7-2023

Improving Decision Support Systems with Machine Learning: Identifying Barriers to Adoption

Skye Brugler
South Dakota State University

Maaz Gardezi
Virginia Tech

Ali Dadkhah
University of Vermont

Donna M. Rizzo
University of Vermont

Asim Zia
University of Vermont

See next page for additional authors

Authors

Skye Brugler, Maaz Gardezi, Ali Dadkhah, Donna M. Rizzo, Asim Zia, and Sharon A. Clay

Received: 6 December 2022 | Accepted: 14 July 2023

DOI: 10.1002/agj2.21432

Agronomy Journal

SPECIAL ISSUE: MACHINE LEARNING IN AGRICULTURE

Agronomy, Soils, and Environmental Quality

Improving decision support systems with machine learning: Identifying barriers to adoption

Skye Brugler[1] | Maaz Gardezi[2] | Ali Dadkhah[3] | Donna M. Rizzo[3] | Asim Zia[4,5] | Sharon A. Clay[1]

[1]Department of Agronomy, Horticulture, and Plant Science, South Dakota State University, Brookings, SD, USA

[2]Department of Sociology, Virginia Tech, Blacksburg, VA, USA

[3]Department of Civil and Environmental Engineering, University of Vermont, Burlington, VT, USA

[4]Department of Community Development and Applied Economics, University of Vermont, Burlington, VT, USA

[5]Department of Computer Science, University of Vermont, Burlington, VT, USA

Correspondence
Sharon A. Clay, Department of Agronomy, Horticulture, and Plant Science, South Dakota State University, 1030 N Campus Dr, Brookings, SD 57007, USA.
Email: sharon.clay@sdstate.edu

Assigned to Associate Editor Scott Fausti.

Funding information
National Science Foundation, Grant/Award Number: 2202706; South Dakota Nutrient Research and Education Council

Abstract

Precision agriculture (PA) has been defined as a "management strategy that gathers, processes and analyzes temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production." This definition suggests that because PA should simultaneously increase food production and reduce the environmental footprint, the barriers to adoption of PA should be explored. These barriers include (1) the financial constraints associated with adopting decision support system (DSS); (2) the hesitancy of farmers to change from their trusted advisor to a computer program that often behaves as a black box; (3) questions about data ownership and privacy; and (4) the lack of a trained workforce to provide the necessary training to implement DSSs on individual farms. This paper also discusses the lessons learned from successful and unsuccessful efforts to implement DSSs, the importance of communication with end users during DSS development, and potential career opportunities that DSSs are creating in PA.

1 | INTRODUCTION

1.1 | What are decision support systems?

Decision support systems (DSSs) are models that use information and communication technologies for complex decision-making (Manos et al., 2004). The models embedded in DSSs take data stored in the database to produce a

Abbreviations: AgMIP, Agriculture Model Intercomparison and Improvement Project; AI, artificial intelligence; DAWN, Dashboard for Agricultural Water Use and Nutrient Management; DSS, decision support system; FICO, Fair Isaac and Company; FRST, Fertilizer Recommendation Support Tool; ML, machine learning; PA, precision agriculture.

user-specific result (Alenljung, 2008; Manos et al., 2004). These models can be created using many techniques including process-based, empirical models, and/or machine learning (ML)/artificial intelligence (AI) techniques. In agriculture, process-based models are generally mathematical representations of biogeochemical and physical systems; empirical models are statistical models based on observations among variables; and ML models make predictions based on patterns learned from the data set. A difference between process, empirical models, and ML/AI models is that ML/AI models learn as new input data are added, which makes them uniquely suited for precision agriculture (PA).

However, as with all models, errors exist when the underlying understanding of the processes or model assumptions is incorrect. For example, a very common assumption is that weeds reduce yields by competing with the crop for water, nutrients, light, space, and carbon dioxide. However, current research, made possible by the ability to decipher the crop genomes, has shown that weeds can reduce yields regardless of resource availability. This finding is based on the ability to quantify transcriptomic changes (e.g., downregulation of photosynthesis, root growth reductions) that are induced by weed presence, long before direct competition occurs (Clay et al., 2009; Horvath et al., 2023). Models, based on incorrect assumptions, may provide acceptable recommendations under some conditions but flawed recommendations in others.

1.2 | Why are DSSs needed?

