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REVIEW ARTICLE

Geospatial assessment of cropping intensity: Advances, challenges and future directions

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Abstract

Cropping intensity (CI) is an important parameter used for evaluating agricultural land use efficiency, with significant implications for global food security, sustainable land management and economic stability. As the world's population continues to grow, effective monitoring of CI is vital for fulfilling the rising food demand and addressing challenges caused by climate change. This review article explains the current state of the field, discusses significant advances made possible by remote sensing and geospatial technologies. The paper explores the evolution of methodologies, from traditional time-series analysis to modern machine and deep learning algorithms and highlights regional applications across different continents. However, persistent and critical challenges were identified that limit the full potential of these tools. some of the Key issues and significant data gaps were included. A major research gap remains due to less integration of socio-economic and policy data into geospatial models, which limits our ability to understand the complex drivers behind the changes observed in CI. The future of this field requires a coordinated, interdisciplinary approach. Recommendations include promoting open-access platforms and harmonized standardized datasets, developing automated algorithms that leverage multi-source data fusion and using the ground truth data to fill the gaps. This comprehensive approach is needed to provide the reliable, predictive intelligence required for accurate policy decisions and sustainable agriculture worldwide.

Keywords: cropping intensity; food security; remote sensing; sensors

Introduction

Cropping intensity (CI) defined as the rate of Gross Cropped Area (GCA) to Net Sown Area (NSA). It is represented as a percentage or index (1). It is used to measure the extent to which agricultural land is utilized in several harvests in a year and it is an important indicator of land use efficiency and agricultural productivity (2). It is used not only for measurement but also as an important driver in addressing global food security, strategic land use planning and agricultural sustainability initiatives (3). Higher cropping intensity is generally associated with increased food production, which is important to compensate the increasing food demand due to increasing world population (4). However, it also measures the intensive land use, which can lead to problems such as resource depletion, soil degradation, increased water demand and higher greenhouse gas emissions if not managed sustainably (5). Thus, monitoring the cropping intensity should be viewed both as a measure of productivity and as an indicator of environmental stress. To mitigate negative impacts, sustainability metrics must be integrated (6).

The importance of spatial and temporal monitoring of cropping intensity cannot be overstated. Traditional methods of data acquisition are typically time-consuming, labour-intensive and lack the spatial and temporal variations to enable effective agriculture management and policymaking (7, 8). Understanding the changes in cropping intensity across diverse landscapes and over time is important for identifying areas with potential for intensification, identifying the agricultural stress regions and creating targeted interventions (9). In this context, geospatial technologies, like remote sensing and Geographic Information Systems (GIS), have emerged as necessary tools. Remote sensing offers a cost-effective and expandable approach to monitor agriculture land use over large areas and over several seasons, which enable objective and reproducible observations (10). GIS, on the other hand, helps in combining, analysing and portraying these complex spatial data sets, allowing to carry out detailed evaluations and decision-making on the basis of evidence (11).

Despite the improvements, the field faces with several issues. There are notable gaps observed in the synthesis of cropping intensity studies based on geospatial methods, particularly on regional to global scales. While numerous studies provide valuable insights, the absence of a general framework limits comparative analysis and its application to global agricultural policy (12, 13). Furthermore, a continues challenge lies in the lack of consistent definitions and measures across various studies. Based on the how the cropping intensity defined and measured across various studies and geographical areas show difficulty in comparison and also limit the development of overall evaluation frameworks (14, 15).

The real potential of geospatial analysis in global initiatives, such as the Sustainable Development Goals (SDGs) and strategies on climate change adaptation lies in the ability to uniform, large-scale and timely data. Despite technological progress, the application of these tools for large-scale impact is still in its infancy, highlighting the need for cloud-based platforms and automated workflows (16, 17).

Conceptual framework of cropping intensity

The theoretical foundation of cropping intensity is built based on basic terms of agricultural land use that quantify the intensity of land use over a period, typically a year. Understanding these definitions allows for accurate assessment and comparability of studies.

Basic concepts

Net Sown Area (NSA) refers to the area of land that has been sown with crops at least once during an agricultural year. Gross Cropped Area (GCA) is nothing, but the total area cultivated and counting the cultivated area multiple times if the cropping done more than once in a year (18, 19). The Cropping Intensity (CI) calculates based on the ratio of GCA and NSA (Eqn. 1) and expressed as a percentage. A Cropping Intensity (CI) of 200 % indicates the land cropped twice annually this index measures land use intensity (20)

$$\text{Cropping Intensity} = \frac{\text{Gross Cropped Area (CGA)}}{\text{Net Sown Area (NSA)}} \times 100 \qquad \text{(Eqn.1)}$$

Drivers of cropping intensity

Cropping intensity is not a single phenomenon but is closely related to a multi-faceted association between biophysical and socio-economic determinants (21, 22). Irrigation is a major facilitator for successive cropping, especially in arid or semi-arid areas. The reliability and availability of water resources have a direct impact on the viability of successive harvests (23, 24). Soil health is important; highly fertile and well-managed soils can sustain more than one cropping cycle, but low-quality or degraded lands can minimize intensification(25, 26). Climate, such as rainfall regimes, temperature conditions and growing degree-days, sets the inherent potential for having multiple crop cycles. Favourable weather with proper moisture and heat conditions favours to enhance the intensity of cropping (27, 28).

