Research
Report No: AP_01

Spatial monitoring of Chickpea Cultivation in Nandyal and Y.S.R. Kadapa districts of Andhra Pradesh (Rabi 2025-26)

ICRISAT
INTERNATIONAL CROPS RESEARCH
INSTITUTE FOR THE SEMI-ARID TROPICS

Spatial monitoring of Chickpea Cultivation in Nandyal and Y.S.R. Kadapa districts of Andhra Pradesh (Rabi 2025-26)

Report Submitted

to

Government of Andhra Pradesh

Date: February 2026

INTERNATIONAL CROPS RESEARCH INSTITUTE FOR THE SEMI-ARID TROPICS

Transforming Dryland Agriculture

2026

ICRISAT, Patancheru-502324, Telangana, India

Contents

Contents iii

1. Introduction 1

2. Methodology of Crop classification, ... 1

3. Spatial maps and statistics 3

3.1 Area statistics of chickpea cultivation in Nandyal district 4

3.2 Area statistics of chickpea cultivation in Y.S.R. Kadapa district 5

3.3 GEE application for monitoring chickpea cultivation at parcel levels 7

Conclusion 8

Figures

Figure 1: Methodology for crop classification 2
Figure 2:Spatial distribution map of crop classification 3
Figure 3: User Interface of GEE application for chickpea monitoring 7

Tables

Table 1:Mandal wise chickpea cultivation area statistics in Nandyal district 4
Table 2:Mandal wise chickpea cultivation area statistics in Y.S.R. Kadapa district 5

1. Introduction

Chickpea is a key rabi pulse crop in Andhra Pradesh, contributing to nutritional security, soil fertility through biological nitrogen fixation, and the economic stability of small and marginal farmers. In the semi-arid Rayalaseema region, particularly in Nandyal and Y.S.R. Kadapa districts, chickpea is widely cultivated under rainfed and residual soil moisture conditions. However, productivity in these districts is highly sensitive to spatial and temporal variability in rainfall, temperature, and field management practices, making consistent monitoring of crop extent and condition essential.

Conventional field-based assessments are often limited in their spatial coverage and timeliness, especially across large and heterogeneous landscapes. Remote sensing and geospatial techniques offer a reliable alternative by enabling repeatable, large area monitoring of chickpea cultivation throughout the growing season. Spatial analysis of satellite-derived information can support mapping of chickpea extent, understanding of crop dynamics, and identification of variability within and between seasons. This study focuses on the spatial monitoring of chickpea cultivation in Nandyal and Y.S.R. Kadapa districts of Andhra Pradesh to generate decision-relevant information for crop management, yield assessment, and regional agricultural planning.

2. Methodology of Crop classification

Crop-type classification is carried out using a semi-automatic workflow that combines satellite data processing, spectral analysis, and ground-truth integration[1-5]. This approach balances automation with expert intervention to ensure both scalability and accuracy.

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.

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.

