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Intelligent Decision Support for Sustainable Agriculture Through Big Data, Predictive Analytics, and Automation

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ABSTRACT: Digital technologies create new opportunities for solving paramount societal challenges. Within the agriculture and food production area, the digital transformation is driven by the concept of Sustainable Agriculture 4.0, a paradigm shift towards resource-efficient and demand-driven production supported by Sustainable Development Goals. A key supporting technology is Artificial Intelligence, which seeks greater autonomy by simulating human-like cognitive functions. However, AI currently excels at narrow tasks and requires a great amount of clean training data. Predictive models and modeling frameworks, particularly, can comprehensively leverage existing knowledge and experience to predict outcomes, assess risks, and ultimately support decision-making. These AI services can assist, empower, or control stakeholders in management tasks. Sustainable progress therefore requires a higher-level decision support capability, encompassing Big Data Analytics to process past evidence and feeding Predictive Modeling for future scenarios.

Research design is based on the Smart AgriTech Platform developed at the University of São Paulo. It embraces Sustainable Agriculture 4.0 by adapting the digital transformation and digital twinning frameworks for the AgriTech domain. The design integrates capabilities for Data Processing and Mining, Predictive Modeling, and Automation of Decision Workflows. Insights from Big Data Analytics on crop management data and climate conditions contribute to a better understanding of annual cropping systems, underpinning more precise Risk Assessment and Resilience Planning. Agribusiness decision workflows are formally modeled and choreographed in a Decision Operation System. Produce forecasted models (e.g., crop yield, price) become readily available for external consumption through a Decision Model and Notation engine, enabling value-addition in AgriTech products and services.

KEYWORDS: AgriTech, Artificial Intelligence, Big Data Analytics, Decision Support, Predictive Modeling, Smart Agriculture, Workflow Automation.

I. INTRODUCTION

The global population is projected to nearly reach 10 billion by 2050, necessitating an increase of 70% in food production. An estimated 16% of this required output must be produced by smallholder farmers in developing countries. These food producers are currently unable to fully realise their output potential due to a lack of logistics, processing and market distribution data, talent, investment and financial support. They also face many significant challenges: unpredicted weather patterns, extreme events, failure to produce food surplus, the Covid-19 pandemic and new challenges linked to climate change. The recent disruption of agricultural supply chains adds to these difficulties and emphasises the importance of fresh data that can inform real-time decision-making in support of resilient food production.

The provision of better-quality information would enable these farmers to make more informed decisions and to respond to crises in a timely manner. Artificial Intelligence (AI) and Big Data Analytics (BDA) provide the very solution that emerging smallholder farmers need to reduce their technical and decision-making barriers and achieve tangible production increases. Development of a dedicated AI-based Decision Support System–AgriTech (DSS-AI-AgriTech) for the smallholder farming segment is constrained by the necessary combination of BDA, predictive analytics and custom

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decision/operational workflow integration and automation that can cover the full farmer decision-making process and remove the need for individual analysis of separate modelling outputs.

1.1. Background and Significance: Agricultural soils, plant, and microbial activity are the main providers of ecosystem services that sustain natural and agrarian ecosystems. Soils are responsible for the purification and regulation role of nutrient cycles, carbon conversions, and carbon stock potential. They constitute the ultimate source for food, agricultural raw materials, livestock products, and other agricultural resources. However, the impact of agricultural intensification, global climate change, and excessive anthropogenic activities cause detrimental effects on soil, plant, and microbial functions and alter the fragile balance between the chemical, physical, and biological properties of soils.659 The resulting environmental crises, including soil erosion and depletion, nutrient depletion, acidification, pollution, and salinization, threaten the very basis of the earth's agricultural systems.690 Poor soil health has led to declining agricultural productivity and resilience to uncertain weather events.659 A checklist for building soil resilience and approaches to mitigate the negative impact of climate change on soil health in conjunction with soil microbiome research are of paramount importance.

In addition, an alarming decline in farmers' income is observed, particularly in tropical and sub-tropical regions, due to the declining yield of important crops.607 Perennial fruit crops are also being replaced with annual vegetable crops due to globalization and the increasing demand for vegetable crops.659 Under these circumstances, there is a pressing need for forecast models with acceptable prediction accuracy to develop viable, long-term yield prediction systems for important crops, which will help in efficient planning and sustainable management of G-Agriculture. Hence, it is concluded that contributions should extensively cover aspects of climate change-induced environmental effects on agricultural productivity and the ecosystem, mitigation strategies to cope with climate change, and precision agriculture.659 Geospatial technology and artificial intelligence offer powerful visual analytical and predictive modeling capabilities for better crop growth and yield.659.