Apart from these biophysical factors, socio-economic factors play an important role in shaping farmers' decisions on cropping intensity. Demand from the market for certain commodities like labour availability and its price, credit access and government policies like subsidies, minimum support prices and systems of land tenancy, all of these have major impacts on farming operations (29, 30). These human choices are the eventual determinants of cropping intensity that is measured. However, a recurring problem lies in the inconsistencies in cropping intensity definition and measurement between areas and studies. Different national or sub-regional data collection practices and conceptual frameworks can result in non-comparable findings that complicate syntheses at a larger scale (31).

In addition, there is also an obvious need for harmonized classification systems within multi-temporal analysis to properly monitor changes and compare CI through time and over different geographical locations (32, 33).

The "hidden" influence of socio-economic drivers on geospatial observables is commonly undervalued. Geospatial techniques tend to measure mainly biophysical properties such as the presence of crops and phenology, whereas the varied socio-economic contexts that determine farm practices too often are behind the variation in definition and measurement (34, 35). For example, the broken-up landholding pattern typical of smallholder farm systems or the regional market incentives can result in intricate, non-standard planting regimes that are hard to reproduce using homogenous geospatial models. This implies that geospatial analyses, although powerful, can only measure the outcome of complex human-environment interactions. To accurately predict and understand cropping intensity, models have to go beyond strictly biophysical parameters and incorporate socio-economic layers, which in turn are usually less available or spatially explicit (36, 37). For example, a study in Ghana combined remote sensing and GIS with census and socio-economic survey data to map the "proximate causes" of land use change, including slash-and-burn cultivation and intensive cultivation areas (38). A research on Indian smallholder farms revealed that a Landsat threshold approach was most accurate, highlighting the need for methods that can handle fragmented landscapes and heterogeneous cropping patterns, which are socio-economically driven (39). In Malawi and Ethiopia, scientists were able to integrated Sentinel-2 imagery with georeferenced plot-level data of national household surveys and successfully map maize cultivation at 10-meter resolution. This study highlighted how gathering complete plot boundaries in surveys offers the highest quality data for training such geospatial models (40). Another study in Fiji Islands utilized a geographical method to combine maps in a national agricultural census with socio-economic drivers such as population and market pressures data (41). Through creating "critical maps," the researchers were able to measure where high land use intensity overlapped with certain socio-economic drivers and so unveil significant relationships. These example demonstrate that while challenging, the integration of geospatial and socio-economic data is feasible and provides strong insights that cannot be possible from either data sources alone.

A second important factor to take under consideration is the difference between "effective" and "observed" cropping intensity. Geospatial techniques are particularly good at identifying when crops are present and their phenological cycle, accurately determining that there are multiple cropping seasons. However, they tend to have difficulty in assessing the effectiveness or productivity of each cropping cycle (42, 43). A field may be seen to be cropped twice, but if the second crop fails to deliver well because of drought, pest attack, or market failure, its contribution to food security or economic production is negligible (44, 45). This points out that there could be a high geospatial cropping intensity concealing low productivity or crop failure in particular seasons. Therefore, it is an overwhelming necessity to incorporate yield estimation and monitoring of crop health with cropping intensity measurement to offer a more discriminative and useful insight into farm productivity(46, 47).

Remote sensing platforms and data sources

The ability to assess the cropping intensity accurately at a global scale is highly dependent upon the availability and nature of different remote sensing platforms and data sources (Table 1). Technology provide varied capabilities in spatial, temporal and spectral resolution, each with different advantages and limitations in sensing cropping cycles.

Table 1. Comparative analysis of key satellite sensors for cropping intensity assessment

Sensor Name	Type	Spatial Resolution	Temporal Resolution	Key Bands/Frequencies
MODIS	Optical	250-1000m	Daily	Visible, NIR, SWIR
Landsat-8/9	Optical	30m	16-day	Visible, NIR, SWIR, Thermal
Sentinel-2	Optical	10-20m	5-day	Visible, Red Edge, NIR, SWIR
Sentinel-1	SAR	5-20m	6-12 days	C-band (VV, VH)
Sensor Name	Type	Spatial Resolution	Temporal Resolution	Key Bands/Frequencies
MODIS	Optical	250-1000m	Daily	Visible, NIR, SWIR

Overview of optical sensors

MODIS (Moderate Resolution Imaging Spectroradiometer) is a satellite sensor on board the NASA's Terra and Aqua satellites, offers high temporal resolution (daily revisits) but at coarse spatial resolution (250-1000m). This renders MODIS data suitable for regional to global scale monitoring and the detection of broad phenological cycles, like the onset and end of growing seasons over continents (48, 49). Due to the coarse spatial resolution, it can produce mixed pixels that reduces field level accuracy. MODIS can miss short duration crops or phenological stages of the crop causing miscounting of cropping events. That suggest it is not reliable for field scale cropping intensity monitoring.

