Enhancing Crop Estimation in Telangana: A Pilot LULC Mapping Study Linked to Rythu Bharosa

INTERNATIONAL CROPS RESEARCH
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Enhancing Crop Estimation in Telangana: A Pilot LULC Mapping Study Linked to Rythu Bharosa

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Enhancing Crop Estimation in Telangana: A Pilot LULC Mapping Study Linked to Rythu Bharosa

Report

on

Crop acreage estimation

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Contents

Figures

Introduction

The Government of Telangana is leveraging advanced technologies to enhance the accuracy and reliability of its crop estimation system. As part of this initiative, a pilot project was assigned to ICRISAT to generate high-resolution land use and land cover (LULC) maps, focusing on differentiating cultivated, non-cultivated, and other land and crop categories.

For the Kharif 2024 season, two mandals were selected for the pilot: Raghunadhapalem in Khammam district and Sirikonda in Nizamabad district. The mapping outputs were validated against official government statistics and cross-referenced with Rythu Bharosa, the state's acre-based farmer incentive program. The analysis revealed that approximately 15 percent of uncultivated land had received benefits under the scheme, highlighting discrepancies between actual land use and scheme records. Beyond identifying overestimated areas, the study provided detailed insights into cropping patterns, crop intensity, and land utilization at the mandal level. These insights can support better targeting of agricultural support programs, optimize resource allocation, and guide procurement planning by anticipating sowing and harvest schedules, which can be effectively utilized by Village Revenue Officers (VROs) and Agriculture Extension Officers (AEOs). The pilot also demonstrated the potential of integrating high-resolution LULC data with policy frameworks to reduce errors, prevent misuse of incentives, and support evidence-based decision-making at both operational and strategic levels.

Furthermore, a dedicated web portal has been developed for parcel-level, evidence-based monitoring of crop sowing and harvest dates. By linking this system with agricultural schemes, it enhances transparency, minimizes the risk of fraud, and enables more informed planning for procurement, input allocation, and timely policy interventions. Collectively, the pilot establishes a technology-driven framework that can be scaled across Telangana, strengthening crop estimation, improving resource efficiency, and ensuring that agricultural incentives reach the intended beneficiaries.

Methodology of Crop classification[1,2]

Crop-type classification is carried out using a semi-automatic workflow that combines satellite data processing, spectral analysis, and ground-truth integration (Figure 1). This approach balances automation with expert intervention to ensure both scalability and accuracy.

a. Satellite Data Processing in Google Earth Engine

The classification process begins with the acquisition and preprocessing of multi-temporal satellite imagery, typically from sensors like Sentinel-2 or Landsat. Key preprocessing steps include:

- Cloud masking and atmospheric correction
- Stacking multi-spectral bands over the crop growing season
- Generating maximum NDVI composites at monthly or fortnightly intervals to capture crop phenological patterns

This processed dataset forms the basis for further analysis and classification.

b. Unsupervised Classification and Pre-Clustering

An initial unsupervised classification is applied to group pixels with similar spectral behavior. This helps identify broad land cover categories and guides the selection of representative training samples. These pre-clusters also help isolate noise and identify spectral confusion zones that may need further ground validation. In cases where crops exhibit similar spectral and phenological profiles, such as rice vs. wetlands or maize vs. sugarcane, classification confusion is more likely. To address this, additional indices like LSWI and EVI, crop calendar information, and region-specific phenology profiles will be used to improve class separability and reduce misclassification.

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[1] Gumma, M.K., Thenkabail, P.S., Panjala, P., Teluguntla, P., Yamano, T. and Mohammed, I., 2022. Multiple agricultural cropland products of South Asia developed using Landsat-8 30 m and MODIS 250 m data using machine learning on the Google Earth Engine (GEE) cloud and spectral matching techniques (SMTs) in support of food and water security. *GIScience & Remote Sensing*, *59*(1), pp.1048-1077.

[2] Gumma, M.K., Tummala, K., Dixit, S., Collivignarelli, F., Holecz, F., Kolli, R.N. and Whitbread, A.M., 2022. Crop type identification and spatial mapping using Sentinel-2 satellite data with focus on field-level information. *Geocarto International*, *37*(7), pp.1833-1849.

