



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.

Addresses

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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].

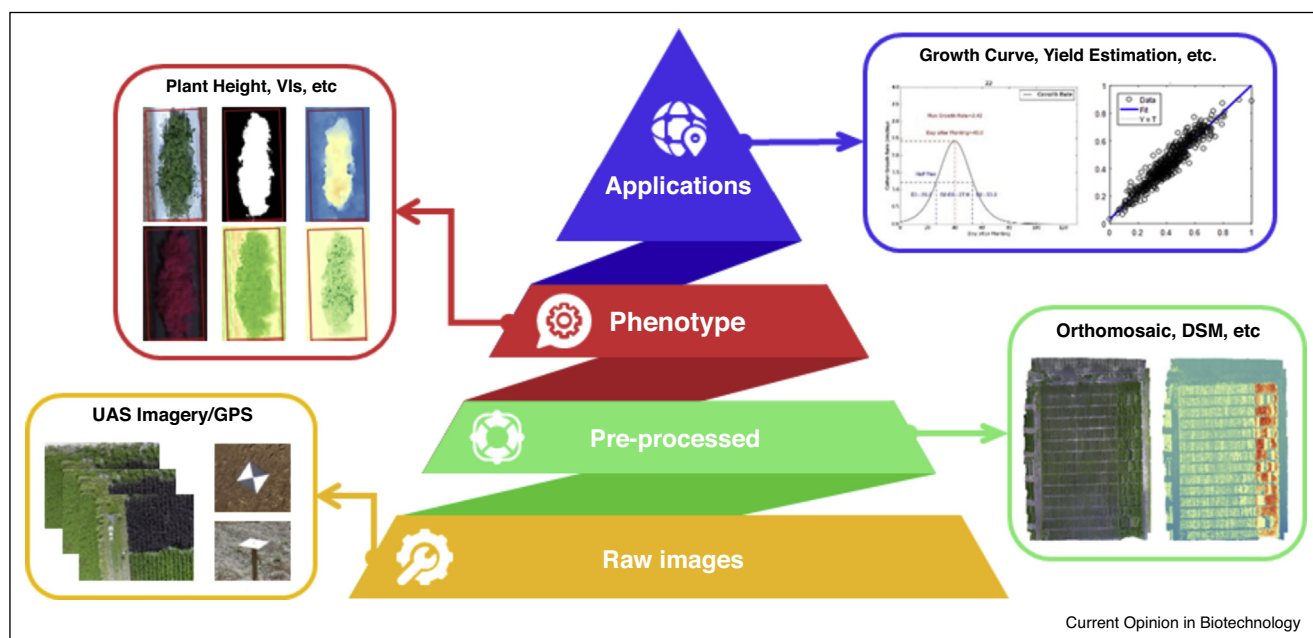
Although some breeding programs began adopting UAS, significant long-term challenges related to data collection/processing and interpretation of the processed data need to be addressed before breeders can fully embrace these

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 multi-disciplinary 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]
Yield prediction	Soybean	Genotypic and phenotypic data	DCNN	PCC > 0.4	[32*]
	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]
Fruit detection	Maize	2018 Syngenta Crop Challenge	DNN	RMSE: 46%	[35]
	Citrus	UAS images (RGB)	R-CNN	Precision > 90%	[36]
Weed detection	Apple	UAS images (RGB)	R-CNN	R ² : 0.8	[37]
	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]
Biomass	Maize	Field images	CNN	Overall accuracy: 99%	[42]
	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**

