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HR-SAGE

SPECIAL PROJECT

Tabilas, Ernest Henley L.,
Khan, Concepcion L.

INTRODUCTION

Background of the Study

Sugarcane crop cultivation is an integral part of the Philippines' economy supplying national sugar, fertilizers, biofuel, animal feeds, and many more fundamental resources.

Timely harvest scheduling is extremely crucial in preserving crop quality and maximizing yield. Harvesting them prematurely or overdue results in a significant loss in cane yield, poor juice quality, and issues in sugar recovery and milling [1].

Statement of the Problem

Frequent on-site visits

Traditional practice of determining sugarcane crop harvest-readiness is dependent on frequent visits to the farms, which are inefficient and time-consuming.

Visual Inspection is challenging

Traditional estimates of the harvest also reflect inaccuracy and inconsistencies due to subjective human judgments.

Sugarcane's growth stage is hard to distinguish visually.

Statement of the Problem

Unique Growth Pattern

Sugarcane has a unique and delicate growth pattern.

Harvesting them too early or too late might result to poor quality and yield loss.

Deep Learning Curve on Modern Solutions

Modern solutions like data extraction using geospatial platforms and GIS tools require deep learning curve.

HR-SAGE

Harvest
Ready

-

Sugarcane
Assessment
GIS
Earth Observation

HR-SAGE

Automated Sugarcane Assessment

Automatically determines when crops are ready for harvest using satellite imagery and NDVI analysis.

! Data updates every **5 days** !

HR-SAGE

Geospatial Mapping and Visualization

Provides users with interactive maps that display the growth phases and harvest preparation in a specific area.

Significance of the Study

The interests of the stakeholders will be better served by the development of HR-SAGE if it uses a more streamlined, automated, and cost-effective method for monitoring the sugarcane growth stage.

01
Reduced on-site visits

02
Well-informed decisions

03
Provide easy-to-use Tool

Objectives of the Study

1

Implement verified crop masking techniques using satellite imagery to detect and distinguish sugarcane crops from other vegetation;

2

Develop a web-based GIS mapping tool integrating satellite imagery data for sugarcane pixel visualization and growth stage analysis;

Objectives of the Study

3

Provide nationwide information about the sugarcane lo cation and growth stage; and

4

Assess the application's usability and acceptability using SUS.

Scope and Limitations

- The dataset and geographic information will be confined to the Philippines.
- Will focus on addressing the concerns in identifying sugarcane crop locations (provided in Tommaso et al., 2024 study) and classifying them according to growth stage.
- Growth stage classification will make use of NDVI values and canopy structure.
- The study assumes full visibility of the planet in the satellite imagery data derivation.

REVIEW OF RELATED LITERATURE

Growth Stages

GERMINATION

TILLERING

GRAND GROWTH

RIPENING

Growth Stages

Fig 1: Phenological phases of sugarcane and their corre sponding time frames, as well as indicative heights and plant geometries. Adapted and modified from NaanDanJain [6]

Spectral Analysis

Spectral analysis is a popular remote sensing technique that uses distinctive reflectance properties of crops across specific wavelengths in determining and differentiating specific vegetation types.

Sugarcane has been known to exhibit unique spectral signatures that largely depend on the phenological stage the crop is currently in.

Spectral Plot of Sugarcane Growth Stages

Fig. 2: Spectral Plot of Sugarcane Growth Stages at 500 to 600 nm [7].

Spectral Plot of Sugarcane Growth Stages

Fig. 3: Spectral Plot of Sugarcane Growth Stages at 600 to 700 nm [7].

Spectral Plot of Sugarcane Growth Stages

Fig. 4: Spectral Plot of Sugarcane Growth Stages at 400 to 500 nm [7].

Vegation Indices

A vegetation index is a mathematical transformation of the spectral reflectance data extracted from various bands of satellite imagery [9].

In the context of crop monitoring, the most preferred index is the Normalized Difference Vegetation Index or NDVI.

Vegation Indices

NDVI is computed using the following:

$$NDVI = \frac{(NIR - R)}{(NIR + R)}$$

Vegation Indices

Growth Stage	NDVI Value Behavior	NDVI Value Range
Germination or Early Stage	Low NDVI	0.25 - 0.34
Tillering	NDVI increasing quickly	0.35 - 0.54
Grand Growth	NDVI is reaching its peak	0.55 - 1.00
Ripening and Harvesting	NDVI sharply decreasing	0.55- 0.7

Table 1: Sugarcane Growth Stage and NDVI Value Behavior Table [9].

Vegation Indices

Fig. 5: Temporal Patterns of NDVI (standard NDVI curves) and growing stages for sugarcane in China for both SR and TOA data [9].

GEDI and Sentinel-2

The 2024 study by Di Tommaso et al. developed a global 10 m resolution sugarcane map by integrating GEDI LiDAR canopy height data with Sentinel-2

ESA WorldCover + GLAD land cover

Fig 6: EESD Sugarcane Field Comparison [16]

INCLUDING PHILIPPINES

GEDI and Sentinel-2

The data is validated and cross-examined with raster data and government statistics.

Fig 7: EESD Comparison against Government Statistics Per Country [16]

GEDI and Sentinel-2

The data is validated and cross-examined with raster data and government statistics.

