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EDITORIAL

Progress and Challenges in Earth Observation Data Applications for Agriculture at Field Scale in India and Small Farm Holdings Regions

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Abstract

The paper traces the evolution of agricultural remote sensing in India through its four phases: initial exploratory and aerial data based (1969–1982), IRS Utilization Program led (1983–1995), post-IRS-1C launch (1996–2011) and since the establishment of a dedicated institution for EO-based crop forecasting and other agricultural applications (2012 onward). Published field-scale studies are discussed before introducing the submissions to the special issue of the journal, namely Advanced Geospatial Technologies for Agriculture with Special emphasis on field level Applications. A total of 17 articles grouped under crop discrimination and mapping, crop yield estimation, crop suitability analysis, irrigation management and others (UAV, fodder and field boundary extraction) and 15 of these describe work over India and remaining two have Iran as their study area. These studies are linked to other published work as well as challenges under major issues of data access, use of UAV, use of smartphones, data processing and crop simulation models. Taken together, these articles report substantial improvements in capabilities of field-scale monitoring for developing new class of agricultural applications in India as well as other regions in the world with small farm holdings.

Keywords Crop mapping · Yield estimation · Crop assessment · Small-fields · Crop simulation models

Introduction

Applications of EO data for agriculture have been area of prime focus since dawn of satellite remote sensing, and crop forecasting under LACIE was the forerunner program (MacDonald & Hall, 1980) which globally spawned research on crop mapping, yield estimation, condition assessment and monitoring. Fritz et al. (2019) provide a comparative account of current eight major global crop monitoring systems and identify gaps in data, methodology and operational use highlighting need for enhancements in EO data capability and access, integration of field data, methodology development and evaluation across different agricultural scenario. Weiss et al. (2020) have reviewed EO applications in agriculture, including, land use monitoring, precision farming and ecosystem services as applied from local to global scales and also identified areas for future research. International EO community is also focusing on cooperative programs such as GEOGLAM in order to meet UN sustainability development goals (SDG) Whitcraft et al., 2019). However, as pointed out by Samberg et al. (2016), small holder farming is practiced in 83 countries by 380 million households which produce 70 percent of the food calories in their region. Special attention is required to meet food security, poverty reduction and to meet SDGs.

Agriculture scenario in India is of small holder with a great diversity of crops, climate, cultural practices and socio-economic conditions and history of focus on agricultural research and agricultural information system. Application of EO in Indian agriculture would have the challenge of small fields and large variability due to crops, cultivars and crop management practices. EO agricultural application community is very active and focused in meeting current gaps in methodology development. This special issue on "Advanced Geospatial Technologies for Agriculture with special emphasis on field-level

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applications" is thus focused on small holders and small fields, which require modifications in approach and analysis methodology. A number of recent developments including high resolution and open-access data, processed multi-date data sets, biophysical retrieval models and processed data sets and integration of smartphones in field data collection and demand from user community for crop insurance, crop advisory services, crop diversification and adaptability to increasingly variable weather are fueling this research.

Before introducing the papers of this special issue, we trace the evolution of EO Applications in Agriculture in the country and also briefly indicate the growing list of published literature on field-level applications in India. Opportunities and challenges in this area are presented in last section to guide further research.

EO Data For Agricultural Crops in India—Evolution Over Five Decades

The origin of agricultural remote sensing is traced to a pioneering coconut root wilt disease detection study using aerial platform over plantations in Kerala in 1969 that involved international collaboration from USA and France. The results were presented in International Astronautical Federation Congress in Germany in 1970 (Dakshinamurthy et al., 1971). The progress since then has been phenomenal and can be summarized in four distinct phases.

