# A PROJJECT TOPIC ON
# DESIGN AND DEVELOPMENT OF A WEB-BASED CHANGE DETECTION DASHBOARD FOR LAND USE MONITORING


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# CERTIFICATION PAGE

This is to certify that this is an undergraduate project written by MOSES NOAH ADEWALE with matriculation number 210903055, and has been prepared and compiled in accordance with the regulations guiding the preparation of projects in the DEPARTMENT OF COMPUTER SCIENCE, EKITI STATE UNIVERSITY, ADO-EKITI.

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# ABSTRACT

This project presents the design and development of a Web-Based Change Detection Dashboard for monitoring land use and land cover (LULC) dynamics using multi-temporal Sentinel-2 satellite imagery. Built on Google Earth Engine (GEE) and Streamlit, the system provides an interactive platform where users can select areas of interest through custom input, or polygon drawing, and specify time ranges for analysis. An unsupervised K-Means clustering algorithm was implemented to detect and quantify changes between two temporal periods, with results displayed as side-by-side satellite images, cluster-based classification maps, and comparative tables and charts. A case study of the Ekiti State University (EKSU) Environs demonstrated the dashboard's ability to reveal significant land cover transitions, with some clusters showing expansion while others contracted. The system's strengths lie in its accessibility via a web browser, automation of complex geospatial analysis, and provision of downloadable reports. However, the use of an unsupervised model limits precise class labeling, suggesting future integration of supervised models for improved accuracy and interpretability. Overall, the project demonstrates how open-source satellite data and cloud-based geospatial platforms can be combined to deliver practical tools for land monitoring, supporting urban planning, environmental management, and sustainable development.

# CHAPTER ONE

# INTRODUCTION

## 1.1 Background of the Study

Land use and land cover changes have become one of the most visible consequences of human interaction with the environment. Driven by factors such as urbanization, agricultural expansion, deforestation, and infrastructure development, these changes significantly affect biodiversity, hydrology, climate, and socio-economic systems. Monitoring these changes is critical to supporting environmental sustainability, informed decision-making, and responsible urban planning.

Traditionally, land use assessments have been conducted using field surveys, aerial photography, and manual interpretation of satellite imagery. While effective to a degree, these methods are time-consuming, resource-intensive, and often limited in spatial or temporal resolution. The emergence of satellite remote sensing, particularly through platforms like Sentinel-2, has revolutionized the field by providing consistent, multi-temporal, and high-resolution data suitable for monitoring large areas over time.

However, having access to satellite data alone is not sufficient. The real challenge lies in analyzing and translating this data into actionable insights especially in a form that is accessible to policymakers, environmental agencies, academic researchers, and even the general public. This is where a change detection dashboard comes into play. This is a web-based platform designed to visualize, analyze, and communicate land cover changes over time in an interactive, user-friendly format.

## 1.2 Problem Statement

Most existing studies on land use and land cover in Nigeria rely on static outputs such as maps embedded in PDF reports, research papers, or printed atlases. These outputs are often not easily accessible to non-specialists and lack interactivity, making them unsuitable for real-time exploration or decision-making. Furthermore, tools like ArcGIS and QGIS, though powerful, often require specialized skills and licensing, placing them out of reach for many local stakeholders therefore, there is a clear need for a web-based system that enables users to view, analyze, and interpret land use changes in a specific area of interest, such as the environs of a university campus. This system must be easy to use, up-to-date, and capable of translating complex geospatial data into actionable insights bridging the gap between data availability and real-world utility.

Moreover, the absence of an onlibe dashboard that leverages freely available satellite imagery like Sentinel-2 and open-source platforms like Google Earth Engine represents a missed opportunity to democratize environmental intelligence. In an era where web-based visualization has become a standard for data communication, relying solely on desktop GIS tools or static maps is both outdated and inefficient.

## 1.3 Aim and Objectives

Aim: The aim of this study is to design and implement an online change detection dashboard that utilizes multi-temporal satellite imagery to monitor and visualize land use and land cover changes in a target environment.

Objectives:

**i.** To design an online system for visualizing land use and land cover changes using open-source data and web development libraries.
**ii.** To develop an online dashboard following the designed system previously mentioned
**iii.** To implement the developed system by conducting a focused case study on the land cover dynamics of the immediate environs of Ekiti State University using the developed dashboard.

**iv.** To evaluate the usability and effectiveness of the dashboard in terms of accessibility, visualization quality, and potential use cases by non-specialist users.

## 1.4 Research Methodology

Research in this project adopts a structured approach that integrates satellite remote sensing, geospatial analysis, and web application development to monitor land use and land cover changes within the study area. The methodology is organized into four major stages as follows.

**i.** Data Acquisition: Multi-temporal satellite imagery will be obtained from the Sentinel-2 mission, which provides high-resolution optical data suitable for land use and land change monitoring. The imagery will be accessed through the Google Earth Engine (GEE) Python API, which enables scalable, cloud-based retrieval and preprocessing of satellite data.

**ii.** Image Processing and Change Detection: Using the GEE platform, satellite imagery will be preprocessed to correct for cloud cover and extract relevant spectral indices. A supervised classification algorithm will be applied to categorize land cover into distinct classes such as vegetation, built-up area, water bodies, and bare land. Change detection will be performed using a post-classification comparison technique to quantify land cover transitions across a selected time range.

**iii.** Dashboard Design and Implementation: An interactive, web-based dashboard will be developed using Streamlit, a Python framework designed for building data-driven web applications. The dashboard will integrate geospatial visualization tools to display satellite imagery and change detection results. Users will be able to input a location and date range, navigate through time-series imagery using a slider interface and view summarized land use statistics below the map. Additionally, the ability to export a detailed analysis report as a PDF will be included.

**iv.** Case Study Evaluation: A focused case study will be conducted on the immediate environs of Ekiti State University. The analysis will be evaluated for visual accuracy and, where feasible, compared with high-resolution reference imagery. Additionally, the usability of the dashboard will be assessed to determine its effectiveness for non-expert users, particularly in academic or environmental planning contexts.

## 1.5 Significance of the Study

This study holds significant value in several key areas, ranging from technological innovation to academic contribution. By leveraging freely available satellite data and open-source web technologies, this project demonstrates a cost-effective and scalable approach to environmental monitoring, this approach serves as a practical model for similar projects in low-resource environments.

The project contributes to the growing body of research in remote sensing, land change science, and web-based geospatial visualization, it also provides a working case study for future research on the application of machine learning and cloud-based platforms for land use analysis. By making complex geospatial data accessible through a user-friendly dashboard, this study contributes to the democratization of environmental information. It empowers not only specialists but also policymakers, educators, students, and the general public to engage with and understand the spatial dynamics of land use changes.

## 1.6 Limitations

While this project is designed to be practical, scalable, and scientifically sound, several limitations are acknowledged

**i.** Cloud Cover and Image Availability: Satellite imagery, particularly from optical sensors like Sentinel-2, is often obstructed by cloud cover. This can reduce the quality and availability of usable images, especially during rainy seasons, which may limit temporal analysis or introduce gaps in the dataset.

**ii.** Spatial Resolution Constraints: Although Sentinel-2 provides relatively high-resolution imagery (10–20 meters), it may still be insufficient for detecting small-scale or subtle land use changes, particularly in densely developed or fragmented urban areas within the study zone.

**iii.** Lack of Ground Truth Data: Due to logistical and time constraints, ground-truthing (on-site validation of land cover classes) may not be possible. As a result, classification accuracy will rely primarily on visual inspection and where available, high-resolution reference imagery.

**iv.** Tool and API Limitations: While Google Earth Engine offers powerful tools, it has usage quotas, API limitations, and lacks full support for some advanced spatial operations. These restrictions may affect performance or limit advanced custom analyses during dashboard development.

**v.** Time Constraints and Scope: Given the academic timeline and focus of this study, the dashboard will be limited to specific years and land cover classes. Expanding its scope to cover longer temporal scales, more complex classifications, or real-time data updates is reserved for future work

Despite these constraints, the project remains technically feasible and academically valuable, offering a functional and replicable model for localized LULC change detection using free and open technologies.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.1 Introduction

Change detection using satellite imagery has become an essential technique in environmental monitoring, land management, and urban planning. With the increasing availability of high-resolution, multi-temporal remote sensing data, researchers and institutions now have the capacity to track land use and land cover changes over time (Adebayo et al, 2019). However, the practical utility of this data often depends on the accessibility and interpretability of the tools used to analyze and visualize it. According to Alegbeleye et al. (2024), one of the major challenges in land use and land change monitoring in Nigeria is the limited accessibility and usability of available tools/data, most of which require technical expertise and are not publicly available or interactive.

As a result, there is a growing interest in developing online tools that democratize access to geospatial intelligence. Adegboyega (2021) highlights the need for dynamic systems that support real-time analysis and visualization of land use changes, particularly in fast-developing urban regions. Online dashboards address this need by enabling users from researchers to planners to engage with spatial data more effectively and make informed decisions.

## 2.2 Applications of an Online Change Detection Dashboard

An online change detection dashboard bridges the gap between remote sensing data and actionable insights, enabling informed decisions across multiple domains. Below are key areas where such dashboards have been successfully applied or have significant potential.

**i.** Urban Planning and Infrastructure Development: One of the most prominent applications of land use change dashboards is in urban planning. As cities expand, decision-makers must monitor urban sprawl, identify patterns of informal settlement, and manage land use conflicts. Dashboards provide real-time visualizations of land development, helping urban planners assess whether growth aligns with zoning regulations or sustainable development goals for example, Ashaolu et al. (2019) used geospatial techniques to assess urban development in the Osun drainage basin, highlighting how uncontrolled land use expansion alters hydrological patterns. A localized dashboard could have enhanced such work by supporting dynamic visualization of change across time and space. Similarly, Alegbeleye et al. (2024) emphasize the importance of developing systems that provide planners with accessible platforms for evaluating land conversion in urban corridors.

