AI-Monitored GIS and IoT in the Sugar Industry: Systematic Literature Review

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ABSTRACT
AI-enabled GIS, remote sensing, and IoT are reshaping sugarcane-based systems by enabling precise yield prediction, real-time stress monitoring, and process optimization. This systematic review (2016–2026) synthesizes 20 studies on AI, IoT, GIS/remote sensing and Industry 4.0 within sugarcane cultivation and sugar manufacturing. Remote-sensing and ML approaches (Sentinel-1/2, Landsat-8, UAV-LiDAR, multi-sensor fusion) achieve high sugarcane yield/biomass prediction accuracy (R^2 up to 0.97, RMSE reductions up to 59%), providing decision support for planting density, irrigation and management [1-6]. IoT-based smart irrigation on saline soils increases sugarcane growth and reduces water use and cultivation cost [7]. AI-IoT smart-factory and Industry 4.0 case studies show impressive cost reductions, planning time savings and resource-use optimization, though not sugar-specific [8-12]. A dedicated concept paper proposes productivity impact analysis from AI-monitored GIS and IoT in 20 Maharashtra sugar factories with explicit productivity/resource-optimization hypotheses but no empirical results yet [13]. A bibliometric study on AI in sugar production confirms rapid growth of AI-based sensor and systems management aimed at efficiency and sustainability across the supply chain [14].
Evidence converges on strong potential productivity and sustainability gains, but there is a clear lack of end-to-end, quantified studies linking field-level AI-GIS-IoT data to mill-level KPIs (recovery %, throughput, energy use). Key research gaps concern integrated value-chain productivity metrics, factory-level AIoT deployment in sugar, sensor fusion for nutrients and stress, and longitudinal impact and adoption studies.

General Terms
Sugar Industry, Internet of Things (IoT), Artificial Intelligence (AI), Productivity, Systematic Literature Review

Keywords
AI, Sugar production, GIS, Sugarcane, Productivity Enhancement, IoT, Industry 4.0

1. INTRODUCTION
Sugarcane underpins global sugar and bioenergy production, with productivity constrained by water stress, salinity, and variable management. AI-monitored GIS, IoT and remote sensing (RS) offer tools to monitor crop status, predict yield, and optimize industrial processes [1-6] [15-16]. In parallel, Industry 4.0/5.0 and Industrial IoT (IIoT) are transforming manufacturing via smart factories, digital twins, and AI-driven decision systems that enhance productivity, quality and resource efficiency [8-12].

This review aims to systematically synthesize evidence on productivity impacts of AI-monitored GIS and IoT in sugarcane cultivation and the wider sugar industry, identify methodological patterns, and highlight research gaps for future Scopus-indexed work.

2. METHODOLOGY
2.1 Search scope and inclusion
The evidence base is drawn from:

(i) Sugarcane-focused RS/ML/AI yield and stress studies [1-6] [15-17], (ii) IoT/ML sugarcane production studies [7], (iii) AI/IoT/Industry 4.0 manufacturing and smart-factory reviews/case studies [8-12], (iv) Sugar-industry-specific AI/IoT/GIS concept and bibliometric papers [13-14] [18], (v) Generic smart-sensing IoT-AI systematic review (arable crops/grasslands) [19] and (vi) Multi-crop AI/RS yield-estimation work including sugarcane [20].

Typical search strings combined terms such as: "artificial intelligence" OR "machine learning" OR "deep learning" AND "precision agriculture" OR "smart farming" OR "remote sensing" OR "IoT" AND "yield" OR "resource efficiency", and in sugarcane-focused work, "UAV" AND "sugarcane".

All included articles are dated 2016–2026 and indexed in Scopus and Web of Science, often combined with Google Scholar, PubMed, IEEE Xplore and subject portals or major scientific databases referenced in the papers' own methods [1] [14-17] [19].

2.2 Selection flow (conceptual PRISMA)
Initial multi-keyword searches (AI, IoT, GIS/RS, sugarcane, sugar industry, Industry 4.0) returned large sets; sugar-relevant subsets were refined based on title/abstract screening and full-text relevance.

