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Review

Breeding Smarter: Artificial Intelligence and Machine Learning Tools in Modern Breeding—A Review

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Abstract

Climate challenges, along with a projected global population increase of 2 billion by 2080, are intensifying pressures on agricultural systems, leading to biodiversity loss, land use constrains, soil fertility declining, and changes in water cycles, while crop yields struggle to meet the rising food demand. These challenges, coupled with evolving legislation and rapid technology advancements, require innovative sustainable agricultural solutions. By reshaping farmers' daily operations, real-time data acquisition and predictive models can support informed decision-making. In this context, smart farming (SM) applied to plant breeding can improve efficiency by reducing inputs and increasing outputs through the adoption of digital and data-driven technologies. Examples include the investment on common ontologies and metadata standards for phenotypes and environments, standardization of HTP protocols, integration of prediction outputs into breeding databases, and selection workflows, as well in building multi-partner field networks that collect diverse envirotypes. This review outlines how AI and machine learning (ML) can be integrated in modern plant breeding methodologies, including genomic selection (GS) and genetic algorithms (GAs), to accelerate the development of climate-resilient and sustainably performing crop varieties. While many reviews address smart farming or smart breeding independently, herein, these domains are bridged to provide an understandable strategic landscape by enhancing breeding efficiency.

Keywords: smart breeding; digital agriculture; artificial intelligence; modeling; ethics; integrated management

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1. Introduction

In agriculture, it is essential to improve traits to address the various challenges that impact crop production [1]. In plant breeding, this improvement is accomplished by combining genomic (DNA markers), phenomic (trait expression or plant phenotype), and enviromic data, all contributing to desired trait expression. These three factors are interdependent and necessary for gene discovery and manipulation via modern breeding tools, including gene editing and epigenetic engineering. Methods that aid in this discovery include quantitative analysis through linkage mapping and associated traits—either using a genome-wide association study (GWAS) approach or mapping quantitative trait loci (QTLs). Other methods include biometrics and genomic selection (GS), particularly targeting multi-environmental scales [2–4]. With the current ongoing advancements in next-generation sequencing and, consequently, the discovery of a greater number of molecular markers, their effects can be further explored in terms of the number of variants as well as their contribution to trait variability in specific environments to be used in forward and reverse crop genetics through mutation breeding and CRISPR [5]. Chawade et al. [6] pointed out that "the degree of success in changing the population's genotypic structure by altering its gene frequency depends on precise phenotyping and selection". Consequently, given favorable allele frequency, selection efficiency and phenotyping accuracy are directly correlated.

Smart breeding refers to the integration of advanced tools, including genomic, phenomic, artificial intelligence (AI), and machine learning (ML) tools, to enhance efficiency of processes and their accuracy, speed, and effectiveness of breeding processes and enviromics [7] (Table 1). Hence, a variety of tools are currently available to assess the changes encoded by the genome at the phenomics level. Yet, one must be aware that phenotyping procedures can be highly time-consuming and complex, particularly when thousands of plots need to be measured, which likely pose challenges in terms of time–cost–quality triangulation outputs.

Table 1. Conceptual synergies between 'Farming Smarter' vs.'Breeding Smarter' and their intersections.

Aspects	Farming Smarter	Breeding Smarter	Intersection: Smart Agriculture Integration	References
Focus	Managing and optimizing production systems using data and technology	Improving the genetic potential of crops/animals using genomic and artificial intelligence (AI) tools	Integrating genetic, environmental, and management data to co-optimize variety/breed performance and management practices.	[8–10]
Scale	Field, farm, or regional level	Population or breeding program level	Multi-scale: linking genotype × environment × management (G × E × M) interactions across farms and breeding programs.	
Core tools	Sensors, drones, IoT, robotics, ML-driven decision support, remote sensing for management	Genotyping, phenotyping, genomic prediction, gene editing, bioinformatics for selection	Shared AI and big data analytics platforms for both genetic and management optimization.	
Time Horizon	Short- to medium-term (seasonal improvements)	Long-term (genetic gains over generations)	Continuous: real-time feedback from farm data informs breeding targets; new varieties feed back into optimized farming.	
Data used	Environmental, soil, weather, and management data	Genetic, genomic, and phenotypic data	Integrated datasets combining genotypic, phenotypic, and environmental information for holistic modeling	
Outcome	Higher efficiency, sustainability, and profitability of production systems	Higher yield potential, resilience, and quality in new cultivars	Accelerated genetic gain and improved field performance through adaptive management and precision breeding	
Type of innovation	Process innovation: improving how farming is performed **Better decisions → higher efficiency**	Product innovation: improving what is farmed (cultivars/breeds) **Better varieties/breeds → higher yield/resilience**	System innovation: co-designing crops, environments, and practices for maximum synergy	
Role of technology, particularly AI	Support on decision-making for input use, disease and pest control, irrigation, and logistics	Predicts genotype performance, identifies key genes, and enhances selection accuracy	Enabling predictive agriculture, linking genomic prediction with environmental sensing and management optimization	

In this context, high-throughput remote sensing provides a methodology for detecting real-time crop responses that can be immediately connected with the genotype, providing a tool for making immediate decisions (Figure 1). Because the overall goal in agriculture is to develop an integrated system that optimizes both plant and animal outputs in a sustainable and cost-effective manner, optimizing crop and animal production can minimize costs and maximize outputs. This optimization in crop production includes the integrated use of crossbreeding and agronomic practices with advanced technologies [11]. This includes the integrated use of sensors in agronomic practices such as sowing and spraying [6], robotics as an extension of precision farming [12], weed detection and management [13], germplasm selection, and physiological and photosynthesis efficiency evaluation [14,15], as well as for sustainable decision fertilization modeling [16]. In the forestry industry, which also involves tree breeding and conservation, the efficient assessment and tracking of worldwide afforestation and deforestation, land degradation, and ecological management depend heavily on product analysis based on satellite imagery [17].

In this area, robust remote sensing techniques and equipment are necessary due to the large scale of operations to maintain forest ecosystems and structural diversity. Remote sensing is also key to support regulatory bodies and policy-making in areas such as wood and cork productivity, greenhouse gas (GHG) emissions, and palm oil certification [18]. Additional areas of support include estimations of biodiversity loss and degradation due to fires [19,20], along with monitoring of the water status in various orchard crops, including almond, lime, and olive trees [21]. Climate change is expected to make water availability increasingly unpredictable and stressed, thereby affecting agricultural systems more frequent and aggressively [22]. In remote sensing applied to breeding, unmanned aerial vehicles (UAVs) are of great value, as they can rapidly assess phenotypic traits across large breeding populations. With their ability to gather high-resolution imagery, UAVs detect variations in traits such as growth patterns, disease resistance, and stress responses, which are essential for improving breeding outcomes. Because machine learning (ML) and artificial intelligence (AI) possess the ability to process large volumes of heterogeneous data generated by remote sensing platforms, including UAVs, they have become crucial tools in modern breeding pipelines. By incorporating ML using recognition methods including convolutional neural networks (CNNs) or supervised regression models, UAV data can reveal hidden patterns that are difficult to observe through traditional breeding methods [23,24].

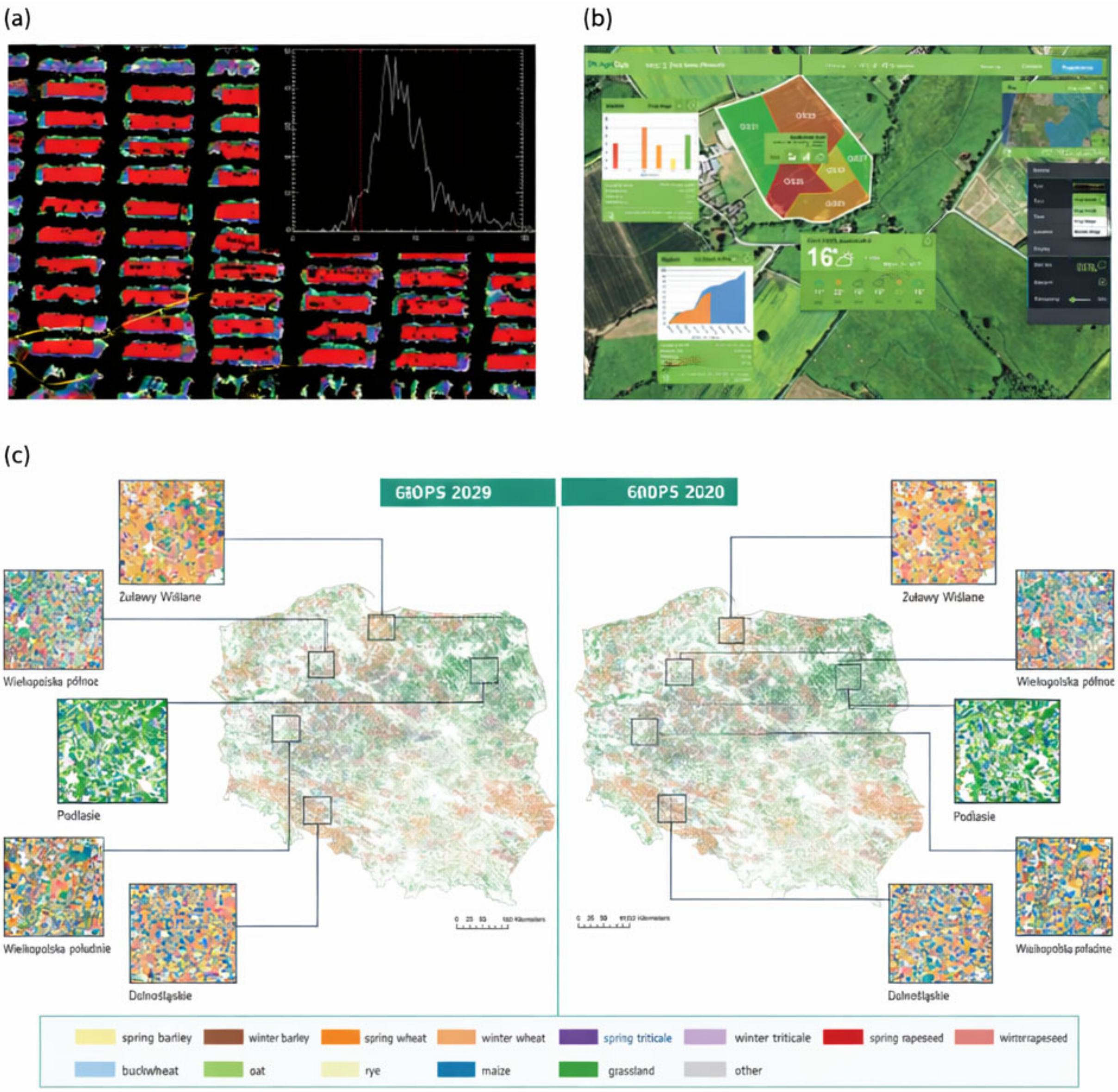

Figure 1. Case studies on unmanned aerial vehicle (UAV) utility: (**a**) Tattaris et al. [25] demonstrated the capability of using image processing for monitoring crop growth and yield. This methodology involved the capture of high-resolution images of a crop field from a UAV, which were processed to calculate vegetation indices including the Normalized Difference Vegetation Index (NDVI) and Green Area Index (GAI). The technique was efficient in tracking both growth and yield over time with a high level of accuracy. (**b**) The Satellite Applications Catapult (Accessed on 21 December 2025; https://sa.catapult.org.uk/industry-news/ahdb-satellites-for-agriculture/) is an online farm management platform called FarmSAR that integrates satellite data with farm management practices. The platform allows farmers to observe real-time information on weather, soil moisture, and crop growth, thereby allowing them to make informed decisions about irrigation, fertilization, and harvesting. Machine learning algorithms were additionally used to analyze the data and provide recommendations for optimal crop management. (**c**) Using Sentinel-2 satellite imagery data, the European Space Agency (ESA) monitored crop growth and yield across different regions in Poland during two consecutive years. The data were then processed to develop crop maps and predict both yield and crop health in order to demonstrate the proof-of-concept on the feasibility and reliability of using satellite data in crop monitoring and yield forecasting [26].

