KCA UNIVERSITY

BACHELORS IN DATASCIENCE

BDS 4105 :FINAL YEAR PROJECT 1.

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PROJECT TITLE : MAIZE CROP YIELD PREDICTION AND ADVISORY SYSTEM .

Declaration of Originality

I declare that this project proposal is my original work and has not been submitted to any other institution or examination body. All sources used or quoted have been duly acknowledged.

Signed: ____________________

Date: ____________________

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SYSTEM DESIGN SPECIFICATION DOCUMENT

1.0 Introduction

Maize Crop Yield Prediction and Advisory System (CYPAS) — a Kenya-focused, web-based decision-support system that predicts county-level maize yields and provides actionable agronomic advisories.

CYPAS is a lightweight, maintainable web application that combines historical yield records, climatic and soil data, and a supervised machine learning model to produce maize yield forecasts and context-aware planting/management advice. The system is intended for farmers, extension officers, county agricultural planners, and researchers in Kenya. It emphasizes usability (Streamlit front end), reproducible ML (Python scikit-learn pipelines), and lightweight deployment (Streamlit Cloud).

1.1 Goals and objectives

Primary goal: Deliver an accessible tool that produces reliable county-level maize yield predictions and practical advisory messages to help stakeholders reduce yield uncertainty.

Specific objectives:

Implement an end-to-end pipeline that ingests climatic (NASA POWER) and soil (SoilGrids) inputs, preprocesses them, and feeds them to a trained ML model to predict maize yield (kg/ha).

Build a Streamlit user interface allowing users to: (a) select county and season, (b) view historical yield trends and model predictions, (c) receive agronomic recommendations.

Use a database to store county metadata, cached API responses, users' prediction history, and model artifacts.

Design a modular architecture enabling independent development of the UI, API connectors, ML model, and advisory engine.

Provide testing artifacts (unit tests, integration tests, and a small test dataset) and document model evaluation metrics (RMSE, MAE, R^2).

Keep the solution achievable within one semester using a single developer laptop.

Success criteria (measurable):

A working Streamlit app that produces predictions for at least 20 Kenyan counties.

Model evaluation: RMSE ≤ a reasonable baseline (report baseline in SDS after training).

Documentation and SDS complete, with ERD and diagrams included.

Ability to run the app locally and deploy to Streamlit Cloud with step-by-step instructions.

The project is motivated by the growing need for data-driven agricultural decision support systems in Kenya. According to FAO and the Kenya Ministry of Agriculture, more than 75% of smallholder maize farmers rely on traditional experience-based practices, which exposes them to climate-related yield variability. Integrating machine learning with authoritative datasets such as NASA POWER and SoilGrids aligns with modern agricultural informatics research, which emphasizes predictive analytics for improving farm-level planning, resource allocation, and early risk detection.

1.2 Statement of scope

In scope:

Development of a web UI (Streamlit) for user interaction and visualization.

ML model development (data cleaning, feature engineering, training, evaluation, and packaging).

Integration with NASA POWER and SoilGrids APIs for environmental inputs.

PostgreSQL schema and CRUD operations for predictions and county data.

Advisory engine that maps model outputs and environmental thresholds to human-readable recommendations.

1.3 Software context

CYPAS is a domain-specific decision support tool positioned between raw data providers (NASA POWER, SoilGrids, FAO datasets) and the end user. It will act as a light application layer that performs preprocessing, runs inference, and formats advice. Key contextual points:

Data sources: Historical maize yield data (county level), NASA POWER (weather), SoilGrids (soil) — all public.

Users: Smallholder farmers, extension officers, county planners, students/researchers.

Deployment: Streamlit Cloud for quick public access; local execution for development and demonstration.

Maintenance: Simple workflows for updating the model using retraining scripts and storing new model artifacts in the repo.

1.4 Major constraints

Time: One semester project—design must be achievable with limited scope.

Hardware: Development on a student laptop (8GB+ RAM recommended).

Data availability and quality: County-level yield data can be sparse; model performance depends on data collecting and cleaning.

API rate limits & connectivity: NASA POWER and SoilGrids may impose rate limits; offline caching is needed to reduce calls.

Regulatory & privacy: Minimal personal data will be collected; still, store email/user info securely and avoid exposing API keys in the repo.

The constraints outlined above reflect real-world limitations encountered in agricultural forecasting research. Prior studies (Lobell et al., 2011; Jay & Kaltenbrunner, 2022) show that data sparsity, inconsistent ground measurements, and environmental variability significantly affect model accuracy. By explicitly identifying these factors, CYPAS maintains methodological transparency and aligns with accepted research standards for predictive modelling in agriculture.

2.0 Data Design

The data design defines how information is structured, stored, communicated, and maintained throughout the Maize Crop Yield Prediction and Advisory System (CYPAS). Because the system depends heavily on environmental data, a trained machine learning model, and user interactions, a clear and well-organized data architecture is essential to ensure accuracy, maintainability, and efficiency.