The Landsat mission, a collaborative USGS/NASA program, has a moderate spatial resolution (30 m) and moderate temporal resolution (16-day revisit). Its unique long-term archive, dating from the 1970s, is irreplaceable for historical trend analysis and decadal scale changes in cropping intensity.

Sentinel-2, which is a European Union Copernicus mission, has high spatial resolution (10-20 m) and high temporal resolution (5-day revisit with two satellites). This renders Sentinel-2 data highly appropriate for intensive field-scale monitoring and recording rapid crop phenological changes, which is essential for differentiating several short-duration cropping cycles.

Overview of radar sensors

Sentinel-1, which is part of the Copernicus mission, is a C-band Synthetic Aperture Radar satellite (50). Its day-night, all-weather capability to penetrate cloud cover makes it an important data source where there is persistent cloud cover, especially during monsoon seasons (51). SAR data is sensitive to crop structure, biomass and moisture content, providing complementary information to optical data(52, 53).

RISAT (Radar Imaging Satellite), designed by the Indian Space Research Organisation (ISRO), includes X-band and C-band SAR satellites, adding to the extent of SAR data availability globally for agricultural monitoring.

Advantages and limitations of each sensor for cropping cycle detection

Optical sensors are superior in offering direct measurements of vegetation greenness as indices such as NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index). These are direct indications of photosynthetic activity and biomass and hence are easy to interpret while detecting crop growth phases. Their greatest shortcoming is their vulnerability to cloud cover, which is more common in tropical and sub-tropical latitudes during monsoon months, creating substantial data gaps that hinder real-time monitoring of crop cycles (53, 54).

SAR sensors, on the other hand, transcend cloud contamination since they can penetrate clouds and function without sunlight. They are thus irreplaceable for constant observing in totally cloudy agricultural regions. However, SAR data processing is more involved and vegetation signal interpretation is less intuitive than with optical data, since SAR signals depend not only on crop structure but also on soil moisture and surface roughness (55).

Emerging sources: PlanetScope, UAVs, Hyperspectral, CubeSats

The remote sensing is evolving at a fast pace with the creation of new data sources. PlanetScope is a fleet of CubeSats with daily 3-5m resolution cover, providing temporal and spatial information for monitoring cropping intensity at micro-scales (56). UAVs (drones) enable ultra-high resolution data for local, farm-level analysis, albeit with limited coverage (57). Hyperspectral sensors yield highly detailed spectral signatures, which enable more accurate crop type and early stress detection, but at the cost of high data volume and processing requirements (43). The abundance of CubeSats, small satellites, provides a cost-effective and adaptable platform for targeted monitoring requirements, adding to the variety of data available (58).

One of the serious issues to consider is the "resolution paradox" in cropping intensity measurement. While high-resolution observation by sensors like Sentinel-2 and PlanetScope allows detailed field-level measurement, essential in precision agriculture and heterogeneity analysis, these data are accompanied by vast volumes, higher processing cost and often narrower swaths. This makes global or even regional coverage computationally intensive and less frequent (58, 59). Coarse-resolution data like MODIS, on the other hand, are best for global trend identification and broad patterns but necessarily have no local resolution (60). This paradox means that there is no "best" sensor; rather, an optimal approach often involves multi-resolution fusion techniques that increase the strength of each (61).

Underestimation of the importance of data fusion for reliable cropping intensity monitoring is a significant bottleneck. Weather conditions of continuous cloud cover over key agricultural areas, e.g., Southeast Asia and some areas of Africa during monsoon periods, directly impedes optical time-series analysis and accurate CI mapping is impossible for key growth stages (58). SAR provides the only feasible solution for uninterrupted monitoring under such conditions. Inability to integrate optical and SAR data effectively means that even with complementary data being available, an exhaustive picture of cropping cycles, particularly in adverse environments, is not clear. This results in less accurate CI estimates in sensitive areas, having a direct impact on food security estimation and policymaking. Methodological innovation in data fusion is therefore not an academic pursuit but a necessity for large-scale global agricultural mapping. It enables comprehensive and reliable CI measurement, ensuring informed decisions in regions most sensitive to climate and food supply concerns (62).

Case studies that demonstrate the effectiveness of data fusion

Adding optical and SAR Data: Optical imagery is best at showing changes in moisture and chlorophyll content in crop leaves and highly used in crop classification, whereas Synthetic Aperture Radar (SAR) is sensitive to morphological structures and growth stages and can see through clouds (63). This combination is crucial for persistent monitoring in cloud-contaminated areas. For instance, a fruit tree mapping study revealed that it significantly enhanced classification accuracy by merging data from Sentinel-1 (SAR) and Sentinel-2 (optical) (64). In another study on predicting soybean yield, researchers discovered that combining optical vegetation indices and SAR imagery enhanced the predictive performance of the model (R^2) from 0.65 to 0.85 (65). Researchers in Brazil also obtained a 3 % increase in accuracy for in-season crop mapping through the combination of Sentinel-1, Sentinel-2 and SRTM data (66).

