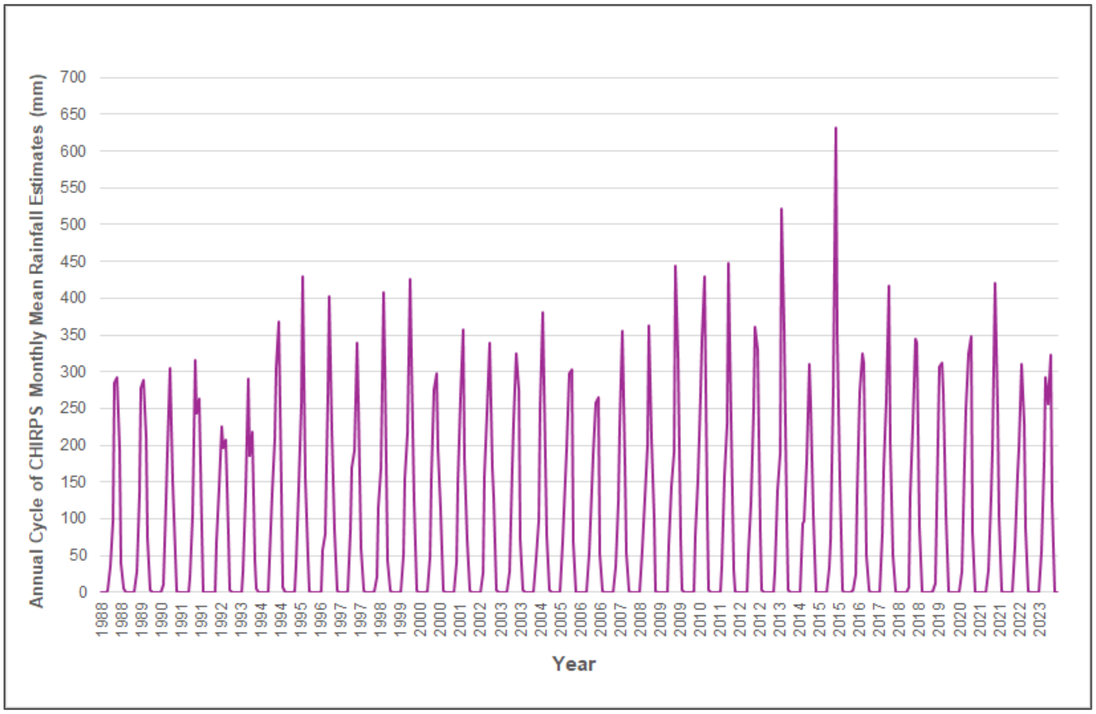


Figure 14. Annual cycle of CHIRPS monthly mean rainfall estimates from 1988 to 2023 for the area of interest in Kedougou, Senegal for this project.

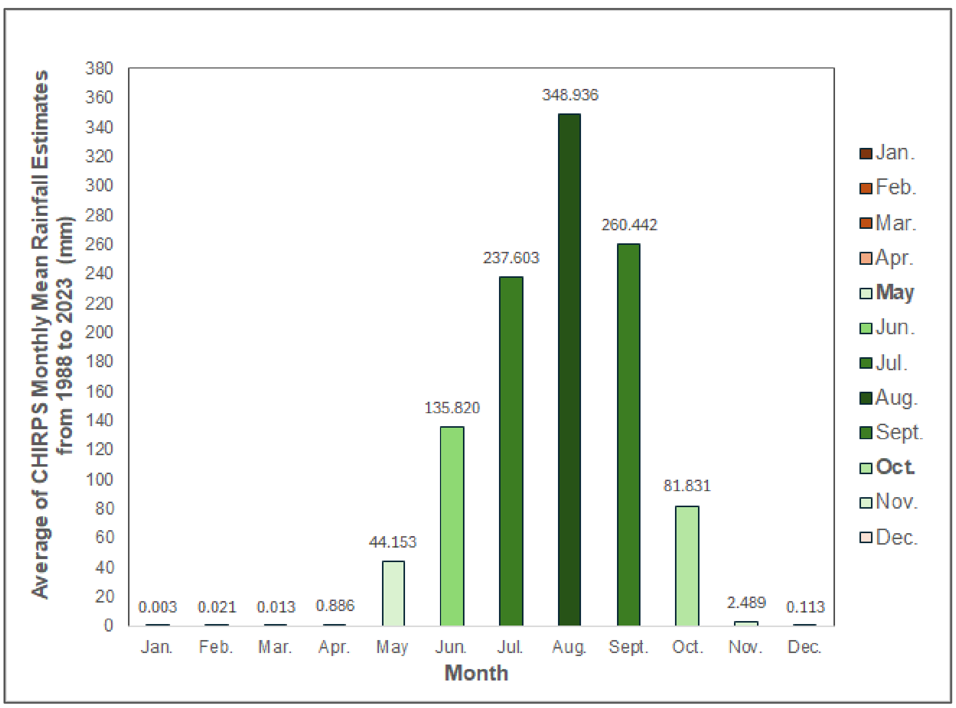


Figure 15. The average of the CHIRPS monthly mean rainfall estimates tied to vegetation growth or greening from 1988 to 2023 in the area of interest in Kedougou, Senegal for this project.

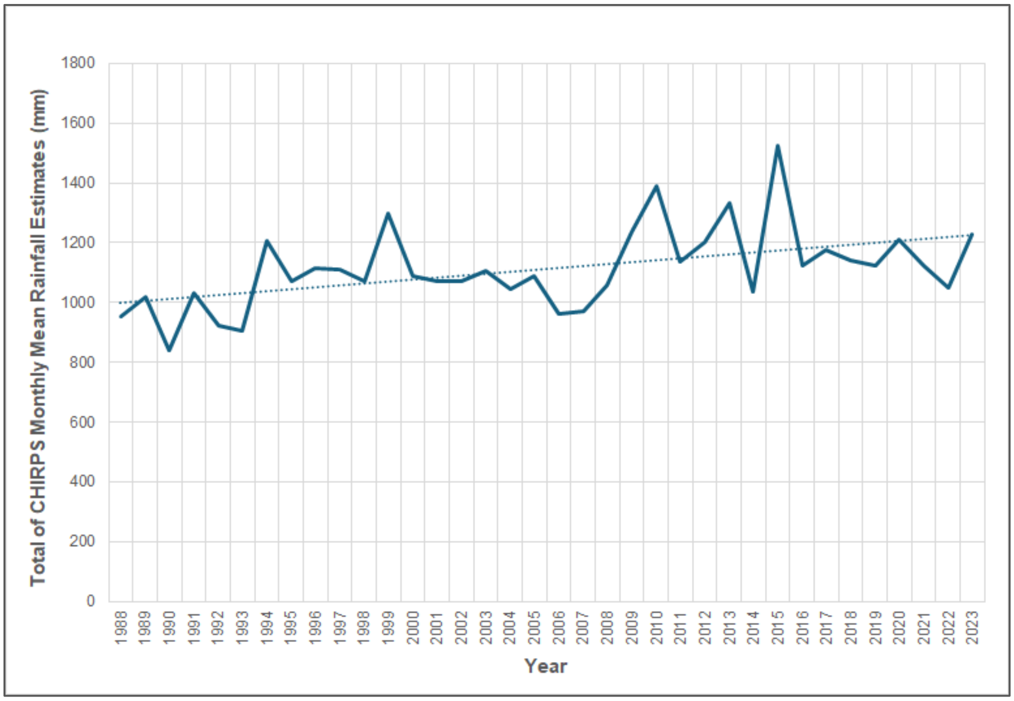


Figure 16. The total of CHIRPS monthly mean rainfall estimates for the area of interest in Kedougou, Senegal for this project. The trendline depicts an increase in rainfall from 1988 to 2023.

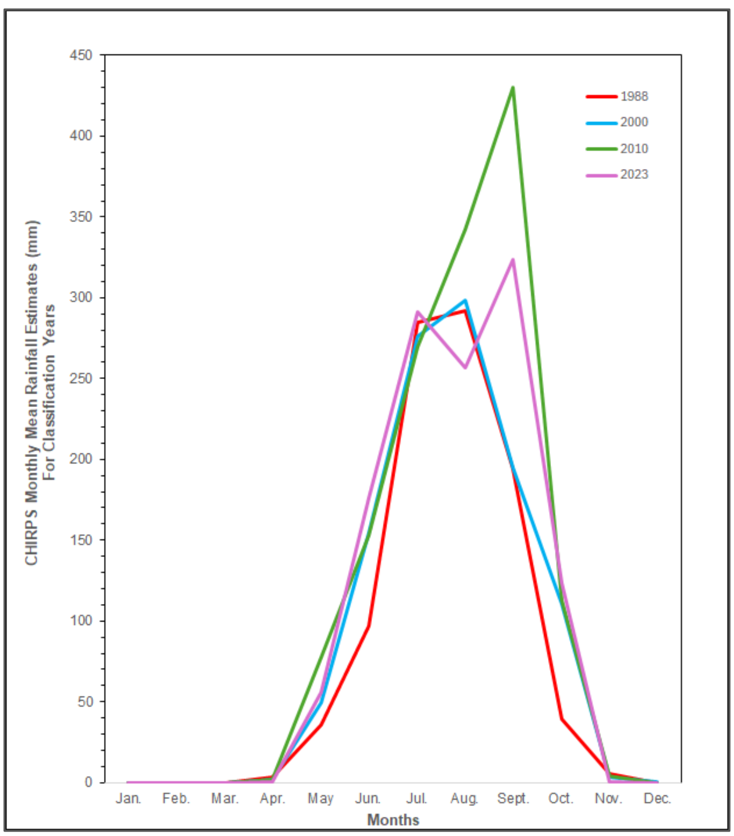


Figure 17. The CHIRPS monthly mean rainfall estimates for each classification year in this project. The chart shows three distinct patterns. Suggesting that rainfall is increasing in the area of interest for this project in Kedougou, Senegal.

MODIS Land Surface Temperature Monthly Mean Estimates

Resolution Imaging Spectroradiometer (MODIS) Terra Land Surface Temperature (LST) and Emissivity 8-Day Global 1 km dataset takes an 8-day average of the surface temperature every 8 days. Figures 18 to 20 show different interpretations of MODIS LST for this project's area of interest from 2000 to 2023. The land surface temperature can be warmer than the air temperature, but an additional benefit is its ability to track the cooling benefits of forests (Mildrexler, Zhao, & Running, 2011). These charts suggest that each month's average temperature from 2000 to 2023 may be increasing incrementally.

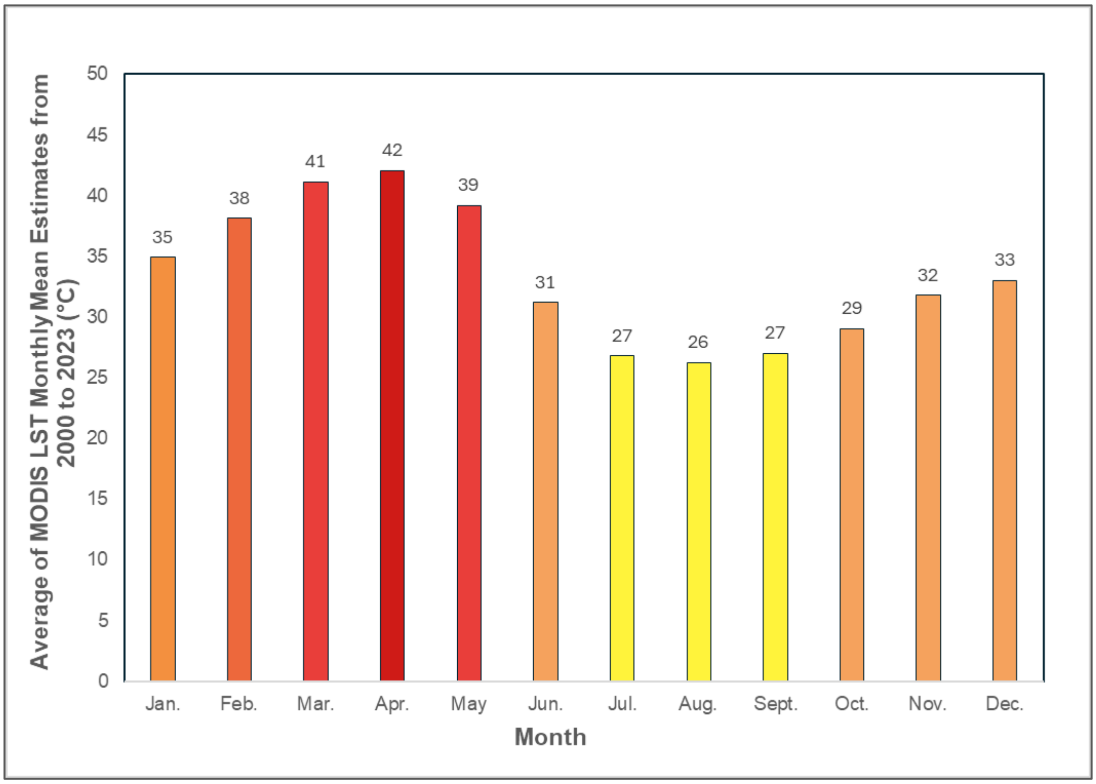


Figure 18. The average of MODIS LST monthly mean estimates from 2000 to 2023 for this project's area of interest in Kedougou, Senegal.

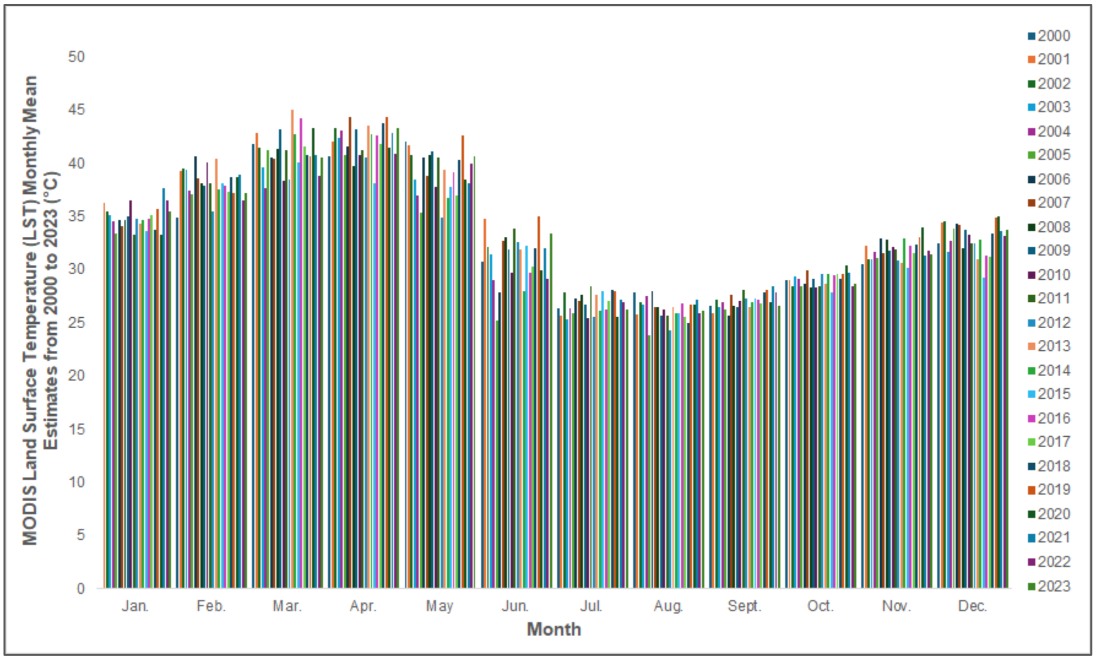


Figure 19. MODIS LST monthly mean estimates from 2000 to 2023 for this project's area of interest in Kedougou, Senegal. The same pattern is observed.

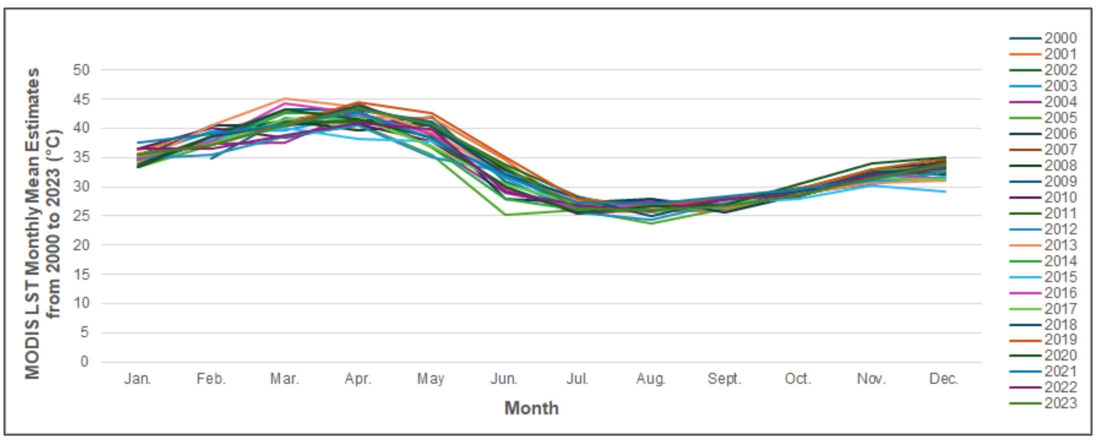


Figure 20. MODIS LST monthly mean estimates from 2000 to 2023 with the years stacked horizontally to check for outliers.

2.3. Data Analyses

2.3.1. Trimble eCognition 10.3 Unsupervised Classification

This project used Trimble's eCognition 10.3 software to perform the unsupervised classification using data fusion and object-based image analysis segmentation. For each year, the highest resolution, cloud-free, publicly available satellite imagery for the month of December was used to create layers for the data fusion used in the unsupervised classification algorithm (Table 1). It was determined through many trials that the best formula is to predominately use layers created from one sensor type. For example, 1988 used 6 bands from the PCA made from Landsat 5 TM, Collection 2, Level 2, Tier 1, and 3 indices, NDVI, SAVI, and NDWI made from Landsat 5 TM, and Landsat 5 TM bands 1, 2, 3 and 4, and the DEM, admittedly from a different sensor, but it had no noticeable adverse effects, totaling 14 layers to create the unsupervised classification output. The unsupervised classification algorithms could take 20 to 30 minutes to complete with a 16 GB GPU. The steps for this process in eCognition have been provided in the Appendix.

Fourteen classifications were used for each year, not all years had all fourteen. A classification key was used to make consistent selections from year to year (Table 3 and 4). The classification key utilizes definitions for closed-vegetation, ecotone, and open-vegetation from Lindshield et al. (2021) to evaluate the authors' recommendations.

The final classification output is a vector layer, and each one was exported to ArcGIS Pro for further analyses.

Table 3. Part 1 of the classification key was used to identify features on the ground to consistently select similar classes from year to year.

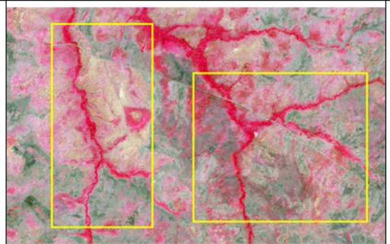
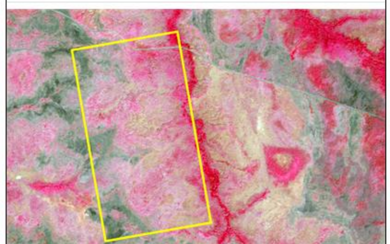
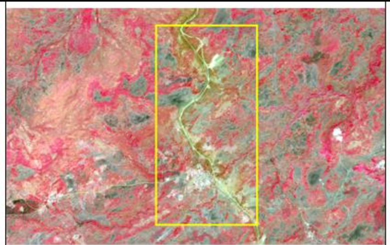
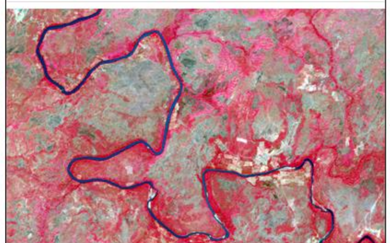
	Classification	Description	Imagery Examples in Infrared	Scale	1988	2000	2010	2023
1	**Closed-vegetation (Gallery Forest)**	"Closed and evergreen (e.g., gallery/riparian or thicket forest;hereafter "closed vegetation")" (Lindshield, et al., 2021).		1:38,000	✓	✓	✓	✓
2	**Ecotone**	"A transitional "ecotone" category for vegetation that is neither mostly open nor mostly closed" (Lindshield, et al., 2021).		1:24,000	✓	✓	✓	✓
3	**Open-vegetation**	"Open and deciduous(e.g., woodland, wooded grassland, and grassland; refered to as "open vegetation")" (Lindshield, et al., 2021).		1:38,000	✓	✓	✓	✓
4	**Bare Soil**	Land with little or no vegetation cover exposing soil, and sandy areas (CILSS, 2016).		1:24,000	✓	✓	✓	✓
5	**Vegetation Degradation**	"The temporary or permanent reduction in the density, structure, species composition or productivity of vegetation cover (Conacher & Sala, 1998). Such as burn scars after natural brush fires or those ignited to clear the land for agriculture. These can also be new or old burn scars and seasonally dry or dead vegetation (CILSS, 2016).		1:38,000	✓	✓	✓	✓
6	**Development**	Settlements such as villages, towns, cities and local roads (CILSS, 2016).		1:38,000	✓	✓	✓	✓

Table 4. Part 2 of the classification key for the area of interest in Kedougou, Senegal. Each thumbnail graphic is displayed in infrared to emphasize the vegetation features.