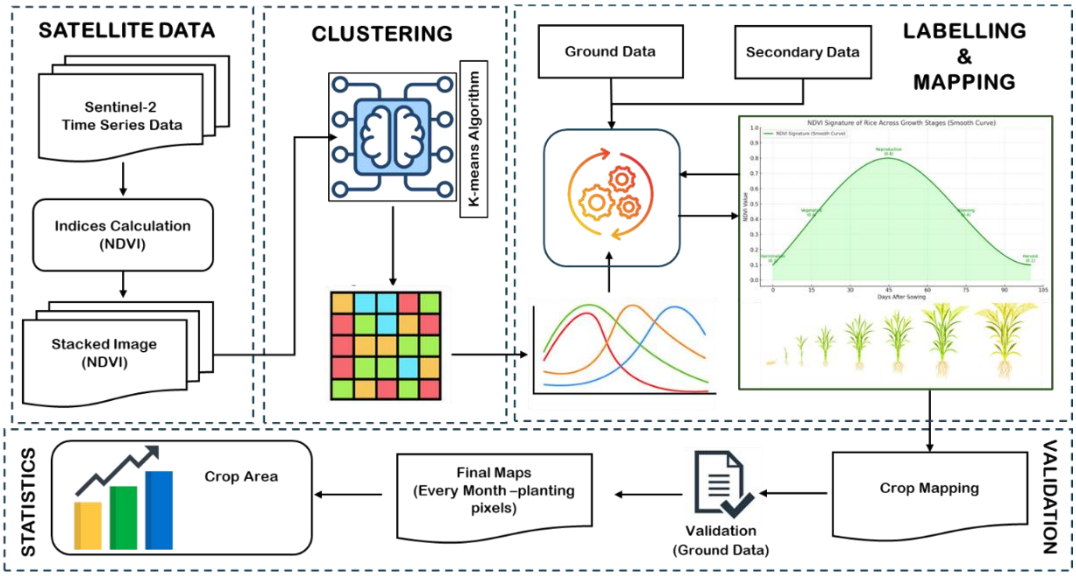

Figure 1: Methodology for crop classification

c. Development of Spectral Signatures

With support from field data collected using the ICROPS mobile application, spectral signatures are developed for each crop type (e.g., rice, maize) and for other land use/land cover (LULC) classes (e.g., water bodies, fallow, settlements). The process involves:

- Extracting pixel values for ground-verified locations
- Analyzing NDVI and other spectral indices over time
- Generating class-wise temporal spectral profiles

This step ensures that each class has a distinct and biologically meaningful spectral identity. To improve adaptability across districts, region-specific classification models and phenology-based crop libraries are being developed. These profiles help capture local crop behaviour and allow the classification approach to be fine-tuned for different agro-climatic zones.

d. Spectral Matching Techniques

Using the developed signatures, spectral matching techniques are employed to identify and classify each pixel into its most likely crop or LULC class. This step is refined using:

- Field-collected training data

- Secondary datasets such as crop calendars, administrative records, and historical land cover maps
- Expert knowledge to adjust thresholds or resolve class confusion (e.g., rice vs. wetlands)

Classification is performed using algorithms available in Google Earth Engine, such as random forest, support vector machines, or minimum distance classifiers, depending on the data and region.

Inseason crop monitoring

The study mapped crop areas during the growing season to enable timely and informed decision-making (Figure 2). Cotton sowing was recorded at 2,674 ha by June 15. The area expanded to 3,616 ha by June 25 and reached 7,005 ha by August 5. Such in-season monitoring provides early signals on sowing progress, helping planners anticipate input requirements, track adoption trends, and align interventions with the pace of crop expansion.