Phase I covered 1969–1982, and major studies used aerial photography for agricultural land use, crop inventory and crop vigor. As scale of aerial photography was 1:30,000 or larger, individual fields, crop plants and crop row structure were detectable and inventory involved field-wise visual delineation. The major crops mapped included (i) wheat in Patiala district of Punjab (Dhanju and Shankarnarayana, 1978) and Mehsana district of Gujarat, (ii) groundnut in Anantapur district of Andhra Pradesh (Sahai et al., 1977), (iii) rice and sugarcane in Mandya district (Karnataka) where 11-channel multispectral scanner was flown and subjected to digital interpretation (Ayyangar et al., 1980) and (iv) agricultural land use of both field and plantation crops (paddy, sugarcane, rubber, coconut, tea, tapioca and others in Idukki district of Kerala) (Sahai et al., 1985), to name a few. Visual interpretation of data of Landsat-1 was feasible at 1:1 million to 1:250,000 scale, and thus, digital crop inventory was not conducted. At these scales, only regional mapping applications were explored and individual fields could not be detected. First Indian EO satellite Bhaskara featured passive microwave radiometer and a television camera and was not designed for crop and field level studies. A number of field experiments to study the spectral response of crops grown under different agronomic conditions to investigate the relationships between the remotely sensed indices and crop biophysical parameters were also undertaken during this phase.

Phase II was the experimental satellite earth observation phase during 1983–1995. An umbrella project of EO applications, namely "IRS Utilization Programme" was launched in 1983 (Navalgund & Kasturirangan, 1983) and included crop production forecasting (CPF), crop stress detection (CSD) and crop yield modeling (CYM) projects, as part of preparatory activities for launch of Indian Remote Sensing Satellite IRS-1A, which was launched in 1988. Successful pilot on wheat acreage estimation for Karnal district of Haryana (Dadhwal & Parihar, 1985) led to rapid growth in crop inventory. India undertook a large number of applications using Landsat and Indian Remote Sensing Satellite (IRS) IRS-1A, IRS-1B and IRS P2 for crop mapping, crop monitoring and yield assessment for wheat, rice and a few other crops were established (Sahai & Dadhwal, 1990).

Phase III was the take-off phase for digital crop applications, which was triggered by launch and data availability from Indian Remote Sensing Satellite -1C (IRS-1C, 1995). The unique single platform combination of LISS-III, AWiFS and LISS-IV with superior radiometry was continued (IRS P6, launched in 2003) and was to a great extent the driver of developments in this phase. In January 2021, the Journal of Indian Society of Remote Sensing brought out a special issue on 25th Anniversary of launch of IRS-1C. The contributions of IRS-1C in enhancing agricultural applications in India have recently been reviewed in much detail by Ray et al. (2021).

Phase IV is the coming of age of operational agricultural applications in India which was to a substantial degree, triggered by the establishment of Mahalanobis National Crop Forecasting Centre (MNCFC) by Ministry of Agriculture, Government of India, in 2012. Since its establishment, it has expanded the number of crops and areas for crop forecasting, added component of horticultural crops monitoring, worked extensively with State Department of Agriculture and service providers in the field of crop insurance and conducted pilot studies on smart sampling for small area (Gram panchayat) yield estimation, regularly monitored crop damage and assesses yield losses. Launch of RISAT 1 carrying a C-band synthetic aperture radar in 2012 added to this progress.

A number of reviews are available covering the all overall scenario of agricultural applications (Ray et al., 2020) as well as specific themes, such as crop inventory (Dadhwal et al., 2002; Navalgund et al., 1991), crop yield and condition assessment (Dadhwal & Ray, 2000; Dadhwal et al., 2003) and.

