PRECISION ORGANIC AGRICULTURE

by

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DEDICATION

To my family,
for all their love and ceaseless support

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Thank you to the farmers, Bob Quinn, Seth Goodman, Casey Bailey, Ole Norgaard, Ty O'Connor, Royden K. Loewen, for doing the hard work of planting the experiments and providing real world feedback. Thank you to my lab mates, Hannah, and Paul, who provided indispensable help, a safe place for stupid questions, and friendship. Thank you to my committee Perry, Anton, Marco, who always kept me on my intellectual toes. Thank you to my advisor, Bruce Maxwell, for many years of mentoring and advice I will never forget.

And, thank you to the indigenous peoples who were here before the settlers, with my recognition that these lands were once treated differently, less intrusively, more lightly and in observance of local ecologies. While this dissertation does not address historic injustices, it is nevertheless my hope that in a small way my work might contribute to a more ancient mentality of working with nature rather than against it.

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ABSTRACT

Organic agriculture addresses some of the shortcomings of industrialized conventional agriculture, but is prevented from more mainstream uptake by reduced yields. Organic agriculture relies on knowledge of intricate biological interactions in place of synthetic inputs used in other forms of agriculture, and in this way reflects an older way of practicing agriculture. Precision agriculture (PA) conversely is a technologically driven method of farming and combines guidance and data collection via remote sensing technologies to bring new efficiencies to farm operations. In this dissertation PA tools were used to explore the potential of improving organic production through site-specific management. By conducting on farm precision experiments (OFPE) with PA farmers can learn quickly about spatial variability across fields enabling well defined management templates. In organic systems this experimentation can be conducted with varied seeding rate inputs of both cover and cash crops. Here, we explored the relevancy of PA in organic settings, first broadly laying the philosophical foundation for the paradigm shift from production-oriented agriculture to precision agroecology. Secondly, a greenhouse experiment was used to develop the first-principle relationship between cover crop and cash crop seeding rates to maximize net return, establishing the basis for field experiments. Field scale experiments on five organic grain farms across the northern great plains deployed OFPE to optimize net returns, or suppress weeds, with varied seeding rates of cover and cash crops. Based on OFPE data, simulations across all sites found net returns could be improved on average by \$45.82 ha^{-1} if economically optimum variable seeding rates were used. While seeding rates were found to have variable effects on weeds across fields, an optimized site-specific seeding strategy to balance net return and weed minimization improved net return and weed suppression compared to farmer-chosen seeding rates in every field tested. Overall, these results reveal the relevancy of precision agriculture to be deployed in organic systems to improve management for increased farmer net returns, and as a weed management method. In this way modern tools can be used to augment farmer knowledge about their local spaces to enable greater understanding and improved management of complex agroecosystems.

CHAPTER ONE

PROLOGUE: AGROECOLOGICAL INTENSIFICATION

Introduction

Since its inception, agriculture has pursued a path of intensification for ever greater yields. This ethos of intensification began with the taming of wild grasses, escalated through the industrial revolution and then even further with the advent of chemicalized agriculture, and continues to this day with genetically modified crops designed for near-continuous agrochemical field treatments. Especially in the most recent steps, yield has been pursued to the detriment of biodiversity, soil sustainability, food quality, and human health (Holleman, 2018). This paradigm of agricultural intensification has been linked to human health crises and ecological disasters, leaving farmers, consumers, and scientists to begin forging a new mode of agriculture and food production known as agroecology (Anderson et al., 2019; Gemmill-Herren, 2020). This approach counters that yield is not the only goal of agriculture, but rather one among many ecosystem services that agroecosystems ought to provide to the land and its diverse inhabitants, from native plants and animals to humans. Due to the need for balancing the tradeoffs between production and sustainability, modern research has propelled a new term, agroecological intensification, to the forefront as a solution to many of agriculture's ailments.

History of Agricultural Intensification

We can trace the path of agricultural intensification throughout history. The earliest agricultural systems, labeled “Ag1.0”, developed as hunter-gatherers gradually found food uses for grass seeds such as wheat, and progressively developed more control over their production. As they began to use the land to produce crops, soils on these lands quickly lost the power to produce seed yields, and so new plots of land were required. This form of agriculture created a group of people dependent on the calories of farmed food, even as the food provided them with less diverse and less nutritious diets than hunting and gathering had (Zabinski, 2020). Over thousands of years, agriculture developed slowly through trial and error by subsistence farmers. “Ag2.0” began with the advent of the chemical revolution in Europe, when agriculture took its first steady steps into the scientific realm. The German Chemist Justus Von Liebig (1803-1873) played a prominent role in this transition. He noted farmers could add nutrients to the soil, mostly nitrogen, to reinvigorate ‘tired’ land and allow for greater yields. Von Liebig’s discoveries led to the desire for farmers to add nitrogen to their soil. In 1909 a method was discovered to isolate nitrogen from the air; the process, termed the Haber-Bosch process after its discoverers, accelerated input-intensive farming (Smith et al., 2020). Farmers could now pay for nitrogen to increase productivity. This was a major step in shifting agriculture from a subsistence farming method to an intensive commodity agricultural system driven by yields and profits. The next step in intensification, “Ag3.0”, came from developments collectively known as the Green Revolution and usually seen as taking off in the 1960s. The Green Revolution accelerated input agriculture with heavy doses of synthetic nitrogen and dwarf varieties of wheat which could handle the added fertility without falling under their own weight (*i.e.,* lodging). Further breeding refinement allowed for the development of uniform crops, the ability to use herbicides to control pests, and mechanization to process huge swaths of homogenous crops in these agroecosystems (Zabinski, 2020). The most recent pursuit of the intensification of agriculture, “Ag4.0”, harnesses new research in genetics and computation to affect change. Advances in molecular genetics have seen the development of genetically modified crops designed to sustain even higher chemical doses. Transgenic plants, or genetically modified organisms, have genes from other species spliced directly into their genome (Kumar et al., 2020). These practices have been used recently to produce crops such as the glyphosate-resistant lines of commodity crops like corn and soybeans, which can survive glyphosate applications that kill nearly all other plants (Duke, 2018). Agriculture has shown a steady increase of intensification over its history.

Recently intensification has been rebranded as sustainable intensification, but nevertheless still bears all the hallmarks of typical intensification defined by externalizing values other than yield production (Weiner, 2017). This intensification process has led to nutritionally deficient diets, loss of biodiversity, and land degradation across the globe (Barański et al., 2014; Díaz et al., 2006; Holleman, 2018; Provenza et al., 2021). A competing paradigm has arisen that redirects agriculture’s focus to sustainability rather than pure production. This new paradigm and its encompassing practices are here referred to as agroecological intensification and include practices such as conservation agriculture, organic agriculture, and regenerative agriculture. While each of these practices has varying definitions, at their core, they all attempt to limit inputs and place value on long-term sustainability goals ahead of short-term yield goals.

Agroecology

Counter to the traditional paradigm, agroecological intensification seeks to use local knowledge of history and variation within fields to work with nature, rather than against it, and incorporates biodiversity management to reduce external inputs and produce enhanced ecosystem services from the land (Altieri et al., 2015; Garbach et al., 2017) . This form of agricultural practice seeks input from traditional farmer knowledge, as well as new methodologies from agroecologists and other researchers. Agroecology lacks a precise definition and has alternatively been described as a science, a social movement, and a practice (Wezel et al., 2009). Scientifically, agroecologists collect ecological information from agricultural systems to understand how agroecosystems function. Socially, agroecology places the farmer and those on the land and their knowledge base at the center of agricultural understanding and production. In combination, scientists and farmers can work together to produce highly relevant spatially and temporally specific understandings of agroecosystems and resultant best management practices (Bullock et al., 2019).

Miguel Altieri, who helped popularize agroecology in Latin America before promoting it in North America, criticizes the loss of farm knowledge through the growing size of farms and the diminishing role of traditional knowledge (Altieri, 1999). Altieri claims that peasant farmers already knew how to farm using ecological systems and had developed a deep understanding of how to accomplish this in every local environment. As a scientist, Altieri provides simple, straightforward messages for how farmers can begin using ecological knowledge in farm systems again. A summary of some of the most important methods includes increasing crop diversity, using legume-based rotations, re-integrating animals into the system, increasing plant biomass, keeping the soil covered as often as possible through plants or mulch, using inputs of compost and manure, and introducing or conserving natural enemies of pests (Altieri et al., 2015; Rosset & Altieri, 1997). A succinct description of best agroecological practices can be described as high biomass farming (Weiner, 2017). In this framework, long-term sustainability is paramount over short-term yield output and can be achieved primarily through improved soil health. In practice, this typically means increasing soil organic matter through increased incorporation of diversified plant biomass. This framework largely overlaps with Altieri's message and promotes plant biomass as the grand agroecological solution; more biomass fuels a more diverse soil ecosystem, which in turn provides a more diverse and resilient ecosystem capable of contributing more ecosystem services. This form of thinking rejects the dominant paradigm of high-input agriculture and takes a long-term view on sustainability.

The prime example of agroecology in practice is organic agriculture. Organic agriculture has slowly and steadily increased in acres of production and popularity around the world and in North America (Willer & Lernoud, 2019). Organic agriculture uses agroecological practices instead of high-input conventional agriculture. Organic farmers follow the principles laid out by Altieri, Weiner and others, and attempt to increase diversity and increase soil organic matter to make real, sustainable gains in production over the long haul rather than short-term bursts of high yields based on high inputs of synthetic nitrogen. This form of agriculture is healthier for the land, the community, and the farmer, and is a form of agroecological intensification. Diversity is higher on organic farms, pollution is decreased, and despite lower yields, profits are also up (Drugova et al., 2019; Durham & Mizik, 2021; Riedo et al., 2021; Seufert et al., 2012). However, it is possible for those outputs to be increased without destroying gains in other areas of sustainability, with precision agriculture being one such tool that could increase outputs of organic agriculture without losing its ecological advantages (Duff et al., 2021).

Precision Agriculture

Precision agriculture is an unusual ally of agroecological intensification, as new technologies are typically associated with conventional high-input agriculture. Precision agriculture is typically considered the collection of tools that allow farmers to capture spatial and temporal data on their fields and deploy inputs through GIS technologies to manage their fields more efficiently (McBratney et al., 2005). Precision tools include GPS, satellites and drones, and equipment or on-farm sensors. The initial goal of precision agriculture was "farming by soil" (Robert, 1993), meaning that precision tools allowed large-scale farmers to apply inputs across their fields specific and relevant to the soil types present. In this initial vision, farmers could spatially sample their fields and develop sub-field zones within which they could apply nutrient additions as needed. This form of thinking re-imagines the dominant paradigm wherein farmers apply average rates of inputs across entire fields and even entire farms in an effort to reduce the complexity on the increasing scale of their operations. Ignoring the complexity of natural systems and overwhelming them with inputs are the hallmarks of intensified agriculture. Precision agriculture allows farmers to acknowledge and manage real field variability and subsequent complexity using technology. While social activist and essayist Wendel Berry decries the use of farm technology, claiming it reduces a farmer's understanding of their fields, we can now see a future where technology can reintroduce a farmer to the nuances of their land (Filipiak, 2011; Pedersen & Lind, 2017).

