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The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems

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Modern agriculture and food production systems are facing increasing pressures from climate change, land and water availability, and, more recently, a pandemic. These factors are threatening the environmental and economic sustainability of current and future food supply systems. Scientific and technological innovations are needed more than ever to secure enough food for a fast-growing global population. Scientific advances have led to a better understanding of how various components of the agricultural system interact, from the cell to the field level. Despite incredible advances in genetic tools over the past few decades, our ability to accurately assess crop status in the field, at scale, has been severely lacking until recently. Thanks to recent advances in remote sensing and Artificial Intelligence (AI), we can now quantify field scale phenotypic information accurately and integrate the big data into predictive and prescriptive management tools. This review focuses on the use of recent technological advances in remote sensing and AI to improve the resilience of agricultural systems, and we will present a unique opportunity for the development of prescriptive tools needed to address the next decade's agricultural and human nutrition challenges.

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Introduction

Agriculture production systems face daunting challenges worldwide, including climate change, dwindling water supply for irrigation, increases in production costs, and an overall reduction in the farm workforce over the past several decades. Besides, the most current issue, the COVID-19 pandemic, threatens the disruption of food production and supply systems everywhere [1•]. These factors threaten the environmental and economic sustainability of current and future food supply systems [2•]. While agriculture is always evolving, significant innovations will be needed to keep pace with persistent climate change [3]. The obvious question here is how to produce sufficient quality food for the fast-growing global population sustainably. Agricultural research scientists have always been utilizing state-of-the-art technologies and exploring ways to integrate them into agriculture systems. Dynamic crop simulation models have been useful tools for integrating diverse components of agriculture systems and allowing us to explore how those components function within the system [4]. Artificial Intelligence (AI) is recently gaining significant attention within agriculture disciplines because of its potential to leverage big data, which is now becoming easily accessible through the use of Unmanned Aircraft Systems (UAS) [5]. UAS brings an unprecedented opportunity to enable advanced analytics for managing agricultural systems, thus improving the resiliency and efficiency of production systems [6,7]. In this paper, we review current research on the use of remote sensing technology for sustainable agriculture. We also discuss current challenges facing the adoption of UAS technologies, as well as future perspectives on its integration with spaceborne remote sensing data for national and global scale studies.

Unmanned Aerial Systems (UAS) as a foundation for digital agriculture

Deploying individual physical sensors is often costly and time-consuming. Maintaining them in the field is also challenging as they frequently interfere with field operations such as tillage, planting, spraying, and harvesting. Plants integrate genetics (G) and its surrounding environments (E) by responding to soil physical and chemical properties, moisture availability, biotic and abiotic factors, as well as management practices (M). In this regard, plants can serve as field-based biological probes that may be assessed by sensors on-board UAS. Traditional methods of collecting crop data often fail to capture in-field variations due to limited sampling size and are prone to a certain level of subjectivity [8,9••]. To that end, UAS equipped with appropriate sensors can measure the time course of plant growth accurately, swiftly, and cost-effectively [8,9••,10,11]. These relatively affordable systems also enable the collection of fine spatial and high temporal resolution data, previously unobtainable through conventional airborne and spaceborne remote sensing platforms.