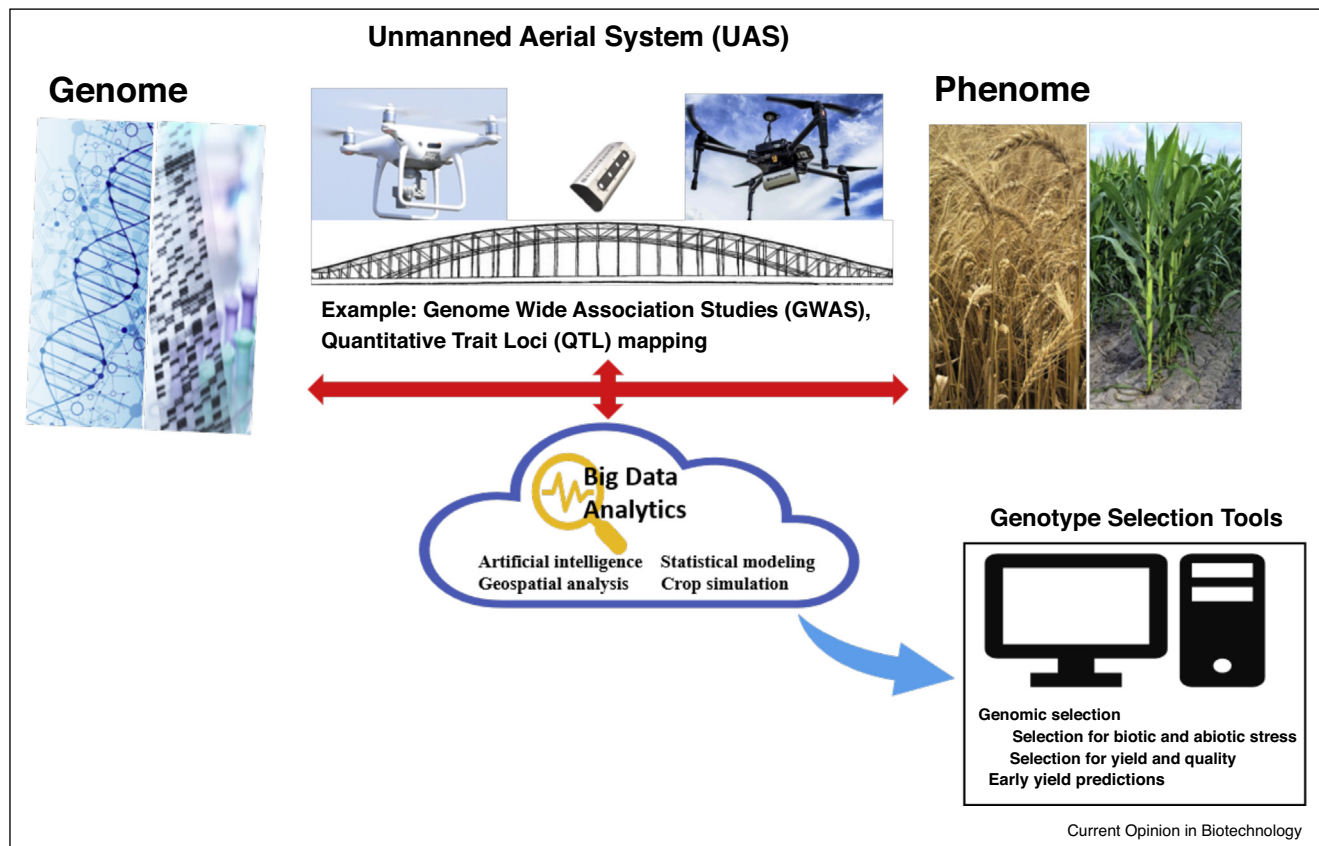
Company	Website	Products/Service
AGEYE Technologies	ageyetech.com	AI-powered platform for indoor farming
aWhere	awhere.com	Weather information with machine learning algorithms in connection with satellites to predict the weather, analyze crop sustainability and evaluate farms for the presence of diseases 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
VineVlew	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.