As precision technologies rapidly developed over the last few decades, certain tools became commonplace, while others have seen very slow uptake by farmers (Lindblom et al., 2017). The technology of autosteer, for example, which allows farmers to use GPS signals to automatically propel equipment in straight lines across fields, is used by most North American farmers (Schimmelpfennig & Lowenberg-DeBoer, 2020). However, variable rate technology, which allows farmers to apply specific input rates of seed, fertilizer, or chemical, across their fields, is used much less frequently. Farmers have yet to be shown the benefits of such technologies (McFadden et al., 2022). An increasingly popular methodology which seeks to demonstrate the power of variable rate technology is called on-farm precision experimentation (OFPE) (Lacoste et al., 2022). In this methodology, farmers and researchers work together to find optimized levels of inputs across a field that goes beyond Robert's initial vision of "farming by soil" (Cook et al., 2018; Kyveryga, 2019). Using OFPE, random rates of an input applied across a field form a whole field experiment, from which crop response data are used from the combine harvester or other sensors to provide information on how the varied rates performed in different areas of the field. This data is then modeled to create optimized input maps which treat the entire field as having varied zones across which disparate inputs can be placed (Bullock et al., 2019). Using precision agriculture and on-farm experimentation, farmers can now work with natural systems and their natural variability on large scales.

Agroecological Intensification

Apprehension to the intensification of agriculture has led to myriad demands for more sustainability in agriculture. In some ways, this means utilizing tools we already have and redeploying them toward new objectives. For example, genetically engineered crops could improve nutrition and be designed to thrive in various environments rather than simply attempting to create plants that thrive in highly unnatural, chemicalized, and monoculture environments (Kumar et al., 2020). In many ways, agroecology rejects modern conventional agriculture and returns to an organic viewpoint, a perspective that pre-dates the green revolution, when farming worked with nature. In any case, consumers, and governments, are asking more from farmers and are expecting a pivot towards agricultural practices that take environmental concerns seriously (Eyhorn et al., 2019). This dissertation envisions this change coming in the form of agroecological intensification, through the combined use of traditional farmer knowledge, new applied ecological understandings, and the harnessing of precision agricultural tools and big data to empower individual farmers.

Precision agriculture is an effective tool to increase both yield and ecosystem services in the pursuit of agroecological intensification (Garbach et al., 2017). It now offers a chance for organic farmers to take advantage of new technologies to increase the level of sustainability of their farms. Technological advances in the realm of satellite imagery, mapping applications, variable rate technology, and open-source software can be used to build on traditional knowledge by integrating data to improve soil health, reduce weed pressure, increase biodiversity, increase yields, and maximize net returns across every acre of their farm (Weersink et al., 2018). To accomplish this, we seek to determine the validity of using varied seeding rates of both nitrogen-fixing green manure cover crops, and following season cash crops, to maximize farmer net return, and increase the use of natural biomass in farm systems. By using freely available web and machine-based data and open-source software already in various stages of development, organic farmers can be enabled to harness the power of precision agriculture to grow food more sustainably (Hegedus et al., 2023).

Within this dissertation, I explore the use of precision agriculture in organic grain systems across the Northern Great Plains. In chapter two, in tandem with my lab members, we explore the potential of precision agriculture to be deployed at the different scales of agroecology, from fields and input substitution to broader networks of farmers and the globe. In chapters three and four, I look at the ability of green manure cover crops to be deployed using variable seeding rates through greenhouse and field-scale experiments, respectively. Chapter five turns to the problem of weeds in organic farming and the possibility of using multi-objective optimization to minimize weeds through variable seeding rates while still focusing on the farmer's overall yield and net returns. Finally, the prologue will touch on the requirements for these techniques to become widely adopted by farmers.

Throughout these chapters, an effort is made to explore the realistic economic value of precision agriculture in its current form, where the greatest uses lie, and where farmers should consider investing or not. Since adopting the precision agriculture techniques that are most effective is key, attempting to quantify their economic use is made, as well as providing clear paths for their deployment by farmers. This work is a small step in the direction of shifting the default position of agricultural intensification away from straight industrialization toward a more holistic, thoughtful management of the globe's productive food spaces.

By reframing intensification with a focus on ecosystem services through an agroecological lens, we can find ways to work with nature to produce adequate yields while producing more nourishing food and sustaining the other necessary functions of land (Provenza et al., 2021).

Precision agriculture tools have enormous potential to combine local farmer knowledge with untapped data resources to enable agroecological intensification. The paradigm of intensified agricultural systems has led to many ecological disasters, and it is now vital that farmers, the research community, and policymakers move to find a new paradigm of agricultural practice. Through the use of modern precision agriculture technology, there is now an opportunity to reincorporate agroecology as the core tenet of farm systems.

References

Altieri, M. A. (1999). Applying Agroecology to Enhance the Productivity of Peasant Farming Systems in Latin America. *Environment, Development and Sustainability*, *1*, 197–217.

Altieri, M. A., Nicholls, C. I., Henao, A., & Lana, M. A. (2015). Agroecology and the design of climate change-resilient farming systems. *Agronomy for Sustainable Development*, *35*(3), 869–890. https://doi.org/10.1007/s13593-015-0285-2

Anderson, C. R., Bruil, J., Chappell, M. J., Kiss, C., & Pimbert, M. P. (2019). From Transition to Domains of Transformation: Getting to Sustainable and Just Food Systems through Agroecology. *Sustainability*, *11*(19), 5272. https://doi.org/10.3390/su11195272

Barański, M., Średnicka-Tober, D., Volakakis, N., Seal, C., Sanderson, R., Stewart, G. B., Benbrook, C., Biavati, B., Markellou, E., Giotis, C., Gromadzka-Ostrowska, J., Rembiałkowska, E., Skwarło-Sońta, K., Tahvonen, R., Janovská, D., Niggli, U., Nicot, P., & Leifert, C. (2014). Higher antioxidant and lower cadmium concentrations and lower incidence of pesticide residues in organically grown crops: A systematic literature review and meta-analyses. *British Journal of Nutrition*, *112*(5), 794–811. https://doi.org/10.1017/S0007114514001366

Bullock, D. S., Boerngen, M., Tao, H., Maxwell, B., Luck, J. D., Shiratsuchi, L., Puntel, L., & Martin, N. F. (2019). The Data-Intensive Farm Management Project: Changing Agronomic Research Through On-Farm Precision Experimentation. *Agronomy Journal*, *111*(6), 2736–2746. https://doi.org/10.2134/agronj2019.03.0165

Cook, S., Lacoste, M., Evans, F., Ridout, M., Gibberd, M., & Oberthür, T. (2018). *An On-Farm Experimental philosophy for farmer-centric digital innovation*.

Díaz, S., Fargione, J., Chapin, F. S., & Tilman, D. (2006). Biodiversity Loss Threatens Human Well-Being. *PLoS Biology*, *4*(8), e277. https://doi.org/10.1371/journal.pbio.0040277

Drugova, T., Pozo, V. F., Curtis, K. R., & Randall Fortenbery, T. (2019). Organic wheat prices and premium uncertainty: Can cross hedging and forecasting play a role? *Journal of Agricultural and Resource Economics*, *44*(3), 551–570. https://doi.org/10.22004/ag.econ.292331

Duff, H., Hegedus, P. B., Loewen, S., Bass, T., & Maxwell, B. D. (2021). Precision Agroecology. *Sustainability*, *14*(1), 106. https://doi.org/10.3390/su14010106

Duke, S. O. (2018). The history and current status of glyphosate. *Pest Management Science*, *74*(5), 1027–1034. https://doi.org/10.1002/ps.4652

Durham, Ti. C., & Mizik, T. (2021). Comparative Economics of Conventional, Organic, and Alternative Agricultural Production Systems. *Economies*, *9*(64), 1–22.

Eyhorn, F., Muller, A., Reganold, J. P., Frison, E., Herren, H. R., Luttikholt, L., Mueller, A., Sanders, J., Scialabba, N. E.-H., Seufert, V., & Smith, P. (2019). Sustainability in global agriculture driven by organic farming. *Nature Sustainability*, *2*(4), 253–255. https://doi.org/10.1038/s41893-019-0266-6

Filipiak, J. (2011). The Work of Local Culture: Wendell Berry and Communities as the Source of Farming Knowledge. *Agricultural History*, *85*(2), 174–194. https://doi.org/10.3098/ah.2011.85.2.174

Garbach, K., Milder, J. C., DeClerck, F. A. J., Montenegro de Wit, M., Driscoll, L., & Gemmill-Herren, B. (2017). Examining multi-functionality for crop yield and ecosystem services in five systems of agroecological intensification. *International Journal of Agricultural Sustainability*, *15*(1), 11–28. https://doi.org/10.1080/14735903.2016.1174810

Gemmill-Herren, B. (2020). Closing the circle: An agroecological response to covid-19. *Agriculture and Human Values*, *37*(3), 613–614. https://doi.org/10.1007/s10460-020-10097-7

Hegedus, P. B., Maxwell, B., Sheppard, J., Loewen, S., Duff, H., Morales-Luna, G., & Peerlinck, A. (2023). Towards a Low-Cost Comprehensive Process for On-Farm Precision Experimentation and Analysis. *Agriculture*, *13*(3), 524. https://doi.org/10.3390/agriculture13030524

Holleman, H. (2018). *Dust bowls of empire: Imperialism, environmental politics, and the injustice of "green" capitalism*. Yale University Press.

Kumar, K., Gambhir, G., Dass, A., Tripathi, A. K., Singh, A., Jha, A. K., Yadava, P., Choudhary, M., & Rakshit, S. (2020). Genetically modified crops: Current status and future prospects. *Planta*, *251*(4), 1–27. https://doi.org/10.1007/s00425-020-03372-8

Kyveryga, P. M. (2019). On-Farm Research: Experimental Approaches, Analytical Frameworks, Case Studies, and Impact. *Agronomy Journal*, *111*(6), 2633–2635. https://doi.org/10.2134/agronj2019.11.0001

Lacoste, M., Cook, S., McNee, M., Gale, D., Ingram, J., Bellon-Maurel, V., MacMillan, T., Sylvester-Bradley, R., Kindred, D., Bramley, R., Tremblay, N., Longchamps, L., Thompson, L., Ruiz, J., García, F. O., Maxwell, B., Griffin, T., Oberthür, T., Huyghe, C., … Hall, A. (2022). On-Farm Experimentation to transform global agriculture. *Nature Food*, *3*(1), 11–18. https://doi.org/10.1038/s43016-021-00424-4

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

McBratney, A., Whelan, B., & Ancev, T. (2005). Future Directions of Precision Agriculture. *Precision Agriculture*, *6*, 7–23.

McFadden, J. R., Rosburg, A., & Njuki, E. (2022). Information inputs and technical efficiency in midwest corn production: Evidence from farmers' use of yield and soil maps. *American Journal of Agricultural Economics*, *104*(2), 589–612. https://doi.org/10.1111/ajae.12251

Pedersen, S. M., & Lind, K. M. (2017). Precision Agriculture – From Mapping to Site-Specific Application. In S. M. Pedersen & K. M. Lind (Eds.), *Precision Agriculture: Technology and Economic Perspectives* (pp. 1–20). Springer International Publishing. https://doi.org/10.1007/978-3-319-68715-5_1

Provenza, F. D., Anderson, C., & Gregorini, P. (2021). We Are the Earth and the Earth Is Us: How Palates Link Foodscapes, Landscapes, Heartscapes, and Thoughtscapes. *Frontiers in Sustainable Food Systems*, *5*, 547822. https://doi.org/10.3389/fsufs.2021.547822

Riedo, J., Wettstein, F. E., Rosch, A., Herzog, C., Banerjee, S., Buchi, L., Charles, R., Wachter, D., Martin-Laurent, F., Bucheli, T. D., Walder, F., & Van Der Heijden, M. G. A. (2021). Widespread occurrence of pesticides in organically managed agricultural soils-The ghost of a conventional agricultural past? *Environmental Science and Technology*, *55*(5), 2919–2928. https://doi.org/10.1021/acs.est.0c06405

Robert, P. (1993). Characterization of soil conditions at the field level for soil specific management. *Geoderma*, *60*(1–4), 57–72. https://doi.org/10.1016/0016-7061(93)90018-G

Rosset, P. M., & Altieri, M. A. (1997). Agroecology versus input substitution: A fundamental contradiction of sustainable agriculture. *Society & Natural Resources*, *10*(3), 283–295. https://doi.org/10.1080/08941929709381027

Schimmelpfennig, D., & Lowenberg-DeBoer, J. (2020). Farm Types and Precision Agriculture Adoption: Crops, Regions, Soil Variability, and Farm Size. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3689311

Seufert, V., Ramankutty, N., & Foley, J. A. (2012). Comparing the yields of organic and conventional agriculture. *Nature*, *485*(7397), 229–232. https://doi.org/10.1038/nature11069

Smith, C., Hill, A. K., & Torrente-Murciano, L. (2020). Current and future role of Haber–Bosch ammonia in a carbon-free energy landscape. *Energy & Environmental Science*, *13*(2), 331–344. https://doi.org/10.1039/C9EE02873K

Weersink, A., Fraser, E., Pannell, D., Duncan, E., & Rotz, S. (2018). Opportunities and Challenges for Big Data in Agricultural and Environmental Analysis. *Annual Review of Resource Economics*, *10*(1), 19–37. https://doi.org/10.1146/annurev-resource-100516-053654

Weiner, J. (2017). Applying plant ecological knowledge to increase agricultural sustainability. *Journal of Ecology*, *105*(4), 865–870. https://doi.org/10.1111/1365-2745.12792

Wezel, A., Bellon, S., Doré, T., Francis, C., Vallod, D., & David, C. (2009). Agroecology as a science, a movement and a practice. A review. *Agronomy for Sustainable Development*, *29*(4), 503–515. https://doi.org/10.1051/agro/2009004

Willer, E. H., & Lernoud, J. (2019). *The World of Organic Agriculture Statistics and Emerging Trends 2019*.