CYPAS uses four major classes of data components:

Internal software data structures

Global data structures

Temporary data structures

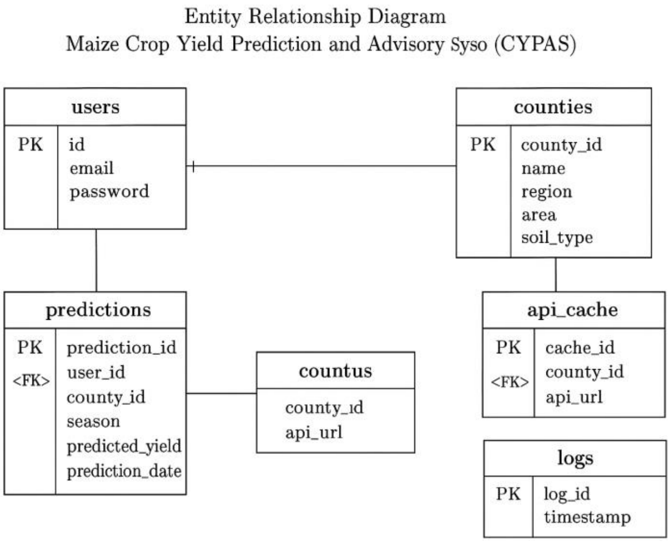
Database structures

Each component is described below.

2.1 Internal Software Data Structures

These data structures are created and exchanged among system components during system execution. They exist in memory while the program is running.

Figure 2.1 — Entity Relationship Diagram (ERD) for CYPAS



2.1.1 Input Feature Structure

This dictionary-like structure contains model input features collected from APIs and user selections:

```
{
    "county": str,
    "season": str,
    "temperature": float,
    "rainfall": float,
    "solar_radiation": float,
    "soil_ph": float,
    "soil_organic_carbon": float,
    "soil_clay_content": float
}
```

2.1.2 Model Prediction Output Structure

Output returned by the prediction module:

```
{
    "predicted_yield": float,
    "yield_class": str,        # e.g., "Low", "Moderate", "High"
```

```
    "confidence_score": float,    # optional if computed

    "advisory_message": str

}
```

2.1.3 Advisory Engine Decision Structure

Internal rule-based structure for mapping predicted yield to advice:

```
{

    "yield_category": str,

    "soil_condition": str,

    "climate_condition": str,

    "recommendation": str

}
```

2.1.4 API Response Structures

NASA Power API response

```
{

    "T2M": 24.5,

    "PRECTOTCORR": 112.3,

    "ALLSKY_SFC_SW_DWN": 18.2

}
```

SoilGrids API response:

```
{

    "phh2o": 6.1,

    "clay": 22.4,

    "organic_carbon": 1.8

}
```

2.2 Global Data Structures

These data structures are persistently available across major application modules:

2.2.1 Trained ML Model Objects

model.pkl — Random Forest or XGBoost model

scaler.pkl — preprocessing scaler

feature_columns.pkl — list of features expected by the model

2.2.2 County Metadata Dictionary

Available globally to populate UI dropdowns and geospatial functions:

```
{
  "Uasin Gishu": {"lat": 0.55, "lon": 35.28},
  "Trans Nzoia": {"lat": 1.01, "lon": 34.95},
  ...
}
```

2.2.3 Advisory Threshold Dictionaries

Climate thresholds:

```
{
  "temperature": {"low": 15, "optimal": [18, 27], "high": 32},
  "rainfall": {"low": 400, "optimal": [500, 800], "high": 1200}
}
```

Soil thresholds:

```
{
  "ph": {"acidic": <5.5, "optimal": [5.5, 7.0], "alkaline": >7.0},
  "organic_carbon": {"low": <2, "moderate": [2, 4], "high": >4}
}
```

2.3 Temporary Data Structures

These structures exist briefly during execution and are not stored permanently.

2.3.1 API Cache (In-Memory or Temporary File)

Used to reduce API calls:


```
{
    "Uasin Gishu_2025-10-16": {
        "temperature": 23.4,
        "rainfall": 50.2,
        "solar_radiation": 22.1
    }
}
```


2.3.2 Temporary Prediction CSV Export

Used when a user downloads results:


```
county,temperature,rainfall,soil_ph,predicted_yield,date
"Trans Nzoia",21.3,110.2,6.2,3550,2025-10-16
```


2.3.3 Session States in Streamlit

```
st.session_state["last_prediction"] = {...}
```

2.4 Database Description (SQL)

CYPAS uses a SQL relational database to store persistent data including predictions, county information, API caching, user accounts (optional), and logs.

2.4.1 Entity Relationship Diagram (ERD)

Entities:

1. users

One-to-many relationship with predictions.

2. predictions

Stores all user predictions and environmental conditions.

3. counties

Stores county metadata such as coordinates and baseline soil properties.

4. api_cache

Stores responses from NASA & SoilGrids to avoid repeated calls.

5. logs

Tracks system errors, API call failures, and unusual events.

