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Precision agrometeorology: Integrating AI and IoT for real-time agro-advisories

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Abstract
Precision agrometeorology leverages high-resolution weather and climate data through IoT sensor networks and advanced AI analytics to provide timely, site-specific farming advice. By combining in-situ microclimate sensors, remote sensing and cloud/edge computing, farmers can monitor soil moisture, temperature, humidity and crop health in real time. Machine learning and deep learning models analyze these data streams to forecast irrigation needs, pest and disease risk and yield outcomes. The AI-enhanced system enables adaptive management e.g., optimizing water and fertilizer use and issuing frost or storm alerts thus enhancing resource efficiency, productivity and climate resilience. Challenges include network connectivity in rural areas, data quality and interoperability, but emerging solutions (edge computing, federated learning, blockchain) are addressing them. This review outlines key IoT sensor technologies and AI methods (Table 1, Table 2), describes architectures for data flow from field to advisory (Figure 1) and discusses applications (Table 3, Table 4) and future directions for global precision agrometeorology.

Keywords: Precision agrometeorology, Internet of Things (IoT), Artificial Intelligence (AI), real-time advisories, Smart farming, machine learning, sensor networks

Introduction
Modern agriculture faces the dual pressures of rising global demand and increasing climatic variability [27]. Traditional farming methods, relying on calendar-based schedules and manual observation, often lead to inefficient resource use and vulnerability to weather extremes. In this context, *precision agrometeorology* the integration of precise weather/climate monitoring with site-specific farming offers a solution by tailoring management to local conditions [42]. Precision agriculture has evolved into "Agriculture 4.0, " characterized by networks of IoT sensors (soil probes, weather stations, UAVs) and data-driven decision systems. This paradigm shift enables real-time agro-advisories, where actionable guidance (e.g. irrigation schedules, pest alerts, frost warnings) is generated by analyzing live data with AI models [62].
IoT networks in fields collect fine-scale data on temperature, humidity, soil moisture, solar radiation and crop status, often segmenting large farms into management zones based on microclimate differences [63]. These high-resolution data supplement traditional meteorological observations and remote sensing (e.g. satellite or aerial imagery) to capture local variability [80]. Artificial intelligence (AI) methods including machine learning and deep learning process this data to forecast future conditions, detect anomalies and prescribe interventions. For example, convolution neural networks (CNNs) can identify disease symptoms from leaf images, while time-series models forecast soil moisture or temperature patterns [26]. The integration of IoT and AI thus transforms raw sensor readings into predictive analytics, enabling farmers to apply water, fertilizers and pesticides with unprecedented precision [43].
Integrating Artificial Intelligence (AI) and the Internet of Things (IoT) in agriculture represents a paradigm shift toward data-driven, precision farming practices [81]. By marrying ubiquitous sensor networks with advanced analytics, AIoT platforms enable real time monitoring and autonomous decision making in crop management [64]. This convergence enhances resource use

efficiency, reduces environmental impact and bolsters yields, addressing both food security and sustainability challenges facing modern agriculture [82].

The Internet of Things (IoT) refers to interconnected devices sensors, actuators, cameras that continuously collect and transmit data over networks to centralized or cloud based platforms for storage and basic preprocessing. Artificial Intelligence (AI), in this context, encompasses machine learning (ML) and deep learning algorithms that analyze these vast data streams to detect patterns, predict outcomes and generate prescriptive advisories [83]. When integrated, AI and IoT (often termed "AIoT") create a closed loop system whereby sensor inputs drive AI models, which in turn issue control signals or recommendations to farming equipment and management platforms [65]. This synergy forms the backbone of precision agriculture, enabling site specific management of irrigation, fertilization, pest control and harvest timing. In the United States, the NSF funded IoT4Ag research center exemplifies real world AIoT adoption [28]. Researchers have developed biodegradable leaf and soil sensors that continuously monitor nutrient levels, moisture content and microclimatic conditions [44]. These low cost devices relay data via ground based robots and drones into cloud dashboards, where ML models identify nutrient deficiencies or disease onset up to two weeks before visible symptoms. Early adopters report up to a 15% increase in yield and a 20% reduction in water use, underscoring the economic and environmental benefits of AIoT deployments [1].

Another compelling example is the integration of AI IoT platforms for hyper local weather forecasting [23]. Scientist proposed a layered AIoT framework comprising data acquisition, storage, processing, application and decision making tiers. Field deployed weather stations equipped with temperature, humidity and barometric sensors feed high resolution data into neural network based forecasting models. Farmers receive optimized irrigation and planting advisories via mobile apps, which have been shown to reduce crop losses from unexpected weather events by up to 30% in pilot deployments across India's semi arid regions [24]. Beyond traditional IoT, the concept of the Internet of Everything (IoE) extends connectivity to molecular and bio nano scale devices. They articulate how IoE sub domains such as the Internet of Nano Things (IoNT) and the Internet of Fungus (IoF) can monitor plant biochemical signals and soil microbiome dynamics. When coupled with AI driven pattern recognition, these systems promise unprecedented precision in nutrient delivery and disease detection at the cellular level, potentially transforming greenhouse and vertical farming operations [25]. The fusion of AI and IoT yields multiple agronomic advantages. Sensor based soil moisture probes, pH meters and spectral cameras generate continuous datasets that AI algorithms translate into actionable insights optimizing irrigation schedules, nutrient management and pest control interventions. Studies demonstrate yield improvements of 1020% and input cost reductions of up to 25% in AIoT equipped fields compared to conventional management. Despite demonstrated benefits, widespread AIoT adoption faces hurdles [29]. Connectivity gaps in rural areas limit real time data transmission, while high upfront costs deter smallholders. Moreover, data privacy, cyber security and digital skill deficits among farming communities present significant barriers. Addressing these challenges requires public private partnerships, affordable network infrastructure (e.g., LoRaWAN, 5G) and farmer training programs. Standardization efforts such as open source IoT platforms and interoperable data schemas will be critical to scale AIoT solutions globally. Integrating AI and IoT in agriculture is no longer a futuristic vision but a present day reality reshaping farm management [45]. Through case studies like IoT4Ag's biodegradable sensors and AI powered weather forecasting, we see tangible gains in yield, resource efficiency and risk mitigation [93]. As IoE and AI model sophistication advance, economies of scale and supportive policy frameworks will be essential to ensure these transformative technologies benefit small and large farms alike, driving a more resilient and sustainable global food system. Figure 1 illustrates a conceptual architecture of a precision agrometeorology system [84]. In practice, multiple sensing technologies feed data into gateways and networks (LoRaWAN, cellular, satellite), which relay information to cloud or edge computing platforms [2]. AI analytics produce insights and generate advisories, delivered via mobile apps, SMS or dashboards. This closed-loop system continuously monitors environmental factors and updates recommendations in near real time [66]. The subsequent sections discuss the components of such systems in detail (IoT hardware, AI models, data flow) and review recent scientific advances supporting real-time agricultural advisories. All claims are grounded in recent literature on smart farming technologies [30].

