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Research Article

Digital Agronomy, Remote Sensing, and Decision Support for Precision Crop Management

Research Article

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Abstract

Digital agronomy promises to make crop management more precise, timely, and efficient by combining remote sensing, weather data, soil sensors, mobile advisories, and decision support tools. Yet many digital tools have produced impressive demonstrations and disappointing adoption, because they were designed for data-rich, well-connected farms and not for the fields where they are most needed. This article reviews digital agronomy as a decision problem, not only as a technology problem. It examines how satellite imagery, drones, soil moisture sensors, weather forecasts, and mobile advisories can improve decisions about variety, planting date, fertiliser, irrigation, pest control, and harvest, and where they add little value without ground validation, agronomic knowledge, and institutional support. It shows that digital tools improve input-use efficiency and yield most when they are locally calibrated, delivered in usable formats, linked to a concrete decision, and trusted by farmers. It proposes a practical framework for designing and evaluating digital agronomy services, and it identifies research and policy priorities for making digital tools inclusive, affordable, and agronomically sound.

Keywords: digital agronomy; remote sensing; precision agriculture; decision support; weather advisory; soil sensors; mobile extension

1. Introduction

Agronomy has always been a science of decisions under uncertainty. A farmer must choose a variety before knowing the season's rainfall, decide how much fertiliser to apply before knowing the price at harvest, and decide when to irrigate or spray before knowing whether the forecast will be correct. Digital tools promise to reduce that uncertainty by providing more, faster, and more spatially precise information: satellite images that show where a crop is stressed, soil sensors that show when water is depleted, weather forecasts that warn of a dry spell, and mobile messages that translate data into a recommendation (Mulla, 2013; Weiss et al., 2020). The promise is real, but so is the risk of digital solutionism: the belief that more data automatically produces better decisions.

In practice, a satellite index, a sensor reading, or an app notification is only useful if it changes a decision that a farmer can actually act on, at a cost the farmer can afford, in a format the farmer can understand, and with enough trust that the farmer will follow it (Fabregas et al., 2019; Hansen et al., 2019). A weather advisory that arrives after planting, a fertiliser recommendation that assumes credit is available, or a pest alert that requires a pesticide the farmer cannot buy will not improve outcomes, however accurate the underlying model. Digital agronomy must therefore be evaluated not by the sophistication of its algorithms, but by whether it helps a farmer make a better next decision.

This article reviews digital agronomy as agronomy first and technology second. It examines the main data sources, how they are turned into decisions, what evidence exists for yield, efficiency, and income effects, and what institutional, equity,

and data-governance conditions determine whether digital services scale or stall.

2. Data Sources: Satellites, Drones, Sensors, and Weather

Satellite remote sensing provides repeated, large-area observations of crop vigour, canopy cover, and stress. Vegetation indices such as NDVI and EVI correlate with leaf area, biomass, and chlorophyll, and can reveal spatial variability within a field that is invisible from the ground (Mulla, 2013; Weiss et al., 2020). Thermal imagery can indicate water stress because stressed leaves close stomata and warm. Radar can penetrate clouds and provide information on soil moisture and crop structure, which is valuable in humid regions where optical imagery is often cloudy. The limitation is resolution and interpretation: a satellite pixel averages many plants, and an index that signals stress does not by itself say whether the cause is water, nitrogen, pests, or disease. Ground validation is essential.

Drones, or unmanned aerial vehicles, provide higher-resolution imagery on demand, with multispectral and thermal cameras that can map nutrient deficiency, pest damage, and water stress at plant or plot scale (Zhang and Kovacs, 2012; Weiss et al., 2020). Drones are useful for research stations, large farms, and service providers, but they face constraints for smallholders: cost, batteries, regulation, pilot skill, and data processing. In many smallholder contexts, a drone service that visits a village once a season is more realistic than farmer-owned drones.

Soil and weather sensors provide the other half of the data picture. Soil moisture probes, tensiometers, and capacitance sensors measure water status continuously, while weather stations and gridded weather products provide rainfall, temperature, and evapotranspiration (Jones, 2004; Hansen et al., 2019). Low-cost sensors can be valuable, but they drift, break, and require calibration. A sensor that is not maintained can produce confident but wrong advice, which can destroy trust faster than no advice at all. The most useful sensor networks are those that are maintained, calibrated, and linked to a decision rule that farmers understand.

3. From Data to Decisions: Advisory Services and Decision Support

Decision support systems translate data into recommendations. They can be simple, such as a rule that says irrigate when soil moisture falls below a threshold, or complex, such as a crop model that simulates growth under different weather and management scenarios (Jones et al., 2003; Keating et al., 2003). Crop models such as DSSAT, APSIM, and WOFOST can help explore what would happen if planting were delayed, fertiliser were split, or irrigation were reduced, but they require local calibration of soil, variety, and management parameters to be useful (Jones et al., 2003). A model that is not calibrated to local varieties and soils can produce precise but misleading recommendations.