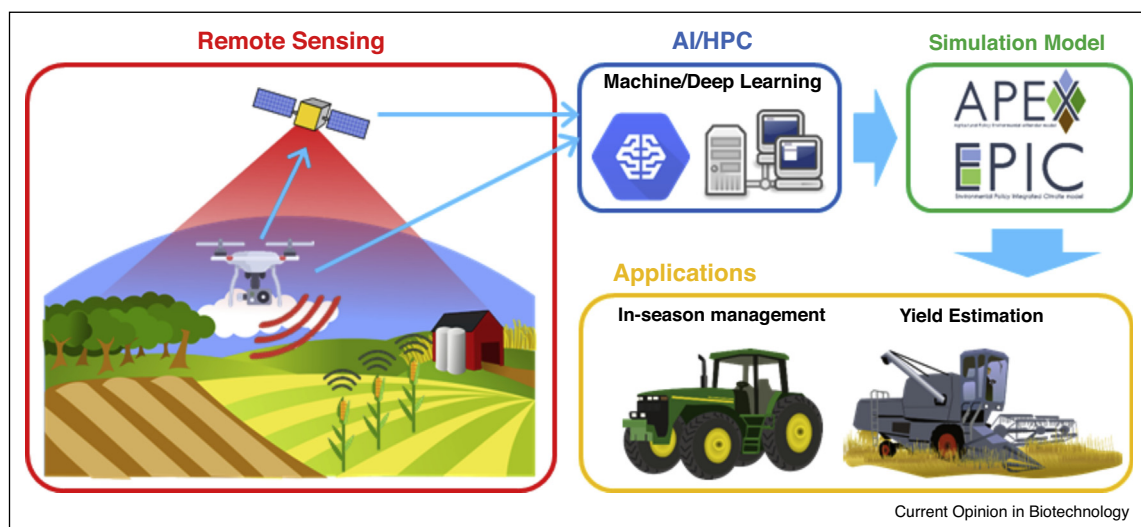
Digital agriculture: a combination of remote sensing, simulation models, and artificial intelligence (AI)

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.

References and recommended reading

Papers of particular interest, published within the period of review, have been highlighted as:

- of special interest
 - of outstanding interest
1. Outlaw JL, Fischer BL, Anderson DP, Klose SL, Ribera LA, Raulston JM, Knappek GM, Herbst BK, Benavidez JR, Bryant HL, Ernstes DP: *COVID-19 Impact on Texas Production Agriculture*. Agricultural & Food Policy Center, Texas A&M University Research; 2020.
 - The authors describe disruption in the agriculture supply chain of major crops in Texas as affected by the COVID-19 pandemic and its consequences to food supply and farm profitability.
 2. Andersen MA, Alston JM, Pardey PG, Smith A: **A century of U.S. productivity growth: a surge then a slowdown**. *Am J Agric Econ* 2018, **93**:1257-1277.
 - The authors presented historical U.S. Agriculture productivity and discussed difficulties in meeting future food needs due to a U.S. productivity plateau.
 3. Hatfield J, Takle G, Grotjahn R, Holden P, Izaurralde RC, Mader T, Marshall E, Liverman D: **Ch. 6: Agriculture**. In *Climate change in the United States: The Third National Climate Assessment*. Edited by Melillo JM, Richmond T, Yohe GW. U.S. Global Change Research Program; 2014:50-174.
 4. Wang X, Williams JR, Gassman PW, Baffaut C, Izaurralde RC, Jeong J, Kiniry RJ: **Epic and apex: model use, calibration, and validation**. *Trans ASABE* 2014, **55**:1447-1462.
 5. Hassler SC, Baysal-Gurel F: **Unmanned Aircraft System (UAS) technology and applications in agriculture**. *Agronomy-Basel* 2019, **9**:618.
 6. Coble KH, Mishra AK, Ferrell S, Griffin T: **Big data in agriculture: a challenge for the future**. *Appl Econ Perspect Policy* 2018, **40**:79-96.
 7. Lezoche M, Hernandez JE, Diaz MDEA, Panetto H, Kacprzyk J: **Agri-food 4.0: a survey of the supply chains and technologies for the future agriculture**. *Comput Ind* 2020, **117** 103187.
 8. Chang A, Jung J, Maeda MM, Landivar J: **Crop height monitoring with digital imagery from Unmanned Aerial System (UAS)**. *Comput Electron Agric* 2017, **141**:232-237.
 9. Ashapure A, Jung J, Yeom J, Chang A, Maeda M, Maeda A, Landivar J: **A novel framework to detect conventional tillage and no-tillage cropping system effect on cotton growth and development using multi-temporal UAS data**. *ISPRS-J Photogramm Remote Sens* 2019, **152**:49-64.
 - The author develops a framework to monitor the cropping system effect using multi-temporal UAS data. This study demonstrates that UAS can be a more efficient and consistent way to measure crop phenotypic data.
 10. Araus JL, Cairns JE: **Field high-throughput phenotyping: the new crop breeding frontier**. *Trends Plant Sci* 2014, **19**:52-61.
 11. Marcial-Pablo MD, Gonzalez-Sanchez A, Jimenez-Jimenez SI, Ontiveros-Capurata RE, Ojeda-Bustamante W: **Estimation of vegetation fraction using RGB and multispectral images from UAV**. *Int J Remote Sens* 2019, **40**:420-438.
 12. Chabot D: **Trends in drone research and applications as the Journal of Unmanned Vehicle Systems turns five**. *J Unmanned Veh Syst* 2018, **6**:vi-xv.
 13. Mesas-Carrascosa F, Torres-Sánchez J, Clavero Rumbao I, Garcia-Ferrer A, Peña J, Borra-Serrano I, Lopez-Granados A: **Assessing optimal flight parameters for generating accurate multispectral orthomosaics by UAV to support site-specific crop management**. *Remote Sens* 2015, **7**:12793-12814.
 14. Shi Y, Thomasson JA, Murray SC, Pugh NA, Rooney WL, Shafian S, Rajan N, Rouze G, Morgan CLS, Neely HL *et al.*: **Unmanned aerial vehicles for high-throughput phenotyping and agronomic research**. *PLoS One* 2016, **11**:e0159781.
 15. Han X, Thomasson JA, Bagnall GC, Pugh NA, Horne DW, Rooney WL, Jung J, Chang A, Malambo L, Popescu SC *et al.*: **Measurement and calibration of plant-height from fixed-wing UAV images**. *Sensors* 2018, **18**:4092.
 16. Yeom J, Jung J, Chang A, Ashapure A, Maeda M, Maeda A, Landivar J: **Comparison of vegetation indices derived from UAV data for differentiation of tillage effects in agriculture**. *Remote Sens* 2019, **11**:1548.
 - The manuscript describes distinct differences in Vegetation Indices (VIs) in the tillage/no-tillage field during the whole growing season. This study shows that Near-Infrared (NIR)-based VIs have better discrimination performance than RGB-based VIs.

