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Research Article

Productivity impact analysis from artificial intelligence monitored GIS and IoT data of Sugar Industries: A Review

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ABSTRACT

Artificial Intelligence (AI), Geographic Information Systems (GIS) and the Internet of Things (IoT) are being embraced to boost productivity throughout the sugar industry. This review aims to look at the way AI assisted GIS and IoT data can be utilized for sugarcane productivity analysis and in sugar-mill operations. The existing literature suggests that GIS and RS are capable of giving spatial information on crop condition, yield variability and resource distribution, and IoT can give up-to-the-minute information on environmental, agricultural and industrial conditions. These datasets are heterogeneous and can be combined using AI and machine-learning techniques to assist with predicting yields, detection of disease, optimisation of resources, predictive maintenance, and optimisation of the industrial process. The review states that the combined use of these technologies is more valuable than if they were used individually, as GIS puts data into spatial context, IoT can capture real-time observations, and AI can transform collected data into predictive and decision-support information. Opportunities for potential productivity improvements involve better yield prediction, better resource management, fewer equipment downtimes, better water and energy usage and better operational planning. But issues involving data quality, interoperability, connectivity, infrastructure, cyber security and technical skills might limit the success of implementing. The review suggests that an integrated AI–GIS–IoT approach can enable a move from reactive productivity assessment to continuous, predictive and data-driven management in the entire sugar-production chain.

Keywords: Artificial Intelligence; Geographic Information Systems; Internet of Things; Sugar Industry; Sugarcane Productivity; Precision Agriculture; Predictive Analytics

1. INTRODUCTION

The sugar industry is an integral part of the global agricultural and food-processing industry, and it connects various operations involved in sugar crop production, harvesting, transportation, milling and energy intensive processing activities (Cheesman O., 2004). Weather, soil nature, water supply, the health of the crop, harvesting practices, the performance of machines and processing efficiency are several factors that interact and affect productivity in this sector. Traditional productivity assessment is based on past experience, on-site inspections, and periodic measurements, which might not be detailed enough or be provided in time in the case of rapidly changing production conditions. Artificial Intelligence (AI), Geographic Information Systems (GIS) and the Internet of Things (IoT) can help overcome these challenges by collecting data continuously, monitoring in space and predicting (Sharma et al., 2024).

AI can process a vast array of data, often very diverse or large, to find patterns that might otherwise not be noticeable with traditional analysis. The application of machine-learning and deep-learning techniques in sugarcane production to predict yield based on satellite, multispectral and other remote-sensing data has increased in recent years (Akbarian et al., 2022; Saini et al., 2023). The use of optical and synthetic aperture radar data has also been shown to be beneficial in the development of machine-learning models for estimating sugarcane yields (Das et al., 2023). Another potential use of AI is crop health monitoring and disease detection, which could allow for earlier detection of potential productivity loss (Daphal and Koli, 2023).

GIS adds the spatial element that is required to appreciate the variations in sugarcane productivity. The agricultural fields are geographically heterogeneous and conditions like soil, topography, irrigation and crop condition may change significantly even within the same production area. The use of remote sensing and GIS for monitoring and yield assessment of crops can be useful for repeated observations in large areas (Som-ard et al., 2021). Aerial images acquired by UAVs can supply extra high-resolution data to evaluate productivity conditions both at field and sub-field scales (Barbosa Júnior et al., 2023). Therefore, GIS can be useful in determining the location of productivity issues and implement geographically specific interventions.

IoT can be used alongside GIS and remote sensing to collect continuous observations on the ground. The environmental and operational parameters, among others, soil and crop parameters, can be monitored by connected sensors (Bashir et al., 2022). For sugarcane production, such as, using IOT-based irrigation system, real-time field information can be used to make more responsive irrigation decisions (Wang et al., 2020). In industrial settings, IoT sensors can also be used to gather data on equipment and processes, enabling predictive maintenance and better equipment uptime (Mallioris et al., 2024).

The presence of AI, GIS and IoT is especially notable as each technology is solving a different issue related to productivity monitoring. GIS provides data on where conditions are present, IoT provides data on when conditions are changing, and AI can provide information about what conditions are changing and what action may be warranted (Sharma & Shivandu 2024). Such an integrated approach can be used to help predict yield, optimise resources, identify disease, carry out predictive maintenance, and plan the production process. The relevance of Industry 4.0 technologies like AI, IoT and data analytics has also been observed in the sugar manufacturing field, which has seen a rise in interest (Vimal et al., 2022).

This review considers the future productivity implications of the use of AI monitored GIS and IoT data in the sugar industry. It is focusing on applications at the sugar cane growing and sugar mill levels, presents the benefits and implementation challenges, and points towards future research directions in the development of more integrated, predictive and resource-efficient sugar production systems.

2. ROLE OF ARTIFICIAL INTELLIGENCE IN SUGAR INDUSTRY PRODUCTIVITY

Artificial Intelligence (AI) is becoming a vital technology in the fields of agriculture and industry to boost productivity (Chandra et al., 2020). Its processing capacity of large amounts of structured and unstructured data is specially fit for the sugar industry where the productivity depends on the complex relationships among environmental conditions, crop characteristics, management practices and industrial operations. Artificial Intelligence techniques can detect patterns in past and current data and apply such patterns to prediction, classification, optimisation and decision making (Vilani & Subhashini, 2023).