Zabinski, C. (2020). *Amber waves: The extraordinary biography of wheat, from wild grass to world megacrop*. The University of Chicago Press.

CHAPTER TWO

PRECISION AGROECOLOGY

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Contributions: Contributed critically to writing of the manuscript.

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Contributions: Co-conceptualized the manuscript and provided critical interpretation of the manuscript for important intellectual content. All authors contributed critically to the drafts and gave final approval for publication.

Manuscript Information

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Abstract

In response to global calls for sustainable food production, we identify two diverging paradigms to address the future of agriculture. We explore the possibility of uniting these two seemingly diverging paradigms of *production oriented* and *ecologically oriented* agriculture in the form of *precision agroecology*. Merging precision agriculture technology and agroecological principles offers a unique array of solutions driven by data collection, experimentation, and decision support tools. We show how the synthesis of precision technology and agroecological principles results in a new agriculture that can be transformative by: 1. Reducing inputs with optimized prescriptions, 2. Substituting sustainable inputs by using site-specific variable rate technology, 3. Incorporating beneficial biodiversity into agroecosystems with precision conservation technology, 4. Reconnecting producers and consumers through value-based food chains and 5. Building a just and equitable global food system informed by data driven food policy. As a result, precision agroecology provides a unique opportunity to synthesize traditional knowledge and novel technology to transform food systems. In doing so, precision agroecology can offer solutions to agriculture's biggest challenges in achieving sustainability in a major state of global change.

Introduction

Agriculture is both a major cause and potential solution for current environmental issues. Modern industrial agriculture has increased yields over time, but this has come at a staggering cost to the environment. Despite modern industrial agriculture contributing to environmental issues like nitrogen pollution, soil degradation and habitat destruction, enhanced information availability and analysis offered by the industry has the opportunity to solve, rather than perpetuate problems in agricultural sustainability. The future of agriculture should promote productive, economically viable, socially just, and environmentally sound agri-food systems (Council, 2010). We have known for decades that sustainable intensification of agricultural production is required to feed and nourish the world's growing population, and there are many avenues being pursued in this endeavor such as changes in land use management, closing organic yield gaps, and shifting diets (Bardgett & Gibson, 2017; Foley et al., 2011. From these pursuits we have identified two dominant paradigms that offer differing solutions to the problems of modern agriculture (Figure 2.1). The production oriented paradigm imagines solutions based on productivity, technology and optimized input management. When pushed to its furthest extreme, the fear of "big data", "agribusiness" and "robot agriculture" deters many stakeholders and practitioners from engaging in such industrialized agriculture solutions (Daum, 2021). Alternatively, the countermovement of ecologically oriented agriculture endorses a more holistic style of ecologically based agriculture that focuses on long term sustainability, ecological solutions and conservation practices (Rosset & Altieri, 2017; Anderson et al., 2019). Critics of the latter suggest these movements are fleeting, unproductive, and lack scientific evidence (Bellwood-Howard & Ripoll, 2020; Tom, 2020). Despite diverging paradigms, we make the case that global calls for the transformation of food systems will require both applications of technology and agroecological transformation to create productive and sustainable agri-food systems. Below we describe *precision agroecology* as the use of modern technological farm instrumentation and tools collectively called "Precision Agriculture" (PA) to accomplish the goals of agroecology.

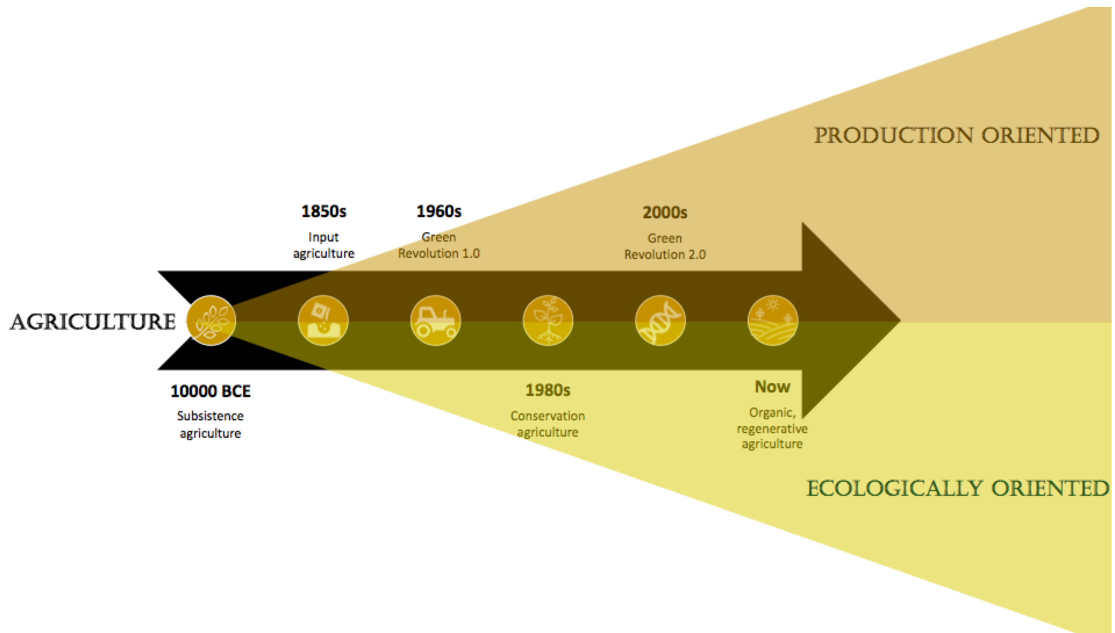

Figure 2.1. Depiction of the timeline of agriculture from subsistence agriculture to the present diverging paradigm of production oriented and ecologically oriented agriculture.

Precision agriculture is often categorized within the production oriented paradigm. Typically, PA is considered the collection of instruments that allow farmers to capture spatiotemporal data on their fields and apply it to management decisions that improve efficiency and quality, and thus sustainability of agriculture (International Society for Precision Agriculture, 2021). Rich data sets are being generated by farms every day and most farm machinery today collects, or at least interacts, with data in one or many ways (Meola, 2021). The amount of farm information such as weather, topography, and vegetation indices available from machines, drones, weather stations and satellite based remote sensing data is continuously increasing (Carolan, 2017) and driving the adoption of big data analytics in agriculture (Coble et al., 2018; Griffin & Lowenberg-DeBoer, 2005; Basso et al., 2021). Field specific data collection has been used to inform sub-field-scale management within fields by reducing generalizations made across spatial scales (Van Es & Woodard, 2017; Lawrence, et al., 2015; Maxwell & Luschei, 2005; Gebbers & Adamchuk, 2010; Luschei et al., 2001). Greater exploitation of the data returned from daily precision farming operations can drastically increase resource use efficiency and produce crops in a manner that not only reduces the environmental impacts but increases the ecological and economic resilience of agroecosystems (Bucci et al., 2018). However, those who pushback against PA lament the loss of stakeholder knowledge, data ownership, and values of small-scale farming. Many fear that PA will further distance producers from their land by substituting technology for local knowledge (Altieri & Nicholls, 2020). Others fear that it will prolong “productivist” values without regard for crop quality and encourage “ecological dystopias” (Daum, 2021). In this sense, PA would only perpetuate the externalized costs of modern industrial agriculture on ecosystem and human health. As a consequence, PA may represent the industrial endpoint that not only encourages increased farm size but substitutes fully automated agriculture for human knowledge and land connection.

On the opposite side of the solutions spectrum, agroecology refers to a scientific discipline, an applied management practice, and a social movement (Wezel et al., 2009). The scientific discipline of agroecology is the study of the application of ecological concepts and principles to agroecosystems. Stemming from indigenous roots, agroecology goes beyond simply using ecological concepts to increase production and reduce environmental impacts, but uniquely adapts principles to communities based on the co-creation and sharing of knowledge, culture and food traditions, diversity, resilience and responsible governance (FAO, 2016; Nyéléni, 2015; Altieri, 1999). Agroecology looks beyond the farm level to the broader regional, national, and global levels of the food system to affect sustainable change. Agroecology also focuses on local knowledge, ensuring that farmers stay connected to their land and their management despite the arrival of technology and broad-based prescriptions (Filipiak, 2011; Shava et al., 2010). Critics of agroecology point to economic realities and projected global food demand to belittle agroecology as nothing more than a local counterculture movement that is not capable of large-scale food production (Connor, 2018). However, we propose the merger of these two movements by using PA technology to manage farms through specific application of agroecological principles.

We propose that PA and agroecology are compatible, rather than divergent strategies for creating sustainable agri-food systems. Although these two disciplines stem from seemingly incompatible backgrounds, they promote a sustainable agriculture that is profitable, equitable, minimizes environmental degradation and efficiently achieves these goals. Key to their integration is the idea that agroecosystems are complex and vary considerably over space and time. Application of agroecology has historically lacked adoption because it could only offer general principles (e.g. crop diversification) due to a lack of local field scale data that could account for the variability that results from reduced inputs and complex biological interactions. PA offers the local information required to make field-specific agroecological recommendations. PA is commonly misperceived as belonging solely to the “big tech” agribusiness world, but in reality, it has roots in stakeholder-driven science and practice (Cook et al., 2018; MacMillan & Benton, 2014). Precision agriculture technology and data are essential to create on-farm experimentation (OFE) and adaptive management (Maxwell and Hegedus, 2022). OFE aims to formalize the research of farmers on their own fields (Cook et al., 2018). Advances in technology, particularly in PA, have opened the door for farmers to formalize, detail, digitally record, and analyze their experiments in ways not possible before the agricultural data revolution (Bullock, 2019). Most farmers in industrialized nations have access to equipment that records inputs and harvest information; yet farmers and industry have not grasped the potential to use this data to manage fields in a site-specific manner. In addition to the massive stream of on-farm data from PA instruments and technology, there are large repositories of open-source satellite imagery that can be used to update management recommendations through adaptive management and apply on-farm experimentation. On-farm experimentation (OFE) is a collaborative form of science that synthesizes farmer's tacit knowledge and data to manage, improve, and even redesign agri-food systems (Cook et al., 2018; Kyveryga, 2019). These on-farm trials place agriculture in an ecological context that is site, history, and time specific.