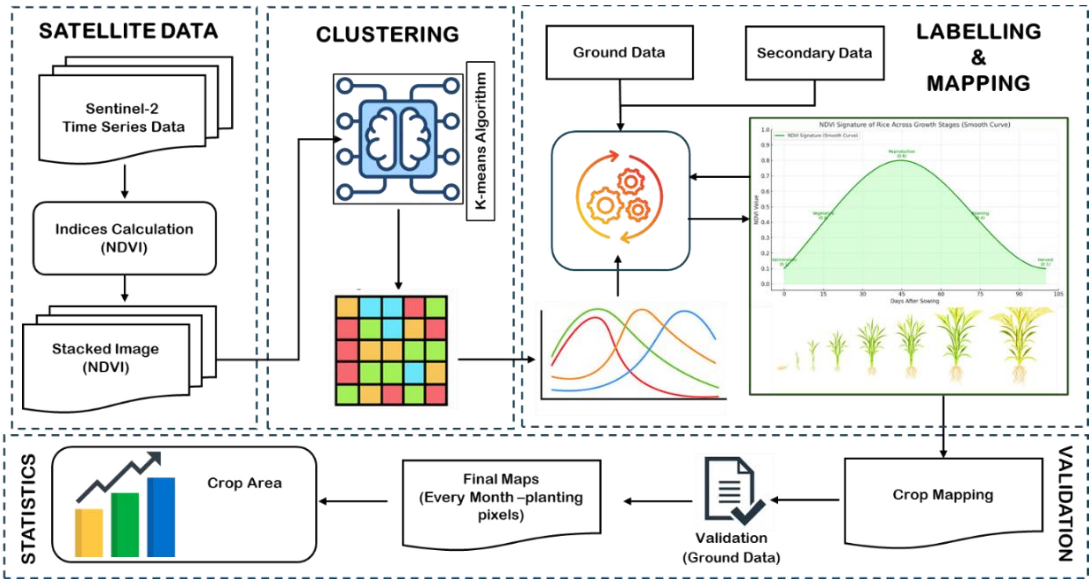

Figure 1: Methodology for crop classification

Development of Spectral Signatures: With support from field data collected using the ICROPS mobile application and previous signatures, 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.

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[6-8]. 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.

3. Spatial maps and statistics

Using Sentinel-2 satellite imagery in combination with machine learning algorithms and spectral matching techniques, chickpea cultivation was successfully classified across Nandyal and Y.S.R. Kadapa districts (Figure 2). The classification captured the spatial distribution of chickpea fields with clear separation from other rabi crops and non-crop land cover classes. Temporal information from multi-date Sentinel-2 observations improved class discrimination, particularly during peak vegetative and flowering stages.

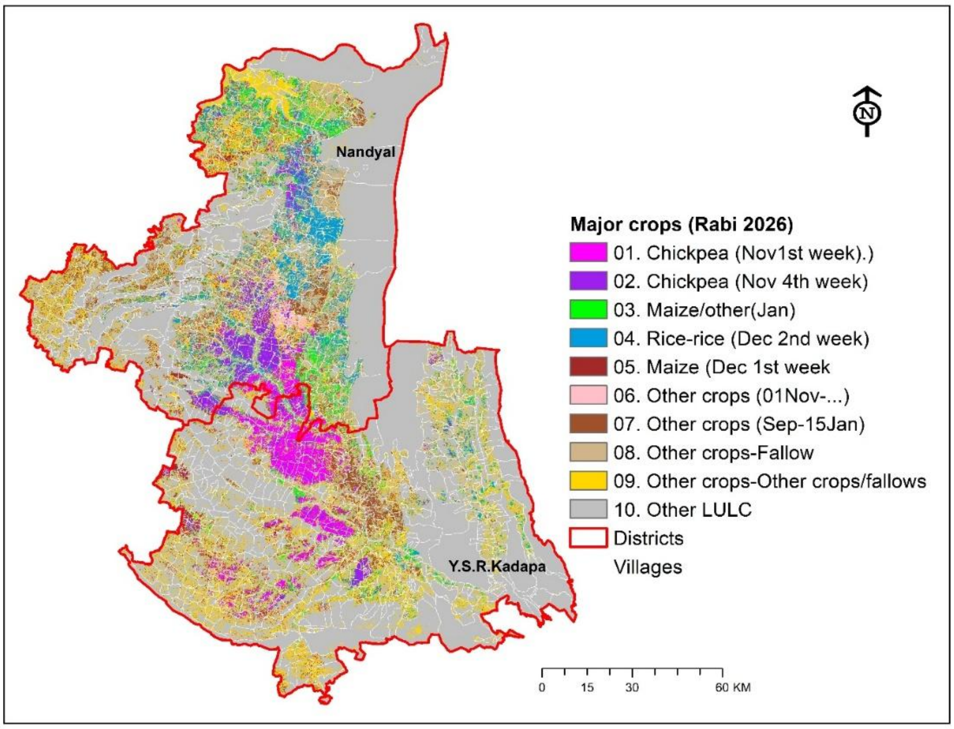

Figure 2:Spatial distribution map of crop classification

The resulting classified maps revealed distinct spatial patterns of chickpea cultivation. These results demonstrate the effectiveness of Sentinel-2–based geospatial approaches for operational-scale monitoring of chickpea cultivation in semi-arid regions.