Despite the fact that there is an increasing number of reviews and research articles in this area [Supplementary Figure S1d], most studies tend to either overlook the genetic aspect or address them in a simpler and non-integrative way. In this context, besides providing an update on proof-of-concept and small-scale technical trials, we discuss the integration of genetic algorithms and phenotyping techniques in the context of plant breeding for easy assimilation.

2. Review Methodology

Data Sources and Exclusion Criteria

Following the PRISMA 2020 guidelines [27], the methodology for this review employed a literature search followed by screening and qualitative synthesis. Relevant research studies were performed via several knowledge platforms including the Scopus, Web of Science, PubMed, and Google Scholar databases. The search was conducted without date restrictions and limited to scientific articles and reviews using the keywords 'plant breeding', 'artificial intelligence', 'machine learning', 'remote sensing', and 'genetic algorithm'. An additional search incorporated the terms 'ethics and regulations' to capture governance-related aspects. The literature search conducted on Scopus resulted in 294 articles chosen (Supplementary Figure S1a–d). As expected, there is a trend in the number of annual publications, which increased markedly over the last 33 years, with a slightly lower number of publications when the keywords 'ethics' and 'regulations' are applied. Inclusion and exclusion criteria are detailed in Supplementary Table S1. Among the non-review articles selected after screening, the dataset also includes published frameworks, thesis, and technical reports. These were consulted selectively to provide context, method, and regulatory insight and are not fully represented in the peer-reviewed literature. Article selection was carried out manually based on the assessment of titles and abstracts, and full texts were consulted when necessary. Additional relevant publications were identified through reference screening of key articles. No formal risk-of-bias assessment or structured frameworks such as PICO were applied, as the aim of this review was narrative synthesis rather than quantitative comparison. Overall, the trends indicate a rapid growth in the research and viability of ML, AI, and genetic algorithms in agriculture. This is particularly evident over the past five years (Supplementary Figure S1a–d), highlighting increasing interdisciplinarity relevant to plant breeding. It is interesting to pinpoint that some publication picks (e.g., 2008) reflect studies from human epidemiology rather than agricultural research, underscoring the need for caution when interpreting keyword bibliometric trends.

3. Smart Farming

The emergence of smart farming has brought together farming management with modern information and communication technologies (ICTs) to increase efficiency. It includes the use of sensors, software, positioning technologies, robotics, and data analytics, which allow for precision agriculture and livestock farming facilitated by the use of AI and ML tools [28]. Regarded as the Third Green Agricultural Revolution, it includes processing, automation, and the use of drones to collect multispectral and thermal imagery. In modern agriculture, ML offers significant advantages in increasing accuracy and problem-solving, as it is used to identify, classify, quantify, and predict (ICQP) challenges within a development cycle [23]. Although often used interchangeably, AI and ML are not synonymous. ML is a subset of AI that focuses on algorithms capable of learning patterns from data without being explicitly programmed. In agricultural breeding and management, ML models enable data-driven decisions at increasingly fine spatial and temporal resolutions. For example, sensor data analyzed with ML can support decision-making at the level of individual plants or animals or per square meter in the field. This allows breeders and farmers to tailor interventions in operations such as irrigation, fertilization, or selection based on site-specific conditions [29].

4. Satellite Imaging, UAVs, and Proximal Phenotyping in Plants

4.1. Satellite Imaging and GIS

Satellite imaging is a technology that has been in use since the 1960s and is widely applied in agriculture for surveillance and to monitor land and water resources, as well as the land's main agricultural activities under governmental regulations [30]. This is performed through the utilization of Geographic Information Systems (GIS) and online resources to deliver multispectral imagery for superior agricultural management, utilizing data from satellites, aircraft, and UAVs to analyze land surface phenology (LSP) metrics and support effective decision-making. The use of GIS technology in remote sensing has facilitated the updating and correction of plot boundaries, as well as the reclassification of land occupation within a country, alongside photointerpretation [31,32]. These activities aid governments in offering fair subsidies to farmers based on the information gleaned from these resources [33]. Satellite imagery has proven to be incredibly effective, particularly for larger areas where usage restrictions are not a concern, with high- to medium-resolution capabilities. The utilization of satellite imagery has allowed for increased efficiency in various agricultural practices (Table 2).

The European Space Agency (ESA) currently hosts an impressive fleet of 92 satellites in space. Currently, between 70% and 97% of Global Position System/Global Navigation Satellite System (GPS/GNSS) tractors used throughout Europe rely on signals transmitted by the European navigation satellites through Galileo and EGNOS (https://www.euspa.europa.eu/, accessed on 21 December 2025) (Table 3). The system's accuracy enables farmers to precisely steer their tractors. Ongoing projects in this area include ESAWorld Cover and ESA WorldCereal from the European Copernicus Program (https://esa-worldcover.org/en, accessed on 21 December 2025). These platforms are utilized by key users such as the Food and Agriculture Organization of the United Nations (FAO), the Organization for Economic Cooperation and Development (OECD), the Center for International Forestry Research (CIFOR), and the United Nations Convention to Combat Desertification (UNCCD). Such platforms are employed in precision farming to dispense precise doses of fertilizers only where necessary. This is made possible by the knowledge of precise soil mapping and accurate positioning.

4.2. UAV-Based and Proximal Phenotyping

When evaluating small plots with thousands of genotypes (with an average size of approximately 1 m^2), this cannot be adequately performed using satellite sensors such as WorldView-3. Compared with satellite-based techniques, unmanned aerial systems (UASs) increase throughput and frequency for phenotyping to provide the highest resolution [34]. In the event that past or present satellite imagery is required, such data can be accessed through web-based platforms such as the Google Earth Engine, Planet.com, Earth Data Search by the National Aeronautics and Space Administration (NASA), and LandViewer by the Earth Observing System [35]. In this case, unmanned aerial vehicles (UAVs) and drones are of better use, they can be frequently used at any moment of the breeding process, particularly to minimize cost whilst maximizing use. Both technologies are superior to satellite imaging when it comes to taking into account environmental conditions such as cloud cover and spatial resolution. Unmanned aerial vehicles come in different forms, including parachutes, blimps, rotocopters, and fixed-wing systems [36], and they have been tested for their utility in plant breeding for multiple purposes in diverse crops (Table 2). In some cases, single-propeller drones, combined with ML techniques, have been shown to accurately (98.5%) monitor and manage pests [37].

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Table 2. Purposes and resolution systems that can be used in agriculture phenotyping, which serves plant breeding.

Purpose	Organism	Reference
High resolution satellite systems (HRSS)		
Mapping leaf area index	Grapevine; giant bamboo	[38–40]
Surface soil property, soil mapping, soil salinity, moisture, and pH	Soil	[31–45]
Yield monitoring and prediction	Sorghum, cotton, sugar beet, spring wheat, corn/maize, and sunflower	[46–51]
Disease detection	Wheat, rice, citrus	[52–54]
Agronomic parameters, N quantification and fertilization, protein content	Maize, barley, wheat, turfgrasses	[55–61]
Crop identification		[62]
Forest burn index evaluation	Trees and forest ecosystem	[19]
Photosynthetic capacity	Various	[15]
Unmanned aircraft Vehicle (UAV)		
Growth stages determination	Bambara groundnut; cotton	[63,64]
Structural/morphological trait evaluation (biomass, heigh, count)	Barley, sugarcane, maize	[65–67]
Leaf area index (LAI)	Soybean, maize, sorghum, bambara groundnut, vineyard	[39,68–72]
Yield forecast	Maize, wheat, barley, canola, field peas, rice, sugarcane, rye, cotton, bambara groundnut, soybean	[72–81]
Vegetation and soil segmentation		[82]
Crop row detection, tree detection and classification, fire monitoring	Coniferous trees, forest ecosystem	[82–84]
Nitrogen (N) estimation	Soybean; bread wheat; sugarcane	[85–88]
Crop stress and crop phenotyping monitorization and evaluation	Sugarcane, citrus, wheat, oilseed rape, maize; black poplar	[85,89–93]
Must quality parameters, vigor zones, yield, diversity	Grapevine	[94–98]
Disease detection	Citrus, avocado, banana, wheat, groundnut	[99–104]
Irrigation scheduling	Fruit trees	[105]
Carbon stock and sequestering above ground, carbon dynamics	Forest trees, mangrove	[84,106,107]
Reproductive traits (floral opening)	Lettuce	[108]
Unnamed ground Vehicle (UGV)		
Row detection	Lettuce	[109]
Operations on peat fields		[110]
Ground properties of greenhouses		[111]

Table 3. Machine learning models related to crops.