Precision Agrometeorology: Scope and Data Sources

Agrometeorology traditionally studies the interactions between weather, climate and agriculture. *Precision agrometeorology* extends this by using fine-grained measurements and analytics to tailor advice to specific fields or even zones within fields [22].

Data sources include

(a) Ground-based weather stations and automated micro-weather sensors (recording rainfall, temperature, humidity, wind, solar radiation),
(b) Soil sensors (soil moisture, temperature, nutrient content),
(c) Crop-monitoring platforms (drones, UAVs, tractor-mounted cameras capturing plant health and growth), and
(d) External forecasts/models (numerical weather predictions, satellite remote sensing of vegetation indices). These multimodal data capture the "state" of the farm ecosystem [31].

Satellite and UAV imagery provide periodic overviews (NDVI, LAI maps), while IoT devices provide continuous local data. For example, an agro meteorological IoT station may include temperature/humidity probes, a tipping-bucket rain gauge and soil moisture sensors, all connected wirelessly [85, 92]. Networks of these stations often one per management zone can reveal microclimates across a farm. In Brazil, for instance, researchers deployed a sensor network to monitor climate factors by management zone, noting that "climate factors directly influence yield at each stage" [67]. By capturing microclimates, such precision monitoring informs zone-specific fertilization or irrigation, maximizing yield potentials [3].

Table 1 summarizes common sensor types and their roles in agrometeorology. Temperature, humidity, wind and solar sensors typically use weather station setups, soil probes measure volumetric water content and nutrients, plant health is accessed via optical or multispectral cameras. Together, they enable continuous environmental monitoring. The IoT connectivity layer (e.g. LoRaWAN, NB-IoT, satellite) ensures that data flows reliably even in remote areas (though connectivity remains a challenge in many rural regions) [21, 32].

Fig 1: Integrating IoT sensors and smart data analytics in precision farming. IoT devices (bottom) measure environmental variables and crop status, while AI/analytics (center) generate advisories (top). Sensors depicted include soil moisture probes, weather station, drones, cameras.

Table 1: IoT sensors and data parameters for precision agrometeorology [90, 91].

Sensor/Device	Measured Data	Purpose	Example Network
Ambient weather station	Air temperature, humidity, rainfall, wind speed, solar radiation	General climate monitoring, frost/flood warnings	GPRS/LoRaWAN
Soil moisture probe	Volumetric water content	Optimize irrigation scheduling, drought alerts	LoRaWAN, 5G
Soil nutrient sensor	Soil N-P-K levels, pH	Fertilizer management, nutrient deficiency alerts	NB-IoT
Plant health camera/UAV	Multispectral images (NDVI, RGB)	Crop growth, biomass/yield estimation, disease/pest detection	Wi-Fi/5G/LPWAN
Humidity/leaf wetness	Leaf wetness index	Disease outbreak prediction (e.g., fungal risk)	ZigBee, LoRa
On-board machinery GPS	Tractor position, variable-rate seeding/appl. logs	Mapping management zones, yield mapping	ISOBUS, Bluetooth
Satellite sensors	Meteorological forecasts, vegetation indices	Macro-weather forecasts, stress indices	Satellite link

IoT Networks and Data Infrastructure

The IoT infrastructure forms the backbone of precision agrometeorology. Field sensors must reliably transmit data, often over unlicensed or cellular networks [20, 89]. Technologies like LoRaWAN, NB-IoT or low-cost GSM modules are common for rural connectivity [4]. Data are typically aggregated at on-field gateways or edge devices which may perform initial pre-processing [46]. As summarized in Table 1, sensing layers feed data into multi-tier architectures. Architecturally, data can be processed at various layers (edge, fog, cloud). Edge computing (e.g. a local Raspberry Pi or smart gateway) allows immediate analytics and compression near the source, mitigating latency and bandwidth issues. For example, an edge device could run a lightweight AI model to detect soil moisture anomalies and trigger local irrigation control [47]. More sophisticated processing (deep neural network training, multi-sensor fusion) typically occurs in the cloud, where scalable resources and data stores reside [68]. Cloud platforms facilitate integration of heterogeneous data (e.g. public weather forecasts, satellite imagery, field sensor logs) and support machine learning pipelines [33, 88].

Table 2 compares key architectural choices. Cloud-centric systems offer high computational power and easy scalability, at the cost of dependency on network uplink and data privacy concerns. Edge-focused designs reduce bandwidth and allow local autonomy (critical during connectivity outages), but may be limited by device resources [48]. A hybrid approach is emerging: initial processing at the edge, with aggregated features sent to cloud AI models for deep analysis. In any case, data security and interoperability are essential considerations, blockchain and standardized schemas are being explored to ensure trust and seamless data exchange across vendors and platforms [69].

AI and Analytical Methods

Artificial intelligence lies at the core of generating actionable advisories from raw IoT data. Recent reviews highlight the growing use of machine learning (ML) and deep learning (DL) in agrometeorology [19]. ML models ingest historical and real-time data to learn patterns and predict outcomes. For instance, supervised methods such as Random Forests, Support Vector Machines (SVMs) and Convolution Neural Networks (CNNs) are widely applied to tasks like yield estimation, irrigation scheduling and disease detection. Unsupervised techniques (clustering, anomaly detection) identify unusual sensor readings that may indicate equipment failure or emerging threats [70].

