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Iona Ecological Conservation
Utilizing Earth Observations to Understand Landscape Patterns and Assist in Wildlife Management in Iona National Park, Angola

DEVELOP Technical Report
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1. Abstract

Following the end of the Angolan civil war in 2002, human and livestock populations have increased exponentially within Iona National Park. An ongoing drought since 2017 has brought these people and livestock into increasing competition with local wildlife for resources – highlighting a conservation challenge that will become more entrenched as the effects of anthropogenic climate change increase. In 2019, African Parks began co-managing Iona National Park in Angola with the Angolan government, hoping to enact scientifically grounded management strategies to meet this challenge. To accomplish this, African Parks needed contemporary and historic information on the spatial distribution of landcover types within Iona and adjacent areas. We constructed and applied a Random Forest classifier in Google Earth Engine to multispectral imagery gathered from Landsat 5, 7, 8 and Sentinel-1 and 2 to meet this need. Using the classifier, we generated a time-series of land cover maps between 1990–2023, from which landscape metrics and change detection analysis were calculated to show how certain habitats and formations had changed over time. The resulting maps have producer and user's accuracies above 87% and show four broad landcover regions within the study area. Notably, we observed a decrease in the park's diversity as per the Shannon Diversity Index – an index that considers the richness of classes, as well the evenness of their distribution. A lack of arid specific land cover indices and ground-truthed training data from earlier years limited the accuracy and resolution of our landcover maps. However, this project still demonstrates that Earth observations can be used to form the basis of conservation policy in arid environments, where ground-truth data may be difficult to obtain or non-existent.

Key Terms
Remote sensing, landcover classification, Google Earth Engine, random forest classifier, arid environment, Landsat

2. Introduction

2.1 General Background

Considered one of the "oldest unchanged deserts in the world", the Namib Desert stretches across large swaths of the Angolan, Namibian, and South African coastlines (Fitzsimons, 1961). The desert contains a variety of ecozones such as high dunes, grasslands, wetlands, and mountains and supports several rare species endemic to the region. Iona National Park (INP) in southwest Angola—along with the neighboring Namibe Partial Reserve to the North and Skeleton Coast Park to the South in Namibia—protects a critical piece of the 47,698 km² Transfrontier Conservation Area (TFCA), preserving the northern tip of the Namib desert (SADC, 2024).

The Portuguese colonial government established INP as a game reserve in 1937, but it officially became a national park in 1964; the largest in Angola with 15,150 km² of protected land (Huntley et al., 2019; African Parks, 2024). From the mid-twentieth century to the early twenty-first century, Angola experienced prolonged periods of political insecurity which negatively impacted INP. The Angolan people fought a war for independence between 1961 and 1974, which ended when the colonists left Angola following the deposition of the autocratic regime on mainland Portugal. The resulting power vacuum led the country immediately into civil war in 1975. The conflict between the People's Movement for the Liberation of Angola (MPLA) and the National Union for the Total Independence of Angola (UNITA) culminated in an MPLA victory in 2002 (Thornton et al., 2024). During this tumultuous period, the poaching and bushmeat industries went unchecked, resulting in widespread species loss in INP (Huntley et al., 2019).

Although direct human-wildlife conflict was a major threat during the independence and civil war, human competition now poses an ever-increasing risk to wildlife wellbeing. INP has long been home to a small population of Himba people, along with other tribes (Corbett, 1999). Since 2005, human habitation within the park has grown exponentially, as has the livestock population. Current managers estimate an average of seven livestock individuals for every one wild individual (African Parks, personal communication, 2024). An ongoing drought from 2017 has exacerbated the situation by bringing people, livestock, and wildlife into increasing competition for scarce resources within the park and forcing wildlife into sub-optimal habitats (Huntley, 2017). Future projections on the effects of climate change in the region indicate that this ecological stress and subsequent competition will only become more evident and severe over time.

2.2 Project Partners & Objectives
African Parks, a non-governmental organization which manages and preserves African ecosystems, signed a co-management agreement with the Angola Ministry of Environment (MINAMB) and the National Institute for Biodiversity and Protected Areas (INBAC) in 2019 for the rehabilitation of INP. They seek to protect and ensure Iona's long-term ecological, social, and economic sustainability for both its wildlife and its people amidst the significant challenges facing the park (Oglethorpe et al., 2018). They currently monitor the landscape using ground and aerial wildlife surveys, camera-trapping programs, and perimeter patrols. In addition, they are formalizing a Land Use Plan and would like to consider the possibility of employing remote sensing techniques to inform this process. Our NASA DEVELOP team partnered with the African Parks management team for Iona National Park in Angola to map critical vegetation and landscape change across INP from 1990–2024. The main objectives were to use NASA Earth observations to create land use/land cover (LULC) time series maps to document long-term climate and landscape patterns. These results were essential for understanding the effects of human behavior in the park, the subsequent movements of wildlife, and in developing plans to aid in restoration of the park's biodiversity.

2.4 Study Area and Period
The study area focused on Iona National Park and included the neighboring Namibe Partial Reserve to the north, former hunting grounds, and animal migration routes to capture the core area of this continuous ecosystem. Our study period, between 1990 and the present day, was determined by the availability of cloud free remote sensing data with the earliest dates beginning soon after the launch of Landsat 5 (USGS, 2022).