Agriculture is facing immense challenges, such as reducing greenhouse gas emissions and topsoil loss due to erosion, while increasing yields in an unstable climate (United Nations, 2022). The failure to manage these challenges can result in societal and environmental upheaval. As examples, the French revolution (1789–1799) has been linked to the Little Ice Age, when crops failed in cold climates, which led to starvation and societal instability (Ljungqvist et al., 2021). The Middle Eastern Arab Spring in 2011 has also been linked to climate change with low crop yields and increased food prices, which again led to social upheaval (Zurayk, 2016). To reduce the risks of future agricultural failures, sustainable intensification needs to be implemented to optimize production and simultaneously decrease agriculture's environmental impact (Lindblom et al., 2017). Sustainable intensification requires enhanced management that can be delivered in part using DSSs (Lindblom et al., 2017).

1.3 | Low adoption of DSSs

While some components of PA, such as autosteer and yield monitors, were quickly adopted, to date variable rate fertilizers, another PA tool, have not been widely adopted (Baumeister et al., 2015; Lindblom et al., 2017; McCown et al., 2002; Rossi et al., 2013; Winter, 2018). The discrepancy between the adoption of some PA tools and not others suggests that there are barriers to long-term use of PA tools. Many barriers have been suggested and may include financial constraints, a hesitancy to change from a known trusted decision processes to an unknown decision system, uncertainty of data ownership and privacy, and workforce availability (Erickson et al., 2018; Mitchell et al., 2021; USDA, 2022).

In addition to these barriers, it is important to understand that fully integrating data collection, processing, and implementing is difficult and requires diverse knowledge, skills, and abilities. For example, processing remote sensing data into useful information may require a human pilot to collect the data, a geographic information specialist to create a map, an agronomist to confirm yield limiting factor(s), machines that can perform these tasks, knowledgeable applicators to apply the treatments at the right time, place, and rate, and follow-up with economists and agronomists to determine if savings, yield, or other tangible outcomes have occurred. It is important to point out that currently each step requires time, and that skipping steps that often require human involvement can reduce the value of the information (Priya & Ramesh, 2020).

1.4 | Barriers to adoption of DSSs

1.4.1 | Financial constraints

Agricultural retailers have been surveyed about producer attitudes at least every other year since the mid-1990s (Erickson & Lowenberg-Deboer, 2022). These surveys provide insights into the adoption barriers. In 2021, about 37% of the dealers reported that economic limitations were one of the most important barriers. However, this barrier fluctuates with crop prices and is reduced when prices are high and increased when prices are low. For greater use of these technologies, uncertainties must be balanced with an increased return on investment (Baldin et al., 2021; Rinaldi et al., 2014).

1.4.2 | Financial constraints of small farms

Farm size also influences the amount of capital that can be invested in DSSs and PA tools that can be used by DSSs (Akaka et al., 2021; Baldin et al., 2021). In general, large farms have more capital and manpower to test and implement new practices (Akaka et al., 2021). A good example of this barrier was discussed by Ashworth et al. (2018), where partial budgeting determined that the break-even farm size for autoguidance was between 10 and 50 ha. The implication of this analysis is that the cost of the equipment per hectare decreases with increasing farm size. For example, if the equipment costs

$100,000 and the farm size is 100 ha, then the cost/ha is $1000. However, if the farm size is 1000 ha, then the cost/ha is $100. This difference in cost/ha may result in lower adoption rates of PA on small farms (Denmark Statistics, 2022; Thompson et al., 2021). The difference in price/ha between small and large farms results in small farms taking longer to return a profit than large farms. Another barrier is that DSS recommendations do not provide protection from uncertainty (Ara et al., 2021). Uncertainty results from any given treatment having a chance that it may or may not be effective.

Solving cost differences between small and large farms (financial equity) is a complex problem, but solutions have been proposed to overcome this adoption barrier. One potential solution is for DSS designers and manufacturers to provide free or inexpensive trial periods or monthly subscriptions to DSS services. A free trial period would allow a farmer to see if the DSS fits their operation and provides useful actionable recommendations (Akaka et al., 2021). Small farms could work together to spread technology costs over many producers. In addition, university extension services could provide training that reduces the investment costs or federal agencies and/or industry could provide financial incentives to use DSSs (McFadden et al., 2023).

1.4.3 | Farmers hesitancy to change the decision process

On many farms, agricultural decisions result from one-on-one discussions between the producer and their trusted advisor. Many producers do not feel comfortable replacing the trusted advisor with a DSS (Gardezi et al., 2022). This discomfort or lack of trust may be attributed to poor communication between the users and DSS developers, who may or may not have agriculture experience. This often manifests as recommendations that are acceptable to a developer but not considered acceptable or actionable by the end user. For example, if the recommendation is to apply water, but the field is not, or cannot be, irrigated, the recommendation is useless. The difference between a recommendation and what is possible is called the paradox of acceptability (Hochman et al., 1994).