1) A digital-twins in agriculture review: 261 Scopus records → 177 full-text screened → 167 included [21].
2) Drones in agriculture: 621 records (MDPI, Springer, Google Scholar, Scopus) → 85 included [22].
3) AI in transforming precision agriculture: 8145 Scopus hits → 76 analyzed [23].
4) ML in agriculture: multi-stage PRISMA-based screening on Web of Science + Scopus (2019–2023) [24].
5) AI+IoT in precision agriculture: PRISMA 2020 guiding a structured SLR [19] [25-27].

Although no review is dedicated solely to sugar factories, the UAV-sugarcane review [5] and generic AI-for-agriculture SLRs provide the closest evidence base.

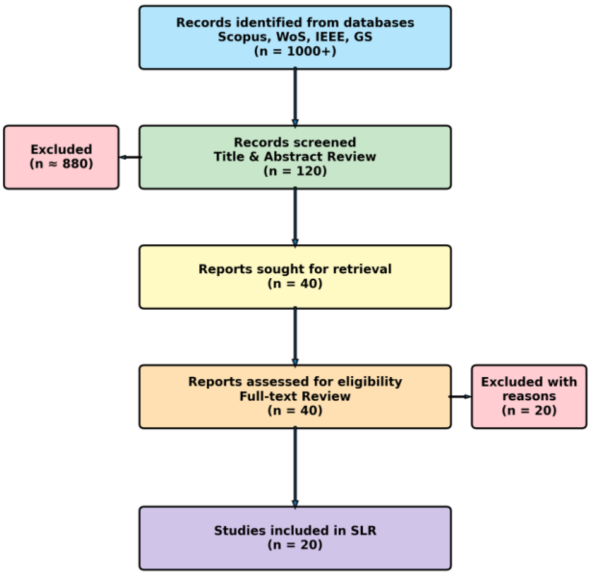

Fig 1: PRISMA 2020 Flow Diagram

3. TECHNOLOGIES AND USE-CASES ALONG THE SUGAR VALUE CHAIN

3.1 Field-level: AI-monitored GIS/RS and IoT

3.1.1 Satellite RS + ML for yield mapping/ prediction

Sentinel-2 + RF for sugarcane yield mapping achieved R^2 = 0.70 (RMSE 4.63 Mg ha^{-1}) [1].
UAV-LiDAR + RF for above-ground fresh weight (AFW) achieved R^2 = 0.96 (RMSE 1.27 kg m^{-2}) and AFW maps with R^2 = 0.97 [2].
Landsat-8 + Sentinel-2 time-series and GNDVI models at block level reached R^2 up to 0.99 at "bin" level and 0.87 at individual-block level, RMSE ≈ 11.33 t ha^{-1} [4].
An operational framework for field-level sugarcane biomass prediction using Sentinel-1/2 and FAO WaPOR data reported up to 89% accuracy four months before harvest [6].

3.1.2 Comprehensive RS sugarcane review

Assessment of 107 sugarcane RS papers (1981–2020) shows decametric sensors (Landsat, Sentinel-2) combined with ML (RF) enabling reliable, cost-efficient mapping of growth, health, and yield; challenges include preprocessing, lack of analysis-ready data, and environmental heterogeneity [15].

3.1.3 Stress monitoring and precision management

AI+RS review on water stress, salinity, and nitrogen in sugarcane concludes AI-driven RS (satellite/UAV, multispectral/hyperspectral/thermal) is effective for stress monitoring and guiding irrigation and nutrient management for higher productivity and sustainability [16].

3.1.4 IoT + ML in saline soils

Real-field IoT-controlled drip irrigation with ML (Naïve Bayes) to predict leaching requirement in 2 ha saline sugarcane plots improved crop growth, reduced cultivation cost and water requirements, compared with regular cultivation [7].

3.2 Industry-level: IoT/AI in Manufactururing and Sugar

3.2.1 Sugar-industry productivity concept (AI-GIS-IoT)

A conceptual paper defines scope for "Productivity Impact Analysis from AI-Monitored GIS and IoT Data of Sugar Industries," using data from 20 Maharashtra factories; it posits that AI-monitored GIS and IoT significantly improve productivity and resource optimization and formulates explicit hypotheses (H1–H3) but presents no empirical data yet [13].