Growing Experience on Field-Scale Agricultural Applications in India

EO applications for agricultural crops started for crop identification and mapping with aim at district-level crop inventory and yield estimation. Early in the application program it was understood that agricultural scene in India as viewed by Landsat MSS would be comprised of mixed pixels only. The estimated median size of fields was 0.56 and 0.62 ha for mustard and wheat in Mehsana district of Gujarat (Dadhwal, 1985), 0.76 ha in Sabarkantha district of Gujarat (Sahai et al., 1989) and 0.26, 0.21 and 0.10 ha for wheat, mustard and fodder in Hisar district of Haryana (Dadhwal et al., 1991), individual fields cannot be delineated with Landsat MSS and IRS LISS-I, while only bigger fields would be detected with Landsat TM and LISS-II. Thus, for majority of cropped areas the classification would be on mixed signatures from multiple fields and crops. The success in crop inventory at district level, either through complete area enumeration or sample-segment-based analysis, is made feasible by synthetic fields (i.e., adjoining fields under same crop). In an early evaluation of SPOT of 20 m, a larger proportion of individual fields were discernible and multi-crop discrimination was feasible (Sahai et al., 1989). Improvements in multiple crops discrimination was possible through use of SWIR spectral bands or data acquisition of specific bio-window (Dadhwal et al., 1989). Multi-sensor comparative studies highlighted decrease in classification accuracy at larger spatial resolution. These studies provided necessary support for arriving configuration of IRS-1C (Singh et al., 2001, 2002) and its launch in December 1995 with LISS-III and LISS-IV sensors with 23.5 m and 5.8 m spatial resolution. Early evaluation of IRS-1C data supported the detection and delineation of larger number of fields with LISS-III (Navalgund et al., 1996) and significant delineation of field boundaries with LISS-IV (Tiwari et al., 2009).

Crop biophysical parameters retrieval as input in crop simulation model is a critical need and two most common inputs are leaf area index (LAI) and crop phenology (Sehgal et al., 2005). Small area inventory at village level indicated RS-based area was comparable to field data acquired by National Sample Survey Organization (NSSO) for dominant crops only (Singh et al., 2005). Field-scale LAI retrieval has been demonstrated over wheat in Gujarat (Chaurasia et al., 2006) and recently with Sentinel-2A MSI and Landsat-8 OLI (Dhakar et al., 2021) RS-derived field scale LAI have been assimilated in crop simulation models for making production forecasts (Dhakar et al., 2022). Horticultural crop identification and mapping studies in India have shown higher accuracy with LISS-IV in comparison with LISS-III and also highlighted use of object-based classifiers in a number of case studies covering citrus (Singh et al., 2016), Banana (Nishant et al., 2016), mango (Nagori, 2021) and over sites with multiple horticultural crops (Hebbar et al., 2014).

Introducing Contributions to the Special Issue

Seventeen articles included in this special issue can be broadly grouped under five themes, namely (i) crop discrimination and mapping, (ii) crop yield estimation, (iii) crop suitability analysis and zonation, (iv) crop water use assessment and (v) mixed group comprising single contributions for UAV, Fodder and field boundary extraction. These articles provide procedures and results of application in India except two studies which are from Iran.

Crop Discrimination and Mapping

Jayanth et al. (2022) successfully demonstrate crop sequence/rotation assessment over a very diverse cropping area in Mysore district of Karnataka. The study monitored crops and cropping pattern over three years and used LISS-IV and Sentinel-2 data which were gap-filled with LISS-III and Landsat-8. Multi-resolution data were harmonized by transferring crop identification to cadastral/land records GIS base. Crop sequence classification uses a flowchart-like hybrid structure experienced bee which is integrated in GIS.

Nihar et al. (2022) describe use of multi-date Sentinel-2 data to discriminate and map sugarcane fields in a study area in Saharanpur district of Uttar Pradesh state. Classification approach adopted random forest and SVM and successful separation of ratoon and planted fields was demonstrated.

Rawat et al. (2022) compare the classification accuracies from two spectral-temporal domain techniques, namely modified possibilistic c means (MPCM) and 1-D convolution neural network (CNN) for mapping transplanted rice using Sentinel-2A/2B multi-temporal data over northern region of Haryana state. Results indicated superior performance by CNN in this study.

Crop Yield Assessment

Milesi and Kukunuri (2022) describe successful application of terrestrial observation and prediction system (TOPS) approach for crop yield estimation to support crop insurance scheme at gram panchayat level with case study of pear millet in Faizabad district of Uttar Pradesh and rice in Kendujhar district of Odisha. The challenge of crop discrimination and mapping in monsoon season was overcome with a combined used of SAR and optical data.