Trust can also be lost due to miscommunication between the development team and the end user. One form of miscommunication is the selection of a DSS tool that assists in short-term planning (tactical) when a tool for long-term (strategic) planning is required (Ara et al., 2021). A DSS could combine strategic and tactical systems, which would provide the initial short-term decision and aid in long-term strategic planning (Ara et al., 2021).

To improve trust in DSSs, producers and their advisors should carefully consider the benefits and deficiencies of the various options before purchase. Similarly, the marketing of a DSS as tactical, strategic, or both needs to be made clear to the end user. The failure to select an appropriate system can result in a general distrust of PA (Ara et al., 2021; Lindblom et al., 2017; Rossi et al., 2013). A milestone is reached when a farmer decides to trust a DSS recommendation because each decision has economic implications that can be devastating. For example, a farmer may not have the income to make land payments, purchase farm inputs for the next cropping season, and/or cover their personal expenses. These financial concerns, especially when combined with distrust, can result in farmers deciding to keep a trusted decision process that has worked reasonably well in the past (McCown et al., 2002). However, trust in DSSs can be cultivated by providing demonstrations, training, and clear examples on how to successfully integrate the technology into their operations (Akaka et al., 2021).

1.4.4 | Questions about data ownership and privacy

Many producers and lawmakers are concerned about data ownership and privacy of farm data (Erickson & Lowenberg-DeBoer, 2022). Examples of on-farm data include current and historical yield, seeding rates, applied soil nutrient rates, and remote sensing (Ellixson, 2022). When these data are combined with public information through models connected to "the cloud" or the internet, the models may produce sensitive information. Unlike a bushel of corn that is tangible, data are intangible, easily transmitted over long distances, stored in "the cloud," and can be subject to security breaches. Additionally, farm data ownership is legally difficult to protect because it is considered unrivaled, meaning one person's access does not prevent another's, and due to its uncertain excludability (the right of the owner to deny another's access) (Goeringer, 2016; Jouanjean, 2020; Kaur et al., 2022).

Farm data ownership is akin to a Fair Isaac and Company (FICO) credit score. FICO collects data on an individual and calculates their score. Although FICO does not own the data, it does own the credit score because it is newly generated data (Goeringer, 2016). It is currently legally and ethically ambiguous whether a third-party technology provider has the right to generate new data from technology owned by individual farmers and then sell the "new" data back to them after it has been combined with data from the same geographical region (Jouanjean, 2020). This problem is further confounded by efforts to make programs and data collected by "smart machinery" freely available as "open source" (Rinaldi et al., 2014) to other companies, which then take the free data and profit by selling it back to farmers in DSS technologies.

Laws are often slow to catch up with technology, and currently laws that protect farmers and their data are limited (Ellixson, 2022; Goeringer, 2016; Kaur et al., 2022). Moreover, the term "ownership" itself is only the tip of the iceberg. Legally speaking, "ownership" is a relatively weak protection for farm data and does not necessarily mean the kind of control that farmers seek. Conditions and rights are often specified separately in individual contracts; therefore, there is no such thing as an all-inclusive data ownership law (Jouanjean, 2020). Determining where to draw the line is a challenge that law makers and stakeholders must define together, highlighting many new career opportunities for those interested in the legal protection of farm data as well as opportunities to bridge the gap between companies and farmers through legal communication and advocacy of farmer's data rights.

1.4.5 | Limited trained workforce

A 2015 survey asked agriculture retailors about their minimum education requirements for careers in PA such as equipment operator, agronomist, equipment technician, technical support, and PA specialist (Erickson et al., 2018; Fausti et al., 2021). Results at that time revealed that most of the PA workforce met or exceeded the education expectations of employers by completing either a 2-year associate degree or a 4-year bachelor's degree. However, employers indicated difficulty in locating and recruiting qualified applicants. Additionally, necessary skills, such as data-intensive thinking, the ability to understand statistical standards to produce means and standard deviations, as well as their ability to install, calibrate, troubleshoot, and repair PA hardware and equipment, were lacking (Erickson et al., 2018; Fausti et al., 2021). Further analysis suggested that there was a mismatch between the training received and the training required to proficiently perform the job.