Classification		Description	Imagery Examples in Infrared	Scale	1988	2000	2010	2023
7	**Roads**	Major roads.		1:24,000	X	X	X	✓
8	**Water Bodies**	Areas with permanent or semi-permanent surface water such as the Gambia River and smaller waterways (CILSS, 2016).		1:38,000	✓	✓	✓	✓
9	**Large-scale Mine**	Open pit where gold is mined (CILSS, 2016).		1:38,000	X	X	X	✓
10	**MineTailing Ponds**	Structure or embankment that is built to retain gold mining waste or the byproduct of open pit mining such as fine-grained particles, waste water, arsenic and mercury (Adapted from Morrill, et al., 2020).		1:38,000	X	X	X	✓
11	**Small-scale Artisanal Mine**	Shallow-pocked mining locales usually near a water source where mineral extractions are mined from surface sand or gravel with little need for sophisticated tools (Allan, 2015).		1:15,000	X	✓	✓	✓
12	**Intermediate-scale Artisanal Mine**	The intermediate-scale gold mine that is not as expansive as a large-scale mine but also not as small as an ASGM mine either. The intermediate-scale mine has more infrastructure than an ASGM and is adjacent to a village or town.		1:24,000	✓	X	✓	✓
13	**Other**	Unidentified class or pixels, shadows, smoke, clouds, reflections of clounds in the water.	To be decided as needed.		X	X	X	X
14	**NoData**	Frame border in eCognition.	To be decided as needed.		✓	✓	✓	✓
Class Count					9	9	10	13

2.3.2. Accuracy Assessment

The accuracy assessment was performed in ArcGIS Pro using stratified random sampling for 663 points, and the points were distributed according to the proportional size of the individual classification. Due to the difficulties acquiring reference data for 1988, 2000, and 2010, the accuracy assessment was only applied to the 2023 classification which was created using Sentinel 2A at 10-meter resolution. The reference data was selected for the same day as the 2023 classification, December 27, 2023, for PlanetScope at 4.77 meters.

2.3.3. Change Detection Analysis

The change detection analysis was performed in ArcGIS Pro on only the closed-vegetation class from 1988 to 2023 for the month of December.

2.3.4. Presence-only Prediction

The presence-only prediction model or Maxent was performed in ArcGIS Pro 3.2.2 using the layers created in the project and converted to rasters. The 2023 classified layer, dominant parent soils, dominant soils, landforms, elevation, aspect, slope, the stream network, roads acquired from OpenStreetMap, and 296 chimpanzee nesting GPS points for the Bantan group in 2003 (6), 2004 (9), 2008 (172), 2010 (98), and 2012 (11).

3. RESULTS

3.1. Unsupervised Classification Results

3.1.1. eCognition Unsupervised Classification Outputs

Figure 21 shows the outputs or products produced by eCognition's unsupervised classification algorithm. These rasters were created by data fusion. The next step was to create the segmentations using multi-threshold segmentation to capture the clusters or classes.

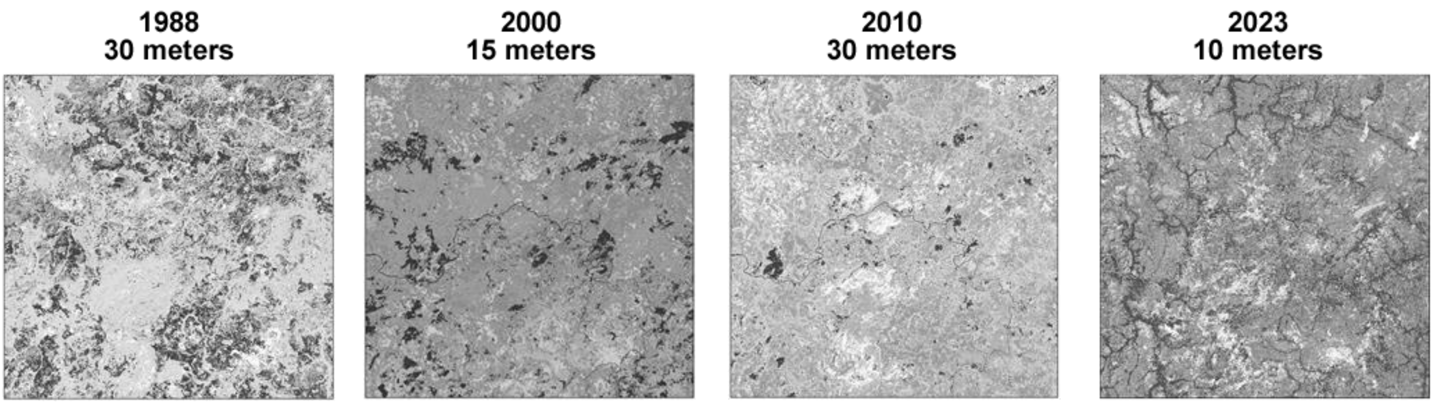


Figure 21. These are the products produced from eCognition's unsupervised classification algorithm for 1988, 2000, 2010, and 2023 for the area of interest in Kedougou, Senegal.

3.1.2. Area of Interest Classification

Figure 22 is the final classification for each year in the area of interest. The visual inspection suggests that vegetation is moving more towards open-vegetation. The values in Figure 23 and 24, and Table 5 confirm that these classifications for the month of December show the land cover from 1988 to 2023 shifting to more open-vegetation. Ecotone was increasing from 1988 to 2010; however, in only 13 years, the ecotone has dramatically declined, and open-vegetation has expanded.

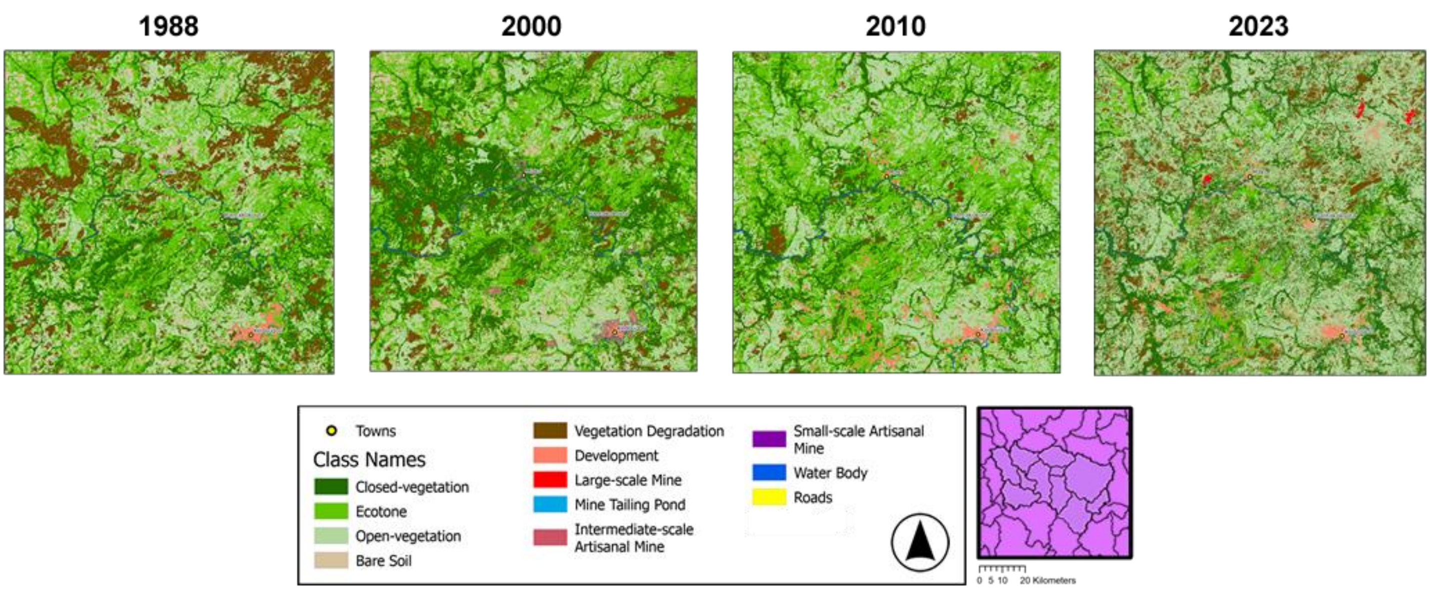


Figure 22. The final classification for 1988, 2000, 2010, and 2023 in the area of interest in Kedougou, Senegal.

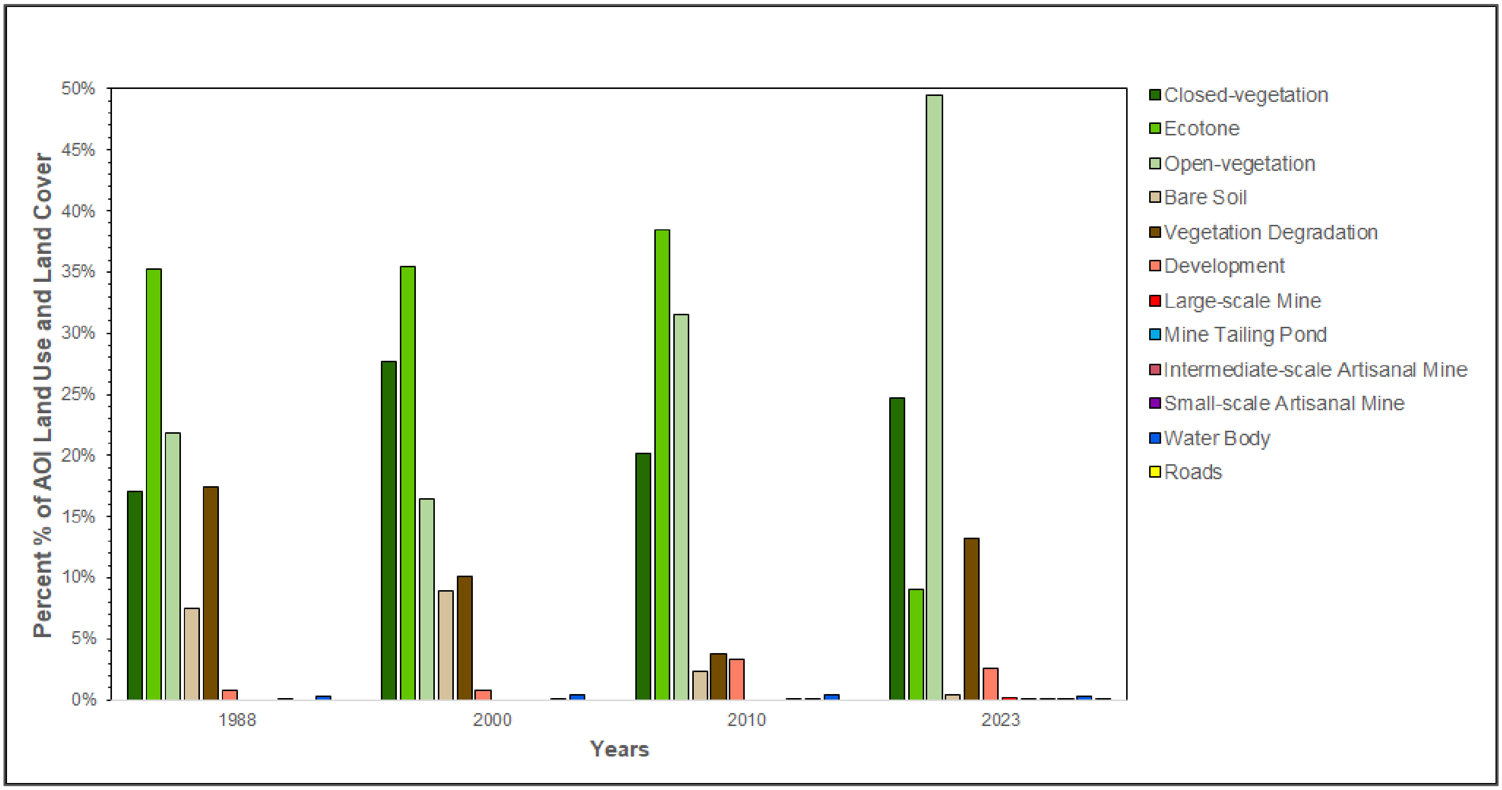


Figure 23. The percent of land use and land cover present in the area of interest in Kedougou, Senegal for the month of December in 1988, 2000, 2010, and 2023.

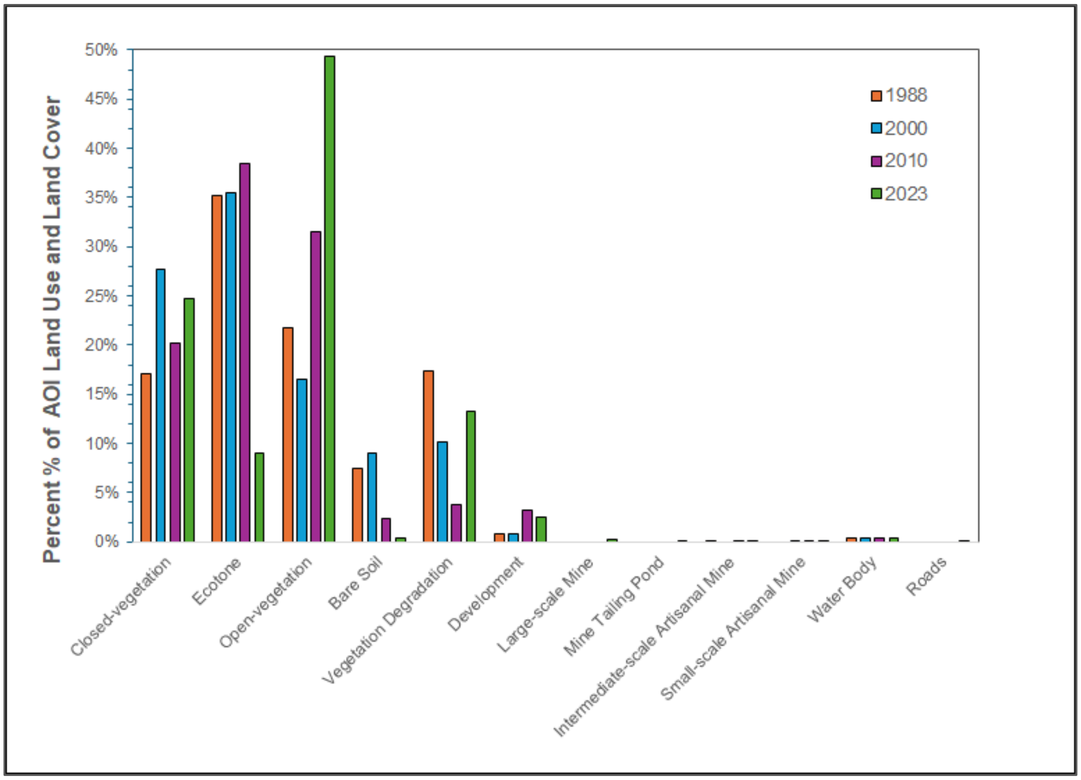


Figure 24. Percent of the land cover and land use in the area of interest by class in Kedougou, Senegal.

Table 5. The percentage values and kilometers squared calculated for each class in the area of interest for 1988, 2000, 2010, and 2024.

Area of Interest Land Use and Land Cover	1988 (km^2)	1988 (%)	2000 (km^2)	2000 (%)	2010 (km^2)	2010 (%)	2023 (km^2)	2023 (%)
Closed-vegetation	752	17%	1224	28%	889	20%	1091	25%
Ecotone	1554	35%	1567	35%	1699	39%	398	9%
Open-vegetation	961	22%	728	16%	1392	32%	2179	49%
Bare Soil	328	7%	396	9%	102	2%	20	0.45%
Vegetation Degradation	769	17%	446	10%	166	4%	585	13%
Development	35	1%	35	1%	144	3%	113	3%
Large-scale Mine	0	0%	0	0%	0	0%	9	0.19%
Mine Tailing Pond	0	0%	0	0%	0	0%	0.93	0.02%
Intermediate-scale Artisanal Mine	0.37	0%	0	0%	0.14	0%	0.83	0.02%
Small-scale Artisanal Mine	0	0%	0.03	0%	0.01	0%	0.09	0%
Water Body	14	0.32%	19	0.44%	20	0.45%	14	0.32%
Roads	0	0%	0	0%	0	0%	1	0.02%
Total	4414	100.00%	4416	100.00%	4413	100.00%	4411	100.00%

3.1.3. Subregional Watershed Classification

The subregional watershed is 1291 km^2 and it was clipped from the area of interest to demonstrate the value of investigating the classifications at different scales. The visual inspection of Figure 25 shows more variation, but the same shift to more open-vegetation can be seen. The closed-vegetation has a slightly higher presence; however, in 2000 it is noticeably higher in the subregional water than in the area of interest and the ecotone is slightly higher too as seen in Table 26 and 27 and Table 6.

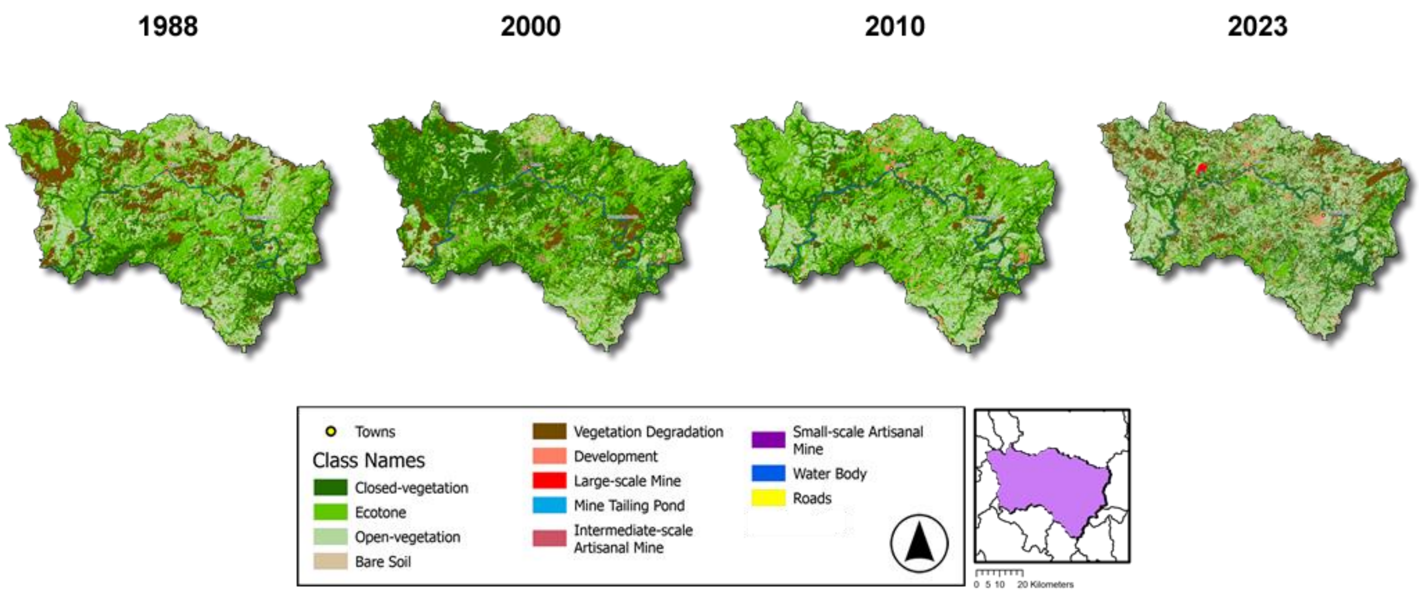


Figure 25. The final classification for 1988, 2000, 2010, and 2023 in the regional watershed in Kedougou, Senegal.

