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Assessing Wetland Dynamics Using Digital Earth Africa: A Case Study in Zambezi Delta Mozambique

Abstract

Wetlands globally are under increasing pressure causing their decline. Understanding the dynamics ecosystems is important in effective management as wetlands provide important services for the environment and human population. This study aims to develop and demonstrate a workflow for assessing wetland dynamics in Zambezi delta using Digital Earth Africa, a cloud-based Earth Observation (EO) platform that provides access to analysis ready data and tools. The workflow involved integrating Landsat 8 Surface Reflectance, Water Observations from Space (WOfS), and Fractional Cover (FC) accessed using the DE Africa Spatio-temporal Access Catalog (STAC). The Tasseled Cap Wetness (TCW) index, derived from Landsat, is used to detect wet areas, WOfS for identifying open water pixels and FC to identify the vegetation cover classes. A rule-based classification approach is then applied to generate five classes: 'open water,' 'wet,' 'green vegetation,' 'dry vegetation' and 'bare soil.' The classes are quantified as percentage area covered within the study area for the period 2017 to 2024. The results indicate general consistent proportions of wetness and green vegetation over time, both characteristics of wetlands. Seasonal variation is observed for the open water, dry vegetation, and bare soil classes due to varied factors including anthropogenic or precipitation patterns. This study demonstrates the effectiveness of a multi-indicator EO approach for capturing complex wetland dynamics, providing insights for conservation initiatives and other application areas like public health. Future work includes exploring integration of Synthetic Aperture Radar (SAR) data, which can penetrate cloud cover and dense vegetation and is sensitive to moisture, making it suitable in detecting inundation in mixed-signal pixel areas and improving the overall accuracy of the assessment.

Key Words: Digital Earth Africa, Wetland Dynamics, Tasselled Cap Wetness (TCW), Water Observations from Space (WOfS), Fractional Cover (FC).

1. Introduction

Wetlands are one of the most valuable but vulnerable ecosystems, providing several functions such as ecological, hydrological, and socio-economic services. They buffer against floods, sustain biodiversity, and support local livelihoods through fishing and agriculture. Increasingly, wetlands have been threatened by climate change, land use change and change in hydrological patterns which have led to significant changes in wetland extent and composition (Dunn et al., 2023).

Accurate assessment of wetland dynamics is therefore essential for informing conservation initiatives, supporting environmental management, and mitigating public health risks associated with wetland environments. Advances in Earth Observation (EO) technologies and cloud computing enable large-scale monitoring of complex and often inaccessible ecosystems such as wetlands. An example of this is Digital Earth Africa (DE Africa), a cloud based EO platform provides open-source analysis ready data, products and analysis tools for the African continent enabling easy and continuous assessment of wetlands ecosystems (*Digital Earth Africa*, 2025).

This study utilizes DE Africa's platform and datasets, including Tasseled Cap Wetness (TCW) derived from Landsat Surface Reflectance data, Water Observations from Space (WOfS), and Fractional Cover (FC) products accessed via DE Africa Spatio-Temporal Asset Catalog (STAC) API, to analyse wetland dynamics in the Zambezi Delta, a designated Ramsar wetland in Mozambique, over the period 2017 to 2024. The main aim of this study is to show how open-access EO data and cloud-based platforms can be used to quantify and classify temporal changes in wetland extent and composition, providing actionable insights for wetland monitoring and management.

2. Background

2.1 Wetlands

Wetlands are defined as areas of soil covered with water or where water is close to the surface, either all year or at some periods of the year. They are mostly found in humid and moist climatic regions that support their formation (Adeeyo et al., 2022). Wetlands are dynamic and diverse ecosystems that vary in type. They van be broadly classified into marine, coastal, and inland systems and further subdivided into types such as open water, mangrove, swamps (including bogs and fens), riverine and lacustrine, floodplains, and marshes.

Globally, wetlands provide essential functions and services for both the environment and the human population around them. These include, water storage, coastal erosion and land stabilization, groundwater discharge and recharge, nutrient retention, regulation of pollutants and sediments, local climate conditions stabilization and biodiversity support (Adeeyo et al., 2022; Gumbricht et al., 2017).

The Zambezi Delta is a large and complex wetland ecosystem that regulates water flow, supporting rich biodiversity, and sustaining local livelihoods through fisheries and agriculture in the Zambezia and Sofala provinces of Mozambique (*Zambezi Delta | Ramsar Sites Information Service*, 2025). It acts as a natural buffer against floods and droughts and influences the prevalence of water-borne diseases. Given the deltas large area and in some parts inaccessibility, assessing the spatial and temporal dynamics including identifying the land cover types, and extent is important because seasonal and annual changes affect majority of the functions the wetland provide to the surrounding communities.

Despite their importance, wetlands are under increasing pressure from climate change, changing flow and flooding regimes and encroaching human populations leading to a decline in wetland area over time (Dunn et al., 2023). Wetlands respond to these impacts near-instantaneously such as vegetation loss, or lagged responses. Despite decrease in natural wetland area, there has been an increase in artificial wetlands which has also led to an increase the risk of infectious diseases, such as *schistosomiasis* (Bilharzia), *onchocerciasis* and malaria, which have been long associated with wetlands (Zimmerman, 2001).

The decline in natural wetlands, which affects the human population and adjacent environment makes it necessary to quantify and classify the temporal changes in wetland dynamics. The increasing availability of Earth Observation data and platforms such as Digital Earth Africa offers tools and products necessary for wetland dynamics assessment.

2.2 Digital Earth Africa

Digital Earth Africa (DE Africa) is a cloud-based platform founded in 2019 that provides free and open satellite imagery and Earth Observation (EO) data for the African Continent. The goal of the platform is to democratize access of analysis ready EO products to the continent that will support decision making and promote sustainable development outcomes across Africa across areas including food security, water management, sustainable urbanisation, and coastal management.

The platform's mission to process openly accessible and freely available data to produce decision-ready products is done through a suite of tools and infrastructure that include:

- **DE Africa Map:** is an interactive visualisation service that provides users with the tools to visualise satellite images and decision ready data over the African continent.
- **DE Africa Sandbox:** is a cloud-based computational platform that operates through a Jupyter Lab environment. It has free but limited compute resources for development or analysis by users. It is by default loaded with a repository of a notebooks also available on their GitHub that enable users to load, process, analyse and visualize DE Africa datasets and tools. The User Guide is also available for users to explore how to use the DE Africa tools and datasets.
- **DE Africa Metadata Explorer:** is a website that uses the Open Data Cube to inspect metadata for Digital Earth Africa services and datasets including a time-picker and coverage map to help users find datasets.