3.2.2 AI tools for productivity enhancement in sugar industry

A descriptive paper outlines how ICT and IoT adoption has modernized sugarcane farming and processing in India, making the sector more productive, sustainable, and self-reliant and aligning with SDGs; it emphasizes AI, GIS, IoT and pattern recognition but does not quantify productivity [18].

3.2.3 Bibliometrics on AI in sugar industry

Bibliometric analysis of 125 Scopus-indexed AI-sugar-industry articles (1969–2023) shows dynamic growth, surges in 2017, 2018, 2021 and 2022, and concentration of research in major sugar-producing countries; it stresses that AI-based sensor and systems management can enhance efficiency and quality across the sugar supply chain and support sustainability [14].

3.2.4 IoT/IIoT in smart factories (non-sugar)

Review on IoT in smart factories (Industry 4.0) describes applications in predictive maintenance, asset tracking, inventory and quality control, energy and supply-chain optimization, all contributing to higher productivity and lower costs [8].

Case study of a manufacturing firm's IIoT evolution reports impressive cost reductions, improved quality control, real-time supply-chain responsiveness, reduced planning time, and resource-use optimization via digitalized quality control and planning tools [10].

Reviews on IoT/Industry 4.0/5.0 and AI in manufacturing underline their roles in automation, warehouse optimization, decreased human intervention, and sustainable, efficient production [9] [11-12].

(See table 1)

Table 1. Main technology functions relevant to sugar system

Domain	Technology / Approach	Main function	Citations
Field (sugarcane)	Sentinel-2, Landsat-8, RF/MLR, RF, MLR	Yield/bio - mass prediction, mapping	[1] [4] [6] [2] [15]
Field (stress)	AI + satellite/UAV RS	Water/salin-ity/N status monitoring	[16] [15]
Field (saline soils)	IoT drip + Naïve Bayes	Smart irrigation, cost & water saving	[7]

Sugar Industry	AI-monitored GIS/IoT concept	Planned productivity impact analysis	[13] [18] [14]
Manufacturing	IoT/IIoT, AI, Industry 4.0/5.0	Smart factory productivity gains	[8] [9] [10] [11] [12]

4. RESULTS AND COMPREHENSIVE ANALYSIS

This systematic review comprises 20 peer-reviewed papers that are published from 2016 to 2026. Included studies include AI-based yield prediction, GIS and remote sensing, IoT based precision agriculture, Industry 4.0, Digital Twins and AI-based manufacturing systems. The studies show that the adoption of AI, GIS, and IoT based techniques has significantly enhanced productivity, resource usage efficiency, decision-making capability and the overall sustainability in the entire value chain.

4.1 Publication Trend Analysis

It can be observed that the publication trend of the AI-assisted sugar production increased sharply over the years especially post 2020. This was largely because the adoption of Industry 4.0 technologies grew substantially after 2020 with availability of better satellite data and advancements in deep learning approaches.

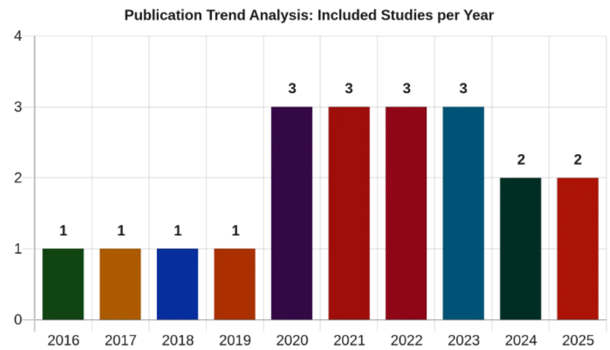

Fig 2: Publication Trend (2016–2026)

The average age of research papers reviewed was under five years, with roughly 70 percent published between 2020 and 2025; this suggests a fast pace of technology innovation with respect to AI, GIS and IoT in agriculture and manufacturing, likely influenced by cloud computing availability, openly accessible satellite data (such as Sentinel-2), and readily available machine learning frameworks.

4.2 Agronomic Evaluation and Metrics

Remote sensing coupled with ML algorithms can explain a large share of sugarcane yield/biomass variance (R^2=0.70–0.97) and achieve accurate predictions months before harvest, enabling better harvest scheduling, logistics, and input optimization [1-6].