2.1 AI in Sugarcane Yield Prediction

An area in the sugar industry that has been extensively studied is the prediction of sugarcane yield using AI. The reliable estimate of yield is necessary as it affects the harvesting schedule, transportation planning, labour allocation and the volume of sugarcane that can be supplied to processing plants. Traditional methods of yield estimation involve significant field sampling and may not reflect spatial differences in large plantations (De França et al., 2024).

Multiple data sources can be incorporated into machine-learning algorithms to address some of these challenges. The authors of Akbarian et al. (2022) showed that the multi-year multispectral imagery can be used for row-level sugarcane yield prediction, emphasizing the need for spatial information. Likewise, Das et al. (2023) used optical and synthetic aperture radar (SAR) remote-sensing data along with machine-learning models to estimate sugarcane yield. Complementary data sources can offer more holistic information to AI models on crop conditions.

Additionally, using deep learning can further enhance the complexity of agricultural data analysis. Saini et al. (2023) presented CNN-BI-LSTM for sugarcane yield prediction, which integrated space and time features into AI-based prediction. These can offer the potential for earlier and more detailed information on expected productivity.

2.2 AI for Crop Health and Disease Monitoring

Crop health is directly related to final productivity of sugarcane. Plant growth may be reduced by disease outbreaks, nutrient deficiencies and environmental stresses, which will impact yield. It takes a long time to inspect manually over large areas of agricultural land and can result in a delay in detection of emerging issues (Mehdi et al., 2024).

Image-processing and deep learning techniques are potential ways to automate crop health assessment using AI. Daphal and Koli (2023) explored deep-learning algorithms that can classify sugarcane diseases, demonstrating the promise of artificial intelligence in identifying diseases and differentiating healthy and diseased plants. These models, if combined with remote sensing and GIS, can be used to potentially identify and spatially map affected areas, enabling farmers to prioritise field inspection and intervention (Patange et al., 2024).

2.3 AI for Resource Management

In addition, AI can play a role in boosting productivity by optimizing agricultural resources. Water is a crucial resource in sugarcane production, and wrong irrigation practices can lead to high production expenses, and low use efficiency of this resource. Using AI, patterns can be uncovered from sensor readings, weather data, historic records, and remote sensing data that are related to the water needs of the crops (Mana et al., 2024).

Research on closed-loop irrigation with IoT reveals the possibility of using real-time field information to help make irrigation decisions, either automatically or semi-automatically (Wang et al., 2020). Machine learning coupled with remote sensing can also aid in the evaluation of sugarcane water use and water footprints (Somard et al., 2021). The applications suggest that productivity should be measured not only in terms of crop output, but also in terms of the efficiency of the resource-to-output conversion process.

2.4 AI in Sugar-Mill Operations

AI can be used in areas of sugar-mill operations. The sugar processing industry consists of a series of interconnected equipment and processes, and the time of failure, energy consumption, and operating conditions can affect the productivity. IoT sensors can continuously collect equipment data, while AI models can analyse these data to identify abnormal operating patterns and predict potential failures (Mana et al., 2024).

Thus, Predictive Maintenance is a crucial application of AI in the manufacturing of sugar in industries. AI-based systems can help prevent unplanned downtime and enhance equipment availability by detecting the signs of equipment degradation before it even becomes an issue (Mallioris et al., 2024). The study of Industry 4.0 in the Sugar Industry also highlights the significance of technologies such as AI, IoT and Data Analytics for enhancing manufacturing readiness and operational performance (Vimal et al., 2022).

Table 1. Applications of AI, GIS and IoT technologies for improving productivity in the sugar industry.

Technology	Data/Information Generated	Main Application	Productivity Benefit
Artificial Intelligence	Historical production, crop and operational data	Yield prediction	Improved production forecasting
Machine Learning	Multispectral and SAR imagery	Sugarcane yield estimation	Better harvesting and resource planning
Deep Learning	Crop images and remote-sensing imagery	Disease and crop-health detection	Earlier intervention and reduced crop losses
GIS	Spatial crop, soil and field information	Productivity mapping	Targeted field management
IoT Sensors	Soil moisture, temperature and environmental conditions	Real-time crop monitoring	Improved resource utilisation
IoT + AI	Equipment sensor data	Predictive maintenance	Reduced unplanned downtime
GIS + AI	Spatial and historical	Productivity-risk	Targeted interventions

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	productivity data	mapping	
GIS + IoT + AI	Spatial, real-time and historical data	Integrated productivity monitoring	Data-driven decision-making

3. AI-BASED MONITORING AND PRODUCTIVITY ANALYSIS

Artificial Intelligence (AI) has been gaining more and more attention in the fields of agriculture and industry, where large amounts of complex data are analysed. AI can analyze the data from satellite images, GIS databases, IoT sensors, weather data and historical production records to detect patterns and make predictions in the sugar industry. Therefore, its use can help to monitor the productivity at several stages – of sugarcane cultivation to sugar-mill processing. AI-based monitoring can offer predictive insights that help to intervene before production happens, as opposed to traditional methods that measure productivity once it has taken place (Marcello et al., 2024).