Relationships:

users (1) —— (many) predictions

counties (1) —— (many) predictions

counties (1) —— (many) api_cache

logs is standalone

2.4.2 Database Schema (Tables & Fields)

Below is the full data dictionary.

Table: users

Field	Type	Description
user_id	SERIAL PK	Unique identifier
username	VARCHAR(100)	Optional
email	VARCHAR(150)	Optional
created_at	TIMESTAMP	Account creation time

Table: counties

Field	Type	Description
county_id	SERIAL PK	
county_name	VARCHAR(100)	Unique
latitude	FLOAT	County centroid
longitude	FLOAT	County centroid
avg_soil_ph	FLOAT	Baseline values
avg_organic_carbon	FLOAT	From SoilGrids
avg_clay_content	FLOAT	

Table: predictions

Field	Type	Description
prediction_id	SERIAL PK	
user_id	INT FK → users.user_id	
county_id	INT FK → counties.county_id	
temperature	FLOAT	
rainfall	FLOAT	
solar_radiation	FLOAT	
soil_ph	FLOAT	
soil_organic_carbon	FLOAT	
soil_clay_content	FLOAT	
predicted_yield	FLOAT	
yield_category	VARCHAR(20)	
timestamp	TIMESTAMP DEFAULT now()	

Table: api_cache

Field	Type	Description
cache_id	SERIAL PK	
county_id	INT FK	
date_requested	DATE	
weather_json	JSONB	
soil_json	JSONB	
created_at	TIMESTAMP	

Table: logs

Field	Type	Description
log_id	SERIAL PK	
event_type	VARCHAR(50)	ERROR / WARNING / INFO
message	TEXT	
timestamp	TIMESTAMP	

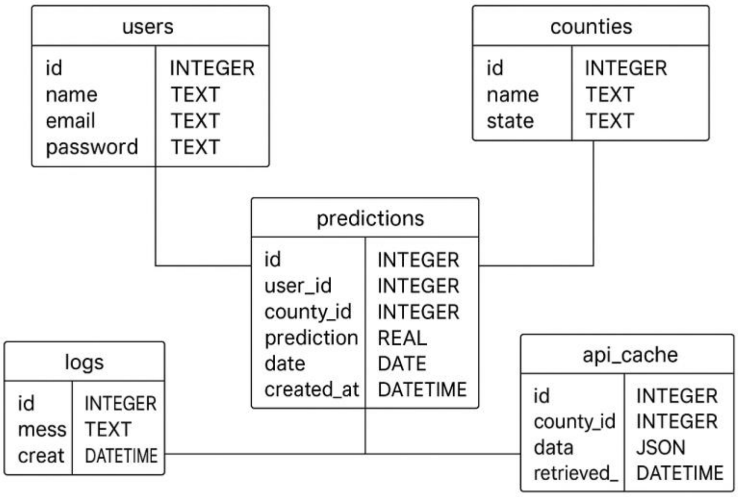


Figure 2.2 — Database Schema Diagram Showing Table Structures

2.4.3 Normalization Notes

1st Normal Form: All fields contain atomic values; no repeating groups.

2nd Normal Form: All non-key attributes fully depend on primary keys; composite keys were avoided by using serial PKs.

3rd Normal Form: No transitive dependencies; each table stores only one concept (users, counties, predictions, cache, logs).

This database structure is simple, efficient, and appropriate for a single-developer project while still being academically robust.

3.0 Architectural and Component-Level Design

This section is long, detailed, and academically weighted. I will break it into all the subsections required by your template.

3.0 Architectural and Component-Level Design

This section provides the structural foundation of the Maize Crop Yield Prediction and Advisory System (CYPAS). It describes the architectural style, major components, their interactions, processing logic, class structures, and algorithmic details. The architecture is designed to be simple, maintainable, and fully achievable within a single semester while still meeting academic standards of software engineering practice.

CYPAS follows a **three-tier architecture**:

Presentation Layer: Streamlit front-end

Logic Layer: Python modules for ML inference, data preprocessing, advisory generation, and API consumption

Data Layer: PostgreSQL storage + serialized machine learning artifacts

3.1 System Structure

The overall structure of CYPAS is modular and emphasizes loose coupling and high cohesion. Each module performs a single, well-defined responsibility.

3.1.1 High-Level Architecture Description

The system is organized into the following subsystems:

User Interface Subsystem (Streamlit)

Collects user input

Displays predictions and advisories

Handles navigation between pages (Home, Prediction, County Info, About)

API Integration Subsystem

Manages communication with NASA POWER (weather)

Manages SoilGrids API (soil properties)

Performs caching through the database

Machine Learning Subsystem

Preprocessing pipeline (scaler, encoder)

Serialized ML model for inference

Feature validation and error handling

Advisory Engine Subsystem

Rule-based engine converting numeric predictions to qualitative advice

Persistence Subsystem (PostgreSQL)