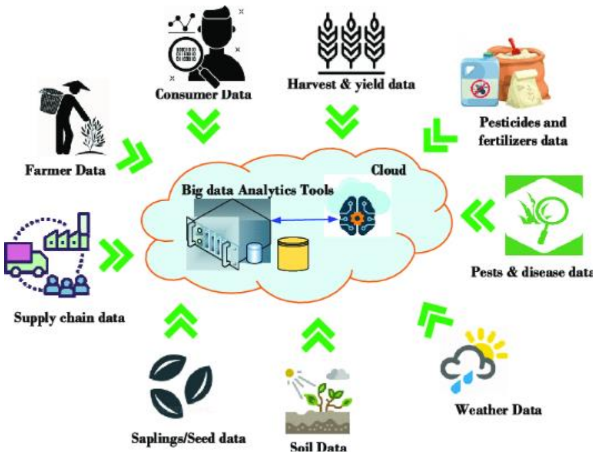

Fig 1: Big data-based decision support system

II. BACKGROUND AND RATIONALE

SAP HANA Vora is a distributed, in-memory computing engine designed to meet the diverse analytical needs of businesses and organizations today, providing a platform for real-time analytics on big data from SAP environments and beyond. It provides a robust environment for retaining and manipulating larger, richer sets of multi-structured data, such as log files or social media feeds. Moreover, it transforms an organization's data lake from a hidden source of operational failure into a golden asset. By empowering business users to leverage all data for predictive and operational modeling, SAP HANA Vora helps organizations manage unpredictable behavior while greatly improving business performance.

SAP HANA Vora offers the comprehensive set of capabilities that organizations need to take action on big data across a wide range of projects. Data processing and data management tools purify data for analytics, avoiding bad decisions based on untrustworthy sets.

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Equation 1: Bayes theorem (foundation for "modified Bayesian models")
Start from the definition of conditional probability:

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)} \quad \text{and} \quad P(B \mid A) = \frac{P(A \cap B)}{P(A)}$$

Solve both for $P(A \cap B)$:
$P(A \cap B) = P(A \mid B)P(B)$ $P(A \cap B) = P(B \mid A)P(A)$
Set them equal:

$$P(A \mid B)P(B) = P(B \mid A)P(A)$$

Divide by $P(B)$ (assuming $P(B) > 0$):

$$\boxed{P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}}$$

Mapping to modeling language:
- A = model parameters θ
- B = observed data D

$$\boxed{P(\theta \mid D) = \frac{P(D \mid \theta)\, P(\theta)}{P(D)}}$$

Where:
- $P(\theta)$ is the **prior**
- $P(D \mid \theta)$ is the **likelihood**
- $P(\theta \mid D)$ is the **posterior**
- $P(D)$ is the **evidence** (normalizing constant)

2.1. Research design: The research approach addresses the operational aspects of applying AI to grow sustainable AgriTech. Agriculture is intrinsically a socio-technical system in which collaboration across planning, technical and production layers of an organisation is vital to achieving crop production objectives. In this context, Decision Workflows and Orchestration are defined as the sequences of collaborative decision-making activities undertaken to achieve an AgriTech objective. Given the resource and time constraints faced by such organisations, a Decision Workflow Operation facilitates the orchestration of a defined workflow by a single agent or supported by automation tools. It is within these workflows that automating specific steps contributes to achieving AgriTech sustainability objectives. A Workflow Automation System combines Automation Tools with an orchestration capability to operate defined Decision Workflows. Automating a decision workflow in AgriTech-Decision Workflow Operation: The operational aspects of applying AI to AgriTech are now addressed. AgriTech, through crop production, is the establishment of a suitable socio-technical system producing marketable yields at minimal environmental impact. Given the business pressure to use automation techniques to reduce cost, while still remaining sustainable, AI offers the means to integrate Big Data Analytics and Prediction Models.

AI, through Big Data and Prediction Models, provides the capability to improve and automate Decision Workflows employed in achieving AgriTech objectives. In applying AI, formalising these Decision Workflows is critical, not as a mechanism for knowledge capture but as an understanding of how these socio-technical systems function. AgriTech is intrinsically a socio-technical system in which collaboration across planning, technical and production layers of an organisation is vital to achieving crop production objectives.

III. BIG DATA ANALYTICS IN SUSTAINABLE AGRICULTURE

The sheer volume and diversity of data producing in agriculture on a global scale are enormous. Global large-scale catastrophe data's associated losses in agriculture sector have been collected by the Centre for Research on the Epidemiology of Disasters (CRED) and Disaster Emergency Committee. Detection and monitoring of crop diseases are one of the most important tasks faced by agriculture today.