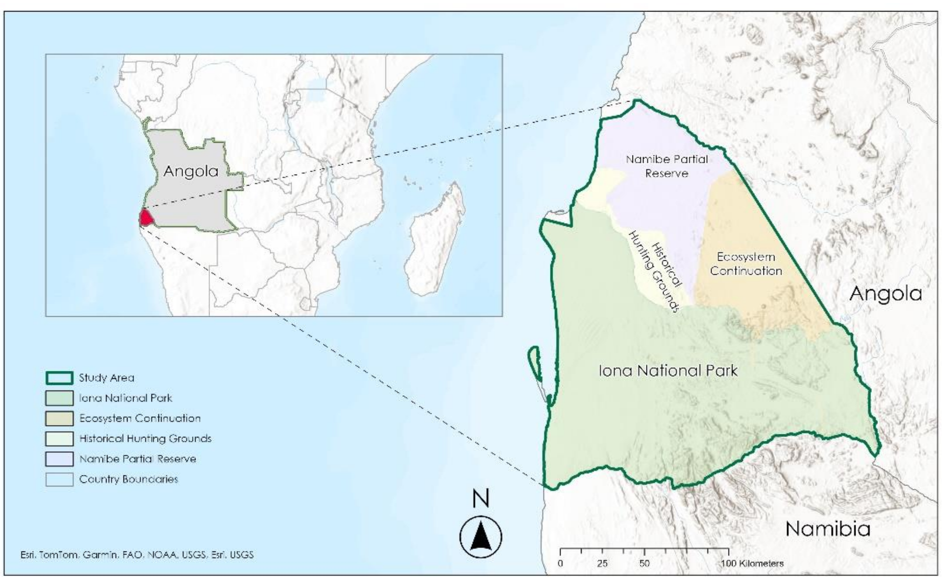

Figure 1. Iona National Park and Surrounding Regions

2.5 Scientific Basis
Maps of LULC changes allow for a detailed understanding of the long-term impacts of natural processes and human activities on landscape patterns (Kadri et al., 2023). Currently, machine learning algorithms, such as Random Forest, are the preferred method to generate LULC classification due to their demonstrated high accuracy in identifying various landcover classes (Belgiu & Drăguţ, 2016). Random Forest is a sophisticated

technique that creates numerous decision trees using bootstrap sampling and random feature selection to reduce overfitting and improve generalization. This method effectively processes high-dimensional remote sensing data, captures complex spectral and topographical patterns, and calculates feature significance. Almalki et al. (2022) utilized remote sensing data in combination with the Random Forest algorithm and change detection analysis to generate historical time series mapping and monitoring vegetation cover changes in arid and semi-arid regions similar to INP. Similarly, Yonaba et al. (2021) applied spatial and transient modeling to analyze LULC dynamics in a Sahelian landscape with a semi-arid climate in northern Burkina Faso, demonstrating the effectiveness of these techniques for understanding landcover changes in diverse environmental conditions. The Google Earth Engine (GEE) cloud computing platform is commonly used to perform LULC analysis as it facilitates large-scale raster data analysis by leveraging Google servers for both processing and storage (Becker et al., 2021). Results from similar research formed the basis for evidence-based conservation and sustainable resource management in arid areas (Amani et al., 2020).

3. Methodology

3.1 Data Acquisition

This study used Earth observation data sources to examine landscape patterns and aid in wildlife management in Iona National Park, Angola (Table 1). Through USGS Earth Explorer, we collected Landsat 5 TM (1984–2013), Landsat 7 ETM+ (1999–2024), and Landsat 8 OLI (2013–present) surface reflectance and top of atmosphere (TOA) reflectance imagery at 30-meter (m) resolution to provide an overview of land cover changes. In the Copernicus Data Space Ecosystem, Sentinel-1 Synthetic Aperture Radar (SAR) data (2014–present) and Sentinel-2 Multi-Spectral Instrument (MSI) data (2015–present) provided higher-resolution ground range detected (GRD), surface reflectance, and top-of-atmosphere (TOA) reflectance imagery at 10-m. Additionally, Shuttle Radar Topography Mission (SRTM) Global 1-arc sec data from Endeavour provided a global elevation dataset with a 30-m resolution. This combination of optical and radar data spanning multiple decades enabled a comprehensive examination of vegetation changes, land use changes, and topographical features in the study area.

Table 1

Earth observations used in this study (USGS 2020; Copernicus Sentinel-1; Copernicus Sentinel-2).

Spacecraft & Sensor	**Products and Processing Level**	**Imagery Used**	**Spatial & Temporal Resolution**
Landsat 5 TM	Collection 2 Tier 1 TOA Reflectance (LANDSAT/LT05/C02/T1_TOA)	1990–1998	30-m, ~16-day revisit
Landsat 7 ETM+	Collection 2 Tier 1 +Real Time TOA Reflectance (LANDSAT/LE07/C02/T1_RT_TOA)	1999–2012	30-m, ~16-day revisit
Landsat 8 OLI	Collection 2 Tier 1 TOA Reflectance (LANDSAT/LC08/C02/T1_TOA)	2013–2016	30-m, ~16-day revisit
Sentinel-1 C-SAR	Ground Range Detected, Level-1 (COPERNICUS/S1_GRD)	2016–2021	10-m, ~5-day revisit
Sentinel-2 MSI	Harmonized Level-2A Surface Reflectance (COPERNICUS/S2_SR_HARMONIZED)	2017–2023	10-m, ~5-day revisit
Endeavour SRTM	NASA SRTM V3 (SRTM Plus) Digital Elevation 30m (USGS/SRTMGL1_003)	2000	1-arc second [equivalent to 30-m], 11-day mission

3.2 Data Processing

Working with published data products, some processing had already been applied to the raw data from the satellite sensors. These include cloud masks and reflection corrections for all products. We used the 15-m panchromatic band to pan-sharpen the Landsat 7 and 8 data to increase the spatial resolution and therefore our ability to discern between similar landcover types (Figure 2; Amini et al., 2022). Utilizing the cloud mask, we created composite images from Landsat 5 and 8 data, as well as Sentinel–1 and 2, for each year of interest, selecting pixels with less than 10% cloud cover. Due to the scanline error in Landsat 7, we utilized two years of data, 2001–2002, to create a cloud-free composite.