**ii.** Environmental Monitoring and Conservation: Change detection dashboards are critical for monitoring ecological systems. They can detect deforestation, degradation of wetlands, desertification, and agricultural encroachment. Conservation agencies and environmental scientists use these tools to track the health of protected areas and respond quickly to unauthorized land use changes. Adegboyega (2021), for instance, applied land use change detection techniques to assess watershed degradation, showing how land cover shifts directly impact ecological stability. An online dashboard would allow such findings to be made publicly available and continuously updated, improving transparency and encouraging broader stakeholder involvement. Alegbeleye et al. (2024) also argue that dashboards can support environmental justice by empowering local communities with data access.

**iii.** Disaster Management and Risk Assessment: In disaster-prone areas, dashboards can be used to assess land cover changes caused by events such as floods, wildfires, or landslides. These tools help emergency response teams evaluate affected regions and plan interventions based on up-to-date satellite imagery. The real-time accessibility of dashboard tools can provide a much-needed upgrade to the static nature of traditional post-event reporting.

**iv.** Academic Research and Education: Change detection dashboards serve as powerful tools for geospatial education and research. Students, lecturers, and academic researchers can use them to conduct spatial analysis, generate datasets, and visualize results without needing to install or learn complex GIS software.

This aligns with the work of Alegbeleye et al. (2024), who advocate for platform-driven land use change research that lowers technical barriers in educational contexts. An online tool would also serve as a replicable model for future geospatial coursework and student-led research.

**v.** Community Engagement and Policy Advocacy: Finally, user-friendly dashboards have the potential to empower local communities, NGOs, and policy advocates. By making complex satellite-derived information understandable, these tools can support community-led environmental monitoring, encourage public participation and drive evidence-based advocacy.

## 2.3 Benefits of an Online Change Detection Dashboards

Online change detection dashboards offer a powerful solution for transforming raw satellite data into usable insights. By merging cloud-based geospatial processing with interactive user interfaces, these systems provide significant improvements in data accessibility, usability, and decision-making support. The following sub-sections highlight key benefits of such systems.

**i.** Accessibility and Usability: One of the most critical benefits of web-based dashboards is their ability to make complex geospatial analysis accessible to non-specialists. Unlike traditional GIS software, which often requires installation, licensing, and technical expertise, web dashboards operate directly within a browser interface, requiring only an internet connection and basic digital literacy.

According to Alegbeleye et al. (2024), most land use change research in Nigeria still relies on desktop GIS tools, which limits the dissemination and reuse of environmental data. Dashboards overcome this barrier by providing intuitive tools such as clickable maps, date range sliders, and simple report downloads. This makes them suitable for use by planners, educators, community stakeholders, and students alike.

**ii.** Cost-Effectiveness and Open Data Integration: Dashboards built with open-source technologies such as Streamlit and Google Earth Engine can significantly reduce the cost of land use change monitoring systems. These platforms leverage publicly available satellite datasets and free processing tools, eliminating the need for costly commercial licenses or proprietary software.

Adegboyega (2021) emphasizes the importance of affordability and sustainability in land use change research, particularly in developing countries. A web-based dashboard built entirely on open infrastructure addresses this challenge by enabling long-term, scalable monitoring at minimal financial cost.

**iii.** Real-Time Visualization and Interactive Exploration: Another major strength of dashboards is the ability to visualize and interact with spatial data in real-time. Users can explore multi-year changes by adjusting time sliders, compare land cover transitions side-by-side, and view statistical summaries that update dynamically based on selected parameters.

This kind of real-time feedback loop enhances user engagement and allows for more informed interpretation of results. Ashaolu et al. (2019) argue that dynamic visualizations improve the ability to detect subtle land use shifts that static maps or tables may obscure.

**iv.** Transparency and Democratization of Environmental Intelligence: By making land use change data and results available in a public, interpretable format, dashboards support transparency and promote evidence-based policy. They also facilitate community involvement in environmental monitoring by equipping stakeholders with timely, localized insights, dashboards reinforce this by enabling users to explore their surroundings in a data-rich but approachable format.

**v.** Scalability and Replicability: Online dashboards are inherently scalable and easily replicable across different geographic regions. Once the system is built for one location or time frame, it can be adapted for others with minimal configuration making it ideal for regional monitoring projects, academic institutions, or government agencies.

Alegbeleye et al. (2024) highlight this adaptability as a key reason why dashboard-based systems are increasingly being considered for national land use change observatories and educational platforms.

## 2.4 Review of Related Literature

**a.** Adegboyega (2021) conducted a study to detect and quantify land use and land cover changes in Olorunda Local Government Area of Osun State, Nigeria, with a focus on urban watershed degradation. Using multi-temporal Landsat satellite imagery and supervised classification techniques, the research identified significant urban expansion and a corresponding loss of vegetative cover between 1984 and 2015. The

study demonstrated the value of remote sensing in environmental monitoring and emphasized the need for spatial data integration in urban planning processes. This work provides a methodological foundation for localized change detection efforts and supports the importance of developing systems that allow for continuous land monitoring.

**b.** Alegbeleye et al. (2024) presented a systematic review of land use and land cover research in Nigeria, focusing on the data sources, methodologies, tools, and platforms used in over 100 studies. Sentinel-2 and Landsat datasets were identified as the most commonly used imagery, while supervised classification techniques and platforms like Google Earth Engine gained popularity. The review also highlighted challenges such as limited accessibility, methodological inconsistency, and a lack of user-friendly interfaces. The authors advocated for open, web-based systems to democratize access to spatial analysis, particularly in educational and planning contexts, providing strong justification for the development of an interactive dashboard.

**c.** Adebayo et al. (2019) examined land use changes in Abeokuta, Nigeria, using Landsat imagery spanning from 1984 to 2015. The study applied supervised classification through ERDAS Imagine 9.3 and found a substantial reduction in vegetation and water bodies, coupled with a marked increase in built-up areas, largely due to urbanization. The findings underscored the effectiveness of geospatial tools in environmental change monitoring and emphasized the need for timely spatial data to guide sustainable land management policies. This work supports the value of periodic satellite-based LULC assessments in rapidly developing urban regions.

**d.** Komolafe and Akintunde-Alo (2022) focused on deforestation and human-induced land use changes in Akure Forest Reserve, Nigeria, from 1984 to 2021. Utilizing multi-temporal Landsat imagery and supervised classification in QGIS and ArcGIS, the study revealed significant forest loss and expansion of built-up areas and agricultural zones. NDVI analysis further confirmed vegetation degradation. The study highlighted the critical role of geospatial technologies in forest monitoring and underscored the need for policy interventions to address environmental degradation. These insights reinforce the importance of building systems that make such data easily available to decision-makers and conservation stakeholders.

**e.** Ashaolu et al. (2019) analyzed LULC changes in the Osun drainage basin, using satellite imagery and hydrological modeling to assess impacts on water resources from 1984 to 2015, with projections to 2046. Their findings showed massive increases in built-up areas and agricultural zones, alongside steep declines in forest and wetlands. The study applied supervised classification and future modeling using QGIS tools like MOLUSCE. It demonstrated how land transformation significantly affects hydrological processes, emphasizing the role of change detection systems in managing water security and environmental planning.

**f.** Ologunde et al. (2025) explored LULC dynamics in the Ado-Odo Ota Local Government Area of Ogun State between 2015 and 2023. Using Landsat 8 imagery and ArcGIS Pro 3.3, they applied pixel-based supervised classification and verified accuracy with confusion matrices and Google Earth Pro. Results revealed increased built-up areas and sparse vegetation, and a reduction in forest and water bodies, attributed to urbanization and agricultural intensification. The study emphasized the urgency of robust land use policies and demonstrated the practical value of geospatial change detection tools for real-world land management applications.

**g.** Koko et al. (2022) investigated LULC change dynamics in Kano Metropolis from 1991 to 2020 and simulated future scenarios for 2035 and 2050 using hybrid Cellular Automata-Markov models in IDRISI TerrSet. With satellite imagery processed in ENVI and ArcGIS, the study revealed substantial loss of barren land and a threefold increase in built-up areas, projecting continued urban expansion. The integration of remote sensing, GIS, and predictive modeling showcased a forward-looking approach to sustainable urban planning. This work illustrates how dashboards with built-in forecasting potential could further enhance land management strategies in fast-growing urban centers.

## 2.5 Research Gaps and Justification for This Study

A consistent limitation across existing studies is the absence of an interactive, online dashboard that enable public access to land use change insights. Most outputs are static and technical, making it difficult for non-experts to benefit from the data. This project addresses that gap by developing an online change detection dashboard that allows users to explore land use trends. A specific case study of the environs of Ekiti State University will be included to demonstrate the dashboard's effectiveness.

## 2.6 Summary of Findings and Conclusion

**i.** Most existing LULC change detection studies in Nigeria rely heavily on Landsat or Sentinel-2 imagery, demonstrating the suitability of freely available satellite data for environmental monitoring.

**ii.** Supervised classification techniques, especially the Maximum Likelihood algorithm, are consistently used for land cover categorization across multiple studies, indicating their effectiveness and broad acceptance in geospatial analysis.

**iii.** A recurring trend across all reviewed studies is the significant increase in built-up areas over time, typically at the expense of vegetation, water bodies, and forest cover often driven by urban expansion and agricultural encroachment.

**iv.** Studies such as those by Ashaolu et al. (2019) and Koko et al. (2022) applied predictive modeling (e.g., MOLUSCE, CA-Markov) to forecast future land cover changes, highlighting a need for dynamic, forward-looking decision-support tools.

**v.** Despite the rich spatial insights offered, none of the reviewed studies implemented a public-facing or online dashboard, which limits accessibility for non-experts.

**vi.** Several studies (e.g., Alegbeleye et al., 2024) emphasized the challenges of accessibility and methodological consistency, recommending the use of open tools like Google Earth Engine to improve reproducibility and collaboration.

**vii.** Most research focused on static reports or offline GIS tools, lacking real-time interactivity or temporal navigation features that could enhance user understanding and engagement.

These findings collectively establish a clear gap in the availability of accessible, user-friendly land use monitoring tools in the Nigerian context, thereby reinforcing the relevance and necessity of the proposed online change detection dashboard detailed in the next chapter.