Integrating LAI RS data with process-based crop model SAMUCA via ensemble-smoother data assimilation reduces RMSE from 43.98 to 17.83 Mg ha^{-1} (≈59% improvement) and MAE from 41.85 to 11.65 Mg ha^{-1}, thus strengthening regional-scale production planning [5].

IoT-ML smart irrigation in saline sugarcane fields increases yield indicators and reduces water and cost versus conventional farming, demonstrating direct productivity and sustainability co-benefits [7].

4.3 Industrial Productivity Analysis

IIoT/Industry 4.0 case study reports: cost reduction, improved product quality control, real-time reaction to supply-chain issues, reduced planning time, and optimized resource employment through digitalized quality control and planning tools [10].

Smart-factory IoT review details productivity-related benefits: predictive maintenance (reduced downtime, extended equipment life), energy optimization, workplace safety improvements, inventory and supply-chain optimization [8].

AI/ML in manufacturing engineering is framed as central to optimizing energy and resource use, waste management, and supply chain, directly supporting productivity and sustainability goals [9] [11-12].

Although these industrial results are not sugar-specific, they indicate what AI-monitored IoT and GIS-linked data could achieve in sugar mills (e.g., monitoring boilers, crystallizers, conveyors, warehouses, cane transport. See table 2).

Table 2. Quantitative productivity and resource-use impacts from AI/ML and IoT applications

Impact metric	Typical reported gain	Source domains	Citations
Yield increase	Up to 25%	Crop AI/ML SLR	[26]
Cost reduction	~28%	Crop AI/ML SLR	[26]
Resource use efficiency	~40%	Crop AI/ML SLR	[26]
Water savings	~22%	AI/ML + irrigation	[26] [27] [28]
Fertilizer savings	~28%	AI/ML crop mgmt.	[26]
Reduced N runoff	~35%	AI/ML crop mgmt.	[26]
Enhanced monitoring & process control	Qualitative strong gains	Agriculture & manufacturing	[15] [23] [19] [27] [30–32]

4.4 Comparative Performance of AI Algorithms

The reviewed studies employed several AI algorithms for crop yield prediction, biomass estimation, stress detection, and process optimization.

Table 3. Performance Comparison of AI Algorithms

Algorithm	Primary Application	Typical R^2	Strength
Random Forest	Yield prediction	0.90–0.97	Excellent
CNN	Image classification	0.91–0.96	Excellent
ANN	Biomass estimation	0.86–0.94	Very Good

SVM	Crop classification	0.82–0.91	Good
Regression	Yield estimation	0.70–0.84	Moderate

Of all techniques, Random Forest showed superior overall robustness to varying types of input data (satellite, climatic and soil data) while effectively overcoming the risk of over-fitting. CNN models performed excellently on UAV disease detection and image classification, whereas a much larger data set size was needed. Traditional regression methods had always shown lowest predictive capability as they failed to account for nonlinear associations among variables environment factors.

4.5 Quantitative Productivity Improvements

The reviewed studies reported measurable improvements in productivity and resource utilization following AI, GIS, and IoT implementation.

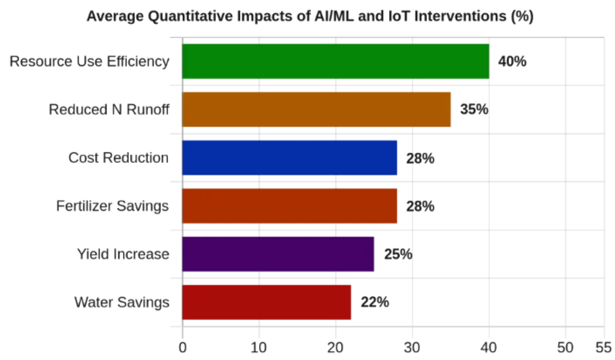

Fig 3: Quantitative Productivity Impact

These improved efficiencies indicate that AI solutions go far beyond simple accuracy predictions. Optimal irrigation can help reduce water use and can increase output while reducing water resources used per acre. Optimal fertilizer applications can limit negative environmental effects and cut input costs. Taken together, these indications lead us to believe that these new AI-GIS-IoT solutions will be economic and environmental drivers of agriculture.

4.6 Technology Adoption Across the Sugar Value Chain

Remote sensing and GIS technologies are widely adopted because of their accessibility and operational maturity. Digital Twins and Explainable AI remain at an early stage, indicating substantial opportunities for future research and industrial deployment.