Weather and Yield Forecasting

Agro meteorology critically involves predicting weather impacts on crops. Numerical Weather Prediction (NWP) models provide regional forecasts, but AI models can downscale and bias-correct these forecasts for local conditions [71]. Transformer networks and auto encoders have been used to enhance spatial resolution of temperature, precipitation and humidity forecasts for farms [49]. AI-driven ensembles combine satellite data, local station readings and crop growth models. For example, one study used CNNs with regional climate data to forecast sub-national crop yields weeks ahead, achieving error reductions of ~5% compared to no-AI forecasts. AI-based weather forecasting thus enables adaptive decisions: farmers can adjust irrigation or apply frost protection if a cold snap is predicted [34].

Irrigation and Water Management

Soil moisture prediction and irrigation scheduling are among the most mature AI applications. Models trained on historical rainfall and sensor data can predict soil moisture several days ahead [18]. Real-time moisture sensors, combined with irrigation control, form closed-loop smart irrigation. For example, AI-augmented drip irrigation systems use sensor networks to detect which zones are dry, then automatically activate valves only where needed [72]. Table 2 lists common AI methods by application. Deep neural nets and LSTM recurrent networks are especially useful for multi-step time series predictions (soil moisture, evapotranspiration). Rule-based and fuzzy logic systems also exist for straightforward advisory logic (e.g., if soil moisture < threshold then irrigate) [5].

Pest and Disease Alerts

Integrated pest management benefits from AI-powered early warning. Historical models relate pest lifecycles to weather patterns, but now image-based detection is possible [73]. Farmers can use IoT cameras or drone imagery analyzed by CNNs to spot pest outbreaks or leaf diseases (downy mildew, blight) as soon as symptoms appear. When combined with weather data (humidity and temperature conditions), predictive models can issue warnings days before pests reach damaging levels [50]. The system might alert: *"Risk of late blight is high in 48 hours under predicted dew formation, apply fungicide."* This anticipatory advisory relies on both sensor data and learned relationships in the AI models.

Fertilization and Nutrient Management

AI can optimize fertilization by interpreting soil and plant data. Spectral imaging reveals nutrient stress (e.g., low nitrogen causing yellowing), which AI algorithms translate into variable-rate fertilizer maps [74]. Coupled with IoT soil nutrient sensors, systems can dynamically adjust fertilizer application [51]. For instance, if a local sensor reports declining nitrogen, the advisory system may schedule an additional fertilization in that zone. Such precision fertilization reduces waste and runoff [35].

Decision Support Systems (DSS)

The end product of AI analytics is a farmer-facing advisory. Modern DSS platforms compile model outputs into user-friendly recommendations. Cloud-based dashboards and smart phone apps present key metrics (soil moisture, expected rainfall) and prescribe actions (Figure 1) [17]. Studies emphasize that these platforms must be intuitive and adaptive to farmer inputs. Some systems allow farmers to input goals or constraints (e.g. "water budget", "organic-only treatments") and then use AI to generate a plan. Research shows IoT-DSS platforms providing real-time alerts via SMS or mobile app significantly improve on-time interventions (e.g., irrigation right when needed) [6, 86].

Table 2: AI/ML methods and their applications in precision agrometeorology.

Application Area	AI/ML Model(s)	Input Data	Output/Purpose
Weather forecasting	LSTM, Transformer, CNN	NWP data + local sensors	Local weather predictions
Soil moisture prediction	LSTM, SVM, ensemble trees	Past moisture, rainfall	Irrigation scheduling
Crop yield estimation	CNN, RF, regression	Time series & imagery	Yield forecasting (weeks ahead)
Pest/disease detection	CNN, Vision Transformer	Field images, weather	Early pest/disease alerts
Nutrient management	KNN, Decision Trees, ANN	Soil NPK sensors, imagery	Variable-rate fertilization plans
Anomaly detection	Clustering, Autoencoder	Sensor network streams	Fault detection (sensor/crop health)
Farm-level DSS	Rule-based, fuzzy logic, AIoT	Synthesized data	Actionable advisories (alerts)

System Architecture and Data Flow

A typical real-time advisory system involves multiple integrated layers (Figure 1). Data flow (Figure 2) starts at the field sensors (data layer), moves through communication gateways, into cloud/edge servers (processing layer) and ends with user interfaces (application layer). Figure 1 depicted an abstract flow, we now detail each component [52].

At the sensing layer, myriad IoT devices continuously sample environmental variables (see Table 1). Sensor data are tagged with timestamps and GPS locations. Data may first be collected by on-site controllers (e.g. Arduino or industrial PLC) which apply initial filtering (noise removal, outlier rejection) [75, 85].

The communication layer ensures reliable transmission. Common protocols include LoRaWAN for low-power wide-area networking, NB-IoT or LTE for broader coverage and even satellite for very remote areas. Farmers may use local gateways (solar-powered if off-grid) that connect via GSM to data centers. In well-connected areas, Wi-Fi or 5G can support high-bandwidth streams (e.g. drone imagery) [36].

The processing layer consists of edge and cloud computing. On the edge (field gateway or farm computer), lightweight analytics (e.g. simple threshold checks, basic ML inferencing) enable immediate actions (like shutting off an irrigation valve) [16]. Edge computing also helps in data compression and encryption before sending to the cloud. The cloud platform aggregates data from many sources (sensors, satellites, external weather services) into big data lakes. There, advanced AI pipelines run: cleaning, model training, forecasting and DSS logic. Containerized AI models and services (e.g., TensorFlow or PyTorch deployments) process data in near real-time [54]. Importantly, the system closes the loop. Feedback and actuation may occur: e.g. cloud-issued irrigation commands sent back to field actuators (valves, pivot systems) in an automated controlled loop [76]. Alternatively, advisories are sent to farmers or agronomists through mobile apps or SMS. The APIs of advisory apps translate complex recommendations into clear messages (e.g. "Apply 30 mm irrigation in Zone A before midnight") [7, 53].