Widespread adoption of viable crops that are more productive and protective against environmental variables such as climatic change will require extensive knowledge by farmers on characteristics of available cultivars. Farmers face extreme risks due to natural disasters. Decisions on crop insurance, crop diversification strategies and variety diversification provide farmers with an effective approach in managing production risk to some extent due to natural disaster.

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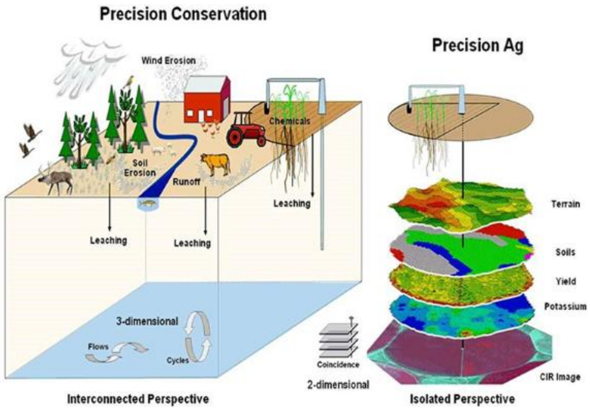
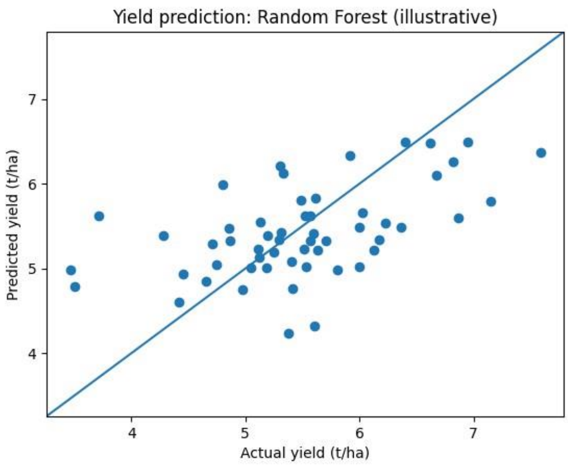


Fig 2: Big Data Analysis for Sustainable Agriculture

3.1. Data Sources and Data Quality: Systematic integration, correlation, and interpretation of large, heterogeneous datasets are essential for all aspects of Big Data Analytics in sustainable agriculture. Such datasets include geographical information system (GIS) data, data from the meteorological department (temperature, rainfall, humidity, wind speed), mechanization data (tractor power, draught animals), crop production data, soil characteristics (pH, organic carbon, nitrogen, phosphorous, potassium), and market price for important crops. Time series data is crucial for crop yield forecasting, pest population forecasting, irrigation requirement forecasting, drought assessment, and weather forecasting. Quality-controlled, reliable time series data will yield a reliable predictive surface. The development of crop yield forecasting models using modified Bayesian models requires a lot of information, such as state-wise district-wise crop area, yield statistics for major food crops, and remote-sensing data on growing-season rainfall.

Collating and curating all these datasets, considering data at the block level, district level, and state level, and the increment of data in years, is a Herculean task. Reliable, quality data at smaller geographical scales, especially at the district level rather than the block level, would attract the attention of many researchers, as district-level forecasting remains a research gap in the AgriTech domain. Integration of crop production statistics and remote-sensing data at the district level, with a focus on the northern states of India, will facilitate quality research in crop production and crop yield forecasting.



3.2. Data Governance and Privacy: The use of identifiable data for Big Data is subject to various regulations, whose goal is minimal impact on the subjects in addition to protecting their privacy—especially children, sick persons, and persons who, due to other external situations, are considered in a position of vulnerability—as well as ensuring accurate predictions. Protective measures with respect to the client’s data also constitute significant selling points for the firms and products that introduce and manage systems capable of meeting these requirements. In artificial intelligence, these elements refer to privacy-preserving artificial intelligence (PPAI) systems for data integration using machine learning.

PPAI concepts are explored in the context of digital Twins-X (DT-X), a model of business ecosystems supported by digital twins and artificial intelligence/PPAI.

Providing personal data constitutes a burden for subjects mainly due to the fear of possible data leaks, misuse, or illegal use. Hence, clients involved in giving consent for donating their data are in fact requesting services that minimize the impact of accepting the subsequent decision of donating sensitive data. By engaging with PPAI solutions, clients seek assurance that their donated data would be integrated into databases only for legal uses and in situations where the expected benefits from the outcomes were above a given line and accrued to them as well. Digital technologies therefore look to support such initiatives by developing tools capable of fostering attractive dialogue with client subjects in an evolving virtual environment.