At first glance, PA is an unusual ally of agroecology, as new technologies are most typically associated with conventional high input agriculture. However, the initial goal of PA was "farming by soil" (Robert, 1993). This means that precision tools allowed large scale farmers to apply inputs across their fields specific and relevant to the soil types that were present. In this initial vision, farmers could spatially sample their fields and develop sub-field zones within which they could apply nutrient additions as needed. This form of thinking re-imagines the dominant paradigm wherein farmers apply average rates of inputs across entire fields and even entire farms in an effort to reduce the complexity of their operations. Using high input rates to overwhelm complex and variable natural systems is a hallmark of intensified agriculture. On the other hand, PA allows farmers to work with real field complexity using technology (Garbach et al., 2017). While Wendell Berry decried the use of farm technology, claiming it reduced a farmer's understanding of their fields (Filipiak, 2011), we can now see a future where technology can reintroduce a farmer to the complexity of the ecological interactions on their land (Pedersen & Lind, 2017).

Furthermore, PA has the potential to substitute data for synthetic inputs. Technologies of PA, including aerial maps and combine-mounted yield monitors, are used by producers and researchers alike to gain detailed site-specific (and free) data about agri-food systems. We argue that rather than distancing producers from their land, PA can reacquaint farmers with large fields and give them more extensive knowledge about the variation within their system (Mcfadden et al., 2021). This approach can help not only to improve farm management, but to mitigate environmental externalities by providing detailed quantitative analyses at the field and farm scale. For example, PA can reorient agricultural values away from pure production and facilitate “nutrition-sensitive agriculture” that prioritizes food quality by incentivizing producers and markets to manage and price crops for their quality rather than quantity (Nicholson et al., 2021). Incentivizing producers to grow food for nutrient content and best management practices rather than net-return alone would align modern agriculture with the values of agroecology.

Although agroecology is commonly referred to as “a science, a movement and a practice” (Wezel et al., 2009; Tomich et al., 2011), the quantitative side of the discipline is often overlooked, and it should in fact be recognized as a mechanism to bring objective science to management, thus relieving the inefficiency of the trial-and-error approach. More commonly understood as a social movement, agroecology indeed emerged as a potential solution to the crisis of industrial agriculture in tandem with the environmental movement. Agroecological farming practices of the 1980s were well aligned with social movements of the 1990s that called for radical transformation of agriculture (Levins, 1990). The goal was to remedy the social, economic and environmental externalities of agro-industry with an alternative agriculture movement (Rosset & Altieri, 1997). Today, agroecology is a transdisciplinary concept that encompasses ecological, social and economic dimensions of food systems (Francis et al., 2003). From a scientific perspective, agroecology draws from ecological principles and applies them to manage agricultural systems (Ewing et al., 2021; DiTommaso et al., 2016). This includes concepts of evolutionary fitness, competition dynamics, and plant population modeling not commonly considered by traditional agronomists or producers (Weiner, 2017; Gliessman & Engles, 2015; Vandermeer, 2011; Vandermeer et al., 1998; Altieri, 1995). Agroecology also values an ecological systems approach that considers production impacts at multiple spatial scales.

We propose that PA and agroecology are an unlikely, yet necessary pair for creating sustainable agricultural solutions. Precision agroecology is grounded in an ecological framework but employs the benefits of modern technology and data-intensive management from PA to monitor beyond the plot scale (Marchant, 2019). The fusion of PA and agroecology offers transformative agri-food systems solutions that were not previously possible. Therefore, we explore the potential of precision agroecology as the future of agriculture.

Five Tiers of Precision Agroecology

Uniting these two disciplines as precision agroecology offers a unique array of agroecological solutions driven by data collection, experimentation, and decision support tools. Stephen Gliessman, in his textbook on Agroecology, criticized yield maximization as the main goal of industrial agriculture and instead prioritized healthy ecosystem function as the foundation of food production (Gliessman & Engles, 2015). Meeting current food requirements and protecting soil and water for future agricultural demand are vital (Foley et al., 2011), however, sustainable agriculture also requires reducing inequalities in food systems from the local to global scale. Sustainable agriculture requires collaboration and cohesion at all levels of food systems, from producers, processors, distributors, retailers, consumers, and the political entities that operate at each scale. We refer to Gliessman's (2016) proposed five levels of transformation as a framework to convert conventional industrial food systems to agroecological systems using precision technology. Precision agroecology facilitates the first four levels through (1) increasing agrochemical efficiency, (2) substituting more sustainable inputs, (3) maximizing ecosystem services, and (4) reestablishing consumer-producer connections. The fifth level moves beyond the control of PA and calls for (5) creating a just and equitable global food system (Gliessman, 2016). Within each agroecological tier, we show how precision agriculture (PA) technology can be used to execute agroecological concepts and enhance agri-food system sustainability (Table 2.1). Throughout the text, we provide examples of how components of both PA and agroecology can be merged into precision agroecology practices at each tier of sustainable transformation. While this paper provides case studies of tiers one through four, we propose potential solutions for merging PA technology and agroecology in regard to tier 5 in the discussion section.

Table 2.1. Precision Agroecology Framework

Tiers of Agroecological Transformation	Precision Agriculture Component	Agroecology Component
Tier 1: Reduce Inputs	Create optimized prescriptions for site-specific nitrogen fertilizer/manure/cover crop application	Reduce environmentally damaging inputs and externalities
Tier 2: Substitute Sustainable Inputs	Use Variable Rate Technology to optimize cash crop, cover crop, and animal manure application rates	Replace environmentally damaging input rates with renewable, sustainable, site-specific ones
Tier 3: Redesign Agricultural Systems to Incorporate Biodiversity	Use yield maps and remote sensing to monitor beneficial ecosystem services from non-crop habitat	Increase biodiversity to increase ecosystem resilience and ecosystem services
Tier 4: Reconnect Producers and Consumers	Optimize values-based supply chains via production and transportation data	Form alternative food networks that are based on direct relationships
Tier 5: Create a Just and Equitable Global Food System	Utilize the data stream associated with PA to inform policy at all levels of agricultural and food systems	Account for the environmental and societal relationships surrounding agriculture and food systems

Tier One: Reduce Inputs

The first agroecological tier calls for increasing efficiencies of applied agrochemical inputs used in modern conventional agriculture to maximize crop production. Elliot and Cole (1989) recognized that tradeoffs between maximization of production and minimization of pollution were inevitable and called for the shift towards optimization of profits and sustainability in agricultural production. Gliessman's (2015) first step moves conventional modern agriculture away from inefficient practices such as uniform applications of fertilizer and pesticides towards site-specific approaches that optimize production and increase economic and environmental sustainability of agricultural communities.

Site-specific management is an application of PA that can increase efficiency and address the issues surrounding excess agrochemical input rates. Precision agriculture accomplishes this by reducing input rates in areas where the crop response does not result in increased net-returns. A common input for which site-specific management is utilized is nitrogen fertilizer. Divesting resources from low profit potential areas into high profit potential areas has two major results: in most cases reduction of total nitrogen applied over a field and fewer expenditures by producers for fertilizer (Khosla et al., 2008; Koch et al., 2004). Site-specific nitrogen management varies greatly in the methods used to develop prescriptions and the scale at which management units are applied (Link et al., 2008; Huggins, 2010; Farid et al., 2016; Khosla et al., 2008; Koch et al., 2004; Moshia et al., 2014). Site-specific fertilizer applications have been investigated in diverse crop systems throughout the US (Bronson et al., 2006; Guillard, 2018; Stevens, 2017; Flowers et al., 2004; Biermacher et al., 2009) and profit maximizing site-specific nitrogen management has been shown to increase net-returns in the wheat-belt from Oklahoma to Montana (Biermacher et al., 2009; Lawrence et al., 2015). Reducing nitrogen fertilizer contributes to the sustainability of the natural resource-base that agriculture relies on and improves farmer net-returns by increasing the efficiency of fertilizer applications. This puts more money in the pocket of producers and thereby the broader rural community.

Site-specific management of inputs is best optimized through OFE applied to crop production, to intentionally understand crop responses to variable rate application management. Site-specific management and OFE both require harnessing the stream of data gathered on-farms and from remotely sensed data sources to power analyses and augment decision making. The automatic collection of data from farm machines is becoming easier through cloud software such as “MyJohnDeere” and from satellite image repositories such as Google Earth Engine (Gorelick et al., 2017). The spatiotemporal availability of remotely sensed data allows for enrichment of any on-farm dataset by, for example, providing information from remotely sensed weather estimates or topographical variables at the sub-field scale locations of harvest data points. Statistical and machine learning approaches can be used to characterize the response of the crop, in terms of production (yield) or quality (e.g. grain protein content), to variable nitrogen (N) fertilizer inputs and other environmental covariates. These models can then be used to simulate outcomes of various complex management approaches where farmers are provided with an array of management options that they can choose from, while ultimately leaving decision making in the hands of the farmer.

Current decision support systems have mainly been developed with models focused on profit maximization and have shown promise not only to increase farmer net-returns but to minimize the amounts of chemical inputs within fields. Future work will be development of models optimized on maximizing profits and minimizing pollution, driven by OFE. Using our precision agroecological approach, site-specific optimization of competing goals can apply an agroecological lens to harness the power of PA and address issues of economic and environmental sustainability. Increasing chemical efficiency serves as the initial steppingstone for the transformation of industrial agriculture towards an agroecological framework but must not be an endpoint where agroecology is conformed to current agricultural practices (Nyéléni, 2015). Early conceptualization of agroecology envisioned the substitution of industrial synthetic inputs with information about ecological interactions. We now have the data availability to realize that substitution.

Tier Two: Substitute Sustainable Inputs

The second agroecological tier calls for substituting organic inputs, or knowledge, for industrial synthetic inputs. Organic agricultural systems have been attempting this at scale for decades at least, and PA can be an important tool in efficiently shifting towards more sustainable inputs (Tully & McAskill, 2020). As noted in tier one, synthetic nitrogen is one of the most ecologically damaging industrial agricultural inputs, alongside pesticides. Broadly, organic agriculture removes chemical inputs from the agroecological environment by substituting synthetic inputs with animal manure, cover crops, and local knowledge (Carr et al., 2019; Osterholz et al., 2020) This practice of substitution produces healthier food and reduces nonpoint agricultural pollution (Barański et al**.**, 2014). Animal manure is rich in nitrogen but is unavailable in many locations in North America. Cover crops, which include nitrogen fixing plants such as peas and hairy vetch, provide nitrogen where animal manure access is limited. Additionally, these crops can reduce weed pressure through competition and varied termination methods (Carr et al., 2020). Organic farmers, faced with diverse challenges, rely on local knowledge to apply inputs with greater precision and timing than conventional farmers. The emphasis on understanding local conditions is greater in organic systems as they do not rely on pesticide options to manage pest outbreaks or synthetic fertilizers to correct low soil fertility.

This notion of farming with local knowledge is something all farmers do, but organic farmers in particular tend to be systems thinkers who seek out new information to aid whole-farm planning and decision making (Church et al., 2020). Thus, they are well suited to add precision agricultural data management to their tool kit.