# CHAPTER THREE

# METHODOLOGY

## 3.1 Introduction

This chapter outlines the methodology employed in the design and implementation of a web-based change detection dashboard for monitoring land use and land cover changes. The methodology combines geospatial analysis with modern software development techniques to achieve a system that is both analytically robust and practically accessible.

The core of this chapter focuses on the methodological workflow, which includes data acquisition, preprocessing, supervised classification, change detection analysis, and the development of the web-based dashboard interface. Each stage of the workflow is broken down into discrete components to clearly articulate the procedures followed in this project. The chapter concludes by addressing ethical considerations and summarizing the methodology in preparation for the presentation of results in the subsequent chapter.

## 3.2 Research Design and Approach

The methodology adopted for this study is a combination of applied research, descriptive analysis, and experimental system development. The study aims to build a practical tool a web-based dashboard that leverages satellite imagery to monitor land use and land cover (LULC) changes over time. As such, it integrates both scientific investigation and software implementation, making use of remote sensing techniques and user-centric web design principles.

**i.** The research design follows a quantitative and geospatial approach in the analysis of multi-temporal satellite imagery. This involves acquiring and preprocessing satellite data, classifying land cover types using machine learning techniques, and performing change detection through post-classification comparison. These analytical methods are used to produce interpretable visual outputs that support environmental monitoring and decision-making.

**ii.** In parallel, the project adopts a design-oriented software development methodology to implement the dashboard interface. This involves the translation of analytical results into an interactive, browser-based platform that allows users to select a location and time period of interest and visualize the resulting land cover changes. The user interface is designed to be intuitive and responsive, allowing non-experts to engage with satellite data without requiring GIS training or specialized software.

## 3.3 System Overview

At a conceptual level, a typical land use and land change detection dashboard integrates three main layers of functionality:

**i.** Data Input Layer: This component involves the ingestion of multi-temporal satellite imagery. The data may be acquired from public repositories and often preprocessed through cloud-based services like Google Earth Engine (GEE), which allow for scalable processing, filtering by date, cloud masking, and index calculation (e.g., NDVI, NDWI) (Alegbeleye et al., 2024). In some systems, users are allowed to define parameters such as location of interest, date range, or land cover types, enabling customized analysis.

**ii.** Processing & Analysis Layer: In this layer, computational routines detect and quantify changes between selected dates or time intervals. Change detection is typically performed using techniques like post-classification comparison, pixel differencing, or time-series trend analysis. Classifiers are often used to categorize satellite imagery into distinct land cover classes such as vegetation, built-up area, water, and bare land (Adegboyega, 2021). The result is a spatial map that highlights where, how, and to what extent land cover has changed.

**iii.** Visualization & Interaction Layer: This is the front-end interface where users engage with the system. Visualization tools may include interactive maps, time sliders, charts, and data tables. Dashboards commonly use web mapping libraries to display change detection results. Some systems allow users to

compare different years side-by-side or animate changes through time. Summary statistics, such as percentage change in land cover types, may also be included to enhance user interpretation (Adebayo, Otun, & Daniel, 2019).

These three layers work together to provide a streamlined, user-centric experience. Unlike traditional GIS software, which requires technical expertise and may be confined to desktop environments, web-based dashboards emphasize accessibility, immediacy, and ease of interpretation. According to Alegbeleye et al. (2024), the shift toward web-enabled geospatial tools is a key trend in making environmental data more actionable and inclusive.

The overall structure of a typical online land use change detection dashboard is presented in Figure 2.1 below, showing the flow from data acquisition to user interaction.

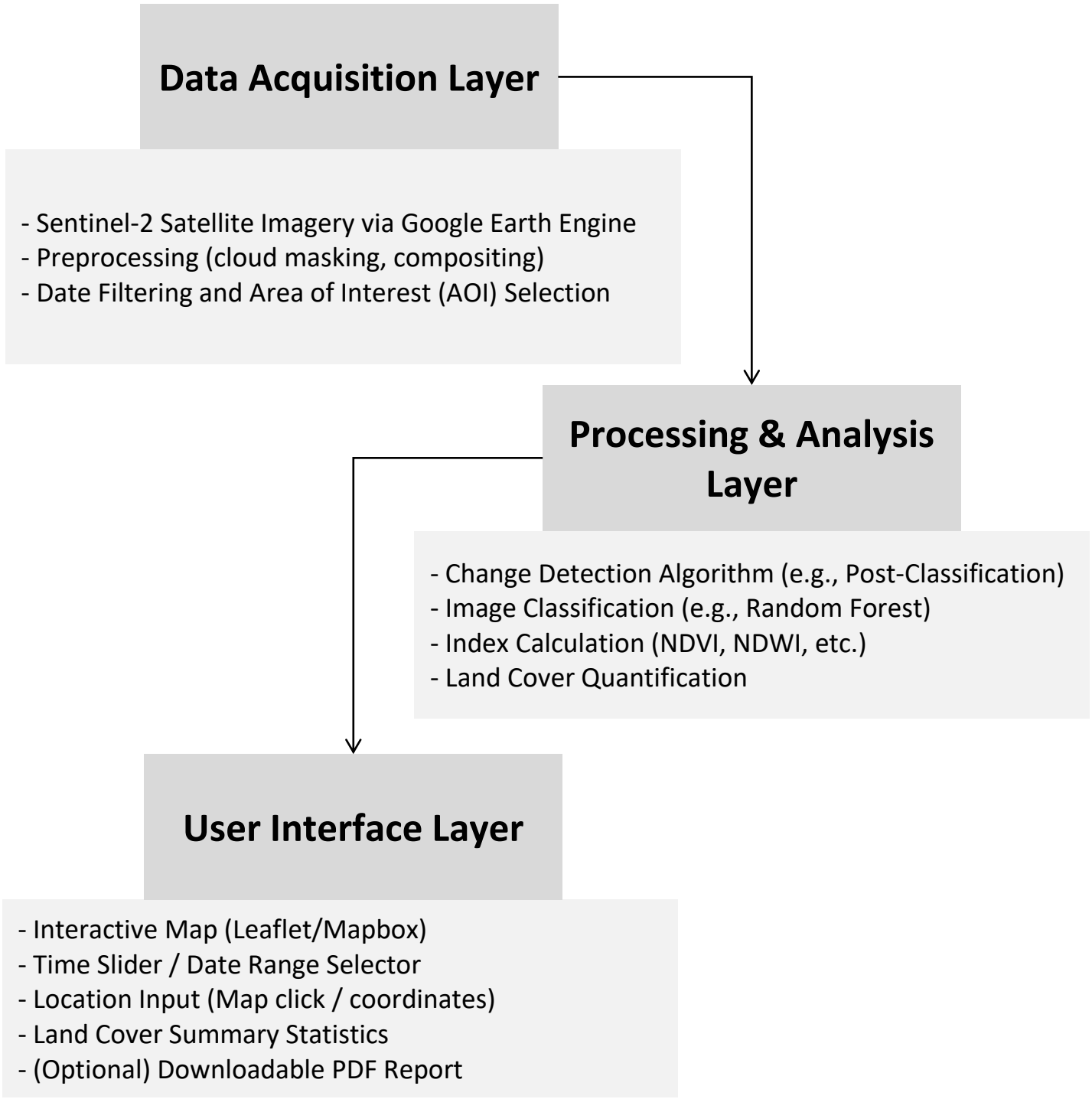



Figure 2.1: Conceptual Structure of the Proposed Change Detection Dashboard

In summary, the change detection dashboard is conceptualized as a lightweight, interactive platforms that enable users to visualize spatial and temporal patterns in land cover dynamics. They represent a new paradigm in environmental monitoring by reducing technical barriers and increasing the usability of satellite-derived insights.

## 3.4 Data Source

This study relies on freely available, multi-temporal satellite imagery and supporting datasets to analyze land use and land cover changes in the study area. The primary data source is described below.

**Satellite Imagery (Sentinel-2)**: The main dataset used for LULC analysis is Sentinel-2 imagery, obtained through Google Earth Engine (GEE). Sentinel-2, operated by the European Space Agency (ESA), provides high-resolution multispectral imagery with a spatial resolution of 10 meters for visible and near-infrared bands suitable for detailed LULC classification. The imagery offers a 5-day revisit frequency, enabling frequent monitoring and temporal comparisons. For this project, images will be selected from two distinct time periods (e.g., 2016 and 2024) to facilitate change detection. Only cloud-free images or those with minimal cloud interference will be selected, and preprocessing steps such as cloud masking and atmospheric correction will be applied using GEE's built-in functions.

## 3.5 Functional Requirements

This define the core capabilities that the proposed system must deliver to satisfy user expectations and fulfill the project's objectives. These requirements serve as a structured blueprint for development, ensuring that all essential features are implemented in alignment with the goals of the research.

i. **Location Selection**: Users must be able to define their area of interest (AOI) using a map interface or by entering coordinates or place names. This enables targeted analysis over specific geographic regions.
ii. **Date-Range Input**: The dashboard shall include controls to allow users to define a start and end date for their analysis. This supports flexible temporal comparison and user-defined change intervals.
iii. **Data Retrieval and Preprocessing**: Upon receiving the AOI and date range, the system will retrieve the relevant Sentinel-2 imagery from Google Earth Engine, perform cloud masking, and compute vegetation indices where necessary. These pre-processing steps ensure clean and standardized input for classification.
iv. **Land Cover Classification**: The system will classify satellite images into predefined land cover categories (e.g., vegetation, built-up area, water body, and bare land) using a supervised machine learning model.
v. **Change Detection Engine**: The system will compare classified images from different dates to identify and quantify changes in land cover types. The result will be visualized as a change mask highlighting transitions over time.
vi. **Interactive Slider Visualization**: The interface will include an interactive slider that allows users to navigate between different time slices of imagery and see corresponding changes dynamically on the map.
vii. **Summary Statistics Panel**: The system will compute and display the area covered by each land cover class for the selected dates, along with the magnitude of change between time points.
viii. **Export Functionality**: Users will be able to download processed outputs, including classified maps (GeoTIFF), summary statistics (CSV), and a full analysis report in PDF format.
ix. **Error Handling and Notifications**: The system will notify users of issues such as unavailable satellite imagery, high cloud cover, or processing failures. Progress indicators will also be included to enhance the user experience during data retrieval and analysis.