Fusing multi-resolution satellite data: Another usual challenge is the trade-off between temporal and spatial resolution in satellite sensors. Researchers are overcoming this problem by merging data from multiple satellite constellations. For example, a technique was created to merge Landsat and MODIS data to produce a dense time series of images with 30 m resolution. This facilitated the creation of high-resolution cropping cycle maps for China with overall accuracies up to 92.5 %, which is not achievable using either sensor individually (67).The AgriFM architecture follows a similar strategy, taking advantage of temporally dense data from MODIS, Landsat-8/9 and Sentinel-2 and applying deep learning to dynamically integrate these representations for applications such as early-season crop mapping (68).

Fusion of satellite, airborne and ground-based sensors: To get higher accuracy and maximum information, data fusion goes beyond satellite-to-satellite combinations. Satellite and drone data fusion, for instance, takes advantage of the large coverage of satellites with the high spatial resolution of airborne systems. A Multi-sensor Machine-Learning Approach use data from different sensors such as on the ground IoT devices to provide cultivation recommendations, resulting in high crop yield (69).This multi-layered analysis offers accurate, localized information that can validate and calibrate many satellite measurements.

Geospatial methodologies for estimation of cropping intensity

The accuracy of geospatial techniques for estimation of cropping intensity relies on different methodologies, from conventional vegetation index time-series analysis to cutting-edge machine and deep learning algorithms. Each method uses different unique aspects of satellite data to identify and quantify the cropping cycle (Table 2).

Time-series NDVI/EVI-based approaches

NDVI and EVI are frequently used because they are simple, widely available, easy to compute from common satellite bands, enabling global and long-term records that are useful for phenology, trend analysis. EVI reduces atmospheric effects and soil background and to reduce saturation in dense canopies. These techniques identify different agricultural growth cycles by observing seasonal variations in vegetation indices like Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI) (70, 71). Peaks in the time-series correspond to periods of peak biomass or crop maturity (72). These time series are then processed and analyzed by using methods such as include harmonic analysis (modelling periodic signals), Savitzky-Golay filtering (which smooths data and reduces noise while preserving signal features) and Fourier series analysis (decomposing signals into their frequency components), which smooth noise and extract important phenological parameters (71, 73).

Phenology-based classification and land use trajectory analysis

Phenology-based classification consists of the extraction of key phenological measurements from time-series data, including the beginning of the growing season, season end and growing period length (71, 72). These are subsequently used to classify various cropping patterns, by separating single, double, or triple cropping systems (72, 74). Land use trajectory analysis is an extension of this, by examining changes in land use and cropping patterns over long periods, allowing agricultural intensification or abandonment trends to identify (75).

Machine learning and deep learning algorithms

The advent of the latest computational techniques has significantly improved the performance of cropping intensity estimation. Machine Learning (ML) models like Support Vector Machines (SVM), Random Forest and Gradient Boosting are popular for crop type identification and cropping cycle detection from multi-temporal spectral characteristics (76, 77). The ML models can automatically address complex, non-linear relationships in remote sensing data and offer robust classification capabilities (78).

Deep Learning (DL), a subset of machine learning, is also emerging at the cutting edge of geospatial data processing. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are being widely applied for the automatic extraction of features from time-series satellite imagery in an attempt to classify crops correctly and identify phenological events (79, 80). DL models possess the unique ability of learning high-level spatio-temporal patterns directly from the raw data and, in the process, are extremely useful in multi-season cropping estimation, particularly in very complicated agricultural landscapes (81).

Table 2. Overview of methodological approaches for geospatial cropping intensity estimation

Method Category	Core Principle	Typical Data Requirements	Strengths for CI Estimation	Limitations/Challenges	Example Algorithms/ Techniques
Phenology-based	Analyze vegetation index time-series to detect growth cycles	Optical time-series (NDVI, EVI)	Intuitive, captures seasonality, good for distinct cycles	Sensitive to noise/gaps, struggles with complex/overlapping cycles	Harmonic analysis, Savitzky-Golay filtering, thresholding
Machine Learning	Classify pixels based on multi-temporal spectral features	Multi-temporal optical/SAR, ancillary data	Handles non-linear relationships, good for complex patterns	Requires labeled training data, interpretability can be challenging	Random Forest, SVM, Gradient Boosting
Deep Learning	Learn hierarchical spatio-temporal features from raw data	Dense time-series optical/SAR	High accuracy, automated feature extraction, handles complexity	Data-hungry, computationally intensive, black-box nature	CNNs, RNNs, LSTMs, U-Net

Despite the promises of these advanced methodologies, there are several research gaps were observed. Several methods used in various agro-ecological zones are not widely benchmarked. The effectiveness of various approaches can greatly fluctuate based on the local climate, particular crop varieties and current agricultural methods (82, 83). The lack of a thorough and methodical comparison across a broad variety of environmental circumstances makes it challenging to determine which method is best for a particular situation. Additionally, it is to be noted that deep learning models are rarely used explicitly for multi-season cropping assessment (81). Although it has a lot of promise, its broad use and thorough validation for recognizing and measuring the subtleties of multi-season cropping patterns are still emerging. This suggest that the implementation and evaluation of these techniques in various real-world agricultural contexts are lagging behind; the availability of data and algorithms is insufficient (79). The regular production of comparable, high-quality cropping intensity data required for regional and international evaluations is impeded by this problem. In order to promote an open scientific and code-sharing culture, it suggests that the focus should shift from creating new algorithms to thoroughly testing and standardizing current ones under a greater variety of circumstances (84).