17. Gracia-Romero A, Kefauver SC, Fernandez-Gallego JA, Vergara-Diaz O, Nietro-Taladriz MT, Arous JL: **UAV and ground image-based phenotyping: a proof of concept with durum wheat.** *Remote Sens* 2019, **10**:1244.
18. Santesteban LG, Gennaro SFD, Herrero-Langreo S, Miranda C, Royo JB: **High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard.** *Agric Water Manage* 2017, **183**:49-59.
19. Shakoor N, Lee S, Mockler T: **High throughput phenotyping to accelerate crop breeding and monitoring of diseases in the field.** *Curr Opin Plant Biol* 2017, **38**:184-192.
20. Gašparović M, Zrinjski M, Barković Đ, Radočaj D: **An automatic method for weed mapping in oat fields based on UAV imagery.** *Comput Electron Agric* 2020, **173** 105385.
21. Niu Y, Zhang L, Zhang H, Han W, Peng X: **Estimating above-ground biomass of maize using features derive from UAV-based RGB imagery.** *Remote Sens* 2019, **11**:21.
22. Olson D, Chatterjee A, Franzen DW, Day SS: **Relationship of drone-based vegetation indices with corn and sugarbeet yields.** *Agron J* 2019, **111**:2545-2557.
23. Duan B, Fang S, Zhu R, Wu X, Wang S, Gong Y, Peng Y: **Remote estimation of rice yield with unmanned aerial vehicle (UAV) data and spectral mixture analysis.** *Front Plant Sci* 2019, **10**:204.
24. Moeckel T, Dayananda S, Nidamanuri RR, Nautiyal S, Hanumaiah N, Buerkert A, Wachendorf M: **Estimation of vegetable crop parameter by multi-temporal UAV-borne images.** *Remote Sens* 2018, **10**:805.
25. Jung J, Maeda M, Chang A, Landivar J, Yeom J, McGinty J: **Unmanned aerial system assisted framework for the selection of high yielding cotton genotypes.** *Comput Electron Agric* 2018, **152**:74-81.
- The authors demonstrated that phenotypic features extracted from the UAS data could be utilized to screen high yielding varieties for cotton.
26. Zhou X, Zheng HB, Xu XQ, He JY, Ge XK, Yao X, Cheng T, Zhu Y, Cao WX, Tian YC: **Predicting grain yield in rice using multi-temporal vegetation indices from UAV-based multispectral and digital imagery.** *ISPRS J Photogramm Remote Sens* 2017, **130**:246-255.
27. Rolnick D, Veit A, Belongie S, Shavit N: **Deep learning is robust to massive label noise.** *arXiv* 2018, **1705** 10694v3.
28. Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D: **Machine learning in agriculture: a review.** *Sensors* 2018, **18**:2674.
29. Kamilaris A, Prenafeta-Boldú FX: **Deep learning in agriculture: a survey.** *Comput Electron Agric* 2018, **147**:70-90.
30. Jha K, Dosh A, Patel P, Shah M: **A comprehensive review on automation in agriculture using artificial intelligence.** *Artif Intell Agric* 2019, **2**:1-12.
31. Ma W, Qiu Z, Song J, Li J, Cheng Q, Zhi J, Ma C: **A deep convolutional neural network approach for predicting phenotypes from genotypes.** *Planta* 2018, **248**:1307-1318.
32. Liu Y, Wang D, He F, Wang J, Joshi T, Xu D: **Phenotype prediction and genome-wide association study using deep convolutional neural network of soybean.** *Front Genet* 2019, **10**:1091.
- The authors used agricultural benchmark dataset, SoyNAM, including genotypes, phenotypes, yield collected at Purdue University.
33. Maimaitijiang M, Sagan V, Sidike P, Hartling S, Esposito F, Fritschi FB: **Soybean yield prediction from UAV using multimodal data fusion and deep learning.** *Remote Sens Environ* 2020, **237** 111599.
- The authors developed the soybean yield prediction model using multimodal data fusion and deep learning. This work shows that crop phenotypes such as canopy structure, temperature, and texture from a low-cost multi-sensor UAV data are essential features for the yield prediction model.
34. Fu Z, Jiang J, Gao Y, Krienke B, Wang M, Zhong K, Cao Q, Tian Y, Zhu Y, Cao W, Liu X: **Wheat growth monitoring and yield estimation based on multi-rotor unmanned aerial vehicle.** *Remote Sens* 2020, **12**:508.
35. Khaki S, Wang L: **Crop yield prediction using deep neural networks.** *Front Plant Sci* 2019, **10**:621.