Organism	Trait	Model	Reference
		Yield	
Coffee tree	Number of branches, % of fruit weight and maturation	SVM	[112]
Cherry tree	Harvesting mechanization	BM/GNB	[113]
Citrus tree	Early yield mapping	SVM	[114]
Grass	Estimation of biomass	ANNs and multitemporal remote sensing data	[115]
Wheat, apple	Yield prediction	Satellite imagery + soil data; MLP/CNN, SVR	[116–118]
Tomato	Fruit detection/counting	Sensed RGB images, CNN	[119,120]
Rice	Development stage prediction	SVM and basic geographic information	[121]
Sugarcane	Plant heigh and stalk density		[80]
Lemon	Quality assessment/control	CNN	[122]
Rice	Grain protein content	DCGAN	[123]
Land vegetation	Soil heavy metal monitorization	Various	[124]
		Biotic stresses	
Mediterranean milk thistle	Infection rate to smut fungus, weed detection	ANN/XY-Fusion, ANN/CP	[125]
Strawberry	Thrips detection; Botrytis sp., Penicillium sp., and Rhyzopus sp. discrimination	SVM, NN	[126,127]
Rice	Disease and geographical origin detection	SVM, EL/RF	[128,129]
Wheat	Disease infection rate to yellow rust and Septoria, N and H_2O stress, weed management	ANN/XY-Fusion, ANN/MLP, SVM/LS-SVM, ANN/SOM, DNN	[13,125,130–133]
Maize, soybean	Weed detection and control	ANN/one-class SOM; CNN; UFAB/DNN, DL	[134–137]
Pears	Fragrancy detection	SVM/SPA-SVM	[138]
Beans, soybean	Identification and classification, root system architecture (RSA)	DL/CNN, CNN	[139,140]
Common grape vine	Health status, powdery mildew, black rot, downy mildew	SVM, Gaussian Mixture Model (GMM)/LBPs	[141]
Banana	Disease and pest detection (e.g., Black Sigatoka)	CNN/DCNN, CNN-VGG	[101,142]
		Quality Control/Quality assurance	
Tobacco	Recognition of non-tobacco-related materials	CNN: LRNTRM-YOLO	[143]

Overall, the precision of error estimation and capturing of images can be enhanced by using high-resolution cameras, flying at lower altitude, and employing ground control points (GCPs) [144]. Proximal phenotyping utilizes ground-based vehicles and sensors, which bring together automated AI with genomics, agronomy, and ecophysiology. The stress sensors are attached to vehicles, pegged in the ground, or attached on strings to obtain data from the visible and thermal ranges on the one hand. On the other hand, they are used to collect canopy data of chlorophyll, plant water, nitrogen, leaf area, plant height, seedling vigor, maturity, biomass, diseases such as rust, and pests [145]. In the last few decades, several investigations have demonstrated the practical utility of proximal phenotyping in different crops [146–152]. Mobile platforms provide multiple benefits over handheld sensors by conducting numerous features (multiple traits) simultaneously, leading to a significant decrease in time consumed in each task, cost, and labor savings. However, achieving the best results still may require technical expertise. In the context of wheat cultivation, an accurate yield forecast of productivity can be achieved, with an average accuracy of up to 70% attainable if the secondary traits are phenotyped at a high level of precision [153]. These types of devices in agriculture are amongst the most notable ones. Examples include the robot Oz used for mechanical weeding (https://www.naio-technologies.com/en/oz-robot/, accessed on 21 December 2025) and the autonomous sprayer GUSS (https://gussag.com, accessed on 21 December 2025) used for spraying by means of a laptop or robot systems capable of autonomously identifying and removing weeds such as the one offered by Blue River (https://www.theblifemovement.com/blue-river-technologys-precision-weed-control-machine/, accessed on 21 December 2025), among others. These types of innovative solutions help farmers to manage weeds without relying on herbicides or to enhance the efficiency of herbicide spraying via the use of a laptop computer, respectively.

4.3. Precision and Generalist Agriculture

Although phenotyping for precision and generalist agriculture may seem to have opposing goals, they actually converge towards the same target through different approaches. Phenotyping in generalist agriculture aims to maximize yield, with a focus on broad adaptability, ideal conditions, and average performance, while phenotyping for precision seeks to prevent factors that limit yield maximization, with a focus on site-specific management, stress response, and environment–genotype interaction [6]. Even if the ultimate objective of both approaches is the increase in crop productivity at a reduced production cost, they differ in focus. Generalist agricultural phenotyping aims to select traits that perform well under optimal conditions, whereas precision agricultural phenotyping aims to ensure consistent performance across variable or stressful conditions. In the latter, the key requirement for success will be the choice of appropriate sensors and methods that best fit the specific trait, environment, and costs. To maximize the return on investment, decision support platforms or systems (DSP or DSS) should be designed to integrate the data coming from phenotyping, weather, genotyping, economics, and satellite imaging [6]. This would enable more timely and informed decision-making in agriculture. Low-cost UAV data can be correlated with global satellite remote sensing databases to improve data integration and enhance decision-making. Furthermore, combining information from UAVs and Unmanned Ground Vehicles (UGVs) can lead to better decision-making outcomes.

5. Integration of Remote Sensing AI and Genetic Algorithms in Phenotyping to Identify Loci Associated with Agronomically Beneficial Traits

5.1. Genetic Algorithms: Principles and Optimization

The integration of machines, vehicles, and systems provides an accurate and reliable tool for the adoption of low-input, high-efficiency, and sustainable (LHS) agricultural decision support [154]. In the field of AI, several metaheuristic single and multiple population-based evolutionary algorithms have been proposed, including the genetic algorithm (GA) methods [155]. The difference between traditional algorithms and Gas is well established, with former following a fixed set of rules and logic to obtain a solution. Therefore, these are broader and may refer to standard algorithms that solve common tasks such as sorting and searching and are not tied to evolutionary principles. Instead, GAs seek to optimize problem-solving strategies based on a natural genetic selection process that mimics biological evolution and incorporates search fine-tuning mechanisms such as selection, crossover, and mutation [156]. GAs works by trial and error, and during the selection stage, individuals are chosen for reproduction, and poor solutions are discarded, while both crossover (also known as recombination) and mutation stages (same as genetic operators) explore the search space and retain less-fit individuals [157]. In certain cases, these less-fit individuals are kept in later stages to maintain the genetic diversity, as well to avoid premature convergence, which can occur if the population becomes too similar [158], preventing the algorithm failing to explore promising areas of the search space. In addition, there may be a case where there is a need to prevent 'local optima', as these 'to-discard' individuals may contain useful traits to be combined with later generations [159]. This may ensure a more robust search where the algorithm has the chance to explore multiple niches, in a so-called 'steady-state and niching technique' [160]. Therefore, these GAs (also referred to as individuals of the problem) have been constructed and applied to a variety of optimization problems in which a population of chromosomes encodes potential solutions (Figure 2). These solutions then undergo mutation and recombination, giving rise to new offspring throughout a number of generations. To create an effective encoding and apply genetic operators, it is crucial to know input parameters such as the population size (Pop), the maximum number of iterations (iter), and stopping criteria. Additionally, the size of the cloning proportion (Elite) maintained through interactions, as well as the proportions of individuals generated by mutation (Mut) and crossover (Xover)—which simulates reproduction between two parent solutions—must fulfill the following expression:

$$1 = \text{Elite} + \text{Mut} + \text{Xover}.$$

Genetic encoding allows for the assignment of hypotheses to diverse options, and individuals can be generated either randomly or obtained by constructive methods. It is expected that the initial population will explore the maximum number of solutions consisting of random permutations to improve the GA. In order to perform a natural selection, each individual evaluation is based on its fitness value, which is used for individual selection in line with the Darwinian theory of "survival of the fittest". The cloning and mutation stages induce small random changes in the solution by adding new characteristics gradually, while the elitism stage maintains certain individuals from one generation to the next by cloning them [161].

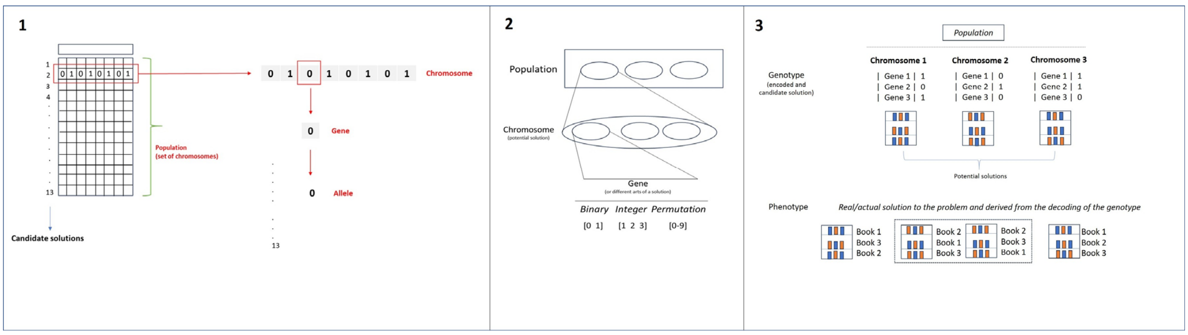

Figure 2. (**1**). Oversimplified look of a genetic algorithm (GA). (**2**). The basis of a GA: Herein, the phenotype is the actual solution/result we obtain from testing, whereas the genotype is the encoded version of the solution and which the algorithm works with. For simple problems, the encoded version (genotype) and the actual solution (phenotype) are the same, whereas for complex problems these are different. The population refers to the possible solutions (chromosomes) that the algorithm works with—the encoded solution of the problem—while the chromosome is a single solution in the population—a "candidate" for the best solution. As a part of the chromosome, a gene is a specific element or position in the solution, while an allele is the actual value that a gene takes within the chromosome. If a gene represents "color," an allele might be "blue" or "green." In this space, a chromosome can be represented in different manners: (1) as a binary value (using 0 s and 1 s or 'yes' and 'no'), (2) as an integer (using numbers such as 0, 1, 2, 3), and (3) as permutation representations (using a sequence of numbers such as 0 to 9). As a real-life analogy, we want to organize a bookshelf, and the genotype will be the distinct ways of how to organize it (e.g., in list of numbers), whereas the phenotype is the way this bookshelf looks after we organize it—the actual result. The algorithm will try different genotypes (i.e., ways of organizing) to find the best solution (phenotype). The GA will try to find the best real-world solution (phenotype) by manipulating coded versions of possible solutions (genotype). (**3**). Example of a GA and analogy to a bookshelf organization.

5.2. Integration with Remote Sensing and UAV-Based Phenotyping

Remote sensing AI technology readings are based on the correlation between captured radiation and the properties of the targeted objects. This radiation or reflectance contains information at physical and chemical levels, which is strongly associated with vibration molecular bonds such as carbon–hydrogen (C-H), oxygen–hydrogen (O-H), or nitrogen–hydrogen (N-H) bonds [162]. The final output is a specific signature of reflected light used to calculate spectral indices based on algorithms [25]. To find the weights to each trait index evaluated, either by satellite or UAVs, the normalized spectrum values for each image pixel can be translated into a GA to identify an optimal function that can relate the generated data [163]. The GA is based on the evolution of individuals, which carry alleles that represent them as a population. In each generation, new allele combinations are produced, and the best individuals are chosen as parental lines for a particular environment, passing on their genes to the next generation. The GA model created by [163] ranks a set of individuals with their individual weights for every generation using a fitness function, giving a score to each and every individual. This will ultimately select the best fit on the basis of three main steps: initialization (1), selection (2), and genetic operators (3) (Figure 3). This model could serve as a low-cost alternative to current plant phenotyping methods. Recently, the third-generation non-dominated sorting GA (NSGA-III) was described and is intended to address optimization problems with multiple conflicting objectives, thereby focusing on improving the diversity of solutions and enhancing efficiency [164]. Ref. [108] utilized ML as a versatile tool to analyze large amounts of data and correlate it with genomic data. Specifically, they used drone-mediated imagery to track the spatiotemporal behavior of lettuce individuals and associated it with genetic profiles through ML and Bayesian inference methods. By performing this, they were able to identify two casual loci (daily floral opening, qDFO2.1 and qDFO8.1) related to differential floral opening and closing times, explaining 30% of the phenotypic variation in floral opening time. This study demonstrates the potential of UAV imaging technology to accelerate breeding efforts and adapt research frameworks of crops like lettuce, where flowering is a critical trait for genetic improvement [108].