Gumma et al. (2022) describe a multi-site study conducted in Kharif season covering rice, groundnut and maize crops and use of multi-date Sentinel-2 and Landsat-8 data. A large number of crops were mapped including rice, groundnut, cotton, maize, pigeon pea, millet based on the study area. Efficient VI-based stratification was used to identify fields to conduct crop cutting experiments for yield estimation. Using LAI-SAVI empirical models, multi-date LAI was assimilated in crop simulation models for rice and groundnut yield assessment. The study captured the yield variability in the farmer's field and opens up avenue for implementing EO-based crop insurance program for Indian farmers.

Tripathy et al. (2022) demonstrate yield prediction for rice, cotton and wheat using a multi-sensor EO-based approach that uses geostationary INSAT data for insolation, high temporal MODIS for phenology and fAPAR and Sentinel for water scalar and crop mapping.

Jafari and Keshvarz (2022) demonstrate Landsat-8-based LAI assimilation in CERES wheat crop simulation model over farmer's fields in Iran.

Krupavathi et al. (2022) describe a field-scale sugarcane empirical yield model development that uses artificial neural network (ANN). Yield predictors were multi-date Landsat-8 derived NDVI, absorbed photosynthetically active radiation (APAR), canopy surface temperature and crop water stress index (CWSI). Similarly, Kumar et al., (2022) developed empirical models using NDVI and water scalar (WS) as predictors for sugarcane yield over four factory mill areas in Gujarat and Maharashtra. The successful multi-year evaluation suggests that such empirical approach would be easy to adopt be sugarcane factories to plan for their gate arrivals.

Crop Suitability and Zonation

Handique et al. (2022) summarize the methodology and results from a large operational study that aimed at expanding area under horticultural crop in North eastern region of India under CHAMAN program of Ministry of Agriculture, Government of India.

Upadhyay et al. (2022) integrate eight important parameters, namely altitude, chilling temperature, agricultural and use, rainfall, crop growing temperature, soil texture, slope and aspect in GIS framework of analytical hierarchy process (AHP) to map areas suitable for apple crop in Nainital district of Uttarakhand.

Rukhsana and Molla (2022) present an evaluation of rice cropping zone in GIS framework using multi-criterion evaluation for 24 Parganas district of West Bengal.

Water Use and Irrigation Management

Parmar and Gontia (2022) describe use of surface energy balance (SEBAL)-based evaporative fraction for irrigation management in a canal command area. Pandey and Mogarekar (2022) describe implementation of a framework in GIS for spatial irrigation management which has the potential to be scaled up to farm level with the required input data.

Other Applications

Bahuguna et al. (2022) describe UAV data acquisition and analysis for Rosa damascene, a pharmaceutical and cosmetic plant. Their study used 6-band multispectral data of 1.5 cm pixel for plant counting, canopy height and quantitative plant growth assessment to support crop management.

Dutta et al., (2022) describe an operational large area application of fodder crop monitoring in the state of Gujarat, working with the operational milk collection and marketing agency. The study addressed multi-temporal monitoring of crop fields for inventory of fields being used for fodder collection due to multiple foliage harvests, a mobile-based field data collection application as well as assessing suitable fields during the fallow season for expanding area under fodder with a Soil Wetness Index (SWI) application.

Sharifi et al. (2022) describe application of an efficient approach for field boundary extraction over agricultural fields using a convolutional neural network over study area in Iran with Sentinel-2 and Landsat-8 images.

Way Forward

Successful field-scale applications in small holder conditions would address crop mapping, crop growth, yield estimation, irrigation and water use, crop management, crop damage assessment, crop insurance. These applications of EO data are realized with an optimal system of EO data (spatial, spectral and temporal monitoring), data processing and information extraction (multi-sensor normalization, temporal profiles, biophysical parameters), sample field data through smartphones (geolocated field data, pictures, crowdsourcing). Some of the challenges and the way forward for each of the component of a field-scale advanced geospatial application are briefly discussed here.

EO Data and Accessibility

Current EO observation capabilities support field-scale applications for agriculture in most of the small field and smallholder regions. Most preferred data currently are

Sentinel-2 for optical region and Sentinel-1 for SAR. Global open-access and 10 m spatial resolution for Sentinel-2 are major advantages. High capacity global coverage with small satellites from Planet with 4 m spatial resolution and daily coverage is also likely to figure more prominently. Although there are a number of multispectral sensors with 1 m and better spatial resolutions, these are less frequently used for agriculture and more for infrastructure as these applications are dependent on repeated large area coverage at low cost.