DE Africa is based on the open data cube infrastructure, and it stores a range of data products on Amazon Web Service's Simple Cloud Storage (S3) with free public access. It also provides a Spatio-Temporal Asset Catalog (STAC) endpoint for listing or searching the metadata, e.g. collection, date and time, bounding box, which is specifically utilized in this study.

2.2.1 Open Data Cube

The Open Data Cube (ODC) is a free, open-source software package that simplifies the management and analysis of large amounts of satellite imagery and other Earth observation data(*Open Data Cube | Open Source*, 2025). Digital Earth Africa foundation is the open data cube infrastructure which allows the platform to handle the huge amount of satellite imagery and other gridded geospatial information, making it easier to access, process, and derive insights from datasets including satellite such as Landsat, Sentinel 1 and 2, and Analysis ready products.

ODC offers the following key features:

- Efficient cataloguing and organization of vast EO datasets along with robust metadata management and data provenance tracking which ensures data transparency and enhances reliability and reproducibility of derived products.

- Supports the integration of multi-sensor data i.e. Landsat and Sentinel data and other gridded datasets.
- Flexible data access through its python-based API that enables high-performance querying and facilitates the development of custom analysis workflows.
- Supports efficient processing of data ranging from localized to continental-scale analyses. It also enables parallel processing for handling petabytes of data through cloud deployment and high-performance clusters.
- Interoperability by adhering to open standards for EO and geospatial data ensuring that data and derived products can be integrated into other systems or software.

Overall, the Open Data Cube aims to allow users to access, process and analyse decades of geographical data to make better-informed decisions in a wide range of applications form environmental issues to resource management.

2.2.2 Spatio-Temporal Asset Catalog (STAC)

STAC is a specification that provides a common structure for describing and cataloging spatiotemporal assets. A *spatiotemporal asset* is any file that represents information about the earth captured in a certain space and time. The STAC specification consists of four components:

- **Items**: represents a single spatiotemporal asset as a GeoJSON feature with datetime and links.
- **Catalog**: a simple, flexible JSON file of links that provides a structure to organize and browse STAC Items.
- **Collection**: an extension of the STAC Catalog with additional information such as the extents, license, keywords, providers, which describe STAC Items that fall within the Collection.
- **API**: a RESTful endpoint that enables search of STAC Items, specified in OpenAPI, following OGC's WFS 3.

This study directly accesses DE Africa EO data using the DE Africa STAC endpoint with the odc-stac module. The odc-stac converts STAC metadata to the Open Data Cube data model. This approach enables loading of STAC items locally or on a cloud service for efficient analysis of EO datasets in python environments.

3. Data & Methods

3.1 Study Area

The study area is on the Zambezi Delta in Mozambique, specifically the Mopeia area as shown in Figure 1. The Zambezi Delta is one of the most diverse and productive river delta system in the world labelled as a global biodiversity conservation hotspot. It covers approximately 3,000km² featuring rivers, floodplains, woodland, swamps and mangrove (*Zambezi Delta | Ramsar Sites Information Service*, 2025)

For this study, the analysis is narrowed to the Mopeia area within the delta due to computational constraints. Mopeia lies within the broader floodplain and is representative of the delta's ecological complexity and dynamic wetland processes. This area is particularly suitable for remote sensing analysis due to its diverse wetland types and significance for regional conservation and resource management.

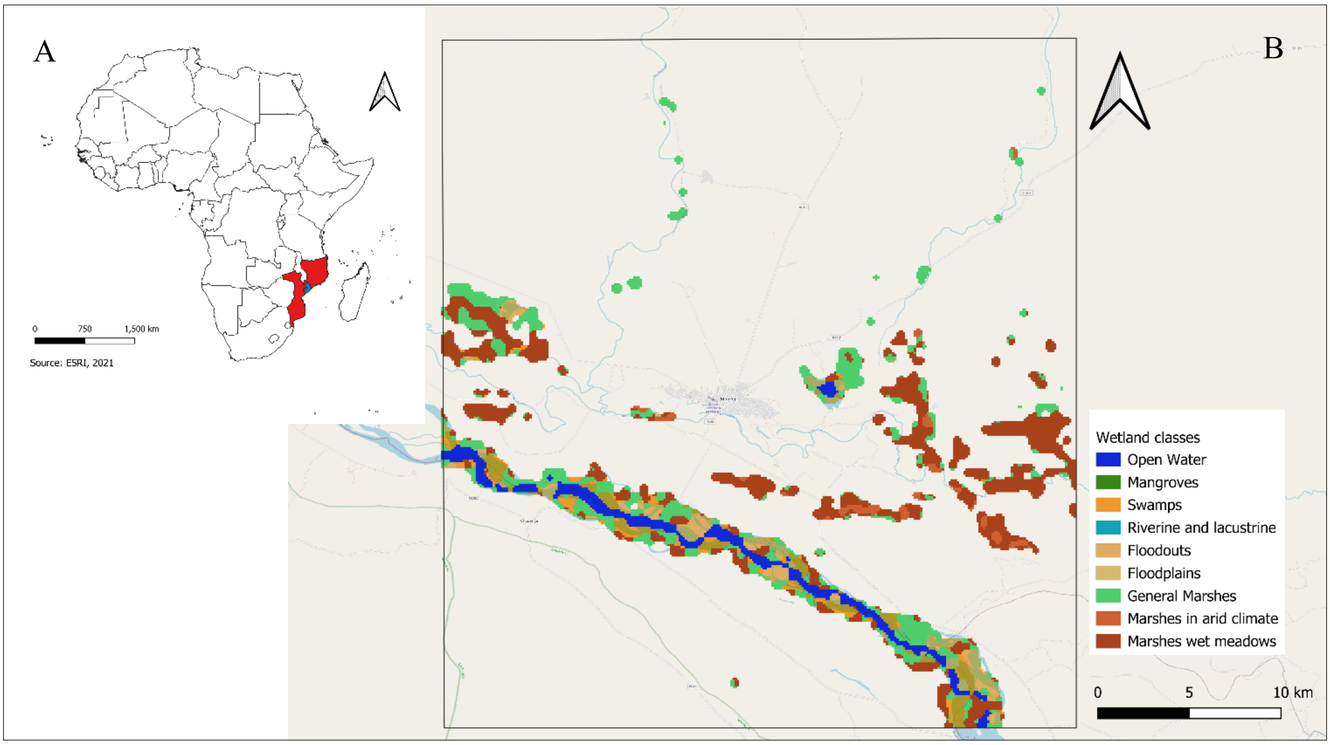

Figure 1: Study area map: a) Zambezi Delta, Mozambique, b) Wetland classes of Mopeia Area within Zambezi delta

3.2 Datasets

This study utilizes Analysis Ready Data provided by Digital Earth Africa, Landsat 8 surface reflectance, Water Observations from Space (WOfS) and Fractional Cover (FC). Wetlands are complex ecosystems that include open water, inundated soil and vegetation which need different datasets to assess dynamics.