A new multi-species binary coded algorithm METO approach was proposed, differing from the traditional GA, since it produces two consecutive generations of offspring in each evolution epoch instead of just one [F1 = crossbreeding of F0 generation parents; F2 = self-breeding of the F1 generation parents] [165,166]. The METO algorithm uses two parallel routes for transferring genes from one generation to the next and may be helpful in resolving more complex problems. In soybean, it was shown that near-infrared spectroscopy (NIR) data can be used for phenotypic prediction at different stages of a breeding program in soybean, with comparable, and in some cases, greater, predictive ability than genomic predictions [167]. The authors found that phenomic predictions—a term introduced by [168]—were less sensitive to relatedness between the training and prediction sets and could outperform genomic prediction in certain scenarios, including those involving seed yield and plant height. When applied to a GA (Figure 3), a small number of wavelengths utilizing NIR devices may be sufficient without a loss in phenotypic prediction abilities when using biallelic genotypic markers such as single-nucleotide polymorphisms (SNPs) [167].

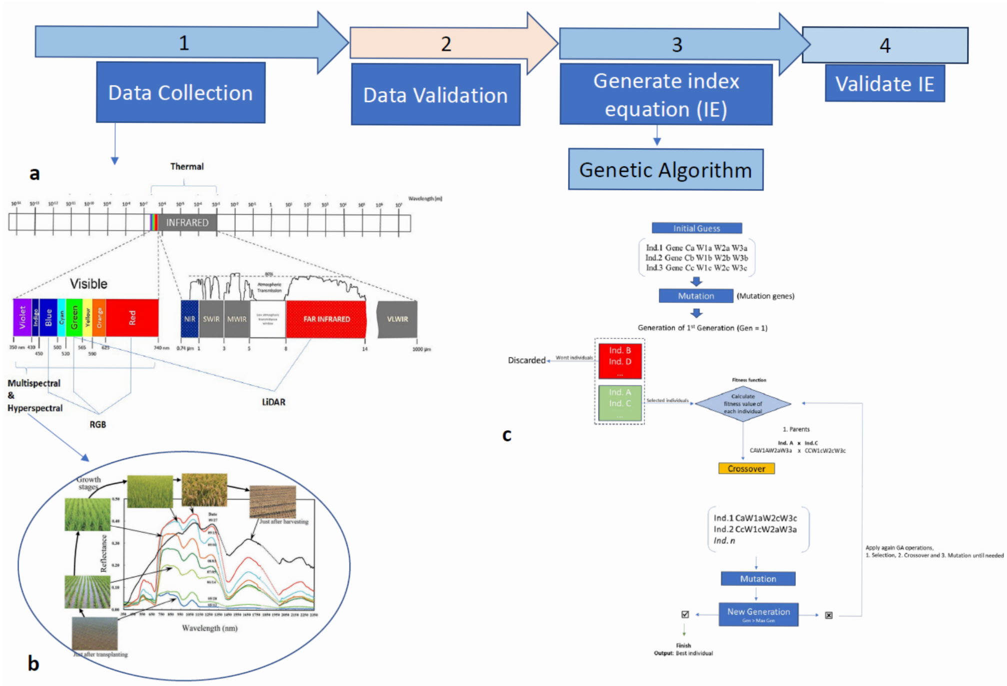

Figure 3. Workflow for developing a genetic algorithm (GA) using unmanned aerial systems (UASs): (**a**) spectrum image-based indicating the several spectral ranges used by tools (retrieved from https://en.wikipedia.org/wiki/Infrared_vision, accessed on 21 December 2025) and used in the (**b**) collection of phenotypic data with a specific example on how to use hyperspectral reflectance in a rice paddy and reflecting the seasonal change in the crop for better decisions [14]. After the dataset is chosen, data analysis is performed, including statistical analysis, visualization of input and output features [169], and a pre-processing step, as highlighted by Figure 1 of [170], which can occur for label encoding, data imputation, and data mapping and splitting, followed by the development of a GA per se. (**c**) The developed GA (based on [163]). In the elitism stage, the top individuals of the population are selected for the next generation. In the crossover stage, the parents are mated to create the progeny with a combination of their genes. After crossover, the remaining population is then completed by removing the two parents and progeny and adding a mutation factor. At the end of the workflow, the best recommendations are made, which may lead to performance testing or evaluation.

In diploid organisms with three allelic classes (AA, Aa, and aa), the variations obtained by authors were as simple as 3k, with k indicating the number of markers utilized. NIR data outcomes were found to be similar to multi-allelic markers observed in transcriptomic data, as these do not rely on a predefined number of elements and instead present a continuous variation with multiple informative states [167]. Each wavelength must be therefore regarded as a phenotype influenced by many loci and must be treated in an interdependent manner. In such cases, the substantial reduction in the wavelength number utilized for the prediction can maintain the phenomic predictive ability. However, this predictability is most effective for traits that produce clear trait-specific signals.

In contrast, for traits that vary primarily due to subtle differences in allelic states at a specific QTL, the signals may not be distinct enough to enable reliable predictions. In case diagnostic markers are available for a specific trait, these could be used in the pre-selection of lines and before phenotypic prediction in models (Table 4). Zhu et al. [167] suggested that phenomic prediction would be preferred in the case of traits with non-additive genetic effects, where interactions between genes are important. In contrast, genomic prediction is more efficient and accurate for traits with additive effects, where each gene contributes independently and breeding values are needed [171]. However, phenomic prediction may be more useful in cases of higher complexity. In any case, a training population is needed for accuracy in all the scenarios. In the case of genomic predictions, higher accuracy is obtained in full-sibs, half-sibs, and unrelated families in that order. In contrast, phenomic accuracy achieved similar results in full- and half-sibs, whereas other families obtained similar results as half-sibs [167]. In triticale, it was seen that the prediction accuracy when applying models from one family to another was lower than the average accuracy seen within the same family, based on full siblings [172]. The highest prediction results obtained in half-sib families in triticale were also obtained in other crops such as barley [173].

Table 4. Indices that can be used to measure in trait-related breeding agriculture using artificial intelligence.

Group	Indices	Sensor Wavelength	Examples of Sensor
Broadband Greenness [Chlorophyll content, crop biomass, N deficiency at crop senescence, Leaf Area Index (LAI)]	Normalised Difference Vegetation Index (NDVI) + visible atmospheric resistance index (VARI), RGB-based vegetation index 2 and 3 (RGBVI2 and RGBVI3)	Near-infrared (NIR) and visible (VIS) regions of the electromagnetic spectrum	Trimble Greenseeker Handheld NDVI Sensor; UAV imagery
	Optimized soil-adjusted vegetation index (OSAVI)	Red, NIR	
	Soil-adjusted vegetation indices (SAVI)	Red, NIR	
	Renormalized Difference Vegetation Index (RDVI)	Red, NIR	
	Enhance vegetation indices (EVIs)	Blue, red, NIR	
	Color vegetation indices (CVIs)	RGB sensors	
Light Use Efficiency	Photochemical Reflectance Index (PRI)	Green	SRS sensor
Leaf Pigments	Modified Chlorophyll Absorption Ratio Index (MCARI)	Green, red, NIR	FieldSpec 4; TriFlex; FRT GmbH's Specim IQ
	Chlorophyll Content Index (CCI)	Green, NIR	
	Transformed Chlorophyll Absorption Ratio Index (TCARI)	Green, red, NIR	
	Anthocyanin Reflectance Index 2 (ARI2)	Blue, red, NIR	
	Carotenoid Reflectance Index 2 (CRI2)	Blue, red	
Water Stress	Crop water stress index (CWSI)	RGB, thermal infrared	MicaSense RedEdge, FLIR Vue TZ20; Flir A6750sc thermal camera
Water Content	Water Band Index (WBI)	Red, NIR	SFC/AIEE-based fluorescence sensor TPE-(An-CHO)$_4$, Kapta™ 3000 series; i::SCAN probe

Source: Improved from [77].

5.3. Broader Applications in Agriculture and Food Systems

Besides their use in crop field, the importance of GAs in the agrifood industry lies in their potential to enhance operational efficiency and optimization. Examples of their use in this area include the determination of the most efficient production schedules in food manufacturing facilities. Optimized schedules reduce costs and ensure the timely delivery of fresh produce products [174]. Here, both productivity and customer satisfaction increase, as they contribute to waste reduction within the supply chain. In soil sciences, which is a key integrative area in crop genetics and breeding, a recently introduced model combines multiple factors, including soil composition, weather conditions, and historical crop yields. This combined approach, referred to as a 'hybrid model', allows for a better optimization of random forest (RF) classifiers while improving their ability to predict crop outcomes more accurately [175,176]. Using this model, ref. [170] achieved an impressive 99.3% accuracy in predicting the outcomes for 22 different crop groups [pulses & beans, cereals, fruits, oilseeds and fiber crops, vegetables and spices & beverages]. In Spain, the use of a GA as a decision support system to manage the irrigation frequency plan in the fields not only reduced water and energy consumption but also ensured optimal irrigation coverage, thereby contributing to resource efficiency [177]. This is particularly important in addressing sustainability challenges in water-scarce agricultural regions such as the south of the Iberian Peninsula, northern Africa, or the arid northern regions of India. Moreover, GAs can be used in various UVA optimization applications, including Particle Swarm Optimization (PSO), differential evolution (DE), and other bioinspired search methods. Such an example includes the gains added by GA adjustment performed on a UVA fuzzy controller, leading to improvement in the path tracking of the UAV device [178]. Yet, and as outlined by the authors, this tuning method may not be applicable to all devices. Similarly, in winter wheat, the optimization of RF parameters through a GA led to improvement in the accuracy of predicting both chlorophyll and anthocyanin contents [179,180]. However, and as pointed previously [181,182], this approach is not enough, and caution must be made when making recommendations. While hybrid models are useful in making accurate predictions made through modeling [61], these can provide highly inaccurate input application recommendations. Here, the choice of machine learning algorithm and covariate selection are crucial, as insufficient consideration of model uncertainty may lead to making highly undesirable input use decisions [181]. The study conducted by the authors showed a difference in gains of about 340% due to these differentiated selections. Using the HI-WUE integrated index, combining the harvest index and water use efficiency, ref. [183] suggested a framework that is able to identify rice ideotypes optimized for resource efficiency. Through using a wide range of virtual cultivars under diverse environmental conditions, this multidimensional analysis optimizing GA CERES-Rice Crop was able to quantify the genetic distance between computationally optimized ideotypes and field-characterized cultivars. This approach shows that co-development of crop models and phenotyping platforms has the potential to translate predictions into practical breeding outcomes for climate-resilient crop varieties. Despite work emphasizing the predictive potential of mechanistic models and AI-based optimization strategies in defining crop ideotypes [183], it is also clear that the way a crop's genetics interact with local environmental factors is very important for its performance. It is evident that these interactions create barriers in providing breeding methods that work universally across all regions, as crops need to be tailored to specific climates.