3.1 AI for Sugarcane Yield Prediction

AI is playing a crucial role in the sugarcane industry, particularly in the domain of yield prediction. Precise yield estimates can help in scheduling harvest, planning transportation, labor scheduling and managing mill capacity. Estimates of crop performance using traditional techniques, which rely on past data or field sampling, may not adequately reflect spatial and temporal crop performance variability. By using machine-learning models instead, a number of variables can be taken into account at once (Canata et al., 2024).

AI yield prediction models benefit greatly from the remote-sensing data. The multispectral imagery provides information about the characteristics of the vegetation and about the development of a crop, which can be correlated with yield. Multi-year multispectral imagery was used by Akbarian et al. (2022) to predict sugarcane yield at the row level, highlighting the potential of spatially detailed data for estimating productivity. In a similar manner, Das et al. (2023) fused optical data with synthetic aperture radar data and machine learning for improved representation of the condition of crops based on multiple remote-sensing sources.

Deep-learning techniques offer further potential ways of analysing complex agricultural data. Environmental variables, crop conditions and productivity can be related in a nonlinear way, and such models can be learned (Huiren et al., 2024). In a recent study, Saini et al. (2023) explored the use of deep learning to predict sugarcane yields, highlighting the increasing adoption of sophisticated AI methods in sugarcane cultivation.

3.2 Use of AI in Crop health and disease detection

Sugarcane productivity can be greatly affected by the crop diseases and environmental stresses. This is because conventional field inspection demands a lot of labour, and may not offer adequate coverage in large plantations, particularly where it is required on a regular basis. Therefore, there is an opportunity to use AI-driven image analysis to automate parts of the crop-health monitoring process (Daniel et al., 2020).

Deep-learning algorithms can detect visual patterns for disease or stress of plants. The study on sugarcane disease classification proves that deep learning methods can accurately classify sugarcane plants as healthy or not (Daphal and Koli, 2023). Early detection may be able to facilitate timely action and minimize the extent of disease.

3.3 AI for Resource Optimisation

AI can also contribute to productivity by making effective use of agricultural resources. The use of water, fertiliser and energy are significant inputs in sugar production, and sub-optimal use of these resources can lead to higher costs and environmental impact. AI models can analyze field data from IoT sensors to estimate resource needs, and provide real-time data about field conditions (Bhatt et al., 2024).

For example, in water management, using a different lens to look at the same phenomenon yields different conclusions. Closed-loop irrigation for sugarcane cultivation has been assisted by IoT-based monitoring, with irrigation decisions made based on what is observed in the field (Wang et al., 2020). Water-use analysis can also be aided by remote sensing, which can detect spatial variations in crop conditions and water needs, and machine learning. The use of remote sensing and machine learning techniques was shown by Somard et al., (2021) to support the estimation of water footprint of sugarcane cultivation.

3.4 Application of AI in Sugar-Mill Operations

AI can be used for other purposes outside of agriculture. Sugar mills are very complex processes where the equipment performance, throughput, energy usage and extraction efficiency are all factors that affect the productivity. Data-driven optimisation can be used to study the relationships between operating conditions and production results and make better operating decisions (Mana et al., 2024).

Another vital application is predictive maintenance. IoT sensors can track the health of machinery in real time, and AI models can detect patterns that are out of the ordinary and anticipate equipment issues. These predictive methods can help minimize unplanned downtime and increase equipment uptime. Predictive maintenance is one of the applications of data-driven Industry 4.0 systems identified by broader industrial research (Mallioris et al., 2024).

The trend of embracing Industry 4.0 technologies by the sugar industry is another confirmation for this. The strategic integration of AI, Internet of Things (IoT), big-data analytics and predictive maintenance can all contribute to enhancing operational visibility and decision making in the sugar manufacturing sector (Vimal et al., 2022).

3.5 Measuring Productivity Impact

It is crucial to acknowledge the difference between the performance of the AI models and actual productivity gains. A high prediction accuracy does not automatically lead to increase in productivity (Mishra et al., 2024). Measurable benefits do not come until AI-generated information affects the operations, for example, irrigation, disease management, harvesting, maintenance, process optimisation, etc.

Several parameters should therefore be used to evaluate productivity such as yield per hectare, sugar recovery, water-use efficiency, availability of equipment, downtime and operating costs etc. The wider view enables the evaluation of the impact of AI in terms of production and resource efficiency.

4. GIS AND IOT DATA FOR SUGAR INDUSTRY MONITORING

The accuracy of AI productivity analysis heavily relies on the accuracy, availability and variety of the data used in the modelling process. In the sugar industry, Geographic Information Systems (GIS) and the Internet of Things (IoT) complement each other with data capabilities. GIS can be used to present agricultural and industrial information spatially, and IoT can be used to collect real-time observations continuously from agricultural fields, and agricultural machinery and processing environments. These technologies can offer a more holistic solution for productivity monitoring in sugarcane production and sugar-mill processing, when coupled with AI (Sharma et al., 2023).