3.2.1 Landsat 8 Surface Reflectance

DE Africa provides free and open access to a copy of Landsat Collection 2 Level 2 products over the African continent. These products are produced and provided by the United States Geological Survey (USGS), include Surface Reflectance and Surface Temperature. The DE Africa archive has historical observations from Landsat 5, 7-9 satellites since 1987 onward with a return time of 16 days and regularly updated new acquisitions (Dunn et al., 2023). The long-term, free, and open access to Landsat imagery, enabled by data policy changes since 2008, has significantly advanced scientific analysis and applications, especially for monitoring and understanding land surface changes over large areas (Wulder et al., 2012).

This study utilizes the Landsat 8 Surface reflectance product. Surface reflectance is the fraction of incoming solar radiation that is reflected from Earth's surface. The variations in satellite measured radiance due to atmospheric properties have been corrected for images acquired over the same area at various times are comparable and can be used readily to detect changes on Earth's surface.

The Landsat 8 surface reflectance is used to derive the Tasseled Cap Wetness (TCW) index, a key indicator of surface moisture useful for wetland analysis. The TCW index is calculated using a linear combination of Landsat 8 reflectance bands, following the coefficients developed for the Operational Land Imager (OLI) sensor (Baig et al., 2014). This approach allows for sensitive detection of changes in wetland extent and condition over time.

3.2.2 Water Observations from Space (WOfS)

Water Observations from Space (WOfS) is a data product provided by DE Africa that uses Landsat satellite imagery to provide historical surface water observations of the whole African continent. It shows where water is usually present, where it is rarely observed and where inundation of the surface has been observed by satellite. WOfS algorithm is a decision tree classifier as shown in Figure 2 that identifies unobstructed open water on a per-pixel basis with an accuracy of 98% over open water (Dunn et al., 2023; Mueller et al., 2016).

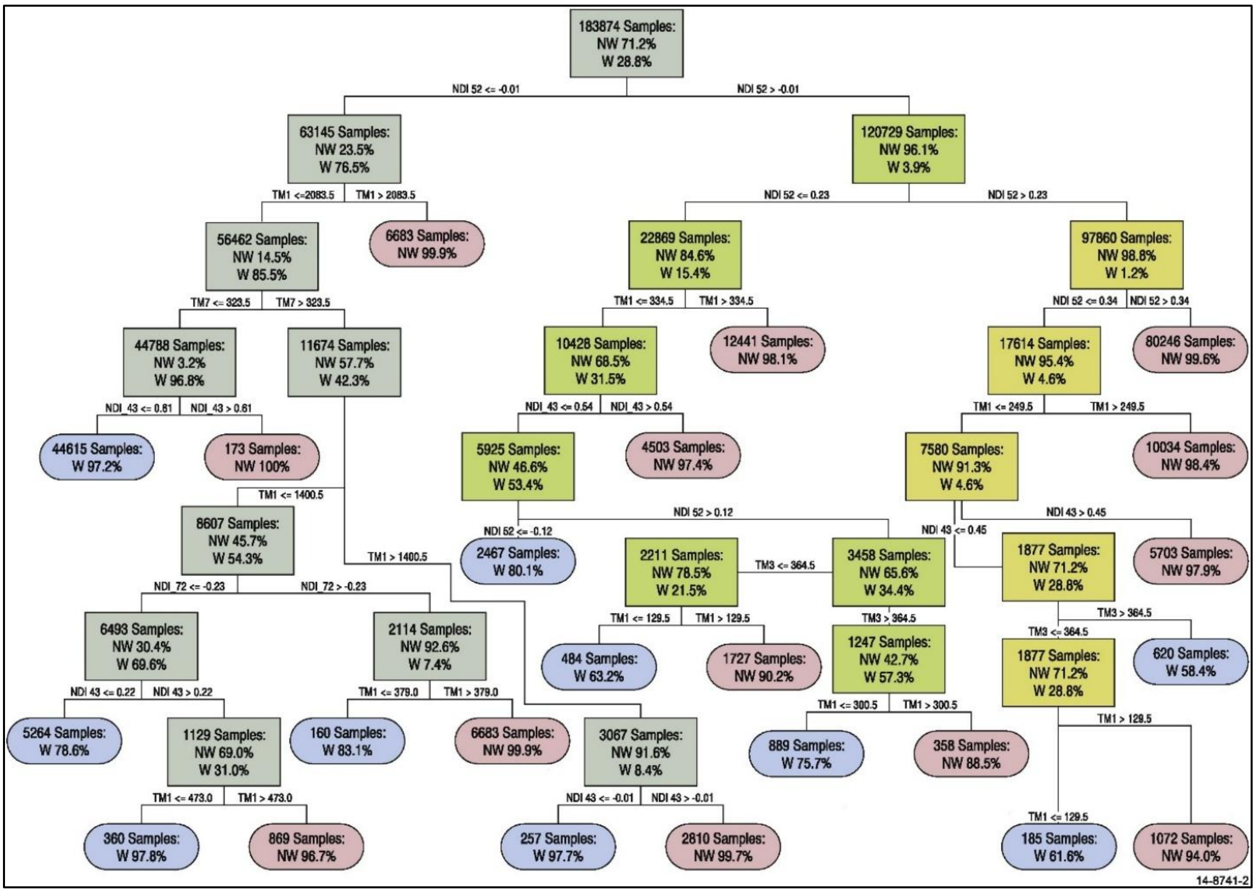

Figure 2: Diagram of the regression tree underlying the water detection classifier.(Mueller et al., 2016)

DE Africa offers several WOfS products for the continent: *WOfS Annual Summary* which gives the ratio of wet to clear observations from each calendar year, *WOfS All-Time Summary* which gives the ratio of wet to clear observations over all time, WOFLs (*WOfS Feature Layers*) which gives pixel-level water and non-water classification generated per scene meaning there is one WOFL for each satellite dataset processed for the occurrence of water.

