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Abstract

Paddy field segmentation using remote sensing is crucial for agricultural monitoring, yield prediction, and resource allocation. In this research, we employ Google Earth Engine (GEE) for paddy segmentation using Sentinel-2 satellite imagery. Our method leverages Normalized Difference Vegetation Index (NDVI) and Land Surface Water Index (LSWI) to mask paddy fields efficiently. We collected 2000 images (masked and unmasked), trained a ResNet model achieving 91% accuracy, and implemented a real-time mobile application. This paper details the dataset preparation, masking methodology, implementation pipeline, and mobile app integration.

1 Introduction

Precision agriculture is a growing field that utilizes remote sensing and AI to improve farming efficiency. Paddy fields, being highly dynamic, require specialized detection techniques. We propose a segmentation model using Google Earth Engine, NDVI-based filtering, and machine learning to automate paddy field identification. Additionally, we integrate this segmentation pipeline into a mobile application for real-time monitoring and analysis.

2 Dataset Preparation

I collected Sentinel-2 imagery over India, with the following specifications:

- **Time Range:** January 2022 - July 2023
- **Spatial Resolution:** 10 meters
- **Bands Used:** Blue (B2), Green (B3), Red (B4), Near-Infrared (B8), Shortwave Infrared (B11)
- **Filters:** Cloud coverage ¡ 20%
- **Ground Truth Data:** 2000 images labeled manually (masked and unmasked)

The dataset was processed by applying NDVI and LSWI calculations to extract water and vegetation features. These indices helped in identifying flooded paddy fields in early growth stages.

3 Methodology

Our approach consists of the following steps:

1. Load and preprocess Sentinel-2 imagery.
2. Compute NDVI and LSWI.
3. Apply thresholding to segment paddy fields.
4. Use ESA WorldCover data for cropland masking.
5. Export processed images and train a ResNet classifier.

4 Code Implementation

4.1 Defining the Study Area

```
var telanganaBoundary = ee.Geometry.Polygon(
        [[[78.317073, 18.859838],
          [78.317073, 18.763643],
          [78.426421, 18.763643],
          [78.426421, 18.859838]]], null, false);
Map.centerObject(telanganaBoundary, 7);
```

4.2 Loading and Preprocessing Sentinel-2 Data

```
var s2 = ee.ImageCollection('COPERNICUS/S2_SR')
  .filterBounds(telanganaBoundary)
  .filterDate('2024-01-01', '2024-07-31')
  .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20))
  .select(['B2', 'B3', 'B4', 'B8', 'B11']);
```

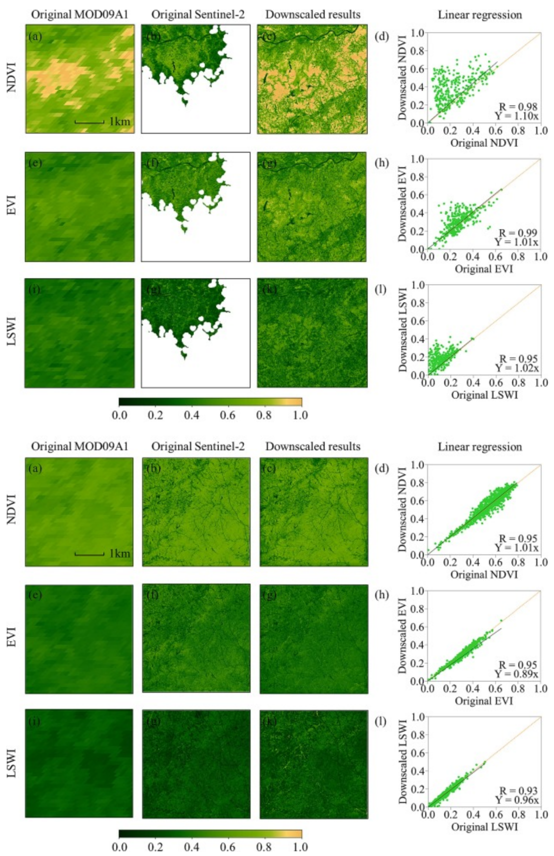

Figure 1: Computing NDVI and LSWI

4.3 Computing NDVI and LSWI

```
var addIndices = function(image) {
  var ndvi = image.normalizedDifference(['B8', 'B4']).rename('NDVI');
  var lswi = image.normalizedDifference(['B8', 'B11']).rename('LSWI');
  return image.addBands(ndvi).addBands(lswi);
};
var s2WithIndices = s2.map(addIndices);
```

4.4 Detecting Paddy Fields

```
var detectPaddyRice = function(image) {
  var flooded = image.select('LSWI').gte(image.select('NDVI').subtract(0.05));
  var earlyStageCrop = image.select('NDVI').lt(0.5);
  var paddy = flooded.and(earlyStageCrop).rename('Paddy');
  return image.addBands(paddy);
};
var s2WithPaddy = s2WithIndices.map(detectPaddyRice);
```