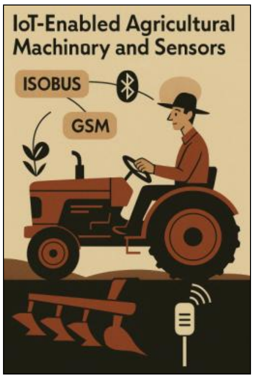

Fig 2: IoT-enabled agricultural machinery and sensors. Modern farm equipment (tractors, implements) are connected via networks like ISOBUS, Bluetooth and GSM to exchange data

Table 3: Comparison of IoT computing architectures for agro meteorology [83, 84].

Architecture Type	Description	Advantages	Limitations	Use Case Example
Cloud-centric	Sensors → Cloud via gateway, all processing in cloud	Unlimited compute, easy updates, multi-farm analytics	Needs strong connectivity, latency may be high	Regional yield forecasting, long-term climate analysis
Edge-centric	Local processing (gateways/controllers), selective cloud sync	Low latency, works offline, data privacy	Limited compute/storage, update complexity	Immediate irrigation control, on-board vehicle control
Hybrid (Fog)	Edge pre-processing + cloud for heavy tasks	Balance of latency and power, resilient operations	More complex design and maintenance	Real-time pest detection (edge) + seasonal forecasting (cloud)
Distributed (Blockchain-federated)	Peer-to-peer data sharing, local AI models	Data ownership control, secure sharing	Emerging tech, integration overhead	Cross-farm data sharing, community advisories

Real-Time Agro-Advisories and Decision Support

The ultimate goal of precision agrometeorology is actionable advice for farmers and stakeholders [15]. Real-time advisories span a range of decision contexts, as illustrated in Table 4. These are typically delivered via mobile applications, text messages or embedded tractor dashboards. For example, a system might push a *"Frost Alert"* when overnight temperatures are predicted to drop below crop tolerance or an *"Irrigation Notice"* when soil moisture falls under a threshold [37].

Key advisory domains include

- **Irrigation management:** Combining weather forecasts and soil moisture, the system advises when and how much to irrigate. This prevents both drought stress and water logging. For instance, if no rain is expected and soil moisture is low, an alert may suggest a specific volume of water for each field zone [55].
- **Nutrient management:** Based on soil nutrient sensors and growth stage models, advisories suggest fertilizer timing and rates. For example, if a crop is entering rapid vegetative growth and soil nitrogen is low, the alert might recommend top-dressing nitrogen [77].
- **Pest/disease risk:** When conditions favour pest outbreaks (e.g. warm, humid weather for fungal diseases), the system sends pest or disease risk alerts. These alerts often include recommended interventions (e.g. particular biocontrol agents or pesticides) [78, 82].
- **Harvest and planting scheduling:** Phenology models and yield forecasts help time planting or harvesting. An advisory might warn of an upcoming high-heat event that could damage flowering crops, prompting an earlier harvest. Or it might estimate optimal sowing dates based on future rainfall predictions [8].
- **General weather warnings:** Alerts for extreme events (storms, heavy rain, frost) help farmers take protective actions (reinforce structures, deploy frost fans or schedule irrigation to prevent soil compaction) [56].

These advisories are supported by the decision support systems (DSS) that weigh economic and risk factors. For instance, an advisory system may compute the cost-benefit of applying a fungicide given the predicted disease pressure and market prices. Such ROI analysis is increasingly built into AI-driven platforms [38].

Table 4: Examples of real-time agro-advisory services enabled by AI+IoT [13, 14].

Advisory Type	Trigger Data	Recommended Action	Benefit/Outcome	Typical Delivery
Frost warning	Air temp < 2°C prediction	Deploy frost fans/sprinklers or cover crops	Protects sensitive crops from freeze damage	Mobile alert, SMS
Irrigation schedule	Soil moisture < 30% + no rain expected	Apply 20 mm water to Zone A	Maintains yield, conserves water	App dashboard alert
Pest outbreak alert	High humidity + warm night, pest models	Scout fields and apply biological control	Early control, reduced yield loss	SMS/email
Nutrient deficiency	Low leaf N index or soil N sensor	Top-dress 50 kg/ha N fertilizer	Optimized input use, prevents stall	Push notification
Harvest timing	Nearing crop maturity window + forecast	Plan harvest within 3 days	Maximize quality, avoid losses	App calendar note

Implementation Considerations and Case Examples

Numerous pilot projects and research efforts globally demonstrate precision agrometeorology in action. While many are region-specific, the underlying principles are general [9]. For instance, India's AgriTechnology programs have used IoT weather stations and AI to issue SMS advisories to smallholder farmers, enhancing climate resilience. In the Midwest US, research combines regional climate models with crop simulations to forecast yields weeks in advance, enabling market and policy planning [12]. An interdisciplinary European network (e.g. the AgDataBox-IoT initiative) has developed open-source IoT platforms for microclimate monitoring that feed into cloud DSS. These examples illustrate the technology, though specific weather regimes or crops vary, the system architectures and algorithms are adaptable worldwide [39].

In practice, deployments must be tailored to user needs and contexts. Smallholder systems may rely on SMS or interactive voice response to reach farmers, whereas large commercial farms use tablet apps and automated equipment integration [57]. Figure 1's architecture can be scaled: a hobby farm may have a single gateway and cloud service, while a large enterprise might have an on-premise server farm with private 5G. The key is that the same principles of IoT sensing and AI processing apply at all scales. Table 3's hybrid model, for example, is common: a research project found that "smallholder farms adopt simpler, in situ sensing" while "large farms benefit from high-resolution satellite/UAV data" [58].

Importance and benefits

The integration of AI and IoT in precision agrometeorology holds transformative promise but also faces challenges. Connectivity and infrastructure are major concerns: many productive agricultural regions lack reliable broadband or power [59]. Solutions include energy-efficient protocols (LoRaWAN), low-power sensors and solar-powered nodes. Data quality and standardization are crucial: sensors can drift and without calibration the AI outputs degrade. Interoperability between sensor brands and data formats is an ongoing hurdle, semantic web frameworks and common data schemas are being developed to alleviate this [10].