36. Apolo-Apolo OE, Martínez-Guanter J, Egea G, Raja P, Pérez-Ruiz M: **Deep learning techniques for estimation of the yield and size of citrus fruits using a UAV.** *Eur J Agron* 2020, **115** 126030.
37. Apolo-Apolo OE, Pérez-Ruiz M, Martínez-Guanter J, Valente J: **A cloud-based environment for generating yield estimation maps from apple orchards using UAV imagery and a deep learning technique.** *Front Plant Sci* 2020, **11**:1086.
38. Huang H, Deng J, Lan Y, Yang A, Deng X, Zhang L: **A fully convolutional network for weed mapping of unmanned aerial vehicle (UAV) imagery.** *PLoS One* 2018, **13**:e0196302.
39. Bah MD, Hafiane A, Canals R: **Deep learning with unsupervised data labeling for weed detection in line crops in UAV images.** *Remote Sens* 2018, **10**:1690.
- The authors adopted CNN on an unsupervised training data to identify weeds in the row crops. Although unsupervised approach reduces the time and effort of manually training the data, it might have some accuracy issues on its generalizations.
40. Zhang X, Han L, Dong Y, Shi Y, Huang W, Han L, González-Moreno P, Ma H, Ye H, Sobeih TA: **Deep learning-based approach for automated yellow rust disease detection from high-resolution hyperspectral UAV images.** *Remote Sens* 2019, **11**:1554.
41. Selvaraj MG, Vergara A, Ruiz H, Safari N, Elayabalan S, Ocimati W, Blomme G: **AI-powered banana diseases and pest detection.** *Plant Methods* 2019, **15**:92.
42. Wiesner-Hanks T, Wu H, Stewart E, DeChant C, Kaczmar N, Lipson H, Gore MA, Nelson RJ: **Millimeter-level plant disease detection from aerial photographs via deep learning and crowdsourced data.** *Front Plant Sci* 2019, **10**:1550.
43. Näsi R, Viljanen N, Kaivosoja J, Alhonoja K, Hakala T, Markelin L, Honkavaara E: **Estimating biomass and nitrogen amount of barley and grass using UAV and aircraft based spectral and photogrammetric 3D features.** *Remote Sens* 2018, **10**:1082.
44. Zeng D, Tian Z, Rao Y, Dong G, Yang Y, Huang L, Leng Y, Xu J, Sun C, Zhang G et al.: **Rational design of high-yield and superior-quality rice.** *Nat Plants* 2017, **3**:1-5.
45. Liu W, Maccaferri M, Bulli P, Rynearson S, Tuberosa R, Chen X, Pumphrey M: **Genome-wide association mapping for seedling and field resistance to *Puccinia striiformis* f. sp. *tritici* in elite durum wheat.** *Theor Appl Genet* 2017, **130**:649-667.
46. Raboin LM, Ballini E, Tharreau D, Ramanantsoanirina A, Frouin J, Courtois B: **Association mapping of resistance to rice blast in upland field conditions.** *Rice* 2016, **9**:59.
47. Ayana GT, Ali S, Sidhu JS, Gonzalez Hernandez JL, Turnipseed B, Sehgal SK: **Genome-wide association study for spot blotch resistance in hard winter wheat.** *Front Plant Sci* 2018, **9**:926.
48. Arruda MP, Brown P, Brown-Guedira G, Krill AM, Thurber C, Merrill KR, Foresman BJ, Kolb FL: **Genome-wide association mapping of fusarium head blight resistance in wheat using genotyping-by-sequencing.** *Plant Genome* 2016, **9**:1-14.
49. Watanabe K, Guo W, Arai K, Takanashi H, Kajiya-Kanegae H, Kobayashi M, Yano K, Tokunaga T, Fujiwara T, Tsutsumi N et al.: **High-throughput phenotyping of sorghum plant height using an unmanned aerial vehicle and its application to genomic prediction modeling.** *Front Plant Sci* 2017, **8**:421.
- The authors laid out the prospects of integrating high-throughput genotyping and high-throughput phenotyping and showed the additional advantage of using UAVs over single-point measurements.
50. Anderson SL, Murray SC, Chen Y, Malambo L, Chang A, Popescu S, Cope D, Jung J: **Unoccupied aerial system enabled functional modeling of maize height reveals dynamic expression of loci.** *Plant Direct* 2020, **4**:e00223.
- The authors presented the significance of multitemporal UAS data to understand the temporal dynamics of expressing the Quantitative Trait Loci (QTLs), which can lead to the development of additional genomic tools to understand the genes associated with trait expression.