3.1 Area statistics of chickpea cultivation in Nandyal district

The mandal-wise area statistics indicate substantial spatial and temporal variation in chickpea cultivation across Nandyal district between the first week and fourth week of November (Table 1). During the first week of November, chickpea area was concentrated in a few mandals, with Uyyalawada (6220.7 ha), Allagadda (3335.1 ha), Chagalamarri (1776.7 ha), Gadivemula (1135.4 ha), and Sanjamala (1133.2 ha) emerging as major early-sown regions. Several mandals such as Mahanandi, Sirvel, and Bandi Atmakur showed very limited chickpea area, indicating delayed sowing or preference for other crops during the early rabi phase.

Table 1:Mandal wise chickpea cultivation area statistics in Nandyal district

District	Mandal	Chickpea (Nov-1st Week) (ha)	Chickpea (Nov-4th Week) (ha)
Nandyal	Allagadda	3335.1	548.2
Nandyal	Atmakur	454.1	191.0
Nandyal	Banaganapalle	136.4	2633.6
Nandyal	Bandi Atmakur	10.2	522.1
Nandyal	Bethamcherla	194.4	111.2
Nandyal	Chagalamarri	1776.7	103.7
Nandyal	Dhone	136.3	390.4
Nandyal	Dornipadu	46.1	4174.5
Nandyal	Gadivemula	1135.4	1758.1
Nandyal	Gospadu	15.3	1425.6
Nandyal	Jupadu Bungalow	457.7	581.3
Nandyal	Koilkuntla	345.2	7623.7
Nandyal	Kolimigundla	199.9	2825.3
Nandyal	Kothapalle	374.9	45.2
Nandyal	Mahanandi	2.2	82.2
Nandyal	Midthur	231.3	690.2
Nandyal	Nandikotkur	138.8	1053.1
Nandyal	Nandyal	15.2	1034.4
Nandyal	Owk	151.5	508.9
Nandyal	Pagidyala	237.2	211.1
Nandyal	Pamulapadu	420.7	1160.1
Nandyal	Panyam	37.1	876.0
Nandyal	Peapally	123.4	286.1
Nandyal	Rudravaram	624.6	655.7
Nandyal	Sanjamala	1133.2	5453.7
Nandyal	Sirvel	4.4	577.8
Nandyal	Srisailam	0.0	0.0
Nandyal	Uyyalawada	6220.7	4972.8
Nandyal	Velgode	89.9	1208.8

By the fourth week of November, a pronounced expansion of chickpea area was observed across most mandals, reflecting staggered sowing practices driven by soil moisture availability and rainfall conditions. Koilkuntla (7623.7 ha), Sanjamala (5453.7 ha), Uyyalawada (4972.8 ha), Dornipadu (4174.5 ha), and Kolimigundla (2825.3 ha) recorded substantial increases, indicating peak sowing activity during this period. In contrast, mandals such as Allagadda and Chagalamarri showed a marked reduction in mapped chickpea area, suggesting early crop establishment followed by spectral changes or transition to other land uses. Overall, the results highlight strong intra-district heterogeneity in chickpea sowing windows, underscoring the importance of multi-temporal satellite observations for accurately capturing crop extent in semi-arid production systems.

3.2 Area statistics of chickpea cultivation in Y.S.R. Kadapa district

The mandal-wise statistics for Y.S.R. Kadapa district show pronounced temporal variability in chickpea cultivation between the first and fourth weeks of November (Table 2). During the first week of November, chickpea area was highly concentrated in a few mandals, notably Peddamudium (13,800.5 ha), Rajupalem (9,650.9 ha), Yerraguntla (5,330.5 ha), Jammalamadugu (4,305.7 ha), Proddatur (4,094.6 ha), and Kamalapuram (3,917.7 ha). This pattern indicates early sowing in large contiguous tracts, while several mandals such as Chennur, Gopavaram, Sidhout, and Y.S.R. Kadapa recorded negligible chickpea area, reflecting delayed planting or alternative rabi cropping choices.