To help PA employees meet the job expectations, professional societies and higher education institutions must commit to curricula that will close this gap. For example, the American Society of Agronomy and Ag*IDEA have created PA certificate programs (Erickson et al., 2018). Those trained in both the technical and human dimension of DSSs can act as important communicators between program developers and the end users (Lundström & Lindblom et al., 2018). Additionally, communicators between education institutions and industry professionals, such as retail dealerships, can help to align academic programs for students pursuing PA positions with the qualifications required by industry professionals. This will aid in creating employees proficient in the knowledge, skills, and abilities in math and statistical skills required by the PA industry (Fausti et al., 2021).

1.5 | Lessons learned

While there are a range of barriers slowing DSS adoption, it is also important to evaluate why some succeed (e.g., Vite.net and Pigs2Win) and others fail (e.g., FEEDMAN). Vite.net has been adopted successfully in both small and large European vineyards since 2013 (Rossi et al., 2013). Vite.net uses real-time data from sensors placed around a vineyard to produce recommendations for pest (disease, weed) control, fertilization, and irrigation management decisions that have increased the overall vineyard productivity (Lindblom et al., 2017; Rossi et al., 2013). For example, in 2016, organic producers who used Vite.net saved about €195 ($205) per hectare relative to their usual practices. The savings were attributed to the DSS making site-specific recommendations about the application of nonorganic herbicides, pesticides, and fertilizers. Specifically, growers using Vite.net reduced copper application by 37% when compared to producers who did not use the DSS (TpOrganics, 2016).

Along with observable savings, Vite.net designers focused on communication with end users with feedback throughout development. Vite.net also focused on specific vineyard problems that were identified by vineyard managers. The communication between developers and users was deliberate and allowed the developers to understand how to best convey and make recommendations through the system's user interface. This communication/training had value because it improved end user trust.

Another example of a successful DSS is Pigs2win, which improves swine production and reduces environmental impact (smell and nutrient losses) of the operation (Lindblom et al., 2017; Meensel et al., 2012). These decisions were traditionally made using key performance indicators such as productivity costs, labor income, and feed conversion (kg of feed per kg of live weight). However, the Pigs2Win development team worked closely with the farmers and stakeholders to ensure that results are aligned with the expectations of the end user. Objectives were defined by the development team, and farmers and stakeholders identified how an objective could be met by using a DSS. For example, Pigs2Win was built using Excel as a framework because it was easily accessed and understood by end users. Several prototypes were presented and farmers were encouraged to provide feedback and familiarize themselves with the system. A benefit of this open communication process was that it built trust by demonstrating transparency (Meensel et al., 2012).

FEEDMAN, a feed to dollars beef management package, in contrast to Vite.net and Pigs2Win, was an unsuccessful DSS. FEEDMAN was designed in 1998 to help farmers and farm managers make strategic and tactical decisions about feeding options, animal performance, market options, and economic decisions for livestock (Newman et al., 2000). While the development team understood the need to make the system user-friendly, users found it to be easy to use but not useful. Many users indicated that they were reluctant to take recommendations from DSS that did not provide clear benefits. Users also cited abandoning the program due to a lack of maintenance. These issues likely could have been avoided by communicating with the end users throughout the process such as in the case of Vite.net and Pigs2Win. Potential users and stakeholders were brought into the process at the end of FEEDMAN development, instead of being allowed to shape the DSS in the process.

Vite.net, Pigs2Win, and FEEDMAN are different DSSs; however, communication is a common thread linking their successes and failures. Vite.net and Pigs2Win worked with the end users throughout the process to ensure that the software would provide real value, whereas FEEDMAN was marketed as a complete system that did not provide real value to the users. Additionally, Pigs2Win took steps to appeal to smaller farms by ensuring that the users did not need to purchase additional software, building part of the system in Excel to reduce the financial burden. While this represents only a few of the many examples of successful and not successful DSSs, it is important to learn from what has and has not worked.

1.6 | The future of DSSs and the importance of improved communication

Decision tools are being developed to provide more accurate recommendations to farmers. Future DSSs that are empowered by ML algorithms will have the capacity to collect and process enormous amounts of site-specific information (Priya & Ramesh, 2020). However, because research scientists tend to work very narrowly and silo themselves, our ability to address “big questions” may take a long time. Dr. Cynthia Rosenzweig, the 2022 World Food Prize winner, addressed the scope of these problems and stated, “Climate change is so challenging: We must solve it; but no one group or discipline or sector of society is going to solve it on their own. – Such ‘silos’ do not work for finding solutions to climate change” (Coyne, 2022).