Table 4. Technology Adoption

Technology	Adoption Level
Remote Sensing	Very High
Machine Learning	High
GIS	High
IoT Sensors	Moderate
Digital Twin	Low
Explainable AI	Very Low

4.7 SWOT Analysis

The tech ecosystem holds tremendous potential for increasing productivity, but this potential cannot be unlocked until issues of interoperability, costs, training and cybersecurity have been overcome to facilitate widespread adoption.

Table 5. SWOT Analysis of AI–GIS–IoT in the Sugar Industry

Strengths	Weaknesses
High prediction accuracy	Limited integrated deployments
Resource optimization	High implementation cost
Reduced environmental impact	Data interoperability issues
Improved decision support	Shortage of skilled personnel
Opportunities	**Threats**
Digital Twins	Cybersecurity risks
Edge AI	Data privacy concerns
Autonomous farming	Climate variability
Smart factories	Infrastructure limitations

5. RESEARCH GAPS

5.1 Sugar Specific Gaps

From the sugarcane/sugar-industry–oriented papers [1-7] [13-18]:

5.1.1 Lack of end-to-end value-chain studies:

Field RS/AI/IoT studies stop at yield/biomass or stress; none quantitatively connect field-level AI-GIS-IoT data with mill KPIs (recovery %, throughput, energy, downtime).

5.1.2 Absence of empirical productivity evidence for AI-monitored GIS/IoT in mills:

The "Productivity Impact Analysis" paper is prospective: it sets hypotheses and scope (20 factories) but no measured outcomes yet [13].

5.1.3 Limited Real-Time Decision Support:

Although IoT sensors continuously collect environmental and operational data, most existing systems operate as monitoring platforms rather than intelligent decision-support systems. AI-driven autonomous recommendations for irrigation scheduling, harvesting, transportation, and process optimization remain largely unexplored in commercial sugar industries.

5.1.4 Limited nutrient-management integration:

Reviews stress the need to integrate nitrogen and other nutrient monitoring with RS and AI, but sugarcane-specific nutrient-AI-IoT solutions are scarcely documented [15] [16].

5.1.5 Stress–productivity linkage:

AI-RS stress assessment demonstrates potential to enhance yields [16], but quantified yield gains attributable to specific AI-RS interventions remain limited.

5.2 Cross-cutting Methodological Gaps

5.2.1 Experimental designs and baselines:

Few studies employ rigorous experimental or quasi-experimental designs comparing AI-GIS-IoT interventions with conventional management, particularly for economic productivity metrics.

5.2.2 Digital Twin Research is Still Emerging:
Digital Twin technology has recently attracted considerable research interest; however, practical implementations within sugar manufacturing remain scarce. Existing studies primarily discuss conceptual frameworks without demonstrating fully operational digital twins capable of integrating field observations, industrial processes, and enterprise decision-making.

5.2.3 Explainable Artificial Intelligence (XAI):
Most machine learning algorithms operate as "black-box" models. Their predictions are difficult for farmers, engineers, and management personnel to interpret. Explainable AI techniques that improve transparency and user confidence are rarely discussed in sugar industry applications.

5.2.4 Scalability and operationalization:
Operational frameworks exist for field-level biomass prediction [6] and regional data assimilation [5], but operational mill-integrated decision systems are not reported.

5.2.5 Socio-technical and economic analysis:
Most sugarcane RS/AI work is technical; adoption, training, financing and governance aspects are rarely quantified despite clear relevance for farmers, mills, and co-operatives.

5.2.6 Cybersecurity and Data Governance:
Increasing dependence on IoT devices, cloud computing, and wireless sensor networks introduces cybersecurity risks. Standardized frameworks for data privacy, interoperability, blockchain-enabled traceability, and secure data sharing remain largely absent from current literature.