Table 2:Mandal wise chickpea cultivation area statistics in Y.S.R. Kadapa district

District	Mandal	Chickpea (Nov-1st Week) (ha)	Chickpea (Nov-4th Week) (ha)
Y.S.R.Kadapa	Atlur	21.3	13.5
Y.S.R.Kadapa	B.Kodur	23.4	148.6
Y.S.R.Kadapa	Badvel	10.6	60.3
Y.S.R.Kadapa	Brahmamgarimattam	122.8	264.8
Y.S.R.Kadapa	Chakrayapet	217.6	56.2
Y.S.R.Kadapa	Chapad	152.3	60.5
Y.S.R.Kadapa	Chennur	0.9	11.0
Y.S.R.Kadapa	Chinthakommadinne	46.4	125.5
Y.S.R.Kadapa	Duvvur	849.4	15.8
Y.S.R.Kadapa	Gopavaram	1.0	7.1
Y.S.R.Kadapa	Jammalamadugu	4305.7	747.7
Y.S.R.Kadapa	Kalasapadu	275.8	322.8
Y.S.R.Kadapa	Kamalapuram	3917.7	449.3

Y.S.R.Kadapa	Khajipet	132.7	20.5
Y.S.R.Kadapa	Kondapuram	278.1	212.8
Y.S.R.Kadapa	Lingala	160.1	188.7
Y.S.R.Kadapa	Muddanur	666.1	100.7
Y.S.R.Kadapa	Mylavaram	3729.9	1360.5
Y.S.R.Kadapa	Peddamudium	13800.5	3006.3
Y.S.R.Kadapa	Pendlimarri	151.3	1059.4
Y.S.R.Kadapa	Porumamilla	47.0	63.2
Y.S.R.Kadapa	Proddatur	4094.6	450.6
Y.S.R.Kadapa	Pulivendla	469.9	43.7
Y.S.R.Kadapa	Rajupalem	9650.9	335.8
Y.S.R.Kadapa	S.Mydukur	108.7	94.7
Y.S.R.Kadapa	Sidhout	2.1	7.5
Y.S.R.Kadapa	Simhadripuram	737.1	815.6
Y.S.R.Kadapa	Sri Avadhutha Kasinayana	92.5	168.3
Y.S.R.Kadapa	Thondur	1682.1	212.7
Y.S.R.Kadapa	Vallur	13.8	1915.6
Y.S.R.Kadapa	Veerapunayunipalle	3011.4	297.5
Y.S.R.Kadapa	Vempalle	1052.0	273.8
Y.S.R.Kadapa	Vemula	1597.9	383.6
Y.S.R.Kadapa	Vontimitta	10.8	10.9
Y.S.R.Kadapa	Y.S.R.Kadapa	1.2	3.6
Y.S.R.Kadapa	Yerraguntla	5330.5	1036.8

By the fourth week of November, the spatial pattern shifted markedly, with a reduction in mapped chickpea area in many early-sown mandals and notable expansion in others. Peddamudium (3,006.3 ha), Mylavaram (1,360.5 ha), Vallur (1,915.6 ha), Pendlimarri (1,059.4 ha), Yerraguntla (1,036.8 ha), and Simhadripuram (815.6 ha) emerged as prominent chickpea-growing mandals during this period. The decline observed in major early-sowing mandals such as Rajupalem, Jammalamadugu, Kamalapuram, and Proddatur suggests early crop establishment followed by spectral transition as the crop advanced phenologically, while increases in mandals like Vallur and Pendlimarri reflect staggered sowing linked to localized soil moisture and rainfall conditions. Overall, the results highlight strong intra-district heterogeneity in chickpea sowing windows across Y.S.R. Kadapa, emphasizing the importance of multi-temporal Sentinel-2 observations for accurately capturing dynamic cropping patterns in semi-arid regions.