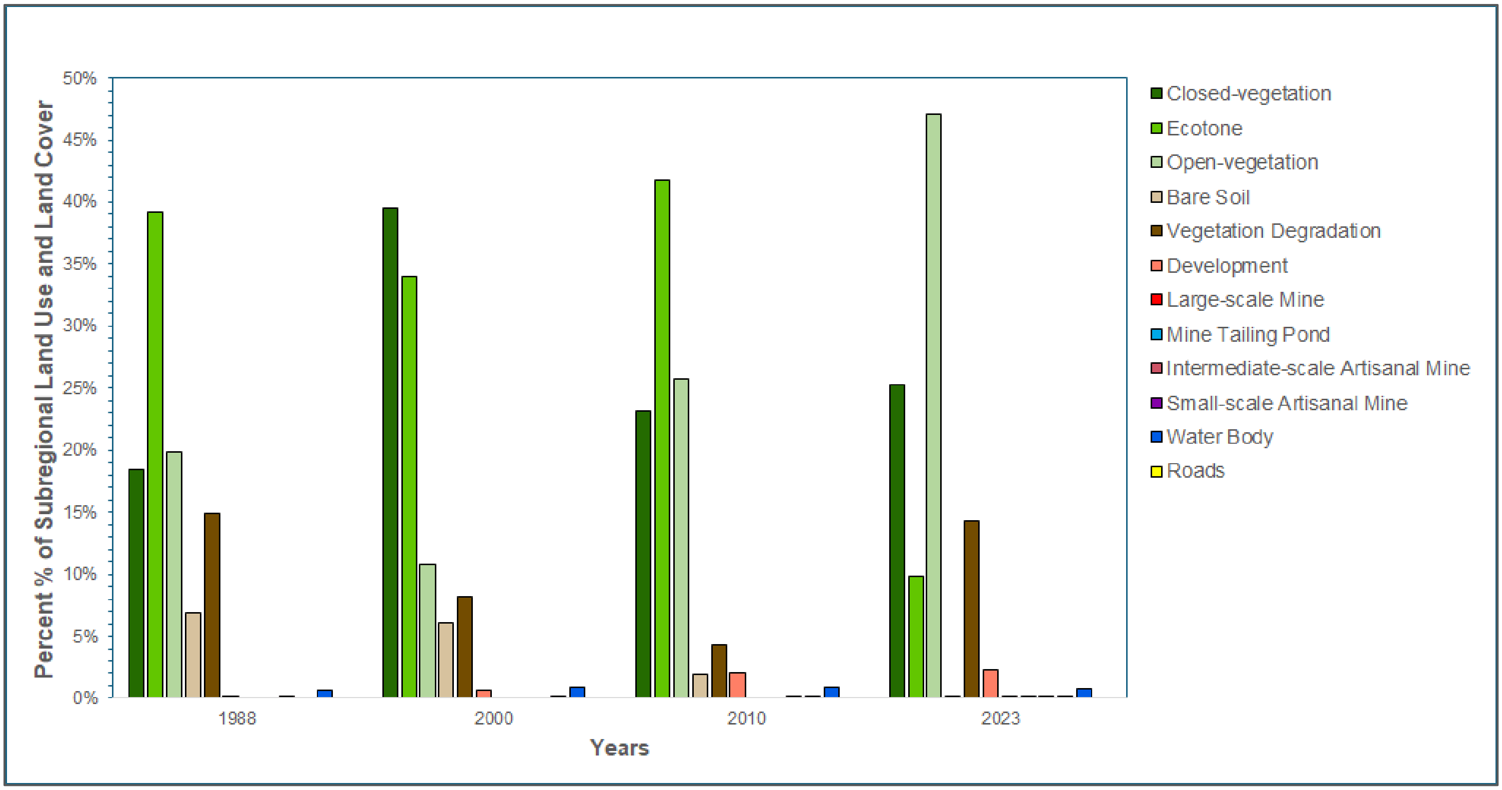


Figure 26. The percent of land use and land cover present in the subregional watershed in Kedougou, Senegal for the month of December in 1988, 2000, 2010, and 2023

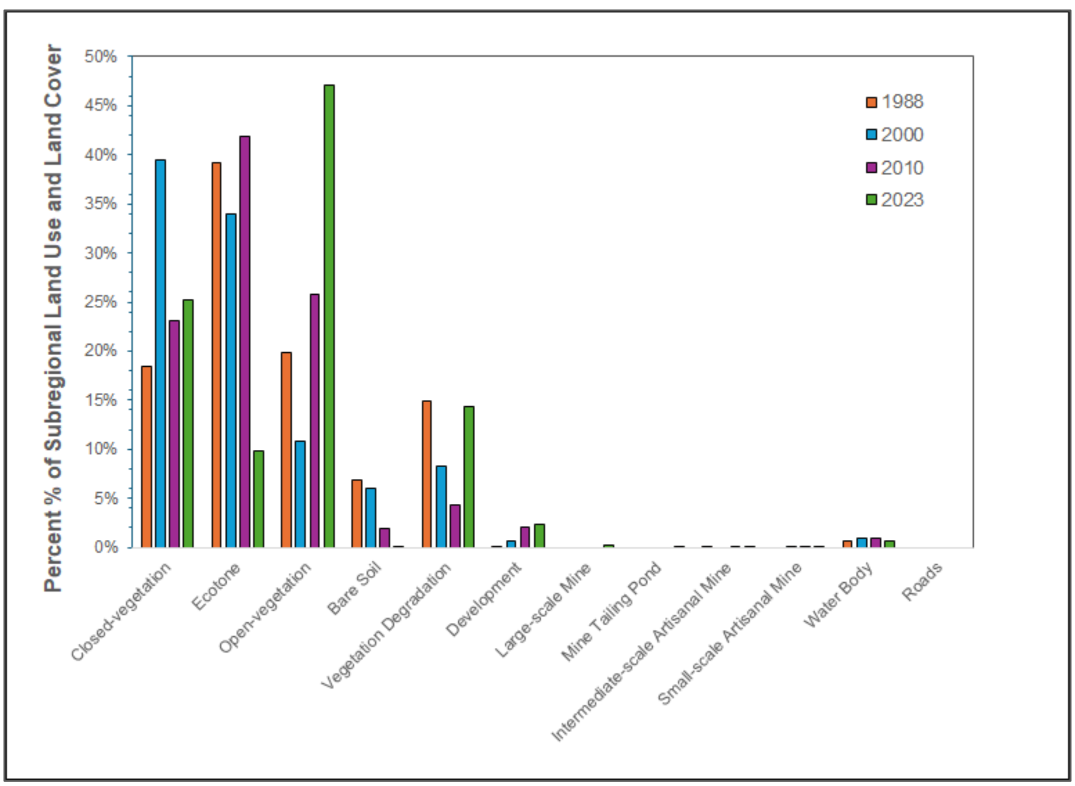


Figure 27. The percent of the land cover and land use in the subregional watershed by class in Kedougou, Senegal

Table 6. The percentage values and kilometers squared calculated for each class in the subregional watershed 1988, 2000, 2010, and 2024.

Subregional Watershed Land Use and Land Cover	1988 (km^2)	1988 (%)	2000 (km^2)	2000 (%)	2010 (km^2)	2010 (%)	2023 (km^2)	2023 (%)
Closed-vegetation	239	18%	511	39%	299	23%	327	25%
Ecotone	506	39%	439	34%	541	42%	128	10%
Open-vegetation	257	20%	139	11%	333	26%	608	47%
Bare Soil	89	7%	78	6%	26	2%	2	0.12%
Vegetation Degradation	192	15%	106	8%	55	4%	185	14%
Development	2	0.14%	8	0.64%	27	2%	30	2%
Large-scale Mine	0	0%	0	0%	0	0%	2	0.19%
Mine Tailing Pond	0	0%	0	0%	0	0%	0.47	0.04%
Intermediate-scale Artisanal Mine	0.37	0.03%	0	0%	0.08	0.01%	0.83	0.06%
Small-scale Artisanal Mine	0	0%	0.03	0%	0.01	0%	0.09	0.01%
Water Body	9	0.70%	12	0.91%	12	0.92%	9	0.70%
Roads	0	0%	0	0%	0	0%	0	0%
Total	1293	100.00%	1294	100.00%	1293	100.00%	1293	100.00%

3.1.4. Local Watershed Classification

The local watershed is 157 km^2. The visual inspection at the local level is even more evident as it appears that open-vegetation has expanded (Figure 28), but closed-vegetation has slightly increased as well, and ecotone has significantly declined as seen in Figure 29 and 30 and Table 7 in 2023 for the month of December.

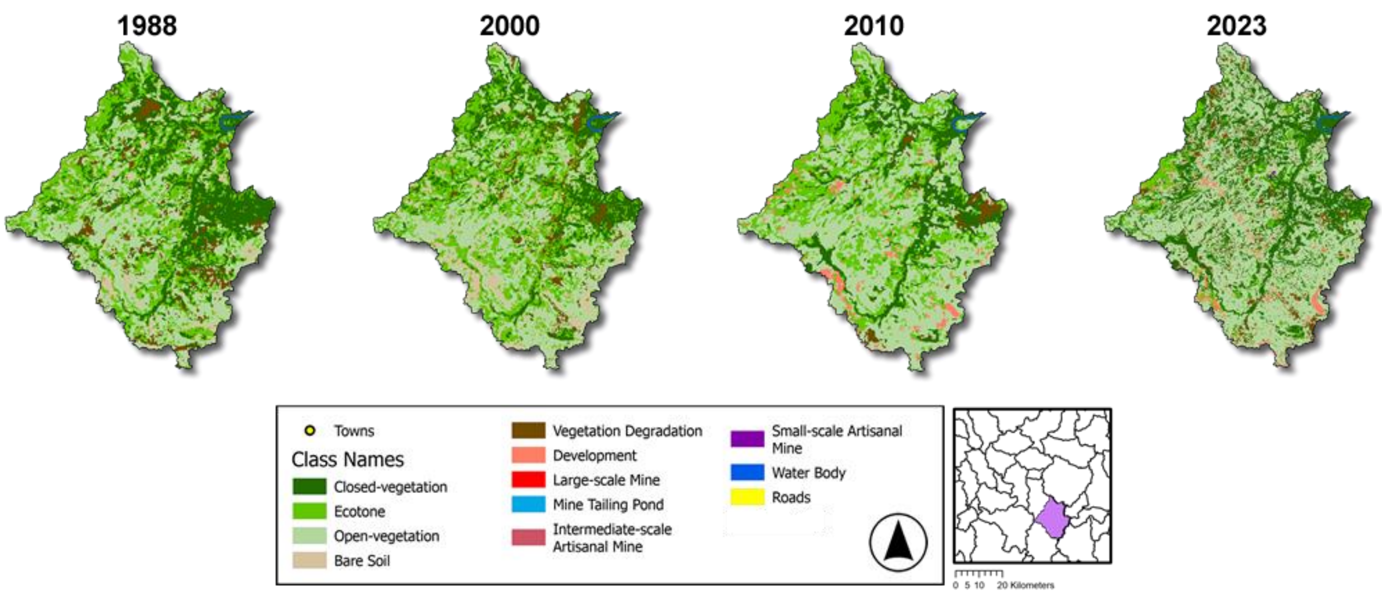


Figure 28. The final classification for 1988, 2000, 2010, and 2023 in the local watershed in Kedougou, Senegal

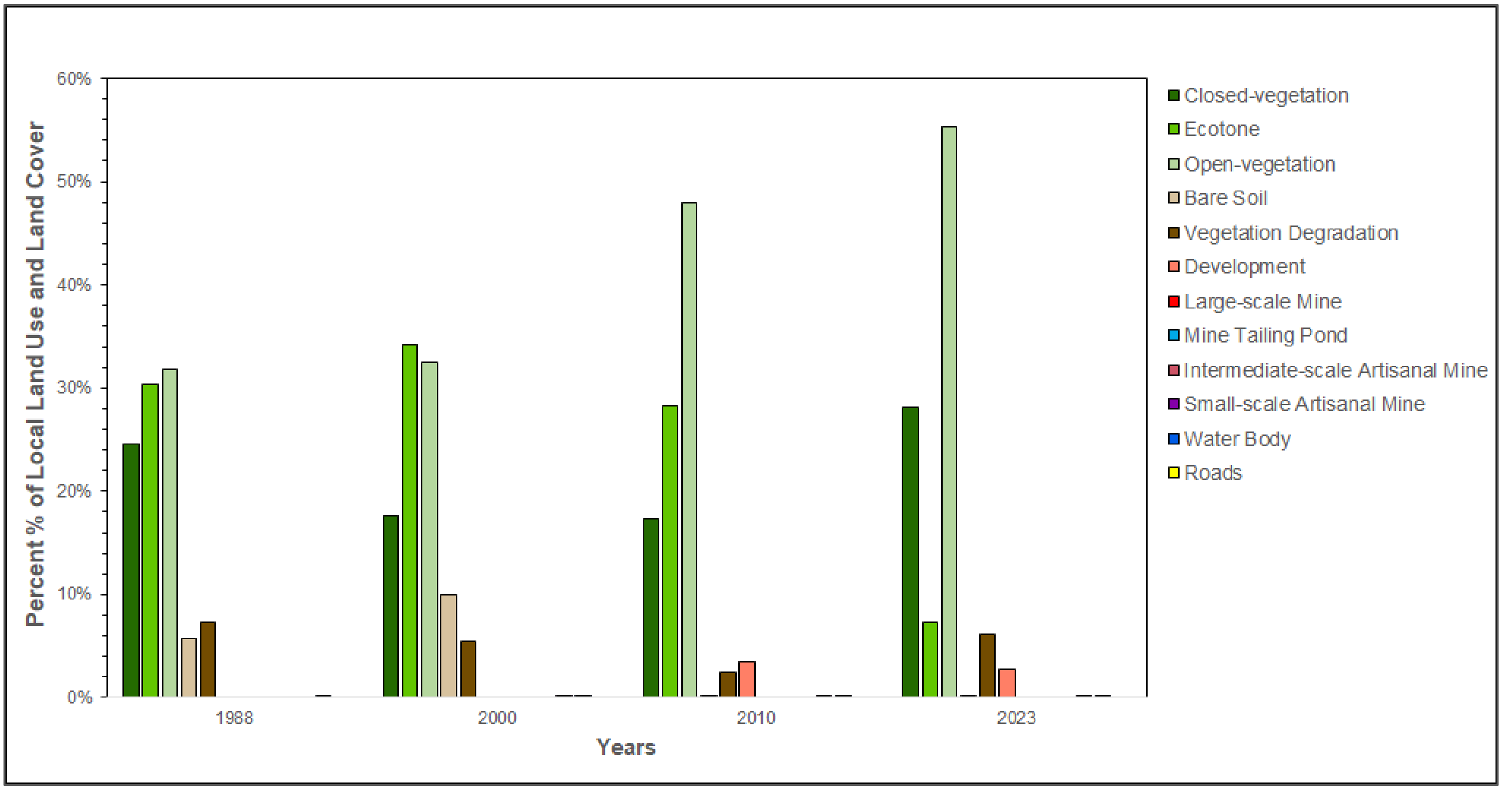


Figure 29. The percent of land use and land cover present in the local watershed in Kedougou, Senegal for the month of December in 1988, 2000, 2010, and 2023.

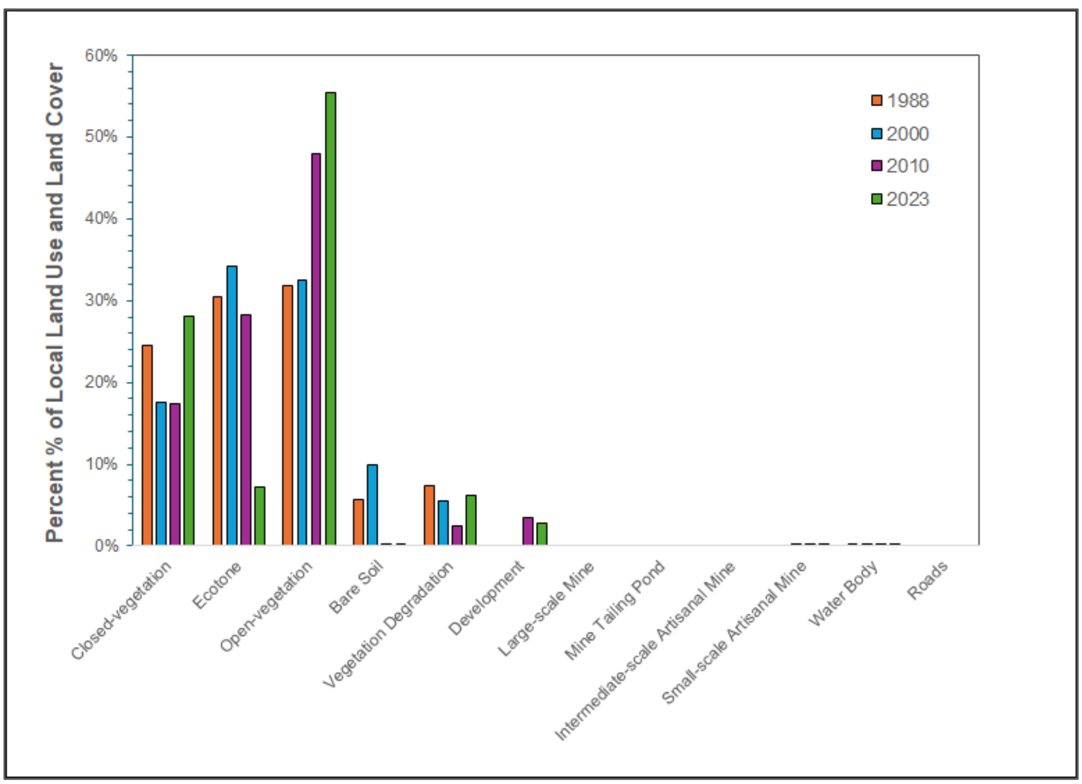


Figure 30. Percent of the land cover and land use in the local watershed by class in Kedougou, Senegal.

Table 7. The percentage values and kilometers squared calculated for each class in the local watershed for 1988, 2000, 2010, and 2024.

Local Watershed Land Use and Land Cover	1988 (km^2)	1988 (%)	2000 (km^2)	2000 (%)	2010 (km^2)	2010 (%)	2023 (km^2)	2023 (%)
Closed-vegetation	39	25%	28	18%	27	17%	44	28%
Ecotone	48	30%	54	34%	45	28%	11	7%
Open-vegetation	50	32%	51	33%	75	48%	87	55%
Bare Soil	9	6%	16	10%	0	0%	0	0%
Vegetation Degradation	12	7%	9	5%	4	3%	10	6%
Development	0	0%	0	0%	5	3%	4	3%
Large-scale Mine	0	0%	0	0%	0	0%	0	0%
Mine Tailing Pond	0	0%	0	0%	0	0%	0	0%
Intermediate-scale Artisanal Mine	0	0%	0	0%	0	0%	0	0%
Small-scale Artisanal Mine	0	0%	0.03	0.02%	0.009	0.01%	0.09	0.06%
Water Body	0.29	0.19%	0.36	0.23%	0.37	0.23%	0.29	0.18%
Roads	0	0%	0	0%	0	0%	0	0%
Total	157	100.00%	158	100.00%	157	100.00%	157	100.00%

3.2. Accuracy Assessment Results

Table 8 shows an overall accuracy = 80%, and Kappa = 74%. Figure 31 is the distribution of the 663 random points. The small-scale artisanal mines were located 100% by the user and producer and this was because there were only four mines to locate in the classification as these four were defined with GPS points to establish whether or not the small-scale artisanal mines *could* be seen in the imagery and when they were seen, they were classified. Bare soil was found 100% by the user and only 45% by the producer and this because bare soil is easily mixed with other classifications and it was misclassified. Vegetation degradation was found 93% by the user and 84% by the producer and this is because vegetation degradation is sometimes hard to separate from other classifications and it can get misclassifed with the water bodies. Closed-vegetaion was found 63% by the user and 83% by the producer and this was because closed-vegetation is mixed with ecotone at the closed-vegetation edges. Development was found 73% by the user and 55% by the producer and that is because development is difficult to tease away from other classifications. Ecotone was found 70% by the user and 38% by the producer. Ecotone is the hardest class to deferentiate and classify. The intermediate-scale artisanal mine was found 100% by the user and 91% by the user, and this is for nearly the same reason as the small-scale artisanal mines, there was only one intermediate-scale artisanal mine in the area of interest and it is hard to miss. The same logic was applied to the large-scale mine, it was found 100% by the user and 100% by the producer. The mine tailing ponds were found 90% by the user and 100% by the producer. The tailing ponds are located near development so it is easy to misclassify. Open-vegetation was found 86% by the user and 95% by the producer. Open-vegetation is the dominant classification so the probability of classifying it correctly is high. Roads were found 60% by the user and 86% by the producer. Roads were misclassified along the edges of the area of interest. Water body was found 80% by the user and 100% by the producer. Water body was misclassified at the single pixel level in closed-vegetation and vegetation degradation along the Gambia Rivers' edges.

Table 8. Accuracy Assessment results for the 2023 classification.