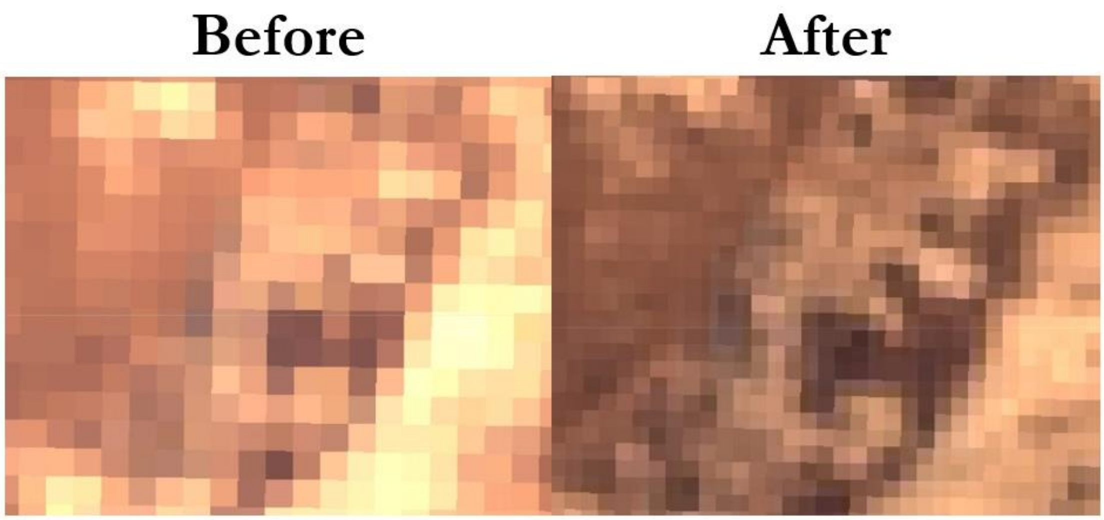

Figure 2. Effects of pan sharpening on image quality and resolution (From Landsat 8 OLI, 2016-2017)

Using the SRTM Digital Elevation Model (DEM) product, we incorporated elevation, aspect, and slope across our study area. We calculated Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Normalized Difference Water Index (NDWI) in GEE for inclusion within the model (Equation 1, Equation 2, Equation 3; McGarigal et al., 2023; Huete, 1988; McFeeters, 1996). We also applied the Distance function in GEE to a shapefile of waterways within Angola, as well as a shapefile of oases locations. Finally, we clipped these data to our study area.

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}} \tag{1}$$

$$\mathrm{SAVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R} + 0.5} \times 1.5 \tag{2}$$

$$\mathrm{NDWI} = \frac{\mathrm{G} - \mathrm{NIR}}{\mathrm{G} + \mathrm{NIR}} \tag{3}$$

Equations 1-3. Indices for the classification model that include near-infrared (NIR), green (G), and red (R) bands (Kriegler et al. 1969).

3.3 Data Analysis

After incorporating the above pre-processing methods, we trained a Random Forest classifier model using 50 decision trees to generate a LULC map for 2023 using Sentinel-1 and 2 data. We generated the training point data using two methods: manual collection and random sampling. African Parks provided us with a ground truth-verified shapefile containing polygons that delineated 24 land cover types within the region. They expressed interest in a classification that included all 24 classes, however, given the spectral resolution of our data, we grouped certain classes together, forming 14 achievable classes (Table 2). Using Google Earth Pro data from 2023, we chose points that specifically targeted vegetated patches within each class's polygon perimeters. We collected at least 70 points per class (excepting Marsh/River), often greatly exceeding this target for classes that cover a larger area within the park (Appendix B1). Our team also explored using random sampling to collect points in ArcGIS Pro, generating 100 random points for each class within their respective polygons.

Table 2

Landcover Classes used in Random Forest Classifier.

Broad Class	Narrow Class
Drainage Lines	Mixed vegetation
	Mopane dominated
	Vachellia dominated
Dunes	Bare
	Oases
	Vegetated
Mountains	Bare
	Vegetated
Plains	Grasslands
	Gravel
	Mopane dominated
Shrublands	Mopane-*Commiphora*
	Vachellia-Commiphora
Marsh/River	Marsh/River

Once collected, we randomly divided the point data, with 80% dedicated to training the model and 20% to validating it. Our team then fed the training split into a random forest classifier. We primarily used our manually collected points, only using random sampling for the Mopane-dominated Drainage Lines and *Vachellia-Commiphora* Shrubland classes that otherwise underperformed on user's accuracies. After a working model had been established for 2023, we populated the rest of our time series using the trained model. We focused on dates that captured important events over the past 30 years, including the end of the civil war and the beginning of the ongoing drought: 1990 using Landsat 5 TM, 2002 using Landsat 7 ETM+, and 2016 using Landsat 8 OLI.

Next, we used several accuracy metrics to assess the accuracy and validity of our results. We calculated Overall Accuracy (OA), User's Accuracy, Producer's Accuracy, Kappa Coefficient, and F1 Score (Table A1). As defined in the appendix, we also calculated landscape metrics on our LULC cover maps to assess how different land cover types had changed over time and the overall relative diversity within the landscape. We used the landscapemetrics library in R to calculate Total Class Area, Mean Patch Size, Number of Patches, and the Patch Cohesion Index for each LULC map (McGarigal et al., 2023). We also calculated the Shannon Diversity Index for the entire study area (Table A2). Additionally, we performed change detection analysis in ArcGIS Pro to analyze how each class changed over time. Using this technique, we determined the specific progression of each pixel between 1990–2023.

4. Results & Discussion

4.1 Analysis of Results

4.1.1 Random Forest Results

Our model successfully produced four LULC maps, comprising the years 1990, 2002, 2016, and 2023, using Earth observation data (Figures 3–6). The confusion matrices indicated that all four maps were accurate overall, in terms of the producer's and user's accuracy (Table 3). In all four maps, four broad regions were visually apparent, on a west to east gradient. On the coast, Dune classes dominated up to the banks of the Curoca River. Plains and Grasslands classes were most prominent on the eastern side of the Curoca River, eventually giving way to *Vachellia* Shrublands. The final region, to the southeast, consisted mostly of Mopane Shrublands and Vegetated Mountains. These trends aligned well with our expectations, based on ground-truth surveys and the raw imagery. However, the model did overclassify Oases, whose abundance and placement do not align with reality. Additionally, the model oscillated between classifying certain areas as Vegetated Mountains and Mopane Shrublands in the southeast.