3.3 GEE application for monitoring chickpea cultivation at parcel levels

The Google Earth Engine–based application provides an interactive interface for monitoring chickpea cultivation at parcel scale (Figuure 3). The application includes dropdown menus to select district, mandal, and village, allowing users to navigate seamlessly from regional to local levels. Upon selection, the corresponding crop classification map is displayed along with parcel boundaries, enabling visual assessment of chickpea distribution within the selected administrative unit. At the parcel level, the application supports on-demand area analysis. Clicking on an individual parcel generates class-wise area statistics, reporting the extent of chickpea and other land-use classes within that parcel.

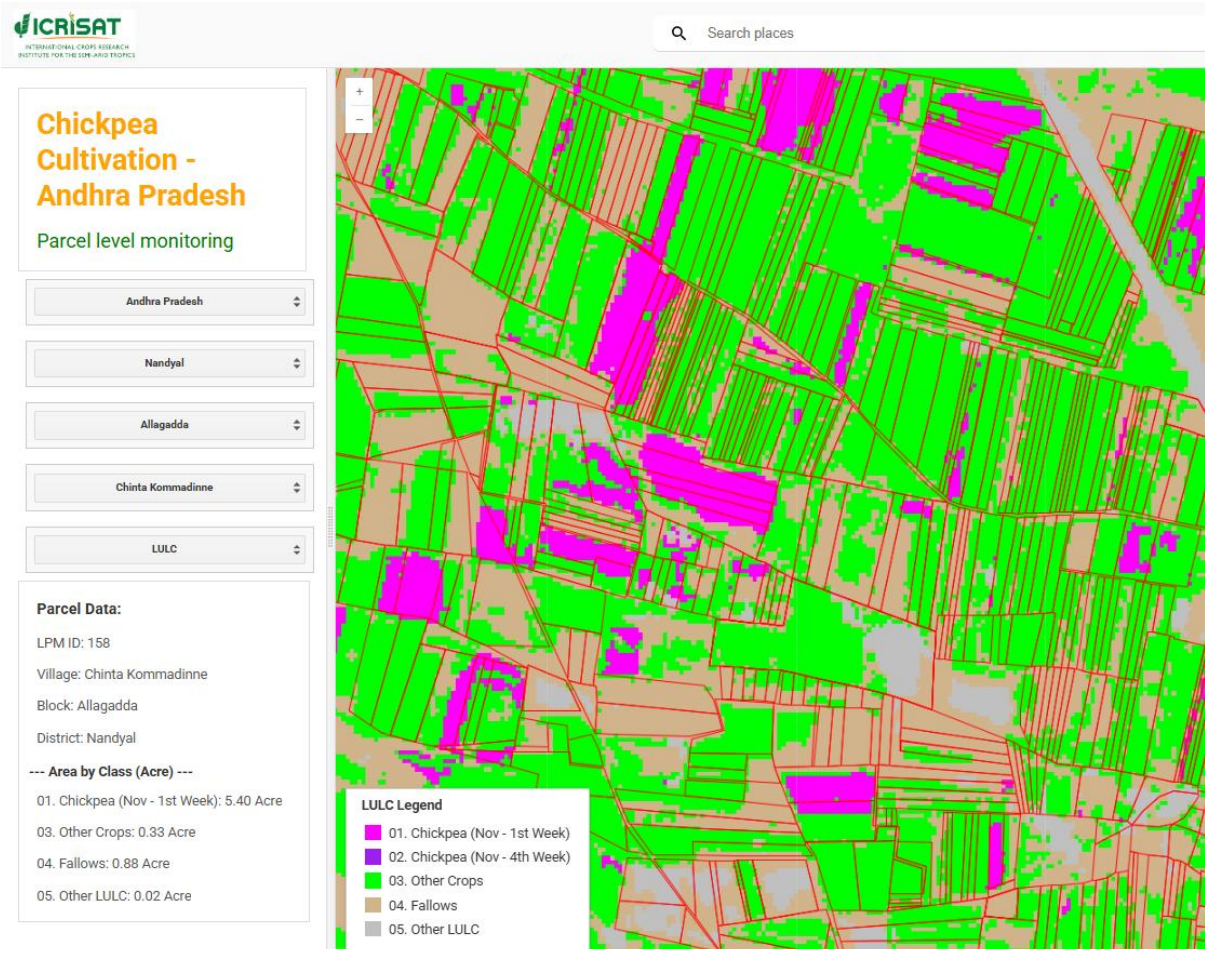

Figure 3: User Interface of GEE application for chickpea monitoring

This functionality enables precise field-level assessment of crop presence and extent, supporting validation, localized crop monitoring, and informed decision-making by planners and extension agencies. Overall, the application demonstrates the utility of GEE for scalable, interactive, and parcel-based crop monitoring workflow

Conclusion

This study demonstrates the effectiveness of satellite-based geospatial approaches for spatial and temporal monitoring of chickpea cultivation in Nandyal and Y.S.R. Kadapa districts of Andhra Pradesh. The use of multi-temporal Sentinel-2 imagery, combined with machine learning algorithms and spectral matching techniques, enabled reliable classification of chickpea fields and captured district- and mandal-level variability in sowing patterns. The results clearly show staggered sowing windows and strong intra-district heterogeneity, emphasizing the need for multi-date observations to accurately represent chickpea extent in semi-arid production systems.

The Google Earth Engine–based application further extended this analysis to the parcel level through an interactive framework that allows users to select district, mandal, and village and visualize crop classification maps along with parcel boundaries. Parcel-wise area statistics generated through user interaction support precise field-level assessment of chickpea cultivation, reducing uncertainty associated with mixed pixels and fragmented landscapes. Overall, the study highlights the potential of cloud-based geospatial platforms to support operational crop monitoring, improve decision support for agricultural planning, and enable scalable implementation of parcel-level crop intelligence for pulse-based farming systems.

Related Papers:

[9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [1]

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. Gumma, M.K., et al., *Mapping rice-fallow cropland areas for short-season grain legumes intensification in South Asia using MODIS 250 m time-series data.* International Journal of Digital Earth, 2016. **9**(10): p. 981-1003.
3. Gumma, M.K., et al., *Agricultural cropland extent and areas of South Asia derived using Landsat satellite 30-m time-series big-data using random forest machine learning algorithms on the Google Earth Engine cloud.* GIScience & Remote Sensing, 2020. **57**(3): p. 302-322.
4. Gumma, M.K., et al., *Crop type identification and spatial mapping using Sentinel-2 satellite data with focus on field-level information.* Geocarto International, 2022. **37**(7): p. 1833-1849.

5. Panjala, P., M.K. Gumma, and P. Teluguntla, *Machine learning approaches and sentinel-2 data in crop type mapping*, in *Data science in agriculture and natural resource management*. 2021, Springer. p. 161-180.
6. Gumma, M.K., et al., *Mapping rice areas of South Asia using MODIS multitemporal data.* Journal of applied remote sensing, 2011. **5**(1): p. 053547-053547-26.
7. Gumma, M.K., et al., *Mapping seasonal rice cropland extent and area in the high cropping intensity environment of Bangladesh using MODIS 500 m data for the year 2010.* ISPRS journal of photogrammetry and remote sensing, 2014. **91**: p. 98-113.
8. Gumma, M.K., et al., *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, 2022. **59**(1): p. 1048-1077.
9. Bellam, P.K., et al., *Soil Organic Carbon Mapping Using Multi-Frequency SAR Data and Machine Learning Algorithms.* Land, 2025. **14**(11): p. 2105.
10. 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.
11. 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.
12. 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.
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., et al., *Geospatial Analysis of Crop Residue Burn Areas and Their Dates for Emission Mitigation Strategies.* Sustainability, 2025. **17**(6): p. 2508.
15. 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).
16. 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.
17. 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.
18. 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.
19. Gumma, M.K., et al., *Real Time Monitoring of Cropping Pattern Using Geospatial Analysis.* 2024.
20. 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.
21. 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.
22. 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.
23. 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.