The primary drawback of organic agriculture is reduced yield outputs due to nitrogen deficiencies and weed pressures. However, PA and OFE can help close this yield gap (Seufert & Ramankutty, 2017). Organic farmers can use OFE to rapidly understand the patterns of spatial and temporal variation across their fields and thus manage them more efficiently. Seeding rates of cash crops and cover crops impact crop quality, yield, and competitive ability (Miller et al., 2011; Ma et al., 2018; Alba et al., 2020; Pes et al., 2022). Subsequently, organic OFE methodology focuses on applying experimental randomized seeding rates across entire fields to find optimum site-specific seeding rates. This methodology is applied to both green manure nitrogen fixing cover crops, and cash crops like wheat or hemp, in order to minimize weed pressure, optimize yields, and maximize farmer net-return. Beyond the yield maps and other topographic variables mentioned in tier one, weed survey maps can also be incorporated into models to reveal best management practices. Early results from organic OFE research have revealed new spatially varied optimum seeding rates which outcompete farmer chosen uniformly applied whole field seeding rates. The farmer can choose to site-specifically optimize seeding rates to maximize profits and minimize nitrogen losses and the knowledge gained through OFE complements the farmer's historic of a field. Through OFE, an organic farmer can speed the process of understanding their land and the impact organic inputs have on outcomes such as yield and weeds. Increased local knowledge helps an organic farmer manage their land without the use of synthetic inputs, thereby enabling PA tools to enable sustainable transition from ecologically damaging inputs to organic ones.

Tier Three: Incorporate Diversity

The third tier of agroecological transformation entails redesigning agri-food systems to incorporate more diversity in ecosystem structure and facilitate ecological function (Gliessman, 2016). Simplified agricultural systems are criticized as “ecological sacrifice zones” that disrupt ecosystems (Garbach et al., 2017). In contrast, diverse agroecosystems that conserve natural ecosystem structure have more complex ecosystem function. As a consequence, they provide many more ecosystem services that benefit producers in agricultural landscapes. Beneficial ecosystem services associated with biodiversity include pollination, pest predation, and weed seed predation (Capmourteres et al., 2018; Isaacs et al., 2009; Losey & Vaughan, 2006; Tilman et al., 2002; Landis, 2017), though tradeoffs may include increased pest habitat, increased weed density, and yield reduction (Gurr et al., 2003). In theory, agroecological principles such as diverse crop rotations, high biomass cropping systems and soil fertility building are key to maximizing ecosystem services in agri-food systems (Weiner, 2017). Plant diversity plays an important role in ecosystems and agroecosystems alike by enhancing ecosystem structure and function. Associated ecosystem services of higher plant diversity include enhanced nutrient cycling, soil quality, and habitat for beneficial insects (Garbach et al., 2014; Power, 2010; Isaacs et al., 2009). In turn, these ecosystem services may provide agronomic benefits such as lower input costs, higher nutritional content in crops, and maintained or increased crop yields (Tscharntke et al., 2005, Benayas & Bullock, 2012; Zuo & Zhang, 2008). However, ecosystem services are notoriously difficult to quantify and monitor in ecological systems, making them extremely difficult for producers to manage (Tscharntke et al., 2005; Kremen, 2005). We propose that site-specific, quantitative data from PA technology can be used as an on-farm conservation tool to optimize ecosystem services and manage tradeoffs in agricultural systems (Duru et al., 2015).

Precision conservation is facilitated by PA and can aid a transformation towards diverse agroecosystems (Basso, 2021; Swinton et al., 2007). Precision conservation accounts for spatial and temporal variability by using a suite of spatial variables to manage natural and agricultural systems (Berry, 2003). In agricultural settings, precision conservation uses profit mapping technology to identify low-producing areas to create non-crop habitat in agricultural landscapes (Capmourteres et al., 2018). While most on-farm conservation efforts have focused on planned biodiversity, habitat management, and remnant habitats such as buffer zones and roadside margins, a broader category of ecological refugia can function as in-field precision conservation areas. Ecological refugia are uncropped patches in fields that serve as patch habitat to harbor biodiversity, beneficial insects and provide ecosystem services for producers (Fiedler et al., 2008; Cousins, 2006; Power, 2010). Ecological refugia may be naturally occurring areas of terrain that are too difficult to cultivate or low-producing areas that are intentionally treated for restoration. In practice, ecological refugia can range from uncultivated riparian areas and rocky patches to intentionally planted patches of cover crops or pollinator strips.

Quantifying the economic and ecological effects of refugia is essential to producer adoption of this potential conservation practice in agricultural systems. Refugia must show an economic benefit in terms of crop production and ecological benefit in terms of biodiversity. Profit maps are an effective farm management tool that can be easily generated by PA technology. Annual profit maps can be used to monitor the effects of ecological refugia on crop production by quantifying crop yield and protein content as a function of distance from refugia. Producers may see the effects of beneficial ecosystem services via higher crop yields or nutrient content near the refugia compared to other locations in the field. Furthermore, precision conservation can save farmer's time and money by taking low-yielding areas out of production. Ideally, this would increase their return on investment while increasing patch habitat and ecosystem services across the agricultural landscape (Tscharntke et al., 2005). At present, biodiversity surveys are typically required to quantify plant, insect and small mammal diversity surrounding the refugia, as remotely sensed data lacks the level of detail required for species-specific identification. However, recent developments in entomological lidar have made it possible to remotely monitor insect population and activity using sensors to assess insect wingbeat frequency, color and wing to body ratio (Brydegaard & Jansson, 2019). In addition, near-infrared spectroscopy can now accurately identify sagebrush up to the species (75-96%) and subspecies (99%) level, with vast implications for remotely monitoring vegetation at larger spatial and temporal scales (Robb, et al. 2021).

Precision agroecology can merge PA data and agroecological principles to enhance the diversity of ecosystem structure and function in production systems. Agroecological concepts of biodiversity, ecosystem stability and ecosystem function can be monitored with precision technology and improved through agroecological management. Thus, PA's burgeoning technology and field automated data collection can augment efforts to assess if ecological refugia support biodiversity, enhance ecosystem services, or increase food production and quality. In this way, precision agroecology will reduce barriers to adoption and provide the tools needed for producers to participate in agri-environment schemes that offer payments to incorporate biodiversity into farmscapes (Tscharntke et al., 2012).

Tier Four: Reestablish the Consumer-Producer Relationship

Gliessman's (2016) charge for tier four of food system transformation suggests reestablishing a more direct connection between those who grow our food and those who consume it. This goal is exemplified by growing demand for local food, both in terms of consumer interest and entrepreneurial activity. Local food sales were estimated at $4.8 billion in 2008 and $6.1 billion in 2012 (Low & Vogel, 2011; Low et al., 2015), with subsequent iterations of these reports likely to show continued growth. To answer the charge, producer-consumer relationships must be restored by strengthening local/regional food systems (LRFSs) and fostering "food citizenship" on a large scale.

In contrast to traditional agricultural supply chains, an LRFS is better described as a values-based supply chain that aims to enhance producer profitability by paying price premiums for the environmental and social values implicit in their products (Feenstra et al., 2011). Therefore, values-based supply chains require a high level of transparency and information sharing at each stage of the supply chain (Feenstra et al., 2011). In this regard, values-based supply chains foster a food system that compensates producers for food quality, rewards best management practices, and relies on open accessible data flows to relay information to consumers. Fortunately, PA technology generates ample data that is free and site-specific to producers, that could be made readily available for consumers. This data holds the potential to transform value-based supply chains by offering evidence of producer practices and food nutritive quality that consumers are willing to pay for when made explicit. For instance, consumers have been found to be both “quality-focused” and “price-sensitive” in their willingness to pay when provided with traceable codes relaying information on food safety and quality (Xu et al., 2019). By scaling up transparent data flow and traceable food choices, evaluations of consumer purchasing behavior can illuminate consumer’s attitudes towards food nutrition and quality (Doub et al., 2015). Accordingly, PA data flow can be scaled up to increase traceability, for example by using QR codes as labels to convey detailed information on production practices. Alternatively, data flow can be scaled down, for example many producers now use the Square App to interact with consumers face to face in small, local markets. In this sense, at scales both large and small, data-intensive labeling and software applications are reconnecting producers and consumers.

In contrast to conventional food systems, characterized by large-scale production, vertical integration and rigid controls of inputs and environmental variables, LRFSs are more embedded in the ecology and social structures of their location. The participating businesses and consumers more explicitly recognize human values and seek positive social and environmental benefits throughout the system. As a result, LRFSs restore a sense of food citizenship among consumers. A food citizen is a resident-participant in a food system who possesses subsequent rights, duties and responsibilities therein (Wilkins, 2005). To foster food citizenship, the information and values flowing through a food system and its embedded values-based supply chains must be accessible to all stakeholders from producer to consumer. One aspect of restoring food citizenship is restoring confidence in credence goods in terms of quality assurance for the consumer and profitability for the producer (Holland, 2016). Because information in the food supply chain is imperfect, both producers and consumers take a risk on credence goods due to customer uncertainty surrounding appropriate price values and producer uncertainty concerning tradeoffs between certification costs and price premiums (Caswell & Mojduska, 1996). One approach to build trust is to rely on regulation via third-party certification that justifies the cost of both producer compliance and consumer buy-in (McCluskey, 2000). This type of third-party regulation necessitates a food system with a values-based supply chain, reliable data flow and an effective labeling scheme for credence goods.

While LRFSs are expanding and replicating organically, they can be fragile systems, and little is known about their behavior at the systems level. Through a precision agroecological lens, a theoretical framework for LRFSs can be developed. Evaluation can then lead to initial design, modification, or significant reorganization in order to promote replication and durability. Precision tools accounting for variables of the social and organizational realms in which LRFSs exist may include spatial and temporal system models. Precursor diagrammatic models of food systems can identify important aspects of structure and relationships throughout the system (Stave & Kopainsky, 2015). Parameterizing models with economic, production, environmental, and social data, and simulating LRFSs, can lead to identifying the variables that influence successes and failures. Such an approach would bring a level of data-driven precision to building and managing LRFSs. Diagrammatic models and outputs from computational models can also be used as outreach tools to educate all LRFS stakeholders on system components and the flow of goods, services and information throughout. As a result, precision agroecology has the potential to restore producer consumer relationships by strengthening LRFSs, reestablishing trust in credence goods and fostering a sense of food citizenship.

Discussion

The convergence of agroecological principles and precision technology we suggest is an unusual but necessary trajectory for future farming solutions. Typically, PA falls within the production oriented paradigm of agricultural solutions, while agroecology falls within the ecologically oriented paradigm. Though PA is often perceived as perpetuating the industrialization of agribusiness (Altieri & Nicholls, 2020; Laforge, 2021) we have shown how it can be incorporated into decision support systems parameterized with OFE to ultimately inform stakeholder-driven practices. In the same manner, agroecology has been commonly underestimated as a counterculture, low-yielding, farming movement (Connor, 2018; Tal, 2018); but we have shown how it is also a site-specific, quantitative science that pairs well with the management tools offered by precision technology. The merger of precision technology and agroecological principles results in a new agriculture that can be transformative by reducing inputs, substituting synthetic with sustainable inputs, incorporating more biodiversity into the system, and reconnecting producers and consumers.