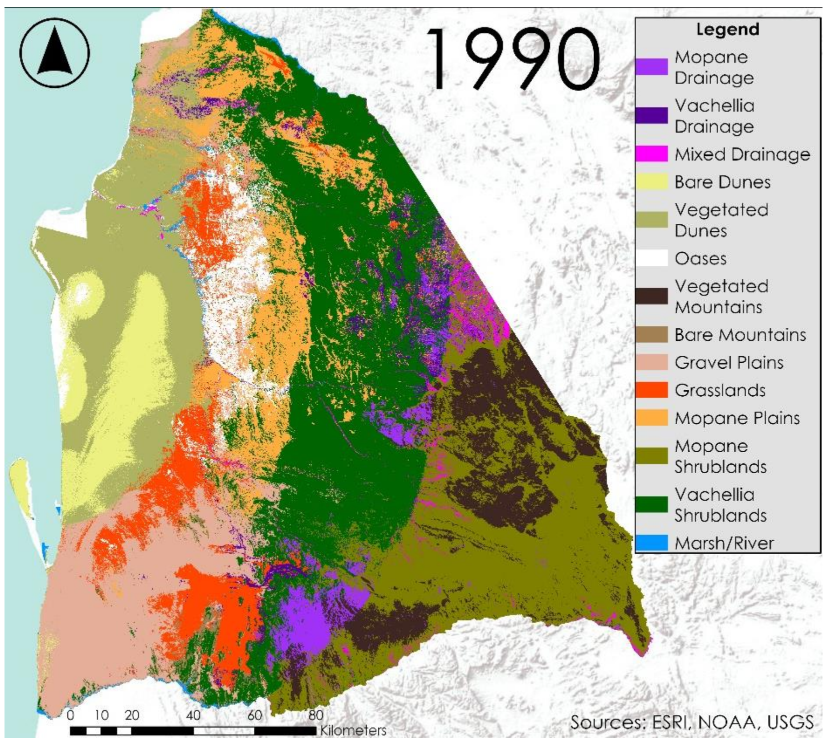

Figure 3. LULC map of 1990, detailing 14 landcover classes.

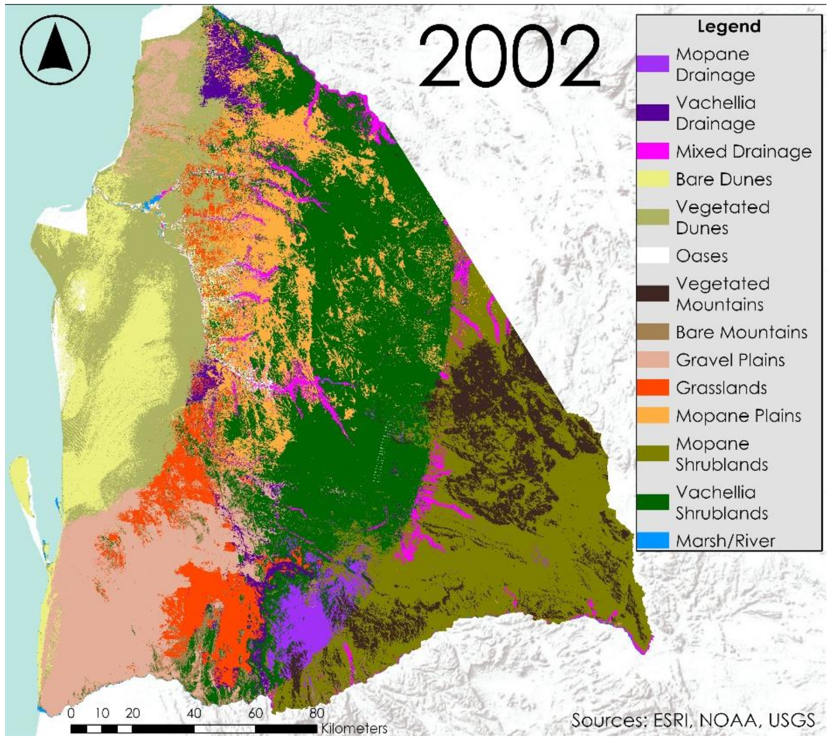

Figure 4. LULC map of 2002, detailing 14 landcover classes.

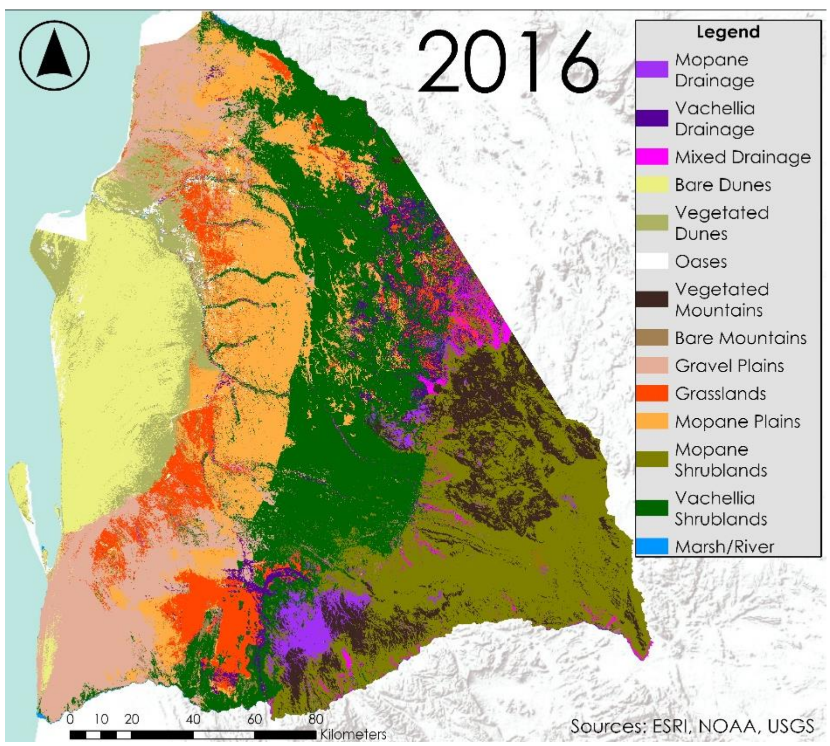

Figure 5. LULC map of 2016, detailing 14 landcover classes.