6. Data Integration—Multi-Omics Data to Enhance Genetic Predictions

6.1. Metabolomics, Multi-Sensor Integration, and ML Approaches

In plant phenotyping, metabolome analysis is helpful to understand complex biological traits, particularly if the integration of extensive physical and spectral data is required, including chemistry data. However, accurately identifying metabolites to determine their biological relevance still is a significant challenge. Here, the identification of specific biomarkers could support the understanding of the biological significance of the data [184]. Despite the promise of non-invasive, automated metabolomics, cost remains a major obstacle. The datasets generated from metabolomics are usually difficult to visualize and interpret and require the use of advanced modeling approaches, as these assays usually do not capture the systematic environment of metabolites [185]. Integrating multiple sensors, such as optical molecular spectroscopy, imaging, and mass spectrometry, into automated plant phenotyping facilities can improve the understanding of complex plant features. Data fusion techniques, such as statistical multimodal data analysis and deep learning, can enhance the knowledge obtained from metabolomics, transcriptomics, and imaging data supported by software tools that are available to integrate omics data (Table 1; [184]). In this context, the application of ML and network analysis not only allowed for the prediction of biochemical pathways in tomato with metabolite data [186] but also allowed for phenotype predictability through the use of genes, transcripts, and metabolites altogether [187]. At this data analysis stage, ML can improve accuracy, and, depending on the datasets, supervised, unsupervised, and semi-supervised approaches may be used [188]. In order to categorize or generate predictions based on input attributes, the supervised ML method uses a labeled dataset. The labeled examples from the training datasets are then used to teach the algorithm a mapping from the input data to a target output or label. It has been shown that supervised models like 'DeepGS' [189] can perform better than conventional GS models when used in genome-wide (GW) analysis predictions [190]. Suggestion exist that other models may perform better than DeepGS [191]. However, this needs more evidence, as it seems that there is not a unique model that works well in all traits studied in wheat [192]. Nevertheless, the goal of unsupervised ML models is to find patterns, structures, or correlations in unlabeled data without the need for explicit supervision or a predetermined target variable [193] (Figure 4). By using a hybrid approach, the model can enhance its performance by utilizing both the additional unlabeled data and the limited amount of labeled data.

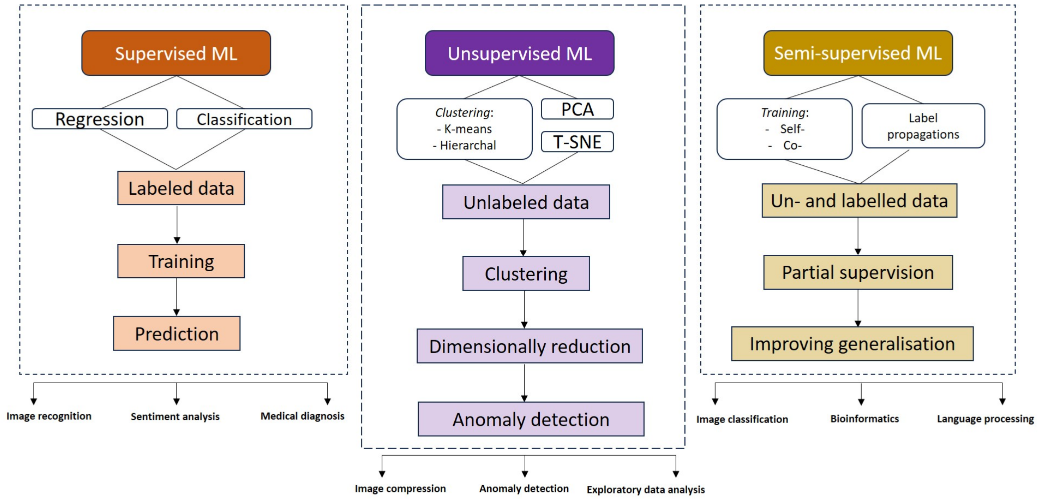

Figure 4. Different steps involved in the three types of algorithms that can be applied to genomic data. t-Distributed Stochastic Neighbor Embedding (t-SNE) is used for visualizing high-dimensional data by mapping it to a lower-dimensional space while preserving similarities between data points, whereas principal component analysis (PCA) reduces the dimensionality of data while preserving as much variance as possible by finding linear combinations of features. In the unsupervised machine learning methodology, historical data is a mandatory requirement. Basically, the approach involves training a dataset that includes both labeled and unlabeled data points in semi-supervised machine learning (ML) models, which mix aspects of supervised and unsupervised learning.

Overall, integrating metabolomics with multi-sensor data and ML enables more accurate phenotype prediction since it captures complementary biological signals that are not accessible through single-omics approaches alone, thereby reducing breeding cycle time and resource use.

6.2. Genomic Resources, Causal Gene Discovery, and Smart Laboratory Platforms

In the field of genomics, it is important to pinpoint that it is crucial to have foundational reference genomes to act as a ‘map’ where genetic variations, gene locations, and structural features of DNA are known [194]. Lacking this information is analogous to training a navigation system without access to a map of roads and cities, resulting in unreliable predictions despite ML demonstrating utility in identifying genomic regions in crops [195–198], multi-omics and/or multi-regulation networks analysis, as performed in maize [199] and rice [200], respectively, are preferred. ML algorithms such as QTG-Finder2 can support the discovery of causal genes in agricultural plant species and facilitate agricultural trait improvement [201]. Still within the genomics space, and to support this, AI is employed for real-time PCR analysis and endpoint PCR data analysis to create a connected platform for smart and digital laboratories (https://www.illumina.com/informatics/ai-in-genomics.html, accessed on 21 December 2025). Marker scoring after sequencing is one of the most time-consuming processes during genotyping, and it is a subjective process as there is no identifiable root cause for underperforming assays. Therefore, non-standardized pieces of software are common in multiple PCR platforms. For instance, FastFinder from UgenTec (www.ugentec.com; https://www.ugentec.com/fastfinder, accessed on 21 December 2025) can help diagnostic laboratories by automating assay scoring through AI, saving operational time, providing data intelligence for quality assurance and improvement, and being customizable to customers. Such software can be used for genotyping, pathogen testing at scale, and quality control (QC) in industry, animal, and seed health. The software from UgenTec can save up to 80% of the scoring time and can provide a solution for multiple platform usage such as KASP SNP (Kraken), Nexar, Araya, IntelliQube, and Fluidigm, among others (https://www.ugentec.com/fastfinder/genotyper, accessed on 21 December 2025). The usage of such software offers several benefits, including access to historical data repositories and the ability to apply intelligent algorithms tailored to specific assays, organisms, and workflows. By incorporating HTP into ML-driven genotype/phenotype models, breeders can not only enhance the pace at which they develop new cultivars but also work more efficiently in trait discovery. Together, reference genomes, causal gene discovery tools, and AI-enabled laboratory platforms form an integrated framework that accelerates trait discovery to improve breeding efficiency.

7. Simulation Models in Support of Plant Breeders

7.1. Crop, Environmental, and Genomic Prediction Models

To predict how different genotypes perform under various environmental growth developmental conditions, plant breeders can take advantage of simulation models. These models use computational tools to simulate biological, genetic, and environmental processes, helping to predict genotype performance under various conditions. Simulation models support breeders not only to understand trait interactions and evaluate breeding strategies but also to optimize selection decisions without relying solely on field experiments. Using crop models, one can test and refine breeding strategies more efficiently to take better-informed decisions in terms of trait selection and cultivar development. Taking the example of coupling pest and disease damage modules using CSM-NWheat, this module in the CSM-NWheat model simulates the effects of biotic stresses on wheat crops, allowing farmers/researchers accurate predictions of yield losses [202]. In the northern Indo-Gangetic basin of Bangladesh, crop simulation models such as APSIN and DSSAT were further calibrated and validated to understand the impacts of climate change on rice and wheat production [203]. The results provide insights for adjustments in practices such as sowing and irrigation. Using genomic prediction models through deep learning on maize, it was possible to demonstrate that this tool could provide better prediction accuracy, although without considering the GxE interactions. This is because deep learning (DL) models may not be as transparent and easy to interpret as other models, such as BMTME, which was found more superior when considering the GxE interactions [204]. The opposite was shown for barley and to predict Fusarium Head Blight (FHB), where the DL model, using multiple networks through the transformer-based genomic prediction model, was shown to be as good as or better than GS methods such as BLUP and MLP [205]. Independently of model preference, currently, three user-friendly software packages are known to be able to integrate multi-data sources. The R software package 'learnMet' 1.0.0 [206] allows users to employ traditional ML methods in their data, whereas the statistical machine-learning toolkit 'SKM library' was designed to be used in any prediction task with input–output data [207]. More recently, the Hyperfidelis 1.0 geospatial software package was presented to support researchers as a user-friendly graphical interface employing machine learning techniques, merging information from plant science, agronomy, remote sensing, and data science [208]. These are user-friendly tools that streamline genomic selection workflows, including model fitting and performance evaluation. Other practical examples of use include aiding rice yield estimates during the peak season in Bangladesh [209] and salinity forecasting [210], both of which contribute to improving food security management and decision-making. Remote sensing and ML are also valuable tools to monitor and evaluate large regional interventions, minimizing the need for extensive data collection from the field. This is evident in the case of assessing rice production resilience to climate in Senegal [211]. Such examples are just few among many described elsewhere [212–219]. Altogether, these examples illustrate how simulation models, when supported by genomic prediction and remote sensing data, can serve as a powerful decision-support tool. Allowing for the anticipation of genotype performance across environments and optimization of selection strategies, such models bridge the gap between field experimentation and predictive breeding, ultimately accelerating cultivar development under climate change.

7.2. Generative Adversarial Networks (GANs): The Next Frontier

Generative adversarial networks (GANs), primarily introduced by [220], are generative models that generate new data instances resembling the training data. GANs discover and learn patterns in input data in such a way that the model can generate new examples based on a set of attributes or variables from the original dataset. These networks consist of two sub-models: the generator and discriminator; the former generates new hypotheses, while the latter classifies the hypothesis as real (or false). This process generates numerous plausible and realistic hypotheses for researchers to address diverse problems. As is known, one application of GANs includes the translation of satellite photographs into map-style renderings, as shown by early image-to-image translation models [221]. As of today, GANs are commonly used for tasks including image synthesis [222], super resolution [223,224], anomaly detection [225], and handling missing data [226], as well text-to-image processing [227] across various domains. In agriculture, GANs are useful to model high-dimensional data produced from multispectral imaging [228] and provide multimodal outputs through deep-learning-based methods [61,229,230]. Specifically in plant breeding, with their ability to simulate genetic variation, predict environmental adaptability, and accelerate breeding cycles, GANs can be a powerful tool in the quest to develop crops that are more resilient to climate change and therefore capable of feeding a growing global population. This is supported, for example, by software packages such as Scion Image 4.0.3.2 [231], Leaf Doctor [232], and Quantitative Plant (https://quantitative-plant.org, accessed on 21 December 2025), which allow for imaging analysis. As practical example, the LeafGAN system provides an image-to-image translation model and has been used as a data augmentation tool to improve plant disease diagnostics performance [233,234]. ML is widely utilized to increase crop productivity and quality, namely, at seed retail systems, but it is also employed to create better crops and identify natural enemies of crop pests and diseases. The uses of robotics and sensors for predicting crop health and yield, monitoring deforestation, providing updates on cartography for agricultural registration, land occupation confirmation, and boundary monitoring are all part of the suite of apps and services designed to improve agricultural productivity [235]. In this realm, the EarthOne Platform (previously known as Descarts Labs Platform; https://ag.earthdaily.com, accessed on 21 December 2025) promotes sustainable farming practices by allowing data providers and diverse stakeholders to access and manage large datasets of information. The data collected can be then used to generate ML-based predictions without requiring cross-checking with other datasets. Previously it has been demonstrated that using ultrasonic sensors could lead to input savings ranging from 22% to 70% in crop production [236], where deep learning models have enhanced the performance of traditional image processing techniques, achieving an average accuracy of 92.51% across various agricultural applications [237]. In plant breeding, the availability of a diverse set of datasets, such as genomic, transcriptomic and metabolomic, and predictive models, can help in predicting complex agronomic traits [238].