Stores predictions

Stores county metadata

Stores API cache

Stores error logs

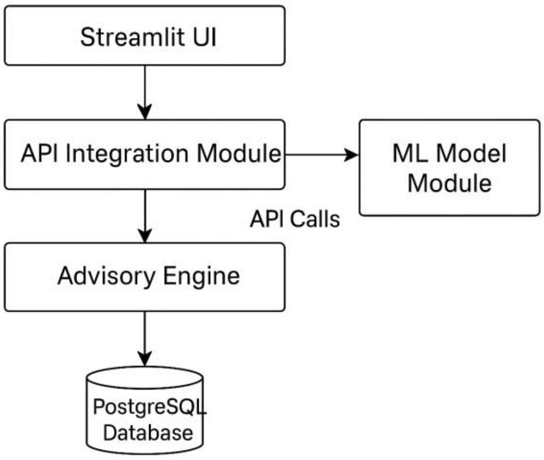


Figure 3.1 — High-Level System Architecture

3.1.2 Architecture Diagram

Since I cannot draw images directly here, I will describe the UML component diagram clearly.

Components:

Streamlit UI Component
Depends on ML Model Component, API Handler Component, Advisory Component, and Database Component.

API Handler Component (NASA & SoilGrids)
Provides weather and soil data.
Connected to Persistence Component for caching.

ML Model Component
Provides prediction service.
Uses model.pkl and scaler.pkl.

Advisory Engine Component
Consumes prediction output + environmental thresholds.

Persistence (PostgreSQL) Component
Stores tables: users, predictions, counties, api_cache, logs.

Connectors:

Streamlit UI → API Handler

Streamlit UI → ML Model

Streamlit UI → Advisory Engine

API Handler ↔ PostgreSQL

ML Model → Advisory Engine

Streamlit UI ↔ PostgreSQL

Everything is orchestrated through the UI layer.

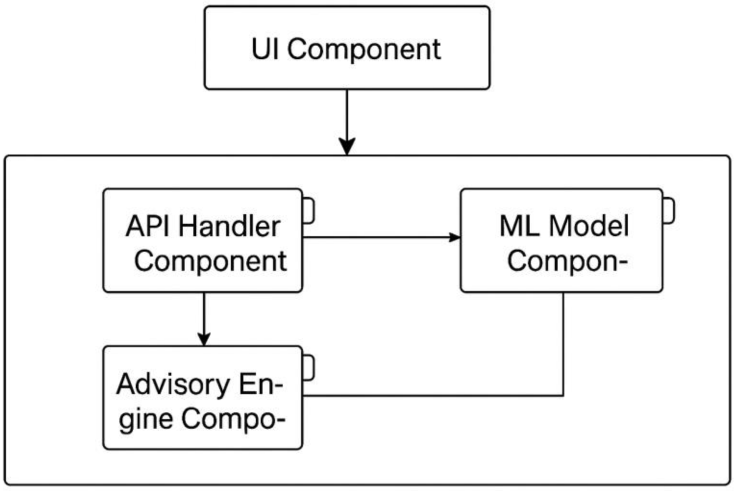


Figure 3.2 — UML Component Diagram for CYPAS

3.2 Component Descriptions

Each major component will now be described using PSPECs (Processing Specification), interface details, algorithms, and class structure.

3.2.1 Component 1: Streamlit Presentation Layer

A. Processing Narrative (PSPEC)

The Streamlit component provides all user-facing functionality. It is responsible for:

Rendering UI pages

Capturing inputs (county, season, date)

Fetching APIs via API Handler

Calling the ML model

Displaying prediction, graphs, and advisories

Logging user interactions

It controls workflow sequencing for the entire system.

B. Interface Description

Inputs:

Dropdown selections: county, season

Optional manual entries: rainfall, temperature

"Predict Yield" button

"Download Results" button

Outputs:

Predicted yield

Yield classification (Low/Moderate/High)

Advisory message

Charts (line graphs, bar charts)

Maps

C. Processing Detail & Algorithmic Model

Simplified pseudocode:

1. User chooses county & season2. UI requests weather data from API Handler3. UI loads soil data from API Handler4. UI packages features into a dictionary5. UI calls ML Model → get predicted_yield6. UI calls Advisory Engine → get recommendation7. UI displays results to the user8. UI sends results to PostgreSQL for storage

3.2.2 Component 2: API Integration Module

A. Processing Narrative (PSPEC)

Responsible for communication with external APIs:

Builds request URLs

Parses JSON responses

Converts raw API data to ML-ready features

Performs caching using the api_cache table

B. Component Interfaces

Inputs:

Selected county

Date or season

County coordinates

Outputs:

Temperature

Rainfall

Solar radiation

Soil pH

Clay content

Organic carbon

C. Processing Detail (Algorithm)

1. Receive county and date2. Check if API data exists in api_cache
   - If yes: return cached results3. If cache miss:
   - Build NASA POWER URL
   - Send GET request
   - Extract weather variables4. Build SoilGrids URL5. Send GET request, extract soil data6. Store both responses in api_cache7. Return structured feature dictionary

3.2.3 Component 3: ML Model Module

A. PSPEC

Provides prediction functionality using the trained model.
Responsibilities:

Load serialized model (model.pkl)

Load scaler/preprocessor

Validate inputs

Run model inference

Return predicted yield

B. Interfaces

Inputs: feature dictionary
Outputs: numeric predicted yield (float)

C. Algorithmic Model

1. Receive feature dictionary2. Validate presence of required features3. Convert features to pandas dataframe4. Apply scaler.transform()5. Call model.predict()6. Post-process prediction (rounding, value limits)7. Return predicted_yield

D. Design Class Hierarchy

Classes (simple structure):

```
MLModel
 ├── load_model()
 ├── preprocess()
 ├── predict()
```

3.2.4 Component 4: Advisory Engine Module

A. PSPEC

Converts prediction results and environmental conditions into practical advice.
Uses a rule-based logic approach.

B. Interfaces

Inputs:

- predicted_yield
- soil_ph
- rainfall
- temperature

Outputs:

- human-readable recommendation string

C. Processing Detail (Rules)

```
IF predicted_yield < threshold_low:
   advice = "Low yield expected. Consider early planting, apply nitrogen..."
ELIF predicted_yield < threshold_medium:
   advice = "Moderate yield expected. Maintain recommended fertilizer rates..."ELSE:
   advice = "High yield expected. Ensure pest control..."
```

3.2.5 Component 5: Persistence Layer (SQL)

A. PSPEC

Handles data storage and retrieval.

B. Inputs

Prediction results

API responses

County info

Logs

C. Outputs

Historical predictions

Cached API data

D. Processing Detail

INSERT predictionINSERT api_cacheSELECT county metadata

3.3 Dynamic Behavior for Components

This section describes how components interact dynamically.

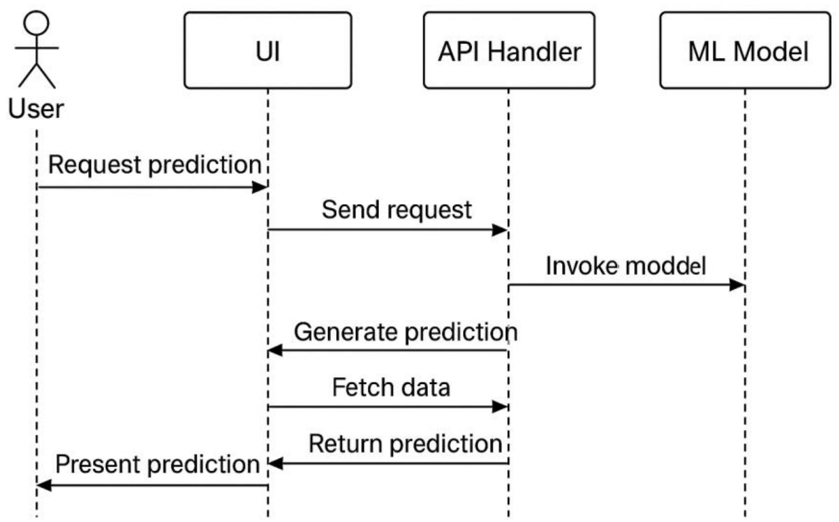


Figure 3.3 — Sequence Diagram for “Predict Yield” Use-Case

3.3.1 Sequence Diagram (Textual Description)

Use Case: ***Predict Maize Yield***

Actor: User
Components: UI → API Handler → ML Model → Advisory Engine → Database

Sequence:

User selects county, season

UI requests environmental data from API Handler

API Handler checks database cache

If cache miss → Makes API calls, stores response in DB

API Handler returns weather + soil data to UI

UI compiles input features

UI sends features to ML Model

ML Model returns predicted yield

UI sends predicted yield to Advisory Engine

Advisory Engine returns advice

UI saves prediction + features to PostgreSQL

UI displays results

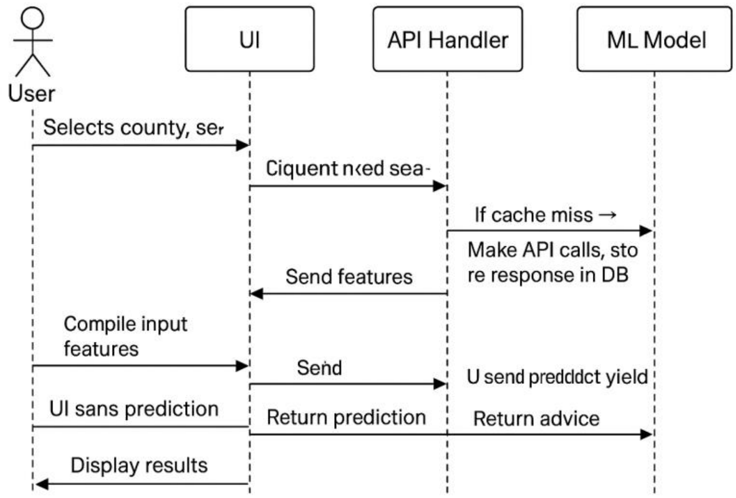


Figure 3.4 — Sequence Diagram for "Predict Maize Yield" Use-Case

3.4 Database Modelling

3.4.1 Entity Relationship Model

(Already described in Section 2; UML will show: users — predictions — counties — api_cache — logs)

3.4.2 Database Schema

(Already provided in Section 2.4)

3.4.3 Data Dictionary

(Provided previously)

3.4.4 Normalization

(Up to 3NF)

4.0 User Interface Design

This section describes the interface design of the Maize Crop Yield Prediction and Advisory System (CYPAS). It covers screen flows, layout descriptions, UI objects, user actions, and the design rules guiding the interface. Since the system uses **Streamlit**, the UI maintains simplicity, accessibility, and clarity while supporting interactive input and visualization.