Map Classified Data (Producer's Data)	Reference Data (User's Data)														
Class For 2023	Small-scale Artisanal Mine	Bare Soil	Vegetation Degradation	Closed-vegetation	Development	Ecotone	Intermediate-scale Artisanal Mine	Large-scale Mine	Mine Tailing Pond	Open-vegetation	Roads	Water Body	Total	User's Accuracy	
Small-scale Artisanal Mine	10	0	0	0	0	0	0	0	0	0	0	0	10	100%	
Bare Soil	0	10	0	0	0	0	0	0	0	0	0	0	10	100%	
Vegetation Degradation	0	1	74	1	0	1	0	0	0	3	0	0	80	93%	
Closed-vegetation	0	1	1	93	3	44	0	0	0	6	0	0	148	63%	
Development	0	3	0	1	11	0	0	0	0	0	0	0	15	73%	
Ecotone	0	4	0	8	2	38	0	0	0	2	0	0	54	70%	
Intermediate-scale Artisanal Mine	0	0	0	0	0	0	10	0	0	0	0	0	10	100%	
Large-scale Mine	0	0	0	0	0	0	0	10	0	0	0	0	10	100%	
Mine Tailing Pond	0	0	0	0	1	0	0	0	9	0	0	0	10	90%	
Open-vegetation	0	3	12	8	3	14	1	0	0	254	1	0	296	86%	
Roads	0	0	0	0	0	2	0	0	0	2	6	0	10	60%	
Water Body	0	0	1	1	0	0	0	0	0	0	0	8	10	80%	
Total	10	22	88	112	20	99	11	10	9	267	7	8	663		
Producer's Accuracy	100%	45%	84%	83%	55%	38%	91%	100%	100%	95%	86%	100%		Overall Accuracy	
														80%	Kappa
															74%

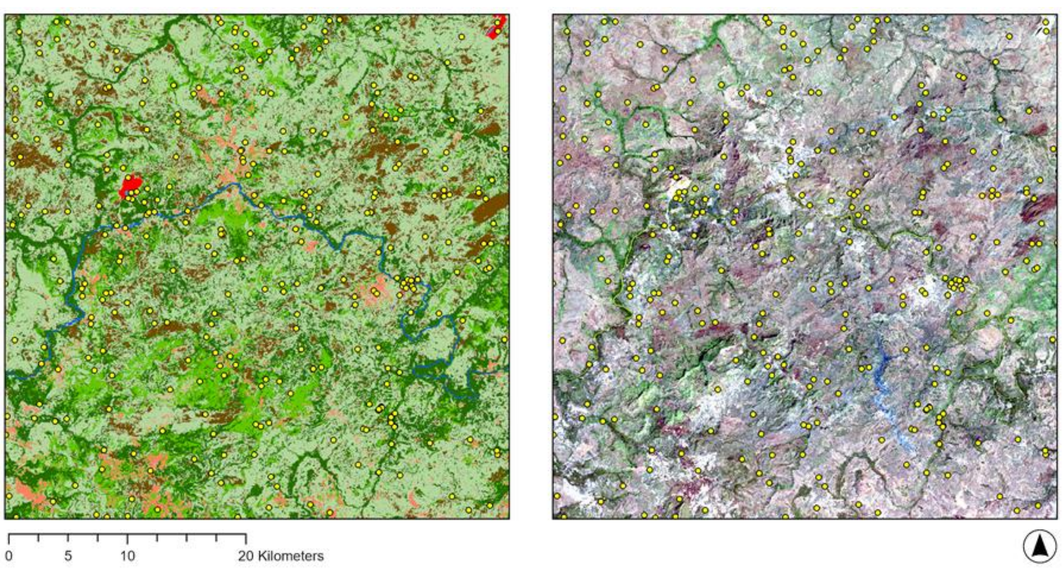


Figure 31. The distribution of 663 random points on the producer's map (left) and the user's reference data (right).

3.3. Change Detection Analysis Results

Figure 32 and Table 9 show a slight gain in closed-vegetation for all three scales from 1988 to 2023. The area of interest has a gain 376 km^2, the subregional watershed has a gain of 103 km^2, and the local watershed has a gain of 7 km^2.

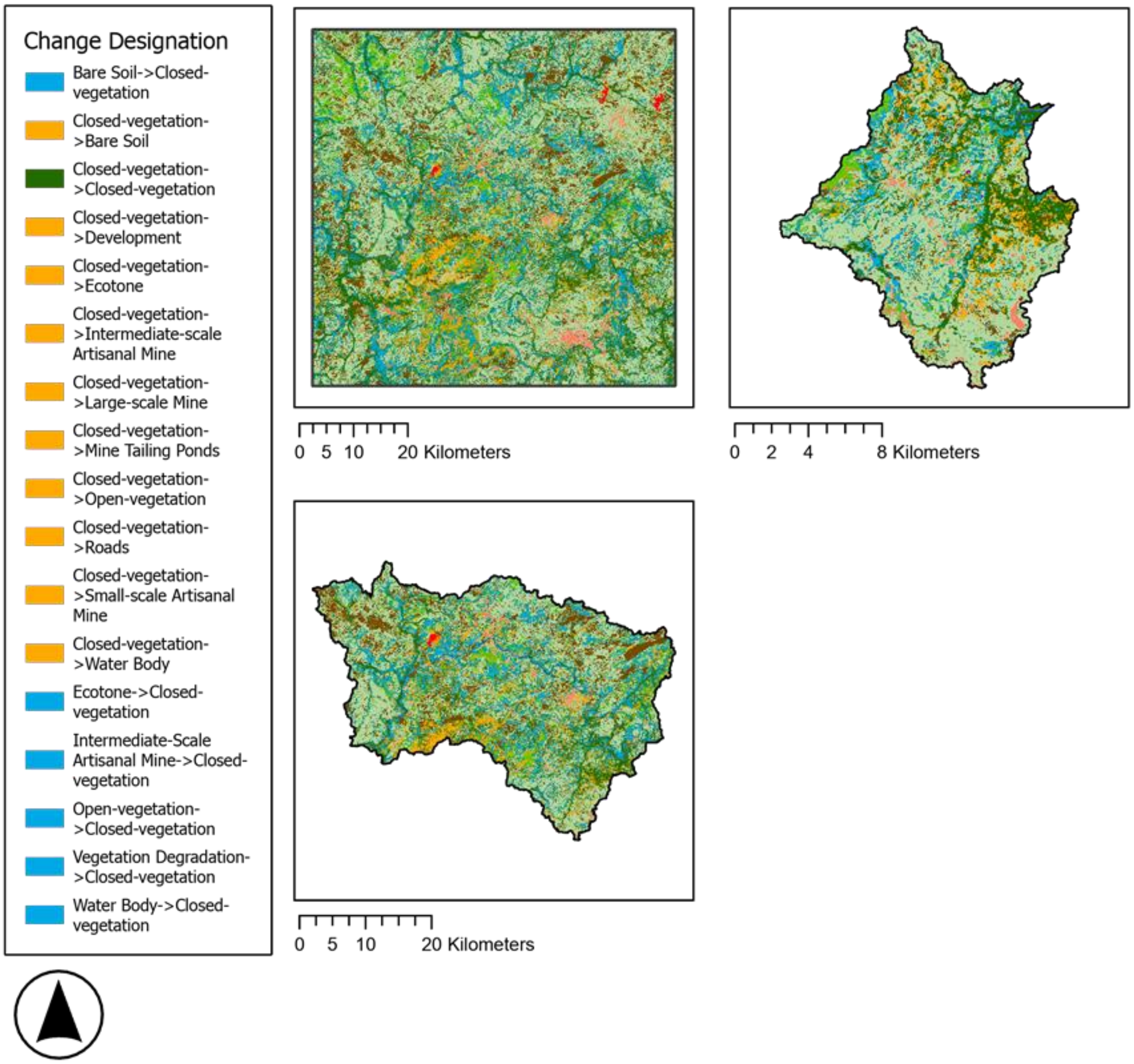


Figure 32. Change detection results from 1988 to 2023 for the area of interest, the subregional watershed, and the local watershed.

Table 9. The change detection gain and loss for closed-vegetation at the three scales.

Closed-vegetation Survey Scale	**A** No Change from 1988 to 2023 Color Code: Forest Green	**B** LULC from 1988 to Closed-vegetation in 2023 (Added) Color Code: Morea Blue	**C** Closed-vegetation from 1988 to LULC in 2023 (Subtracted) Color Code: Electron Gold	A + B = 2023 Total km^2	A + C = 1988 Total km^2	Closed-vegetation Gain/Loss from 1988 to 2023
AOI Change from 1988 to 2023	443	642	267	1,086	710	376
Subregional Change from 1988 to 2023	121	205	102	327	223	103
Local Change from 1988 to 2023	24	21	14	44	37	7

3.4. Presence-only Prediction Results

The AUC = 0.8242, and the Omission Rate = 0.2748. The model was given 296 GPS nesting points and it used 262, and classified 190 as presence. The model trains on the available layers and then selects the layers for the training set to process the probability of presence only predictions. The following variables were selected for the probability of presence: vegetation degradation = 20%, closed-vegetation = 85%, development = 60%, ecotone = 52%, open-vegetation = 22%, roads (N7) = 99%, roads absent = 85%, landforms (plain) = 85%, landforms (valley floor) = 85%, slope = 48%, aspect = 84%, elevation = 84%, dominant parent soils: slate, phyllite (peltic rock) = 85%, fluvial = 27%, colluvial = 20%, dominant soils: eutric regosols = 85%, eutric gleysols = 40%, dystric regosols = 85%, stream network present = 59%, stream network not present = 85%. The presence-only prediction model predicted suitable habitat as far out as it could with a limited and narrow amount of information clustered around the nesting points. If the nesting points were distributed throughout the area, the model likely would have raised the probability of the chimpanzees being present in the surrounding gallery forests too. Figure 33 shows the faint appearance of gallery forests surrounding the nest points, and when the layer for confirmed chimpanzee groups from 2012 is overlayed on the results, the Kanoumering group helps to confirm the model's prediction.

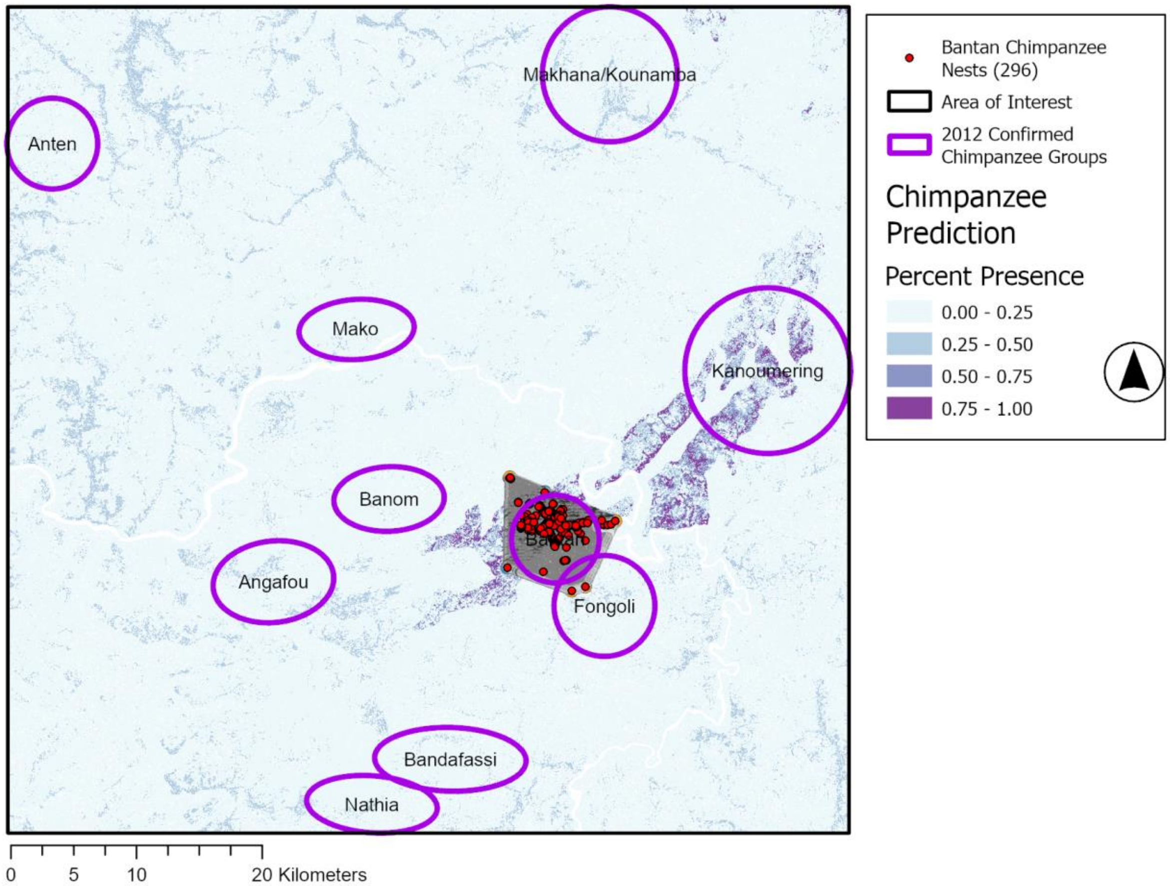


Figure 33. The results of the presence-only prediction model for savanna chimpanzees in 2023 in the area of interest in Kedougou, Senegal.

3.5. Extra: PlanetScope Classification

The reference data, PlanetScope, was classified in eCognition as a last task and mainly out of curiosity to see how well eCognition would support high-resolution imagery at 4.77 meters. The unsupervised classification took close to 4 hours to complete (Figure 34). The multi-threshold segmentation helped to locate another level of ecotone, and made bare soil more difficult to differentiate. There are many more vegetation types in Kedougou, Senegal to classify in the classification hierarchy and high-resolution satellite imagery can make it easier.

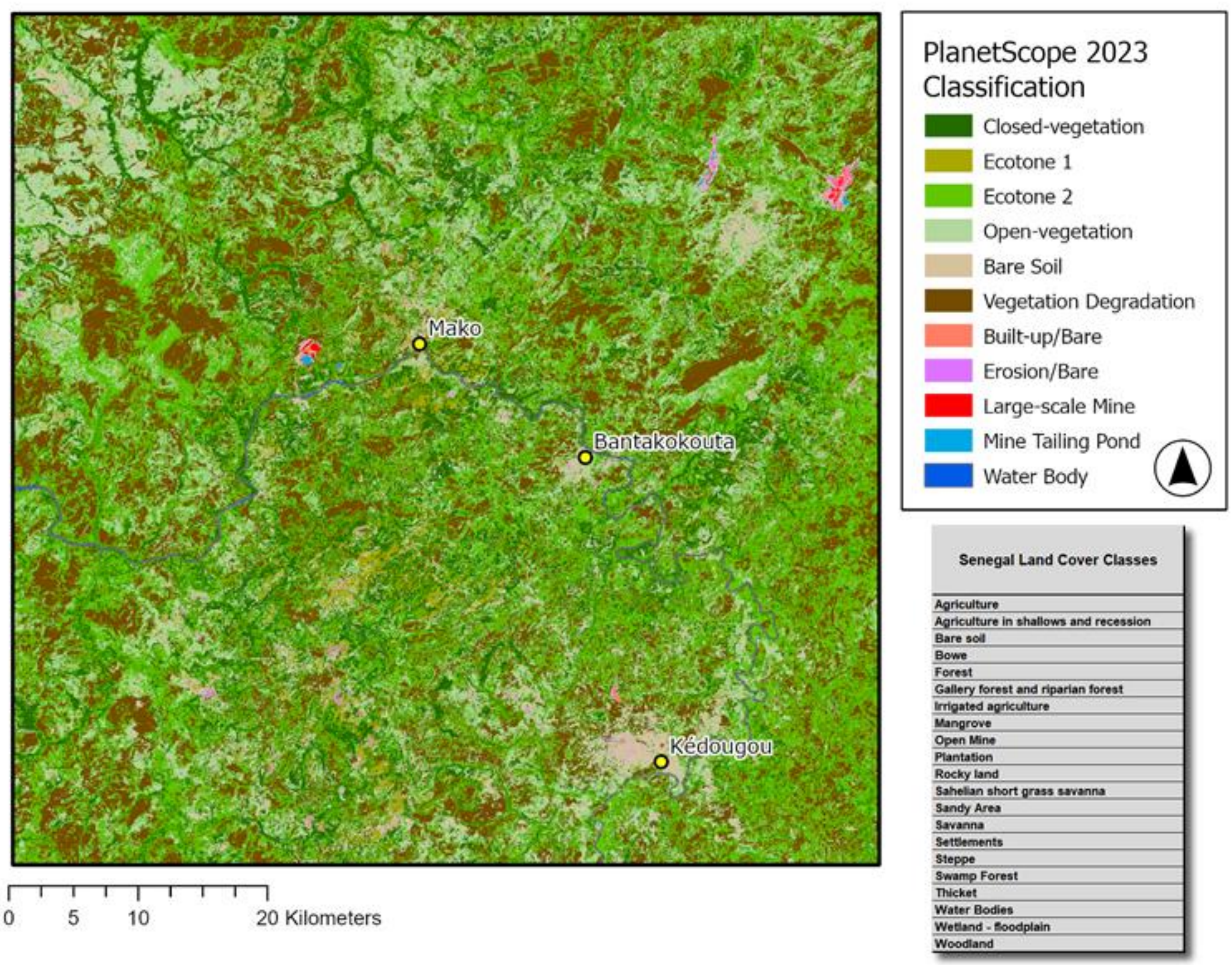


Figure 34. PlanetScope (4.77 meters) classified in eCognition using unsupervised classification and the multi-threshold segmentation. The results demonstrate that more detail can mean more vegetation classifications.

4. DISCUSSION AND FUTURE WORK

The preservation of gallery forests is becoming a critical need for savanna chimpanzee conservation, and this project provides a reasonable roadmap for using satellite imagery and advanced GIS techniques to support conservation efforts. First, this work developed a successful method for tracking and mapping gallery forests in Kedougou, Senegal, showing detection with medium and finer-scale satellite imagery and input data, and, expectedly, more reliable detection is possible with higher quality data such as high-resolution imagery, lidar, and up-to-date digital elevation models. Second, the vegetation classifications revealed a possible shift in land cover from 2010 to 2023, in the month of December, to more open-vegetation, corresponding to the gold mining boom taking place in the study area. Third, the results of the change detection suggest a slight increase in closed-vegetation (gallery forests) from 1988 to 2023, possibly driven by climate change.

Classification in a highly mosaic and complicated landscape may require two people at the very least; the remote sensing analyst coupled with a partner who has intimate knowledge of the area. The results downstream in this project are only as good as the results upstream. This project used three categories to classify the savanna landscape, closed-vegetation, ecotone, and open-vegetation. These categories worked well for medium resolution imagery, such as Landsat (30-meters); however, higher resolution imagery, such as Sentinel (10-meters) and PlanetScope (4.77 meters), gives up some detail in the generalization, as would be expected.

The accuracy assessment will likely always be a problem to perform on imagery older than 2016 (Sentinel released publicly) if adhering to Russell Congalton’s practices (Congalton & Green, 2019), or unless you can afford to purchase expensive satellite imagery.

The change detection tool in ArcGIS Pro 3.2.2 is superior to other change detection methods such as using a Con statement in the raster calculator to look for differences; however, plan plenty of time to sift through the data that the tool outputs, because it is copious amounts.

The relatively new presence-only prediction tool in ArcGIS Pro 3.2.2 has potential for future use with the right data layers. This project merely attempted exploratory trials and found promising results.

Next steps include using hyperspectral imagery and perhaps multi-dimensional analysis to track restoration, degradation, disruptions, and nonpoint source pollution using scenes from several months in the dry season (i.e., cloudless scenes). Now is the time to start as more advanced data becomes available.

In closing, I highlight two satellite images that clearly show the intrusion of mining into the gallery forests of Kedougou. It is my hope that in the future, new mines are prohibited from cutting through gallery forests and placing tailing ponds directly next to a watercourse (Figure 35). This would help to avoid the inevitable end of these practices as pictured in Figure 36.

This project supports the effort to protect gallery forests and savanna chimpanzees simultaneously, because they are inextricably linked to each other's survival.