Model generalization and explainability are also topics of research. AI models trained in one climate zone may not directly transfer to another. Ongoing model training with local data and use of federated learning (where models learn from distributed data without sharing raw data) are emerging best practices. Additionally, stakeholders often require interpretability ("why did the system advise this action?"). Hybrid approaches that combine statistical models (which are more interpretable) with AI are being explored [40].

Socio-economic and policy aspects are equally important. Machine-driven advisories assume that farmers trust and act on them. Building user-friendly interfaces and providing extension training are essential for adoption. Studies have noted that digital advisory tools have varied adoption rates in the Global South due to factors like literacy and cost [79]. Ensuring equitable access for example, using languages and platforms familiar to local farmers is critical [60]. On the policy side, governments are starting to support agromet services, for instance, national weather agencies are integrating their forecasts with farm-level platforms. Moreover, issues of data ownership and privacy surface when private companies are involved in data platforms. Ethical frameworks recommend that farmers retain ownership of their field data and benefit from any aggregated analytics [61].

Finally, emerging technologies promise to enhance the integration further. Edge-AI chips on sensors, blockchain for secure data exchange and swarm robotics (multiple drones) for rapid field surveys are under development. As computing power becomes ubiquitous, the vision is a fully autonomous smart farm that continuously senses, learns and advises in a closed loop, significantly reducing the decision-making burden on farmers while optimizing productivity and sustainability [11, 41].

Conclusion

Precision agrometeorology leverages the synergy of IoT and AI to provide real-time, site-specific agro-advisories, fundamentally improving decision-making in agriculture. By deploying dense sensor networks and applying sophisticated analytics, these systems transform diverse environmental and crop data into actionable guidance from irrigation scheduling to pest alerts thereby maximizing resource efficiency and resilience to climate variability. The literature shows that such technologies can boost yields, conserve water and reduce input waste. While technical and social challenges remain (connectivity gaps, data privacy, user adoption), continuous innovations in edge computing, federated AI and affordable sensor hardware are lowering barriers. Looking forward, the integration of precision agrometeorology into mainstream farming will require interdisciplinary effort: agronomists, meteorologists, data scientists and policymakers must collaborate. Global-scale platforms that combine local IoT data with satellite and weather model outputs could support crop forecasting and food security planning. Equally, farmer-centric design will ensure that advisories are practical and trusted. In sum, the convergence of IoT and AI in agrometeorology represents a key pillar of sustainable agriculture, enabling proactive management and steering global farming toward higher productivity with lower environmental impact.

References

1. Abdulraheem MI, Zhang W, Li S, Moshayedi AJ, Farooque AA, Hu J. Advancement of remote sensing for soil measurements and applications: A comprehensive review. Sustainability. 2023;15:15444. doi:10.3390/su152115444
2. Abioye AE, Abidin MSZ, Mahmud MSA, Buyamin S, Mohammed OO, Otuoze AO, *et al*. Model based predictive control strategy for water saving drip irrigation. Smart Agric Technol. 2023;4:100179. doi:10.1016/j.atech.2023.100179
3. Afzaal H, Farooque AA, Abbas F, Acharya B, Esau T. Precision irrigation strategies for sustainable water budgeting of potato crop in Prince Edward Island. Sustainability. 2020;12:2419. doi:10.3390/su12062419
4. Aggarwal S, Verma A. Transformations in the ways of improving from agriculture 1.0 to 4.0. In: 2022 5th International Conference on Contemporary Computing and Informatics (IC3I); 2022. p. 170-4.
5. Ahmad SF, Dar AH. Precision Farming for Resource Use Efficiency. In: Kumar S, Meena RS, Jhariya MK, editors. Resources Use Efficiency in Agriculture. Springer; 2020. doi:10.1007/978-981-15-6953-1_4
6. Akbar JUM, Kamarulzaman SF, Muzahid AJM, Rahman MA, Uddin M. A comprehensive review on deep learning assisted computer vision techniques for smart greenhouse agriculture. IEEE Access. 2024. doi:10.1109/ACCESS.2024.3349418
7. Akhigbe BI, Munir K, Akinade O, Akanbi L, Oyedele LO. IoT technologies for livestock management: a review of present status, opportunities and future trends. Big Data Cogn Comput. 2021;5:10. doi:10.3390/bdcc5010010
8. Bollero GA, Bullock DG, Hollinger SE. Soil temperature and planting date effects on corn yield, leaf area and plant development. Agron J. 1996;88:385-90. doi:10.2134/agronj1996.00021962008800030005x
9. Borgogno Mondino E, Gajetti M. Preliminary considerations about costs and potential market of remote sensing from UAV in the Italian viticulture context. Eur J Remote Sens. 2017;50:310-9. doi:10.1080/22797254.2017.1328269
10. Botta A, Cavallone P, Baglieri L, Colucci G, Tagliavini L, Quaglia G. A review of robots, perception and tasks in precision agriculture. Appl Mech. 2022;3:830-54. doi:10.3390/applmech3030049
11. Burton L, Jayachandran K, Bhansali S. Review The "Real-time" Revolution for in situ soil nutrient sensing. J Electrochem Soc. 2020;167:37569. doi:10.1149/1945-7111/ab6f5d
12. Burton L, Jayachandran K, Bhansali S. The "Real-Time" revolution for in situ soil nutrient sensing. J Electrochem Soc. 2020;167:037569. doi:10.1149/1945-7111/ab6f5d
13. Childs PRN, Greenwood JR, Long CA. Review of temperature measurement. Rev Sci Instruments. 2000;71:2959-78. doi:10.1063/1.1305516
14. Chin R, Catal C, Kassahun A. Plant disease detection using drones in precision agriculture. Precis Agric. 2023;24:1663-82. doi:10.1007/s11119-023-10014-y
15. Chlingaryan A, Sukkarieh S, Whelan B. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. Comput Electron Agric. 2018;151:61-9. doi:10.1016/j.compag.2018.05.012