## 3.6 Tech Stack Overview

The development of the proposed change detection dashboard leverages a combination of open-source tools, cloud platforms, and Python-based libraries to support geospatial analysis, classification, and web deployment. The selected technologies prioritize cost-effectiveness, ease of use, and compatibility with AI-assisted development workflows, making them suitable for rapid prototyping and research-grade

implementation without requiring advanced web development experience. Below is a breakdown of the key components of the technology stack:

**i. Google Earth Engine (GEE)**

Purpose: Acquisition, filtering, and preprocessing of satellite imagery.
Rationale: GEE provides cloud-based access to a vast archive of Earth observation datasets, including Sentinel-2 imagery. Its JavaScript and Python APIs support scalable operations such as cloud masking, spectral index generation, and image clipping.
Relevance: GEE drastically simplifies remote sensing workflows, especially for users without access to high-performance local machines.

**ii. Python Programming Language**

Purpose: Backend scripting, image processing, classification, and integration with the web interface.
Rationale: Python is well-suited for scientific computing and has robust geospatial libraries.
Relevance: Python serves as the glue between geospatial processing and front-end dashboard development.

**iii. Streamlit**

Purpose: Web-based dashboard development.
Rationale: Streamlit allows developers to create interactive data apps using only Python, eliminating the need to learn HTML, CSS, or JavaScript. It supports widgets, map components, file upload/download, and real-time interactivity.
Relevance: Streamlit is ideal for solo developers or small teams building rapid, research-focused tools with user-friendly interfaces.

**iv. Geospatial Python Libraries**

geemap: For integrating Google Earth Engine with Python in a Jupyter or Streamlit environment.
folium / Leafmap: For rendering interactive maps inside the dashboard.
rasterio / numpy / matplotlib: For handling raster data, array-based analysis, and visualizing classification results.
scikit-learn: For implementing machine learning models, particularly Random Forest for land cover classification.
pandas: For manipulating tabular data (e.g., class-wise statistics).
Relevance: These libraries support end-to-end geospatial data manipulation and visualization without switching to proprietary GIS software.

**v. PDF and File Export Libraries**

WeasyPrint / ReportLab / pdfkit: For converting text and visual output into downloadable PDF reports.
Streamlit.download_button(): Built-in method for exporting results such as CSVs or PDFs to the user.
Relevance: Adds professionalism to the system by allowing users to archive or share their results in offline formats.
A tabular summary of the tech stack is included below.

| Technology / Library | Purpose | Justification |
|---|---|---|
| Google Earth Engine (GEE) | Data acquisition and preprocessing | Cloud-based platform for scalable access to satellite imagery and geospatial data |
| Python | Core development language | Supports both geospatial processing and Streamlit-based web apps |
| Streamlit | Dashboard development (frontend) | Simplifies UI creation with Python-only syntax for non-web developers |
| geemap | GEE integration with Python | Bridges Earth Engine with interactive Python-based mapping and UI tools |
| folium / Leafmap | Interactive map rendering | Enables Leaflet-powered visualizations inside dashboards |
| rasterio / numpy / matplotlib | Raster data processing and visualization | Used for handling arrays, classified images, and generating charts/maps |

| | | |
|---|---|---|
| scikit-learn | Machine learning model (Random Forest) | Robust and widely used for supervised classification tasks |
| pandas | Data manipulation and summarization | Processes class statistics and formatting of outputs |
| WeasyPrint / ReportLab / pdfkit (Optional) | PDF report generation | Converts results and visualizations into downloadable reports |
| streamlit.download_button() | File export (CSV, PDF) | Enables simple, one-click export of processed outputs |

## 3.7 Application Architecture

The application architecture defines how the system components interact, from data access and analysis to visualization and output delivery. The goal is to build a lightweight, modular, and scalable system that can run on a standard machine with internet access and no backend dependencies, the system follows a client-light / serverless design with the following layers:

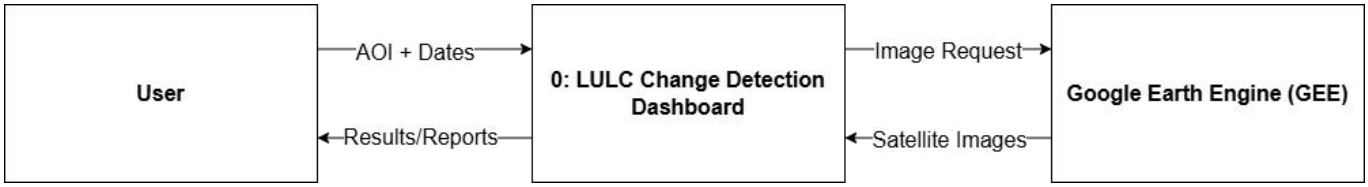
**i. Data Layer**
Source: Google Earth Engine
Function: Provides access to Sentinel-2 imagery, handles data filtering, cloud masking, and preprocessing remotely.
Rationale: Offloads heavy computation to GEE, reducing the need for local infrastructure.

**ii. Processing Layer**
Platform: Python (locally run or on a cloud instance like Streamlit Cloud)
Libraries Used: geemap, rasterio, numpy, scikit-learn, etc.
Function: Performs classification, change detection (raster comparison), and metrics computation.
Role: Acts as the analytical engine behind the dashboard.

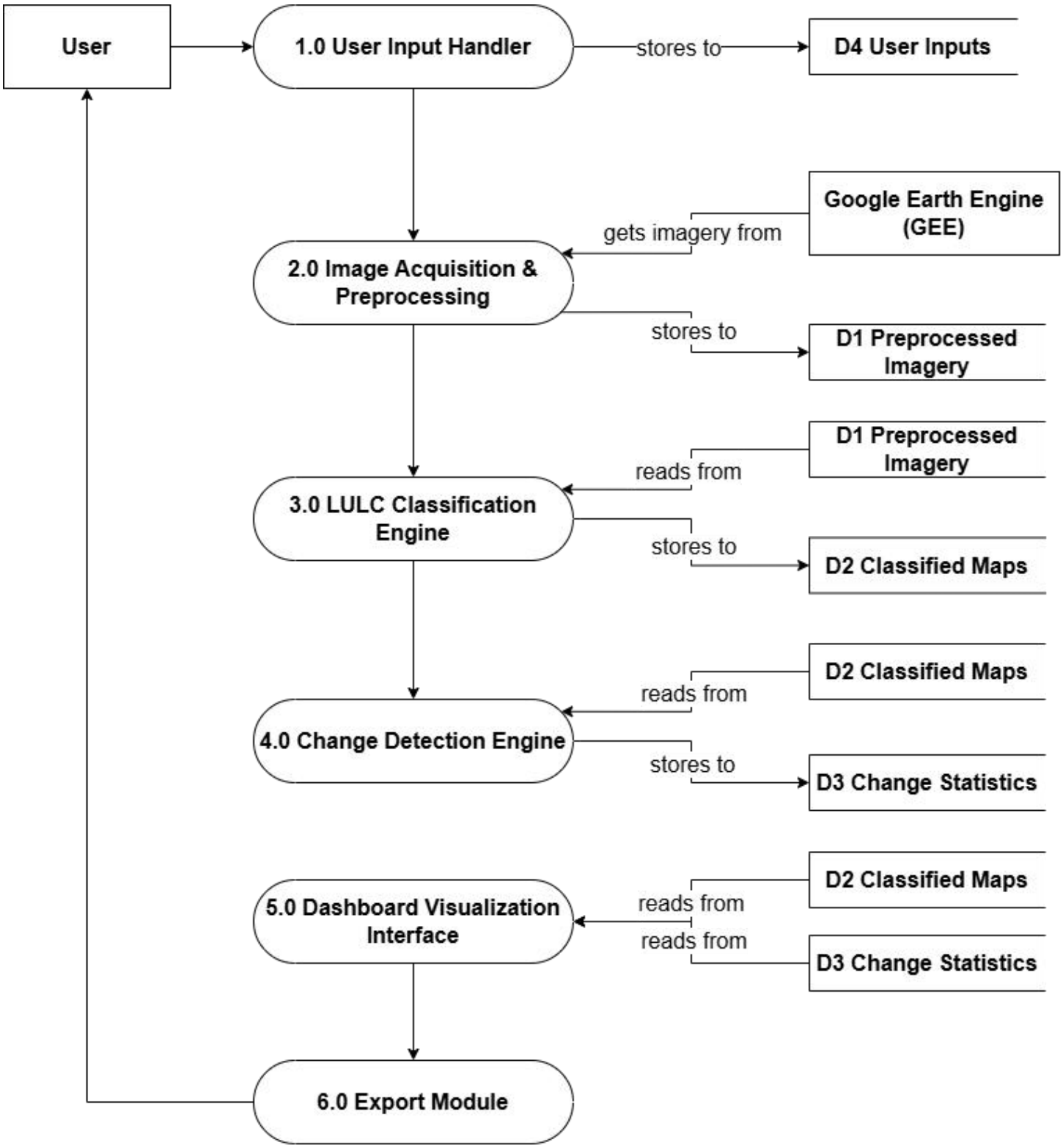
**iii. Application Interface Layer**
Platform: Streamlit
Function: Facilitates user interaction (AOI selection, date input, running analysis, displaying results).
Tools Used: folium, leafmap, streamlit widgets
Key Features: Slider for map layer switching, statistics panel, and download buttons.

**iv. Output Layer**
Formats: GeoTIFF, CSV, PDF
Function: Presents outputs in usable formats for decision-makers and researchers.
Tools: WeasyPrint or ReportLab for PDF generation

**Data Flow Diagram (Descriptive)**




**Level 0 Dataflow Diagram**




**Level 1 Dataflow Diagram**

This architecture ensures the system remains lightweight, flexible, and accessible without needing backend servers or databases.