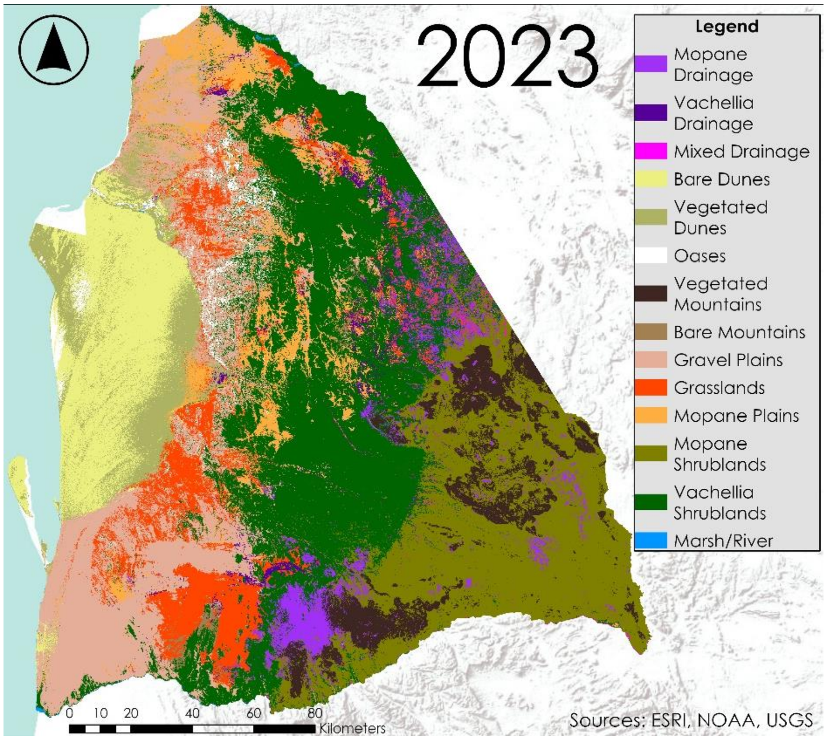

Figure 6. LULC map of 2023, detailing 14 landcover classes.

Table 3

Random Forest Classifier Validation Accuracy.

	1990	2002	2016	2023
Producer's Accuracy	93.8%	94.87%	91.88%	93.65%
User's Accuracy	89.8%	91.02%	88.35%	90.21%
Overall Accuracy	93.5%	94.5%	92.49%	93.91%

4.1.2 Landscape Metrics

Landscape metrics allowed us to quantify several trends over the time series. In terms of total area, Gravel Plains, Bare Dunes, *Vachellia* Shrubland, and Mopane Shrubland increased over the past 30 years (Figure C1). Meanwhile, Vegetated Dunes, Vegetated Mountains, and Marsh/River decreased in total area (Figure C1). For patch size and count, different landcover types had different arrangement patterns. Some, such as *Vachellia* Shrubland, were arranged in smaller, more numerous patches, while others, like Mopane Shrubland, had less numerous, but larger patches (Figures C2-3). Overall, most landcover classes were well connected across the landscape, with all classes scoring higher than 80% for the patch cohesion index (Figure C4). However, there were some differences in connectivity between classes over the past 30 years. All Shrublands and Plains classes were consistently connected with patches of the same type, while all Drainage Lines and Marsh/River classes decreased in connectivity over time (Figure C4). Finally, the diversity of landcover classes, in terms of richness and evenness, decreased slightly but consistently between 1990 and 2023 (Figure 7).

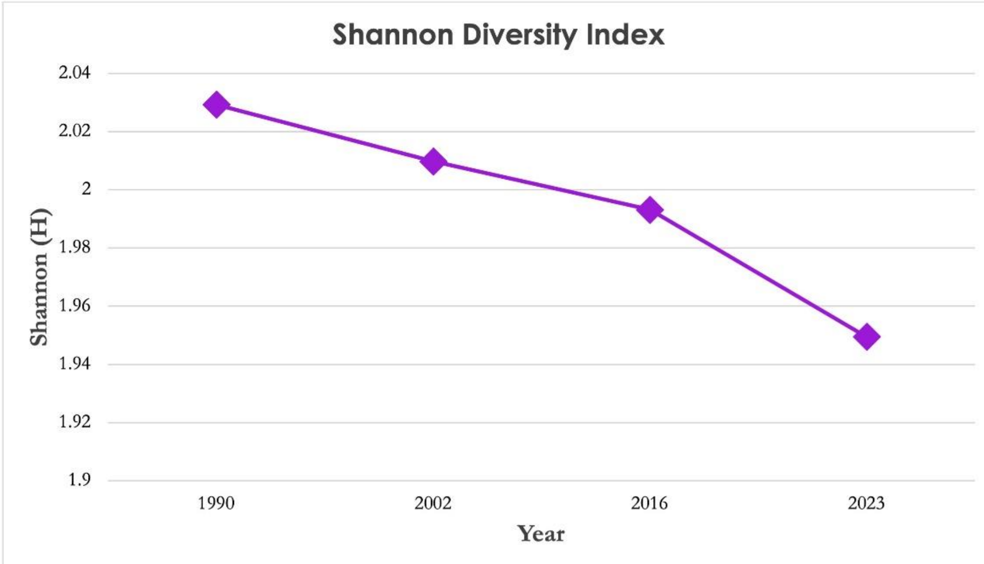

Figure 7. Results from the Shannon Diversity Index.

4.1.3 Change Detection Analysis
Between 1990 and 2002, Mixed Drainage's area increased by 124%, coming mostly from *Vachellia* Shrublands, Mopane Shrublands, and Oases (Figure C5). On the other hand, Oases' area declined by 75%, primarily changing to Mopane Plains, *Vachellia* Shrublands, and Bare Dunes (Figure C5). Between 2002 and 2016, Mopane Plains' area increased by 52%, primarily coming from *Vachellia* Shrubland, Gravel Plains, and *Vachellia* Drainage Lines (Figure C6). In contrast, Vegetated Dunes lost 58% of their total area, which overwhelmingly gave way to Bare Dunes (Figure C6). Finally, between 2016 and 2023, Mopane Drainage's area increased by 106%, coming from Mopane Shrubland, *Vachellia* Drainage, and Grasslands (Figure C7), whereas Mixed Drainage's area decreased by 79%, changing to Mopane Shrubland, *Vachellia* Shrubland, and Gravel Plains (Figure C7).