Low reproducibility and transparency of methods is another important challenge. Many of the researches often lack clear descriptions of algorithms used, specific parameters and publicly available code, which is making it difficult to have other researchers replicate the results, build upon the work of others, or add to cumulative knowledge (85, 86).

The lack of deep learning application to multi-season cropping estimation, where in theory it is ideal and matched to systems that are complex (e.g., mixed pixels in smallholder farms, intercropping, staggered planting), is a vast untapped potential (79, 81). Deep learning's ability to learn hierarchical features and spatio-temporal interactions can unravel such complexities, unleashing breakthroughs in accurately mapping highly dynamic and complex cropping patterns, particularly in data-scarce or challenging areas. This necessitates for more work on transfer learning, explainable AI and producing strong training datasets optimized for deep learning application in cropping intensity estimation (84) (Table 3).

Regional and Global applications

The given geospatial analysis of cropping intensity has been used in various applications. For different scales of geographical and environmental studies. It offers significant information on agricultural productivity, land use changes and their impacts on food security and environmental sustainability.

Case studies from India, Southeast Asia, Sub-Saharan Africa and global syntheses

India is a typical example in which geospatial methods are applied intensively to monitor cropping intensity, driven by factors such as large-scale irrigation and supportive policies for agricultural development (83, 90). In India satellite imagery has been used in studies to identify yield gaps, examine intensification trends and inform water resource management (91). In Southeast Asia, where cropping systems are diverse (e.g., rice-rice, rice-other crops) and cloud cover is a significant issue, SAR data has been essential to the consistent CI evaluation (92). Sub-Saharan Africa, with smallholder agriculture, predominantly rainfed agriculture and highly sensitive to climate variability, which leads to a special requirement for accurate CI assessment in order to allow food security concerns to be considered (93). However, this region is commonly afflicted by severe data and methodology problems. At the global level, global syntheses attempt to map cropping intensity at the continental level, frequently employing coarse resolution data like MODIS or aggregated higher-resolution data (94), to differentiate global food production regimes and land use change at coarse. In Latin America, the major driver force of agricultural intensification and transformation is the mounting world demand for oilseeds and grains. This has caused a phenomenal increase in the use of land for soybean production, which rose more than two-fold from 2000 to 2019. Many of these increases have been by the reclamation of pastures, which themselves were reclaimed from natural vegetation (95). In the Amazon region of Brazil, the cultivated area under soybeans expanded over ten times during this time. The expansion has been sustained by principal drivers such as economic and policy reforms (96), in addition to agricultural research that has brought about new, high-productive crop varieties and farming methods such as no-till agriculture. In addition, most countries in the region, such as Argentina, Chile, Colombia and Brazil, are experiencing a large "cropping intensity gap," which implies there is a theoretical potential for a extra harvest every two years.

Role of cropping intensity in yield gap analysis, land degradation monitoring

Cropping intensity data plays an important role in yield gap analysis, it is an activity that calculates the gap between observed crop yields and the potentially achievable yields under ideal conditions (97). By combining the CI data and yield data, researchers can identify areas where yields are below potential, revealing opportunities for

Table 3. Accuracy metric of algorithms used for CI estimation

Model/Method	Source	Accuracy Metric	Value	Context/Notes
Landsat threshold method	(39)	R^2	≥ 0.71	Most accurate for smallholder farms in India
		RMSE	≤ 0.14	
		R^2 (after spatial aggregation)	up to 0.97	R^2 increased with spatial aggregation (≥ 5 x 5 km)
Stacking2 ensemble model	(87)	R^2	0.923	Highest estimation accuracy for crop residue estimation
		RMSE	3.32 %	
XGBoost	(87)	R^2	0.884	Highest performance among base models
Random Forest (RF)	(87)	R^2	0.865	Base model performance
Support Vector Regression (SVR)	(87)	R^2	0.859	Base model performance
Back Propagation Neural Network (BPNN)	(87)	R^2	0.842	Base model performance
Random Forest (RF)	(88)	Overall Accuracy	0.77 - 0.95	Varied across seasons (summer vs. winter) for crop mapping
Phenology-based (MODIS)	(68)	Overall Accuracy	89 %	National maps of various cropping systems in China
Phenology-based (Sentinel-2)	(68).	Overall Accuracy	> 76 %	Differentiation of wheat and barley
Bayes Net	(89)	Classification Accuracy	99.59 %	Crop classification

agricultural intensification or improved management practices (98). Moreover, changes in cropping intensity, for example, a decline in multi-cropping, can be a sign of land degradation, resource depletion, or underlying socio-economic stress (99). However, sustainable intensification, which is often quantified in terms of improving CI, can mitigate degradation and promote improved land use efficiency (100).