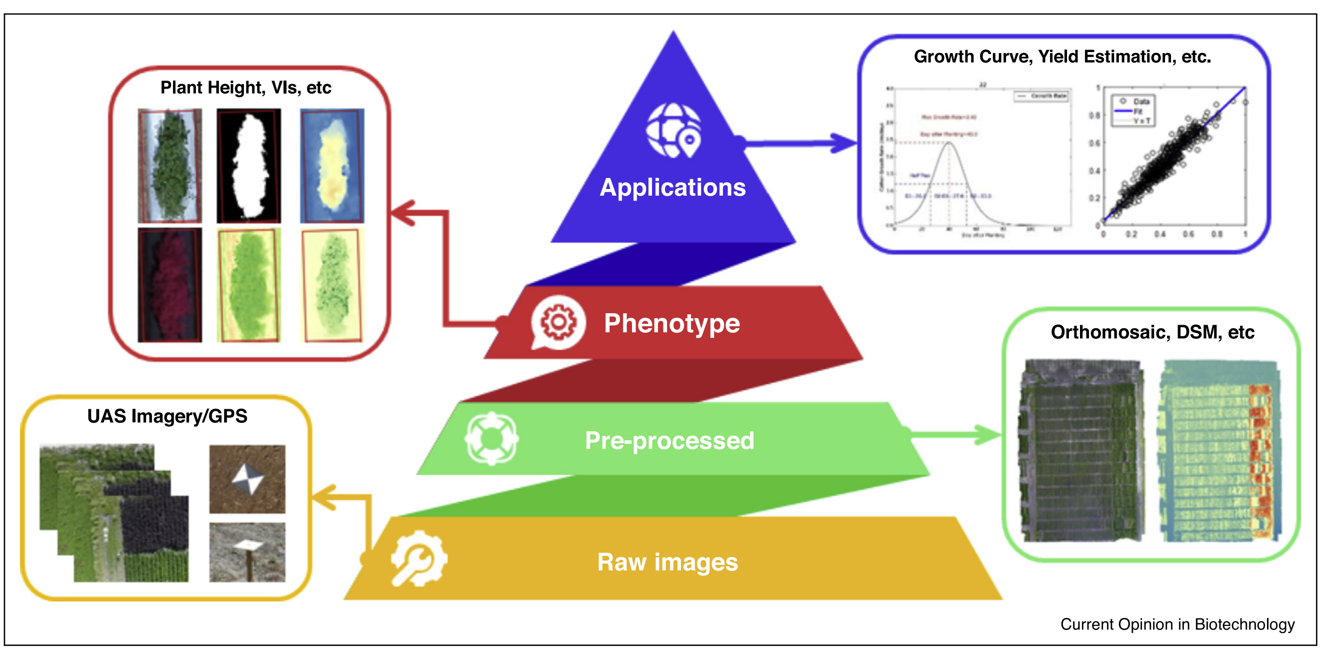
Current literature on Unmanned Vehicle (UV) indicates a significant uptick in interest on the topic. Research papers citing UV have increased from 544 in 2013 to 1593 in 2017, with areas such as remote sensing, imaging, instruments, geosciences, environmental sciences, ecology, wildlife, and agriculture seeing the most significant increases [12]. Most notably, scientists have initially focused on improving georeferencing accuracy [13] and calibration [14,15] of data products. Because of the potential high-throughput benefits, researchers have also investigated the use of UAS data to assess plant phenotypic characteristics at the field level [16••,17]. Additionally, researchers also used UAS to estimate water stress [18], monitor crop disease [19], map weeds [20], and estimate biomass and yield [21–23]. Others have also demonstrated that we can use high temporal resolution data to estimate crop parameters such as canopy height, canopy cover, and vegetation indices [8,9••,24], select genotypes [25•], and predict crop yield [26].

Although some breeding programs began adopting UAS, significant long-term challenges related to data collection/processing and interpretation of the processed data need to be addressed before breeders can fully embrace these systems. As raw data moves through the application development pipeline (Figure 1), it is clear that its integrity and quality of the raw data is crucial to ensure the accuracy of predictive models. One way to accomplish this is to develop standard protocols for data collection, processing, and interpretation. One area where UAS based High Throughput Phenotyping (HTP) system may have a tremendous short-term impact, however, is on the rapidly evolving Artificial Intelligence (AI) arena. In addition to the quality of raw data, when using a large dataset to train AI models, research has shown that performance is outstanding even when noisy data is involved [27], suggesting that the volume of training data is essential in developing robust AI models for agriculture applications. We have recently begun to witness multidisciplinary collaborations between computer scientists and biologists exploring AI for agricultural applications [28–30] (Table 1). Additionally, AI-based agricultural tools are also currently being commercially offered (Table 2).

Bridging the gap between genomics and phenomics with UAS

Advanced genomics offers analytical tools for crop breeding programs to understand the molecular basis of complex traits. Next-generation sequencing (NGS) technology improves the efficiency of marker-assisted and genomic selection by reducing the amount of time and cost needed to genotype a large number of breeding lines. Zeng *et al.* [44] made a breakthrough in the development

Figure 1



UAS based HTP application development workflow. The quality of raw data will have a significant impact on the accuracy of developed applications (VIs-Vegetation Indices, GPS-Global Positioning System, DSM-Digital Surface Model).