4.2 Discussion
The four broad regions observed in the LULC time series appear to be the result of underlying geology combined with regional climate trends, as the regions are consistent throughout the 30-year study period and appear predictably on a west to east gradient. The declining trend in biodiversity, as shown in the Shannon Diversity Index, potentially resulted from the increase in human settlement within the study region and worsened over the period of the drought between 2016 and 2023. In terms of specific landcover classes, we also observed a general increase in non-vegetated classes, such as Bare Dunes and Gravel Plains, at the expense of more vegetated classes, such as Vegetated Dunes and Mixed Drainage. We also noted a decrease in the Marsh/River class. We attribute these changes to global warming and the increase in livestock/human populations in the area, which have stressed vegetated habitats with increased temperatures and destruction.

4.3 Errors & Uncertainties
Our study encountered some possible errors. First and foremost, average precipitation during the rainy season ranges a mere 80 mm–160 mm within the park, making it difficult to discern certain vegetation types spectrally (African Parks, personal communication, 2024). Additionally, as the waterways often dry up within several days, collecting training data for waterways and classifying them was often unsuccessful. To remedy this issue, we decided to use a waterway raster within the park provided by the World Wildlife Fund (WWF). This remedy became another uncertainty as we used a collection dated to 2000 for every year in the time series. Finally, we were confident about the validity of our training points for 2023 as we were able to cross check them with African Parks. However, these same points were used to train the model for all dates, potentially misrepresenting past years and leading to errors in earlier maps.

Additionally, we encountered several limitations to our study. There was a lack of cloud-free imagery before 1990 and a lack of multispectral imagery of 30-m resolution or less before 1982. Thus, we were unable to examine the full effects of the Angolan civil war that began in 1975.

4.4 Feasibility & Partner Implementation

This study will help African Parks and the Angolan government understand the condition and trajectory of Iona National Park's habitats over the past 30 years. The time series of land cover maps and landscape metrics will help managers understand long-term patterns of vegetation cover, water availability, and human impacts within the park. This comprehensive, landscape-level analysis will fill critical knowledge gaps that African Parks' current monitoring strategies have not addressed, allowing decision-makers to identify and prioritize conservation actions and develop more targeted management methods. Specifically, they could be used to inform Africa Parks' future Land Use Plan, which aims to identify important habitat restoration locations, arrange sustainable grazing, and solve water management problems.

5. Conclusion

Overall, we concluded that our model demonstrated success in detecting fine-scale land cover types, achieving overall accuracies of 93.5%, 94.5%, 92.5%, and 93.9% for the years 1990, 2002, 2016, and 2023, respectively. A small decline in overall diversity was observed based on the Shannon Diversity Index over our study period, that may pose a threat to both current species and future reintroductions. Looking to the future, this project's workflow with forthcoming satellite imagery can be leveraged to continually monitor the ecological condition of the park and measure the impacts of policy. This data-driven approach will help park managers combine conservation goals with local needs to inform resource usage, climate change adaptability, and sustainable development policies within and surrounding the park.

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7. Glossary

ArcGIS Pro – a software program, provided by ESRI for geospatial professionals, for processing, analyzing, and presenting spatial data.
Commiphora – a genus of plants found across the world that are highly drought tolerant.
Digital Elevation Model (DEM) – a three-dimensional graphic representation of the elevation and terrain at ground level, excluding any objects or structures above ground.
Earth observations – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time.
GEE – Google Earth Engine, a cloud-based program for processing and analyzing spatial data.
Google Earth Pro – a software program that displays remote sensing and aerial imagery of earth overlayed on a globe, featuring different dates and data sources.
INP – Iona National Park.
Kraals – a southern African term for a livestock enclosure whose boundaries are usually formed from local downed vegetation. Can also be used to refer to a village site.

Land use/landcover (LULC) map – a map that identifies different classes of land, determined by the dominant vegetation, water, topography, and artificial structures.
Machine learning – a subsection of computer science that builds and uses artificial intelligence to perform statistical analysis and project results onto unknown data, without intensive human intervention.
Mopane – a species of tree that grows only in arid regions of southern Africa, with distinct butterfly shaped leaves.
Random Forest classifier – a statistical model that assigns classes to objects by averaging the results of decision trees, whose nodes are determined by training data characteristics.
Transfrontier Conservation Area (TFCA) – a region focused on wildlife conservation that includes two or more areas across international borders.
Vachellia – a genus of flowering plants, found across the world.

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9. Appendices

Appendix A: *Statistical Tests and Metrics*

Table A1

Tests of accuracy applied to classifier model

Test	Description
Overall Accuracy	Assesses the overall number of correctly classified sites compared to the total assessed, expressed as a percentage.
Producer's Accuracy	Assesses Type I error/errors of omission out of 100% success rate.
User's Accuracy	Assesses Type II error/errors of commission out of 100% success rate.
Kappa Coefficients	Evaluates the ability of the model to correctly assign classes compared to random assignment. Expressed on a scale between –1 & 1, with negative being significantly worse than random and 1 being significantly better.
F1 Score	Calculates the harmonic mean of the model's precision and recall. Expressed on a scale between 0 and 1, with zero indicating poor performance of precision and recall and 1 indicating perfect performance and balance.

Table A2

Landscape metrics calculated for each LULC map (Hesselbarth, M.H.K. et al. 2019)

Metric	Description
Total Class Area	Calculates the total area of all patches of a given class type, reported in hectares.
Number of Patches	Counts the number of patches of a given class type
Mean Patch Area	Calculates the arithmetic mean of all patches' areas for a given class type, reported in hectares.
Patch Cohesion Index	Calculates the physical connectedness of a given class's patches within a landscape. It is reported on a scale of 0 to 100, with 0 representing a class whose patches are extremely dispersed from one another and 100 representing a class with extremely concentrated patches.
Shannon Diversity Index	Calculates the overall diversity of a landscape using the proportional abundance of each class. It is reported on a scale of 0 to 1, with 0 representing a landscape with a single class and 1 representing the most varied assortment of classes.