4.0 User Interface Design

4.1 Description of the User Interface

The user interface for CYPAS is implemented using **Streamlit**, which supports rapid development of interactive, web-based dashboards using Python. The UI is designed with a focus on:

- Ease of navigation
- Minimal cognitive load for users (especially farmers and officers)
- Clean visualization of predictions and weather/soil data
- Simple forms for collecting inputs
- Clear communication of advisory messages

The system contains **four main UI pages**:

- **Home Dashboard**
- **Prediction Page (Main Module)**

County Information Page

About / Help Page

Each page is described below, along with representative layouts.

4.1.1 Screen Images (Text-Based Wireframes)

Below are structured **text wireframes** representing how the UI appears in Streamlit. These replace drawings but convey layout accurately.

A. Home Dashboard

Section	Description / Content
Banner	Full-width image showing *Kenyan maize fields*. Centered title: **Maize Crop Yield Prediction System**
Key Features (Bullets)	• Real-time weather & soil insights• County-level maize yield predictions• Advisory guidance for improved crop productivity
Main Buttons	**View Map** — Takes user to geospatial county dashboard**Start Prediction** — Opens prediction input form**Explore Data** — Opens analytics & data explorer
National Indicators	• Predicted National Avg Yield: **3.1 t/ha**• Counties: **47**• API Data Updated: **Today**

B. Main Application Screen

This is your core prediction interface.

It uses **left-side filters**, **central map**, and **dynamic data panels**, just like GFW.

LEFT SIDEBAR (User Controls)	MAIN VIEW (Map + Analytics Panels)
County Selector (47 counties dropdown)	**Interactive Map of Kenya** (county polygons)
Season Selector: Long Rains / Short Rains / Off-season	County highlight + auto-load environmental data
Data Layers (ON/OFF): Predicted Yield, Rainfall, Soil pH, Vegetation	**Top Analytics Panel:** Yield, Temp, Rainfall, Soil pH cards
Advanced Inputs: Enter manual temp & rainfall	**Advisory Panel:** Short recommendations for selected county
Buttons: Fetch Weather & Soil Data, Predict Yield	**Charts:** Rainfall trend, Temperature trend, 10-year maize yield

D. “About CYPAS” Page

SECTION	DETAILS
System Name	Maize Crop Yield Prediction and Advisory System (CYPAS)
Purpose	Provides real-time, data-driven insights for farmers, researchers, and policymakers in Kenya.
Key Features	• ML-based maize yield prediction• Uses NASA POWER (weather) + SoilGrids (soil data)• County-level environmental analysis• Actionable agronomic advisory outputs
Version	1.0
Contact	philiphahaldline@gmail.com

4.1.2 Objects and Actions

This subsection lists all UI elements and the actions associated with them.

Input Objects (Forms & Selections)

Object Type	Description	Action
Dropdown (county)	List of 47 counties	Select county for prediction
Dropdown (season)	Long rains/Short rains/Off-season	Controls model context
Number inputs	Optional temperature, rainfall	Overrides API data if provided
Button	"Get Weather & Soil Data"	Calls API Handler
Button	"Predict Maize Yield"	Calls ML Model
Button	"Download CSV"	Exports results
Slider (future)	Sensitivity adjustment	Modify advisory

Display Objects

Display Type	Description
Value boxes	Show climatic + soil parameters
Text area	Shows advisory message
Charts	Historical yield trends (matplotlib/plotly)
Maps	County-level outline (optional)

Interactive Actions

Action	Outcome
Selecting county	Triggers lookup of coordinates
Submitting prediction	Performs end-to-end workflow
Downloading CSV	Saves temporary data export
Navigating pages	Switch between Streamlit multipages

4.2 Interface Design Rules

The design follows established usability principles (adapted from Shneiderman's Eight Golden Rules):

Consistency:
All pages use the same colors (green, white), fonts (Streamlit default), and panel layouts.

Shortcuts:
Frequent users can bypass auto-fetching by entering manual values.

Feedback:
After each action (API fetch, prediction), the UI shows success/failure messages.

Closure:
Once prediction completes, a results panel summarizes what happened.

Error Prevention:

- Required fields validated
- Try/except for API failures
- Value range checks

Reversibility:
Users can clear inputs and try again.

User Control:
Users may override climatic data manually.