To improve communication among scientists, Dr. Rosenzweig created a program called AgMIP (Agriculture Model Intercomparison and Improvement Project). AgMIP brings together an interdisciplinary and international team of stakeholders and experts to estimate and predict how climate change will produce new risks and vulnerabilities in global agriculture, while also providing risk mitigation and adaptation suggestions (AgMIP, 2022). The model’s framework focuses on four dimensions: adaptation, mitigation, food security, and agriculture policy (Rosenzweig et al., 2017). The user interface provides this information at three different levels of expertise. The first level is the regional summary provided and demonstrated using individual stories about farmers who have benefited. The second level is the spatial dashboard using maps and data to make comparisons among various regions. This approach was designed in response to the United Nations (United Nations Framework Convention on Climate Change) request for information about, and implications of, constraining the global temperature increase to 1.5 and 2.0°C. While there is still much uncertainty in how much the climate will change, the model identified vulnerabilities and uncertainties in managing the future risk to agriculture (Rosenzweig et al., 2017).

Another agriculture DSS that stepped out of its silo and into a broad regional system is DAWN (Dashboard for Agricultural Water use and Nutrient management). DAWN is supported by the U.S. Department of Agriculture (USDA) through NIFA’s Agriculture and Food Research Initiative, with the goal of informing row crop producers about water and nutrient management decisions. The system couples a crop growth model with existing regional climate systems and links them with data about land and water use, agroecology, hydrology economics, and human intervention. The DSS then uses these models to help producers with field-level decisions (DAWN, 2022). This system, produced for both farmer and researcher use, can run scenarios about specific problems and predict outcomes based on soil maps, historical climate data, estimated crop yields, and more. These scenarios look to optimize economic return and minimize environmental impacts. From these various predictions, the producer can choose the most preferred scenario. This tool can help producers explore, risk free, their options for different crops and various irrigation strategies. Even without an irrigation system, this DSS can be helpful by providing land and yield information that relates to potential water quantity and quality needs such as evapotranspiration rates, average precipitation and air temperature, soil moisture, crop yield potential, nutrient loss, runoff, and drainage potential.

The user interface of DAWN is also being co-developed by stakeholders to ensure that the intended users/communities will have their needs met. DAWN will do this by providing information through both text and graphics, allowing users to explore options and strategies easily and quickly, collect statistics about location and crop type, evaluate the producers’ needs, and finally provide education materials such as extension publications and research summaries to keep users informed on the decisions they make. This new and exciting DSS will provide insights into new strategies for sustainable agriculture as well as opportunities for graduate students and early career researchers to work on creating/improving farm management.

The Fertilizer Recommendation Support Tool (FRST) also seeks to take DSSs to a broader scale by being a U.S. Department of Agriculture-operated, national fertilizer recommendation database and tool in the United States. This project takes inspiration from a national soil recommendation project produced in Australia in 2013 called The Australian Better Fertilizer Decisions for Cropping Systems Project (Conyers et al., 2013). FRST is a calibration and correlation study currently focused on potassium and phosphorus but will expand into nitrogen and micronutrient recommendations (Lyons et al., 2020). This collaborative project includes over 30 land grant universities, USDA Agricultural Research Service, and USDA Natural Resources Conservation Service and aims to address the inconsistent information on fertilizer recommendations that can occur across state lines. Future recommendations would be based on local site characteristics, rather than a state boundary (McCauley, 2020). The data set is being populated with historic data from 29 states that meet appropriate criteria and includes crop yield, grain moisture, rainfall, air and soil temperatures, seasonal stresses, and the production system used (Speirs et al., 2013). The web-based, user-friendly platform allows users to select input variables such as soil test methods, geographic locations, yield levels, and crop types to assist in recommendation decisions. This tool is expected to be continuously updated and hosted on a neutral internet space with common access and author attribution for as long as possible. The project leaders are encouraging more collaborative research on soil fertility among researchers and provide new career opportunities for graduate students to work with large historical, as well as current, data sets to produce transparent useful information to producers. We believe that programs such as AgMIP, DAWN, and FRST can help graduate students and professionals cultivate career opportunities, expand their horizons, see how their research can help answer the "big" questions, and move out of their narrow research path.

2 | CONCLUSIONS

In this unprecedented era of environmental crisis and high-tech digital agriculture, which can collect information at high spatial and temporal resolutions, DSS product developers, researchers, and end users need to collaborate and broaden their scope to solve critical issues facing agriculture at multiple scales. When implemented, we believe that DSSs are powerful tools that can help humans make connections in large data sets and find patterns that are crucial to making more sustainable and resilient crop production decisions. While DSS tools demonstrate an exciting future, it is important to recognize five aspects that have implications for PA adoption.