Mobile advisories have expanded access to information. SMS, voice messages, radio, and smartphone apps can deliver weather forecasts, planting advice, pest alerts, and market prices (Fabregas et al., 2019; Aker, 2011). Studies of mobile advisories find that they can improve knowledge and adoption of recommended practices, but effects on yield and income are often modest and depend on whether the advice is timely, specific, and actionable (Fabregas et al., 2019; Aker, 2011). An advisory that says it will rain in three days is more useful than one that says seasonal rainfall will be normal. An advisory that says apply a named fertiliser at a named rate on a named date, with a named supplier, is more useful than a generic recommendation to apply fertiliser.

Trust is a central variable. Farmers trust advice that has been correct in the past, that comes from a source they know, and that they can verify by observing their own field (Hansen et al., 2019; Fabregas et al., 2019). Participatory design, in which farmers test advisories on their own plots and compare them with their usual practice, can build trust and improve design. Advisories that are co-designed with farmers, extension workers, and local agronomists are more likely to be used than those designed in isolation.

4. Precision Management: Nutrients, Water, Pests, and Harvest

Digital tools can improve nutrient management by mapping spatial variability and by timing applications to crop demand. Variable-rate fertiliser application, guided by soil maps, satellite imagery, or handheld sensors such as chlorophyll meters, can reduce over-application in high-fertility zones and under-application in low-fertility zones (Mulla, 2013; Roberts et al., 2010). Leaf colour charts and sensor-based nitrogen management can help farmers decide whether a top-dressing is needed, without a laboratory test. The benefit is largest where spatial variability is high and fertiliser is expensive, and smallest where fields are uniform or fertiliser is already low.

For water, digital tools can improve scheduling by combining soil moisture, weather forecasts, and crop stage. A farmer who knows that rain is likely in two days can delay irrigation and save water, while a farmer who knows that a dry spell is coming can irrigate before stress occurs (Jones, 2004; Hansen et al., 2019). For pests, image-based identification apps and trap data can help farmers recognise pests early and decide whether a threshold has been crossed. For harvest, satellite monitoring and weather forecasts can help plan labour, transport, and drying, reducing post-harvest losses. Figure 1 summarises the pattern from the cited syntheses: digital bundles improve input-use efficiency more than they raise yield alone, and the largest gains appear where baseline management was imprecise.

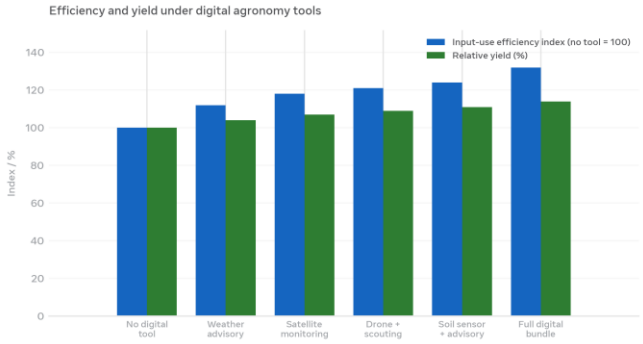


Figure 1. Efficiency and yield under digital agronomy tools, based on synthesis of the reviews and evaluations cited in the text. Values vary by crop, context, and service design.

5. Evidence, Costs, and Adoption

Evidence on digital agronomy is mixed but instructive. Randomised evaluations of mobile advisories and weather

services generally find improvements in knowledge and adoption, and smaller, more variable effects on yield and income (Fabregas et al., 2019; Aker, 2011). Precision agriculture studies on large farms find that variable-rate application and remote sensing can reduce input use and increase profit, but they often require capital, machinery, and data infrastructure that smallholders do not have (Mulla, 2013; Roberts et al., 2010). The gap between large-farm precision agriculture and smallholder digital agronomy is therefore not only about technology, but about business models, service delivery, and affordability.

Costs include devices, data, connectivity, maintenance, and learning. A service that is free during a pilot but expensive afterwards will be abandoned, however useful it was. Sustainable models include public provision of weather and soil information as a public good, subscription or pay-per-use services delivered through cooperatives, and embedded services where an input supplier or buyer provides advice as part of a transaction (Hansen et al., 2019). Each model has risks: public provision can be underfunded, private provision can exclude the poorest, and embedded services can bias advice toward a product.

Adoption is shaped by literacy, language, gender, and age. Services that require reading, smartphones, or data plans can exclude women, older farmers, and those with low literacy, even when they would benefit most (Farnworth et al., 2017; Huyer et al., 2015). Voice messages, local languages, radio, and group-based services can be more inclusive than text-only apps. Services that are designed for a single user, usually a male household head, may not reach the person who actually makes the decision about a particular crop or task.