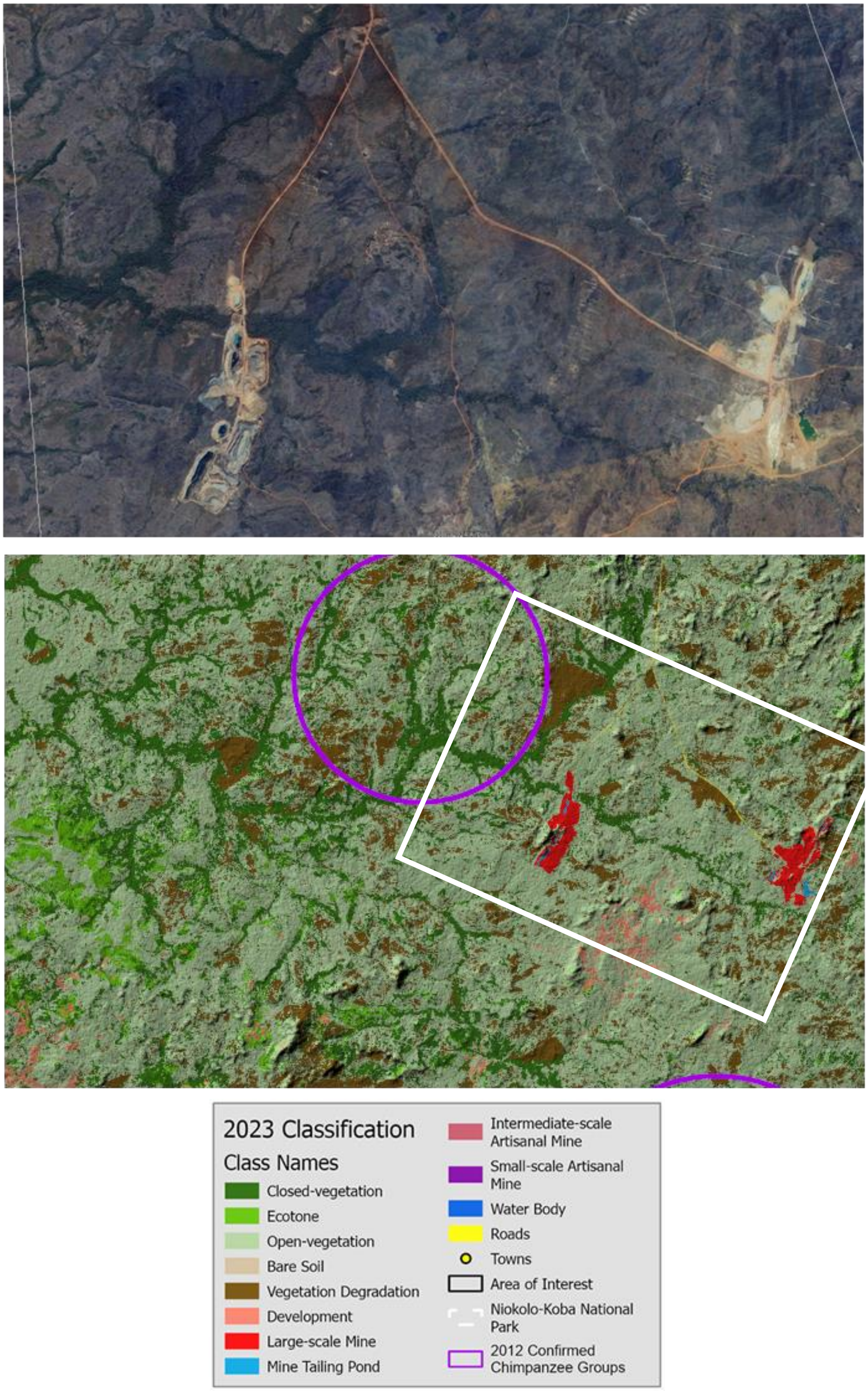


Figure 35. The new extension of the Sabodala mine north of the area of interest in this project. The picture depicts the mining infrastructure cutting through a gallery forest in two locations and the position of the mine tailing ponds next to the gallery forest watercourse (Photo credit to Google Earth).

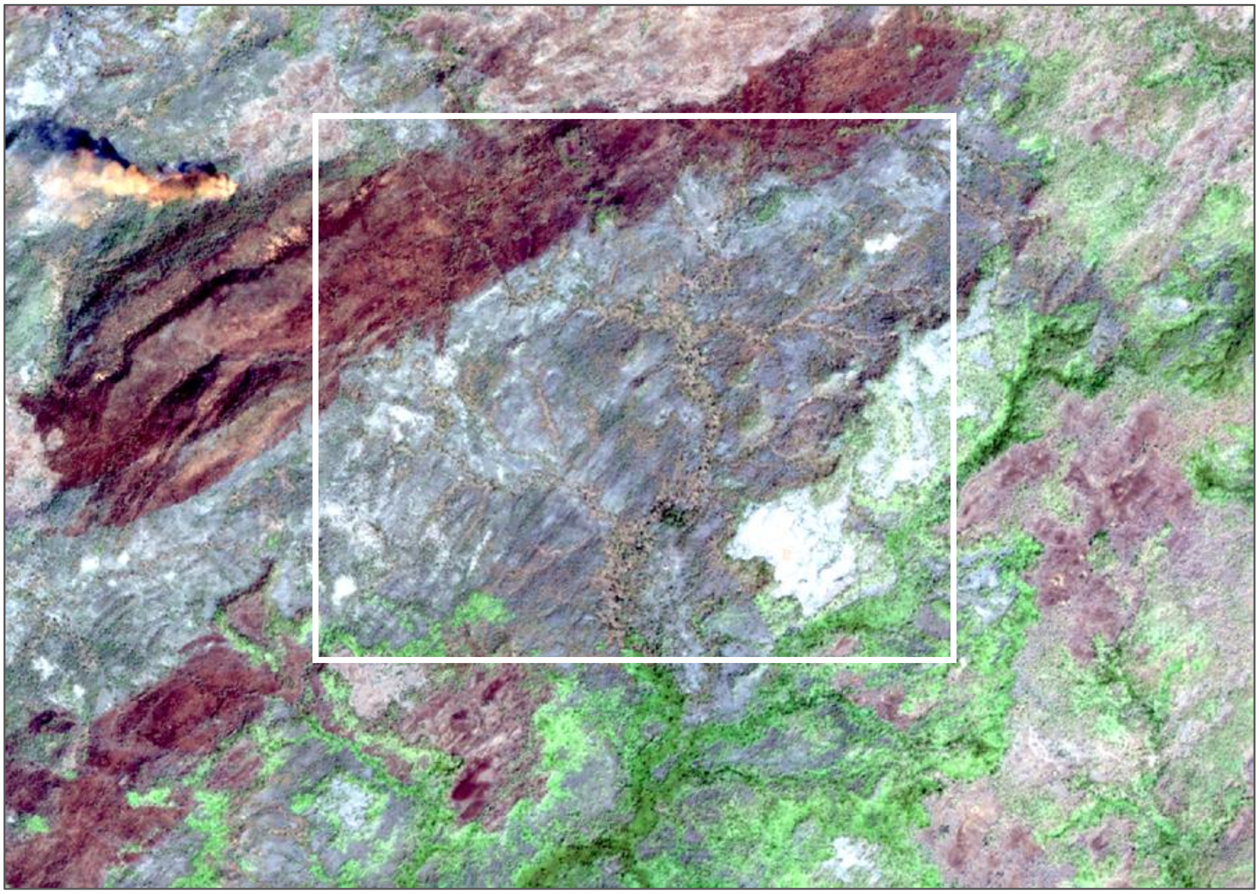


Figure 36. PlanetScope (4.77 meters), December 27, 2023, natural bands (RGB 321). Showing an unhealthy, likely burned, or degrading gallery forest branch.

5. APPENDIX

5.1. Google Earth Engine CHIRPS Precipitation

Below is an example of the Google Earth Engine code by Spatial eLearning to extract monthly rainfall estimates for a specified region. The code below is specific to the study area boundaries, and extracts monthly precipitation from 1988 to 2023 using CHIRPS Daily: Climate Hazards Group InfraRed Precipitation With Station Data image collection. Any Earth Engine user can also use this link to view the code snapshot: https://code.earthengine.google.com/5bab18870af5868c6f8a84175e7cbd53

```
//Extract monthly rainfall from CHIRPS


var aoi_SN = ee.FeatureCollection('projects/my-project-1511160065692/assets/AOI_SN');
Map.addLayer(aoi_SN, {}, "aoi_SN");
Map.centerObject(aoi_SN);

//List of years and months

var years = ee.List.sequence(1988, 2023);
var months = ee.List.sequence(1, 12);

var rainfall = ee.ImageCollection("UCSB-CHG/CHIRPS/DAILY").select('precipitation');
print(rainfall.first());

///Map over the years and create a monthly totals collection
var monthlyImages = years.map(function(year) {
  return months.map(function(month) {
    var filtered = rainfall
      .filter(ee.Filter.calendarRange(year, year, 'year'))
      .filter(ee.Filter.calendarRange(month, month, 'month'))
    var monthly = filtered.sum()
    return monthly.set({'month' : month, 'year' : year})
  })
}).flatten()

var monthlyCol = ee.ImageCollection.fromImages(monthlyImages);
print(monthlyCol);

//Zonal Statistics to Summarize Rainfall
var rainfallKedougou = monthlyCol.map(function(img) {
  var features = aoi_SN.map(function(f) {return f.set('month', img.get('month'), 'year', img.get('year'))});
  var proj = ee.Image(monthlyCol.first()).projection();
  return img.reduceRegions(features, ee.Reducer.mean(), 1000, proj);
}).flatten();
print("Rainfall Summary Mean", rainfallKedougou.limit(432));

//Export the Resulting Mean as a Table (csv) to Google Drive
var selectors = 'month, year, mean'

Export.table.toDrive({
  collection: rainfallKedougou,
  description: 'Rainfall_Timeseries_1988_2023',
  fileNamePrefix: 'Rainfall_Timeseries_1988_2023',
  fileFormat: 'CSV',
  selectors: selectors
});
```

CHIRPS Precipitation Data YouTube Tutorial: Download Climate Data (Rainfall) from 1981-2022 using Earth Engine API by Spatial eLearning: https://youtu.be/TcpG6SbUiYU?si=lFV7KzxpfBJn7hTX

5.2. Google Earth Engine MODIS Land Surface Temperature

Below is an example of the Google Earth Engine code by Spatial eLearning to extract land surface temperature for a specified region. The code below is specific to the study area boundaries, and extracts land surface temperatures from 2000 to 2023 using MOD11A2.061 Terra Land Surface Temperature and Emissivity 8-Day Global image collection. Any Earth Engine user can also use this link to view the code snapshot: https://code.earthengine.google.com/68185a2bacbe6925fe7f23ebf601c1f8

```
//Import Area of Interest
var aoi_SN = ee.FeatureCollection('projects/my-project-1511160065692/assets/AOI_SN');
Map.addLayer(aoi_SN, {}, "aoi_SN");
Map.centerObject(aoi_SN);

// Access Image Collection and Import LST Data
var collection = ee.ImageCollection('MODIS/061/MOD11A2').select("LST_Day_1km")
.filterDate ('2000-01-01','2023-12-31')
.filterBounds(aoi_SN);

//Rescale the Land Surface Temperature from Kelvins to Celsius
var LSTDay = collection.map(function(img) {
  return img.multiply(0.02).subtract(273.15).copyProperties(img, ['system:time_start', 'system:time_end']);
});

//Display LST Annual Variation in Surface Temperature
var chart = ui.Chart.image.doySeriesByYear(LSTDay, 'LST_Day_1km', aoi_SN, ee.Reducer.mean(), 1000);
print(chart);
```

MODIS LST YouTube Tutorial: MODIS Land Surface Temperature (LST) Annual Timeseries using Earth Engine by Spatial eLearning: https://youtu.be/0ASsr6Hj6NU?si=VHDrmLcHqpeRz1RV

5.3. Google Earth Timelapse for Kedougou, Senegal

Google Earth Timelapse for Kedougou, Senegal Gold Mining and Settlement Development from 1984 to 2022: https://byclaudette.com/MGIS_assets/Timelapse.html

Mako Gold Mine: 12.85715,-12.3813

Bantakokouta Intermediate-scale Artisanal Mines: 12.76221,-12.22899

New Endeavor Mine: 12.964235, -12.098134

Sabodala Gold Mine: 13.197605,-12.114124

Copy and paste the coordinates into the search field, click Enter, set the speed to 1x, and then press Play.

5.4. Trimble eCognition Unsupervised Classification Ruleset and Steps

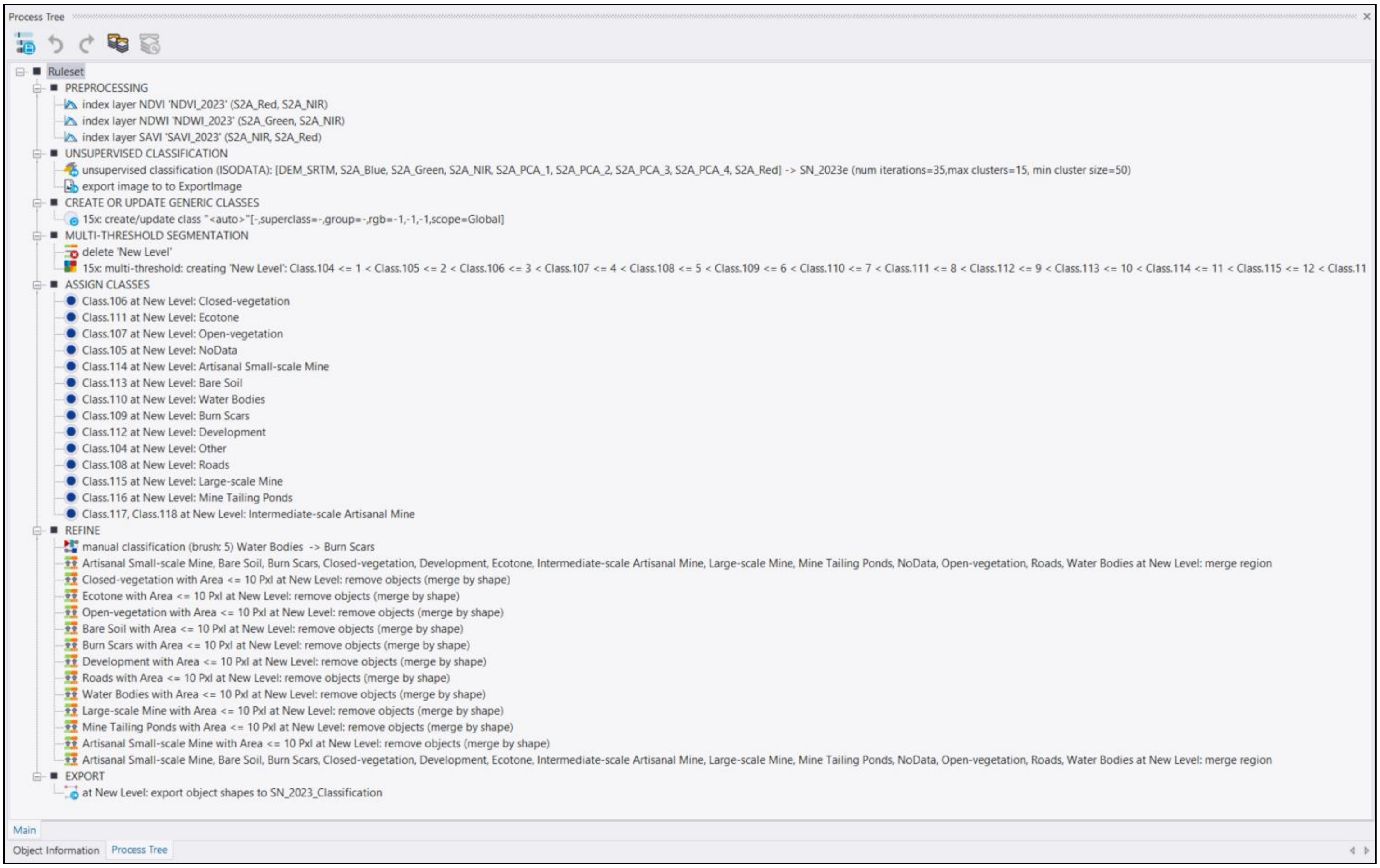
Below is a simplified step-by-step tutorial for using eCognition's unsupervised classification algorithm, with additional links to online resources. These instructions assume that you have some basic knowledge of using the eCognition software. Watch this video before beginning.

eCognition Deconstruction: Unsupervised Classification by eCognition tv: https://youtu.be/QZ083hNoom0?si=UzV6UjLCxhNSTCOk (19:27)

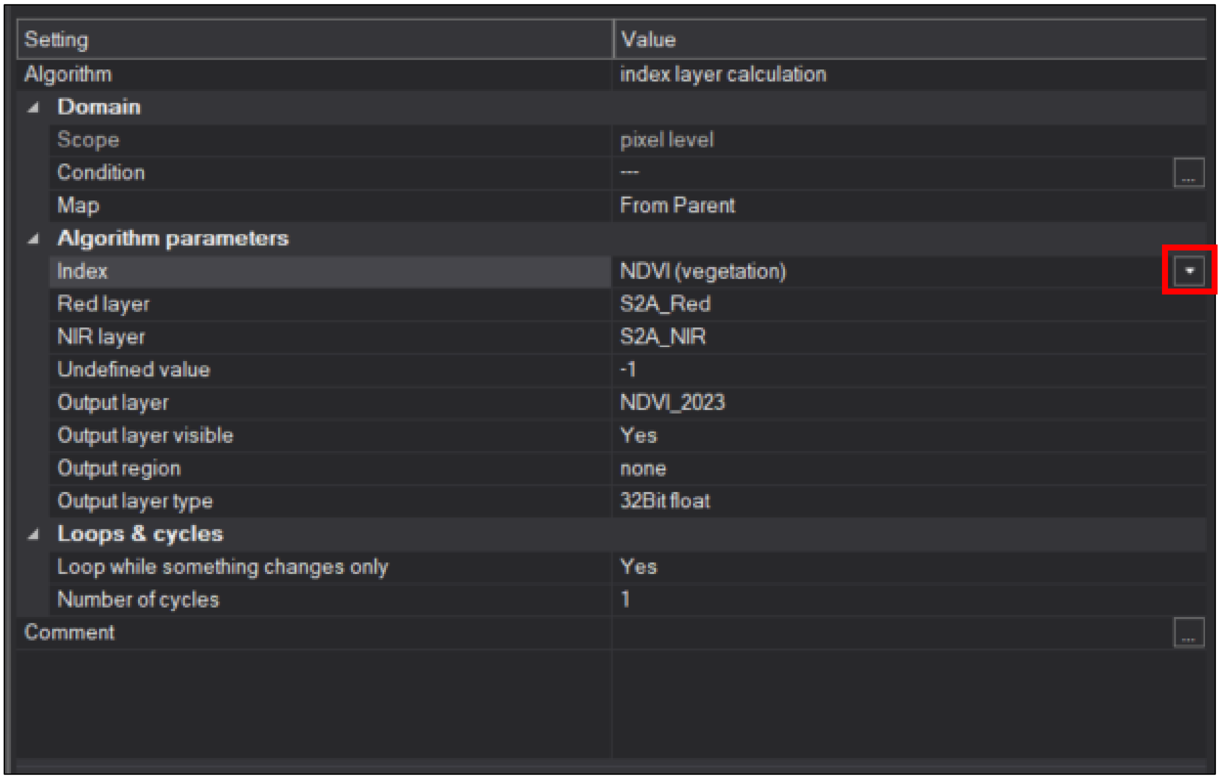
1. Open eCognition and create a **Project** and **Workspace** in the **Data Management Layout**.
2. An example of the ruleset is provided below. It helps to build out the major outline for your ruleset first. The major outline for this project is:

    Ruleset

        PREPROCESSING
        UNSUPERVISED CLASSIFICATION
        CREATE OR UPDATE GENERIC CLASSES
        MULTI-THRESHOLD SEGMENTATION
        ASSIGN CLASSES
        REFINE
        EXPORT



3. In PREPROCESSING you build canned indices within eCognition. You would first **Insert Child Process** and then search for the algorithm **index layer calculation**. There is a drop-down window to select from nine different indices.