IV. PREDICTIVE MODELING FOR DECISION SUPPORT

Forecasting crop yields and assessing risk are two key problems identified in the context of sustainable agriculture. Predictive modeling of these types should be performed under strong assumptions of data governance, quality, and privacy. Such assumptions should guide the organization of the associated decision workflows.

Crop yield forecasting supports many stakeholders of the agricultural ecosystem. Natural phenomena, like climate change and soil depletion, pose a long-term threat of yield decrease, requiring monitoring of the ecosystem or supply chain. Open-data Machine Learning solutions have been developed aggregating many datasets with the aim of enabling a sub-area yield forecasting for areas of at least 25km2. Quality control of the datasets is critical given the insufficient quantity of data for overperformance testing of the forecasting solutions. Machine Learning can be also applied to the optimization of crop yield, like choosing the best combinations of fertilizers, irrigation, and seed species. In this case, the optimum lies on a preference surface, whose detection requires real samples of the crop for correct generalization.

Risk assessment has emerged recently as a pre-competitive field. It addresses the problem of estimating the risk associated to an agricultural area and to extreme phenomena, and the preparation of contingency plans in case of queried extreme events. For each extreme phenomenon or sequence of phenomena, historical cases have to be identified to elaborate a resilience plan for the monitored area, indicating the actions to carry out before, during, and after the event. Decision Trees have been identified as suitable candidates for the risk assessment task.

4.1. Crop Yield Forecasting: Based on historical observations, machine learning methods trained on big data, and deeply simulated processes, predictive models provide estimates of crop yields and distribution throughout the growing season for all relevant crops across specific regions. These yield-predicting cloud services have proven reliable in past seasons and continue to improve with the addition of new data and methods. They can enable a variety of applications throughout the agricultural supply chain, ranging from the provision of initial capital and loans to farmers, to the anticipation of supply and storage needs for food banks. Historically, crop yield forecasts remain limited to key regions and major crops at coarse resolutions. Inclusive yield models would equally account for all crops in a region and for seasons with fewer or smaller crops.

In order to cover all crops with a single machine learning model, high-resolution observed yield data were mapped onto simulated crop season severity (CSS) and recovery (RRS) indicators. Deep learning methods proved especially effective in using CSS and RRS as proxies for climatic detail, but The hyper-meteorology models that can predict yield for Thailand and Vietnam have also demonstrated good generalisation in model transfer to China. Furthermore, the decision-support model Crop College provides an interactive yield estimate for Thailand, using an ensemble of yield predictors. As a result, Yield Mapper services are available, which provide decision support, current yield severity maps for the major crops in Thailand, and risk assessments for crop production in China, modelling both major crops and fruits.

Equation 2: A concrete Bayesian yield-forecast update (Normal–Normal conjugacy)
Likelihood:

$$y_i \mid \mu \sim \mathcal{N}(\mu, \sigma^2) \Rightarrow P(D \mid \mu) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y_i - \mu)^2}{2\sigma^2}\right)$$

Prior:

$$\mu \sim \mathcal{N}(\mu_0, \tau_0^2) \Rightarrow P(\mu) = \frac{1}{\sqrt{2\pi\tau_0^2}} \exp\left(-\frac{(\mu - \mu_0)^2}{2\tau_0^2}\right)$$

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Posterior

By Bayes:

$$P(\mu \mid D) \propto P(D \mid \mu)\, P(\mu)$$

Because Normal prior × Normal likelihood ⇒ Normal posterior:

$$\boxed{\mu \mid D \sim \mathcal{N}(\mu_n, \tau_n^2)}$$

with

$$\boxed{\tau_n^2 = \left(\frac{n}{\sigma^2} + \frac{1}{\tau_0^2}\right)^{-1}} \boxed{\mu_n = \tau_n^2 \left(\frac{n\bar{y}}{\sigma^2} + \frac{\mu_0}{\tau_0^2}\right)}$$

where $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$.

Interpretation (important for decision support):

- μ_n is a weighted average of the prior mean and sample mean.
- τ_n^2 shrinks as n increases → confidence grows with more data.

4.2. Risk Assessment and Resilience Planning: Quantifying climate extremes drives business and land management decisions. The data include cyclone tracks, catastrophic rainfall, storms, floods, and genesis potential fields. A cyclone event is considered extreme if wind gusts exceed 53 knots. Leverages Bayesian approaches to preemptively model cyclone risk on infrastructure using census and insurance data. The data provides empirical estimates of risk brought by cyclone storms to facilitate rapid recovery and resilience planning. Risk distribution maps are generated based on loss estimates from cyclones and scaled scape based indices. The cyclone success metric rate predict ability of future cyclone places.