6. Data Governance, Privacy, and Equity

Digital agronomy generates data about farmers, fields, and practices. Who owns that data, who can use it, and for what purpose are not technical details; they are governance questions (Wolfert et al., 2017; Carolan, 2018). A farmer who shares field boundaries, yield, and input data may benefit from better advice, but may also face risks if data are sold, used to set prices, or used to deny credit. Clear consent, transparent data use, and the right to opt out are essential. Data cooperatives and farmer-owned platforms are being explored as models that give farmers more control, but they require legal, organisational, and technical support.

Equity deserves explicit attention. Digital tools can widen gaps between large and small farms, connected and unconnected areas, and men and women, if they are designed for those who already have assets (Carolan, 2018; Farnworth et al., 2017). Programmes that measure success only by number of app downloads or messages sent can miss whether the poorest farmers, women, and remote communities actually benefited. A more inclusive measure is whether a service improves decisions for those with the least information, the least capital, and the least connectivity. That requires designing for offline use, low literacy, local languages, and group access, not only for smartphone users.

7. A Practical Framework for Designing Digital Services

A practical framework for digital agronomy can be stated in six steps. First, identify the decision: what decision will the service improve, for whom, and when? Second, identify the data needed for that decision, and no more. Third, validate locally: test the data, model, and recommendation against ground observations in the target area. Fourth, design the delivery: choose format, language, timing, and channel that fit the user. Fifth, test with farmers: run a small, farmer-managed comparison and learn from it. Sixth, monitor and adapt: track whether decisions changed, whether yield, efficiency, and income improved, and whether the service reached those who needed it most. Table 1 summarises digital agronomy bundles, while Table 2 proposes indicators for monitoring.

Table 1. Digital agronomy bundles and the decisions they improve.

Bundle	Core tools	Decision improved	Likely outcome
Weather advisory	Forecast, SMS, voice	Planting, irrigation, harvest timing	Lower risk, better timing
Satellite monitoring	NDVI, thermal, radar	Nutrient, water, pest stress	Targeted intervention
Sensor + advisory	Soil moisture, weather, app	Irrigation scheduling	Higher water productivity
Drone scouting	Multispectral, thermal	Pest, nutrient, stress mapping	Early detection, targeted action
Full digital bundle	Satellite, sensor, advisory, model	Multiple decisions	Higher efficiency, steadier yield

Table 2. A balanced indicator set for digital agronomy.

Dimension	Indicator	Practical measurement
Decision change	Share of users changing a decision	User survey, service logs
Efficiency	Input per unit yield	Input and harvest records
Yield and income	Yield, gross margin	Harvest, cost, price records
Trust and use	Retention, repeat use	Service logs, survey
Equity	Use by women, poor, remote users	Disaggregated service data
Data governance	Consent, data use, opt-out	Policy, audit, user feedback

8. Future Research and Policy Priorities

Future research should evaluate digital services with rigorous, farmer-centred designs that report decisions, yield, efficiency, cost, and equity together, rather than downloads or messages alone. Long-term studies are needed because trust and learning build over seasons, and a service that is ignored in year one may be used in year three if it proves reliable. Research on low-cost, offline, voice-based, and group-based delivery is more valuable for smallholders than further development of data-heavy apps that require constant connectivity (Fabregas et al., 2019; Hansen et al., 2019). Research on local calibration, including soil, variety, and management, is essential, because a model that works in one region can fail in another. Policy should treat weather, soil, and market information as public goods, invest in connectivity and digital literacy, and set clear rules for data ownership, consent, and privacy. Public extension should be equipped to use digital tools, not replaced by them, because human trust and local knowledge remain central to adoption.

9. Conclusion

Digital agronomy is not a substitute for agronomic knowledge; it is a way to make that knowledge more timely, precise, and accessible. Satellite imagery, drones, sensors, weather forecasts, and mobile advisories can improve decisions about planting, nutrients, water, pests, and harvest, but only when they are locally validated, delivered in usable formats, linked to a concrete decision, and trusted by farmers. When those conditions are met, digital tools can raise input-use efficiency, stabilise yield, and reduce risk. When they are not met, digital tools can waste money, widen inequity, and erode trust. The priority is therefore practical: identify the decision, validate the data, design for the user, test with farmers, and learn from each season.

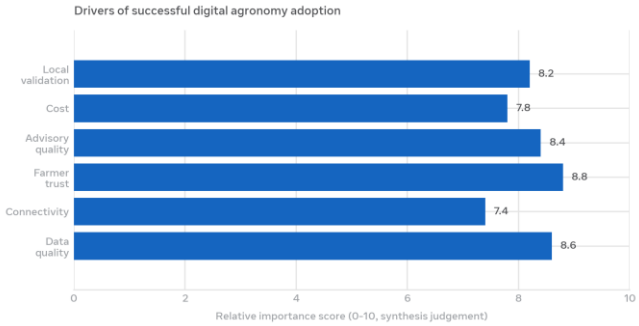


Figure 2. Drivers of successful digital agronomy adoption, based on synthesis judgement from the cited evidence. Farmer trust and data quality are central.