Table 1

Modern Artificial Intelligence (AI) methods currently used in agriculture applications

Applications	Crop	Input	Method/Models	Performance/Result	Ref.
HTP	Wheat	Genotypic and phenotypic data	DCNN	PCC > 0.7	[31]
	Soybean	Genotypic and phenotypic data	DCNN	PCC > 0.4	[32•]
Yield prediction	Soybean	UAS images (RGB, Multispectral, Thermal)	DNN	R^2: 0.72 RMSE: 15.9 %	[33••]
	Wheat	UAS based VIs	PLSR, ANN, RF	(R^2, RRMSE) PLSR: (0.7667, 0.1353) ANN: (0.7701, 0.1126) RF: (0.7800, 0.1030)	[34]
	Maize	2018 Syngenta Crop Challenge	DNN	RMSE: 46%	[35]
Fruit detection	Citrus	UAS images (RGB)	R-CNN	Precision > 90%	[36]
	Apple	UAS images (RGB)	R-CNN	R^2: 0.8	[37]
Weed detection	Rice	UAS images (RGB)	FCN	Overall accuracy weed mapping: 94% weed recognition: 88%	[38]
Disease detection	Bean and Spinach	UAS images (RGB)	CNN	Overall accuracy bean = 89% spinach = 94%	[39•]
	Wheat	UAS images (hyperspectral)	DCNN, RF	Overall Accuracy DCNN: 0.85 RF: 0.77	[40]
	Banana	Field images	DCNN	Overall accuracy >90%	[41]
	Maize	Field images	CNN	Overall accuracy: 99%	[42]
Biomass	Barley	UAS images (RGB, hyperspectral)	RF	PCC: 0.95% RMSE: 33.3%	[43]

ANN: artificial neural network, CNN: convolution neural network, DCNN: deep convolution neural network, DNN: deep neural network, FCN: fully convolutional network, R-CNN: region-convolutional neural network, RF: random forest, PCC: Pearson's correlation coefficient, PLSR: partial least square regression, SLR: simple linear regression, HTP: High Throughput Phenotyping, UAS: unmanned aerial system, RMSE: root mean square error.