Modelings cyclon- generated post-mortem reports are modeled using tornado heat indexes. Decision makers can easily quantify cyclone risks induced by both climate change and human climatic change. Users can operationally infer the risk for future cyclone threats on their local decision making procedure. Indices for disaster impact maintaining-G approximately zero pose cyclone related statistical independence do not require a global ENOS yo be operated. The connection between ENSO and tornado risk, now conclusively positive, support future Ninobased prediction for storm merchandising locations.

Concerns for disasters,resulting in loss of life or property damage, are regularly higher after bad experiences. Disaster reaction nor predictions posses behavioral visibilities for decision making. Connection between a cyclone success score and tornado activities is straddled to future rapid action decision making for future cyclone evaluation work. The prediction time span ideally should be INM, a Nov, De, Jan month, with forecast initiated atleast at last 30days before. ATM prediction using monitoring tools at Fiji Dome ATM/Fiji Dome Cyclon prediction tool using modern tools for To predict ATM,once in 2/3 years. Prediction success data is the ATM catastrophe index.

V. WORKFLOW AUTOMATION AND OPERATIONAL INTEGRATION

Until now, the material has addressed High-level Decision Support relating to large-scale issues of long-term interest. The Proposed AI-Driven Decision Support System now aims at adding on-the-ground, bottom-up Decision Workflows and Decision Automation Tools to support the sites, services, and actors of Sustainable Agriculture and Circular Economy. Such work is relevant to farmers, cooperatives, local governmental agencies, and isolated urban gardeners interested in contributing to a Sustainable, Resilient, and Circular Economy. The focus remains on the use of Artificial Intelligence and Advanced Analytics to support decision making.

Rich difficult-to-access, well-organized, high-quality big data is the key to achieving High-Level Decision Support. High-Level Decision Support Decision Workflows must define the necessary interactions, the owners of the data and services to be contacted, and the information required to support lower-level decisions. For every High-Level Decision Workflow at least one Decision Workflow Orchestration must specify Business Logic and Business Orchestration, while for every Task Decision Workflow a Task Workflow Automation can be implemented. Existing Decision Automation Tools in the form of software libraries and platforms allow automating typical decision tasks but without specific knowledge formalization, monitoring, nor retrieval capability. New domain-specific decision automation tools apply Big Data, Predictive Modelling, and Decision Automation to typical tasks of lower-level actors interested in Agriculture and Circular Economy. A taxonomy identifies decision-support domains related to Higher-Level Decision Workflows.

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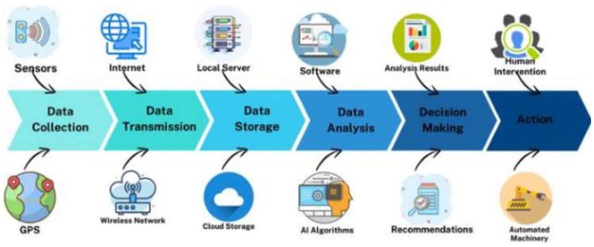

Fig 3: Precision agriculture workflow in automation

5.1. Decision Workflows and Orchestration: Automation tools and services for business process management (BPM) boost productivity by relieving users of repetitive, low-level tasks and by orchestrating complex, multi-step operations. A BPM engine can execute activities of differing nature (e.g. human, automated, data manipulation), across different environments (e.g. cloud, on-premises) and covering all business functions (e.g. customer service, HR, IT maintenance, finance) as long as the relevant services can be made accessible. Automated decision support for sustainable agriculture would typically focus on the automation and orchestration of decision workflows rather than their execution. The orchestration of multi-step collaboration processes among human actors can still improve productivity and decision quality.

Each decision-process cloud service caters for a subset of decision workflows. Decision workflows are typically made explicit and published in a business process modelling notation since the voluminous textual specification typically found in business process descriptions is ill-suited for online performance support. The BPM engine executes the decision workflows by providing the orchestration and by serving as a secure middleware for the distributed web services. Security, logging and auditing are handled in the BPM engine, without any specific implementation effort on the part of the service provider. A client in any location can also make use of the service, since service invocation is independent of the client infrastructure. Furthermore, even services involving peer-to-peer collaboration can be supported, with the BPM engine handling access control and moderation.

The automation of decision workflows is particularly appealing for fast-durable decisions that are repeated often but require multiple inputs and require some deliberation. In such situations, a decision support system (DSS) serves to provide recommendations, especially those needing a high volume of information that are beyond human capability.

5.2. Automation Tools and Interoperability: The recommendations produced by predictive models for sustainable agriculture need to be actionable to achieve their intended objectives. Actionability often requires the execution of complex workflows across multiple organizations and advice domains. Workflow orchestration helps integrate multiple recommendations across processes or organizations to enable effective implementation. When workflows are incorporated into decision support systems, AI-powered orchestration is then possible.