First, while many producers want to increase sustainability of their production, it is difficult to be cognizant of all factors that create the most profitable and sustainable outcomes. Second, the replacement of process or empirical models with ML algorithms within a DSS has the potential to improve accuracy and reduce uncertainty.

Third, policy-makers must continue to reduce the financial burden of acquiring the technology through strengthening programs that provide financial incentives to smaller farms to adopt DSSs. Fourth, industry professionals need to increase opportunities for farmers to engage with technology to build confidence in appropriate DSS products, while lawmakers must begin to address serious questions about data equity such as the legal definition of data ownership.

Fifth, communication barriers between DSS designers and stakeholders also still need to be broken down, and additionally, appropriate training must be provided at higher education levels for those pursuing careers in PA. Once these hurdles have been overcome, DSSs can work as tools to aid farmers in making decisions that will fully allow us to meet both the current and future agronomic needs for food, feed, fuel, and fiber in a sustainable manner.

AUTHOR CONTRIBUTIONS

Skye Brugler: Conceptualization; investigation; writing—original draft. **Maaz Gardezi**: Funding acquisition; project administration; writing—review and editing. **Ali Dadkhah**: Writing—review and editing. **Donna M. Rizzo**: Conceptualization; data curation; resources; writing—review and editing. **Asim Zia**: Funding acquisition; data administration. **Sharon Clay**: Writing—review and editing.

ACKNOWLEDGMENTS

This material is funded by and based upon work supported by the National Science Foundation (grant no. 2202706) and the South Dakota Nutrient Research and Education Council.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ORCID

Skye Brugler https://orcid.org/0000-0003-4540-7392
Maaz Gardezi https://orcid.org/0000-0003-0915-2652
Sharon A. Clay https://orcid.org/0000-0003-4166-6995

REFERENCES

Agriculture Model Intercomparison and Improvement Project (AgMIP). (2022). Overview. https://agmip.org/overview

Akaka, J., Garcia-Gallego, A., Georganitzis, N., & Tisserand, J. C. (2021). Decision support systems adoption in pesticide management. Working Papers 2021/08, Economics Department, Universitat Jaume I, Castellón (Spain). https://ideas.repec.org/p/jau/wpaper/2021-08.html

Alenljung, B. (2008). *Envisioning a future decision support system for requirements engineering. A holistic and human-centered perspective* (No. 1155) [Doctoral dissertation, Linkőpings Universotet]. Linkőpings Universotet.

Ara, I., Turner, L., Harrison, M. T., Monjardino, M., Devoil, P., & Rodriguez, D. (2021). Application, adoption and opportunities for improving decision support systems in irrigated agriculture: A review. *Agricultural Water Management*, *257*, 107161. https://doi.org/10.1016/j.agwat.2021.107161

Ashworth, A. J., Lindsay, K. R., Popp, M. P., & Owens, P. R. (2018). Economic and environmental impact assessment of tractor guidance technology. *Agricultural and Environmental Letters*, *3*, 180038. https://doi.org/10.2134/ael2018.07.0038

Baldin, M., Breunig, T., Cue, R., De Vries, A., Doornink, M., Drevenak, J., Fourdraine, R., George, R., Goodling, R., Greenfield, R., Jorgensen, M. W., Lenkaitis, A., Reinemann, D., Saha, A., Sankaraiah, C., Shahinfar, S., Siberski, C., Wade, K. M., Zhang, F., … Cabrera, V. E. (2021). Integrated decision support systems (IDSS) for dairy farming: A discussion on how to improve their sustained adoption. *Animals*, *11*(7), 2025. https://doi.org/10.3390/ani11072025

Baumeister, J., & Striffler, A. (2015). Knowledge-driven systems for episodic decision support. *Knowledge-Based Systems*, *88*, 45–56. https://doi.org/10.1016/j.knosys.2015.08.008

Clay, S. A., Clay, D. E., Horvath, D. P., Pullis, J., Carlson, C. G., Hansen, S., & Reicks, G. (2009). Corn response to competition: Growth alteration vs. yield limiting factors. *Agronomy Journal*, *101*(6), 1522–1529. https://doi.org/10.2134/agronj2008.0213x

Conyers, M. K., Bell, M. J., Wilhelm, N. S., Bell, R., Norton, R. M., & Walker, C. (2013). Making Better Fertiliser Decisions for Cropping Systems in Australia (BFDC): Knowledge gaps and lessons learnt. *Crop and Pasture Science*, *64*(5), 539–547. https://doi.org/10.1071/CP13068

Coyne, K. (2022). A conversation with Cynthia Rosenzweig. *Crop Science News*, *67*(7), 26–30.