This approach can not only improve the model accuracy but also supports a more complete understanding of the different biological mechanisms that drive trait variability.

8. Ethics on the Use of Aerial Systems, Geospatial Information, 'Big Data', and Governance Policies

8.1. Ethical and Regulatory Considerations for UAVs and Aerial Systems in Plant Breeding

Ethical and regulatory frameworks governing UAVs, geospatial data, and AI directly influence the feasibility, reliability, and fairness of data-driven plant breeding, particularly in high-throughput phenotyping and AI-assisted selection pipelines. The rapid expansion of UAV services has prompted increased regulatory oversight, which directly influences the deployment of UAV-based phenotyping in agriculture [239]. Despite the decreasing costs associated with UAV systems, aviation regulations in many countries continue to restrict drone use, which can limit the frequency, timing, and spatial resolution of high-throughput phenotyping campaigns essential for modern breeding programs [Supplementary Materials—Supplementary File S1]. With respect to drone usage, ethical considerations pertain not only to privacy but also to data sharing, storage, and usage of data. Guidelines also address flight approval times [240], administrative processes and documentation, user demands, and safety during operations concerning individuals and property.

In order to understand the full benefit of UAVs in agriculture, the use of UAVs not only requires transparent rules and strategies to ensure ethical and responsible behavior but also that these rules and strategies are value-laden and have no discriminatory potential. In the context of plant breeding, UAVs are widely deployed for high-throughput phenotyping and monitoring trials; therefore, restrictive or unclear regulations can directly affect breeders' ability to collect timely and reliable data. Consequently, computer scientists and developers need to be responsible for ensuring that their technology operates ethically and responsibly [TUNAT—transparent, unbiased, non-maleficent, accountable, trustworthy while protecting privacy] and that the delegation of tasks to technology should absolve them of the responsibility, as technology's actions and decisions still implicate and involve ethical considerations [241]. For plant breeders, this is particularly relevant when AI-driven genomic prediction or trait evaluation models are used, since algorithmic biases could skew selection outcomes or reduce trust in breeding decisions. It is important for those involved in developing and implementing algorithms to be mindful of the values and biases embedded in their technology and to work actively towards transparency, fairness, and accountability. Potential risks posed by AI technology include the possibility of opaque decision-making, gender-based and other forms of discrimination, privacy concerns, and the potential for criminal activities to be carried out using AI [242]. To address some of these risks, guidelines for AI have been developed, including the Asilomar AI principles [243] and prohibited AI practices [244]; Regulation (EU) 2024/1689 (AI Act) [245].

8.2. Big Data Governance, Ownership, and Ethical Use in Agriculture

Bulk data generation, which includes data that is generated, captured, copied, and consumed, is projected to reach more than 394 zettabytes by 2028 [246]. Yet, the governance of big data remains a major challenge, particularly related to privacy, security, sharing, costs and ownership data analytics level [247,248]. In breeding programs, these issues translate into questions of who owns and controls genomic, phenotypic, and environmental datasets, which are increasingly generated by public–private partnerships. In the EU, organizations processing research data are required to protect the data properly to prevent loss or misuse, as there could be legal, reputational, and financial consequences for the data processor [249]. To increase transparency and trust, the EU voluntarily released its Code of Conduct on Agricultural Data Sharing by contractual agreement in 2018 [250]. Following this initiative, the Farm Data Code Practice was also published by Australia and New Zealand with the purpose of minimizing any potential misunderstandings between farmers and partners [250,251] (http://www.farmdatacode.org.nz, accessed on 21 December 2025). Numerous co-signatory organizations are working together to produce a non-binding code that sheds greater light on contractual relations and provides guidance on the use of agricultural data [250,252] (https://www.fao.org/family-farming/detail/en/c/1370911, accessed on 21 December 2025). In 2020, the GODAN/CTA/GFAR online tool was also released, which provides a platform for users, especially farmers, to create their own codes of conduct based on their specific needs (https://www.godan.info, accessed on 21 December 2025). Besides these codes of ethics, effective risk management policies need to be in place and address the challenges of robotics governance in least-developed countries, where farmers may face difficulties in adopting new technologies [253].

With climate change increasingly affecting agriculture, the adaptability of robotics to changing conditions such as drought, heat, fires, floods, and new pests becomes critical for their continued effectiveness and timely responsiveness. In this context, robotics may raise issues of data ownership similar to those of AI and ML. Farmers must be aware that some agricultural technology providers (ATPs) may include licensing fees for data usage, with penalties for contract breaches [254], but also updating pricing depending on the rising of market costs, independently of the contract provided. Agricultural and environmental organizations, in conjunction with governmental bodies, do play a significant role in storing and managing plant pathological data. These data are usually organized based on taxonomic, symptomatic, and geographical distribution features. Yet, still there is a lack of correlation between these acquired data and genomic sequence data, all together with remote imaging, metadata, and ML [255]. Hence, innovative initiatives need to address this gap to provide accessible resources and information for research, policy-making, and users regarding geospatial data sources and tools, including property rights (https://ethicalgeo.org, accessed on 21 December 2025). The development of online reference databases will aid in the understanding of existing ethics and geospatial technology.

In summary, there are many ethical and legal questions that need to be addressed in agriculture with regards to data, including the establishment of a common set of ethical principles for data handling and transfer, directives on who owns and controls the data, determination of the entitlement value of the data, ensuring accessibility of data to all actors involved in agriculture, ascertaining of compliance with data protection regulations and who will make this work, establishment of fare regulations for farmer rights and benefits in sharing information with agribusiness and vice-versa, and decisions on the appropriate legislation, policies, and ethical considerations for the use of data in agriculture [24,256]. Finaly, the right of farmers to access capacity-building initiatives should also be addressed. This will enable them to cope with new technologies (UAVs, AI, ML) and will mitigate the risks of displacement. For plant breeders, the establishment of ethical and transparent frameworks for UAV-based phenotyping, genomic data sharing, and AI-driven prediction is critical to ensure fair access, reliable trait evaluation, and farmer participation in breeding pipelines.

9. Overcoming Challenges

Integration of data acquisition and analysis, along with decision-making support systems and variable rate application—which involves applying inputs like water, fertilizers, or pesticides at different rates across a field based on specific needs—are the hallmarks of precision agriculture. Here, remote sensing plays a critical role in the process, and despite significant advancements in sensor quality and capacity, challenges such as the selection and processing of satellite images still persist. Current bottlenecks in the efficient use of

HTP systems are the extraction of data, even from simpler devices, as well as the need for larger and labeled datasets. These processes are time-consuming and costly, besides the need for standardized procedures for retrieving specific types of data, such as temperature data, which are currently lacking [257]. End-use protocols, standard operating procedures (SOPs), and guidelines will facilitate the process of retrieving this type of data. For breeders, the lack of standardized and timely data extraction directly slows trait evaluation and reduces the reliability of downstream genomic prediction models.

Another challenge facing precision agriculture relates to choosing and updating devices in response to the demanding market. This challenge could be mitigated by providers offering more frequent and simplified updates, which could then be followed-up by deploying end-user phenotyping devices. In addition, the turnaround time for image delivery is another constraint that could be reduced through a greater number of service providers. However, an increase in service providers may also lead to more stringent rules regarding the use of UASs due to security and privacy concerns. This is because as more service providers use UASs, the risk of misuse or accidental breaches of privacy and security also increases, prompting tighter regulations to protect people and property [258]. Hence, there are key questions to be considered when determining the best type of sensors to use, including the size of the area to be mapped, the complexity of traits relative to crop type, the time available for mapping, the environmental conditions present, and its associated costs. As a result, when considering larger areas, satellite systems may be preferable, while drones may be advantageous for immediate, real-time assessment and greater flexibility in terms of filter range over time. For breeding programs, these decisions determine whether phenotyping campaigns can be scaled to entire nurseries or targeted at specific experimental plots. Although sensors within the BGR + NIR spectrum [Sentinel-2 (European Space Agency, WorldView-3 (Maxar), ASD FieldSpec 4, Parrot Sequoia (Drone-mounted) and Landsat 8] are sufficient for many plant measurements, it is important to consider advancements in fluorescence and LiDAR technologies. Of special importance is the increased battery life of drones, which can greatly benefit farmers with extensive land areas, such as those involved in livestock production. In the case of LiDAR technology, both 2D and 3D sensors use laser pulses and time-of-flight to measure distances to objects along a specific direction. However, one must be aware that in environments with irregular terrain, the laser light can generate positioning errors [259]. Therefore, regardless of the technology used, the accuracy of ML-based assessments is critical, and attention must be given to metrics such as error classification, sensitivity, specificity, and false positive rates, as highlighted by [260], to avoid inaccurate recommendations. In breeding contexts, such errors can propagate into biased trait assessments, undermining the accuracy of selection decisions.

Despite the efforts that are underway to establish such public databases, currently, deep learning (AI) networks still lack sufficient public benchmark datasets that specifically address the full scope of the various agricultural needs, for example, LeafSnap [261] for visual recognition of tree species; CropDeep [262] for species classification and detection; PlantVillage [263,264] (https://plantvillage.psu.edu/plants, accessed on 21 December 2025) as well the former PlantDoc [265] (https://hort.extension.wisc.edu/, accessed on 21 December 2025) for monitoring plant diseases and pests; the Tumaini (https://tumainiaiapp.org/, accessed on 21 December 2025) and Agriculture-Vision databases for large-scale aerial farm land image dataset for analyzing agricultural patterns [266]; the DeepWeeds dataset (multiclass weed species image dataset [267]; https://github.com/AlexOlsen/DeepWeeds, accessed on 21 December 2025) for understanding and managing weed ecology; and FAOSTAT (https://www.fao.org/faostat/en/, accessed on 21 December 2025), the largest agricultural statistical data repository in the world. While many of these databases target general crop management, adapting them for breeding-specific applications such as trait scoring and genomic prediction remains a major unmet need.