Table 2

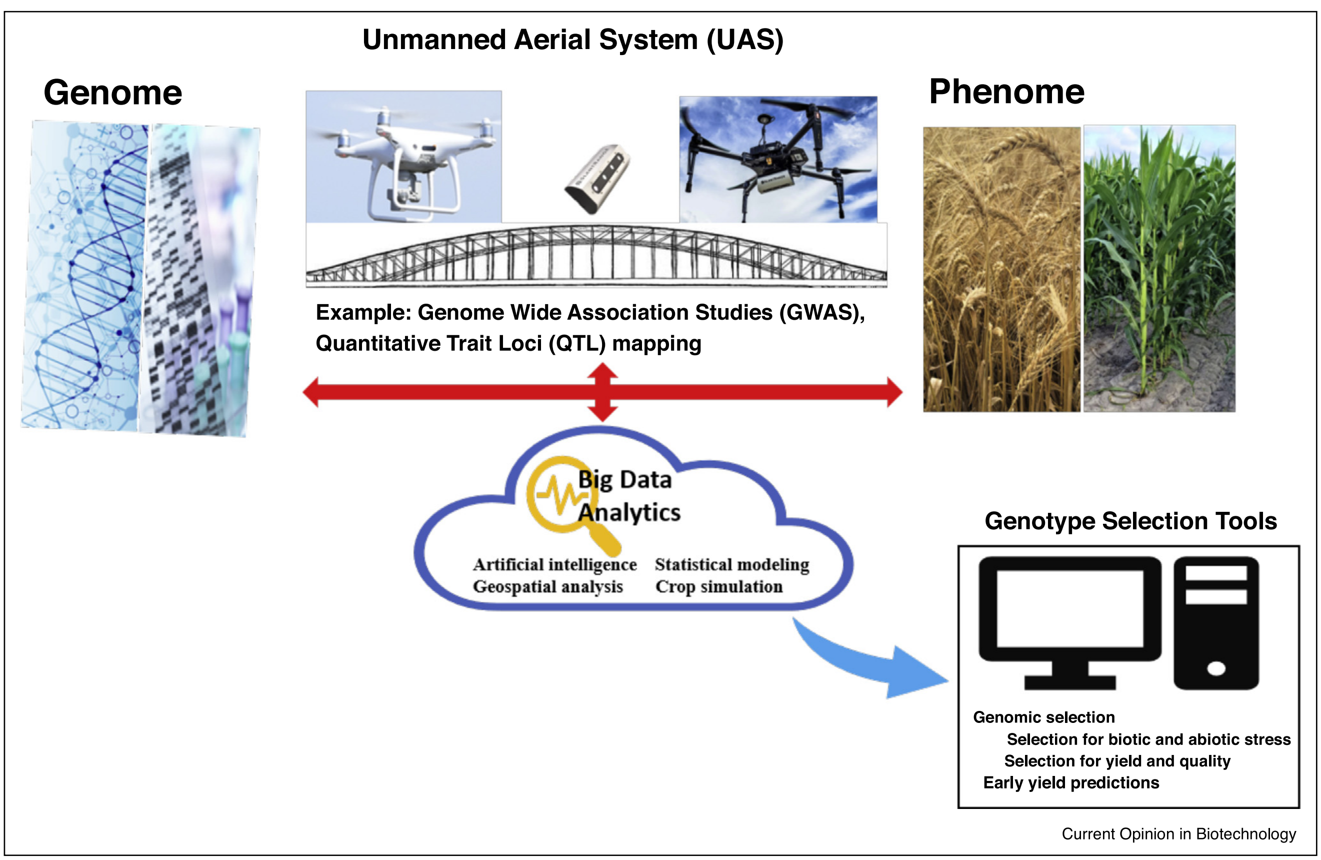
Commercially available Artificial Intelligence (AI)-based tools for agriculture (alphabetical order by company). The list is not comprehensive, and mention/omission does not imply endorsement/discrimination

Company	Website	Products/Service
AGEYE Technologies	ageyetech.com	AI-powered platform for indoor farming
aWhere	awhere.com	Weather information with machine learning algorithms in connection with satellites to predict the weather, analyze crop sustainability and evaluate farms for the presence of diseases and pests
Blue Reiver Technology	bluerivertechnology.com	Smart farm machines to manage crops at a plant-level and protect crops from weeds
FarmShots	farmshots.com	Integrated scouting and variable rate prescription platform for farmers based on images captured by satellites and drones
Fasal	fasal.co	AI-based solutions for the small farmer to provide critical parameters using affordable sensors
Harvest CROO Robotics	harvestcroorobotics.com	Robot system to pick and pack vegetables
HelioPas AI	heliopas.com	AI-based soil moisture monitoring system to control irrigation, fight mildew, and deal with drought
Hortau Inc	hortau.com	Web-based irrigation management service
Ibex Automation	ibexautomation.co.uk	Autonomous agricultural robot systems for farmers, including an autonomous precision weed detection and spraying system
PEAT	plantix.net	Deep Learning-empowered image recognition application to identify potential defects and nutrient deficiencies in soil
Root AI	root-ai.com	AI-based automated and robotic solutions for indoor farmers
Trace Genomics	tracegenomics.com	Soil analysis system to provide a sense of soil's strengths and weaknesses using machine learning
VineVIew	vineview.com	Highly specialized aerial-based spectral sensors, and a cloud-based image processing service to monitor crop health

of high yielding, superior quality rice varieties by pyramiding multiple complex traits using high-throughput genotyping methodologies. Genome-Wide Association Studies (GWAS) has also been used to identify markers linked to Quantitative Trait Loci (QTL) for several traits such as stripe rust in wheat [45], blast resistance in rice [46], spot blotch resistance in winter wheat [47], and fusarium head blight in wheat [48]. Genomic selection models are based on the training population dataset and are used to predict non-phenotyped individuals' performance based on Genomic Estimated Breeding Values (GEBVs). Therefore, to fully utilize the potential of genomic tools for crop improvement, accurate phenotypic measurements are needed, especially at the field level. Additionally, detailed phenotypic data at multiple dimensions will be required to bridge the genotype-phenotype gap. Recent advances in UAS have the potential to overcome the significant phenotyping bottleneck of many breeding programs by providing accurate, consistent, and reliable phenotypic data.