In addition to workflow orchestration, recommendations not bundled into workflows also require AI-based support to implement. Decision automation aims to implement recommendations using automated systems without human involvement, thereby increasing implementation speed. AI-based decision automation relies on data and models, and includes planning capabilities—although planning usually requires human judgement. Human-in-the-loop decision automation relies on data and models to support human operators by recommending actions for their execution. Decision automation becomes fully autonomous when feedback loops can be closed automatically. Predictive reactive systems use AI to learn how to react based on incoming events. Fallback rules provide safety and human supervision for higher-impact decisions. Predictive recommendation systems repackage recommendations from predictive models into different formats (simple status messages, recommendations, ranked lists, bundles, etc.) to facilitate actionable implementations. Following the principle of transparency, recommendation systems enabling human operators to witness why a recommendation was made increase user acceptance. Edge computing architecture is used to deploy the decision support services close to and in the field, as well as data-driven, hybrid-cloud architecture is used to provide real-time analytics for the agri-production system.

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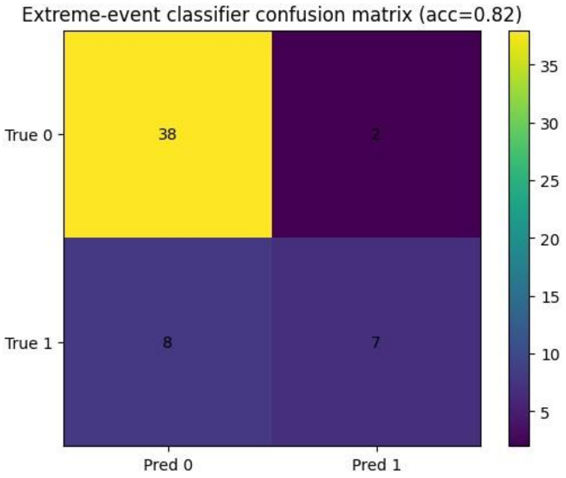

VI. SYSTEM ARCHITECTURE AND DEPLOYMENT CONSIDERATIONS

The proposed AI-driven decision support platform for Sustainable AgriTech integrates Big Data Analytics, Predictive Modeling, and Workflow Automation. Different types of systems and infrastructure are required to provide these components along with edge devices that provide sensing data and allow controlling the physical world. Specialized Data Systems support the analytics components and Data Flows transfer information in any form to and from these systems. The Data Flows then lead to Decision Orchestration Workflows that coordinate multiple Predictive Models and a Decision Resolution Model that can use AI-based or hard-coded knowledge for making decisions.

Decision Orchestration Workflows connect to Automation Tools that automate operational systems in the physical world. Stream-Oriented APIs with publish-subscribe communication patterns actively connect these various components over the Internet. The data-oriented architecture leverages the concept of Data Flows to integrate various decision workflows, predictive models, and data systems. Such decision workflows are built for each of the four decision categories mentioned earlier, that is, actions such as crop credit, inputs, market, and diversification decisions that need to be made at particular points of time during the agri-production cycle.

6.1. Architecture Patterns for AgriTech: The design of an AI-driven decision-support system for sustainable agriculture determines the degree to which the deployed technology can impact the economic or environmental sustainability of operations and provide decision support for decision problems at different organizational levels. Workflows that are too high-level, executed ad hoc as necessary, or unconnected to specific decisions held by decision-makers will lack business value for the user, while those that deal with managing day-to-day operations often do not require advanced AI-enhanced technology. The architecture of the system should therefore combine both top-down and bottom-up patterns of integration into a coherent technology package.

A top-down architecture integrates operational decision-making at the unit level with high-level business forecasts, predictions of climate impact on production processes, integrated risk assessments, or other decision-support tools that typically operate at a higher layer in the organization. The bottom-up architecture focuses on the integration of operational decision workflows (one-off or recurring) of the unit with the day-to-day operations of individuals and lower-level teams. Their usual ad hoc, manual, low-frequency, or internal nature often makes automation unnecessary, but considerable efficiency gains can be gained through technology/automation.

6.2. Edge vs Cloud Computing in the Field: The workloads associated with a decision support system in support of sustainable technologies are likely to affect a variety of stakeholders in the agribusiness value chain. The astute use of edge devices helps minimize latency and communication bandwidth while enhancing data quality through pre-processing close to its source. Nevertheless, many of the tasks of such systems, particularly those involving extensive static information repositories (e.g., weather data and historical yield forecasts), should be performed in the cloud, at low or no marginal cost. Moreover, the complexity of such supporting workflows often calls for the orchestration of individual tasks distributed across different processing locations. For these reasons, it is a good idea to adopt a hybrid architecture that places critical components at the farm level while supporting elements running in the cloud.