Fig 8: EESD Comparison against other crop masks [16]

MATERIALS AND METHODS

Environment

Visual
Studio Code

Dataset

- Sentinel-2

- GEDI-LiDAR
  (Tommaso et al., 2024)

- ESA World Cover + GLAD Cropland Mask

Data Extraction and Analysis

GEE
(Google
Earth Engine)

Python

GitHub
Workflow

Data Extraction and Analysis

Python Libraries

Earth Engine API

Flask API

User Interface

ReactJS

Leaflet

Tailwind CSS

Fig. 9 - HR-SAGE System Architecture

Experimental Research Design

METHODS

Implementation

Data Collection and Processing

Sugarcane Vectorizatio n

Backend Development

Implementation

Frontend Development

Participant Drafting, Feedback Survey

Final Deployment

Fig. 6 - Satellite Data Processing Flow

Growth Stage Classification

using NDVI and n_tallmonths

Stage	NDVI	n_tallmonths
Germination	0.25 - 0.34	0
Tillering	0.35 - 0.54	0
Grand Growth	0.55 - 1.00	4-7
Ripening	0.55 - 0.7	8 - 11

Project Scheduling

Task	Month					
	1	2	3	4	5	6
Literature Review						
Data Collection						
Design of System (GEE Script and Cloud Storage Setting Up)						
Sugarcane Detection and NDVI Classification Development						
Backend Development (API)						
Frontend Development (UI/UX)						
Testing and Evaluation						
Final Deployment						

Fig. 10: GANTT Chart for HR-SAGE Development.

Page Layout and Functionalities

Fig. 11: Home Page/Dashboard Page of HR-SAGE.

Page Layout and Functionalities

Fig. 12: 'Check Harvest' page layout of HR-SAGE (regional map).

Page Layout and Functionalities

Fig. 13: ‘Check Harvest’ page layout of HR-SAGE (field map).

Testing and Evaluation

The **System Usability Scale (SUS)** that John Brooke proposed [15]

DEMO

RESULTS & DISCUSSIONS

Usability Assessment

Ref	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Total
R1	4	2	4	2	4	1	4	1	5	1	85
R2	4	1	5	1	5	2	5	1	5	1	95
R3	4	2	4	4	4	2	4	2	4	2	70
R4	4	2	5	2	5	1	5	1	5	1	92.5
R5	4	1	5	1	4	1	5	1	5	1	95
R6	5	1	4	1	5	1	4	1	4	1	92.5
R7	4	2	5	1	4	1	5	1	5	1	92.5
R8	3	5	1	5	1	4	1	5	5	5	17.5
R9	4	3	5	2	4	2	5	2	4	2	77.5
R10	4	1	5	1	4	2	3	1	5	2	85
R11	3	1	5	1	4	2	5	1	5	1	90
R12	5	2	5	1	5	2	4	1	5	2	90
R13	4	1	5	2	5	1	4	2	4	2	85
R14	5	1	5	1	5	1	5	1	5	1	100
R15	4	1	4	4	4	1	4	1	4	2	77.5

83

A

Table 2: HR-SAGE SUS Score Summary.

Qualitative Feedback

What they liked:

- Easy to use!
- No learning curve
- Pixel-level accuracy
- Informative Popups
- Downloadable Summary
- Accessibility in Mobile

Qualitative Feedback

What they DON’T liked:

- Slow loading times/ Rendering of data

Visual Accuracy Validation

Fig. 14: Visualization of Di Tommaso et al.'s dataset in Palauan, Philippines, using GEE [13].

Fig. 15: Visualization of Di Tommaso et al.'s dataset in Palauan, Philippines, using GEE [13].

Visual Accuracy Validation

Fig. 13: Pie chart of the participants' response to the spatial data accuracy question in the survey

Expert Validation

Dr. Moises A. Dorado

- College of Engineering and Agro-Industrial Technology, UPLB
- Community Level SARAi Enhanced Agricultural Monitoring System (CL SEAMS) Project Leader

Expert Validation

- Scientifically grounded sugarcane pixel detections.

- The process of vectorization and centroid extraction from raster sugarcane pixels is justified and accurate (little spatial distortion due to the resolution).

- The NDVI and nTallmonths classification thresholds align with documented patterns from peer-reviewed publications

Expert Validation

May 13, 2025, ICS Library, UPLB, Via Zoom Meetings

Expert Validation

May 13, 2025, ICS Library, UPLB, Via Zoom Meetings

CONCLUSIONS

HR-SAGE **successfully implements a verified crop masking technique in sugarcane pixel detection**, integrating Sentinel-2 and GEDI-LiDAR data with remote sensing methods.

HR-SAGE is successfully deployed as **a web-based GIS mapping tool for sugarcane pixel visualization and growth stage classification**.

HR-SAGE **provides nationwide meaningful information about sugarcane locations and growth stage**.

SUS indicated high user satisfaction for HR-SAGE, suggesting **high usability in the sugarcane industry**.

The application is praised for its **simplicity** and **small learning curve**, while it is criticized for its **slow rendering** of data.

Stakeholders such as researchers, policy-makers, and mill operators can utilize HR-SAGE to facilitate **better resource management** and **harvest planning for sugarcane**, reducing frequent on-site visits, resource wastage, and maximizing yield.

RECOMMENDATIONS

1. Handle Instances of Satellite Scanning on Cloud-Covered Regions.

2. Integrate Predictive and Machine Learning Models in NDVI trend.

3. Consider authorized data contribution from field technicians.

4. Regionalize or Restrict to Sugarcane Districts

5. Optimize Mobile View

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THANK YOU

+63950-617-7177

eltabilas@up.edu.ph

Ernest Henley L. Tabilas

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