Watanabe *et al.* [49••] demonstrated that UAS-based plant height estimates in sorghum could be done at a performance level similar to manual measurements when using the genomic prediction model. GWAS study of canopy height measurements taken at four key growth stages and their respective growth rates identified 68 unique QTLs and candidate genes controlling plant height. UAS based phenomics can complement high-throughput genomics-assisted crop breeding [49••] in the development of superior varieties. Anderson *et al.* [50•] and Wang *et al.* [51] demonstrated the temporal expression of QTL associated with plant height in maize using multi-temporal measurements obtained by using UAS. Awika *et al.* [52••] linked genomic analysis to UAS based crop parameters such as canopy cover, canopy volume, and excess green index (ExG) in spinach. They identified 99 single-nucleotide polymorphisms (SNPs) significantly associated with the growth parameters. Growth parameters obtained by modeling season-long temporal features were able to reflect the phenotypic details at multiple dimensions better than the conventional manual measurements taken at one or a few times. Condorelli *et al.* [53] and Shokat *et al.* [54] also showed that GWAS of vegetation indices such as the Normalized Difference Vegetation Index (NDVI) could help to identify QTL hotspots that can be used in marker-assisted breeding to enhance drought tolerance in wheat. The possibility of obtaining

Figure 2



The concept for bridging the genome-phenome gap using an Unmanned Aerial System (UAS) based High Throughput Phenotyping (HTP) system.

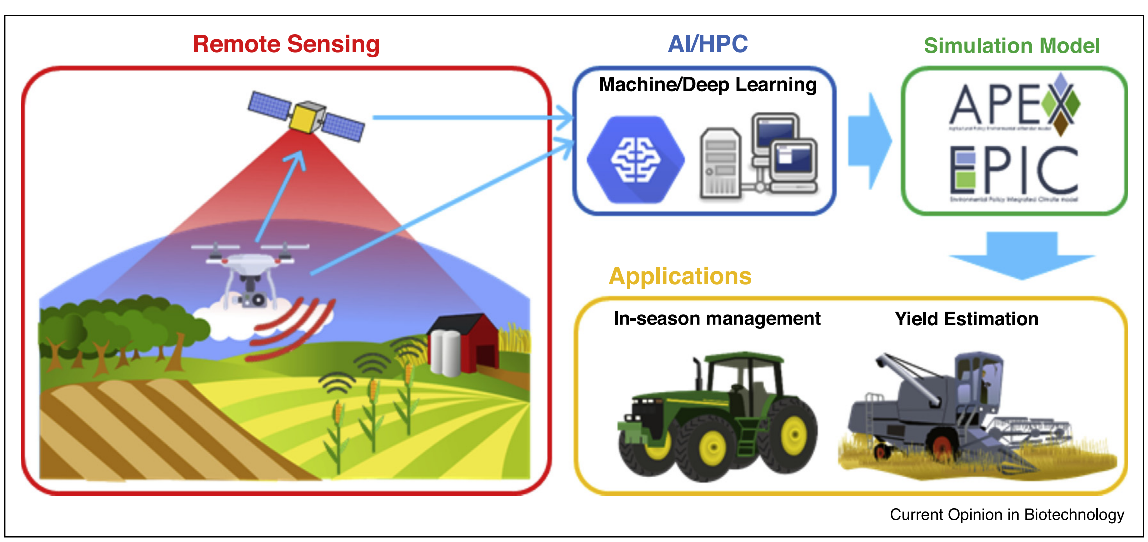
multi-temporal phenotypic traits using UAS can reveal additional information about the genotype, environment, and interactions. The integration of genomics and UAS based phenomics opens new research avenues to dissect complex agronomic traits and identify genes governing these traits (Figure 2). This integration can ultimately increase the size, efficiency, and genetic gain of breeding programs.