Dashboard for Agricultural Water Use and Nutrient Management (DAWN). (2022). Decision support. https://dawn.umd.edu/

Denmark Statistics. (2022). *Stigning i areal med præcisionslandbrug (Increase in area with precision agriculture)*. https://www.dst.dk/Site/Dst/Udgivelser/nyt/GetPdf.aspx?cid=42525

Ellixson, A. (2022). *Farm data: Ownership and protections* (FS1055). University of Maryland Extension. https://extension.umd.edu/resource/farm-data-ownership-and-protections-fs-1055

Erickson, B., Fausti, S., Clay, D., & Clay, S. (2018). Knowledge, skills, and abilities in the precision agriculture workforce: An industry survey. *Natural Sciences Education*, *47*(1), 1–11. https://doi.org/10.4195/nse2018.04.0010

Erickson, B., & Lowenberg-DeBoer, J. (2022). *2022 Precision agriculture dealership survey*. https://ag.purdue.edu/digitalag/_media/croplife-report-2022.pdf

Fausti, S., Erickson, B., Clay, D. E., & Clay, S. A. (2021). The custom service industry's role in precision agriculture adoption: A literature review. *Western Economics Forum*, *19*(2), 58–67.

Gardezi, M., Adereti, D. T., Stock, R., & Ogunyiola, A. (2022). In pursuit of responsible innovation for precision agriculture technologies. *Journal of Responsible Innovation*, *9*(2), 224–247. https://doi.org/10.1080/23299460.2022.2071668

Goeringer, P. (2016). Farm data: Ownership and protections. https://aglawpaul.medium.com/farm-data-ownership-and-protection-b872441153ba

Hochman, Z., Pearson, C. J., & Litchfield, R. W. (1994). Users' attitudes and roles in the development and evaluation of knowledge-based decision support systems for agricultural advisers. *Agricultural Systems*, *44*, 217–235. https://doi.org/10.1016/0308-521X(94)90162-9

Horvath, D. P., Clay, S. A., Swanton, C. J., Anderson, J. V., & Chao, W. S. (2023). Weed-induced crop yield loss: A new paradigm and new challenges. *Trends in Plant Science*, *28*(5), 567–582. https://doi.org/10.1016/j.tplants.2022.12.014

Jouanjean, M. (2020). Issues around data governance in the digital transformation of agriculture: The farmers' perspective. *OECD Food, Agriculture and Fisheries Papers*, No. 146. OECD Publishing. https://doi.org/10.1787/53ecf2ab-en

Kaur, J., Hazrati Fard, S. M., Amiri-Zarandi, M., & Dara, R. (2022). Protecting farmers' data privacy and confidentiality: Recommendations and considerations. *Frontiers in Sustainable Food Systems*, *6*, 903230. https://doi.org/10.3389/fsufs.2022.903230

Lindblom, J., Lundström, C., Ljung, M., & Jonsson, A. (2017). Promoting sustainable intensification in precision agriculture: Review of decision support systems development and strategies. *Precision Agriculture*, *18*(3), 309–331. https://doi.org/10.1007/s11119-016-9491-4

Ljungqvist, F. C., Thejll, P., Christiansen, B., Seim, A., Hartl, C., & Esper, J. (2021). The significance of climate variability on early modern European grain prices. *Cliometrica*, *16*(1), 29–77. https://doi.org/10.1007/s11698-021-00224-7

Lundström, C., & Lindblom, J. (2018). Considering farmers' situated knowledge of using agricultural decision support systems (AgriDSS) to foster farming practices: The case of CropSAT. *Agricultural Systems*, *159*, 9–20. https://doi.org/10.1016/j.agsy.2017.10.004

Lyons, S. E., Osmond, D. L., Slaton, N. A., Spargo, J. T., Kleinman, P. J. A., Arthur, D. K., & Mcgrath, J. M. (2020). FRST: A national soil testing database to improve fertility recommendations. *Agricultural & Environmental Letters*, *5*, e20008. https://doi.org/10.1002/ael2.20008

Manos, B., Bournaris, T. H., Vassiliadou, I., & Papathanasiou, J. (2004). A taxonomy survey of decision support systems in agriculture. *Agricultural Economics Review*, *5*, 80–94. 10.22004/ag.econ.26406

Mccauley, D. J. (2020). The FRST national soil fertility database. *CSA News*, *65*(7), 3–8. https://doi.org/10.1002/csan.20218

Mccown, R. L (2002). Changing systems for supporting farmers' decisions: Problems, paradigms, and prospects. *Agricultural Systems*, *74*, 179–220. https://doi.org/10.1016/S0308-521X(02)00026-4