## 3.8 Evaluation

Evaluation is a critical component in validating both the accuracy of the LULC classification and the usability of the dashboard interface. While the scope of this project limits extensive field validation, a two-pronged evaluation approach is applied:

**A. Classification Accuracy Assessment**

i. **Method**: A confusion matrix is generated by comparing classification results against ground truth samples or visually interpreted reference points from Google Earth.
ii. **Metrics Computed**:

Overall Accuracy – % of correctly classified pixels.
User's and Producer's Accuracy – per class.
Kappa Coefficient – statistical measure of agreement.

iii. **Tools Used**: scikit-learn, numpy, pandas

Note: If no field data is available, the accuracy assessment is done using visually confirmed regions.

**B. System Usability Review**

Given that this is a research-focused prototype, usability was reviewed qualitatively through:

i. Internal testing – Ensuring the dashboard behaves correctly for all expected input types and edge cases.
ii. Heuristic checks – Verifying that the UI is responsive, informative, and doesn't overwhelm users with unnecessary complexity.
iii. Simulated use-case scenarios – Running different AOIs and date ranges to test stability, runtime, and clarity of output.

**Limitations in Evaluation**

i. Lack of large-scale ground truth data limits external validation
ii. Subjective usability testing due to solo or small-group evaluation
iii. Real-world deployment and feedback collection are planned as future work

## 3.9 Ethical Considerations

This research adheres to ethical best practices in data usage, system design, and result dissemination. The following considerations were observed throughout the project life-cycle:

i. Use of Publicly Available Data: All satellite imagery and datasets used were sourced from open, publicly accessible repositories such as Google Earth Engine. No proprietary or restricted data was used.
ii. No Personal or Sensitive Data: The system does not collect, process, or store any personal, biometric, or user-identifiable data. The analysis is entirely environmental and spatial in scope.
iii. Transparency and Reproducibility: The methodology is designed to be fully reproducible using openly documented steps, tools, and code. This ensures transparency and encourages further research or community adoption.
iv. Environmental Integrity: The study promotes environmental awareness and decision-making through transparent monitoring tools. It avoids the misrepresentation of data by incorporating validation steps and disclaimers for classification uncertainty.
v. Responsible Use of AI Tools: AI coding assistants were used ethically to support code generation and documentation. All critical logic was reviewed and tested to ensure correctness.
vi. Non-Exploitative Visualization: The visual outputs presented by the dashboard are factual, unsentimental, and focused on constructive land management outcomes.

These ethical principles ensure that the system is not only functional but also socially responsible and aligned with academic integrity.

## 3.10 Summary

This chapter presented the comprehensive methodology used in the development of an online change detection dashboard for monitoring land use and land cover changes. It detailed the structured work-flow adopted from data acquisition and pre-processing to classification, change detection, and system development.

The chapter also outlined the functional requirements, architectural layout, tool-chain, and user-focused design decisions that shaped the dashboard. Accuracy and usability evaluations were conducted to validate the system, while ethical considerations ensured responsible data handling and system design.

# CHAPTER FOUR

# IMPLEMENTATION AND CASE STUDY

## 4.1 Introduction

This chapter presents the implementation and evaluation of the Web-Based Change Detection Dashboard. The goal is to demonstrate how the system was developed, how it operates, and how it can be applied to real-world land use and land cover monitoring.

The chapter is organized into four major parts. Section 4.2 describes the environment in which the system was developed, including the programming tools, libraries, and cloud services employed. Section 4.3 outlines the system implementation, explaining the workflow and how the dashboard integrates data sources, processing functions, and visualization components. Section 4.4 presents a case study using the environs of Ekiti State University (EKSU) as an Area of Interest (AOI). This case study highlights the practical application of the dashboard for detecting land cover changes between two temporal periods. The analysis is supported with classification maps, statistical summaries, and visual comparisons.

Through this chapter, the performance of the system is validated by applying it to a real-life scenario, thereby demonstrating its usefulness for monitoring urban growth and land use dynamics.

## 4.2 System Development Environment

The development of the Land Use Change Detection Dashboard was carried out using a combination of programming tools, cloud platforms, and supporting libraries. The system was designed to run as a web-based application, making it accessible from any device with an internet connection.

**i.** The dashboard was implemented in **Python**, chosen for its extensive ecosystem of libraries that support data processing, visualization, and integration with cloud-based services. The user interface was built using **Streamlit**, a lightweight Python framework that makes it possible to quickly create interactive web applications without requiring advanced web development skills.

**ii.** The core geospatial processing relied on the **Google Earth Engine (GEE) API**, which provides access to petabytes of satellite imagery and powerful cloud-based analysis tools. By leveraging Earth Engine, the system avoided the need for heavy local computation, as classification, change detection, and image retrieval were executed on GEE's servers.

**iii.** Several Python libraries were also essential in the development process. **Folium** and **streamlit-folium** were used to embed interactive maps for area selection and visualization. **Matplotlib** and **Pandas** were employed for generating charts and tables that summarize classification results and land cover change statistics.

**iv.** The system was developed and tested in a local environment using **Visual Studio Code** for managing Python dependencies. Version control was managed with **Git**, ensuring that different iterations of the code could be tracked and maintained.

Overall, the chosen environment provided a balance of accessibility, computational efficiency, and scalability. This allowed the dashboard to be implemented as a lightweight but powerful decision-support tool for land use and land cover monitoring.

## 4.3 System Implementation

The Land Use Change Detection Dashboard was implemented as a web-based interactive tool using **Streamlit** for the interface and **Google Earth Engine (GEE)** as the backend for satellite data processing. The implementation is modular with **app.py** acting as the main controller and helper functions defined in supporting module files such as **gee_utils.py**(holds all backend logic partaining to GEE) and **report_utils.py**(holds the logic for generating the report) .The system flows as described below.

i. **User Input and AOI Selection**: The dashboard provides two ways for selecting an Area of Interest (AOI)
   1. Predefined option (EKSU environs, 2 km buffer).
   2. Custom input, either by entering latitude/longitude with a buffer radius or by interactively drawing a polygon on the embedded map (powered by Folium and the Draw plugin).

   The selected AOI geometry is converted into an *ee.Geometry* object, which is then used in all subsequent GEE operations.

ii. **Time Range Selection**: The users specify a date range and Internally, the code splits this range into two periods.
   1. Before (from start date to midpoint).
   2. After (from midpoint+1 to end date).

   This ensures a consistent "before vs after" comparison for change detection.

iii. **Image Retrieval and Preprocessing**: The system retrieves Sentinel-2 SR Harmonized imagery (*COPERNICUS/S2_SR_HARMONIZED*) from GEE after which Cloud masking is applied using the Scene Classification Layer (SCL) to remove cloud pixels and noise. Median composites are generated for both "before" and "after" periods, clipped to the AOI and both composites are visualized as true-color images (RGB: B4, B3, B2) and displayed side by side.

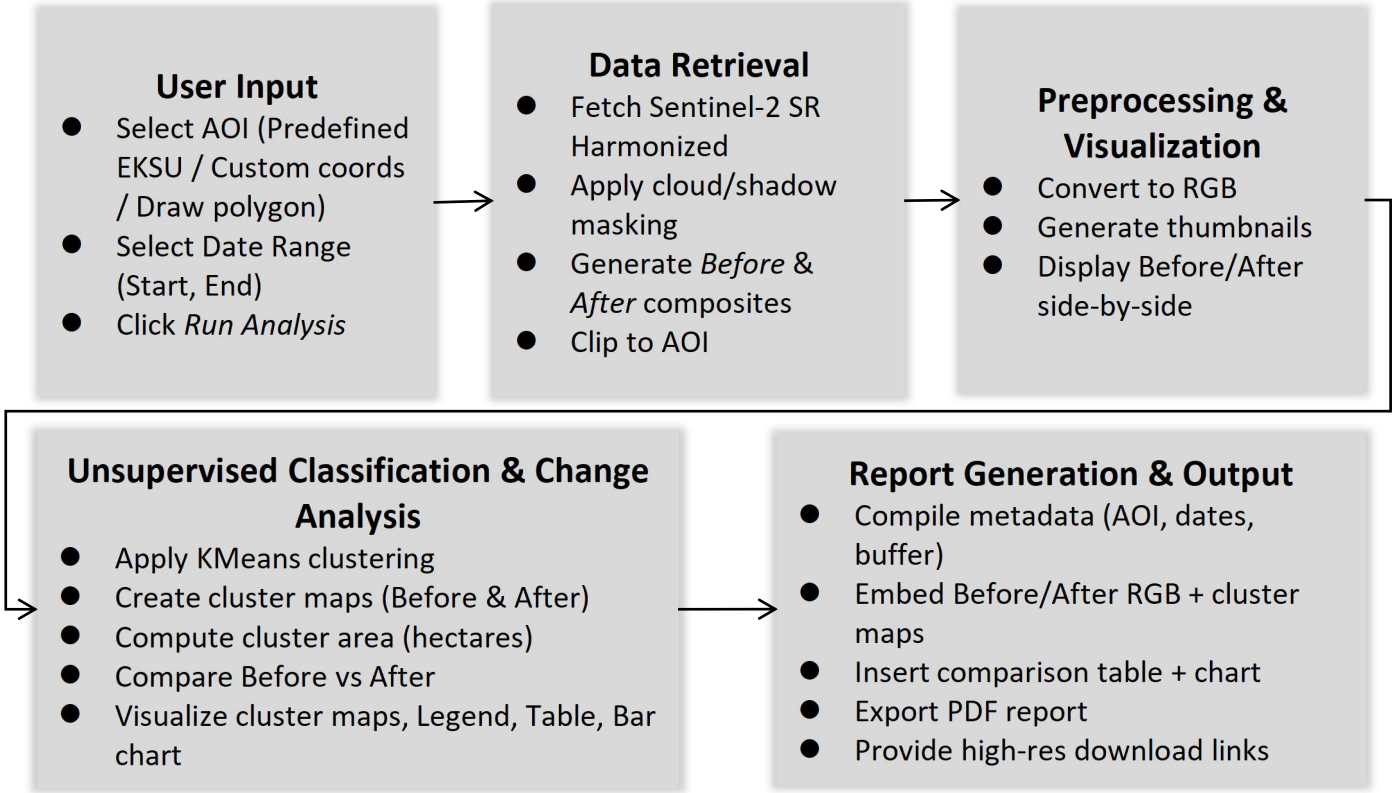
iv. **Unsupervised Classification**: For each composite, the system applies **K-Means clustering** with a fixed number of clusters (n=4), the resulting clustered images are visualized with a fixed color palette (red, green, blue, yellow). Pixel counts for each cluster are converted to area in hectares, allowing a quantitative comparison.

v. **Change Detection Summary**: A side-by-side comparison of "before" and "after" clusters is presented, the outputs include
   1. Cluster maps (visual thumbnails).
   2. Cluster legend showing assigned colors.
   3. Tabular comparison of area per cluster (before, after, absolute change, and % change).
   4. Bar chart comparing before vs after cluster areas (generated using Plotly).