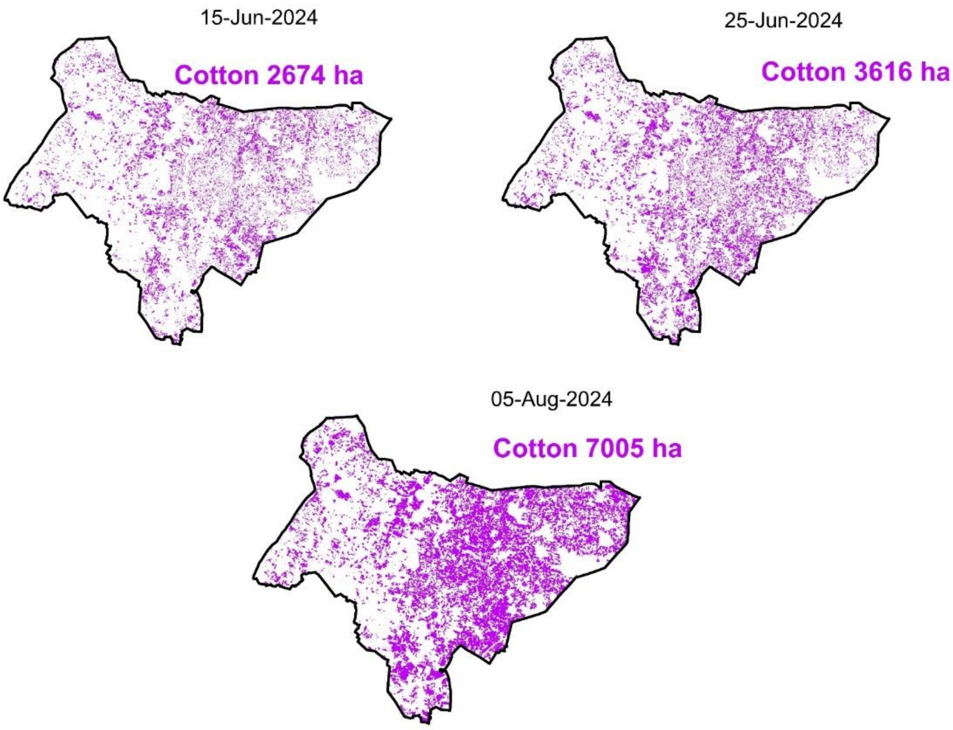

Figure 2:Temporal crop classification

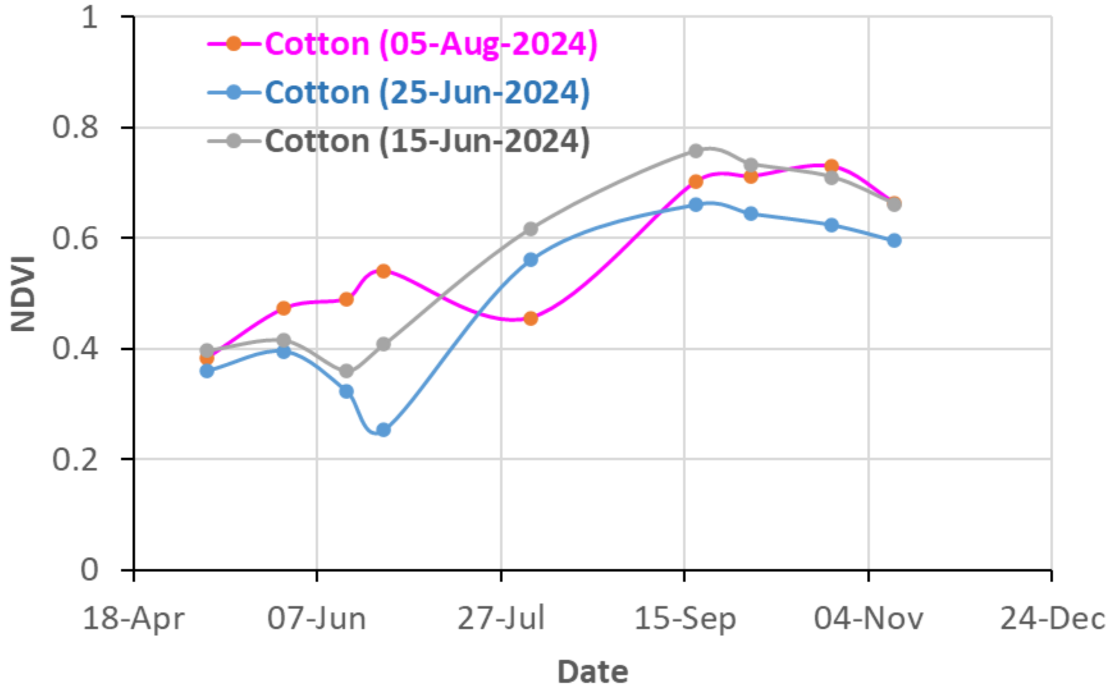

Figure 3: Temporal spectral signatures

Temporal spectral signatures derived from satellite data clearly depict crop growth stages, including establishment, peak vegetative phase, senescence, and harvest. By analysing these phenology curves, variations in sowing dates and harvesting windows across fields can be identified (Figure 3). This technical insight directly translates into decision-usefulness: seed procurement can be aligned with actual sowing patterns, while production procurement and supply chain planning can be synchronized with expected harvest timelines.

LULC and Crop type Mapping

Raghunadhapalem Mandal

The LULC analysis covered a total area of 47,292 acres in Raghunadhapalem (Figure 4, Table 1) . Cotton emerged as the dominant