The WOfS summary products, Annual and All-Time Summaries, are calculated as the ratio of clear wet observations to total clear observations.

$$\boldsymbol{WofS\ ratio} = \frac{\boldsymbol{Number\ of\ clear\ and\ wet\ observations}}{\boldsymbol{Number\ of\ clear\ observations}}$$

This ratio ranges from 0 (never detected as water) to 1 (always detected as water) provides a quantitative metric for assessing the frequency and persistence of surface water at each location (Mueller et al., 2016).

This study utilizes the WOFLs because the data is stored as a bit field, a binary number, where each digit of the number is independently set or not based on the presence (1) or absence (0) of a particular attribute (water, cloud, cloud shadow etc)(*Water Observations from Space (WOfS) — Digital Earth Africa 2021 Documentation*, 2021). In this way, the single decimal value associated to each pixel can provide information on a variety of features of that pixel which is necessary for the temporal assessment of the Zambezi delta wetland dynamics.

3.2.3 Fractional Cover

The Fractional Cover (FC) product from DE Africa provides estimates of the fractions of photosynthetic vegetation (green vegetation), non-photosynthetic vegetation (non-green vegetation) and bare soil for every Landsat pixel. The product uses the vegetation cover algorithm created by the Joint Remote Sensing Research Program (Dunn et al., 2023) providing valuable information for a range of environmental and agricultural applications such as soil erosion monitoring, land surface process modelling, vegetation studies and ecosystem modelling.

The FC algorithm is based on a constrained linear spectral unmixing model, which decomposes the observed reflectance of each pixel into linear combination of three reference endmembers (Scarth, 2011; Schmidt et al., 2010) as shown in (2):

$$\boldsymbol{R_i = f_{green} \cdot R_i^{green} + f_{(non-green)} \cdot R_i^{(non-green)} + f_{bare} \cdot R_i^{bare} + \epsilon}$$

Where R_i is the observed reflectance in band *i*, $R_i^{green}, R_i^{non-green}, R_i^{bare}$ are the endmember reflectance for green vegetation, non-green vegetation, and bare soil, respectively. $f_{green}, f_{non-green}, f_{bare}$ are the fractional covers and ϵ is the residual error.

The fractions are constrained such that:

$$\boldsymbol{f_{green} + f_{(non-green)} + f_{bare} = 1, \quad 0 \leq f \leq 1}$$

The DE Africa FC service has two components: Fractional Cover, which is estimated from each Landsat scene, providing measurements from individual days and the Fractional Cover Annual Summary (Percentiles), which provides 10th, 50th, and 90th percentiles estimated independently for the green vegetation, non-green vegetation, and bare soil fractions observed in each calendar year.

In this study, the individual scene-level Fractional Cover product is utilized for the analysis because it provides information on the terrestrial dynamics of wetlands by tracking the green vegetation, dry vegetation and bare soil allowing us to observe seasonal vegetation cycles over time within a wetland at specific time points.

3.3 Methodology

The methodology used in this study is outlined in Figure 3. The workflow included initial configuration of the working code environment, acquisition of Landsat 8 Surface Reflectance (LS8-SR), WOfS and FC data, preprocessing of the satellite data, computing the relevant indices, generation of the classification types and computing percentage area of each land cover type in the study area, and finally generating wetland dynamics map.

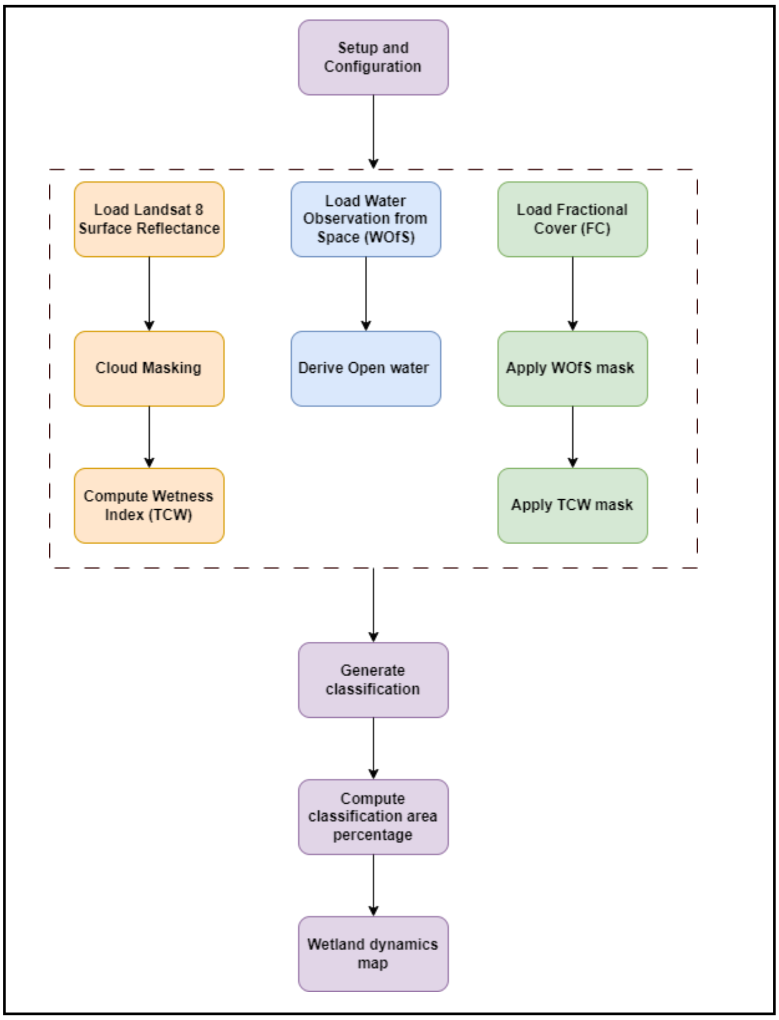

Figure 3: methodology workflow.