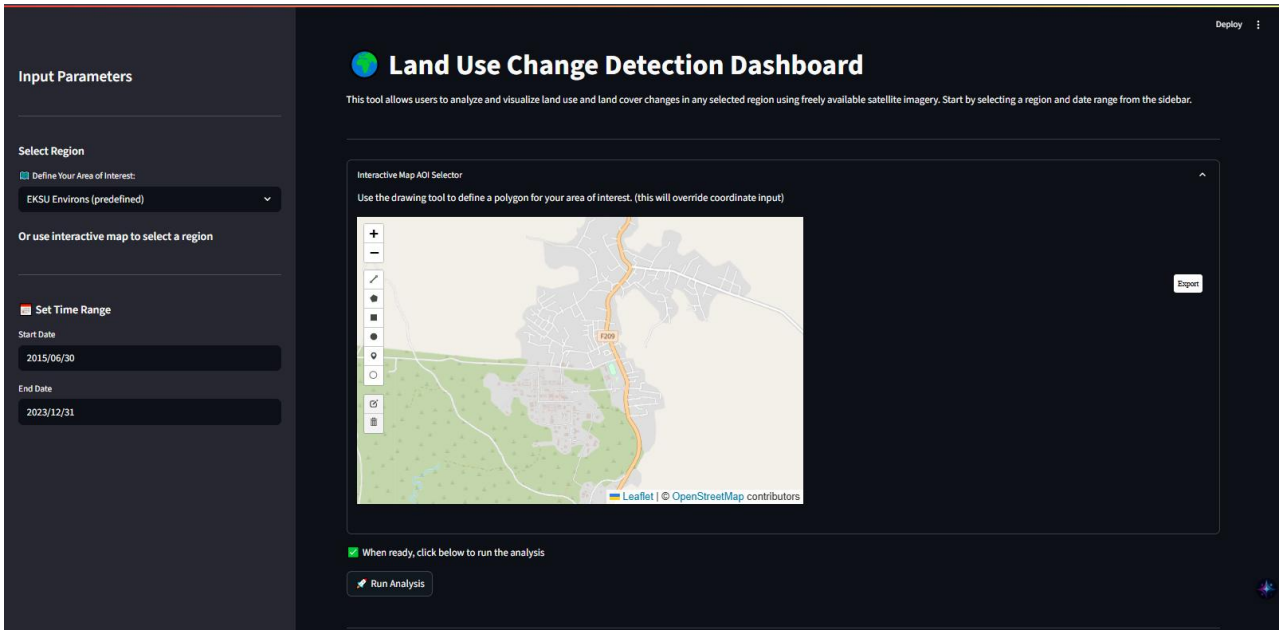
vi. **Report Generation**: The system allows users to generate a PDF report containing the following
   1. Input parameters (AOI, buffer radius, date range).
   2. Before/after true-color images.
   3. Cluster maps.
   4. Cluster maps.

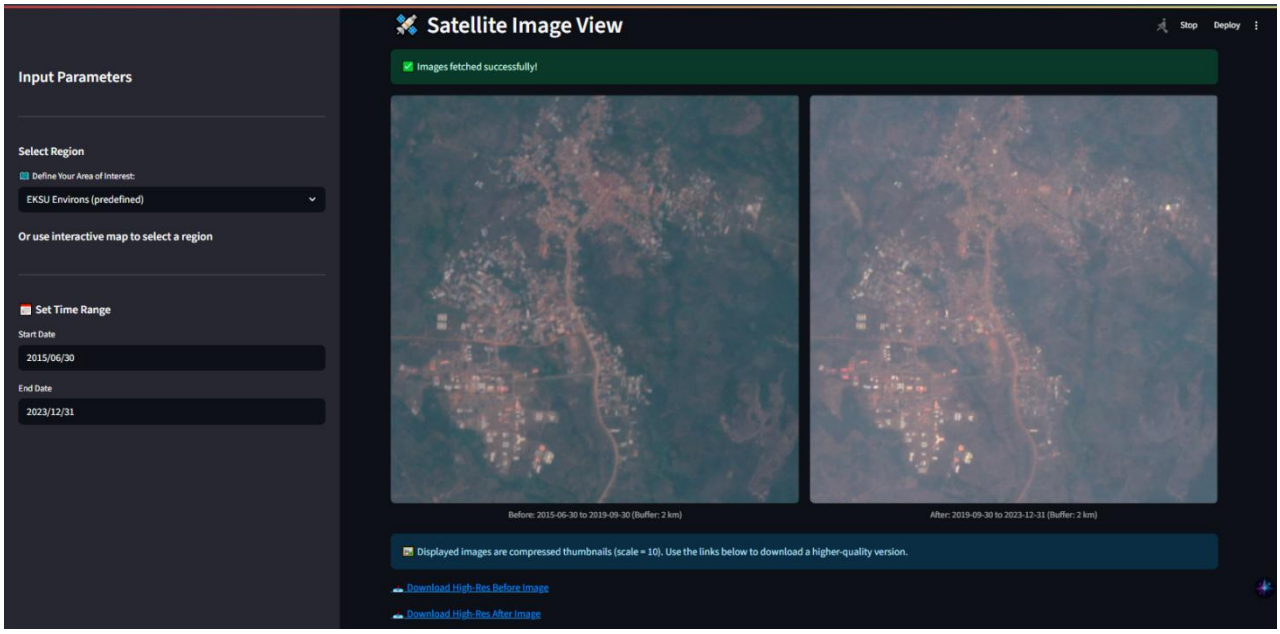
   Reports are dynamically created and downloadable from the dashboard.

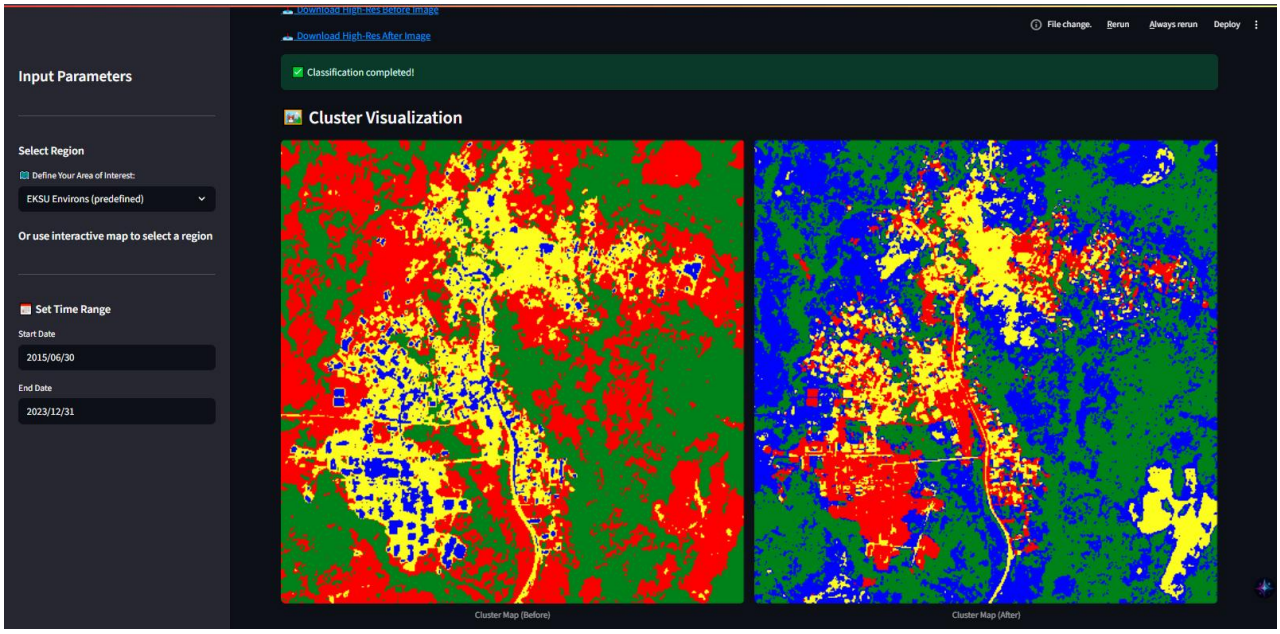
Below is a diagram illustration showing the workflow of the system.