4.1 GIS and Remote Sensing for Sugarcane Monitoring

There are significant spatial variations in sugar cane plantations due to differences in soil properties, topographic factors, water availability, climate, crop health and management. The GIS can serve as a powerful tool to show these differences and study the correlation between these and productivity. GIS enables the agricultural manager to connect an observation to a geographical space, which can be used to determine if there are regions with greater or lesser productivity, and determine what causes the differences in productivity (Vera et al., 2020).

Repeated observations of large agricultural areas are a significant extension of the geographic information system (GIS) capabilities provided by remote sensing. Satellite data can be used to monitor vegetation conditions and crop development and enable spatial variability to be assessed without the need for continuous ground inspections. Previous studies have proven the application of remote sensing techniques in the mapping of sugarcane, monitoring, health assessment and yield estimation (Som-ard et al., 2021). In addition, sugarcane remote sensing is also on the rise in yield estimation and other sugarcane management processes, as shown by a systematic review of the literature (de França e Silva et al., 2024).

The combination of remote sensing and machine learning can offer a more detailed productivity analysis. In particular, the use of complementary remote-sensing data, such as optical data and synthetic aperture radar data, with machine-learning models has been shown to be useful for estimating sugarcane yield (Das et al., 2023). Crop conditions can also be evaluated at the field or sub-field level, as is possible with UAV imagery, which can offer even more spatial detail (Barbosa Júnior et al., 2023).

4.2 IoT-Based Real-Time Monitoring

While remote sensing can offer high spatial coverage, it can't be used to continuously measure ground-level conditions. The Internet of Things (IoT) can overcome this constraint by implementing connected sensors to gather information in real time from the agricultural and industrial settings. Soil moisture and soil temperature, humidity and other environmental parameters may be sensed depending on the application (Pamula et al., 2022).

One of the prime examples of IoT application in sugarcane production system is irrigation. (Wang et al., 2020) designed an irrigation decision system for field measurements and irrigation decisions based on IoT technology. These systems can be used to optimize irrigation based on the conditions in the field, rather than on a fixed schedule. This may help to maximize water use efficiency while maintaining adequate crop conditions.

The IoT system can also be used to monitor large-scale agricultural operations by simultaneously collecting information from various locations. These data can be sent to the central platforms where they can be merged with information from GIS and remote-sensing. Thereby IoT gives the temporal dimension to complement the spatial coverage of satellite and UAV systems (Vijendra Kumar et al., 2024).

In the sugar mills, the IoT sensors can be used to monitor the processing equipment and machinery. Temperature, vibration, pressure and energy consumption can be measured to give data on the condition of equipment and the performance of the process. Through continuous monitoring, predictive maintenance and early problem detection is possible. Research studies on predictive-maintenance show the overall benefit of using sensor-based information and analytical models to optimize equipment management (Mallioris et al., 2024).

4.3 Integration of GIS, IoT and AI

The true power of GIS and IoT is in the fusion of their data with AI. GIS gives information on where a condition occurs, IoT gives information on when it changes, and together with AI, it can offer information on the potential outcomes. The study of AIoT suggests that connected sensing with intelligent analytics can facilitate more advanced agriculture decision-making (AIoT, 2023; Senoo et al., 2024).

Satellite imagery could, for instance, detect reduced vegetation condition in a specific field. GIS technology can be used to find the affected region, and the IoT sensors can give up-to-the-minute data on soil moisture and temperature. These factors, combined with past production data, can then be used to estimate what the impact on potential productivity may be via an AI model. The system could then suggest an intervention like irrigation or targeted inspection of the field (Abdelouafi et al., 2024).

The integration can also be used to help with resource management. The data captured through remote-sensing can be used to detect spatial variability in the crop situation, and the data captured through IoT can give real-time information on the needs of the crop. These datasets can be used together with machine-learning models to estimate resource needs. Spatial and analytical technologies can be applied for resource-efficiency assessment as demonstrated by remote sensing and machine learning approaches in assessing sugarcane water footprints (Somard et al., 2021).

Table 2. Major data sources used for AI-based GIS and IoT productivity analysis in sugar industries.

Data Source	Type of Data	Spatial/Temporal Characteristics	AI Application	Productivity Indicator
Satellite imagery	Multispectral, optical and SAR data	Large spatial coverage; periodic observations	Yield prediction and crop monitoring	Yield per hectare
UAV imagery	High-resolution crop	Field/sub-field level;	Crop-health and	Crop condition

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	images	frequent observations	disease detection	
GIS databases	Soil, field boundaries, topography and land-use data	Spatial	Productivity mapping	Spatial yield variability
Soil IoT sensors	Moisture, temperature and soil conditions	Localised; real-time	Irrigation optimisation	Water-use efficiency
Weather stations	Temperature, rainfall, humidity and other variables	Local/regional; continuous	Yield and stress prediction	Crop productivity
Machinery sensors	Vibration, temperature, pressure and operating conditions	Equipment-level; real-time	Predictive maintenance	Equipment availability
Mill databases	Production, energy and processing records	Factory-level; historical/real-time	Process optimisation	Throughput and efficiency
Historical farm records	Yield, inputs and management practices	Field-level; historical	Predictive modelling	Yield and input efficiency

4.4 Challenges of GIS and IoT Integration

Although the integration of GIS with IoT has great potential, there are several challenges to overcome. Some sensor and data values might be missing, and some data values may have noise or calibration errors; also, some of the satellite images could be cloudy or influenced by environmental conditions. Also, the spatial resolution, measurement frequency and data format can differ between data sets. These differences can be problematic when using information from several sources (Yin et al., 2020).