3.3.1 Data Acquisition and preprocessing

To access DE Africa datasets an instance of the Open Data Cube is needed. Since the analysis was done outside the DE Africa Sandbox environment, the code environment is configured to access this instance to enable querying and retrieving the required datasets using the *odc-stac* python module. A direct connection is configured to the AWS S3 endpoint to access the DE Africa STAC Catalog as shown in Figure 4.

```python
# configure aws
configure_rio(
    cloud_defaults=True,
    aws={"aws_unsigned": True},
    AWS_s3_ENDPOINT="s3.af-south-1.amazonaws.com",
)

#open STAC
catalog = Client.open("https://explorer.digitalearth.africa/stac")
```

Figure 4 setup and configuration

To acquire the required data, a query is made on the STAC collection for the defined study area and time range 2017 to 2024. The query parameters include the product (ls8-sr, wofs or fc), the time and area of interest, the spectral bands required, coordinate reference system and more depending on the specific product. The data acquired is loaded as an *xarray. Dataset* and this are because DE Africa datasets are stored as multi-dimensional data using the xarray data structure. Xarray is built on NumPy extending its functionality by adding labelled dimensions, coordinates and attributes which is suitable for handling temporal satellite data.

```text
xarray.Dataset
- Dimensions:    (y: 1326, x: 1270, time: 363)
▼ Coordinates:
  y              (y)          float64         -1.97e+06 -1.97e+06 ... -2.01e+06
  x              (x)          float64         7.683e+05 7.683e+05 ... 8.064e+05
  spatial_ref    ()           int32           32636
  time           (time)       datetime64[ns]  2017-01-03T07:41:35.867596 ... 2...
▼ Data variables:
  red            (time, y, x) uint16          dask.array<chunksize=(1, 1326, 1270), meta=np.n...
  green          (time, y, x) uint16          dask.array<chunksize=(1, 1326, 1270), meta=np.n...
  blue           (time, y, x) uint16          dask.array<chunksize=(1, 1326, 1270), meta=np.n...
  nir            (time, y, x) uint16          dask.array<chunksize=(1, 1326, 1270), meta=np.n...
  swir_1         (time, y, x) uint16          dask.array<chunksize=(1, 1326, 1270), meta=np.n...
  swir_2         (time, y, x) uint16          dask.array<chunksize=(1, 1326, 1270), meta=np.n...
  pixel_quality  (time, y, x) uint16          dask.array<chunksize=(1, 1326, 1270), meta=np.n...
► Indexes: (3)
- Attributes: (0)
```

Figure 5: loaded Landsat 8 surface reflectance data

The Landsat 8 data acquired contained pixels with clouds and to avoid skewed analysis results, these are masked out first. This was done by including the *pixel quality* band in the Landsat product query because it holds information about the clouds. These attributes were manually added to the data using the metadata provided by DE Africa. Pixels labelled as clouds, cloud shadow, cirrus and snow/ice are masked out to have cloud free pixels only in the analysis. Finally, the Landsat 8 surface reflectance values were normalized toa range of 0-1 to enable to indices calculation.

3.3.2 Deriving wetland indices.

For this study, key indices outlined below that were either derived or directly accessed from DE Africa are utilized.

Tasseled Cap Wetness (TCW) is a component of the Tasseled Cap Transformation (TCT). TCT is a linear principal component analysis of Landsat imagery that produces three component corresponding to brightness (TCB), greenness (TCG) and wetness (TCW) (Dunn et al., 2023).

TCW is used in this study to identify areas in wetlands that are wet but not identified by the WOfS algorithm as open water. This includes areas of mixed vegetation and water like in palustrine wetlands.

TCW is computed per pixel using the following coefficients specifically for Landsat 8 (Crist, 1985)

$$\boldsymbol{TCW} = (\mathbf{0.1511} \times \boldsymbol{B2}) + (\mathbf{0.1973} \times \boldsymbol{B3}) + (\mathbf{0.3283} \times \boldsymbol{B4}) + (\mathbf{0.3407} \times \boldsymbol{B5}) - (\mathbf{0.7117} \times \boldsymbol{B6}) - (\mathbf{0.4559} \times \boldsymbol{B7})$$

TCW is computed using a DE Africa function, available in the *deafricatools* library, *compute_TCW.* The raw TCW values are used to determine the threshold, using Otsu method, required for the binary classification of 'wet' and 'dry' pixels. The Otsu method separates the classes based on the histogram of the TCW values.

One main challenge of using Landsat data is missing data due to factors like pixels near the swath boundaries which can introduce bias. Therefore, the TCW data is aggregated monthly to get the overall observations of the wetland. The TCW is then masked to the area of interest resulting in a binary mask of 'wet' or 'not-wet' pixels.

As TCW values increase, the pixel is indicative of increasing wetness, with open water typically exhibiting TCW values near and above zero.