51. Wang X, Zhang R, Song W, Han L, Liu X, Sun X, Luo M, Chen K, Zhang Y, Yang H *et al.*: **Dynamic plant height QTL revealed in maize through remote sensing phenotyping using a high throughput unmanned aerial vehicle (UAV)**. *Sci Rep* 2019, **9**:1-10.
52. Awika HO, Bedre R, Yeom J, Marconi TG, Enciso J, Mandadi KK, Jung J, Avila CA: **Developing growth-associated molecular markers via high-throughput phenotyping in spinach**. *Plant Genome* 2019, **12**:1-19.
- The authors performed a genomic analysis of multiple traits obtained from UAS to understand the growth of spinach. They showed the possibility of multi-dimensional integration of phenomics and genomics data.
53. Condorelli GE, Maccaferri M, Newcomb M, Andrade-Sanchez P, White JW, French AN, Sciara G, Ward R, Tuberosa R: **Comparative aerial and ground based high throughput phenotyping for the genetic dissection of NDVI as a proxy for drought adaptive traits in durum wheat**. *Front Plant Sci* 2019, **9**:893.
54. Shokat S, Sehgal D, Liu F, Singh S: **GWAS analysis of wheat pre-breeding germplasm for terminal drought stress using next generation sequencing technology**. *Preprints* 2020. 2020020272.
55. Singh KK, Frazier AE: **A meta-analysis and review of unmanned aircraft system (UAS) imagery for terrestrial applications**. *Int J Remote Sens* 2018, **39**:5078-5098.
56. Tsouros DC, Bibi S, Sarigiannidis PG: **A review on UAV-based applications for precision agriculture**. *Information-Basel* 2019, **10**:349.
57. Weiss M, Jacob F, Duveiller G: **Remote sensing for agricultural applications: a meta-review**. *Remote Sens Environ* 2020, **236**:111402.
58. Herbei MV, Popescu CA, Bertici R, Smuleac A, Popescu G: **Processing and use of satellite images in order to extract useful information in precision agriculture**. *Bull UASVM Agric* 2016, **73**:238-246.
59. Duveiller G, Cescatti A: **Spatially downscaling sun-induced chlorophyll fluorescence leads to an improved temporal correlation with gross primary productivity**. *Remote Sens Environ* 2016, **182**:72-89.
60. Yang C: **High resolution satellite imaging sensors for precision agriculture**. *Front Agric Sci Eng* 2018, **5**:393-405.
61. Lukas V, Novák J, Neudert L, Svobodova I, Rodriguez-Moreno F, Edrees M, Kren J: **The combination of uav survey and landsat imagery for monitoring of crop vigor in precision agriculture**. *ISPRS Arch* 2016, **XLI-B8**:953-957.
62. Mazzia V, Comba L, Khaliq A, Chiaberge M, Gay P: **UAV and machine learning based refinement of a satellite-driven vegetation index for precision agriculture**. *Sensors* 2020, **20**:2530.
63. Halevy A, Norvig P, Pereira F: **The unreasonable effectiveness of data**. *IEEE Intell Syst* 2009, **24**:8-12.
- The authors highlighted the importance of big data in developing machine learning algorithms and demonstrated that even simple logic could perform as good as complicated algorithms when big data are used to train the models.
64. Muller B, Martre P: **Plant and crop simulation models: powerful tools to link physiology, genetics, and phenomics**. *J Exp Bot* 2019, **70**:2339-2344.
65. Morell FJ, Yang HS, Cassman KG, Van Wart J, Elmore RW, Licht M, Coulter JA, Ciampitti IA, Pittelkow CM, Brouder SM *et al.*: **Can crop simulation models be used to predict local to regional maize yields and total production in the US Corn Belt?** *Field Crop Res* 2016, **192**:1-12.
66. Manivasagam V, Rozenstein O: **Practices for upscaling crop simulation models from field scale to large regions**. *Comput Electron Agric* 2020, **175**:105554.
67. Pearl J: **The seven tools of causal inference with reflections on machine learning**. *Commun ACM* 2019, **62**:54-60.