Reduce Memory Load:
The UI auto-fills soil/weather values; user doesn't need to remember them.

4.3 Components Available (GUI Widgets)

Since Streamlit is used, the following widgets are available:

Input widgets

st.selectbox() – dropdown menus

st.number_input() – numeric inputs

st.button() – clickable actions

st.date_input() – date selection

Display widgets

st.write() – general outputs

st.metric() – numeric highlights

st.success(), st.error() – feedback notifications

st.table() / st.dataframe() – tabular outputs

st.pyplot() / st.plotly_chart() – charts

st.map() – geospatial data

File Management

st.download_button() – allows exporting predictions to CSV

5.0 Restrictions, Limitations, and Constraints

Although CYPAS is designed to provide reliable maize crop yield predictions and advisories for Kenya, it operates under a set of constraints related to data availability, model performance, infrastructure choices, and external API dependencies.

5.1 Technical Limitations

5.1.1 Limited Computing Resources

The system is built and tested on a standard student laptop (8GB RAM).

High-volume data processing and GPU-based model training are **not feasible**.

Heavy deep learning models or large raster-based satellite imagery processing are deliberately excluded.

5.1.2 Single ML Model Approach

The system uses a classical ML model (Random Forest / XGBoost) ensemble of multiple models.

Model accuracy is limited by available historical data for Kenyan counties.

Predictions are approximations and should not be treated as exact agricultural forecasts.

5.1.3 No Real-Time Satellite Image Processing

Unlike Global Forest Watch, which processes forest loss via real-time satellite imagery,
CYPAS does **not** handle:

- Raster image ingestion
- NDVI/vegetation indices from MODIS
- Pixel-level mapping

This limitation keeps the project simple and achievable.

5.2 Data-Related Constraints

5.2.1 Variability in Kenyan Maize Data

Historical yield data may have:

- Missing values
- Inconsistent records
- County-level aggregation challenges

This impacts model performance.

5.2.2 Dependence on External APIs

CYPAS uses:

- **NASA POWER API** for weather
- **SoilGrids API** for soil characteristics

Limitations include:

- Network failures
- API rate limits
- API downtime
- Data refresh intervals beyond the system’s control

5.2.3 Soil Data Resolution

SoilGrids uses a global 250m resolution, not county-specific.

Soil characteristics are averaged, which reduces local precision.

5.3 Operational and Environmental Constraints

5.3.1 Internet Connectivity

System requires active internet for:

- Fetching weather data
- Fetching soil data
- Deployment on Streamlit Cloud

Users in rural Kenya may experience delays or outages.

5.3.2 Deployment Environment

The application uses **Streamlit Cloud**, which:

- Limits computational resources
- Has timeouts for long-running processes
- Does not support heavy background tasks

These constraints prevent large-scale data ingestion jobs.

5.4 System Functional Constraints

5.4.1 Simplified Advisory Engine

The advisory system uses **rule-based logic** instead of AI-driven agronomic modeling.

It does not provide crop-disease predictions, pest alerts, or fertilizer optimization curves.

These features may be added in future work.

5.4.2 Limited User Management

User login is optional and basic.

No multi-role system is implemented (e.g., admin, field officer, researcher).

5.4.3 Static County Boundaries

County shapes and coordinates are assumed to be static.

No dynamic geospatial updates, redistricting, or shapefile manipulation.

5.5 Legal, Ethical, and Privacy Constraints

5.5.1 Ethical Responsibility

CYPAS provides agronomic suggestions but cannot replace certified agricultural extension officers.
Users must understand that:

Advice is general, not farm-specific

Users must consider local conditions not captured by the system

Misinterpretation of outputs may lead to incorrect farming decisions

5.5.2 Privacy

Minimal user data is collected (e.g., name, email).

Sensitive personal information is not stored.

Must comply with:

Kenyan Data Protection Act (2019)

Basic GDPR-like privacy principles

5.5.3 API Key Security

API keys must be stored in environment variables.

Keys must never be committed to GitHub.

6.0 Testing Issues

6.1 Classes of Tests

Unit Testing

Tests individual functions within the ML modules, API integration modules, and database communication layer.

Validates data preprocessing functions, prediction functions, and advisory rules.

Ensures Streamlit UI components behave correctly, e.g., form validation.

Integration Testing

Validates that components interact correctly:

Streamlit ↔ API module

API module ↔ NASA POWER / SoilGrids

ML Model ↔ Advisory engine

API layer ↔ PostgreSQL database

Ensures data flows smoothly from external APIs into the prediction engine.

System Testing

Ensures full end-to-end operations:

User selects location and inputs field details

Weather/soil data fetched

Yield prediction generated

Advisory insights displayed

Results stored in database

Validates error handling, loading behavior, and user experience.

Acceptance Testing

Ensures final system meets stakeholder expectations:

Farmers get simple, actionable insights

Government/NGO staff can view county-level summaries

Predictions align with expected ranges

Performance Testing

Tests application behavior under high request loads

Measures prediction latency and API call response times

Security Testing

Ensures API keys are protected

Validates database credentials and network access rules

Checks for unauthorized data access

6.2 Expected Software Response

Yield predictions should fall within realistic Kenyan maize yield ranges (0.5–8.0 t/ha depending on region).