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Cloud computing has become the dominant paradigm for data management in a variety of sectors, including agribusiness. By centralizing the processing of heterogeneous data sources, it allows the development of services capable of inferring new information that benefits the entire community. Nevertheless, an excessive burden on the cloud can also lead to increased latency, raised bandwidth requirements and costs, and vulnerability to disconnections. In scenarios involving highly demanding applications such as autonomous vehicles or remote surgery, decisions taken in locations far removed from the event are no longer meaningful and must be processed as close to the data source as possible. Emerging applications in smart cities and the Internet of Things (IoT) also call for low-latency responses that are difficult to achieve with a wholly cloud-centric approach.

Equation 3: Linear regression yield model: derive the normal equation (OLS)
A standard predictive baseline for yield:

$$\hat{y} = X\beta$$

Where:

- $X \in \mathbb{R}^{n\times p}$ features (rainfall, pH, N, P, K, etc.)
- $\beta \in \mathbb{R}^{p}$ coefficients
- $y \in \mathbb{R}^{n}$ observed yields

Define squared-error objective:

$$J(\beta) = \| y - X\beta \|^2 = (y - X\beta)^\top (y - X\beta)$$

Expand:

$$J(\beta) = y^\top y - 2\beta^\top X^\top y + \beta^\top X^\top X\beta$$

Differentiate w.r.t. β:

$$\nabla_\beta J(\beta) = -2X^\top y + 2X^\top X\beta$$

Set gradient to zero for optimum:

$$-2X^\top y + 2X^\top X\beta = 0$$

Divide by 2:

$$X^\top X\beta = X^\top y$$

If $X^\top X$ is invertible:

$$\boxed{\beta = (X^\top X)^{-1} X^\top y}$$

VII. EVALUATION FRAMEWORKS AND EVIDENCE

Proposed decision-support systems and their components must be evaluated according to how they contribute to the twin objectives of increasing agricultural productivity and fostering environmental and societal sustainability. Towards this aim, appropriate sets of evaluation metrics must be chosen from the literature, followed by the consideration of a framework and methodology for putting them into practice. For metrics to be relevant, they need to capture the interconnections between decisions made by multiple stakeholders across multiple scales and their overall impact. Consequently, they need to represent the cumulative effects of local decisions on ecosystem services and on crop production, including indirect interactions between agriculture and its environment. The model base supporting the metric candidates must combine necessary data from sufficiently many crops, countries and years to encompass the diverse possible dependency structures. Additional refinements may consider human resources and other factors in the process of augmenting agricultural quantity and quality.

Specific frameworks and methodologies also need to be worked out for the detailed evaluation of specific components of these complex systems. Specifically, structurally-dynamic modeling experiments designed in accordance with the general principles of resilience display clear vulnerability and resilience signatures within the framework of ecological sustainability and product quality in agriculture, and reveal those zones of ratios where land-use optimization is possible. Other methodologies validate decision workflows by investigating the cyber vulnerability of a whole supply chain to malicious attacks from both outside and inside.

Decision-Workflow and Automation Validation Methodology
The validation of orchestrated decision workflows and their constituent automation tools follows two lines of evidence: (a) evaluation of the decision-automation tools against their specifications and (b) demonstration of the proper integration and execution of the decision workflow by an ensemble of tools, together with appropriate test scenarios. The automation pattern relies on the notion of a toolbox, defined as a composable application component designed to fulfil a specific task (leading to an output) without relying on reusable state information. Workflows integrate multiple toolboxes into a

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pipeline, coordinating their execution to achieve a common goal, and running from receiving to delivering information without maintenance between those points.

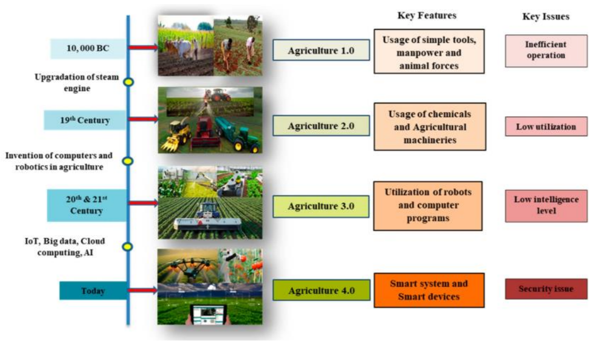

Fig 4: Evaluation Frameworks and Evidence

7.1. Metrics for Sustainability and Productivity: A comprehensive set of quantitative measures addresses local and global sustainability and productivity targets. Immense slaughtering emissions coupled with narrow virtuous cycles and poor alternative utilization of agricultural by-products and waste suggest a growing risk of meat consumption in excessive levels. Reducing red and increasing white and cultivated meat consumption are among the UN Sustainable Development Goals. Efficient allocation of intensive and extensive production can minimize food-borne outbreaks and the consequent economic losses. Deep learning meta-modeling of air pollution influences can improve early warning and risk assessment. Beef and milk production over a country's carrying capacity endanger the territory's sustainability. Input–output analysis of the economic and environmental sustainability of the alfalfa system quantifies the trade-off between high yield, high water consumption and environmental threats to surface and underground water.