16. Anushi AK, Ghosh PK. From seed to succulence: Mastering dragon fruit propagation techniques. J Plant Biota. 2024.
17. Yashasvi GN, Tripathi DV, Awasthi V, Anushi A. Impact of PSB and Vermicompost on Growth, Yield and Quality of Strawberry. Dr VK and Awasthi, Vineet and Anushi, Anushi, Impact of PSB and Vermicompost on Growth, Yield and Quality of Strawberry. 2022.
18. Anushi BPS, Sachan K. Bioformulation: A new frontier in horticulture for eco-friendly crop management. J Plant Biota. 2024.
19. Christy CD, Drummond P, Laird DA. An on-the-go spectral reflectance sensor for soil. In: 2003 ASAE Annual Meeting. American Society of Agricultural and Biological Engineers; 2003. p. 1.
20. Crioni PLB, Teramoto EH, da Cunha CF, Kiang CH. Evaluation of the OPTRAM using sentinel-2 imagery to estimate soil moisture in urban environments. Rev Bras Geogr Física. 2025;18:605-21. doi:10.26848/rbgf.v18.1.p605-621
21. da Silveira FD, Amaral FG. Agriculture 4.0. In: Zhang Q, editor. Encyclopedia of Smart Agriculture Technologies. Springer; 2022. doi:10.1007/978-3-030-89123-7_207-1
22. Ehsani MR, Upadhyaya SK, Slaughter D, Shafii S, Pelletier M. A NIR technique for rapid determination of soil mineral nitrogen. Precis Agric. 1999;1:219-36. doi:10.1023/A:1009916108990
23. Evans D. The internet of things. How the Next Evolution of the Internet is Changing Everything. Whitepaper, Cisco Internet Business Solutions Group (IBSG). 2011;1:1-12.
24. Evett SR, O'Shaughnessy SA, andrade MA, Kustas WP, anderson MC, Schomberg HH, *et al*. Precision agriculture and irrigation: Current US perspectives. Trans ASABE. 2020;63:57-67. doi:10.13031/trans.13355
25. Farooqui NA, Haleem M, Khan W, Ishrat M. Precision agriculture and predictive analytics: enhancing agricultural efficiency and yield. In: Intelligent techniques for Predictive Data Analytics. New Jersey, US; 2024. p. 171-88.
26. Fauziah NO, Fitriatin BN, Fakhrurroja H, Simarmata T. Enhancing soil nutritional status in smart farming: the role of IoT-based management for meeting plant requirements. Int J Agron. 2024;2024:8874325. doi:10.1155/2024/8874325
27. Fraser EDG, Campbell M. Agriculture 5.0: reconciling production with planetary health. One Earth. 2019;1:278-80. doi:10.1016/j.oneear.2019.10.022
28. Freeman PK, Freeland RS. Agricultural UAVs in the US: potential, policy and hype. Remote Sens Appl. 2015;2:35-43.
29. Anushi VK, Shukla P. Influence of biostimulants and organic mulch on soil microbial population in strawberry (*F.× ananassa* Dutch.).
30. Anushi RM, Deshmukh RN, Sharma R. From DNA to Deliciousness: A Journey into Molecular Markers in Fruits.
31. Anushi SS, Krishnamoorthi A, Kumar S, Pareta P, Kalaiselvi P, Sinha G, *et al*. Biotech bounty on verge: gm (genetically modified) crops and the science of sustainable agriculture and horticulture.
32. Anushi M, Jain S, Sharma R, Thapliyal V. The Horticulture Encyclopedia.
33. Anushi FD, Krishnamoorthi A, Singh V. Enhancing Sustainable Food Systems Through the Cultivation of Nutrient-Rich Crops: Millets.
34. Anushi SJ, Sharma R, Thapliyal V, Behera SD. Fron tiers in Crop Im prove ment. Volume 11 Special Issue III July 2023. 2023:1668.
35. Galieni A, D'Ascenzo N, Stagnari F, Pagnani G, Xie Q, Pisante M. Past and future of plant stress detection: an overview from remote sensing to positron emission tomography. Front Plant Sci. 2021;11. doi:10.3389/fpls.2020.609155
36. Gómez Romero CD, Díaz Barriga JK, Rodríguez Molano JI. "Big data meaning in the architecture of IoT for smart cities. In: Data Mining and Big Data: First International Conference, DMBD 2016. Springer; 2016. p. 457-65.
37. Guerrero A, De Neve S, Mouazen AM. Current sensor technologies for in situ and on-line measurement of soil nitrogen for variable rate fertilization: A review. Adv Agron. 2021;168:1-38. doi:10.1016/bs.agron.2021.02.001
38. Gupta M, Abdelsalam M, Khorsandroo S, Mittal S. Security and privacy in smart farming: Challenges and opportunities. IEEE Access. 2020;8:34564-84. doi:10.1109/Access.6287639
39. Han R. Application of inertial navigation high precision positioning system based on SVM optimization. Syst Soft Comput. 2024;6:200105. doi:10.1016/j.sasc.2024.200105
40. Hashim NMZ, Mazlan SR, Abd Aziz MZA, Salleh A, Jaâ AS, Mohamad NR. Agriculture monitoring system: a study. J Teknol. 2015;77. doi:10.11113/jt.v77.4099
41. Hassanpour R, Zarehaghi D, Neyshabouri MR, Feizizadeh B, Rahmati M. Modification on optical trapezoid model for accurate estimation of soil moisture content in a maize growing field. J Appl Remote Sens. 2020;14:34519. doi:10.1117/1.JRS.14.034519
42. Anushi VK, Awasthi V, Yashasvi GN. Frontiers in Crop Improvement. VOLUME 9 SPECIAL ISSUE-III 2021 AUGUST. 2021:1026.
43. Anushi SJ, Krishnamoorthi A, Singh SK. Cultivating Tomorrow: Precision Agriculture and Sustainable Crop Production.
44. Anushi TV, Awasthi V, Yashasvi GN. Impact of pre-harvest application of plant bio-regulators and micronutrients on fruit retention, yield and quality of Mango (*Mangifera indica* L.). Frontiers in Crop Improvement. 2021;9(3):1026-30.
45. Jahn BR, Linker R, Upadhyaya SK, Shaviv A, Slaughter DC, Shmulevich I. Mid-infrared spectroscopic determination of soil nitrate content. Biosyst Eng. 2006;94:505-15. doi:10.1016/j.biosystemseng.2006.05.011
46. Jain HK. Transition to twenty-first century agriculture: change of direction. Agric Res. 2012;1:12-7. doi:10.1007/s40003-011-0008-0
47. Janc K, Czapiewski K, Wójcik M. In the starting blocks for smart agriculture: The internet as a source of knowledge in transitional agriculture. NJAS-Wageningen J Life Sci. 2019;90:100309. doi:10.1016/j.njas.2019.100309
48. Javaid M, Haleem A, Singh RP, Suman R. Enhancing smart farming through the applications of Agriculture 4.0 technologies. Int J Intell Networks. 2022;3:150-64. doi:10.1016/j.ijin.2022.09.004
49. Juwono FH, Wong WK, Verma S, Shekhawat N, Lease BA, Apriono C. Machine learning for weedplant discrimination in agriculture 5.0: An in-depth review. Artif Intell Agricult. 2023.
50. Kumar A, Singh V, Kumar S, Jaiswal SP, Bhadoria VS. IoT enabled system to monitor and control greenhouse. Mater Today Proc. 2022;49:3137-41. doi:10.1016/j.matpr.2020.11.040
51. Kumar S, Meena RS, Sheoran S, Jangir CK, Jhariya MK,