Precision agroecology provides a unique opportunity to synthesize traditional knowledge and novel technology to transform food systems. In doing so, precision agroecology can offer solutions to agriculture's biggest challenges in achieving sustainability. These include environmental issues of pollution, biodiversity loss, and climate change, as well as broader societal issues of rural depopulation and corporate consolidation of the agricultural sector. Within the agroecological framework laid out earlier, tiers one, two and three tackle the prime environmental issues head on. As noted in both tiers one and two, reducing harmful agricultural inputs and substituting chemical inputs with more natural inputs, such as green manure cover crops in place of synthetic nitrogen, will reduce pollution. Synthetic nitrogen is a source of point and nonpoint pollution with cascading effects detrimental to ecological systems (Jones et al., 2019; Freemark & Boutin, 1995; Relyea, 2005; Egan & Mortensen, 2012; Rollin et al., 2016), and is a massive source of greenhouse gas emissions in both its production and field application (Sun et al., 2012; Foley et al., 2011; Vitousek et al., 1997). Tier one can be applied to nitrogen fertilizer as a first step towards increasing efficiency gains on conventionally managed fields of farmers that are not willing to rapidly shift to substitution of inputs. Substituting nitrogen fertilizer use through well measured cover crop management, as described in tier two, pushes conventional agriculture further towards sustainability and represents the next step in shifting modern industrial agriculture to a more sustainable future. While not shown here, the concepts of precision agroecology can also reduce and replace other chemical inputs, such as pesticide applications, across the farmscape (Liebman et al., 2013). The third tier example shows how farmscapes can be managed with precision agroecology for precision conservation of important species and prevention of biodiversity loss, while maintaining or improving agricultural output. These types of precision conservation efforts can contribute to the land sharing strategy in sustainable agriculture by providing patch habitat and ecosystem services throughout the agricultural matrix (Duru et al., 2015). In addition to reducing greenhouse gas emissions and reducing nonpoint source pollution, precision agroecology promotes the adaptive management techniques necessary to constantly adjust to the realities of a changing climate. As farmers practice OFE by collecting and implementing their data, algorithms can be used to update best management practices. Farmers respond to greater weather uncertainty with increased purchase of crop insurance, an input to minimize risk of crop failure. However, PA data and subsequent localized crop response models can be used to quantify the risk and minimize impractical insurance costs. Furthermore, recommended variable rates of seed, fertilizer, and chemical inputs would be constantly revised based on recent climate and weather patterns. In this way, managing fields in a spatially and temporally explicit manner with precision agroecology can increase agroecosystem resiliency by confronting the realities of increasing variability and uncertainty in management outcomes which will undoubtedly increase due to climate change (Tomich et al., 2011).

By transforming food systems with agroecological solutions, precision agroecology can contribute to solving broader societal issues as well. Corporate control and rising corporate profits in the farm sector have shrunk farmer profit margins and prevented small farmers from accessing the land, capital, and the technical assistance they need to succeed (Carlisle et al., 2019). Precision agroecology hopes to reverse this trend through farmer empowerment. Precision agroecology promotes decision support systems for farmers to manage their own data and implement their own farm management plans. By prioritizing stakeholder engagement and empowerment, precision agroecology can avoid becoming yet another tool used by corporations to control farmers the way agrochemical inputs and genetically modified seeds have become (Wolfert et al., 2017). Because precision agroecology aims to be a free technological adaptation for farmers who possess certain minimum PA technologies (which many already do) (Schimmelpfennig & Lowenberg-Deboer, 2020), its implementation will increase their net-returns and improve their economic resiliency. As shown by tier four, by increasing farmer prosperity, precision agroecology can bolster producer-consumer relationships and LRFSs.

Ideally, the use of precision agroecology would also promote farmer-to-farmer networks centered on knowledge exchange surrounding this novel technology (Ingram & Maye, 2020).

Despite the best intentions of researchers and practitioners of agroecology, a fear exists that agroecology movements are being commandeered and commodified by powerful corporations (Laforge, 2021; FAO, 2016; Nyéléni, 2015; Levidow et al., 2014). In order to prevent the co-optation of agroecological transformation by the production oriented paradigm, cautionary calls have been made to direct transition towards types of innovation that foster participatory processes (Uphoff, 2013; Berthet et al., 2015) and safeguard the collective knowledge, rights and agency of producers (Pimbert, 2017; Anderson & Maughan, 2021). The very issues that make PA adoption in support of agroecology challenging also provide an avenue for corporations to move in and dominate the movements. Corporations have the ability to simplify PA processes, automate them and sell the technology to farmers, thus creating a cost barrier to producer adoption. The intellectual property contained in the algorithms, even when developed with academic institutions, should be owned by farmer cooperatives where research and development of the algorithms was cooperatively developed. Incentives need to be created for public institutions to develop precision agroecology algorithms and decision support that does not lead to intellectual property for sale to the highest industrial bidders. With this approach to precision agroecology, corporate power will be reduced, and farm efficiency gains can be passed on directly to the farmer, increasing their overall field-specific knowledge and ultimate economic and environmental sustainability.

Other barriers to adoption of sustainable agriculture include educational barriers, risk barriers, and demographic barriers (Rodriguez et al., 2008). For precision agroecology, these barriers refer to practices which are difficult to learn and employ (PA technology and new agroecology practices), increased risk due to uncertainty about returns on investment (time and money), and resistance to change from an older, more traditional demographic of farmers. Farmers in North America tend to be old; the average farmer in the United states is 58 years old with 92% of farmers in the United States over 35, and 34% over 65 (USDA NASS, 2017). Across all farmer demographics, farmers are less likely to experiment with new practices or technology with increasing economic and climatic uncertainty (Lawrence et al., 2015). However, this resistance also provides an opportunity whereby generational shifts will inevitably occur, and younger farmers, being both more comfortable having grown up in the smartphone era and more willing to try new things, are considerably more likely to adopt new technologies (McFadden et al., 2021). Because of this, precision agroecology remains in a precarious position where uptake is low but must be readied for adoption when generational shifts inevitably occur.

Both PA and agroecology have steep learning curves which make them difficult to employ. Precision agriculture typically requires technological expertise, with devices and large data sets requiring understanding of GPS, GIS, and data management. Agroecology typically requires complex systems thinking involving plants, integrated weed and pest management, and practices such as longer rotations and cover crops. Combining these movements into precision agroecology thus inherits high barriers to adoption in terms of required new learning. In particular, the algorithms designed to wrangle large data sets and provide new management answers are sometimes black boxes even to data scientists, and farmers should not be expected to master advanced statistics. However, through effective communication and well developed and automated but interactive decision support systems, the process of precision agroecology can eventually be made both user-friendly and empowering for the farmer with clearly presented findings. Analysis of the data and algorithms need to be open-source and designed to be interactive with the farmer to gain insights into the complex ecological processes that can result in non-intuitive outcomes of management actions. In this way precision agroecology can augment farmer knowledge, rather than replace it, and thereby become a trusted and powerful tool by farmers who adopt it (McCown, 2001; Baars, 2011; Lindblom et al., 2017). We therefore highlight the importance of designing an approachable interface between data collection and decision-makers, further facilitated by designing applications based on free, open-source data and interactive analysis.

Research Gaps and Future Research Directions

To breach the current research gap, farmers need decision support systems to distill the information and data gathered from farms and OFE to inform management. Development of these systems is of utmost importance for the adoption of precision agroecology (McBratney et al., 2005). While PA technology makes it easy to obtain large quantities of site-specific data for producers, decision support tools are necessary to implement data driven management (Weersink et al., 2018). Start-ups and corporations have been developing decision support systems, such as Adapt-N, FieldNETAdvisorTM, FarmBot, Climate Corporation, FaunaPhotonics and Field to Market to relay PA data to user-friendly formats with the intent to guide sustainable management (Kamilaris et al., 2017; Saiz-Rubio & Rovira-Más, 2020). In response to Ingram & Mayes (2020) recent call for co-created digital technologies that prioritize a user-centric approach, our lab is working to create adaptive management tools that incorporate both big data and producer knowledge through simulation and structured decision making, such as through the 'OFPE' R package (https://github.com/paulhegedus/OFPE.git) and the On-Farm Experimentation Prescription Generator (http://trialdesign.difm-cig.org/home). These tools aim to empower farmers to control and use their own or open-source data, sidestepping corporate middlemen, and thereby retaining decision making processes on-farms.

However, one limitation of this study is that while results and recommendations from OFE are inherently "black box" and enigmatic, they must also be practical and applied on farms to retain their value. The conundrum of OFE is that big data requires advanced analysis to assess a multitude of complex on-farm interactions and yet must remain transparent, inclusive of farmer knowledge and easy to apply. However, a vast research gap currently surrounds stakeholder attitudes towards the adoption of precision agroecology due to uncertainty about data availability, usability and security. This uncertainty underlies the main limitation of this study, which is the lack of trust between the technology industry and farmer stakeholders. This barrier to trust will undoubtedly limit the adoption of the very precision technologies that OFE relies on. Due to the fact that PA is at the crux of an intellectual property battle, this study was limited in its ability to showcase a number of suppressed, small-scale efforts to develop open-source decision support tools and likely overlooked a number of current attempts to do so. Future research and development of user-friendly PA technology is paramount to creating a more equitable and sustainable food system.

Moving forward, precision agroecology can address tier 5 of agroecology by creating a just and equitable global food system. To transform the global food system, policy surrounding agriculture needs to be data driven (King et al., 2019). Policy makers should have access to the stream of data from PA to create incentives and regulations that account for the environmental and social relationships surrounding agriculture and food systems. Specifically, precision agroecology lends itself to shifting the focus of agricultural systems to food and environmental quality rather than quantity of food production. Utilizing precision agroecology can provide a unique opportunity to improve agriculture's impact on human health, an aspect of the social relationships surrounding food systems. Rather than externalizing environmental and human health costs like the industrialized agricultural sector, precision agroecology can price in negative externalities by providing data, derived from PA technology, to support policy that properly pays for food quality. Future research and policy should prioritize crop quality over quantity and incentivize producers and markets to manage and price crops for their quality in terms of nutrient content. In addition, reframing agriculture with a focus on environmental quality would incentivize best management practices such as reimbursing producers for optimizing ecosystem services. By prioritizing both food and environmental quality, precision agroecology can restore the values of nature and nutrition over production and profit to rebalance agri-food systems in a sustainable and resilient manner.

Conclusion

Precision agroecology offers solutions to the problems faced by modern industrial agriculture by utilizing the technologies of industrial agriculture to inform agroecological decisions. Agriculture is one of the largest global markets and change is unlikely to occur quickly. Adapting agroecological philosophies in policy and farmer decisions will require concerted and coordinated efforts at all scales for which the tiers of agroecology span. Precision agroecology shifts the paradigm of agricultural systems towards a more sustainable future by harnessing the technologies and data rapidly developed and generated from industrial management practices like PA. Precision agroecology serves as a compromise between the divergent factions of agriculture and bridges the gap between seemingly opposite ideologies through the use of data and analytics. Precision agroecology increases efficiencies of farms, and with further OFE and policy incentives can lead to data-informed substitution of inputs, conservation of uncropped areas to maximize ecological benefits, and reestablishment of direct relationships between producers and consumers. The data gathered from precision agroecological management thus provides a resource for informing policy decisions at all scales to offer transformative agri-food systems solutions that were not possible previously. Therefore, we propose precision agroecology as an effective and necessary trajectory towards future farm sustainability. As agriculture develops in the age of climate awareness and technological advancement, precision agroecology offers an opportunity to transition agriculture towards agroecological principles.

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References

Alba, O. S.; Syrovy, L. D.; Duddu, H. S. N.; Shirtliffe, S. J. Increased Seeding Rate and Multiple Methods of Mechanical Weed Control Reduce Weed Biomass in a Poorly Competitive Organic Crop. Field Crops Res 2020, 245 (October). https://doi.org/doi.org/10.1016/j.fcr.2019.107648.

Altieri, M. A. Agroecology: The Scientific Basis of Alternative Agriculture; West View Press: Boulder, 1995.

Altieri, M. A. The Ecological Role of Biodiversity in Agroecosystems - ScienceDirect. Agric Ecosyst 1999, 74. http://dx.doi.org/10.1016/S0167-8809(99)00028-6.

Altieri, M. A.; Nicholls, C. I. Agroecology and the Reconstruction of a Post-COVID-19 Agriculture. J Peasant Stud 2020, 881–898. https://doi.org/10.1080/03066150.2020.1782891.

Anderson, C. R.; Bruil, J.; Chappell, M. J.; Kiss, C.; Pimbert, M. P. From Transition to Domains of Transformation: Getting to Sustainable and Just Food Systems through Agroecology. Sustainability 2019, 11 (19), 5272. https://doi.org/10.3390/su11195272.