crop, occupying 17,309 acres, followed by chilli with 6,106 acres. Other crops such as greengram and pulses accounted for 625 acres, while rice covered 1,270 acres. Orchards and plantations extended over 3,254 acres. Non-cropped areas were also significant, with 5,053 acres under fallows, 4,223 acres classified as grasslands, and 5,693 acres under shrublands. Built-up land comprised 1,001 acres, forest areas covered 2,058 acres, and water bodies or wetlands occupied 699 acres. This distribution highlights the prominence of cotton cultivation, while also reflecting the considerable share of non-crop categories that influence land use planning and resource management in the region.

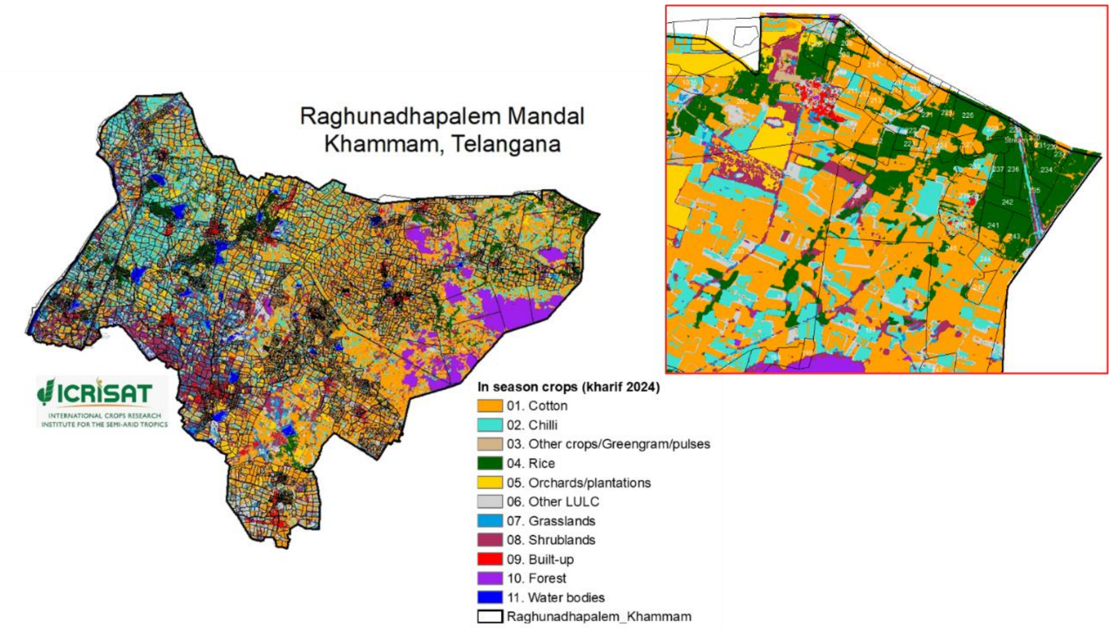

Figure 4: LULC and crop type map of Raghunadhapalem

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Table 1: Area Statistics of Raghunadhapalem mandal