EO applications for water use and irrigation management have an additional requirement of thermal data. While the current thermal sensors have moderate spatial resolution, this gap is proposed to be filled by an ISRO-CNES mission TRISHNA (Thermal infraRed Imaging Satellite for High-resolution Natural resource Assessment) (Lagouarde et al., 2018). Field-scale thermal data can be derived from downscaling data of current sensors (Jeganathan et al., 2011) and SAR data in L and S band would be available from NISAR mission that has proposed open data access and 11-day repeat coverage in addition to interferometric observations. Hyperspectral data also hold much promise for crop discrimination, canopy chemistry, disease detection and providing complementary information to multispectral sensors. However, proposed hyperspectral missions ENMAP will have spatial resolution of 30 m only, restricting its field-scale use to large fields.

Role of UAV

While the use of UAV is addressed in Bahuguna et al. (2022) for a pharmaceutical and cosmetic plant monitoring, the Journal of Indian Society of Remote Sensing brought out a special issue on “Advances in UAV Remote Sensing” in March 2021 (Volume 49, Issue 3) which featured important applications like crop monitoring and thermal data analysis for irrigation management (Meive and Maheswari, 2021) and very high resolution cadastral boundary delineation (Khadanga & Jain, 2021). Role of UAV for agriculture is likely to see large expansion, given its complementary role to satellite earth observation data and progressive policies promoting the use of UAV in agriculture.

Use of Smartphones and Crowdsourcing

Smartphones have become an integral part of field-scale EO application methodology for their geolocation and ground truth collection devise as well as complementary proximal remote sensing and crowdsourcing for big-data analytics for many applications of crop insurance and smart agriculture. Hufkens et al. (2019) describe successful application of smartphone pictures and their processing to derive wheat phenology in Punjab and its integration in MODIS-derived phenology assessment as well as identification of fields which have been affected by lodging. Ceballos et al. (2019) have demonstrated smartphone picture-based damage assessment for crop insurance in wheat-rice cropping system in Haryana and Punjab states.

Extensive field data are collected using smartphones as images, geolocations and field surveys and also through crowdsourcing including with interactive voice response systems. These data are accessible on cloud, and field images are processed through machine learning algorithms for crop type, crop diseases, crop vigor as well as assessment of yield contributing characters.

Data Processing and Crop Simulation Models

Development of digital processing techniques of data preprocessing, crop biophysical parameter retrieval and its integration in crop simulation models and wider use of machine learning tools. Access to high-resolution geospatial database on land cover, DEM and soil through web-GIS and weather data sets from space, field observatories and short- to mid-term weather forecasts has facilitated large-scale use of crop simulation models for crop simulation. EO data assimilation through phenology and LAI has enhanced yield modeling effort.

Rapid accumulations of case studies in various small holder regions in Africa and South Asia and approach to address crop and areas specific challenges points towrd rapid advancements in field-scale studies and adoption of advanced geospatial technology in small holdings area.

Conclusions

Stage is now set for large-scale adoption for EO data and advanced geospatial technologies at field level for multi-stakeholder application needs. The availability of Sentinel 1 and Sentinel-2 data as open-source data, daily global viewing by Planetscope and a number of proposed missions point toward increasing EO data availability. Internet, wide penetration of smartphones, cloud and other computing infrastructure such as Google Earth Engine has overcome infrastructure barriers for large-scale use. New analysis techniques of ML and AI, availability of spatial databases and wide-spread adoption of crop simulation models and entry of a number of startups providing EO-based services suggest that the field-scale EO application is ready for commercial large-scale adoption. To extend the studies for wider number of crops and regions and fine tuning application system design for cost-efficient, timely and accurate diagnosis would lower most of barriers to commercial adoption of this technology. Contributions to this special issue and other studies listed above are paving way for this future.

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Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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