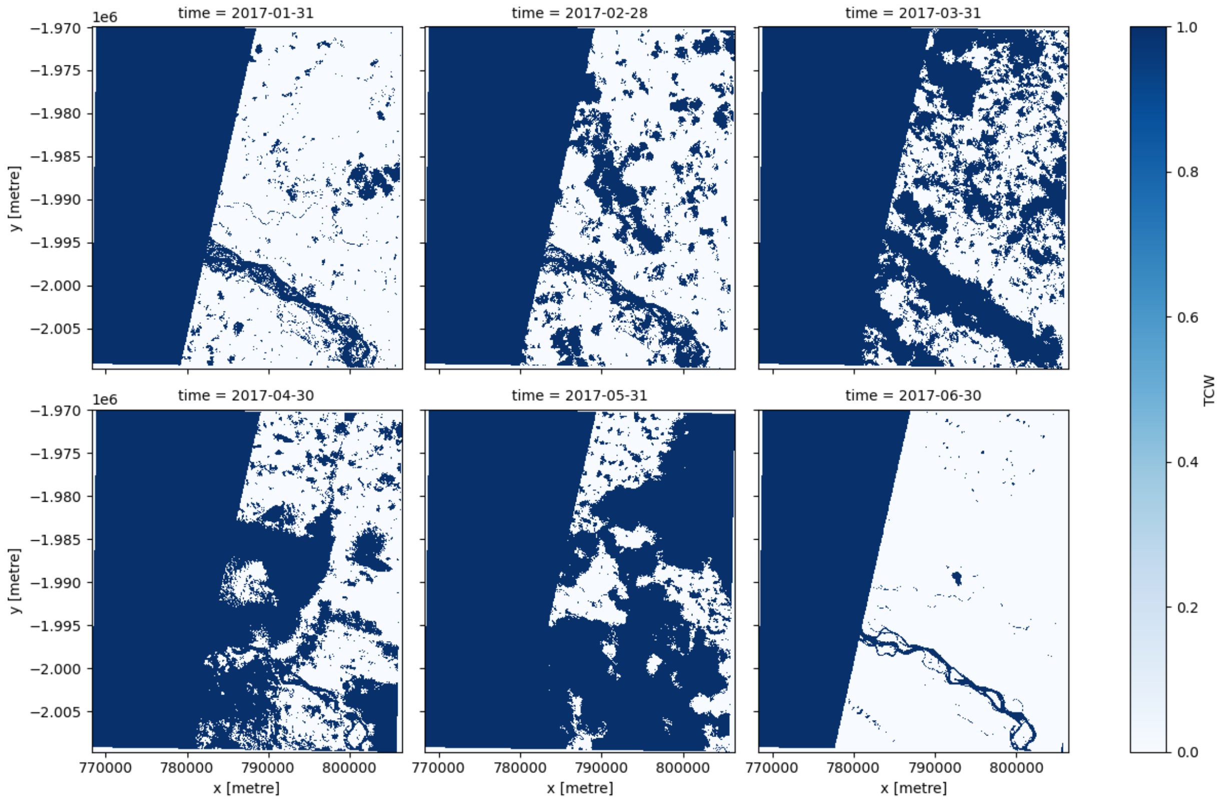

Figure 6: TCW mask result ,6 months example of 2017.

The loaded WOfS Feature Layers provides binary classifications of each pixel. However, due to loading via STAC, the attributes are missing and therefore they are manually added using metadata provided by DE Africa. Having the water band correctly attributed, a wet/dry Boolean mask is created to identify wet pixels with open water pixels is true (value=1) and dry pixels is false (value = 0) as in Figure 6. This is then aggregated monthly then aligned in the time dimension with the TCW data. The mask is then masked to the area of interest to only have open water extent within the area of interest.

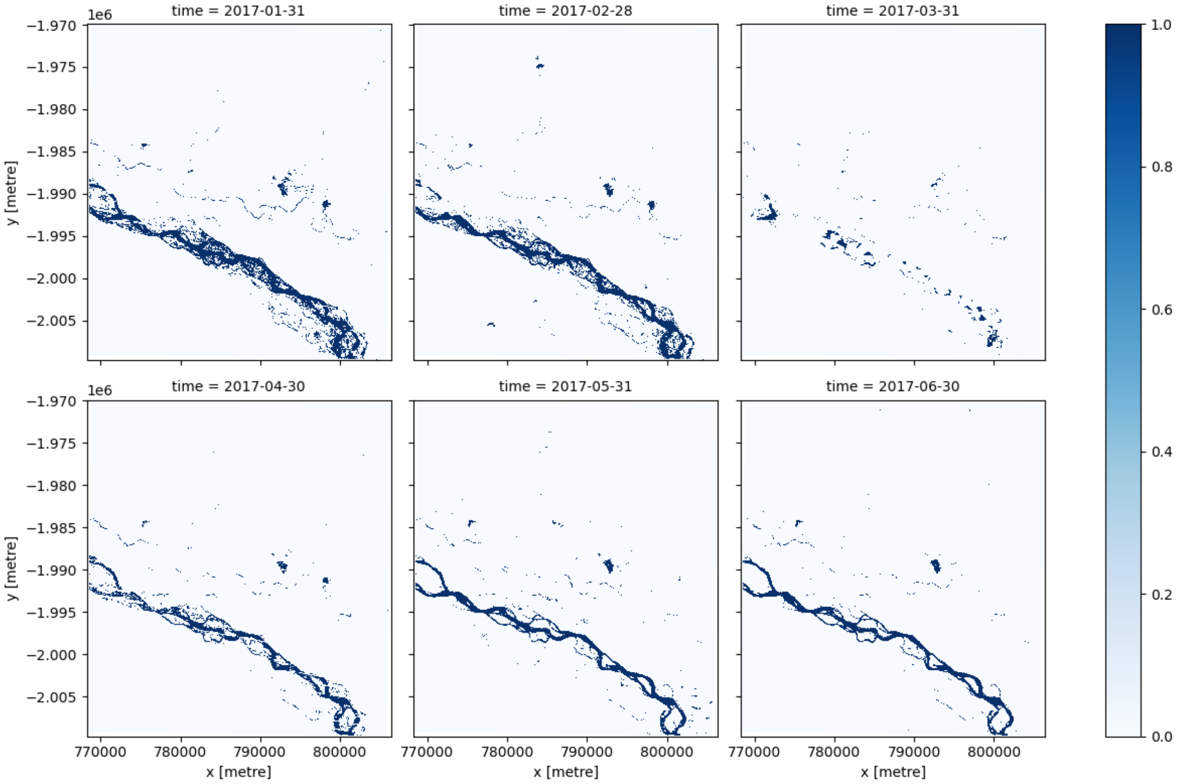

Figure 7: WOfS mask result, 6 months example of the 2017.

To assess vegetation dynamics which is part of the wetland ecosystem, especially in non-inundated areas, the masks derived from TCW and WOfS are applied onto the FC data. This is to allow focus on the vegetation cover type in the FC analysis by removing the open water and wet pixels from the dataset. First, the FC is aggregated monthly, because it also derived from Landsat and to capture the overall vegetation cover it is required. Then the aggregated data is aligned to the similar time dimension as TCW mask. The area of interest mask, TCW mask and the WOfS mask is applied to focus on the desired area of interest and to mask out wet and open water pixels, respectively.

The resulting data is of the fractional cover specific bands only with the brownish tones, green tones and blue tones representing bare soil, green vegetation, and non-green vegetation, respectively.