Despite these applications, significant research gaps still exist. There is a glaring lack of Representation of African and marginal areas in cropping intensity analysis. Despite their extreme vulnerability to food insecurity and climate change, these areas are underserved with appropriate high-resolution CI research due to data constraints, common cloud cover and limited infrastructure to carry out the research (93, 101). This gap makes the areas that is in need of accurate agricultural monitoring data often are the least served, generating a self-reinforcing cycle of data poverty that prevents effective policy intervention, resource allocation and humanitarian response (102). This reveals a severe equity issue with global agricultural research since it means global food security models and agricultural development programs are making decisions based on incomplete data, risking poorly informed strategies and perpetuating existing inequities (103).

Another important gap is the absence of harmonized high -resolution global datasets (less than 30 m). While there are some global datasets available like MODIS, Sentinel-1, etc. they are mostly at coarse resolutions, which limits their application in performing detailed, localized analysis (94). A high-resolution, global cropping intensity dataset is required to perform robust, comparable analysis of all agriculture areas across the world. This gap is directly connect to the "lack of standardized definitions" and "limited benchmarking of methods" (104). In the absence of harmonized, high-resolution global datasets, it is impossible to conduct robust, comparable analysis of CI trends across the world. This severely limits international organizations and national governments from accurately estimating global food production potential, identifying hotspots of agricultural stress or opportunity and performing evidence-based policy for sustainable intensification or climate adaptation worldwide. Absence of such a dataset is a key to the attainment of global food security targets and knowledge of planetary boundaries (105).

Challenges and uncertainties

Despite considerable advances in geospatial technologies, there are certain inherent complications and uncertainties that are still obstacles to get accurate and consistent assessment of cropping intensity at large scale or in highly intricate agricultural environments.

Spectral confusion between crops and natural vegetation

One of the fundamental problems seen in spectral signatures confusion between agriculture crop lands and natural cover. It is difficult to distinguish between natural grassland, weeds, or even some forest covers from cropped fields, especially during off-peak growing seasons or in highly heterogeneous environments (106). This ambiguity can lead to misclassification, where cropped or non-cropped lands are being classified as either cropped or non-cropped, respectively and thus providing inaccurate estimation of cropping intensity (107).

Cloud contamination in optical imagery

Persistent cloud contamination of optical images remains a common and significant challenge, particularly in monsoon-dominated and tropical regions (108). Clouds obscure the land surface, creating enormous data gaps in optical time series. These gaps make it extremely difficult to track entire crop cycles, accurately count the number of harvests and track phenological evolution, producing incomplete or unsound cropping intensity maps (109).

Temporal mismatch in satellite revisit times vs. cropping patterns

Even with the increased revisit rates of modern satellite constellations (e.g., Sentinel-2 5-day revisit), temporal mismatch between satellite observation period and intensive cropping schedules is a viable risk. Short-season crops, e.g., certain vegetables with 60-day cycles, or planting and harvesting rotations in smallholder systems, may be missed or under sampled by satellite overpasses. This can lead to underestimation of real cropping intensity (110).

Insufficient ground truth data for validation

One of the basic and widely known challenges is the inadequate access to ground truth data that required for validation. Accurate validation of geospatial cropping intensity maps requires large, high-quality field surveys, such as farmer interviews, for verification of observed cropping patterns (42). Such data are usually expensive, have logistic limitations and are geographically limited to collect, which limits strict checks of model accuracy, generalizability and uncertainty estimation. The lack of ground truth data is a systemic limit that does not allow complete use of satellite data and advanced algorithms. It limits the use of different methods, introduces uncertainty into cropping intensity estimation (111) and ultimately prevents the development of truly operational and reliable agricultural monitoring systems. This requires coordinated global efforts towards the creation of open-access ground truth networks as well as the development of citizen science initiatives.

Lack of long-term continuous records to study trends over decades

While mission-driven platforms like Landsat offer a valuable long-term history, having steady, fine-resolution data to track continuously over decades remains challenging. The problem is due to numerous reasons such as evolution of sensor technology, temporal change of data processing methods and the inevitable need for harmonization of different satellite missions (112). Absence of continuous, harmonized datasets limits the ability to perform systematic analysis of long-term patterns of cropping intensity and their causes, which are essential in elucidating the effect of climate change and agricultural sustainability over extended periods.