Anderson, C. R.; Maughan, C. "The Innovation Imperative": The Struggle Over Agroecology in the International Food Policy Arena. Front. Sustain. Food Syst. 2021, 5, 33. https://doi.org/10.3389/fsufs.2021.619185.

Baars, T. Experiential Science; Towards an Integration of Implicit and Reflected Practitioner-Expert Knowledge in the Scien-tific Development of Organic Farming. J. Agric. Environ. 2011, 24, 601–628. https://doi.org/10.1007/s10806-010-9281-3.

Barański, M.; Średnicka-Tober, D.; Volakakis, N.; Seal, C.; Sanderson, R.; Stewart, G. B.; Benbrook, C.; Biavati, B.; Markellou, E.; Giotis, C.; Gromadzka-Ostrowska, J.; Rembiałkowska, E.; Skwarło-Sońta, K.; Tahvonen, R.; Janovská, D.; Niggli, U.; Nicot, P.; Leifert, C. Higher Antioxidant and Lower Cadmium Concentrations and Lower Incidence of Pesticide Residues in Organ-ically Grown Crops: A Systematic Literature Review and Meta-Analyses. Br. J. Nutr. 2014, 112 (5), 794–811. https://doi.org/10.1017/S0007114514001366.

Bardgett, R.; Gibson, D. J. Plant Ecological Solutions to Global Food Security. J. Ecol. 2017, 105 (4), 859–864. https://doi.org/10.1111/1365-2745.12812.

Basso, B. Precision Conservation for a Changing Climate. Nat. Food 2021, 2 (5), 322–323. https://doi.org/10.1038/s43016-021-00283-z.

Basso, B.; Antle, J. Digital Agriculture to Design Sustainable Agricultural Systems. Nat. Sustain. 2020, 3 (4), 254–256. https://doi.org/10.1038/s41893-020-0510-0.

Bellwood-Howard, I.; Ripoll, S. Divergent Understandings of Agroecology in the Era of the African Green Revolution. 2020, 49 (2), 103–110. https://doi.org/10.1177/0030727020930353.

Benayas, J.; Bullock, J. Restoration of Biodiversity and Ecosystem Services on Agricultural Land. Ecosystems 2012, 15. https://doi.org/10.1007/s10021-012-9552-0.

Berry, J. K.; Delgado, J. A.; Khosla, R.; Pierce, F. Precision Conservation for Environmental Sustainability.

Berthet, E. T. A.; Barnaud, C.; Girard, N.; Labatut, J.; Martin, G. How to Foster Agroecological Innovations? A Comparison of Participatory Design Methods. J. Environ. Plan. Manag. 2016, 59 (2), 280–301. https://doi.org/10.1080/09640568.2015.1009627.

Biermacher, J. T.; Brorsen, B. W.; Epplin, F. M.; Solie, J. B.; Raun, W. R. The Economic Potential of Precision Nitrogen Applica-tion with Wheat Based on Plant Sensing. Agric. Econ. 2009, 40 (4), 397–407. https://doi.org/10.1111/j.1574-0862.2009.00387.x.

Bronson, K. F.; Booker, J. D.; Bordovsky, J. P.; Keeling, J. W.; Wheeler, T. A.; Boman, R. K.; Parajulee, M. N.; Segarra, E.; Nichols, R. L. Site-Specific Irrigation and Nitrogen Management for Cotton Production in the Southern High Plains. Agron. J. 2006, 98 (1), 212–219. https://doi.org/10.2134/agronj2005.0149.

Brydegaard, M.; Jansson, S. Advances in Entomological Laser Radar. J. Eng. 2019, 2019 (21), 7542–7545. https://doi.org/10.1049/joe.2019.0598.

Bucci, G.; Bentivoglio, D.; Finco, A. Precision Agriculture as a Driver for Sustainable Farming Systems: State of Art in Litera-ture and Research. Qual. - Access Success 2018, 19, 114–121.

Bullock, D. S.; Mieno, T.; Hwang, J. The Value of Conducting On-Farm Field Trials Using Precision Agriculture Technology: A Theory and Simulations. Precis. Agric. 2020, 21 (5), 1027–1044. https://doi.org/10.1007/s11119-019-09706-1.

Capmourteres, V.; Adams, J.; Berg, A.; Fraser, E.; Swanton, C.; Anand, M. Precision Conservation Meets Precision Agriculture: A Case Study from Southern Ontario. Agric. Sysy. 2018, 167 (September), 176–185. https://doi.org/10.1016/j.agsy.2018.09.011.

Carlisle, L.; Montenegro de Wit, M.; DeLonge, M. S.; Iles, A.; Calo, A.; Getz, C.; Ory, J.; Munden-Dixon, K.; Galt, R.; Melone, B.; Knox, R.; Press, D. Transitioning to Sustainable

Agriculture Requires Growing and Sustaining an Ecologically Skilled Work-force. Front. Sustain. Food Syst. 2019, 3, 96. https://doi.org/10.3389/fsufs.2019.00096.

Carolan, M. Publicising Food: Big Data, Precision Agriculture, and Co-Experimental Techniques of Addition. Sociol Ruralis 2017, 57 (2). https://doi.org/10.1111/soru.12120.

Carr, P. M.; Cavigelli, M. A.; Darby, H.; Delate, K.; Eberly, J. O.; Gramig, G. G.; Heckman, J. R.; Mallory, E. B.; Reeve, J. R.; Silva, E. M.; Suchoff, D. H.; Woodley, A. L. Nutrient Cycling in Organic Field Crops in Canada and the United States. Agron J 2019, 111 (6), 2769–2785. https://doi.org/10.2134/agronj2019.04.0275.

Carr, P. M.; Cavigelli, M. A.; Darby, H.; Delate, K.; Eberly, J. O.; Fryer, H. K.; Gramig, G. G.; Heckman, J. R.; Mallory, E. B.; Reeve, J. R.; Silva, E. M.; Suchoff, D. H.; Woodley, A. L. Green and Animal Manure Use in Organic Field Crop Systems. Agron. J. 2020, 112 (2), 648–674. https://doi.org/10.1002/agj2.20082.

Caswell, J. A.; Mojduszka, E. M. Using Informational Labeling to Influence the Market for Quality in Food Products. Am. J. Agric. Econ. 1996, 78 (5), 1248–1253. https://doi.org/10.2307/1243501.

Church, S. P.; Lu, J.; Ranjan, P.; Reimer, A. P.; Prokopy, L. S. The Role of Systems Thinking in Cover Crop Adoption: Implications for Conservation Communication. Land Use Policy 2020, 94 (104508). https://doi.org/10.1016/j.landusepol.2020.104508.

Coble, K. H.; Mishra, A. K.; Ferrell, S.; Griffin, T. Big Data in Agriculture: A Challenge for the Future. Appl. Econ. Perspect. Policy 2018, 40 (1), 79–96. https://doi.org/10.1093/aepp/ppx056.

Connor, D. J. Organic Agriculture and Food Security: A Decade of Unreason Finally Implodes. Field Crops Res. 2018, 225, 128–129. https://doi.org/10.1016/j.fcr.2018.06.008.

Cousins, S. A. O. Plant Species Richness in Midfield Islets and Road Verges – The Effect of Landscape Fragmentation. Biol. Conserv. 2006, 4 (127), 500–509. https://doi.org/10.1016/j.biocon.2005.09.009.

Daum, T. Farm Robots: Ecological Utopia or Dystopia? Trends Ecol. Evol. 2021, 36 (9), 774–777. https://doi.org/10.1016/j.tree.2021.06.002.

DiTommasso, A.; Averill, K. M.; Hoffmann, M. P.; Fuchsberg, J. R.; Losey, J. E. Integrating Insect, Resistance, and Floral Re-source Management in Weed Control Decision-Making | Weed Science | Cambridge Core. Weed Sci 2016, 64 (4), 743–756. https://doi.org/10.1614/ws-d-16-00052.1.

Doub, A. E.; Levin, A.; Heath, C. E.; LeVangie, K. Mobile App-Etite: Consumer Attitudes towards and Use of Mobile Technol-ogy in the Context of Eating Behaviour. J. Direct Data Digit. Mark. Pract. 2015, 17 (2), 114–129. https://doi.org/10.1057/dddmp.2015.44.

Duru, M.; Therond, O.; Martin, G.; Martin-Clouaire, R.; Magne, M.-A.; Justes, E.; Journet, E.-P.; Aubertot, J.-N.; Savary, S.; Ber-gez, J.-E.; Sarthou, J. P. How to Implement Biodiversity-Based Agriculture to Enhance Ecosystem Services: A Review. Agron. Sustain. Dev. 2015, 35 (4), 1259–1281. https://doi.org/10.1007/s13593-015-0306-1.

Egan, J. F.; Mortensen, D. A. Quantifying Vapor Drift of Dicamba Herbicides Applied to Soybean. Env. Toxicol Chem 2012, 31 (5), 1023–1031. https://doi.org/10.1002/etc.1778.

Elliot, E. T.; Cole, V. A Perspective on Agroecosystem Science. Ecology, 70(6), 1597–1602. Ecology 1989, 70 (6), 1597–1602.

Ewing, P. M.; TerAvest, D.; Tu, X.; Snapp, S. S. Accessible, Affordable, Fine-Scale Estimates of Soil Carbon for Sustainable Management in Sub-Saharan Africa. Soil Sci. Soc. Am. J. 2021, 85 (5), 1814–1826. https://doi.org/10.1002/saj2.20263.

Farid, .U.; Bakhsh, A.; Ahmad, N.; Mahmood-Khan, Z. Delineating Site-Specific Management Zones for Precision Agriculture | The Journal of Agricultural Science | Cambridge Core. 2016, 154 (2), 273–286. https://doi.org/10.1017/S0021859615000143.

Feenstra, G.; Allen, P.; Hardesty, S.; Ohmart, J.; Perez, J. Using a Supply Chain Analysis To Assess the Sustainability of Farm-to-Institution Programs. J. Agric. Food Syst. Community Dev. 2011, 1 (4), 69–84. https://doi.org/10.5304/jafscd.2011.014.009.

Fiedler, A. K.; Landis, D. A.; Wratten, S. D. Maximizing Ecosystem Services from Conservation Biological Control: The Role of Habitat Management. Biol. Control 2008, 45, 254–271. https://doi.org/10.1016/j.biocontrol.2007.12.009.

Filipiak, J. The Work of Local Culture: Wendell Berry and Communities as the Source of Farming Knowledge. Agric. Hist. 2011, 85 (2), 174–194. https://doi.org/10.3098/ah.2011.85.2.174.

Flowers, M.; Weisz, R.; Heiniger, R.; Osmond, D.; Crozier, C. In-Season Optimization and Site-Specific Nitrogen Management for Soft Red Winter Wheat. Agron J 2004, 98 (1), 212–219.

Foley, J. A.; Ramankutty, N.; Brauman, K. A.; Cassidy, E. S.; Gerber, J. S.; Johnston, M.; Mueller, N. D.; O'Connell, C.; Ray, D. K.; West, P. C.; Balzer, C.; Bennett, E. M.; Carpenter, S. R.; Hill, J.; Monfreda, C.; Polasky, S.; Rockström, J.; Sheehan, J.; Siebert, S.; Tilman, D.; Zaks, D. P. M. Solutions for a Cultivated Planet. Nature 2011, 478 (7369), 337–342. https://doi.org/10.1038/nature10452.

Food and Agriculture Organization of the United States. The 10 Elements of Agroecology: Guiding the Transition to Sus-tainable Food and Agricultural Systems. 2018, 15.

Francis, C.; Lieblein, G.; Gliessman, S.; Breland, T. A.; Creamer, N.; Harwood, R.; Salomonsson, L.; Helenius, J.; Rickerl, D.; Salvador, R.; Wiedenhoeft, M.; Simmons, S.; Allen, P.; Altieri, M.; Flora, C.; Poincelot, R. Agroecology: The Ecology of Food Systems. J. Sustain. Agric. 2003, 22 (3), 99–118. https://doi.org/10.1300/J064v22n03_10.