Setting	Value
Algorithm	index layer calculation
Domain	
Scope	pixel level
Condition	---
Map	From Parent
Algorithm parameters	
Index	NDVI (vegetation)
Red layer	S2A_Red
NIR layer	S2A_NIR
Undefined value	-1
Output layer	NDVI_2023
Output layer visible	Yes
Output region	none
Output layer type	32Bit float
Loops & cycles	
Loop while something changes only	Yes
Number of cycles	1
Comment	

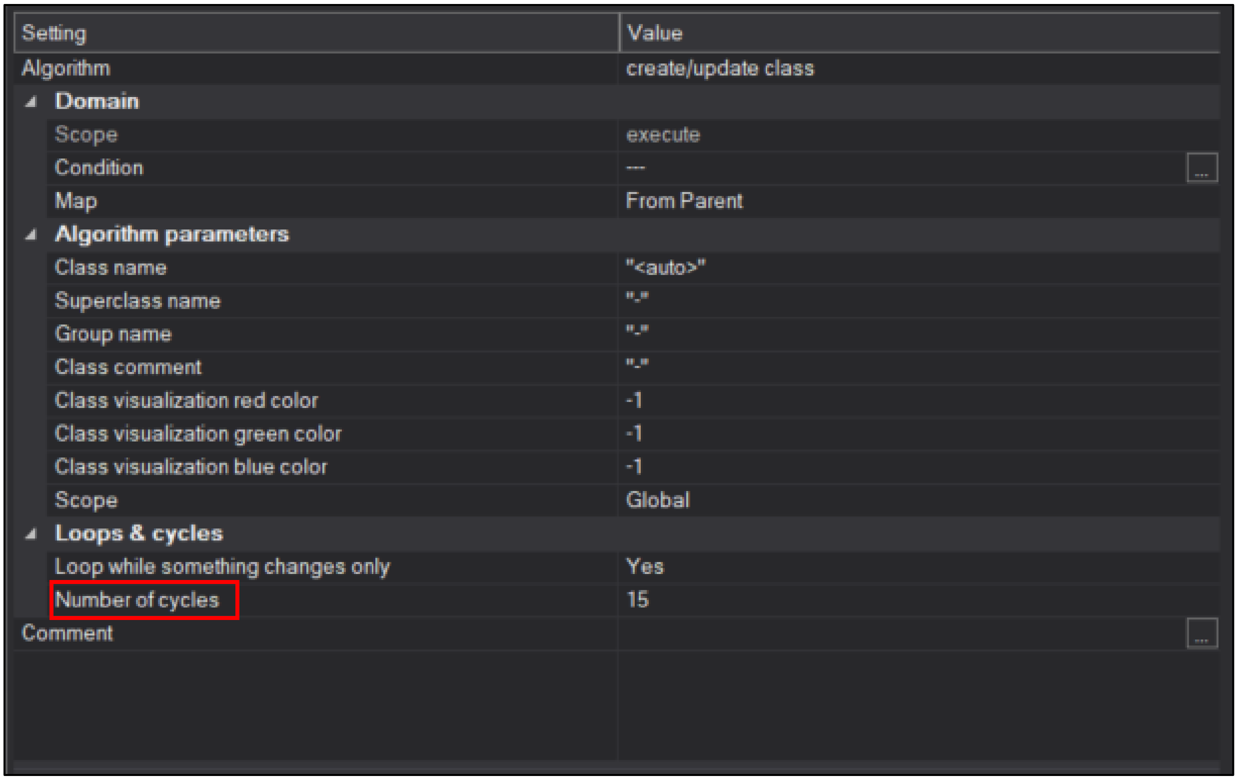
4. Next, you will want to add the algorithm for **export image to**, to create a real .tif file and then import it back into your project layers. If you keep the virtual layer, eCognition rebuilds it every time you save the project (the saves are different versions). This can consume space in your C: drive very quickly if each scene is 1GB or more.

5. The next step is UNSUPERVISED CLASSIFICATION. Add the algorithm **unsupervised classification** and then add your layers. Each cluster is a classification, add an extra cluster or two for unknowns. The unsupervised classification will only take rasters. It seems to work better with rasters made from one sensor. This example had 14 layers. The runs took 20 to 30 minutes with a 16 GB GPU.

Setting	Value
Algorithm	unsupervised classification
Domain	
Scope	pixel level
Condition	---
Map	From Parent
Algorithm parameters	
Use input layer array	No
Input image layers	[DEM_SRTM, S2A_Blue, S2A_Green, S2A_NIR, S2A_PC...
Output layer name	SN_2023e
Number of iterations	35
Maximum number of clusters	15
Initial number of clusters	8
Minimum cluster size	50
Maximum standard deviation.	0
Minimum cluster distance	0
Loops & cycles	
Loop while something changes only	Yes
Number of cycles	1
Comment	

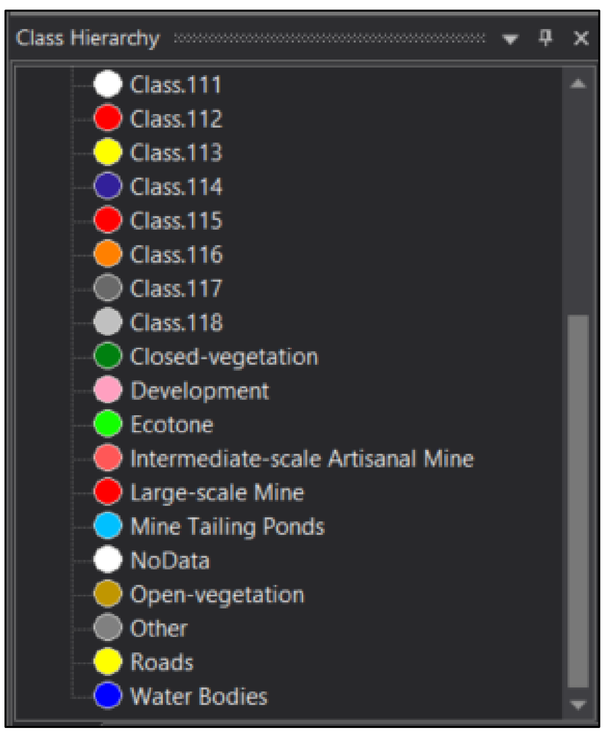
6. Next, use the **export image** algorithm to keep a .tif copy of your unsupervised classification for comparisons later.

7. Next, add the **create/update class** algorithm under CREATE OR UPDATE GENERIC CLASSES. This creates temporary classes for the multi-threshold segmentation algorithm. The number of cycles is the number of classes that you need, fill this in and then click **Execute**.



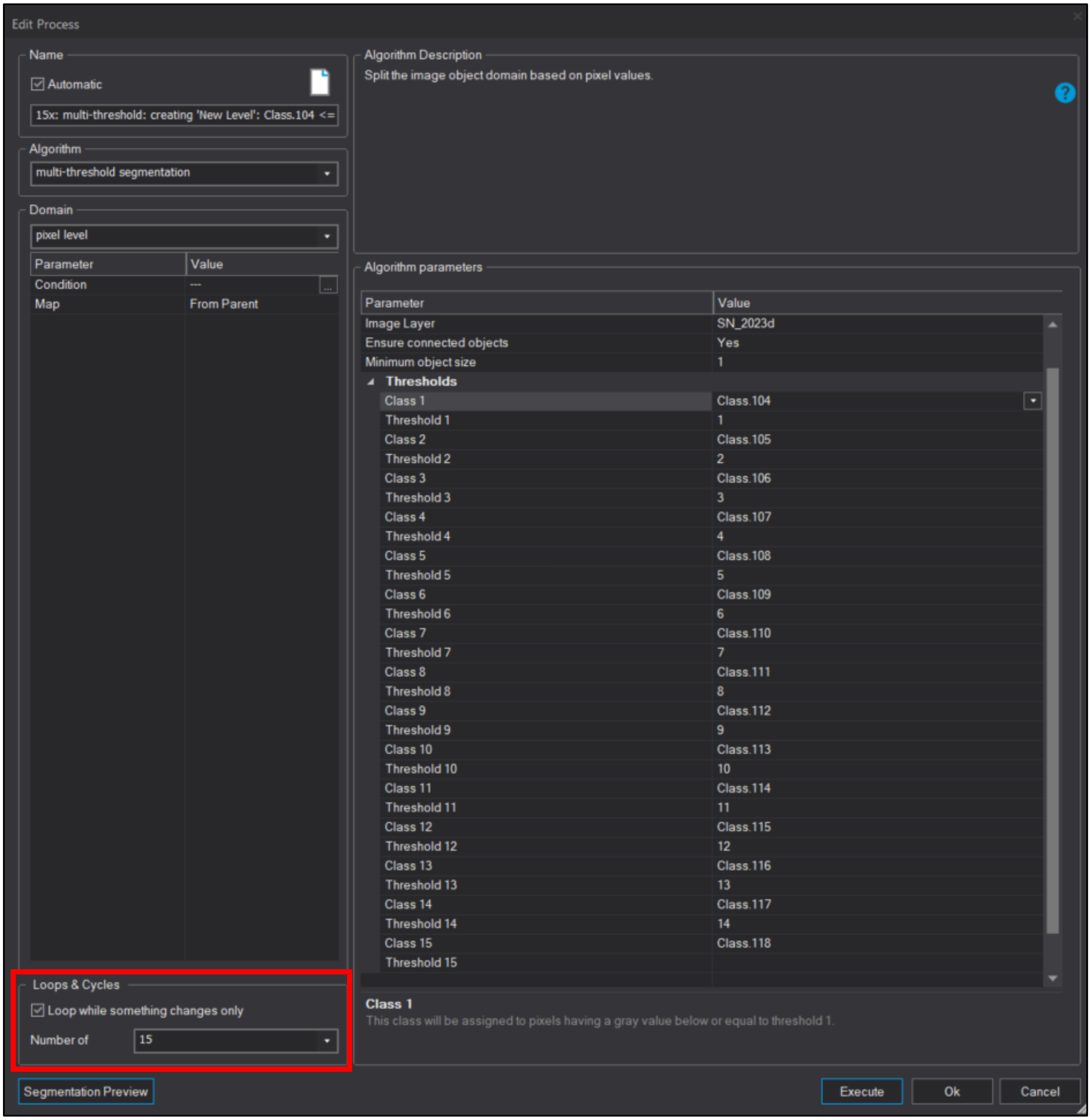
Setting	Value
Algorithm	create/update class
Domain	
Scope	execute
Condition	---
Map	From Parent
Algorithm parameters	
Class name	"<auto>"
Superclass name	"-"
Group name	"-"
Class comment	"-"
Class visualization red color	-1
Class visualization green color	-1
Class visualization blue color	-1
Scope	Global
Loops & cycles	
Loop while something changes only	Yes
Number of cycles	15
Comment	

8. Now go to the **Class Hierarchy** window and right-click in the window and select **Insert Class**. Do this for all of your real class labels. The temporary classes will be added to this window too after you run the **create/update class** algorithm.



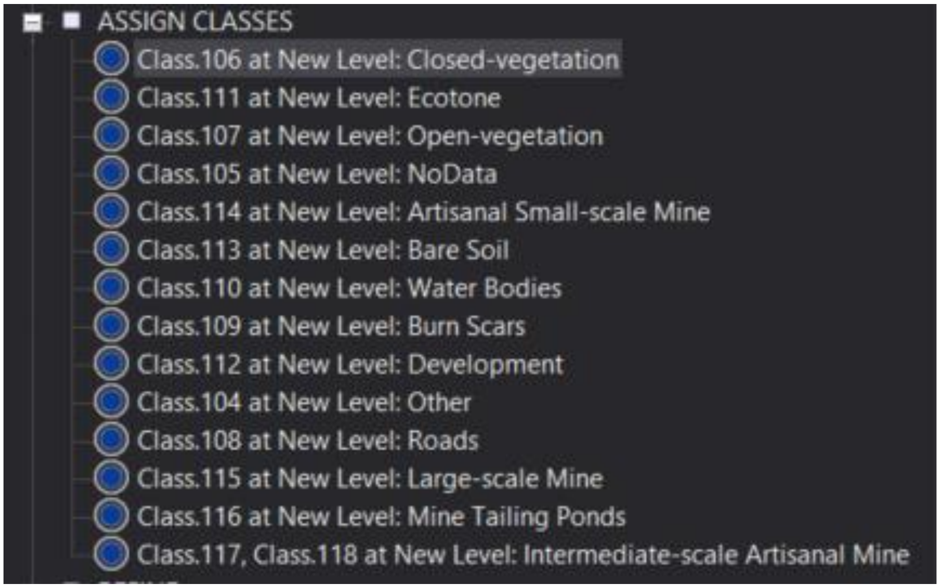
9. Next, under MULTI-THRESHOLD SEGMENTATION add the algorithm **delete 'New Level'** in case you need to start again, this will clear the settings in this algorithm, and clear the temporary classes, and any final classifications that you may have made.

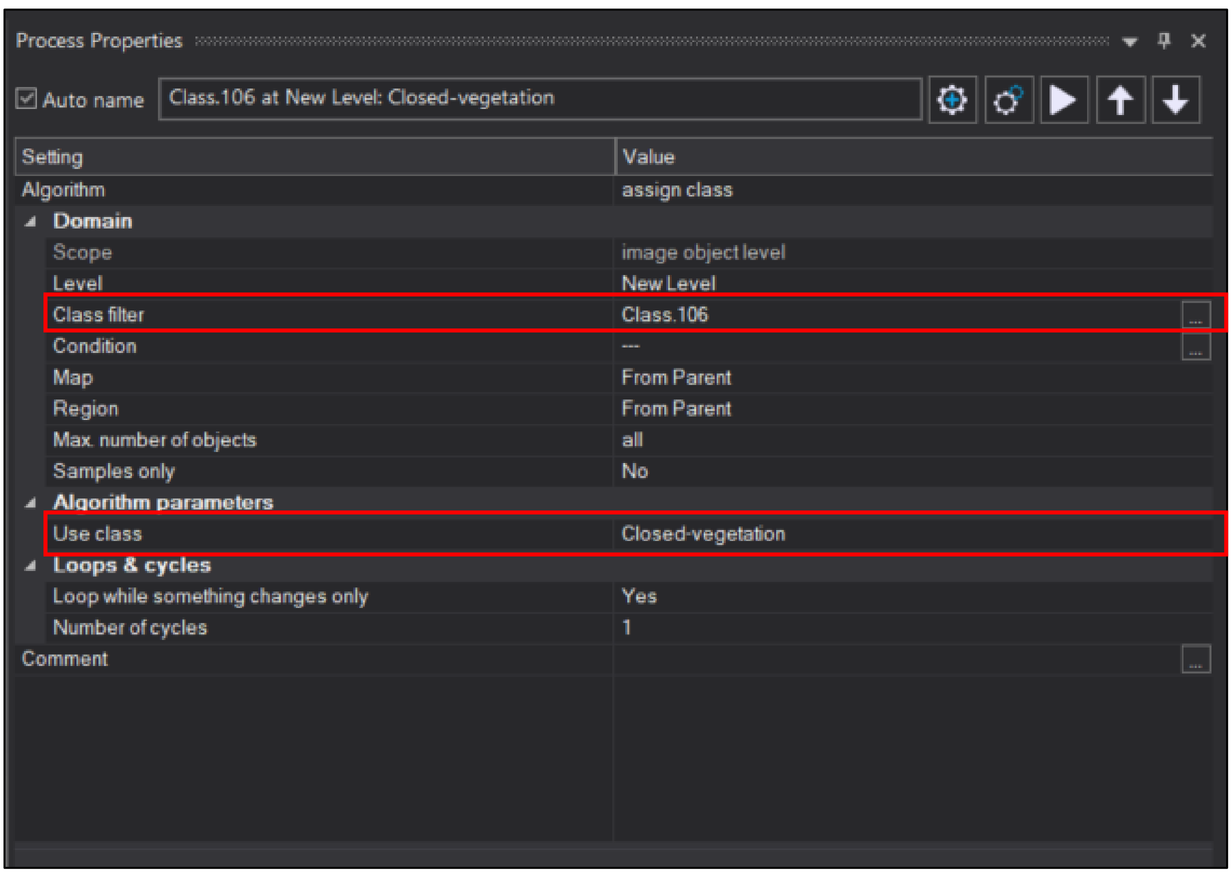
10. Now add the **multi-threshold segmentation** algorithm and add a temporary class from the drop-down menu to **Class 1,** and the number 1 to the **Threshold 1** field. The program will automatically advance to the next entry. Add the next temporary class to **Class 2** and the number 2 to **Threshold 2**, and so on, until the total number of your classifications has been entered. The number of **Loops & Cycles** is the number of clusters or classifications. Click **Execute** when you are done.



11. When the segmentation is complete you will want to investigate it. The temporary classes will be added to the **Object Level** window with temporary color or **Fill** assigned by the multi-threshold segmentation algorithm. Now it is your job to match the temporary classes with your real class labels. As you make matches the temporary classes will go away and be replaced by your real class labels in the **Object-Level** window. If you need more classes **Insert Class** into the **Class Hierarchy window**.

12. To make the matches, add the **assign class** algorithm under ASSIGN CLASSES for each classification.





This is a completed **Object Level** window.

13. Next, you can REFINE your segmentation using the **manual classification** algorithm, **merge regions** by class algorithm, and the **remove objects** by shape algorithm — for your needs. Here are additional videos and documentation for these algorithms:

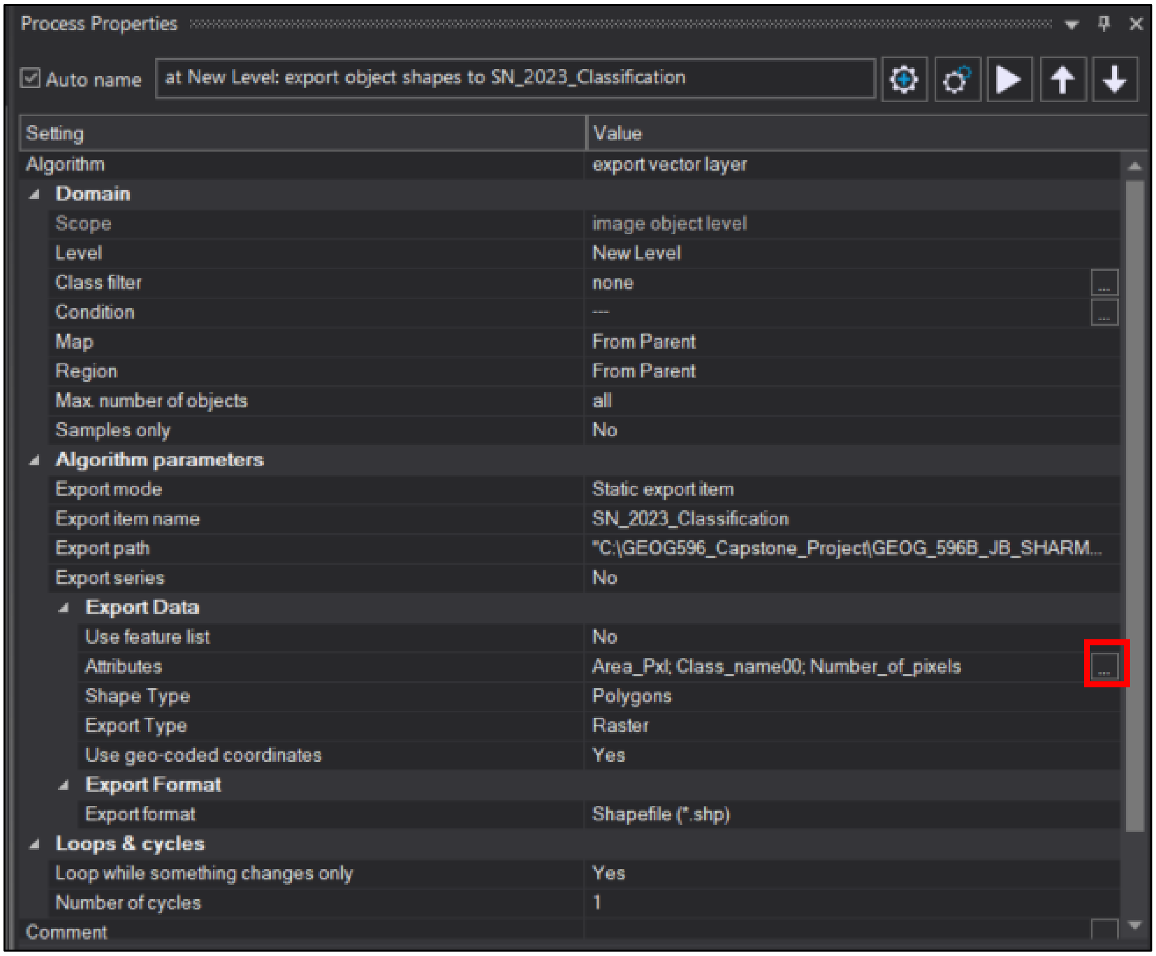
    eCognition Deconstructed: Remove Objects:
    https://youtu.be/c_6PPLFhYpo?si=wGak7A1TaQPadAcg

    eCognition Deconstructed: Merge Region:
    https://youtu.be/_rEKL8rcAbE?si=YKgzyi_rMIC5FBep