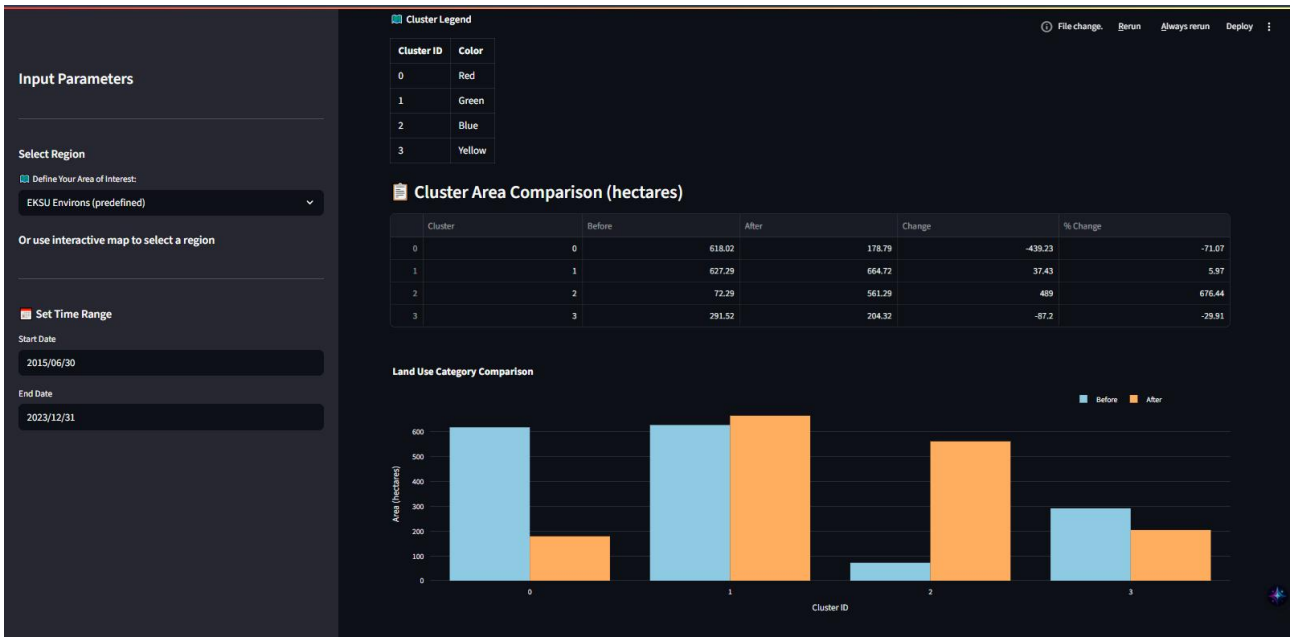


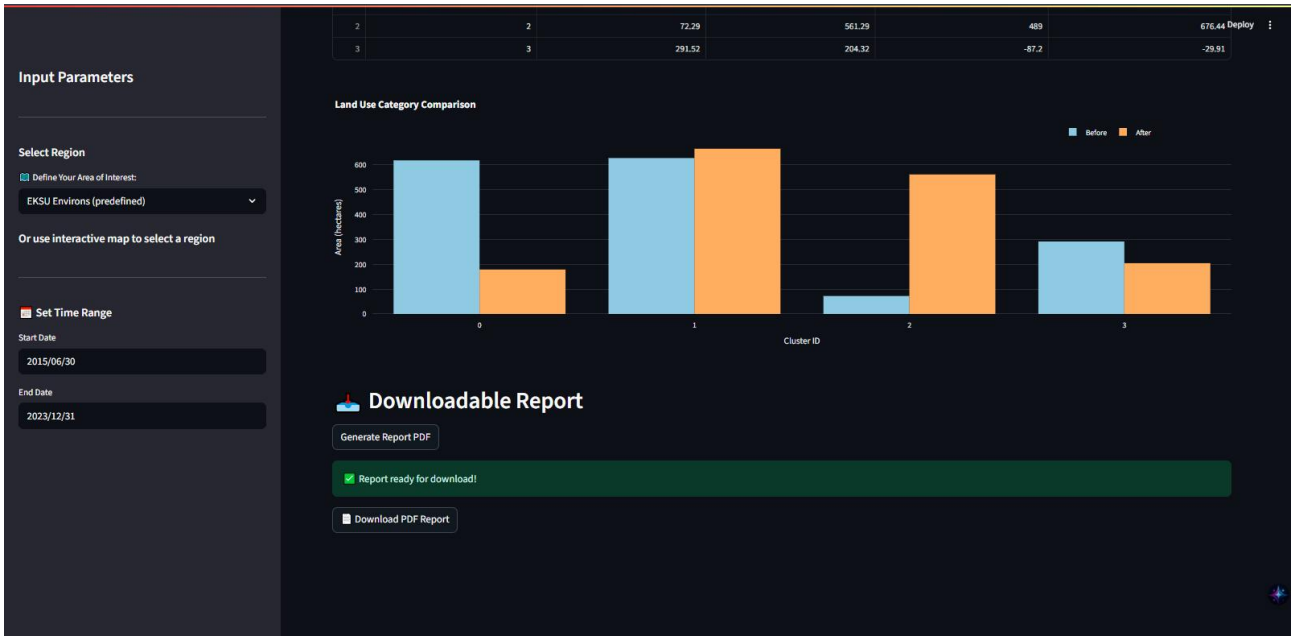
Below are screenshots of the system interface:






**Source Code Repository**

For transparency and reproducibility, the complete implementation of the Land Use Change Detection Dashboard has been made publicly available on GitHub. The repository contains the Streamlit application, supporting utility modules, and report generation scripts as described in this chapter.
https://github.com/moses-noah/lulc-dashboard/releases/tag/v1.0

## 4.4 Case Study

### 4.4.1 Study Area Description

The case study for this project was conducted within the environs of **Ekiti State University (EKSU)**, located in Ado-Ekiti, Ekiti State, Nigeria. The university sits in a semi-urban environment that is characterized by a mixture of academic and residential buildings, farmlands, patches of vegetation, and small road networks that connect the campus to surrounding settlements. This combination of built-up areas and natural cover makes EKSU a suitable test location for evaluating land use and land cover (LULC) changes.

The surrounding environment is dynamic. Over the past decade, the university and its host community have experienced steady expansion, with new residential buildings and commercial activities gradually replacing vegetated areas. At the same time, sections of land around the campus are still used for agriculture and open fields, meaning that the area presents a diverse mix of land cover types that are relevant for testing a change detection system.

The **Area of Interest (AOI)** used in this study was defined as a **2 km buffer zone around the central EKSU campus coordinates (7.7207°N, 5.2606°E)**. This boundary was chosen to capture not only the main university campus but also its immediate surroundings where most visible land cover transitions are taking place.

Satellite image of the AOI is shown below



This image highlights the polygon boundary created using the dashboard's coordinate input and buffer tool, which serves as the spatial extent for subsequent analysis in the case study.

### 4.4.2 Experimental Setup

To evaluate the system, the dashboard was applied to the EKSU environs AOI using its built-in workflow. The experimental setup followed these steps:

**i.** AOI Selection: A 2 km buffer was defined around the central EKSU coordinates (7.7207°N, 5.2606°E). The dashboard's buffer tool automatically generated the polygon boundary.

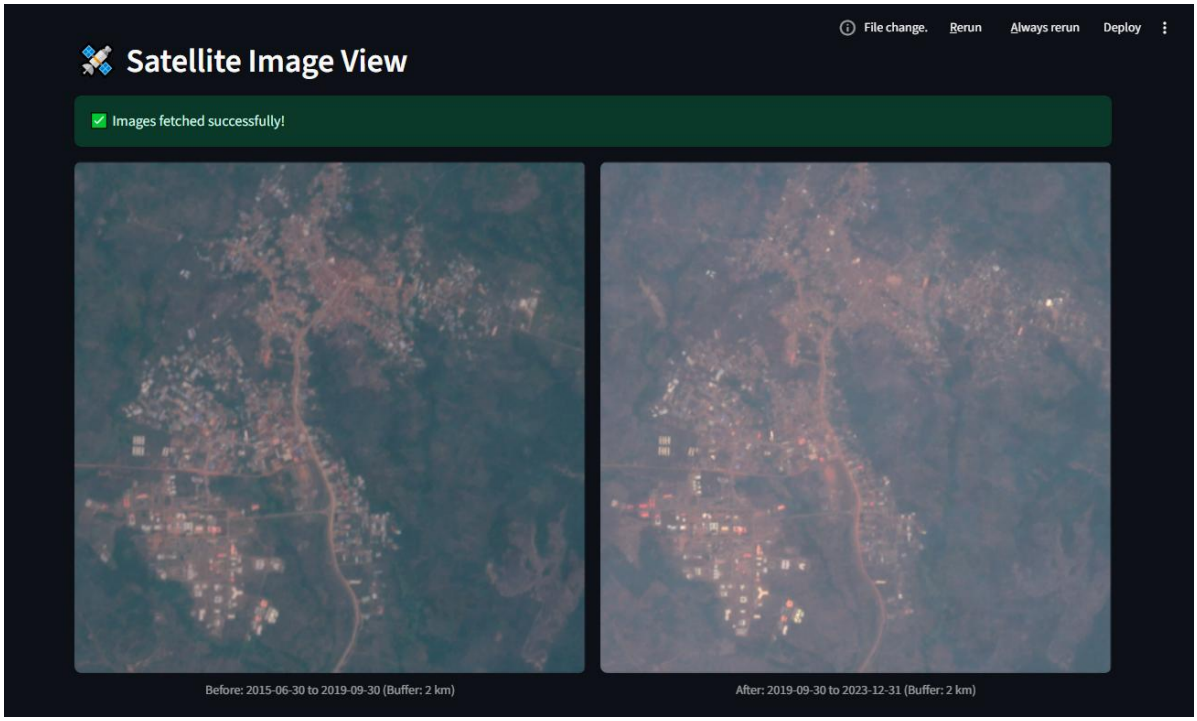
**ii.** Time Frame: The study compared land cover between two periods, Before: 2016–2019 (baseline imagery), After: 2020–2023 (recent imagery).This split captures changes in vegetation loss, new construction, and land conversion over roughly four years.

**iii.** Data Source: Sentinel-2 imagery (10 m resolution) from Google Earth Engine. Median composites were generated to minimize cloud interference.