LULC#	Area (Acre)
01. Cotton	17309
02. Chilli	6106

03. Other crops/Greengram/pulses	625
04. Rice	1270
05. Orchards/plantations	3254
06. Follows	5053
07. Grasslands	4223
08. Shrublands	5693
09. Built-up	1001
10. Forest	2058
11. Water bodies /wetlands	699
Total area	47292

Sirikonda Mandal

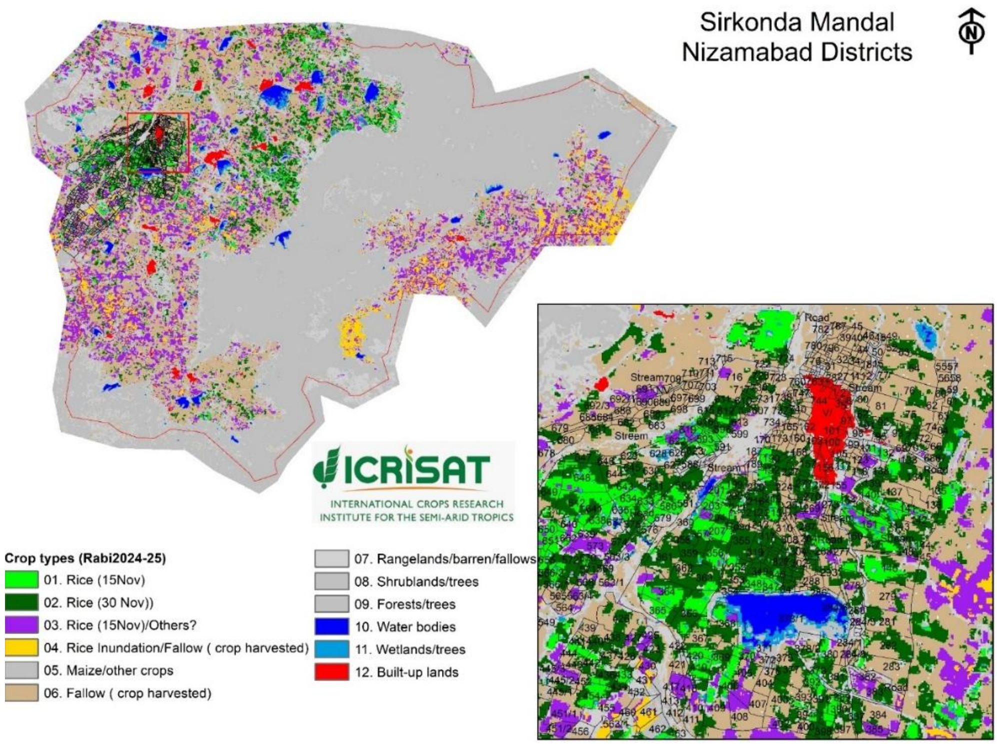

Figure 5: LULC and crop type map of Sirikonda mandal

The LULC assessment covered a total of 67,214 acres in Sirikonda (Figure 5, Table 2). Rice cultivation was mapped in different stages, with 980 acres sown by November 15, expanding to 3,566 acres by November 30, and an additional 6,298 acres where rice was followed by other crops. Areas categorized as rice inundation or harvested fallows accounted for 2,382 acres. Maize and other crops together covered 90 acres. A large portion of land, 11,824 acres, was under harvested fallows, while rangelands and fallows added another 8,704 acres. Shrublands and tree cover occupied 9,432 acres, and forests contributed the largest share with 22,002 acres. Water bodies and wetlands accounted for 718 acres and 576 acres respectively, while built-up lands extended over 641 acres. This distribution underscores the dominance of forest and tree cover, along with substantial areas of fallows and rangelands, while rice continues to be the primary cultivated crop with varying temporal patterns during the season.

Table 2: Area Statistics of Sirikonda mandal

LULC	**Area (Acre)**
01. Rice (15Nov)	980
02. Rice (30 Nov))	3566
03. Rice (15Nov)/Others Crops	6298
04. Rice Inundation/Fallow (crop harvested)	2382
05. Maize/other crops	90
06. Fallow (crop harvested)	11824
07. Rangelands/fallows	8704
08. Shrublands/trees	9432
09. Forests/trees	22002
10. Water bodies	718
11. Wetlands/trees	576
12. Built-up lands	641
Total area	67214

Comparison of LULC Statistics with Rythu Bharosa Records

In Raghunadhapalem mandal, the total geographical area is 47,292 acres, of which 33,618 acres are cultivable, and 13,675 acres are non-cultivable. However, the extent of land for which payments were made under the Rythu Bharosa (RB) scheme stands at 38,988 acres, an overestimation of 5,370 acres or about 16 percent above the mapped cultivable area.