Sustainability assessment of the whole grain supply chain ensures that economic benefits are mutually shared among consumers, producers, and the environment. Increased concentration of different fertilizers on coastal regions provides a scientific basis for the reasonable application of fertilizers. Modelling and downscaled scenario simulations of CO2 emissions originating from biodiversity loss reinforce the importance of biodiversity conservation for climate change mitigation and sustainable development. Ecological adaptation is paramount for the cultivation of ethanol from auxiliary crops of maize. Stakeholders' engagement and cocreation of knowledge with end users are fundamental to improve the quality of products. A deep learning approach to assess the suitability of environmental conditions in agricultural systems integrates multiple data sources and models using automated programming processes supporting prediction and policy making.

7.2. Validation Methodologies: The challenge of providing evidence of the sustainability and productivity of the actions supported by the AI system is most easily dealt with at the highest level of the decision-support hierarchy associated with high-level forecasting, validation of predictive models and risk-assessment tools, as well as the output at the centre of these hierarchies. High-level forecasting is directed at validation, and depending on either of two extremes, predict-and-validate (the prediction proceeds for individual fields without being directed by model suggestions, and subsequently compared to actual outcome) or validate-then-predict (predictive model modules are validated by prediction at the final location, and if they validated as suitable, are subsequently directed by model suggestions for the predict task), it requires either a longer period with less user confidence, or a shorter period with more user confidence respectively. These high-level forecasts also serve as the basis for assessing risk and recommending operational responses, which are designed to enhance resilience and reduce the impact of adverse conditions.

The measures to improve the productivity of the AI decision-support system likewise are primarily associated with either high-risk or low-risk/high-return operational tasks. For high-risk tasks, the foundations for enhancing productivity are the decisions of whether and when to establish the crop, and which variety to use. For the low-risk/high-return tasks, the issue is the timing of operations such as fertilising, pest control, and harvesting; it is these that are generally modelled in detail by crop-modelling approach to yield forecasting, and validated in advance for these extensions into the routine operational domain. Validation of these prediction and decision-support modules delivers measures of their productivity-enhancing capacity.

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VIII. CONCLUSION

The transformation of agriculture into a data-driven industry for improved sustainability, productivity, and resilience offers both opportunities and challenges, with emerging technologies promising to support these objectives. These technologies include: Big Data Analytics, enabling effective extraction, reconciliation, and integration of massive data sources; Predictive Modeling and Risk Assessment for Decision Support, supporting the efficient identification of future states, risks, and opportunities for the agricultural value chain; and Workflow Automation, helping orchestrate decision workflows and integrate machines, agents, and humans in decision operations. Combined, these technologies also facilitate decision-oriented systems, opening opportunities for a new generation of smart decision support systems (DSS) in AgriTech.

Recent developments highlight the growing importance of integrating technologies such as Artificial Intelligence (AI), Machine Learning (ML), Big Data Analytics, Predictive Modeling, and Robotics into a single cohesive system. Clearly specified operational workflows are essential if these technologies are to contribute optimally across/through fully Connected Telematics decision and operational ecosystems. Once integrated, these technologies will bring a whole new intelligent edge to the orchestration of diverse decision operations supporting productivity, quality, and sustainability.

8.1. Emerging Trends: Explosive advancements in Genomic Medicine and AI/ML/DL based biological research have been fuelled by overwhelming amounts of open-access data. The vertical perspective of technology enables faster & smarter prospection of data for training intelligent systems capable of successful bio-discovery. Expanding in the opposite perspective, i.e., the horizontal perspective, also using fundamental changes leveraging information, and finally enabling the generation of business from money, inability of presenting localized and micro-scaled services in heterogeneous situations remains a challenge.

Human socially-determined healthiness & quality of life depend on balance with nature, and thus on food and drinks. AgriTech investments to dispel environmental stressors and boost crop yield must focus on long-term sustainability rather than merely increasing actual production beyond nature's resilience limits. A Big Data Analytics for Decision Support Decision Support tool is emerging that, using multi-source data based Knowledge Management Service Orchestrator / Dispatcher Services Deployed KMS, extends four decisional capabilities: crop yield prediction; risk dispersion; supply chain liquidity mapping.

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