At the local level, systems such as Fruitlook (www.fruitlook.co.za) can serve as pre-operational services by providing weekly estimates of crop parameters to inform farmers about crop growth, water usage, nutrient status, and soil moisture content. At the regional and global levels, the JRC's MARS (Joint Research Center Monitoring Agricultural Resources) crop monitoring service (https://ec.europa.eu/jrc/en/mars, accessed on 21 December 2025) relies on static and real-time data for weather forecasting. Yet, there is a need to integrate the various processes of data analysis, ML implementation, and decision-making in an automated manner so that the overall process is functionally connected to the decision-making level. Therefore, there is ample opportunity to explore how farmers can make the best use of the acquired data. Examples in this area include the development of annual crop maps (https://agriculture.canada.ca/en/agricultural-production/geospatial-products, accessed on 21 December 2025). Additional improvement opportunities also involve optimizing efficient noise reduction and data redundancy, particularly in regression tasks [268], which will be crucial as big data geodatabases continue to expand. With the expectation of a large number of agricultural machines connected to service centers, there will also be a need to anticipate and manage network traffic and storage systems, particularly in real-time data scenarios [165]. For example, a smart self-driving tractor can currently collect more than 240 GB of crop data daily [269]. John Deere launched the first autonomous tractor that enables 360-degree obstacle detection using pixel classification within approximately 100 ms to facilitate decision-making based on the type of obstacle detected. In this case, the farmer only needs to transport the machine to the field and make the necessary configurations. Subsequently, the farmer can leave the field and monitor the machine's status from a mobile device. The private company provides farmers with access to live videos, images, data, and metrics. This efficiency comes with the promise of reducing carbon footprint, improving safety, streamlining operations, and increasing profits. For plant breeding programs, integrating such real-time data into trial management systems could accelerate selection cycles and reduce costs.

The need for effective data management software and applications is equally important. A study conducted in 14 countries provided insights into the information used in this regard [270]. Web-based geospatial applications such as Crop Condition and Soil Moisture Analytics (Crop-CASMA) (https://cloud.csiss.gmu.edu/Crop-CASMA//, accessed on 21 December 2025) have been developed to enable users to remotely access geospatial soil moisture and vegetation index data. This platform has been applied in the USA's territory. The Global Agricultural and Disaster Assessment System (GADAS, https://geo.fas.usda.gov/GADAS/, accessed on 21 December 2025) by the United States Department of Agriculture (USDA) provides real-time satellite information on weather, crops, and disasters. This type of information is critical for policy development, crop productivity forecasting, tracking extreme climate incidences such as floods and droughts, and mitigating natural disasters, including tsunamis and the risk of pandemics. In breeding contexts, such data feeds into environment-specific genomic prediction models, strengthening genotype-by-environment analyses.

In the space of smart crop farming and AI, there is an evolving role for farm advisory services and agricultural advisors, whose expertise is essential for bridging the existing gap between cutting-edge technologies and the respective practical on-farm applications. These findings not only support farmers in understanding and trusting AI tools such as precision irrigation, crop health diagnostics, or yield predictions but also provide direct support in the tailoring of tech solutions to fit local conditions and smallholder realities. This is particularly true in Africa's and Asia's conditions, where in the former, the majority of farms belong to smallholder farmers with no more than 2 hectares to maximize farm production [271]. These technical advisory professionals can also work on the space to provide contextual interpretation of AI-generated insights, further supporting farmers to interpret satellite imagery, drone data, or Internet-of-Things (IoT) sensor outputs for decision-making. The advisory services will be equally important to train farmers on how to use apps, sensors, and AI dashboards as well regarding services offered by third parties. Advisers of organizations such as the Kenya Dairy Farmers Federation (KDFF; https://www.kenaff.org/, accessed on 21 December 2025), the Oromia Coffee Farmers Cooperative Union (OCFCU, https://oromiacoffeeunion.com/, accessed on 21 December 2025) in Ethiopia, the Uganda National Farmers Federation (UNFFE; https://www.fo-mapp.com/farm/uganda-national-farmers-federation-unffe/, accessed on 21 December 2025) in Uganda, the Ghanaian Kuapa Kokoo Cooperative Cocoa Farmers and Marketing Union Limited (KKFU; https://kuapakokoo.com, accessed on 21 December 2025), and the European Research Infrastructure for Plant Phenotyping (EMPHASIS, https://emphasis.plant-phenotyping.eu/, accessed on 21 December 2025) build digital capacity, organize field demonstrations, and conduct digital literacy programs. In this area of extension, both the AI chabot AgriTalk-IoT platform for precision farming of soil cultivation and the assistant created by DigitalGreen also offer support to Asian and East African farmers in a similar manner, respectively [272,273]. Other IoT software used in agriculture is mentioned elsewhere [11,274]. Similarly important, these services also act as the bridge between users and developers by offering feedback to agri-tech companies and NGOs about user experience, the cultural context, and ground realities. As AI provides more granular insight, the advisors can offer hyper-local recommendations as well as personalized plans and risk assessments based on AI models and current support apps. Examples of apps that are currently able to support small-scale farmers include the 2024-launched Darli AI-based chatbot for crop-specific guidance on regenerative farming practices, disease diagnosis, soil health, and water conservation, as well as market and logistics advice [275], the RiceAdvice app for the integration of rice farmers into the value chain (https://www.cari-project.org/, accessed on 21 December 2025), and the FertiCal-P App KP for fertilizer calculations, recommendations, and price breakups [276]. On the side of livestock management, the application of the Datamars Swiss company supports animal farmers to better manage animal productivity and welfare while advising farmers to meet sustainability targets [273]. Another important area to explore and expand includes helping farmers to access digital credit, crop insurance, and cost–benefit analysis, as well as how to use the more frequent and diverse agri-fintech platforms. For breeders, strengthening the advisory role ensures that phenotypic data generated on-farm is both reliable and trusted, directly feeding into breeding databases and genomic prediction workflows.

10. Final Considerations

This review highlights that the convergence of UAV-based phenotyping, multi-omics data, and AI/ML approaches is reshaping plant breeding by enabling higher-resolution trait characterization, scalable data acquisition, and more informed selection decisions. However, the effectiveness of these technologies depends critically on data quality, model robustness, and context-aware implementation. Importantly, while technological advances can enhance breeding efficiency, genetic gains are expected to remain largely incremental and must be supported by breeders' expertise, environmental validation, and integrated management strategies.

Small-scale farmers aim to maximize their profits, and although most current plant breeding programs still rely on manual phenotyping methods, this is changing with the emergence of new technologies, such as smartphone-based AI applications to detect and diagnose diseases, as well as the use of UAV systems, cloud computing, and the IoT. Their synoptic view drives the adoption of these technologies because of the availability of open data standards, high degree of homogeneity, ease in data integration with GIS datasets, inexpensive data acquisition, and availability of data products and services [18]. However, it is important to exercise caution when interpreting traditionally collected data against more recent AI-related data collection methodologies, as the reliability of traditional methods may be lower than that of more recent ones. In addition, it is also important to keep in mind that despite the fact that scaling could lead to a decrease in pricing through usage, indicators point out that many farmer issues are instead context-specific with nuances and governmental legal frames that should be considered. Therefore, it is important for farmers to be aware of the different methodologies developed, as many tools are focused on phenotyping rather than overall management. AI-ML technology has enormous potential for improving crop and livestock management and enhancing pre-breeding efforts. However, priority must be given to the quality and suitability of image datasets used for AI-ML analysis. Advances in forward and/or reverse genetic engineering and mutation breeding can greatly improve the efficiency of genomic selection for increased profits at the farmer level. As the complexity of questions increases, the need for innovations in in situ data collection and analysis will also grow, leading to further opportunities for AI-ML and robotics in agriculture. This is particularly important in the context of labor shortages, efficiency, and the increasing availability of low-cost robotics [277]. A SWOT analysis can help identify the strengths, weaknesses, opportunities, and threats associated with the use of AI-ML in agriculture to guide decision-making for future research and development efforts [278]. An example of SWOT analysis, plus specific study cases, is provided in Table 5. An increase in data throughput and quality, as well as a reduction in data point costs, besides technology acceptance and usage by farmers, will dictate the pace of successful adoption of AI-ML in agriculture.

Because technology runs on comet's tail, one would think that data-driven companies, or those focused on editing crop genomes, could do much of the work for agricultural scientists—as these fields are pushing technological boundaries to an extent never seen. However, a substantial caveat needs to be taken into consideration: *plant yield and tolerance have plateaued for many crops* [279–282]. Even as crops evolved to become more efficient, diminishing returns set in as crops approached the upper limits of their biological potential. This is particularly evident in terms of yield, which is directly measurable, and tolerance to environmental stresses, which is typically assessed through scoring systems or performance under controlled conditions. In many crops, the current genetic pools are limited, which hinders the development of varieties better suited to the current challenges. While genetically modified crops (GMCs) can support agricultural systems, the constraints imposed by Earth's planetary boundaries—some of which are already overstretched (https://www.planetaryhealthcheck.org, accessed on 21 December 2025)—further restrict the sustainability of production.

One may think that finding new genes, or alleles, to allow for incremental gains—either by adopting new genetic innovations to increase photosynthesis, reduce photorespiration, harness genetic variants associated with plant–microbiome interactions, including endophytes, or seed and root microbiomes—is a straightforward task, but this is only a partially true statement. While it is correct that great progress is being made in understanding how to increase photosynthetic efficiency and reduce photorespiration [283], it is not trivial to find new genes or alleles that produce incremental gains. This occurs because genetic innovations in photosynthesis are complex, as they often involve trade-offs, and here, any improvement can have cascading effects across physiological processes. Identification of the specific genetic variants that contribute to beneficial plant–microbiome interactions [284] is still complex and requires detailed study; therefore, it is far from a trivial task. In plant breeding, MAS and GS are two techniques currently targeted to transfer and characterize favorable traits in crops. Yet, limitations include the low level of detection of genes with small effects on the majority of important traits for agriculture [194]. Evidence suggests that comparing predictive ability estimates between phenomic and genomic prediction models is invalid for assessing their relative effectiveness, as it may falsely imply that phenomic models are more accurate [285]. It is suggested, instead, that plant breeding should see phenomic selection to report predictive ability, whereas genomic prediction would be used to report prediction accuracy. Therefore, genetic editing using CRISPR/Cas, mutation breeding, along with ML and artificial systems (ASs) powered by artificial intelligence (AI)—which last through the diversification of training models and cheaper devices [286]—are powerful tools for inclusion and routine use in agricultural research [5]. Nevertheless, the gains these tools bring are also incremental.

Table 5. SWOT analysis for new technologies in precision agriculture.