Banerjee A, *et al*. Remote sensing for agriculture and resource management. In: Natural Resources Conservation and Advances for Sustainability. Elsevier; 2022. p. 91-135.
52. Kumari N, Rathi S. Real-time agro-meteorological advisory systems using AI and IoT: A review of current trends and future directions. Environ Monit Assess. 2021;193(11):688. doi:10.1007/s10661-021-09536-w
53. Latino ME, Menegoli M, Lazoi M, Corallo A. Voluntary traceability in food supply chain: a framework leading its implementation in Agriculture 4.0. Technol Forecast Soc Change. 2022;178:121564.
54. Lavanaya M, Parameswari R. Soil nutrients monitoring for greenhouse yield enhancement using pH value with IOT and wireless sensor network. In: 2018 Second International Conference on Green Computing and Internet of Things (ICGCIoT); 2018. p. 547-52.
55. Li S, Zhang M, Ji Y, Zhang Z, Cao R, Chen B, *et al*. Agricultural machinery GNSS/IMU-integrated navigation based on fuzzy adaptive finite impulse response Kalman filtering algorithm. Comput Electron Agric. 2021;191:106524. doi:10.1016/j.compag.2021.106524
56. Liang C, Shah T. IoT in agriculture: The future of precision monitoring and data-driven farming. Eigenpub Rev Sci Technol. 2023;7:85-104.
57. Lipper L, Thornton P, Campbell BM, Baedeker T, Braimoh A, Bwalya M, *et al*. Climate-smart agriculture for food security. Nat Clim Chang. 2014;4:1068-72. doi:10.1038/nclimate2437
58. Liu C, Jiang X, Yuan Z. Plant Responses and adaptations to salt stress: A review. Horticulturae. 2024;10:1221. doi:10.3390/horticulturae10111221
59. Liu C, Xu D, Dong X, Huang Q. A review: Research progress of SERS-based sensors for agricultural applications. Trends Food Sci Technol. 2022;128:90-101. doi:10.1016/j.tifs.2022.07.012
60. Liu Y, Ma X, Shu L, Hancke GP, Abu-Mahfouz AM. From industry 4.0 to agriculture 4.0: Current status, enabling technologies and research challenges. IEEE Trans Industr Inform. 2020;17:4322-34. doi:10.1109/TII.2020.3003910
61. Ma C, Johansen K, McCabe MF. Combining Sentinel-2 data with an optical-trapezoid approach to infer within-field soil moisture variability and monitor agricultural production stages. Agric Water Manag. 2022;274:107942. doi:10.1016/j.agwat.2022.107942
62. Maffezzoli F, Ardolino M, Bacchetti A. Maturity level and Effects of the 4.0 Paradigm on the Italian Agricultural Industry: A preliminary study. Proc Comput Sci. 2024;232:1819-28. doi:10.1016/j.procs.2024.02.004
63. McCole M, Bradley M, McCaul M, McCrudden D. A low-cost portable system for on-site detection of soil pH and potassium levels using 3D printed sensors. Results Eng. 2023;20:101564. doi:10.1016/j.rineng.2023.101564
64. Mehta P, Agrawal A. Weather prediction and climate modeling using AI techniques: Opportunities and challenges. J Artif Intell Data Sci. 2022;1(2):15-29. doi:10.1007/s44257-022-00021-w
65. Mekala MS, Viswanathan P. Smart farming using IoT, cloud and mobile computing A review. Procedia Comput Sci. 2017;34:93-8. doi:10.1016/j.procs.2017.12.017
66. Mishra RK, Dash AR, Panda AK. IoT-enabled smart farming: A cloud-based approach for polyhouse automation. Expert Syst Appl. 2025:127358. doi:10.1016/j.eswa.2025.127358
67. Mogili UMR, Deepak B. Review on application of drone systems in precision agriculture. Proc Comput Sci. 2018;133:502-9. doi:10.1016/j.procs.2018.07.063
68. Nargotra M, Khurjekar MJ. Greenhouse based on IoT and AI for societal benefit. In: Proceedings of the 2020 International Conference on Emerging Smart Computing and Informatics (ESCI); 2020.
69. Nasir MU, Naseem MT, Khattak HA. Precision agriculture: Remote sensing and IoT integration for crop monitoring. J Sensors. 2021;2021:1-12. doi:10.1155/2021/4297026
70. Nukala R, Panduru K, Shields A, Riordan D, Doody P, Walsh J. Internet of things: A review from 'Farm to fork. In: 2016 27th Irish signals and systems conference (ISSC); 2016. p. 1-6.
71. Onwuka B, Mang B. Effects of soil temperature on some soil properties and plant growth. Adv Plants Agric Res. 2018;8:34-7. doi:10.15406/apar.2018.08.00288
72. Otieno M. An extensive survey of smart agriculture technologies: Current security posture. World J Adv Res Rev. 2023;18:1207-31. doi:10.30574/wjarr.2023.18.3.1241
73. Rahman SA, Khan SA, Iqbal S, Khadka IB, Rehman MM, Jang J, *et al*. Hierarchical porous biowaste-based dual humidity/pressure sensor for robotic tactile sensing, sustainable health and environmental monitoring. Adv Energy Sustainabil Res. 2024;5:2400144. doi:10.1002/aesr.202400144
74. Rahman SA, Khan SA, Iqbal S, Rehman MM, Kim WY. Eco-friendly, high-performance humidity sensor using purple sweet-potato peel for multipurpose applications. Chemosensors. 2023;11:457. doi:10.3390/chemosensors11080457
75. Shantaram A, Beyenal H, Veluchamy RRA, Lewandowski Z. Wireless sensors powered by microbial fuel cells. Environ Sci Technol. 2005;39:5037-42. doi:10.1021/es0480668
76. Srbinovska M, Gavrovski C, Dimcev V, Krkoleva A, Borozan V. Environmental parameters monitoring in precision agriculture using wireless sensor networks. J Clean Prod. 2015;88:297-307. doi:10.1016/j.jclepro.2014.04.036
77. Stańczyk T, Kasperska-Wołowicz W, Szatyłowicz J, Gnatowski T, Papierowska E. Surface soil moisture determination of irrigated and drained agricultural lands with the OPTRAM Method and Sentinel-2 observations. Remote Sens (Basel). 2023;15:5576. doi:10.3390/rs15235576
78. Sudduth KA, Hummel JW, Birrell SJ. Sensors for site-specific management. In: The state of site specific management for agriculture. American Society of America; 1997. p. 183-210.
79. Tan WC, Sidhu MS. Review of RFID and IoT integration in supply chain management. Oper Res Perspect. 2022;9:100229. doi:10.1016/j.orp.2022.100229
80. Tenreiro TR, Avillez F, Gómez JA, Penteado M, Coelho JC, Fereres E. Opportunities for variable rate application of nitrogen under spatial water variations in rainfed wheat systems an economic analysis. Precis Agric. 2023;24:853-78. doi:10.1007/s11119-022-09977-1
81. Verma KK, Song X-P, Joshi A, Tian D-D, Rajput VD, Singh M, *et al*. Recent trends in nano-fertilizers for sustainable agriculture under climate change for global food security. Nanomaterials. 2022;12:173. doi:10.3390/nano12010173
82. Wang L, Zhou F, He M, Liu H. Contribution of osmotic suction to suction stress for unsaturated saline clay and its