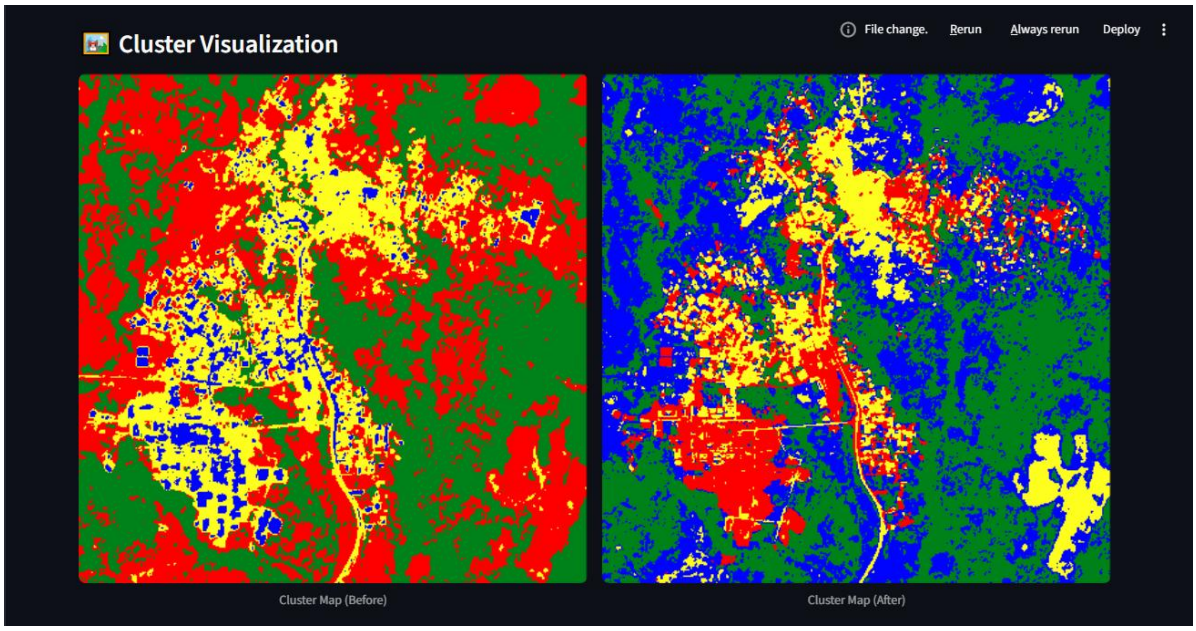
**iv.** Classification Method: The system's unsupervised clustering (K-Means, 4 clusters) was used to group land cover types without predefined labels.

**v.** Outputs Evaluated:

**1.** Satellite image composites (before/after)



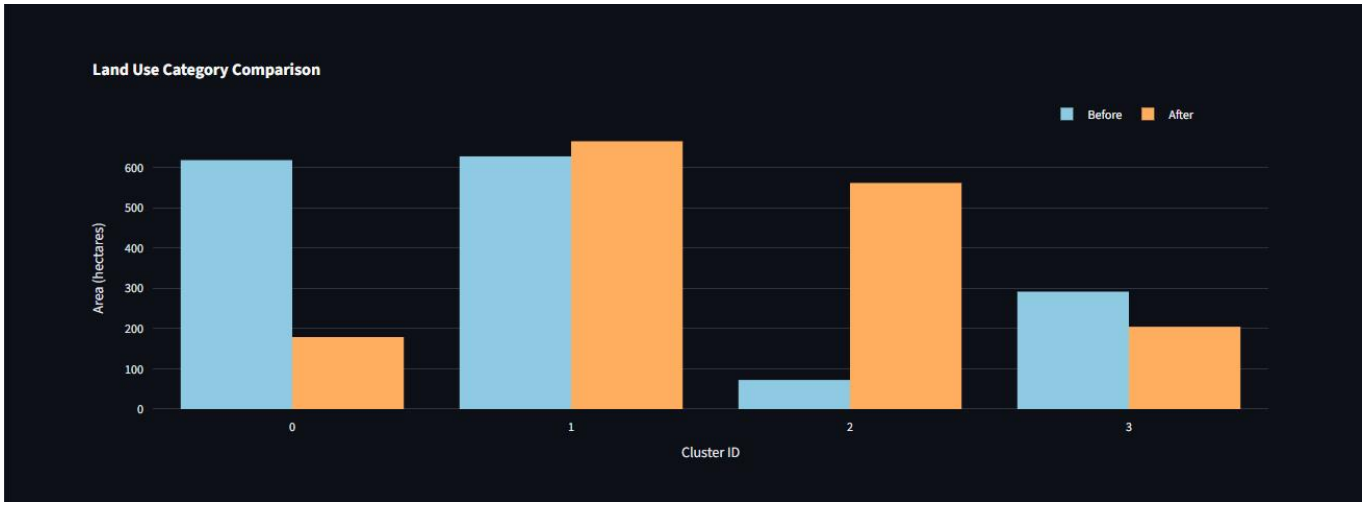

**2.** Cluster maps showing land cover groupings



3. Cluster area summary and change tables




4. Visualization (charts and legends)




This setup reflects how an end-user would practically use the dashboard to analyze land cover change in a specific location.

### 4.4.3 Results and Observations

The change detection analysis for EKSU environs was carried out using the dashboard's unsupervised clustering model. The results show the distribution of four clusters before and after the selected time period.

**i.** Cluster 0 experienced a dramatic decline, reducing from 618.02 ha to 178.79 ha, a 71.07% decrease.
**ii.** Cluster 1 remained relatively stable, with a slight increase from 627.29 ha to 664.72 ha (+5.97%).
**iii.** Cluster 2 recorded the most significant growth, rising sharply from 72.29 ha to 561.29 ha, which translates to a 676.44% increase.
**iv.** Cluster 3 decreased moderately, dropping from 291.52 ha to 204.32 ha (–29.91%).

From these results, several observations can be made:

**i.** The system successfully identified substantial spatial changes, with some clusters expanding massively while others contracted.
**ii.** The stark contrast between Cluster 2's sharp growth and Cluster 0's steep decline suggests that notable land transformation has occurred within the AOI during the analysis period.

**iii.** The relative stability of Cluster 1 demonstrates the system's ability to capture areas of minimal change alongside areas of high variability.

Overall, the results confirm that the dashboard can effectively highlight where and how much change has occurred, even though the unsupervised model does not directly label clusters with real-world land cover categories. This shows the system's strength in detecting shifts and providing a quantifiable basis for further interpretation by domain experts or with complementary supervised models.

### 4.4.4 Evaluation of System Performance

**Strengths**: The dashboard demonstrates strong capabilities in simplifying land use change detection for non-technical users. It integrates seamlessly with Google Earth Engine to provide access to high-resolution Sentinel-2 imagery, automates preprocessing steps like cloud masking and compositing, and delivers clear outputs in the form of cluster maps, tabular summaries, and charts. Its flexibility in defining an area of interest (via coordinates, buffer, or interactive map) ensures adaptability for different use cases. The ability to generate a structured PDF report further enhances its practical value for documentation and decision-making.

**Limitations**: The main limitation lies in the use of an unsupervised clustering model, which groups pixels based on spectral similarity without attaching semantic meaning (e.g., vegetation, built-up, water). This restricts interpretation since users cannot directly associate clusters with specific land cover types. Additionally, the system relies on internet connectivity and Earth Engine's availability, making it less reliable in offline or resource-limited settings. The computation is also constrained by the scale and extent of the AOI—larger regions or longer time ranges may require significant processing time.

**Relevance**: Despite its limitations, the dashboard is highly relevant for academic research, environmental monitoring, and preliminary land management assessments. It provides a rapid, accessible, and cost-free way to identify spatial and temporal changes in land cover, which is particularly useful for local planning authorities, researchers, and students. By serving as a foundation, it can also be extended with supervised models or integrated with domain-specific datasets, making it a valuable baseline tool for land use change analysis.

### 4.4.5 Summary of Findings

The case study on EKSU environs demonstrated that the dashboard is effective in detecting and quantifying land use changes over time using freely available satellite imagery. The system successfully processed Sentinel-2 data, generated composite images for two distinct periods, and applied unsupervised clustering to highlight spatial variations. The outputs—maps, tables, and charts—provided clear evidence of both reductions and expansions across the different clusters, with some categories showing significant increases while others declined.

While the unsupervised model does not label clusters into real-world categories, the magnitude of changes observed indicates that the tool can serve as an early-warning system or preliminary analysis platform. Users can quickly identify where major shifts have occurred and decide if further, more detailed supervised classification is warranted.

Overall, the findings confirm that the dashboard is a practical and accessible tool for land use change detection, particularly for small to medium-sized areas such as university environs. It balances simplicity with functionality, making it suitable for educational, research, and planning purposes.

# CHAPTER FIVE

# SUMMARY AND RECOMMENDATION

## 5.1 Summary

This project set out to design and develop a web-based dashboard for detecting land use and land cover (LULC) changes using multi-temporal satellite imagery. The system was built around Google Earth Engine for data processing and Streamlit for the user interface, making it both powerful and user-friendly. Its key functions include selecting an area of interest, retrieving Sentinel-2 imagery, running unsupervised classification, and producing comparative statistics and visualizations that highlight land cover changes over time.

A case study was carried out using the EKSU environs as the test area. The dashboard successfully retrieved and processed imagery, applied clustering, and generated before–after comparisons of land cover distribution. The results demonstrated that the system is capable of providing quick insights into spatial dynamics without requiring specialized geospatial software or advanced technical expertise from the user.

Overall, the project achieved its primary objective of delivering an accessible tool for monitoring LULC changes. While the classification approach was unsupervised and thus did not assign real-world labels to clusters, the platform still proved effective in capturing shifts in land cover patterns and presenting them in a clear, interpretable format.

## 5.2 Recommendations

Based on the development process and findings of this study, the following recommendations are proposed:

i. **Adopt supervised classification for improved accuracy**: While the unsupervised approach was effective in showing relative changes, future versions of the dashboard should integrate supervised classification methods. This would allow clusters to be mapped to real-world land cover types such as vegetation, water, or built-up areas, making the results more meaningful for planners and researchers.
ii. **Expand spatial coverage and scalability**: The system was tested on the EKSU environs, but its architecture supports larger areas. Future work should extend the system to cover local government or national scales, with optimization for faster processing of large datasets.
iii. **Enhance user interaction**: Adding features such as dynamic legends, side-by-side interactive maps, and comparison sliders could improve usability and make visual analysis more intuitive for non-technical users.
iv. **Integrate additional datasets**: Incorporating data sources such as climate variables, elevation, or population density would enrich the context of land cover change and support multi-criteria decision-making.
v. **Continuous maintenance and updates**: Since Earth Engine datasets and APIs evolve, regular updates are essential to keep the dashboard functional. Future work should also explore lightweight deployment options, such as cloud hosting, to ensure long-term accessibility.

**Open-Source Availability**

To encourage further research and practical adoption, the system has been released as an open-source project on GitHub. Future researchers and developers can build upon this foundation, extend its features, or adapt it to new regions and use cases.

https://github.com/moses-noah/lulc-dashboard

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