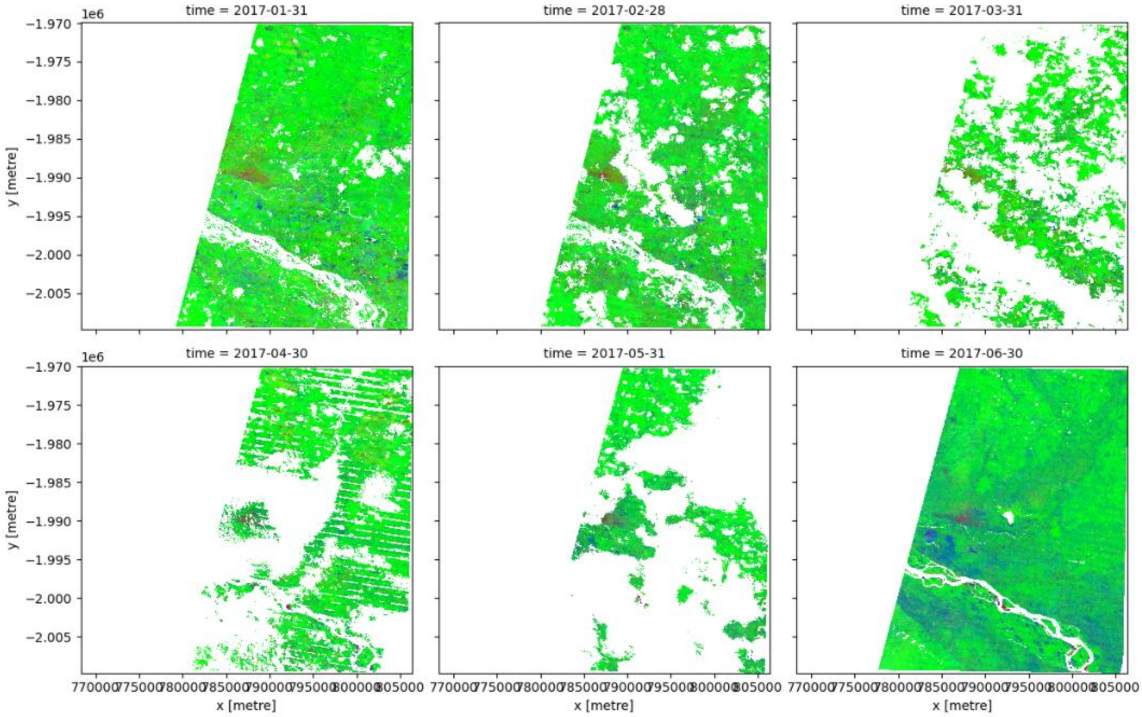

Figure 8: example of monthly FC with TCW and WOfS masked out.

3.3.4 Generating classification.

The process of generating the classification for the wetland area is outlined in Figure 9 below adapted from the Wetland inundation tool from DE Africa. To quantify wetland dynamics, the pixels are classified into the classes 'open water,' 'wet,' and 'green vegetation,' 'dry vegetation,' and 'bare soil.'

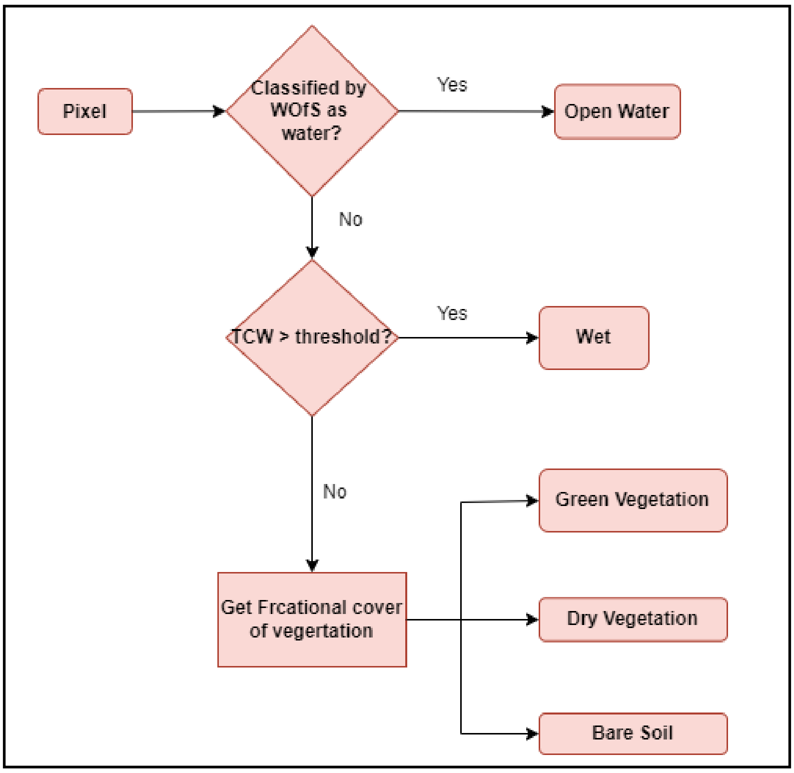

Figure 9: classification workflow.

The WOfS, TCW and FC masks were stacked and the total pixels of the three following a rule-based approach are classified as follows: Pixels classified as water by the WOfS are assigned to the open water class. Pixels thereafter not classified as water but are above the threshold set for TCW are classified as wet. The rest of the pixels are divided into percentages of green vegetation, dry vegetation, and bare soil.

The classified pixels within the polygon for each time step are combined to produce a percentage of the total study polygon area at that time step that was open water, wet, green vegetation, dry vegetation, and bare soil.

4. Results

The classification analysis resulting in the percentage area of the total study area for each of the classes, open water, wet, green vegetation, dry vegetation, and bare soil, is visualized in Figure 10. A stacked line chart is chosen because it is effective in visualizing both the timing and measure of change over the period 2017 to 2024.

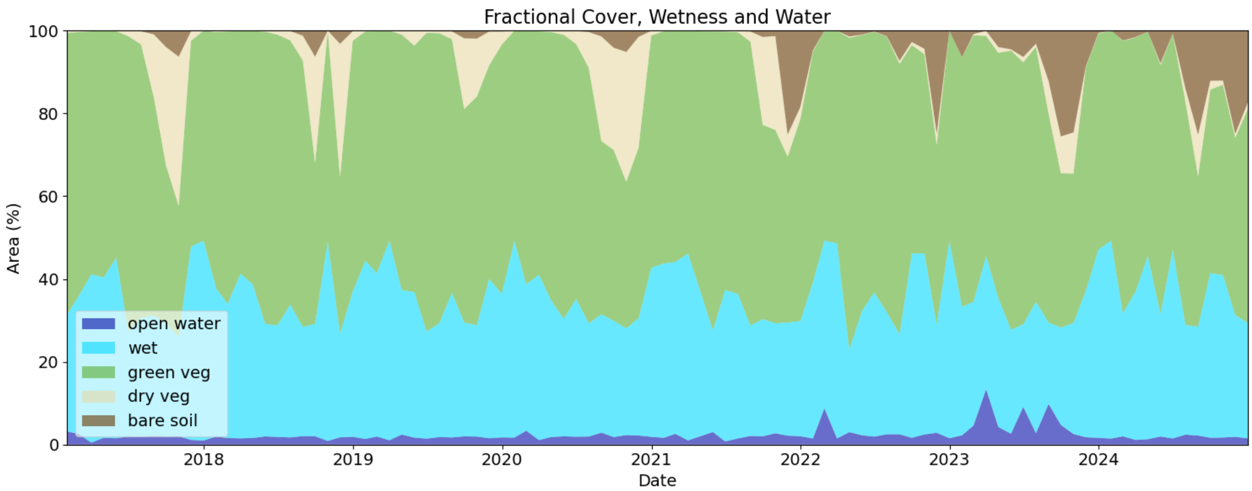

Figure 10: Stacked line chart showing the percentage are covered by the classes (open water, wet, green vegetation, dry vegetation, and bare soil) from 2017 to 2024.