McFadden, J., Njuki, E., & Griffin, T. (2023). *Precision agriculture in the digital era: Recent adoption on U.S. farms* (EIB-248). U.S. Department of Agriculture, Economic Research Service. https://www.ers.usda.gov/webdocs/publications/105894/eib-248.pdf?v=8335.1

Mitchell, S., Weersink, A., & Bannon, N. (2021). Adoption barriers for precision agriculture technologies in Canadian crop production. *Canadian Journal of Plant Science*, *101*, (E-Suppl), 412–416. https://doi.org/10.1139/cjps-2020-0234

Newman, S., Lynch, T., & Plummer, A. A. (2000). Success and failure of decision support systems: Learning as we go. *Journal of Animal Science*, *77*, 1–12. https://doi.org/10.2527/jas2000.77E-Suppl1e

Priya, R., & Ramesh, D. (2020). ML based sustainable precision agriculture: A future generation perspective. *Sustainable Computing: Informatics and Systems*, *28*, 100439. https://doi.org/10.1016/j.suscom.2020.100439

Rinaldi, M., & He, Z. (2014). Decision support systems to manage irrigation in agriculture. *Advances in Agronomy*, *123*, 229–279. https://doi.org/10.1016/B978-0-12-420225-2.00006-6

Rosenzweig, C., Ruane, A. C., Antle, J., Elliott, J., Ashfaq, M., Chatta, A. A., Ewert, F., Folberth, C., Hathie, I., Havlik, P., Hoogenboom, G., Lotze-Campen, H., Maccarthy, D. S., Mason-D'croz, D., Contreras, E. M., Müller, C., Perez-Dominguez, I., Phillips, M., Porter, C., … Wiebe, K. (2017). Coordinating AgMIP data and models across global and regional scales for 1.5 degrees C and 2.0 degrees C assessments. *Philosophical Transactions of the Royal Society A:*

Mathematical, Physical and Engineering Sciences, *376*(2119), 1–26. https://doi.org/10.1098/rsta.2016.0455

Rossi, V., Salinari, F., Poni, S., Caffi, T., & Bettati, T. (2013). Addressing the implementation problem in agricultural decision support systems: The example of Vite.net. *Computers and Electronics in Agriculture*, *100*, 88–99. https://doi.org/10.1016/j.compag.2013.10.011

Speirs, S. D., Reuter, D. J., Peverill, K. I., & Brennan, R. F. (2013). Making better fertiliser decisions for cropping systems in Australia: An overview. *Crop and Pasture Science*, *64*, 417–423. https://doi.org/10.1071/CP13034

Thompson, N. M., Delay, N. D., & Mintert, J. R. (2021). Understanding the farm data lifecycle: Collection, use, and impact of farm data on U.S. commercial corn and soybean farms. *Precision Agriculture*, *22*(6), 1685–1710. https://doi.org/10.1007/s11119-021-09807-w

TpOrganics. (2016). *vite.net: A decision support system for sustainable management of the vineyards – Performance in organic viticulture*. https://tporganics.eu/about-us/

U.S. Department of Agriculture (USDA). (2022). *Adoption of precision agriculture*. https://www.nifa.usda.gov/grants/programs/precision-geospatial-sensor-technologies-programs/adoption-precision-agriculture_

United Nations. (2022). *World Population Prospects 2022: Summary of Results*. https://www.un.org/development/desa/pd/sites/www.un.org.development.desa.pd/files/wpp2022_summary_of_results.pdf_

Van Meensel, J., Lauwers, L., Kempen, I., Dessein, J., & Van Huylenbroeck, G. (2012). Effect of a participatory approach on the successful development of agricultural decision support systems: The case of Pigs2win. *Decision Support Systems*, *54*(1), 164–172. https://doi.org/10.1016/j.dss.2012.05.002

Winter, M. (2018). *Decision support systems for agriculture*. News IOF. https://www.iof2020.eu/latest/news/2018/03/dss-for-agriculture

Zurayk, R. (2016). The Arab uprisings through an agrarian lens. In A. Kadri (Eds.), *Development challenges and solutions after the Arab spring (Rethinking international development series)* (pp. 139–152). Palgrave Macmillan. https://doi.org/10.1057/9781137541406_8

How to cite this article: Brugler, S., Gardezi, M., Dadkhah, A., Rizzo, D. M., Zia, A., & Clay, S. A. (2023). Improving decision support systems with machine learning: Identifying barriers to adoption. *Agronomy Journal*, 1–8. https://doi.org/10.1002/agj2.21432