In Sirikonda mandal, the total area is 67,213 acres. Cultivable land accounts for 25,140 acres, while non-cultivable land extends over 33,369 acres. RB records show payments made for 28,800 acres, exceeding the cultivable extent by 3,660 acres, which translates to an overestimation of about 15 percent.

Table 3: Area Statistics comparison with RB

Class	Raghunadhapalem (Acres)	Sirikonda (Acres)
Total Area	47,292	67,213
Cultivable Land	33,618	25,140
Non-Cultivable Land	13,675	33,369
RB Paid Land Extent	38,988	28,800
Difference (RB vs Cultivable)	5,370	3,660
Overestimation (%)	**16**	**15**

This comparison clearly shows a consistent pattern where the RB-recorded extent surpasses the actual cultivable land mapped through LULC. The overestimation, ranging from 15 to 16 percent, indicates the need for geospatial validation of scheme data to ensure more accurate targeting of agricultural incentives.

Web Portal

A dedicated web portal has been established for parcel-level, evidence-based monitoring of crop and LULC (Figure 6). By linking this system with agricultural schemes, it not only enhances transparency and minimizes the risk of fraud but also enables more informed planning for procurement, input allocation, and timely policy interventions, ensuring that resources reach the right farmers at the right time.

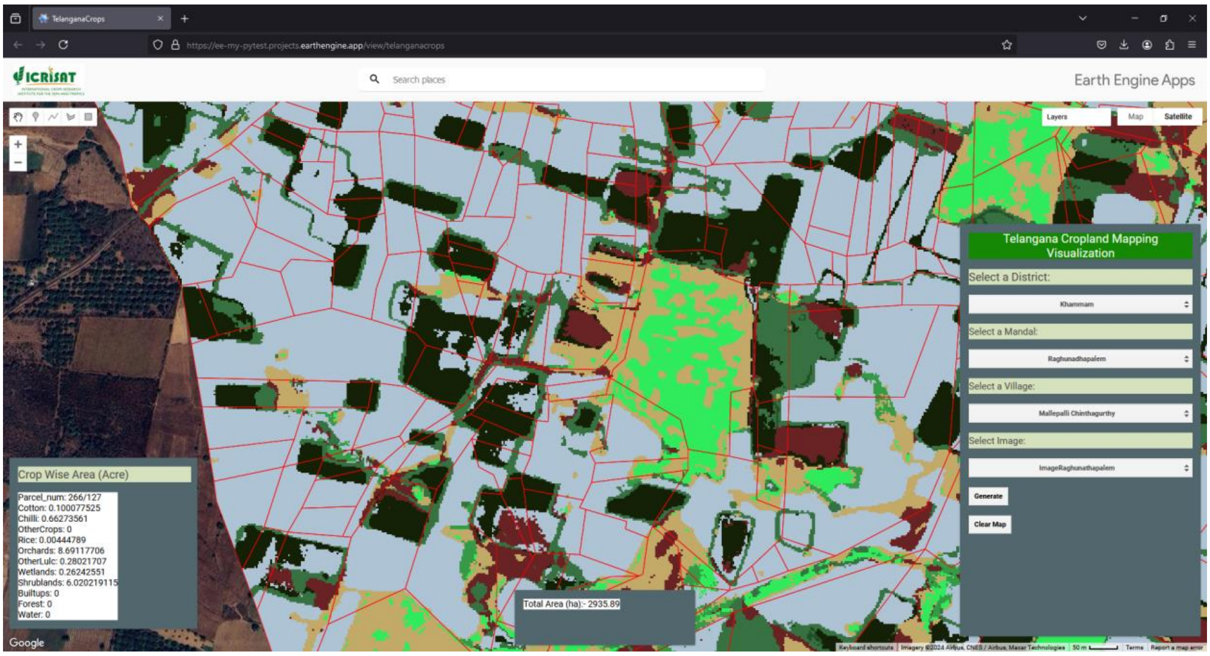

Figure 6: Illustration of web portal

Here are the links to monitor crop at parcel levels

Link for Land Use Land Cover:

https://ee-my-pytest.projects.earthengine.app/view/telanganacrops

Link for Cropland:

https://ee-my-pytest.projects.earthengine.app/view/tgscrops

Related Papers:

[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16]

REFERENCES

1. Gumma, M.K., et al., *Geospatial analysis to identify millet suitable areas in the upland rice ecosystem of Odisha.* Journal of Agriculture and Food Research, 2025. **19**: p. 101593.
2. Mandapati, R., et al., *Field-level rice yield estimations under different farm practices using the crop simulation model for better yield.* Plant Science Today, 2024. **11**(1): p. 234-240.
3. Gumma, M.K., et al., *Optimizing crop yield estimation through geospatial technology: a comparative analysis of a semi-physical model, crop simulation, and machine learning algorithms.* AgriEngineering, 2024. **6**(1): p. 786-802.
4. Gumma, M.K., et al., *Spatial distribution of cropping systems in South Asia using time-series satellite data enriched with ground data.* Remote Sensing, 2024. **16**(15): p. 2733.

5. Panjala, P., M.K. Gumma, and S. Mesapam, *Geospatial assessment of cropping pattern shifts and their impact on water demand in the Kaleshwaram lift irrigation project command area, Telangana.* Frontiers in Remote Sensing, 2024. **5**: p. 1451594.
6. Gumma, M.K., et al., *Real Time Monitoring of Cropping Pattern Using Geospatial Analysis.* 2024.
7. Gajjala, S., et al., *Rice Yield Assessment in Nalgonda: A Comparative Study of APSIM and Semi-Physical Models with Remote Sensing Integration.* Journal of Scientific Research and Reports, 2025. **31**(9): p. 371-384.
8. Teluguntla, P., et al., *Global Food Security Support Analysis Data (GFSAD) Using Remote Sensing in Support of Food and Water Security in the 21st Century: Current Achievements and Future Possibilities*, in *Remote Sensing Handbook, Volume III*. 2024, CRC Press. p. 187-228.
9. Teluguntla, P., et al. *Landsat-derived global rainfed and irrigated area product@ 30m (LGRIP30): A study of irrigated and rainfed areas at the country, state, and county level for conterminous United States (CONUS)*. in *AGU Fall Meeting Abstracts*. 2024.
10. Bellam, P.K., et al. *Soil Organic Carbon Mapping Using Sentinel-1 And ALOS-2 SAR Data*. in *2024 IEEE India Geoscience and Remote Sensing Symposium (InGARSS)*. 2024. IEEE.
11. Gumma, M.K., P. Panjala, and P. Teluguntla, *Mapping heterogeneous land use/land cover and crop types in Senegal using sentinel-2 data and machine learning algorithms.* International Journal of Digital Earth, 2024. **17**(1).
12. Panjala, P., et al., *Geospatial Analysis of Crop Residue Burn Areas and Their Dates for Emission Mitigation Strategies.* Sustainability, 2025. **17**(6): p. 2508.
13. Panjala, P., M.K. Gumma, and S. Mesapam, *Satellite-Based Monitoring of Crop Intensity Changes in Kaleshwaram Lift Irrigation Command Area.* Sustainable Geosciences: People, Planet and Prosperity, 2025: p. 100003.
14. Panjala, P., M.K. Gumma, and S. Mesapam, *Assessing public health risks from crop residue burning: a spatiotemporal case study in Telangana, India.* Air Quality, Atmosphere & Health, 2025. **18**(10): p. 3105-3115.
15. Nukala, R.M., et al., *Strategic Ground Data Planning for Efficient Crop Classification Using Remote Sensing and Mobile-Based Survey Tools.* Geographies, 2025. **5**(4): p. 59.
16. Bellam, P.K., et al., *Soil Organic Carbon Mapping Using Multi-Frequency SAR Data and Machine Learning Algorithms.* Land, 2025. **14**(11): p. 2105.