Interoperability is another challenge as IoT devices, GIS platforms, cloud systems and AI applications could employ different communication protocols, data structures. Reliability in connectivity and infrastructure are also essential in large-scale systems. Data management, scalability, interoperability and connectivity are identified as challenges for the implementation of AIoT research by Adli et al., (2023) and Senoo et al., (2024).

Hence, integration will be in vain without suitable preprocessing, sensor calibration, spatial alignment and data-governance mechanisms. Organisations need to also have the technical expertise to keep systems connected and understand the outputs of the analyses.

4.5 Contribution to Productivity Analysis

The synergy that GIS and IoT offer is valuable for AI tools to analyze productivity as it offers both spatial and temporal data. An integrated system can go beyond saying that productivity has dropped and determine where it has dropped, when (in the past) the conditions changed, and which factors could have led to it. This can help to inform targeted rather than blanket interventions (Hoang, 2024).

Their application at the farm level can help predict yields, manage irrigation, monitor crop condition and optimise resources. On the industrial side they can be used to assist in the monitoring of equipment, predictive maintenance and process optimisation. The sugar industry research on Industry 4.0 also shows that the adoption of technologies such as IoT, AI, and data analytics is key to the digital transformation (Vimal et al., 2022).

5. INTEGRATED AI–GIS–IOT FRAMEWORK FOR SUGAR INDUSTRY PRODUCTIVITY

The adoption of Artificial Intelligence (AI), Geographic Information Systems (GIS) and the Internet of Things (IoT) offers a chance to build a more holistic system to monitor productivity in the sugar industry. These technologies are

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frequently used separately, but can be used together to link spatial data, real-time sensing and intelligent analysis. GIS gives the geographical background of agricultural and industrial data, IoT is used to gather the data from fields and machines, and AI processes the data to make predictions, classifications and optimisation suggestions. The combination of these features can be useful for productivity assessment in sugarcane production, as well as for sugar-mill operations (Adli et al., 2023; Senoo et al., 2024).

5.1 Conceptual Framework

An integrated AI–GIS–IoT framework could be structured as five interdependent phases: data collection, data integration, AI analytics, decision support and productivity assessments. The data-acquisition stage is composed of data gathered from satellite imagery, UAVs, GIS databases, IoT sensors, weather stations, historical production records and industrial monitoring systems. These studies with remote-sensing tools have shown that satellite and UAV data can be useful tools for monitoring and estimating the yield of sugarcane crops (Som-ard et al., 2021; Barbosa Júnior et al, 2023). In addition, the Internet of Things (IoT) system can enhance these sources by continuously monitoring soil and environmental factors and conditions at ground level (Wang et al., 2020).

Data-integration takes all these sources of data and places them into a single analytical environment. Data cleaning, standardisation, spatial alignment and temporal synchronisation are necessary for this process. GIS can facilitate a spatial framework that can link the sensor observations with the specific fields, management zones or industrial sites (Bill, 2022). There is also a need for temporal alignment since observations from the satellites and measurements from the IoT are collected at different frequencies. The value of combining data from various phases of sugarcane development (from growth to maturity) is demonstrated in yield research conducted with the aid of time series of remote sensing data (Dimov et al., 2022).