Overall, as shown in figure 10, green vegetation covered the largest proportion of the wetland, with a mean of **56.9%** (ranging from 31.6% in October 2017 to 75.3% in April 2022) as seen in Table 1. Wet areas averaged **33.5%**, with seasonal peaks up to 48.3% in December 2017. Open water has an average cover of **2.4%**, with spikes especially 13.4% in March 2023 which is a wet month in this region. Dry vegetation and bare soil have a more variability in terms of area covered. Dry vegetation averaged **3.6%**, with a high peak of 36.1% in October 2017 during the late dry season. Bare soil covered an average of **3.7%**, with maximum of 25.5% in September 2023 which is usually a wet period in this study area.

Class	Mean (%)	Min (%)	Max (%)	Max month and year
Green vegetation	56.9	31.6	75.3	Apr 2022
Wet	33.5	19.7	48.3	Dec 2017
Open water (WOfS)	2.4	0.47	13.4	Mar 2023
Dry vegetation	3.6	0.00	36.1	Oct 2017
Bare soil	3.7	0.00	25.5	Sep 2023

Table 1: summary statistics for percentage area covered by each land cover class (2017–2024)

Interannual variation is most observed for open water and bare soil as seen in Table 2. For example, open water area in March 2023 was over five times the long-term mean, while bare soil reached its maximum in late 2023. Green vegetation and wet areas are the dominant classes each year, however variations can be observed too: for example, average bare soil cover increased in 2023–2024 (8.07% and 9.85%) compared to previous years (e.g., 0.40% in 2019). Open water cover peaked in 2023 (4.95%), and dry vegetation also peaked in 2020 (10.20%).

Year	Open Water (%)	Wet (%)	Green Vegetation (%)	Dry Vegetation (%)	Bare Soil (%)
2017	1.77	34.52	55.42	7.30	0.98
2018	1.73	32.78	58.72	5.84	0.94
2019	1.72	34.74	58.98	4.15	0.40
2020	2.07	33.06	53.60	10.20	1.07
2021	1.96	33.07	56.43	4.63	3.90
2022	2.69	35.51	57.27	0.53	4.00
2023	4.95	29.34	54.94	2.69	8.07
2024	1.72	35.17	51.63	1.63	9.85

Table 2: annual average percentage cover by class

5. Discussion

The results observed show seasonal and interannual variation within the Zambezi Delta between 2017 and 2024 with green vegetation and wet areas consistently dominated the study area, while open water and bare soil exhibited high peaks in certain years. This is consistent with the floodplain characteristics of the Zambezi delta. The variation can be because of several factors such as the precipitation patterns of the region and anthropogenic factors like land use change. It is important to note however that these quantifications and visualizations represent surface area rather than water depth, providing a two-dimensional perspective on wetland dynamics.

This study uses a multi-indicator Earth Observation approach, integrating Water Observations from Space (WOfS), Tasseled Cap Wetness (TCW), and Fractional Cover (FC), to capture the complex dynamics of wetland surfaces over an eight-year period. This combination enables us to track not only open water but also wet areas, vegetated surfaces, and bare soil, providing a detailed view of seasonal and interannual variability. WOfS provides reliable detection of open water bodies but is known to underestimate water presence in mixed pixels partially covered by vegetation (Dunn et al., 2023). To address this, TCW is included to detect moist surfaces where water is obscured by vegetation or shallow inundation. FC added further detail by classifying remaining areas into green vegetation, dry vegetation, and bare soil, capturing seasonal vegetation dynamics. When combined these datasets complement each other reducing misclassification.

Several limitations were encountered during the analysis. Missing metadata during data acquisition via STAC such as pixel attributes required manual addition to ensure accurate analysis. In the LS8-SR processing step, cloud masking challenges affected the derivation of the TCW index where the cloud masked pixels are misclassified as wet areas, increasing the wetness estimates in cloud-prone months. This limitation of cloud masking could be addresses by integrating Synthetic Aperture Radar (SAR) data which can in penetrating cloud cover ad is sensitive to moisture, to complement the Landsat data used. In addition, ground truth data is not included in this classification as validation.

Overall, the study demonstrates the utility of integrating open-access satellite datasets and reproducible methods to monitor wetland dynamics over time useful for management and conservation initiatives. However, it also highlights challenges, including data completeness, cloud masking accuracy, and the interpretation of surface indicators, which should be addressed in future research.

6. Conclusion

Wetlands like the Zambezi Delta are vital ecosystems, supporting both biodiversity and human livelihoods, yet they remain threatened by both climate change and human activities. Monitoring their dynamics is therefore essential for conservation efforts and sustainable management.

This study used a multi-indicator Earth Observation approach, integrating Landsat Surface Reflectance derived TCW with DE Africa products WOfS and FC products over an eight-year period (2017–2024). This approach effectively captured the seasonal and interannual wetland dynamics, revealing that wet and vegetated areas consistently dominate the delta, with seasonal peaks in open water and bare soil that can be linked to specific precipitation patterns. By combining these complementary datasets, the method provided a richer view of wetland surface conditions than a sole product alone.

These results demonstrate the value of open-access satellite data and reproducible, cloud-based analysis for long-term wetland monitoring using cloud-based platforms. In the future the recommendation is to integrate additional data sources such as Synthetic Aperture Radar (SAR) which would further improve the detection of inundation under vegetation especially during cloudy conditions. Beyond monitoring, this study can inform other practical applications, for example by applying seasonal wetland dynamics to public health risk assessments in floodplain regions like the Zambezi Delta where water-borne diseases like malaria are endemic.

AI Disclaimer

I have used AI (ChatGPT) to rephrase and restructure some of the content. The output was reviewed and edited before including in the final paper.

Additional Information

The data and code for this work can be accessed here:

https://github.com/Ethel-Ogallo/Wetland_Inundation_DE-Africa

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