These problems are not isolated; they have a cascading impact on the reliability of policy choice. Cloud cover creates data gaps, requiring interpolation or the use of less than optimal data. Spectral ambiguity causes classification error. Both have a direct impact on the accuracy of cropping intensity maps. If the underlying CI maps are not accurate or of high uncertainty, any resultant policy choices or resource allocations based on them, e.g., food aid distribution, irrigation planning, or agricultural subsidies will be deficient (113). This highlights that the "challenges and uncertainties" are not technical impediments to researchers but they represent the basic limitations on the reliability and trustworthiness of geospatial cropping intensity data for actual policy and management. This underscores the imperative need for many uncertainty quantification and transparent reporting of data quality in all cropping intensity products.

Integration with climate and socio-economic data

A complete explanation of cropping intensity requires going beyond purely biophysical data to include climatic and socio-economic determinants. The general method provides more information about causes of agricultural land use and broader implications.

Assessing drivers: Rainfall variability, irrigation access, market influences

Rainfall variability is a significant and important driver, particularly in rainfed agriculture. Drought or extreme rainfall events have the potential to severely limit or obliterate crops, thus reducing the number of harvests in a single year and hence reducing cropping intensity. The availability of irrigation is a significant counter measure that enables farmers to get over the rainfall variability and initiate multiple cropping seasons even in semi-arid or arid regions. Geospatial assessments can improve by inclusion of data on irrigation facilities, such as the spatial distribution of canals, wells and other water resources (114). In addition to environmental conditions, the market also influences farmers' choices. Commodity prices, consumer demand for specific crops and availability of local and export markets directly influence what farmers choose to crop to cultivate and how frequently they invest in improving farm practices and how do they intensify their cultivation.

Linking cropping intensity to food security and poverty indices

The measurement of cropping intensity has a significant role in overall societal well-being. High cropping intensity tends to enhance the availability of food, which is a fundamental component of food security (115). Geospatial cropping intensity maps can clearly distinguish high or low intensification areas and easily correlate with food surplus or deficit areas. Cropping intensity in agricultural economies can be easily related to household income and poverty, as frequent harvests tend to bring better economic returns to farmers and potentially lead the communities out of poverty (116, 117).

In spite the identification of the significance of these drivers and linkages, important research gaps exist in their integration. There is minimal integration of socio-economic layers into spatial models. While the impact of socio-economic factors is recognized, there is minimal effective and scalable integration of these factors into geospatial cropping intensity models. This is a critical oversight here since farmers' decisions to intensify the crop are complicated and influenced by factors such as labour availability, access to markets, government policies and perceived risks of climate variability. These human choices are the final determinant of cropping intensity. Without effective integration of socio-economic and climate data, geospatial cropping intensity measurements remain mostly descriptive (what is happening) and not explanatory or predictive (why it is happening, what happens next). This limits the utility of their active policy interventions to aim at sustainable intensification or climate resilience, since the "human dimension" is frequently the missing link for moving from passive monitoring to genuine insight and forecasting.

In addition, there is limited spatio-temporal modeling of cropping-climate relationships. It is little understood how accurately climate variability, e.g., El Niño-Southern Oscillation (ENSO) events or long-term temperature trends, affects cropping intensity over time and parameterizing this in spatio-temporal models, which are not yet in widespread development and use (118). Most analyses detect correlations between the variables, but correlation does not equal causation. For instance, whereas high cropping intensity may correlate with decreased poverty, one needs to establish whether CI causes reduced poverty directly, or whether other underlying causes (e.g., access to infrastructure, education) facilitate high CI and enhanced socio-economic status. Unless one understands such causal pathways, policy interventions may be misdirected. Promoting greater cropping intensity without removing underlying socio-economic or climatic constraints may not deliver the food security benefits hoped for. Future research must therefore break away from descriptive mapping and correlational analysis towards strong spatio-temporal causal inference models that can untangle the intricate interaction of biophysical, climatic and socio-economic drivers of cropping intensity and its effects. This necessitates sophisticated statistical and machine learning methods with the ability to deal with complicated dependencies.

Future directions and recommendations

The future of measuring geospatial cropping intensity is predicted to be shaped by enhanced access to information, advanced analytical methods and more collaborative efforts. In order to address the current challenges, one must take a concerted effort in several key areas.

Promoting open-access datasets and cloud-based platforms

The general availability of open-access satellite imagery, such as the Landsat and Sentinel data collections and the emergence of powerful cloud computing platforms like Google Earth Engine (GEE) have made the geospatial data and computational infrastructure available more broadly for wider use. This has greatly reduced computational constraints and enabled collaborative research on an unprecedented scale. It is recommended that we further develop and encourage such platforms to enable scalable and consistent cropping intensity assessments at the global scale. Concrete activities involve the creation of harmonized, high-resolution datasets, e.g., the Global Cropping Intensity Dataset (GCI30), a 30 m resolution product derived from Landsat, Sentinel-2 and MODIS data. Others are the GMIE dataset, a global map of irrigated croplands at 100 m resolution and GGCP10, a global crop production dataset at 10 km resolution (119). This shift means that the primary challenge is no longer data acquisition; instead, it is the processing of large, complex and noisy datasets into reliable, valid and actionable information for policymakers. This requires the establishment of many processing techniques, rigorous quality control and proper communication of uncertainties. Therefore, the challenges have shifted from data acquisition into the areas of data processing, validation and interpretation.