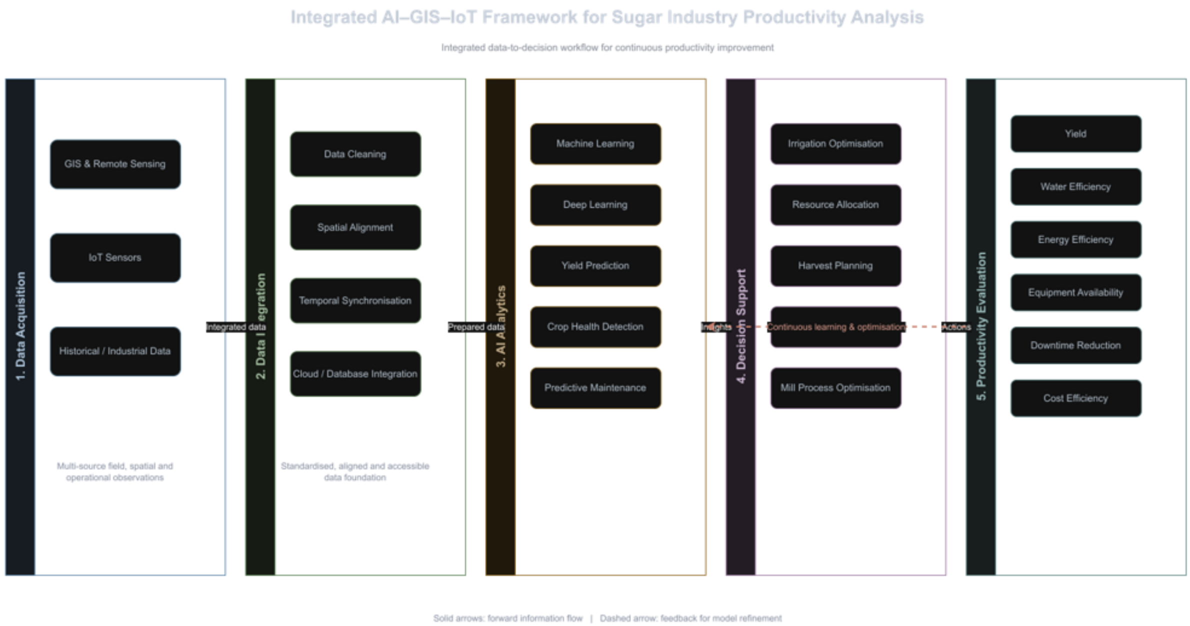

Figure 1. Integrated AI–GIS–IoT framework for productivity monitoring and decision support in the sugar industry.

5.2 AI Analytics and Prediction

AI models can then analyse the resulting datasets after integration, to uncover patterns related to productivity. Yield prediction, assessment of crop stress, detection of diseases and optimisation of resources can be achieved using machine-learning models. Sugarcane yield prediction is a case in point where multispectral imagery has been integrated with machine-learning techniques to boost prediction performance, and optical and synthetic aperture radar data have been integrated for good yield prediction (Akbarian et al., 2022; Das et al., 2023). Deep-learning approaches offer further functionalities which can handle complex spatial and temporal data and have been explored in the field of sugarcane yield prediction and disease classification (Saini et al., 2023; Daphal and Koli, 2023).

AI isn't just for farming; it's for other applications as well. Process data can be analysed in sugar mills to find out the relationships between operating conditions, energy consumption, throughput and sugar extraction performance. The use of computational models to optimize industrial operating decisions is shown in the optimisation of sugarcane milling based on data. As a result, AI can be applied to the entire production chain—from crop level onward.

5.3 Decision Support and Operational Response.

Productivity value of AI will rely on whether the analytical value translates to operational decisions. Not all predictions lead to a productivity improvement. The output needs to be part of management activities like irrigation, disease intervention, harvesting, maintenance or process adjustment. For instance, sensors in the earth can detect reduced soil moisture, GIS can pinpoint the field area, and an AI can project the field's potential productivity impact. This information can then be used by managers to prioritise irrigation (Mohd et al., 2023).

The same procedure may be used for machinery. Sensors can be deployed in the industrial equipment to track operating conditions on a constant basis. The AI models can detect abnormal patterns and forecast potential failures, enabling maintenance to be carried out in advance of an unexpected breakdown. This relationship between sensor-based monitoring and AI prediction and planning for maintenance is one of the key characteristics of Industry 4.0 systems (Mallioris et al., 2024).

5.4 Productivity Evaluation

Several measures of productivity should be used since performance in the sugar industry is related both to output and resource efficiency. Some of the agricultural indicators are sugarcane yield per hectare, sugar recovery, water-use efficiency and input efficiency. Industrial indicators can be throughput at the mill, extraction efficiency, energy consumption, equipment availability, downtime and maintenance. The relevance of water efficiency in crop production, in addition to productivity, has already been looked at through remote sensing and machine learning for water footprints in sugarcane production (Somard et al., 2021).

It's crucial to understand the difference between the accuracy of AI predictions and a boost in productivity. The model can be a good predictor of yield, but without the ability to use the predictions in the management decision making process, it has little utility. Therefore, a productivity-impact analysis will need to consider the full value chain of collecting data to predicting with AI, to managing and measuring operational impacts (Ouyang et al., 2023).

5.5 Integration of Agricultural and Industrial Data

One of the greatest benefits of an integrated framework is that it enables linking agricultural information with the work of sugar mills. Sugar production is an integrated production chain wherein farm level production has an influence on the harvesting, transportation and scheduling of mills. Geography of sugarcane can be represented using GIS and AI based sugarcane yield forecasting can estimate the availability of cane in the future. This can then be used to generate real-time data on field conditions, transportation and factory equipment through IoT data (Huang et al., 2024).

This holistic view aligns with the current trend of the sugar industry towards incorporating Industry 4.0 technologies. The study suggests key digital transformation technologies necessary for industry 4.0 readiness in the sugar industry include the use of IoT, AI, big data, and predictive maintenance (Vimal et al., 2022). Agricultural and manufacturing datasets are not necessarily different information systems; using a method of integration it may be possible to offer continuous information flow from the farm to the factory.

5.6 Expected Productivity Benefits and Limitations

AI, GIS and IoT can work together to impact productivity by providing better prediction, intelligent resource scheduling, quicker problem identification, less equipment downtime and production process optimisation. Spatial targeting of interventions may also minimize unnecessary resource consumption and ongoing monitoring may enable issues to be addressed before they become a significant loss of productivity. An optimisation process based on

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Artificial Intelligence can also be used to help determine the operating conditions that optimise production, energy and resource use (Mussa, 2024).