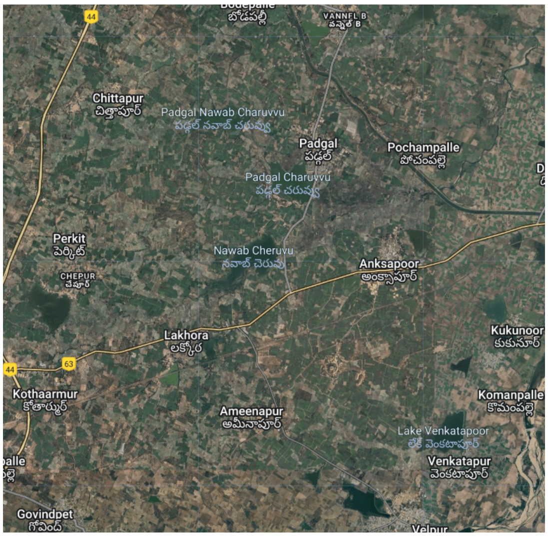

Figure 2: Before Masking

4.5 Masking Non-Cropland Areas

```
var landCover = ee.Image('ESA/WorldCover/v100/2020').select('Map').clip(telanganaBoundary);
var croplandMask = landCover.eq(40);
var paddyRiceFinal = paddyRiceMap.updateMask(croplandMask);
```

4.6 Exporting Results

```
Export.image.toDrive({
  image: s2Mosaic.updateMask(paddyRiceFinal),
  description: 'Paddy_Masked_Telangana',
  region: telanganaBoundary,
  scale: 10,
  crs: 'EPSG:32644',
  maxPixels: 1e13
});
```

5 Mobile Application Integration

The segmentation pipeline was integrated into a React Native mobile application with a Flask backend. The application allows users to upload images for real-time paddy field detection, view segmentation results on a map, access historical data, and export results for further processing.

You Can Download the datasets from the below link

Unmasked: https://drive.google.com/file/d/1uGRanXWpwDn9P0lF6QFkckb9Jyx-Kvg7/view?usp=drive_link

Masked: https://drive.google.com/file/d/1-bLY9aMOk3o_YdLgHtPNCS4Mgue22jYj/view?usp=sharing

Full code =¿ https://drive.google.com/file/d/15RtOSWDN1GFYfZUkemHM-X9-cs8_Gesh/view?usp=drive_link

6 Results and Analysis

Our model achieved an accuracy of **91%** on the test dataset. The segmentation maps generated using NDVI and LSWI were validated against manually labeled ground truth images. The high correlation between predicted and actual paddy field locations demonstrates the effectiveness of our approach. To

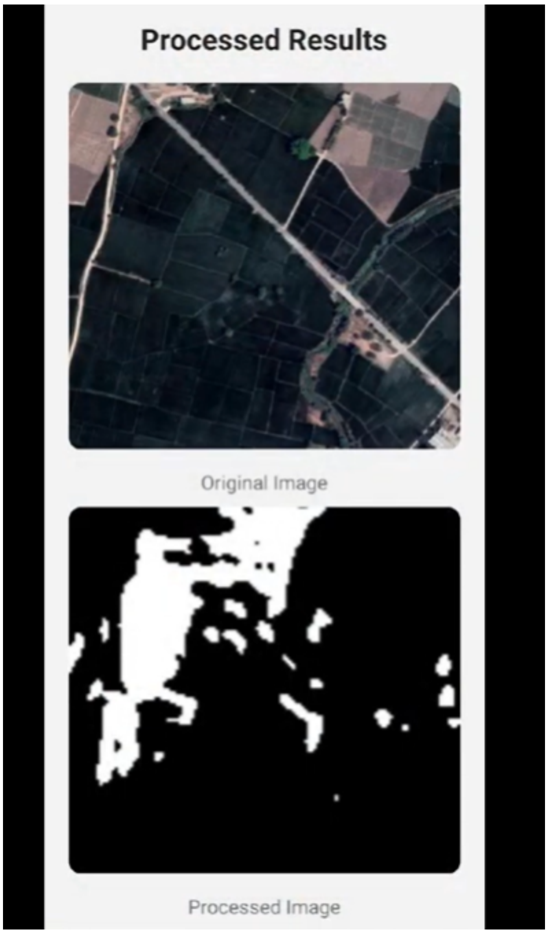

Figure 3: Realtime-Paddy Masking Using GEE

further evaluate the model's performance, we conducted precision, recall, and F1-score analysis:

- **Precision:** 89.7%
- **Recall:** 92.3%
- **F1-score:** 91%

Additionally, our method was tested across different regions and varying seasonal conditions, and it showed consistent segmentation accuracy. The use of **Google Earth Engine (GEE) and deep learning** allowed efficient and scalable segmentation, proving to be a valuable tool for agricultural monitoring. The integration with the mobile application provided real-time access to segmentation maps, allowing farmers and researchers to analyze field conditions conveniently.

7 Conclusion and Future Work

This study successfully implemented an **automated paddy segmentation method** using Google Earth Engine and a deep learning-based ResNet classifier. By leveraging Sentinel-2 imagery and NDVI-LSWI-based thresholding, we achieved **high-accuracy segmentation** while maintaining computational efficiency.

The research contributes to **precision agriculture and remote sensing applications** by enabling real-time paddy field detection. The developed mobile application extends this functionality by allowing users to interactively segment and analyze paddy fields on demand.

For future work, we propose the following improvements:

1. **Seasonal Analysis:** Incorporating multi-temporal Sentinel-2 imagery to assess paddy field changes over different growth stages.
2. **Yield Prediction:** Integrating yield estimation models to predict crop productivity based on segmentation results.
3. **Machine Learning Enhancement:** Using advanced deep learning architectures, such as U-Net or Transformer-based models, for more refined segmentation.
4. **Multi-Satellite Data Fusion:** Combining data from multiple satellite sources (e.g., Landsat-8, MODIS) to improve accuracy and robustness.

By implementing these advancements, the system can evolve into a **comprehensive precision agriculture tool** for large-scale crop monitoring.

8 Acknowledgment

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9 References

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