Appendix B: *Additional Sample Data*

Table B1
Number of sample points per landcover class

Broad Class	**Narrow Class**	**Number of Sample Points**
Drainage Lines	Mixed vegetation	80
	Mopane dominated	100
	Vachellia dominated	86
Dunes	Bare	72
	Oases	72
	Vegetated	126
Mountains	Bare	102
	Vegetated	101
Plains	Grasslands	155
	Gravel	102
	Mopane dominated	96
Shrublands	Mopane-*Commiphora*	245
	Vachellia-Commiphora	100
Marsh/River	N/A	50
TOTAL		1,487

Appendix C: *Additional Figures*

Figure C1. Total Class Area between 1990-2023

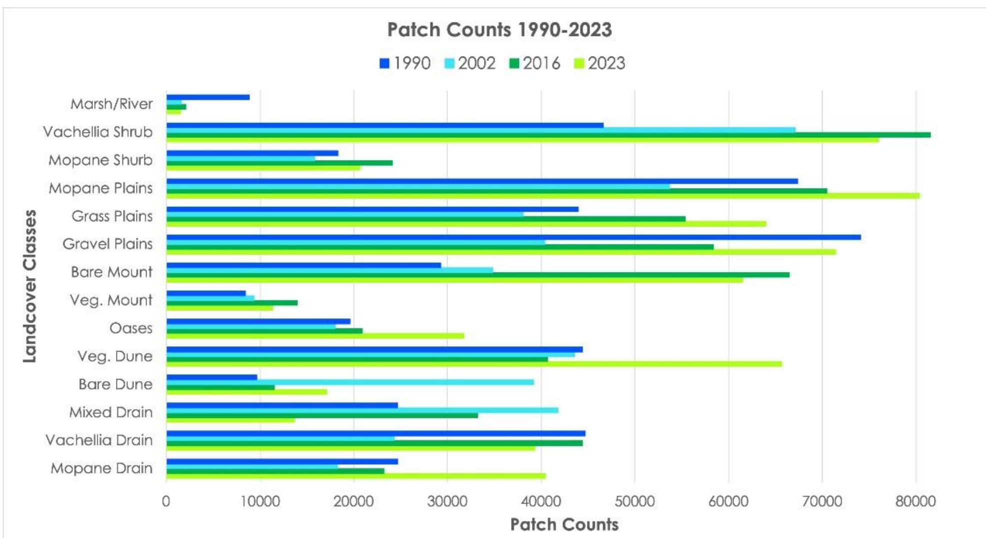

Figure C2. Patch Counts per landcover class

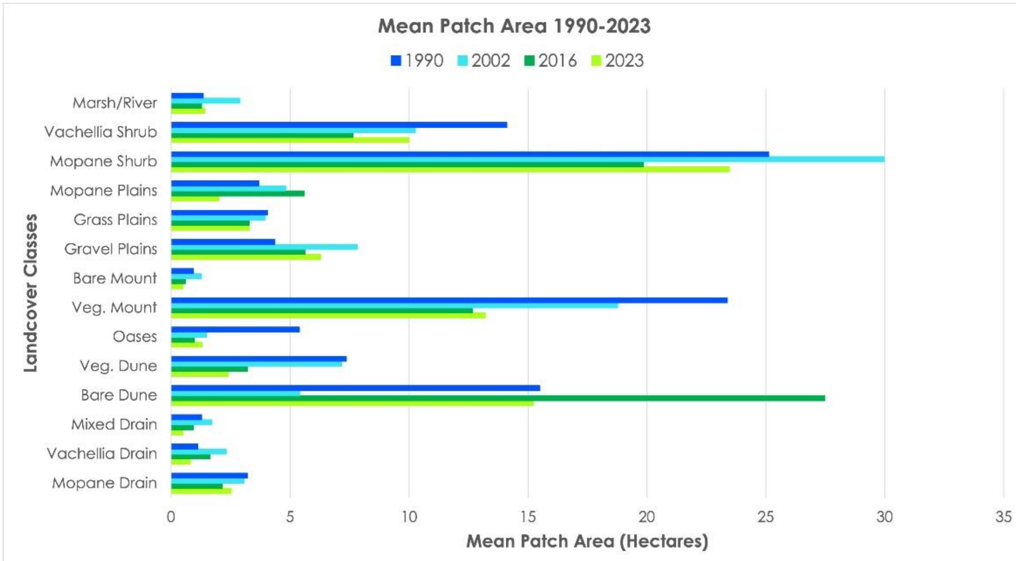

Figure C3. Mean Patch Area (Hectares)