The practical implication is that digital agronomy should be judged by the quality of the next decision it enables, not by the volume of data it collects. A service that helps a farmer choose a planting date, a fertiliser rate, or an irrigation timing with greater confidence has succeeded, even if it uses only a weather forecast and a soil check. A service that produces colourful maps but leaves the farmer unsure what to do has not succeeded, however advanced its technology. Extension workers, cooperatives, and input suppliers can play a bridging role by translating digital outputs into local language, by testing recommendations on farmer plots, and by feeding farmer observations back to service providers so that models improve. That feedback loop, from field to model and back to field, is the core of useful digital agronomy.

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Conflict of Interest

The authors declare no conflict of interest.

References

Aker, J.C. (2011). Dial A for agriculture: A review of information and communication technologies for agricultural extension. Agricultural Economics, 42(6), pp. 631-647.

Carolan, M. (2018). Big data and food: The ethics of data in agriculture. Agriculture and Human Values, 35(2), pp. 375-388.

Fabregas, R., Kremer, M. and Schilbach, F. (2019). Realizing the potential of digital development: The case of agricultural advice. Science, 366(6471), eaay3038.

Farnworth, C.R., et al. (2017). Gender and climate-smart agriculture. In: Huyer, S. et al. eds. Gender, Climate Change and Agriculture. Wallingford: CABI, pp. 1-18.

Hansen, J.W., et al. (2019). Climate services can support African farmers' adaptation. Nature Climate Change, 9, pp. 747-753.

Huyer, S., et al. (2015). Gender and climate change in agriculture. CCAFS Working Paper. Copenhagen: CGIAR.

Jones, H.G. (2004). Irrigation scheduling: Advantages and pitfalls of plant-based methods. Journal of Experimental Botany, 55(407), pp. 2427-2436.

Jones, J.W., et al. (2003). The DSSAT cropping system model. European Journal of Agronomy, 18(3-4), pp. 235-265.

Keating, B.A., et al. (2003). An overview of APSIM. European Journal of Agronomy, 18(3-4), pp. 267-288.

Mulla, D.J. (2013). Twenty five years of remote sensing in precision agriculture. Biosystems Engineering, 114(4), pp. 358-371.

Roberts, D.P., et al. (2010). Precision agriculture and variable rate technology. In: Singh, R. ed. Precision Agriculture. New Delhi: ICAR, pp. 45-68.

Weiss, M., Jacob, F. and Duveiller, G. (2020). Remote sensing for agricultural applications. Remote Sensing of Environment, 236, 111402.

Wolfert, S., Ge, L., Verdouw, C. and Bogaardt, M.-J. (2017). Big data in smart farming. Agricultural Systems, 153, pp. 69-80.

Zhang, C. and Kovacs, J.M. (2012). The application of small unmanned aerial systems for precision agriculture. Precision Agriculture, 13(6), pp. 693-712.

FAO (2020). The State of Food and Agriculture 2020: Overcoming Water Challenges in Agriculture. Rome: FAO.

FAO (2022). Digital Agriculture: Transformation for Sustainable Food Systems. Rome: FAO.

IPCC (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability. Cambridge: Cambridge University Press.

Challinor, A.J., et al. (2014). A meta-analysis of crop yield under climate change and adaptation. Nature Climate Change, 4(4), pp. 287-291.

Antle, J.M., et al. (2017). Towards a new generation of agricultural system data. Agricultural Systems, 155, pp. 115-127.

Ehlers, M.-H., et al. (2021). Data governance in agriculture. Agricultural Systems, 189, 103058.

Kamilaris, A., Kartakoullis, A. and Prenafeta-Boldú, F.X. (2017). A review on the practice of big data analysis in agriculture. Computers and Electronics in Agriculture, 143, pp. 23-37.

Liakos, K.G., et al. (2018). Machine learning in agriculture. Sensors, 18(8), p. 2674.

Pant, L.P. and Odame, H.H. (2017). Broadband for a sustainable digital future. Information Technologies & International Development, 13, pp. 1-16.

Rose, D.C. and Chilvers, J. (2018). Agriculture 4.0: Responsible innovation. Frontiers in Sustainable Food Systems, 2, p. 69.

Steinke, J., et al. (2021). Prioritizing options for multi-stakeholder decision-making. Agricultural Systems, 188, 103049.

Tzounis, A., et al. (2017). Internet of Things in agriculture. Internet of Things, 1, pp. 1-10.