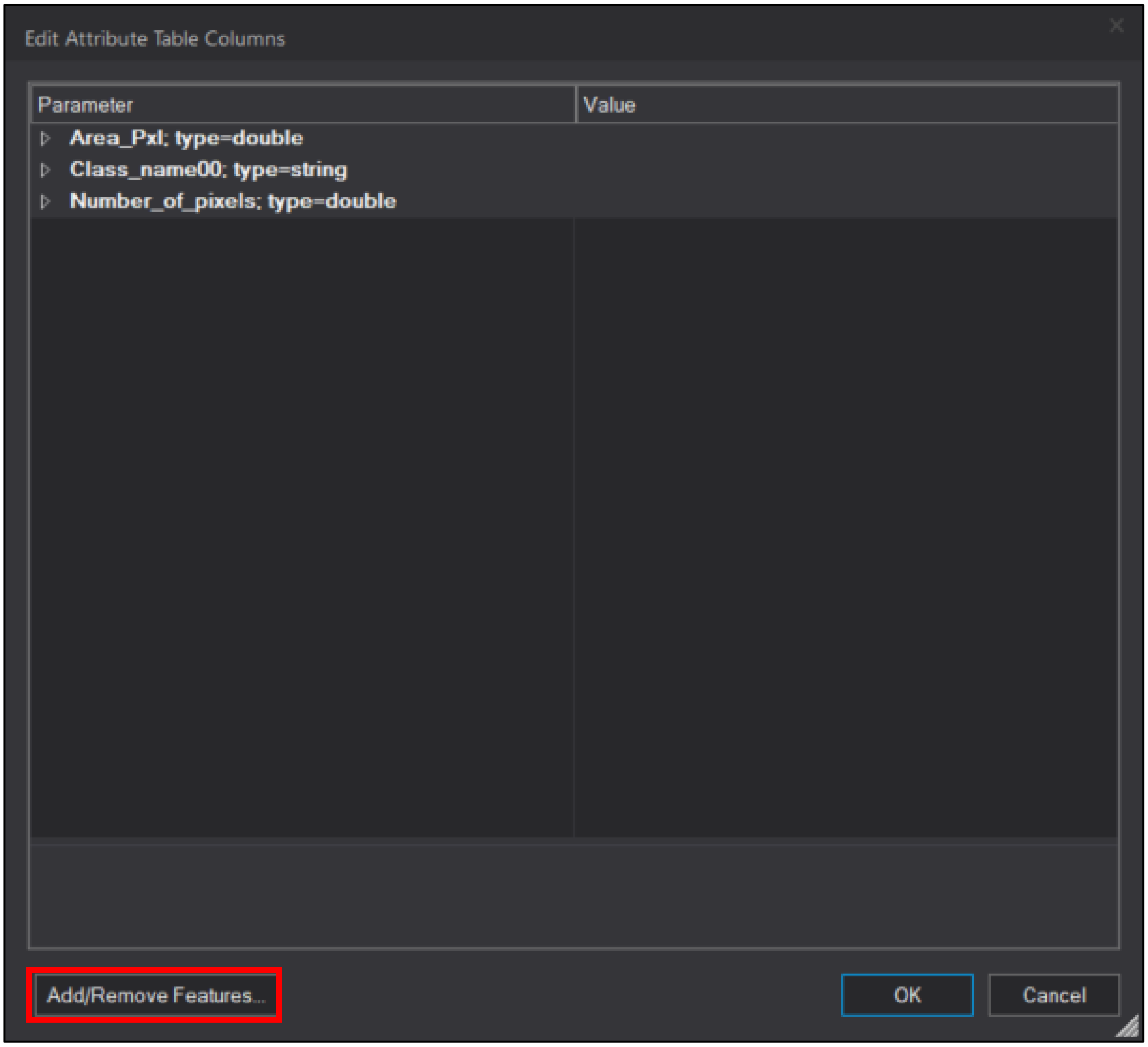
    Manual Editing Documentation

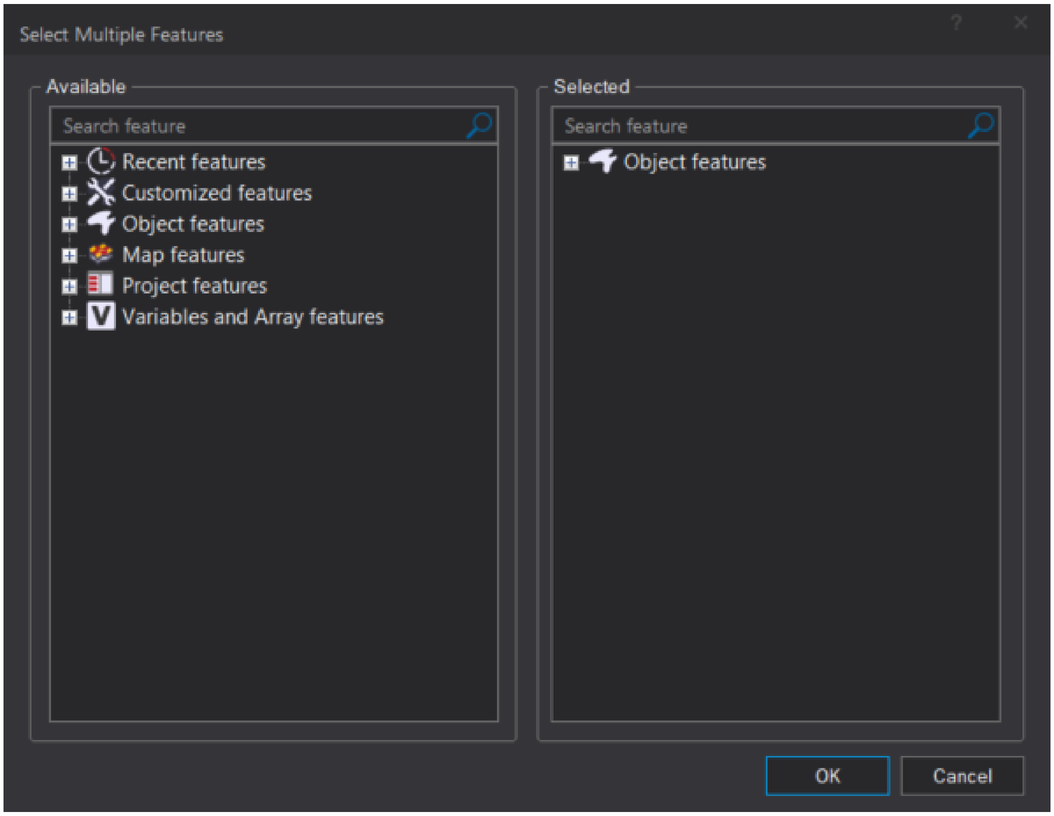
    There are many more editing tools on eCognition TV:
    https://www.youtube.com/@eCognitiontv

14. Last, Export your final vector product using the **export vector layer** algorithm.



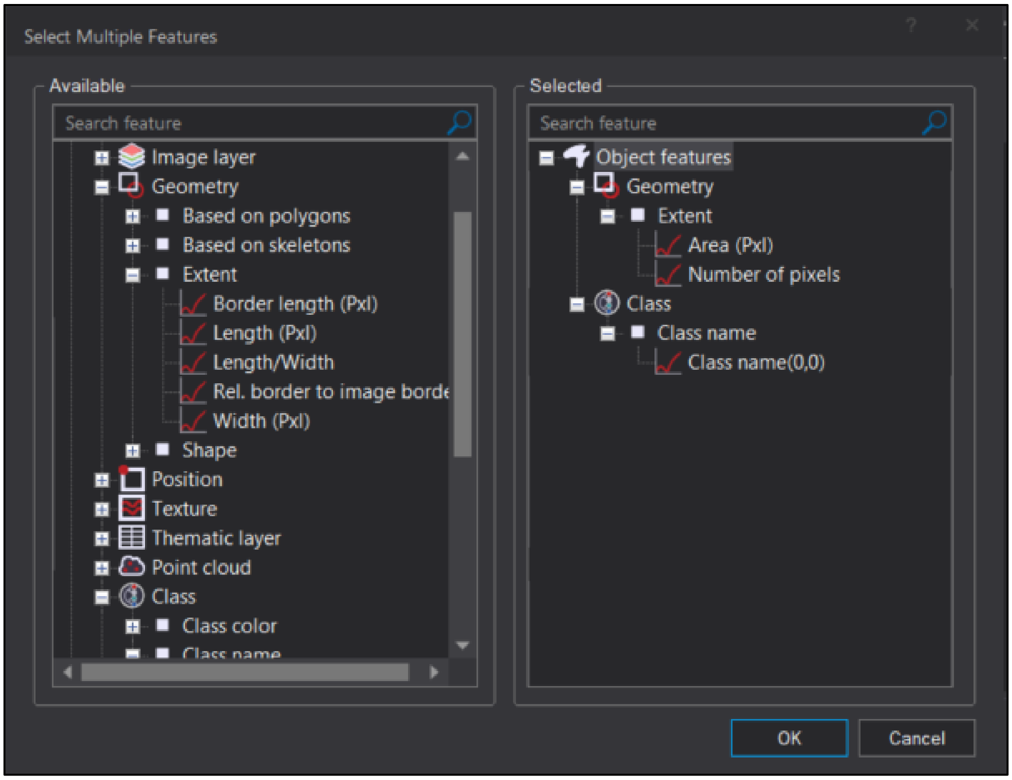
15. Click on the drop-down menu in **Attributes**, and the **Edit Attribute Table Columns** window will open. At the bottom, click on the **Add/Remove Features** button to open the **Select Multiple Features** window as pictured below.


Edit Attribute Table Columns
Parameter
Value
Area_Pxl; type=double
Class_name00; type=string
Number_of_pixels; type=double
Add/Remove Features...
OK
Cancel



16. Next, click on **Object features > Geometry > Extent** and then click on **Area (Pxl)** and **Number of pixels** and also click on **Class > Class name** to move them over to the **Selected** window as pictured below and then click **OK** and **OK** again, and last, click on **Execute** the **export vector layer** algorithm when you have completed the rest of the fields. Here is a video with additional information:

    eCognition Getting Started 4 of 4: Export your results:
    https://youtu.be/tRwTBSJi0oY?si=WjM73MWoeG-4shXE



17. That is basically it! Happy eCognition segmenting.

5.5. Senegal GIS and Remote Sensing Data Resources

Senegal 2019 Administrative Boundaries

OCHA Centre for Humanitarian Data

URL: https://data.humdata.org/dataset/cod-ab-sen/resource/4ef61299-7edb-4529-aa09-76137c14962a

Senegal and the Gambia Soil and Terrain Database (SOTER)

URL: https://files.isric.org/public/soter/SN&GM-SOTER.zip

ISRIC World Soil Information for Senegal and the Gambia

5.6. Enlarged Maps of the Final Classifications

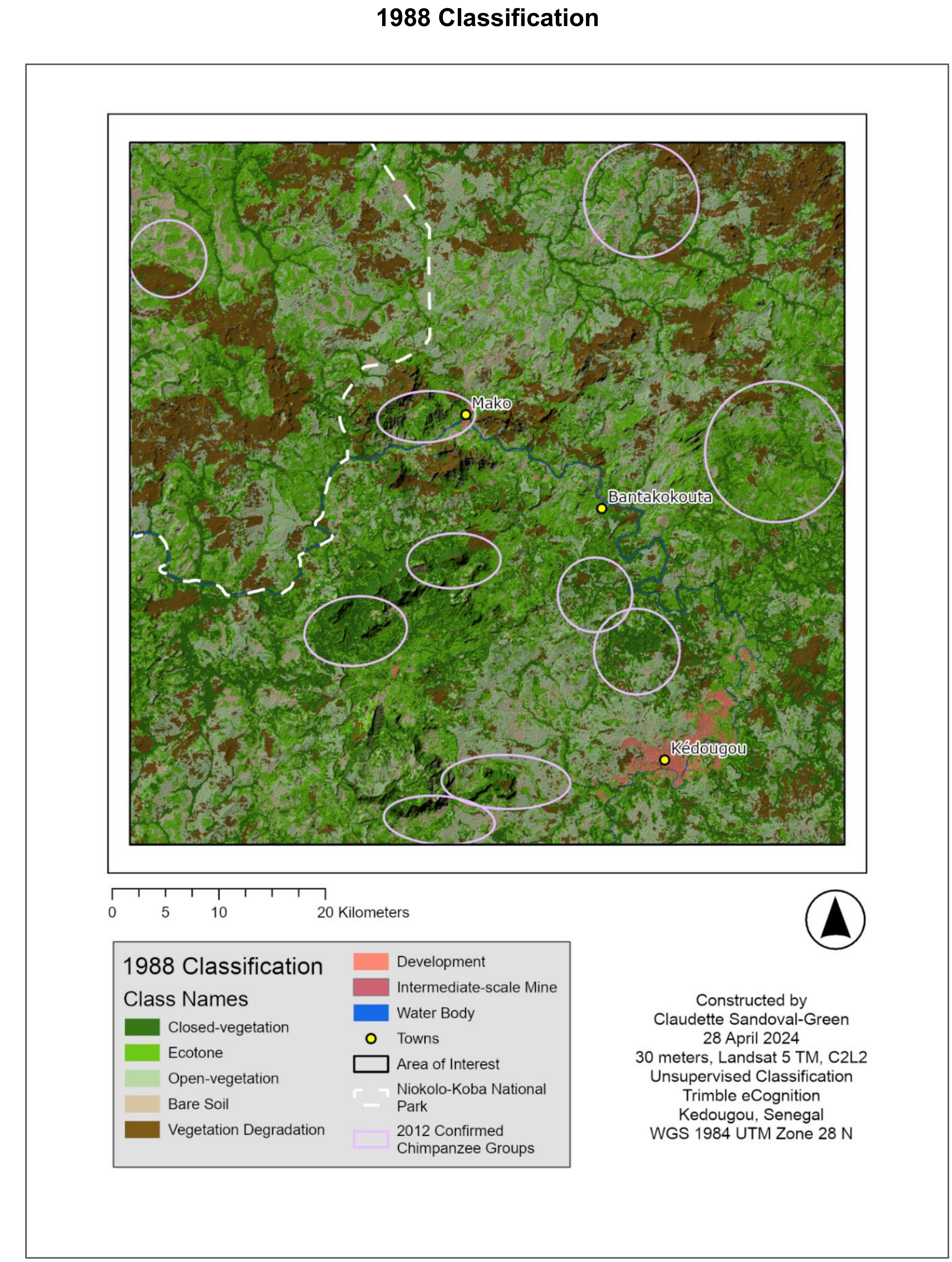


Figure 37. The 1988 Classification for the area of interest in Kedougou, Senegal.

2000 Classification

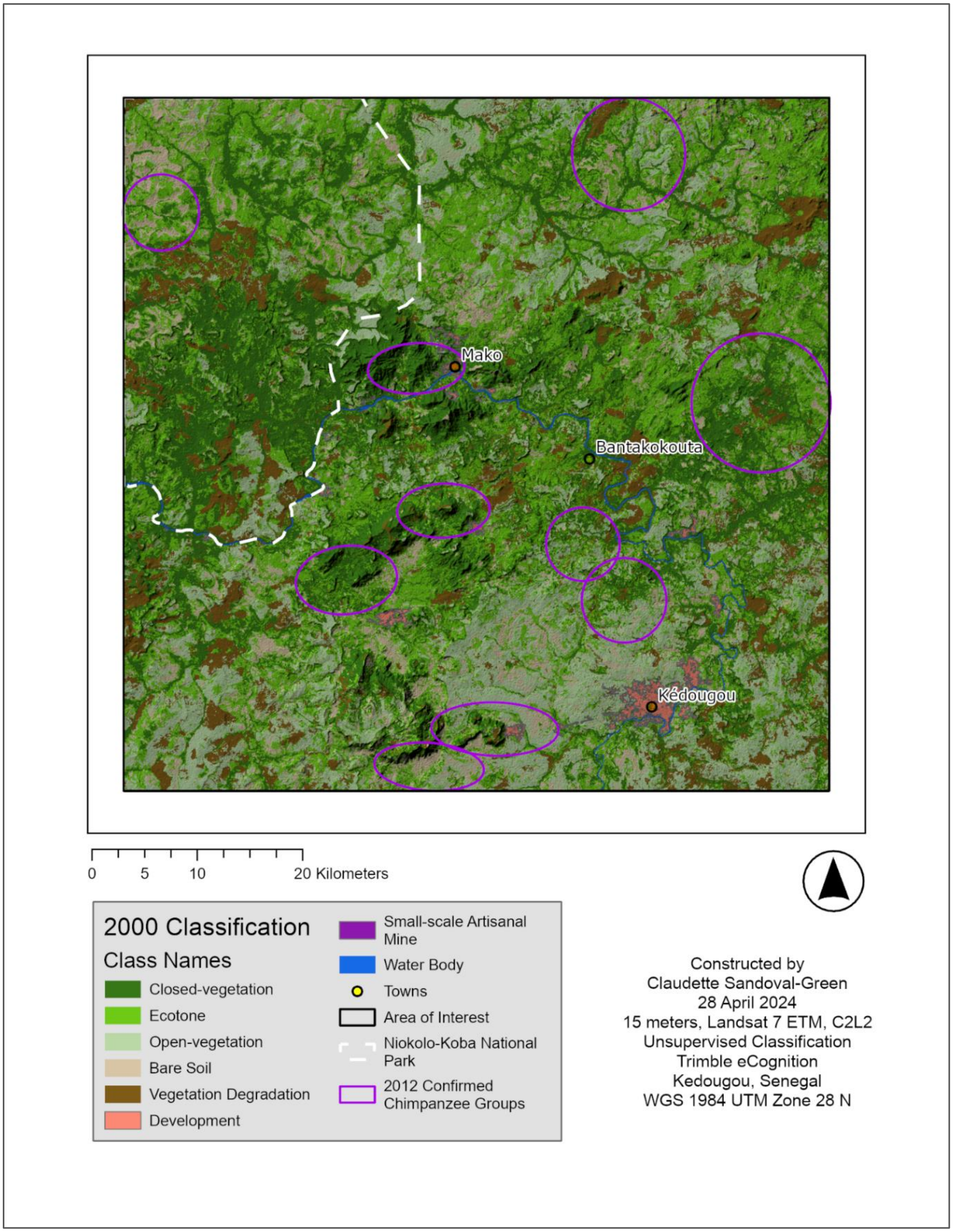


Figure 38. The 2000 Classification for the area of interest in Kedougou, Senegal.

2010 Classification

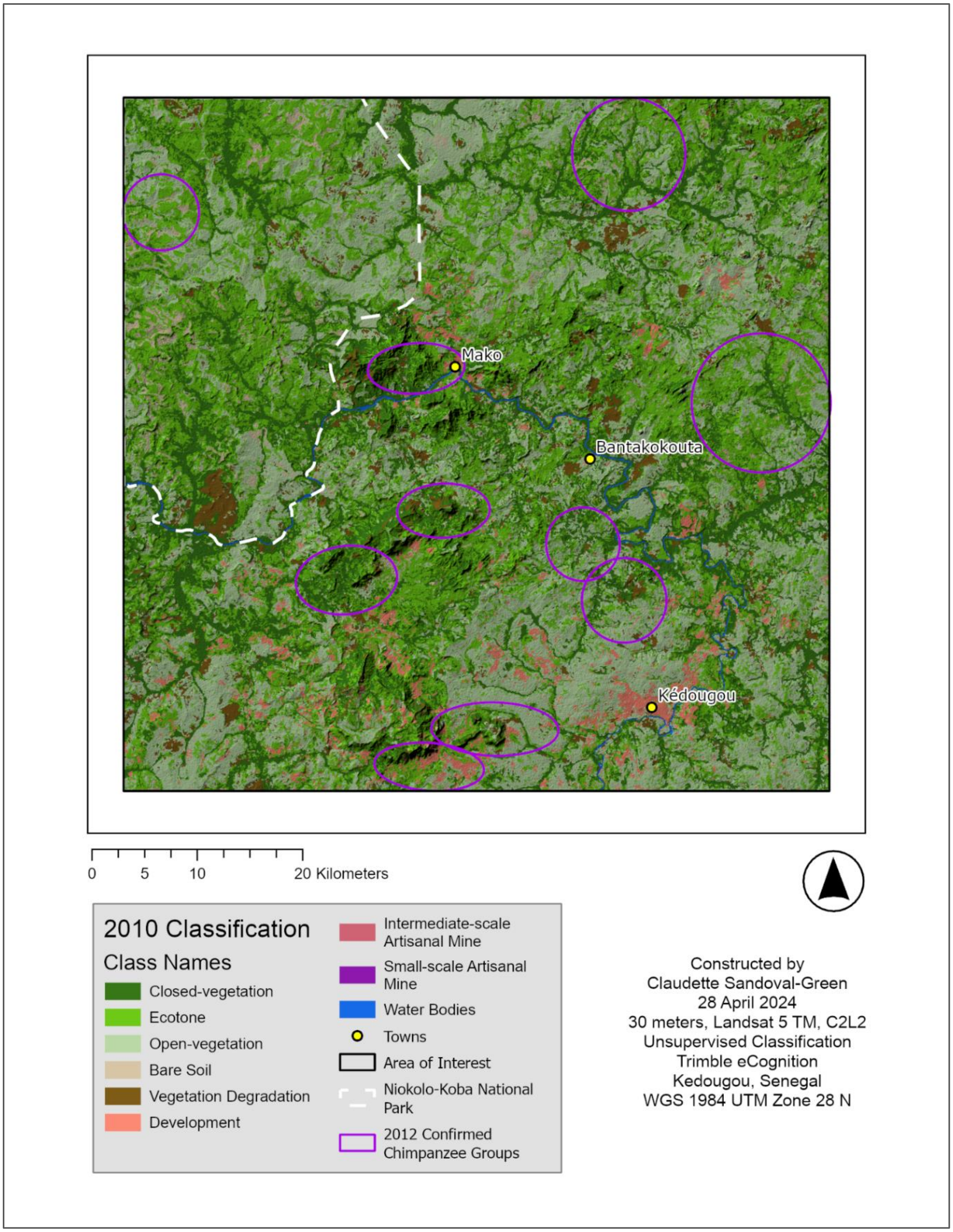


Figure 39. The 2010 Classification for the area of interest in Kedougou, Senegal.