Digital agriculture: a combination of remote sensing, simulation models, and artificial intelligence (AI)

UAS provides efficient, robust, and reliable crop phenotyping [9••,55]. However, extensive spatial coverage by UAS is still not currently feasible due to limited battery and flight time. Additionally, even though UAS has low operational costs, data processing cost increases as the volume of data increase exponentially to cover larger areas [56,57]. Besides UAS based remote sensing technologies, there is a significant amount of research indicating the popularity of satellite data for precision agriculture applications [58]. Freely available satellite data, providing coarser spatial and temporal resolution, have been utilized to monitor vegetation and estimate yields. However, limited attention has been paid on how to adapt them for scale-appropriate precision agriculture applications [59]. Although some commercial satellites do provide finer spatial resolution data, temporal coverage frequency and cost efficiency are often limitations [60]. Since precision agriculture applications require information at a much finer scale, there is a significant challenge in adapting methodologies across different scales [61]. One exciting opportunity is to leverage high-resolution UAS data to finetune satellite-driven phenotypic data [61,62]. Essential advances in Machine Learning (ML) technology create a unique opportunity for the development of accurate, large-scale prediction and prescriptive models. Halevy *et al.* [63••] highlighted the importance of big data in ML algorithm development, especially for extremely complex problems that we cannot model via simple mathematical models. Halevy's paper demonstrated that a large amount of data could outweigh complex issues, such that even simple ML algorithms can outperform sophisticated algorithms. The success of deep learning is mainly attributed to the availability of large, quality training samples [63••]. We argue that one can use crop phenotypic information extracted from UAS data to derive accurate satellite-based crop status information at large scales.

Crop simulation models utilize input variables such as crop management information, weather, and soil data to estimate crop productivity and have become powerful tools to link physiology, genetics, and phenomics [64]. Current research in this direction focuses on the upscaling of crop simulation models from the field to large regions [65,66]. The main challenge involved in the upscaling process includes the calibration of model inputs beyond the field scale [67]. Although still in its infancy, the integration of remotely sensed crop phenotypic data with crop simulation models is a promising approach. While current ML methodologies are deterministic (i.e. limited to available examples based on which the model learns phenotypes), crop simulation models are capable of handling non-experienced scenarios (Figure 3). Benchmarks are common practices in AI and data science to establish

Figure 3



Advances in digital agriculture will benefit from the integration of remotely sensed data, advanced crop simulation models, and artificial intelligence (AI). In-season prescriptive tools and yield forecast capabilities will facilitate crop management and marketing projections.

baselines and evaluate one approach against others. Such benchmarks are beginning to be developed to help solve complex problems in agriculture using AI models to integrate phenotypic and genotypic data at the plot level [31,32•,35].

Conclusions and perspectives

Developing sustainable crop management practices have been a central topic in agriculture research for decades. Moving forward, we need to improve resource use efficiency of agricultural systems in order to meet current challenges and future needs. While agriculture and food production systems have significantly evolved over the past several decades, ongoing technological advances present a unique opportunity to address challenges for the upcoming decades. UAS based HTP system is proven to be a precise and reliable platform to quantify phenotypic information at field scales, and it can also be integrated with the GWAS even to speed up breeding cycles in many crops.

Although still in its infancy, pioneering research scientists are coupling the UAS based HTP system with spaceborne remote sensing, AI, and crop simulation models to develop large-area digital agriculture applications. As it stands, we need to pay significant attention to developing multidisciplinary teams capable of tackling diverse problems across the biological, environmental, and computer sciences disciplines. We also need to dedicate long term efforts to creating standard data collection, processing, and analysis protocols. As a central piece in the future of data-driven digital agriculture, the importance of raw-data quality cannot be underestimated.

Conflict of interest statement

Nothing declared.

CRediT authorship contribution statement

Jinha Jung: Conceptualization, Methodology, Writing - original draft, Writing - review & editing. **Murilo Maeda:** Methodology, Writing - review & editing, Investigation. **Anjin Chang:** Software, Writing - review & editing, Investigation. **Mahendra Bhandari:** Writing - review & editing, Investigation. **Akash Ashapure:** Software, Writing - review & editing. **Juan Landivar-Bowles:** Conceptualization, Methodology, Writing - original draft, Supervision.

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