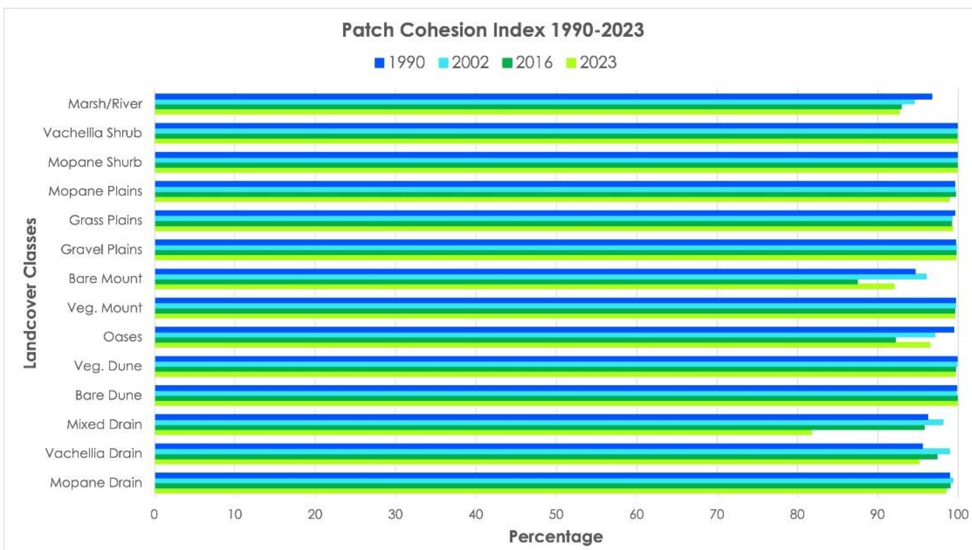

Figure C4. Patch Cohesion Index

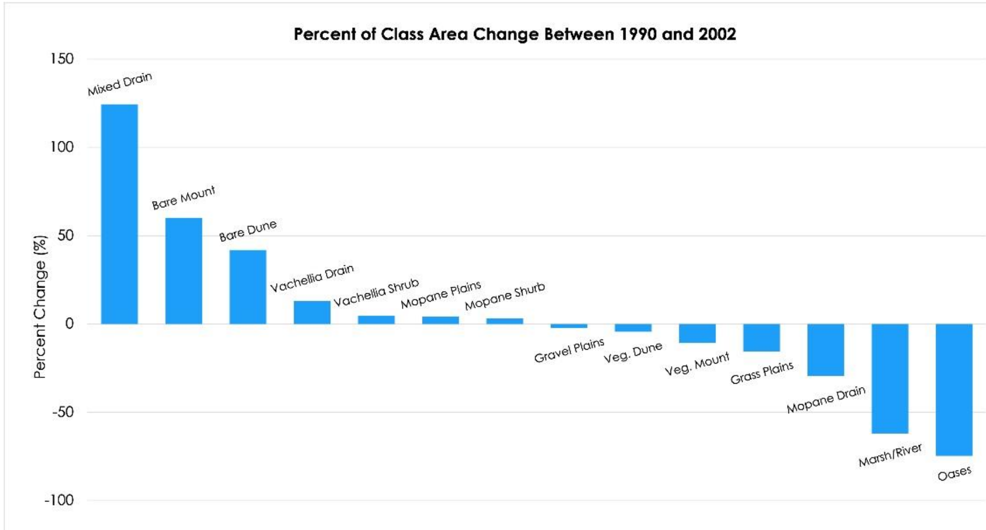

Figure C5. Percent of Class Area Changed Between 1990 – 2002 by Landcover Class

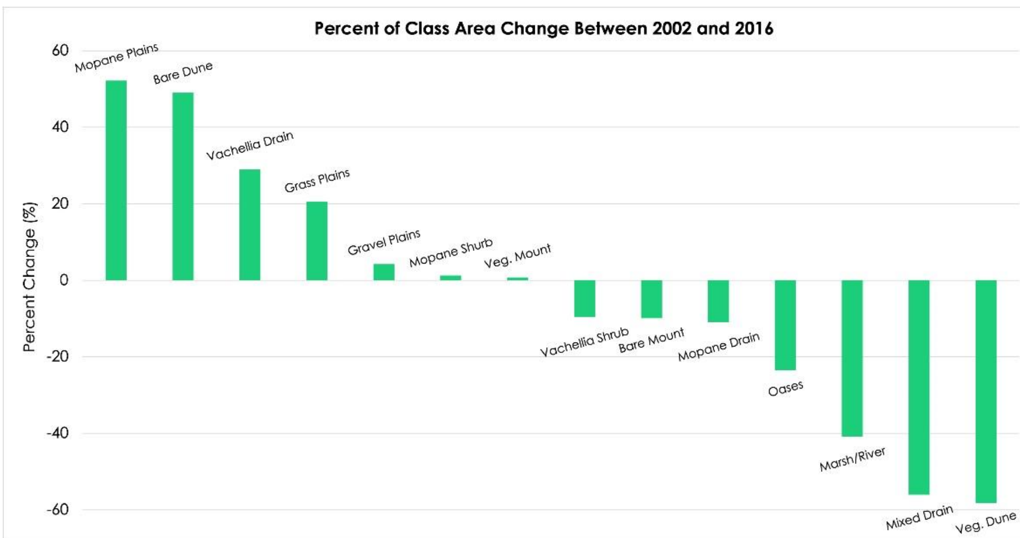

Figure C6. Percent of Class Area Change Between 2002 – 2016 by Landcover Class

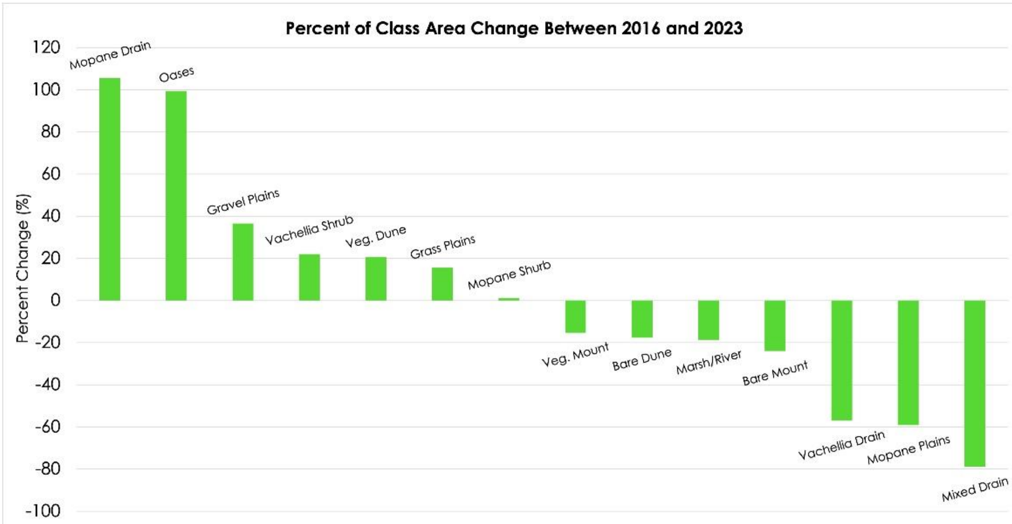

Figure C7. Percent of Class Area Change Between 2016 – 2023 by Landcover Class