suction stress characteristic curve. J Geotech Geoenviron Eng. 2025;151:04024143. doi:10.1061/JGGEFK.GTENG-12813
83. Wang Z, Qiao X, Wang Y, Yu H, Mu C. IoT-based system of prevention and control for crop diseases and insect pests. Front Plant Sci. 2024;15:1323074. doi:10.3389/fpls.2024.1323074
84. Wang Z, Zhao C, Zhang H, Fan H. Real-time remote monitoring and warning system in general agriculture environment. In: 2011 international conference of information technology, computer engineering and management sciences; 2011. p. 160-3.
85. Wanyama J, Bwambale E, Kiraga S, Katimbo A, Nakawuka P, Kabenge I, *et al*. A systematic review of fourth industrial revolution technologies in smart irrigation: constraints, opportunities and future prospects for sub-Saharan Africa. Smart Agric Technol. 2024:100412. doi:10.1016/j.atech.2024.100412
86. Wiseman L, Sanderson J, Zhang A, Jakku E. Farmers and their data: An examination of farmers' reluctance to share their data through the lens of the laws impacting smart farming. NJAS-Wageningen J Life Sci. 2019;90:100301. doi:10.1016/j.njas.2019.04.007
87. Wu Y-D, Chen Y-G, Wang W-T, Zhang K-L, Luo L-P, Cao Y-C, *et al*. Precision fertilizer and irrigation control system using open-source software and loose communication architecture. J Irrigat Drainage Eng. 2022;148:04022012. doi:10.1061/(ASCE)IR.1943-4774.0001669
88. Xu J, Gu B, Tian G. Review of agricultural IoT technology. Artif Intell Agric. 2022;6:10-22. doi:10.1016/j.aiia.2022.01.001
89. Xu L, Li L, Tang L, Zeng Y, Chen G, Shao C, *et al*. Rapid printing of high-temperature polymer-derived ceramic composite thin-film thermistor with laser pyrolysis. ACS Appl Mater Interfac. 2023;15:9996-10005. doi:10.1021/acsami.2c20927
90. Xu L-X, Wang F, Yao Y, Yao M, Kuzyakov Y, Yu G-H, *et al*. Key role of microbial necromass and iron minerals in retaining micronutrients and facilitating biological nitrogen fixation in paddy soils. Fundam Res. 2024. doi:10.1016/j.fmre.2024.02.007
91. Yaghoubi Khanghahi M, Strafella S, Allegretta I, Crecchio C. Isolation of bacteria with potential plant-promoting traits and optimization of their growth conditions. Curr Microbiol. 2021;78:464-78. doi:10.1007/s00284-020-02303-w
92. Yazdinejad A, Zolfaghari B, Azmoodeh A, Dehghantanha A, Karimipour H, Fraser E, *et al*. A review on security of smart farming and precision agriculture: Security aspects, attacks, threats and countermeasures. Appl Sci. 2021;11:7518. doi:10.3390/app11167518
93. Yin H, Cao Y, Marelli B, Zeng X, Mason AJ, Cao C. Soil sensors and plant wearables for smart and precision agriculture. Adv Mater. 2021;33:2007764. doi:10.1002/adma.20200776