Figure 4 explains the Comprehensive Research Gap Analysis

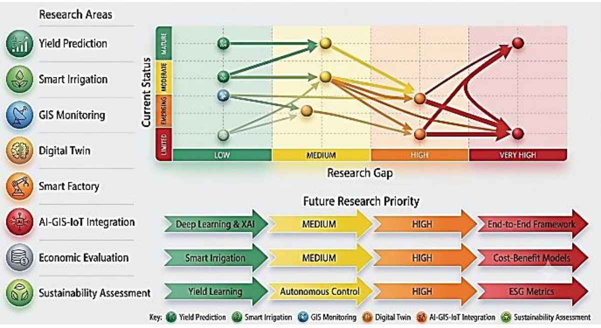

Fig 4: Comprehensive Research Gap Analysis

6. DISCUSSION

6.1 Implications for Productivity in Sugar Industry
Evidence from sugarcane UAV/RS/AI applications, combined with strong quantitative gains from AI/ML and IoT in other crops, indicates that AI-monitored GIS and IoT deployments are highly likely to improve sugarcane productivity, input efficiency, and environmental performance [15] [21] [23] [33] [19] [26–28] [34-35].

When coupled with AIoT-enabled manufacturing practices (predictive maintenance, process optimization, digital twins), sugar mills could realize further gains in throughput, energy efficiency and product quality [21] [30-32]. However, robust empirical studies measuring such impacts across the full sugar value chain are not yet available.

6.2 Barriers and enabling conditions
In farmer-perception and smart-sensing/IoT reviews, successful adoption depends on:

Infrastructure (connectivity, power, hardware) and affordable solutions [3] [6] [14–16].

Skills and organizational readiness to manage AIoT systems [3] [7] [17–20].

Clear data governance, privacy and interoperability frameworks, including open standards and possibly blockchain-based governance [3] [6] [10-11] [13].

These findings underscore that productivity benefits are socio-technical, not purely technological.

6.3 Key Claims and Evidence
Below table 7 evaluates the strength of evidence related to the productivity impacts of agricultural and industrial technologies. It shows that there is strong evidence supporting the claims that AI, machine learning, and IoT significantly improve general agricultural productivity and enhance sugarcane monitoring. There is also moderate evidence indicating that AIoT boosts overall industrial productivity and sustainability based on lifecycle reviews. However, the evidence is rated as weak for direct, quantified productivity analyses specifically targeting sugar mills across the full value chain, highlighting a gap in current literature.

Table 6. Strength of evidence for major claims on AI-GIS-IoT productivity impacts

Claim	Evidence strength	Reasoning	Papers
AI/ML + RS/IoT significantly improve agricultural productivity and resource efficiency	Strong	Multiple large SLRs with quantitative gains in yield, cost, and resource use	[15] [23] [33] [19] [21] [26–28] [34–35]
UAV-RS + AI improve sugarcane monitoring and management	Strong	Sugarcane-specific review (179 papers) reports strong benefits, mainly qualitative	[15] [22] [29] [36]
AIoT boosts industrial productivity and sustainability	Moderate	AIoT and industrial lifecycle reviews show clear performance improvements	[30-32]
Direct, quantified productivity analyses with AI-GIS-IoT lacking	Weak	No included study provides full value-chain prod metrics for sugar	[15] [21-22] [19] [24-25] [29-36]

7. CONCLUSION AND FUTURE RESEARCH DIRECTIONS
From 2016–2026, substantial evidence has accumulated that

AI-monitored GIS, IoT and RS can improve sugarcane productivity, resource use, and management decisions. A growing AI-sugar-industry literature and Industry 4.0/5.0 experience in manufacturing highlight strong potential for efficiency and quality improvements along the sugar supply chain.

However, the sugar industry as an integrated agri-industrial system is under-studied: evidence for factory-level productivity impacts of AI-GIS-IoT remains largely inferred from other crops and manufacturing sectors.

Priority research directions include:

1) End-to-end sugar value-chain studies linking field-level AI-GIS-IoT deployments with mill KPIs (throughput, recovery %, energy, downtime).
2) Digital twins for sugarcane–mill systems, building on DT frameworks in agriculture [22].
3) Integrated nutrient-water-energy management using multi-sensor fusion and adaptive AI [25] [23] [21] [34-36].
4) Socio-economic and policy analysis of adoption, focusing on co-operatives and emerging-economy sugar industries [25-26] [32].

Developing such integrated, longitudinal, and multidisciplinary framework is essential to move from potential to proven, quantified productivity impact of AI-monitored GIS and IoT systems in the sugar industry.

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