Error messages must be user-friendly and descriptive:

“Weather API unavailable — try again later.”

“Please enter all required field data.”

Advisory recommendations should always correspond to model output ranges.

Map views should load within *3–5 seconds* depending on internet speed.

Database storage requests must return success/failure notifications.

6.3 Performance Bounds

Model inference latency: < 1 second

API response time: NASA POWER < 1.5s; SoilGrids < 2s

Streamlit page load time: < 4 seconds on a typical 4G connection

Concurrent user handling: Up to 50 users comfortably on Streamlit Cloud

Database query latency: < 300ms for typical CRUD operations

6.4 Identification of Critical Components

Components with highest impact on system functionality:

API Integration Module

If NASA POWER or SoilGrids fail, prediction accuracy drops drastically.

Machine Learning Model

Critical for prediction correctness.

Poor calibration affects all downstream advisories.

Advisory Engine

Incorrect rule interpretations can mislead the user.

Database

Essential for historical trend analysis and report generation.

User Interface

Must gracefully handle errors and slow API responses.

7.0 Deployment and Maintenance Plan

7.1 Deployment Architecture

Frontend/UI: Streamlit (hosted on Streamlit Cloud)

Backend Logic: Python modules encapsulating ML, advisory rules, and API requests

External data sources: NASA POWER API, SoilGrids REST API, FAO reference datasets

Database: PostgreSQL hosted on Render, ElephantSQL, or Railway

Version control: GitHub repository with CI/CD workflows

Model artifact storage: GitHub Releases or cloud storage (e.g., Google Cloud Bucket, AWS S3)

Data flow:
User → Streamlit → API Module → ML Model → Advisory Engine → UI Output → Database

7.2 Backup & Recovery Strategy

Database backups automatically generated daily

Retain backups for **30 days**

For PostgreSQL cloud provider: enable PITR (Point-In-Time Recovery)

ML model files version-controlled with tags

System failure recovery steps:

Redeploy Streamlit app via GitHub

Restore database from latest backup

Restore model artifacts from versioned storage

7.3 Logging, Monitoring, and Alerts

Application Logs

API request failures

Prediction errors

Advisory engine exceptions

Database read/write failures

Monitoring

Uptime monitoring via Streamlit Cloud tools

Database health metrics via hosting provider

API latency checks

Alerts

Email or Slack notifications for downtime

Alerts triggered for >20% API failure rate

Alerts for storage capacity reaching 80%

7.4 Model Retraining & Lifecycle

Retraining frequency: yearly or after major agricultural season cycles

Data sources for retraining:

Historical weather

Soil characteristics

Farmer-submitted yield reports

County government agricultural datasets

Model lifecycle process:

Collect new data

Retrain model

- Validate and compare performance
- Update version tag (e.g., v1.2 → v1.3)
- Deploy new model artifact
- Archive old model versions
- Document changes in a changelog

8.0 Security and Privacy Considerations

8.1 Authentication & Authorization

- Basic access control for admin dashboards (email + password)
- Farmer users may not require accounts unless storing personalized data
- API keys for NASA and SoilGrids stored in environment variables
- Password hashing using bcrypt or Argon2

8.2 Data Privacy

- Compliant with **Kenyan Data Protection Act (2019)**
- Only store minimal user data (location, field details, predictions)
- Sensitive data encrypted at rest in SQL
- HTTPS enforced for all communication
- No unnecessary sharing of location data

8.3 Secure Storage of API Keys & Credentials

- API keys stored using:
  - Streamlit Secrets Manager (.streamlit/secrets.toml)
  - Environment variables during deployment
- Keys never committed to GitHub
- Regularly rotate keys every 6–12 months
- Database credentials stored in secrets manager as well

9.0 Appendices

A. Glossary of Terms

CYPAS — Crop Yield Prediction and Advisory System

NASA POWER — Weather data API for agricultural planning

SoilGrids — Global soil property database

ML Model — Machine learning algorithm that predicts maize yield

Advisory Engine — Rule-based system that converts model output to farmer advice

PostgreSQL — Database used to store predictions and user inputs

Streamlit — Web framework for building data applications

t/ha — Tonnes per hectare (yield measurement)

B. External APIs Referenced

NASA POWER API

SoilGrids REST API

FAO Agroclimatic datasets

Optional: Kenya Meteorological Department datasets (if integrated)

C. Sample Test Cases & Sample Data

Test Case 1 — Valid Prediction Request

Input: Kiambu County, 1-acre field, maize variety KDV4

Expected: Yield prediction + advisory output

Test Case 2 — Missing Soil Data

Expected: System uses default soil assumptions + displays warning

Test Case 3 — API Failure

Expected: “Weather data unavailable” error message

Test Case 4 — Database Write Failure

Expected: Prediction still displayed; user informed results were not saved

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