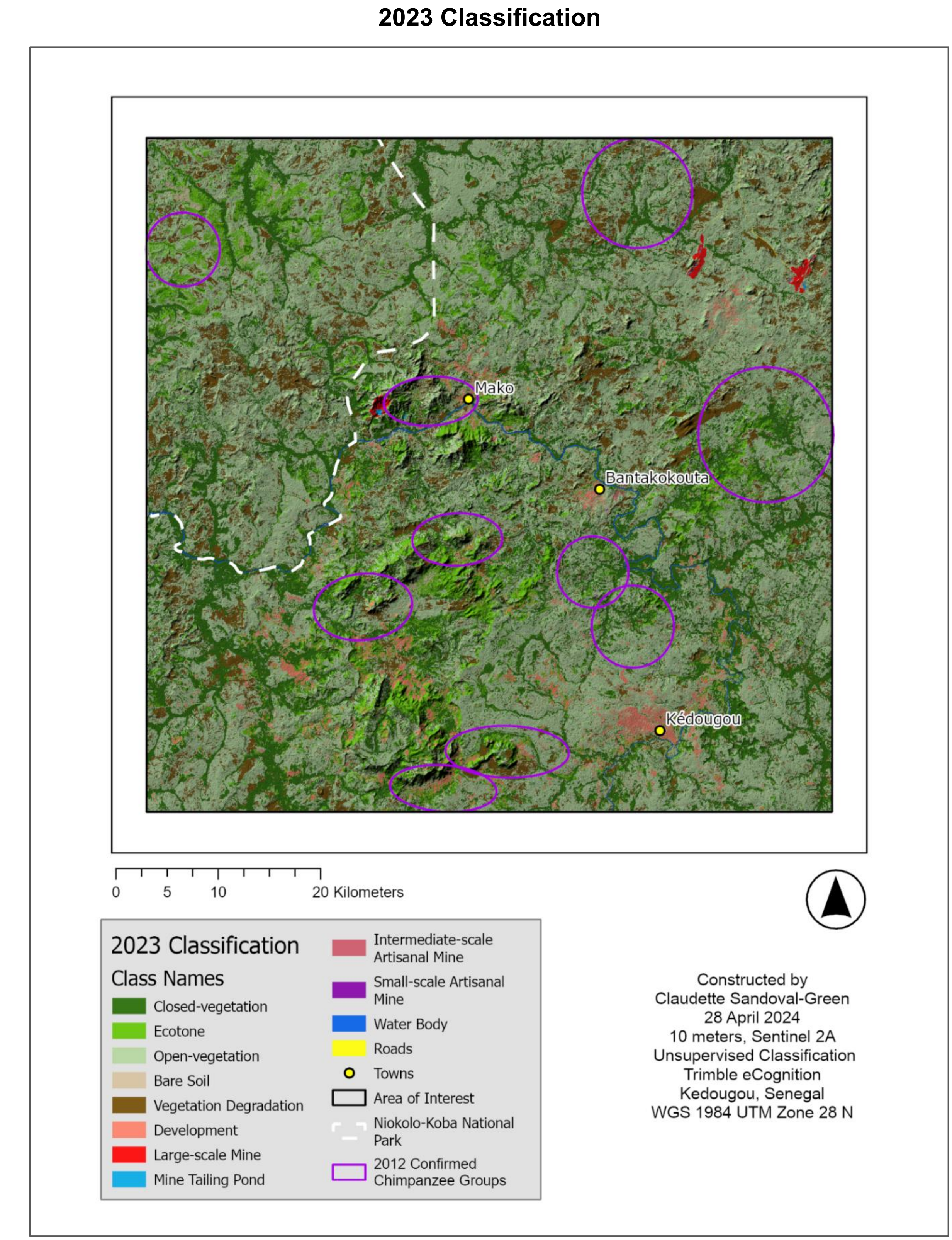


Figure 40. The 2023 Classification for the area of interest in Kedougou, Senegal.

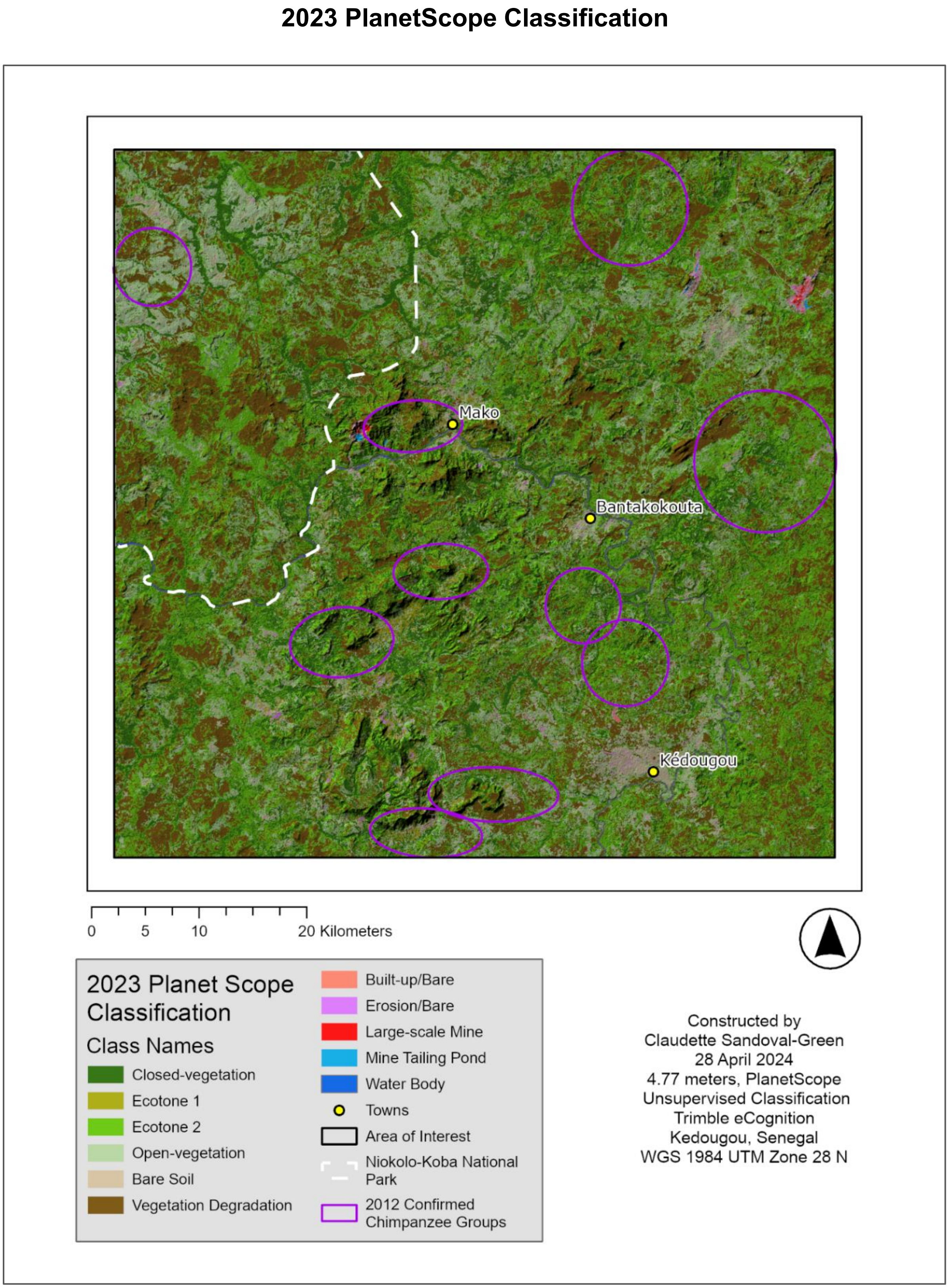


Figure 41. The 2023 PlanetScope Classification for the area of interest in Kedougou, Senegal.

6. REFERENCES

Allan, C. (2015, April 14). *What is Placer Gold Mining?* Retrieved from National Parks Service: https://www.nps.gov/yuch/learn/historyculture/placer-mining.htm

Amponsah-Tawiah, K., & Dartey-Baah, K. (2011). The Mining Industry in Ghana: A Blessing or a Curse. *International Journal of Business and Social Science*, 62-69.

Baldwin, P. (1979). The natural history of the chimpanzee (Pan troglodytes verus) at Mt. Assirik, Senegal (Doctoral dissertation). Stirling, Scotland: University of Stirling.

Birane, N., Mortiz, R., Guedron, S., Ngom, P. M., Pfeifer, H. R., Mall, I., & Pote, J. (2014). Effect of recent artisanal small-scale gold mining on the contamination of surface river sediment: Case of Gambia River, Kedougou region, southern Senegal. *Journal of Geochemical Exploration, 144*, 517-527.

Boyer Ontl, K. M. (2017). Chimpanzees in the Island Of Gold: Impacts of artisanal small-scale gold mining on chimpanzees (Pan troglodytes verus) in Fongoli, Senegal (Doctoral dissertation). Ames, Iowa: Iowa State University. Retrieved from https://lib.dr.iastate.edu/cgi/viewcontent.cgi?article=6601&context=etd

Boyer Ontl, K., & Pruetz, J. D. (2020). Mothers Frequent Caves: Lactation Affects Chimpanzee (Pan troglodytes verus) Cave Use in Southeastern Senegal. *International Journal of Primatology, 41*, 916-935.

Carter, J., Ndiaye, S., Pruetz, J., & McGrew, W. C. (2003). Country Reports: Senegal. In R. Kormos, C. Boesch, M. I. Bakarr, & T. M. Butynski, *West African Chimpanzees: status survey and conservation action plan* (pp. 31-50). Gland, Switzerland: IUCN.

Central Intelligence Agency. (2014). Retrieved from The World Factbook: Senegal: https://web.archive.org/web/20140626170658/https://www.cia.gov/library/publications/the-world-factbook/geos/sg.html

Central Intelligence Agency. (2023). Retrieved from The World Factbook: Senegal: https://www.cia.gov/the-world-factbook/countries/senegal/

CILSS, USGS, & USAID. (2016). *Bioclimactic Regions Map*. Retrieved from West Africa: Land Use and Land Cover Dynamics: https://eros.usgs.gov/westafrica/node/147

Congalton, R. G., & Green, K. (2019). *Assessing the Accuracy of Remotely Sensed Data: Principals and Practices.* Boca Raton: CRC Press.

Data Commons: Place Explorer. (n.d.). Retrieved from Senegal: https://datacommons.org/place/country/SEN#

Down, C. G., & Stocks, J. (1978). *Environmental Impact of Mining.* Barking, Essex, England: Science Publisher Ltd.

Edwards, D. P., Sloan, S., Weng, L., Dirks, P., Sayer, J., & Laurance, W. F. (2014). Mining and the African Environment. *Conservation Letters, 7*(3), 302-311.

European Space Agency: Copurnicus. (2023, December 27). Sentinel-2 L2A. Retrieved from https://docs.sentinel-hub.com/api/latest/data/sentinel-2-l2a/

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., . . . Michaelsen, J. (2015). The climate hazards infrared precipitation with stations - a new environmental record for monitoring extremes. *Scientific Data, 2*(1), 1-21.

Gerson, J. R., Driscoll, C. T., Hsu-Kim, H., & Bernhardt, E. S. (2018). Senegalese artisanal gold mining leads to elevated total mercury and methylmercury concentrations in soils, sediments and rivers. *Elementa Science of the Anthropocene, 6*(11). doi:https://doi.org/10.1525/elementa.274

Geward, J. B. (2010). *Gold The True Motor Of West African History: An Overview Of The Importance Of Gold In West Africa And Its Relations With The Wider World*. Retrieved from Rozenberg Quarterly The Magazine: http://rozenbergquarterly.com/gold-the-true-motor-of-west-african-history-an-overview-of-the-importance-of-gold-in-west-africa-and-its-relations-with-the-wider-world-2/

Heinicke, S., Mundry, R., Boesch, C., Amarasekaran, B., & Barrie, A. (2019). Advancing conservation planning for western chimpanzees using IUCN SS A.P.E.S. o the case of taxon-specific database. *Environmental Research Letters, 14*(064001). doi:https://doi.org/10.1088/1748-9326/ab1379

Hruschka, F., & Echavarria, C. (2011). *Series on Responsible ASM No. 3: Rock-Solid Chances for Responsible Artisanal Mining.* Medellin, Colombia: Alliance for Responsible Mining, ARM.

Humle, T., Boesch, C., Campbell, G., Junker, J., Koops, K., Kuehl, H., & Sop, T. (2016). *IUCN Red List: Western Chimpanzee, Pan troglodytes ssp. verus (errata version published in 2016)*. doi:http://dx.doi.org/10.2305/IUCN.UK.2016-2.RLTS.T15935A17989872.en

Koops, K., McGrew, W. C., de Vries, H., & Matsuzawa, T. (2012). Nest-Building by Chimpanzees (Pan troglodytes verus) at Seringbara, Nimba Mountains: Antipredation, Thermoregulation, and Antivector Hypothese. *International Journal of Primatology, 33*, 356-380.

Kormos, R., Boech, C., Bakarr, M., & Butynski, T. (2003). *IUCN/SSC Primate Specialist Group: West African Chimpanzees. Status Survey and Conservation Action Plan.* Gland, Switzerland, Cambridge: IUCN.

Kuhl, H. S., Sop, T., Williamson, E. A., Mundry, R., Brugiere, D., Campbell, G., . . . Boesch, C. (2017). The Critically Endangered western chimpanzee delines 80%. *The American Journal of Primatology, 79*(9), e22681.

Lindshied, S., Danielson, B. J., Rothman, J. M., & Pruetz, J. D. (2017). Feeding in fear? How adult male western chimpanzees (Pan troglodytes verus) adjust to predation and savanna habitat pressures. *American Journal of Physical Antrhopology, 163*(3), 480-496.

Lindshield, S., Hernandez-Aguilar, R. A., Korstjens, A. H., Marchant, L. F., Narat, V., Ndiaye, P. I., . . . Yoshikawa, M. (2021). Chimpanzees (Pan troglodytes) in savanna landscapes. *Evolutionary Anthropology: Issues, News, and Reviews, 30*(6), 399-420. doi:DOI: 10.1002/evan.21924

McGrew, W. (2010). In search of the last common ancestor: new findings on wild chimpanzees. *Philosophical Transactions of the Royal Society B: Biological Sciences, 365*(1556), 3267-3276.

McGrew, W. C., Baldwin, P. J., & Tutin, C. E. (1981). Chimpanzees in a Hot, Dry and Open Habitat: Mt. Assirik, Senegal, West Africa. *Journal of Human Evolution, 10*(3), 227-244.

McGrew, W. C., Pruetz, J. D., & Fulton, S. J. (2005). Chimpanzees Use Tools to Harvest Social Insects at Fongoli, Senegal. *Folia Primatologica, 76*, 222-226.

Micheletti, K. (2018). Influence of human disturbance on Western Chimpanzee (Pan troglodytes verus) nesting behavior in a savanna mosaic habitat, southeastern Senegal. *Master's Thesis, Iowa State University*.

Mildrexler, D. J., Zhao, M., & Running, S. W. (2011). A global comparison between station air temperatures and MODIS land surface temperatures reveals the cooling role of forests. *Journal of Geophysical Research, 116*, 1-15. doi:doi:10.1029/2010JG001486

Mulroy, T. (2008). *Senegal.* Broomall, PA, US: Mason Crest.

NASA JPL. (2013). NASA Shuttle Radar Topography Mission Global 1 arc second number [Data set]. NASA EOSDIS Land Processes Distributed Active Archive Center. doi: https://doi.org/10.5067/MEaSUREs/SRTM/SRTMGL1N.003

Ndiaye, P. I., Badji, L., Lindshield, S. M., & Pruetz, J. D. (2018). Nest-Building Behaviour by Chimpanzees (Pan troglodytes verus) in the Non-Protected Area of Diaguiri (Kedougou, Senegal): Implications for Conservation. *Folia Primatol, 89*, 316-326.

Ndiaye, P. I., Lindshield, S. M., Badji, L., Pacheco, L., Wessling, E. G., Boyer, K. M., & Pruetz, J. D. (2018). Survey of Chimpanzees (Pan troglodytes verus) outside protected areas in southeastern Senegal. *African Journal of Wildlife Research, 48*(1). doi:https://doi.org/10.3957/056.048.013007

Ndiaye, Y. H., Ndiaye, P. I., Lindshield, S. M., & Pruetz, J. D. (2024). Updating Chimpanzee Nesting Data at Mount Assirik (Niokolo Koba National Park, Senegal: Implications for Conservation. *Animals, 14*(553).

Planet Team. (2017). Planet Application Program Interface: In Space for Life on Earth. San Francisco, CA. Retrieved from https://api.planet.com/

Pruetz, J. D. (2007). Evidence of cave use by savanna chimpanzees (Pan troglodytes verus) at Fongoli, Senegal: implications for thermoregulatory behavior. *Primates, 48*(4), 316-319.

Pruetz, J. D., & Bertolani, P. (2009). Chimpanzee (Pan troglodytes verus) behavioral responses to stresses associated with living in a savanna-mosaic environment: implications for hominin adaptations to open habitats. *PaleoAnthropology*, 252-262.

Robertson, M., & Peters, L. (2016). West African Goldfields. *Episodes: Journal of International Geosciences, 39*(2), 155-176. doi:https://doi.org/10.18814/epiiugs/2016/v39i2/95773

Senegal - Subnational Administrative Boundaries. (2018, November). Retrieved from Humanitarian Data Exchange: https://data.humdata.org/dataset/cod-ab-sen?

Soil and Terrain Database (SOTER) for Senegal and the Gambia . (2022). Retrieved from Ag Datahub: https://data.moa.gov.et/dataset/soil-and-terrain-database-soter-for-senegal-and-the-gambia

Sylla, S. F., Ndiaye, P. I., Lindshield, S. M., Bogart, S. L., & Pruetz, J. D. (2022). The Western Chimpanzee (Pan troglodytes verus) in the Antenna Zone (Niokolo Koba National Park, Senegal): Nesting Ecology and Sympatirics with Other Animals. *Applied Ecology and Environmental Research, 20*(3), 26632681.

Taylor, C. D., Schulz, K. J., Doebrich, J. L., Orris, G. J., Denning, P. D., & Kirschbaum, M. J. (2009). *Geology and Nonfuel Mineral Deposits of Africa and the Middle East.* U.S. Department of Interior , U.S. Geological Survey. Reston: U.S. Geological Survey.

Trimble Germany GmbH. (2021). Trimble Documentation eCognition Developer 10.3 Reference Book. Munich, Germany: Trimble Germany GmbH.

U.S. Geological Survery. (2000, December 19). Landsat 7 ETM Collection 2 Level 1 Tier 1. doi:https://doi.org/10.5066/P9C7I13B

U.S. Geological Survey. (1988, December 10). Landsat 5 TM Collection 2 Level 2 Tier 1. doi:https://doi.org/10.5066/P9IAXOVV

U.S. Geological Survey. (2000, December 19). Landsat 7 ETM Collection 2 Level 2 Tier 1. doi:https://doi.org/10.5066/P9C7I13B

U.S. Geological Survey. (2010, December 23). Landsat 5 TM Collection 2 Level 2 Tier 1. doi:https://doi.org/10.5066/P9IAXOVV

United States Census Bureau. (2020). Retrieved from South Dakota: https://data.census.gov/profile?g=040XX00US46

Wan, Z., Hook, S., & Hulley, G. (2021). MODIS/Terra Land Surface Temperature/Emissivity Daily L3 Global 1km SIN Grid V061 [Data set]. NASA EOSDIS Land Processes Distributed Active Archive Center. doi:https://doi.org/10.5067/MODIS/MOD11A1.061

Wessling, E., Humle, T., Heinicke, S., Hockings, K., Byler, D., & Williams, E. A. (2020). *Regional action plan for the conservation of western chimpanzees (Pan troglodytes verus) 2020-2030.* Gland, Switzerland: International Union for Conservation of Nature and Natural Resources.

We need another and wiser and perhaps a more mystical concept of animals. Removed from universal nature, and living by complicated artifice, man in civilization surveys the creature through the glass of his knowledge and sees thereby a feather magnified and the whole image in distortion. We patronize them for their incompleteness, for their tragic fate of having taken form so far below ourselves. And therein we err, and greatly err. For the animal shall not be measured by man. In a world older and more complete than ours they move finished and complete, gifted with extensions of the senses we have lost or never attained, living by voices we shall never hear. They are not brethren, they are not underlings; **they are other nations**, caught with ourselves in the net of life and time, fellow prisoners of the splendor and travail of the earth.

— Henry Beston, *The Outermost House*