Internal	
Strengths	**Weaknesses**
- Time saving in performing tasks; - Increased homogeneity; - Reduced redundancy and increased accuracy; - Predictions for problem-solving; - Automation in data collection, processing, and analyzing large volumes of data in a shorter time; - Upscaling; - Better solutions to farmers; - Cost-effectiveness; - Environmentally friendly and sustainable systems; - Data transparency and public availability benefit farmers through awareness for better choices, particularly through phenotypic data apps, soil nutrition, and preservation apps levels.	- Technology may not be applicable in areas with heterogeneous landscapes or terrain, where data collection may be inconsistent or unreliable; - The use of AI-ML in agriculture may be hindered in areas with limited access to continuous energy supply, which is required for data collection and processing. The significant need of computational power leads to higher consumption of energy that contributes to more global warming, since such housing facilities require extreme cooling systems; - Reduced coordination at the human–AI interface, particularly when multiple robots are involved; - Lack of use of management tools to incorporate new technologies in farms (SWOT and PESTEL analysis); - Non-consideration of small farming businesses, particularly applied to Africa and Asia; - Tasks that lack precision movements are better performed. - Small holder farmers are not all small start-ups; - Limited to use only in developed countries; - Lack of real data in majority of training models used in AI and ML.
Opportunities	**Threats**
- Best applied in areas where there is a shortage of labor or where labor costs are too high; - Increase in robotics/AI, sensors, big data, ML, knowledge, and availability, enabling real-time monitoring and precise irrigation, pesticide, and fertilizer application; - Better understanding of where robotics/AI/ML can be used without excluding human workforce knowledge; - Best used in practices where human health is in danger; - Real-time predictions for usage; - Higher safety conditions for farmers and the environment and to reduce the agricultural environmental footprint; - Predictions for problem avoidance.	- Lack of understanding of where the new technologies are best used depending on the use case; - Lack of substantial experience in modeling, particularly when regards to deep learning models; - Safe use of new technologies with *no harm*; - Social–human aspects are not considered, including farmers' concerns; - Lack or misuse of information and technology; - Lack of leadership vision and resistance to embrace change; - Availability of funds and software solutions; - Lack of trust among partnerships, due to non-existing agreeable frameworks; - Not all technologies are able to scale-up.
External	
Examples of successes: Study cases	
Increase in data throughput, better-quality data, reduced cost by datapoint, fewer safety incidents, large usage of technology https://pestdisplace.org/; http://www.terra-i.org/terra-i.html; https://croppie.org/, all accessed on 21 December 2025	

To address complexities in agricultural systems, companies and institutes in the forefront will need to be able to support advances into practical solutions, even if scalable solutions in the real world promise to be a complex task. Future progress in data-driven plant breeding will rely on the integration of UAV-derived phenomics with genomic, transcriptomic, and metabolomic data across environments and seasons, supported by large-scale, cross-location training datasets. Advances in model interpretability and transparency will be essential to foster breeder trust in AI-assisted decision-making, while hybrid approaches combining phenomic and genomic prediction are likely to improve robustness for complex traits. Continued investment in interoperable data infrastructures, explainable ML models, and real-world validation will be key to translating technological innovation into sustainable breeding outcomes. In conclusion, more investments in agricultural research, stronger partnerships, and the switching inter-use of the diverse tools in a holistic manner—including more advanced genetic algorithms—can accelerate agricultural applicability while supporting sustainability for the coming generations. While informatics and artificial intelligence will empower the next generation of plant breeders, real-world validation, environmental adaptability, and breeders' knowledge and intuition will remain irreplaceable in guiding effective crop improvement.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agronomy16010137/s1, Figure S1: (a): Published work shown in the search platform Google Scholar using the chosen keywords * in the last 33 years; (b): Published work shown in the search platform Google Scholar using the chosen key words * in the last 33 years; (c): Publications with and without ethics and regulations on artificial intelligence related (directly and indirectly) to agriculture; (d): Distribution of publications used in this research review by year and only from Google Scholar platform. Table S1: Inclusion and exclusion criteria used in this review. Supplementary File S1: Market forecasts, regulatory insights, country-by-country UAV legislation and licensing, and operational constraints with references.

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Glossary

Accuracy check	Related to the genetic algorithm, this is the evaluation of how well a given individual (solution) in the population performs with respect to a predefined fitness function (objective).
ANNs	Acronym for artificial neural networks, which are widely used for various tasks, including classification, regression, pattern recognition, and prediction in a AI models.
Binary variables	Variables that can take on one of two values (e.g., 0 and 1) and that are often used in classification tasks where the outcome is either one of two possible classes or values.
Biological pressure	Percentage of individuals that reproduce, where the values can vary between 0% and 100% [0% indicates that no individuals reproduce and 100% indicates that all individuals reproduce].
BM/GNB	Refers to the Bernoulli Naive Bayes variant of the Naive Bayes classifier used for binary features.
BP	Acronym for backward propagation neural network, which is a key algorithm used for training neural networks, including multilayer feed-forward networks. It involves propagating the error backward through the network to update the weights and minimize the loss.
Breed	Refers to a specific group of animals, plants, or organisms that share specific characteristics that distinguish them from other groups within the same species.
BREEDING 4.0.	Refers to the advanced integration of artificial intelligence (AI), genomics, and multiplex gene editing technologies to optimize crop breeding. This approach enables the precise identification, modification, and enhancement of multiple genetic traits simultaneously, leading to the development of crops that are more resilient, resource-efficient, and high-yielding.
CNN	Acronym for convolutional neural network, which is a type of artificial neural network (ANN) designed to process and analyze grid-like data, such as images, video frames, and time series.
DCGAN	Acronym for deep convolution generative adversarial network, which is a type of *generative adversarial network* (*GAN*) that uses *deep convolutional neural networks* for both the generator and discriminator and is used to generate new data, such as images, that are similar to a given training dataset.
DCNN	Acronym for deep convolutional neural network, which is another type of convolutional neural network (CNN) with multiple layers of convolutions designed for automatically and hierarchically learning features from data such as images, video frames, and even time-series data.
Elitism	Number of individuals in the search.
Elitism stage	In the general sense, elitism refers to the process in GA where the best individuals (solutions) from the current generation are carried over to the next generation without modification; elitism stage means that there is the preservation of the best individuals from one generation to the next, thereby avoiding losing good solutions.
Fitness function	Function to evaluate the performance of any proposed gains.
GA	Acronym for genetic algorithm, which is used to find approximate solutions to optimization and search problems by mimicking the process of evolution. GA uses techniques such as selection, crossover (recombination), mutation, and inheritance to evolve a population of candidate solutions over generations, improving the solutions with each iteration.
GA optimization	Refers to the optimization of the parameters of the random forest (RF), backpropagation (BP), and kernel extreme learning machine (KELM) models.
GMMs	Acronym for Gaussian mixture models, which used for clustering and density estimation.
GS	Acronym for genomic selection, which refers a breeding method that uses DNA data to predict genetic potential and select candidates based on estimates from genomic prediction models.
KELM	Acronym for kernel extreme learning machine, which and refers to a learning machine based on the kernel function.
Ideotypes	In the context of AI and ML, ideotypes are crop models that combine beneficial traits to improve performance in specific environmental conditions. This concept differs from genetic ideotypes, which are specific genetic profiles designed to optimize performance based on inherited traits.

Index equation (IE)	This is an equation used to access specific data in an indexed collection, such as arrays or databases, and is particularly relevant when dealing with large datasets where indexing helps in retrieving data efficiently.
Integer	An integer is a discrete variable that represents discrete categories or quantities, such as the number of items in a group, the number of visits to a website, or the count of certain features or events.
Labeled dataset	Here, dataset refers to each input example (or data point) paired with a corresponding target output or label. For example, in genomic studies, the input attributes might include genetic markers or sequence data, while the label could be the phenotypic trait (e.g., yield, disease resistance, etc.) associated with those markers.
MLP	Acronym for multilayer perceptron, which refers to a type of neural network used for classification and regression.
Mutation probability	The probability that individuals have a mutation. The value can vary from 0 and 1, where 0 means no mutation occurs and 1 means every individual will undergo mutation.
NIR	Acronym for near infrared, typically ranging from approximately 750 to 1400 nanometers on the electromagnetic spectrum.
NN	Acronym for neural network, which is a type of machine learning model (MLM) inspired by the structure and functioning of the human brain and is composed of interconnected layers of nodes—neurons or artificial neurons—which work together to solve various tasks such as classification, regression, and pattern recognition.
Parity	In the context of this review, parity refers to the number of times the cattle have given birth.
Permutation	Arrangement or re-arrangement of objects or elements in a specific order, and in some machine learning (ML) algorithms (e.g., decision trees or ensemble methods), permutations can be used in feature selection or bootstrapping.
Population	Number of individuals used in the search.
Proximal phenotyping	This is the process of measuring traits or characteristics using sensors and technologies that are physically close to the plants, but not in direct contact. This can be performed using drones, robotic systems, or ground-based devices, which collect high-resolution data on various attributes (e.g., leaf area, chlorophyll content, water stress, among others). Unlike traditional methodologies, which are quick and accurate, these are used for large-scale and non-invasive agricultural practices.
R^2	Refers to the coefficient of determination, which measures how well the regression model fits the data. An R^2 value closer to 1 is better, as it indicates that a greater proportion of the variance in the dependent variable is explained by the model.
Range of the search	Values between which best gains are used in the search. It ranges from the minimum value and the maximum value of the search space.
RGB	Acronym for red, green, and blue, which refers to the color a model uses for representing images.
RF	Acronym for random forest regression (also known as RFR), which refers to the data-driven integrated learning approach.
RMSE	Acronym for root mean square error, and ideally, the smaller the value is, the better, since it measures the average magnitude of the error between the values that are predicted and the values that are observed. A smaller value means that the model's predictions are closer to the actual values.
RPD	Acronym for relative percentage difference, which is used to check the quality of a predictive model, particularly in the context of spectroscopy or chemometrics. It compares the prediction error to the variation in the data. The values used include the following: <1.4: impossible estimation, indicating that the model's predictions are highly inaccurate; ≥ 1.4 and <2: rough estimation, indicating that the predictions are moderately accurate but not precise; and ≥ 2: good estimation, indicating that the predictions are reliable and accurate (as described by [177]).
Small Scale Farmer (SSF)	Both FAO and CGIAR operate with this definition, although the exact criteria may differ depending on the region, crop/livestock type, and context. The system refers to SSF, which often operates <2 hectares for crops, relies primarily on family labor, and focuses on subsistence or local markets. Regarding livestock, SSF refers to systems that own small herds or flocks.
SOM	Acronym for self-organizing map, which is a type of unsupervised neural network that is used for dimensionality reduction, clustering, and visualization of high-dimensional data.

Stop condition	The number of iterations in which a search is performed, which can vary from 1 to any specified maximum number of iterations. The exact number depends on the problem and the algorithm being used.
SVR	Acronym for support vector regression, which is usually used for regression tasks to predict continuous values instead of predicting discrete categories as in the classification tasks. It is a powerful algorithm when the relationship between the input features and the target variable is complex and non-linear.
SVM	Acronym for support vector machine, which is also used for regression tasks. Its main strength lies in its ability to work efficiently with both linear and non-linear data using kernel functions.
UFAB	Acronym for universal function approximation block, which is a component used for approximating any given function.

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