But, those benefits aren't guaranteed. The quality of the data, reliability of the sensors, connectivity, interoperability of the systems and the model accuracy and organisational readiness can have a huge impact on outcomes. The study on AIoT reveals technical and implementation issues related to data management, interoperability and scalability (Adli et al. 2023; Senoo et al. 2024).

6. PRODUCTIVITY IMPACTS, CHALLENGES AND FUTURE DIRECTIONS

AI, GIS and IoT can help achieve productivity gains in the sugar sector by making accurate predictions, maximising resource utilization, optimising processes and equipment performance. The extent of these benefits, however, will be determined by the extent to which the digital technologies are embedded in the current agricultural and industrial processes. Thus, the literature indicates that productivity should be viewed as a multi-dimensional product, characterized by quantity, efficiency in using resources, reliability, lowering costs, and enhancing decision making processes (Sharma et al., 2023).

6.1 Productivity and Resource Efficiency

One of the major possible effects of the use of AI in monitoring would be the enhancement of resource efficiency. Sugarcane is a water-intensive crop, consuming significant amounts across its entire lifecycle, and inefficient water use can result in higher production costs but not necessarily yield greater production. The Internet of Things can give real-time information of the field condition and GIS can detect spatial variation in the water requirement. These data can then be used by AI to identify the need for interventions and when and where they are needed (Sharma, 2024).

Closed-loop irrigation is an example of real-time sensing that can be used to help improve water management in sugarcane production (Wang et al., 2020). Likewise, remote sensing along with machine learning have been applied to evaluate the water footprint of sugarcane, establishing potential to integrate spatial aspects of crop information with water-use analysis (Somard et al., 2021). These approaches imply that the production of tonnes of sugarcane is not the only measure of productivity but the amount of resources that is needed to produce that amount of sugarcane.

AI can further aid in energy productivity in the sugar mills. Data-driven optimisation can discover correlations between process parameters and energy usage, and operators can then look for process operating conditions that find the optimum production while maintaining a control on energy usage. This is especially significant as the use of energy is an important consideration in sugar production.

6.2 Operational Efficiency and Predictive Maintenance

The reliability of the equipment has significant impact on industrial productivity. Milling and processing operations can be affected by unexpected failure of machinery causing production losses, maintenance costs and inefficiency of labour. With the use of IoT sensors, real-time data on equipment conditions can be collected and used to detect shifts in their operation, and AI can model these trends to anticipate equipment failure (Elkateb et al., 2024).

In this way, AI can bring about a significant change in productivity, which is why predictive maintenance is an important area. Rather than being based on a fixed maintenance schedule, equipment can be monitored based on its condition. This research on predictive-maintenance demonstrates that sensor data and machine-learning methods can be used in conjunction to assist with the early detection of equipment degradation and maintenance planning (Mallioris et al., 2024).

The impact on productivity for sugar mills may be measured by parameters like reduction in unplanned downtime, increase in equipment uptime, decrease in maintenance expenses, and increased production continuity. But predictive maintenance can only be effective if the organisation can act on the warnings generated. Highly accurate prediction is only useful if spare parts, technicians and/or maintenance is available at the time of need.

6.3 Better projections and planning

AI-powered forecasting can help minimize uncertainty in future production and enhance planning efforts. The yield prediction of sugarcane through remote sensing and machine learning can provide information before harvest, which can help the managers to estimate the availability of sugarcane for transport and processing (Das et al., 2023; Akbarian et al., 2022).

Additionally, more detailed predictions can provide spatial information on the expected production. Field-level or management-zone prediction can help it identify some areas that may have reduced productivity, rather than just total farm output. This information can assist with purposeful interventions and better utilization of agriculture resources.

6.4 Major Implementation Challenges

While AI–GIS–IoT systems have the promise of improving the quality of life, there are a number of challenges that can limit their use. One of the top issues is data quality. The measurements that these IoT sensors can take can be missing, noisy or inaccurate; and the satellite observations can be hampered by cloud cover or other environmental constraints. AI models that are trained on faulty data can produce inaccurate predictions (Mazhar et al., 2023).

Interoperability is another significant challenge. Different formats and communication protocols may be used for GIS platforms, IoT devices, remote-sensing systems, databases and AI applications. Appropriate data architectures and standardisation are needed to integrate these technologies. The issue of interoperability, connectivity, scalability and data management remains as a challenge for the implementation of AIoT and smart-agriculture systems (Adli et al., 2023; Senoo et al., 2024).

There is also an Infrastructure and Connectivity element that can impact implementation. Sugar cane fields can extend over a broad area with limited communication coverage. Thus, the network architecture, power sources and data communications need to be in place for continuous IoT monitoring.

Other barriers are cost and technical skills. Significant capital investment can be needed for sensors, networking, cloud infrastructure, and AI development. There is a need for staff who can keep sensors up and running, handle data and understand the insights from AI. Sugar industry's preparedness for Industry 4.0 suggests that organisational and technological preparedness is a key factor to ensure the success of digital transformation (Vimal et al., 2022).