Development of automated, scalable algorithms

In the framework of large-scale areas, continuous monitoring of cropping intensity, manual or semi-automatic techniques become irrelevant. Future progress requires establishing automated, scalable algorithms that are particularly suitable to handle the growing volumes of satellite image data. It is necessary to focus on creating robust, generalizable and computationally effective algorithms that can handle different agro-ecological conditions and integrate different types of data. For example, researchers are developing and implementing particular deep learning models, such as the U-Net model, for the purpose of tasks such as the segmentation of lavender fields with Sentinel-2 imagery (120) and the classification of ice-water areas to enhance training data for other models. Further examples include a phenology-based algorithm that employs time-series Landsat and Sentinel-2 imagery to precisely map 30 m cropping intensity in a complex basin in China (121).

Leveraging AI (Deep Learning) and Citizen science

As previously highlighted, Artificial Intelligence (AI) and deep learning in particular, have great potential for accurate and automated intensification mapping, especially for heterogenous and complex agriculture systems. Continuous research and application of deep learning tools are important. Citizen science initiatives, however, offer a promising solution to address the ground truth data gaps. Engaging local communities in the process of acquiring data, possibly through mobile applications, can provide highly validation data, thereby making geospatial products more reliable and accurate. Concrete example for this approach is the "Mission LQ" smart grass application, a crowdsourced ground truth data-gathering app for precision agriculture on particular weeds (122).

Need for collaborative efforts in dataset generation and model validation

Addressing challenges such as data harmonization, non-availability of ground truth data and method benchmarking fundamentally which require collaboration among several institutions and nations. Interdisciplinary partnership is required among remote sensing, agronomy, socio-economic and policy-formulation specialists. Such collaboration can enable the development of standard datasets, methodology development with universal applicability and validation of models in various context.

Underutilization of big data and IoT for near real-time monitoring

The possibility of merging real-time sensor readings of the Internet of Things (IoT) with satellite observations and other big data sources like weather forecasts and market prices is not used in the estimation of cropping intensity. Such merging has the potential to enable highly dynamic, near real-time monitoring and forecasting of cropping patterns. Synergies between these heterogeneous data streams have to be investigated to reach a more complete and timely understanding of food crop dynamics. The intersection of these isolated developments promises a revolution in the approaches used to monitor and manage agriculture. Near real-time cropping intensity measurements, together with climate forecasts and market information, have the potential to improve precision agriculture, give early warnings of food insecurity and guide adaptive policy adjustments. This shows a increase beyond static mapping to dynamic, predictive and possibly prescriptive agricultural intelligence. The future of geospatial cropping intensity estimation goes beyond the observation of past events; it is a prediction of future trends and the way of best interventions, thus making an important contribution to food security globally and sustainable use of resources. This is a paradigm shift towards "smart agriculture" (Table 4).

Conclusion

The geospatial assessment of cropping intensity has undergone significant advancements, evolving from basic mapping to sophisticated analysis with the help of modern satellite platforms and advanced algorithms. Despite these advancements, persistent challenges remain, including data gaps from spectral confusion, cloud contamination and a critical lack of ground truth data for validation. Furthermore, there is a need to better integrate socio-economic factors into spatial models to go beyond simple description. The path forward requires a concerted, interdisciplinary approach. By utilizing the potential of AI, vast datasets and by fostering great collaborations, the disciplined field can transition from a descriptive to a predictive one, providing the relevant information necessary to address global food security and sustainable agriculture.

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Authors' contributions

PI and KPR conceptualized the study. PI, KPR involved in data collection and data curation. The original draft was written by PI, KPR. PI, KPR, PS, RKP, SS and APS contributed to writing the review and editing of the manuscript. PI, KPR, PS, RKP, SS and APS provided supervision. All authors read and approved the final manuscript.

Table 4. Identified research gaps and corresponding future directions/recommendations

Research Gap	Corresponding Future Direction/ Recommendation	Rationale/Expected Impact
Limited synthesis of CI studies at regional to global scales	Promote open-access data and cloud-based platforms (e.g., GEE)	Enables scalable, consistent analysis across regions, reduces computational barriers.
Lack of standardized definitions and metrics	Develop unified classification schemes and standardized methodologies	Ensures comparability across studies, facilitates global dataset generation.
Inadequate exploitation of SAR data in cloudy regions	Enhance integration of multi-source data (optical + radar + ancillary)	Provides continuous monitoring in cloud-prone areas, improves robustness of CI estimates.
Limited benchmarking of methods across agro-ecological zones	Conduct systematic, interdisciplinary method benchmarking studies	Identifies optimal methods for diverse conditions, increases reliability and generalizability.
Scarce use of deep learning models for multi-season CI	Invest more in deep learning research and application for complex cropping systems	Unlocks potential for highly accurate, automated mapping in dynamic environments.
Low transparency and reproducibility of methods	Promote open science practices: code sharing, detailed methodology descriptions	Fosters collaboration, accelerates research progress, builds trust in results.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

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