6.5 Data Security and Governance

As more and more devices become connected, cybersecurity and data-governance issues are raised. The information generated by IoT devices is ongoing and can be shared over networks and stored in cloud data. Agricultural and industrial activities may be impacted by unauthorised access, data manipulation or disruption of the system.

Data governance is also relevant in situations where multiple data sources are used. Clear ownership, access, quality assurance, storage and retention policies for data are required by organisations. AI systems should also be monitored to guarantee that predictions are still valid under changing operating circumstances. As organisations shift from a single digital application to an integrated enterprise-wide platform, these requirements become increasingly important.

6.6 Future Research Directions

Future studies should focus on the measurable productivity benefits of integrated systems, rather than on the evaluation of individual technologies. Although prior work has demonstrated the validity of the individual applications like yield prediction, remote sensing, IoT irrigation and predictive maintenance, comparatively little research focuses on the assessment of their combined impact throughout the entire sugar production chain.

Further evidence would be gained from using longitudinal studies and comparing productivity before and after the implementation of the AI–GIS–IoT systems. The economic and operational results of the models (such as input costs, energy usage, downtime, yield, sugar recovery and return on investment) should be also measured.

The other direction is the development of digital twins for sugar production. Digital twins could integrate GIS data, sensor data, and historical data, while also incorporating AI models, to create dynamic datasets that represent agriculture and industrial systems. These can enable managers to see how decisions would work in practice before they have to put them into action on the ground (Peladarinos, et al., 2023).

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Table 3. Productivity impacts, implementation challenges and future research directions for AI–GIS–IoT integration in the sugar industry.

Area	Potential Productivity Impact	Key Challenges	Recommended Future Direction
Yield prediction	Better production and harvesting forecasts	Data variability and model generalisation	Multi-year and multi-source AI models
Irrigation management	Reduced water consumption and improved crop performance	Sensor reliability and connectivity	AI-enabled precision irrigation
Crop-health monitoring	Earlier detection of diseases and stress	Image quality and classification errors	Multimodal AI using UAV, satellite and IoT data
Resource management	Improved water, fertiliser and energy efficiency	Limited real-time data integration	Integrated resource-optimisation platforms
Predictive maintenance	Reduced downtime and maintenance costs	Sensor failure and insufficient historical data	Real-time AI-based predictive maintenance
Mill process optimisation	Improved throughput and process efficiency	Complex process interactions	AI-based process-control systems
GIS-based management	Targeted interventions based on spatial variability	Different spatial resolutions	High-resolution spatial digital twins
Integrated AI–GIS–IoT	Continuous and predictive productivity management	Interoperability and infrastructure	Unified enterprise-level data platforms
Sustainability	Improved resource productivity and reduced waste	Difficulty measuring long-term impacts	Combined productivity and sustainability metrics

7. CONCLUSION

The potential of Artificial Intelligence (AI), Geographic Information Systems (GIS) and the Internet of Things (IoT) can help the sugar industry to boost productivity management. The review illustrates several complementary capabilities that these technologies have: GIS and RS offer spatial information, IoT can be used for continuous monitoring, while AI can use large and complex datasets to make predictions, classifications and optimisation recommendations. Their combined use can then facilitate a shift in traditional, mostly reactive management to predictive and more data-driven productivity management.

The evidence reviewed suggests that AI can support sugarcane productivity in the following ways: yield prediction, disease detection, crop health monitoring and optimising resources. Multispectral, optical and radar data have been used to develop machine-learning methods that have been shown to be effective in predicting sugarcane yield at various spatial scales (Akbarian et al., 2022; Das et al., 2023). In addition, deep-learning approaches can be utilized for further supporting yield prediction and disease classification, which can create opportunities to identify productivity risks earlier (Saini et al., 2023; Daphal and Koli, 2023). GIS enhances these applications by providing the ability to explore the variation in productivity on a geographic basis and provide managers with information about areas that need intervention.

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With IoT, a new dimension is added to the possibilities of observing field or industrial conditions in real time. The use of continuous sensing to facilitate more responsive water management in sugarcane production is well illustrated through the use of IoT irrigation systems (Wang et al., 2020). GIS and AI can be used with sensor data to tie data to a geographical location and to use sensor information together with satellite imagery, weather data and historical production data. This has the potential to enable more targeted resource management and productivity monitoring.

The review also underscores the importance of AI beyond just agricultural production. Data-driven optimisation, predictive maintenance and Industry 4.0 technologies can be used to optimise sugar-mill operations. When coupled with AI-based predictions, continuous equipment monitoring can help minimize unplanned downtime and maximize equipment availability (Mallioris et al., 2024). The growing importance of Internet of Things (IoT), Artificial Intelligence (AI), big data analytics and predictive maintenance in sugar production is further testament to the fact that digital transformation is relevant for the entire sugar manufacturing system (Vimal et al., 2022).

The agricultural and industrial data should also be integrated, and such systems should be explored in the future. Such systems could be combined with field level yield forecasting and harvesting, to sugar-mill planning and complete digital representation of the sugar production chain. Further research includes longitudinal studies, digital twins, explainable AIsystems, and real-time decision-support systems.

Figure 2. Productivity impact pathway linking AI-monitored GIS and IoT data with operational decisions and measurable sugar-industry outcomes.

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