Freemark, K.; Boutin, C. Impacts of Agricultural Herbicide Use on Terrestrial Wildlife in Temperate Landscapes: A Review with Special Reference to North America. Agric. Ecosyst. Environ. 1995, 52 (2–3), 67–91. http://dx.doi.org/10.1016/0167-8809(94)00534-L.

Garbach, K.; Milder, J. C.; DeClerck, F. A. J.; Montenegro de Wit, M.; Driscoll, L.; Gemmill-Herren, B. Examining Mul-ti-Functionality for Crop Yield and Ecosystem Services in Five Systems of Agroecological Intensification. Int. J. Agric. Sustain. 2017, 15 (1), 11–28. https://doi.org/10.1080/14735903.2016.1174810.

Garbach, K.; Milder, J. C.; Montenegro, M.; Karp, D. S.; DeClerck, F. A. J. Biodiversity and Ecosystem Services in Agroecosys-tems. In Encyclopedia of Agriculture and Food Systems; Elsevier, 2014; pp 21–40. https://doi.org/10.1016/B978-0-444-52512-3.00013-9.

Gebbers, R.; Adamchuk, V. I. Precision Agriculture and Food Security. Science 2010, 327 (5967), 828–831. https://doi.org/10.1126/science.1183899.

Gliessman, S. Full Article: Transforming Food Systems with Agroecology. 2016, 40 (3), 287–289. https://doi.org/10.1080/21683565.2015.1130765.

Gliessman, S. R.; Engles, E. Agroecology: The Ecology of Sustainable Food Systems; CRC Press, Taylor & Francis Group: Boca Raton, 2015.

Gorelick, N.; Hancher, M.; Dixon, M.; Ilyushchenko, S.; Thau, D.; Moore, R. Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone. Remote Sens Environ 2017, 202, 18–27.

Griffin, T.; Lowenberg-DeBoer, J. Worldwide Adoption and Profitability of Precision Agriculture Implications for Brazil. Rev Polit Agric 2005, 14 (4), 20–37.

Guillard, K. Improved N Management for Corn Using Aerial Images, Adapt-N, Chemical and Biological Tests, and Cover Crops, 2018.

1.
2. Gurr, G. M.; Wratten, S. D.; Luna, J. M. Basic and Applied Ecology Multi-Function Agricultural Biodiversity: Pest Management and Other Benefits. Basic Appl Ecol 2003, 4, 107–116. https://doi.org/10.1078/1439-1791-00122.

Hegedus, P.B., Maxwell, B.D. Rational for field-specific on-farm precision experimentation, Agric. Ecosyst. Environ. 2022, 338. https://doi.org/10.1016/j.agee.2022.108088.

Holland, S. Lending Credence: Motivation, Trust, and Organic Certification. Agric. Food Econ. 2016, 4 (1), 14. https://doi.org/10.1186/s40100-016-0058-5.

Huggins, D. R. Site-Specific N Management for Direct-Seed Cropping Systems; CSANR Research Report; 2010; p Ch. 16.

Ingram, J.; Maye, D. What Are the Implications of Digitalisation for Agricultural Knowledge? Front. Sustain. Food Syst. 2020, 4, 66. https://doi.org/10.3389/fsufs.2020.00066.

International Society for Precision Agriculture. https://www.ispag.org/about/definition.

Isaacs, R.; Tuell, J.; Fiedler, A.; Gardiner, M.; Landis, D. Maximizing Arthropod-Mediated Ecosystem Services in Agricultural Landscapes: The Role of Native Plants. Front. Ecol. Environ. 2009, 7, 196–203. https://doi.org/10.1890/080035.

Jones, C.; Engel, R.; Olson-Rutz, K. Soil Acidification in the Semiarid Regions of North America's Great Plains. Crops Soils Mag. 2019, 52, 28. https://doi.org/. https://doi.org/10.2134/cs2019.52.0211.

Kamilaris, A.; Kartakoullis, A.; Prenafeta-Boldú, F. X. A Review on the Practice of Big Data Analysis in Agriculture. Comput. Electon. Agric. 2017, 143, 23–27. https://doi.org/10.1016/j.compag.2017.09.037.

Khosla, R.; Inman, D.; Westfall, D. G.; Reich, R. M.; Frasier, M.; Mzuku, M.; Koch, B.; Hornung, A. A Synthesis of Mul-ti-Disciplinary Research in Precision Agriculture: Site-Specific Management Zones in the Semi-Arid Western Great Plains of the USA. Precis. Agric. 2008, 9 (1), 85–100. https://doi.org/10.1007/s11119-008-9057-1.

Kling, C.; Mackie, C. Improving Data Collection and Measurement of Complex Farms; The National Academies Press: Washing-ton, DC, 2019.

Koch, B.; Khosla, R.; Frasier, W. M.; Westfall, D. G.; Inman, D. Economic Feasibility of Variable-Rate Nitrogen Application Utilizing Site-Specific Management Zones. Agron J 2004, 96 (6), 1572–1580. https://doi.org/10.2134/agronj2004.1572.

Kremen, C. Managing Ecosystem Services: What Do We Need to Know about Their Ecology? Wiley Online Libr. 2005, 8 (5), 468–479. https://doi.org/10.1111/j.1461-0248.2005.00751.x.

Kyveryga, P. M. On-Farm Research: Experimental Approaches, Analytical Frameworks, Case Studies, and Impact. Agron J 2019, 111 (6), 2633–2635. https://doi.org/10.2134/agronj2019.11.0001.

Lacoste, M. S.; Cook, S.; McNee, M.; Gale, D.; Ingram, J.; Bellon-Maurel, V.; T., R.; Sylvester-Bradley, R.; Kindred, D. I.; Bram-ley, R.; Tremblay, N.; Longchamps, L.; Thompson, L.; Ruiz, J.; Garcia, F. O.; Maxwell, B.; Griffin, T.; Oberthur, T.; Huyghe, C.; Zhang, W.; McNamara, J.; Hall, A. On-Farm Experimentation: Transforming Innovation Pathways. Nat Food 2 (In press).

Laforge, J. M. L.; Dale, B.; Levkoe, C. Z.; Ahmed, F. The Future of Agroecology in Canada: Embracing the Politics of Food Sov-ereignty. J. Rural Stud. 2021, 81, 194–202. https://doi.org/10.1016/j.jrurstud.2020.10.025.

Landis, D. Designing Agricultural Landscapes for Biodiversity-Based Ecosystem Services. Appl Ecol 2017, 18, 1–12. https://doi.org/10.1016/j.baae.2016.07.005.

Lawrence, P. G.; Rew, L. J.; Maxwell, B. D. A Probabilistic Bayesian Framework for Progressively Updating Site-Specific Recommendations. Precision Agric 2015, 16, 275–296. https://doi.org/10.1007/s11119-014-9375-4.

Lawrence, P.; Maxwell, B.; Rew, L.; Ellis, C.; Bekkerman, A. Vulnerability of Dryland Agricultural Regimes to Economic and Climatic Change. Ecol. Soc. 2018, 23 (1). https://doi.org/10.5751/ES-09983-230134.

Levidow, L.; Pimbert, M.; Vanloqueren, G. Agroecological Research: Conforming—or Transforming the Dominant Agro-Food Regime? Agroecol. Sustain. Food Syst. 2014, 38 (10), 1127–1155. https://doi.org/10.1080/21683565.2014.951459.

Levins, R. The Struggle for Ecological Agriculture in Cuba. Capitalism Nature Socialism, 1(5), 121-141. Capital Nat Social 1990, 1 (5), 121–141.

Liebman, M.; Helmers, M. J.; Schulte, L. A.; Chase, C. A. Using Biodiversity to Link Agricultural Productivity with Environ-mental Quality: Results from Three Field Experiments in Iowa. Renew. Agric. Food Syst. 2013, 28 (2), 115–128. https://doi.org/10.1017/S1742170512000300.

Lindblom, J.; Lundström, C.; Ljung, M.; Jonsson, A. Promoting Sustainable Intensification in Precision Agriculture: Review of Decision Support Systems Development and Strategies. Precis. Agric. 2017, 18 (3), 309–331. https://doi.org/10.1007/s11119-016-9491-4.

Link, J.; Batchelor, W. D.; Graeff, S.; Claupein, W. Evaluation of Current and Model-Based Site-Specific Nitrogen Applications on Wheat (Triticum Aestivum L.) Yield and Environmental

Quality. Precision Agric 2008, 9 (5), 251–267. https://doi.org/10.1007/s11119-008-9068-y.

Losey, J. E.; Vaughan, M. The Economic Value of Ecological Services Provided by Insects. BioScience 2006, 56 (4), 311. https://doi.org/10.1641/0006-3568(2006)56[311:TEVOES]2.0.CO;2.

Low, S. A.; Adalja, A.; Beaulieu, E.; Key, N.; Martinez, S.; Melton, A.; Perez, A.; Ralston, K.; Stewart, H.; Suttles, S.; Vogel, S.; Jablonski, B. B. R. Trends in U.S. Local and Regional Food Systems: A Report to Congress http://www.ers.usda.gov/publications/pub-details/?pubid=42807 (accessed 2021 -12 -16).

Low, S. A.; Vogel, S. J. Direct and Intermediated Marketing of Local Foods in the United States. SSRN Electron. J. 2011. https://doi.org/10.2139/ssrn.2114361.

Luschei, E. C.; Wychen, L. R. V.; Maxwell, B. D.; Bussan, A. J.; Buschena, D.; Goodman, D. Implementing and Conducting On-Farm Weed Research with the Use of GPS. Weed Sci. 2001, 49 (4), 536–542. https://doi.org/10.1614/0043-1745(2001)049[0536:IACOFW]2.0.CO;2.

Ma, S. C.; Wang, T. C.; Guan, X. K.; Zhang, X. Effect of Sowing Time and Seeding Rate on Yield Components and Water Use Ef-ficiency of Winter Wheat by Regulating the Growth Redundancy and Physiological Traits of Root and Shoot. Field Crops Res 2018, 221 (March), 166–174. https://doi.org/doi.org/10.1016/j.fcr.2018.02.028.

MacMillan, T.; Benton, T. Engage Farmers in Research. Nature 509, 25–27. https://doi.org/10.1038/509025a.

Marchant, B.; Rudolph, S.; Roques, S.; Kindred, D.; Gillingham, V.; Welham, S.; Coleman, C.; Sylvester-Bradley, R. Establishing the Precision and Robustness of Farmers' Crop Experiments. Field Crops Res. 2019, 230, 31–45. https://doi.org/10.1016/j.fcr.2018.10.006.

Maxwell, B. D.; Luschei, E. C. Justification for Site-Specific Weed Management Based on Ecology and Economics | Weed Sci-ence | Cambridge Core. Weed Sci 2005, 53 (2), 221–227. https://doi.org/10.1614/ws-04-071r2.

McBratney, A.; Whelan, B.; Ancev, T.; Mcbratney, A.; Bouma, J. Future Directions of Precision Agriculturew. 17.

Mccluskey, J. J. A Game Theoretic Approach to Organic Foods: An Analysis of Asymmetric Information and Policy. Agric. Resour. Econ. Rev. 2000, 1–9.

McCown, R. L. Learning to Bridge the Gap between Science-Based Decision Support and the Practice of Farming: Evolution in Paradigms of Model-Based Research and Intervention from Design to Dialogue. Aust. J. Agric. Res. 2001, 52 (5), 549. https://doi.org/10.1071/AR00119.

McFadden, J. R.; Rosburg, A.; Njuki, E. Information Inputs and Technical Efficiency in Midwest Corn Production: Evidence from Farmers' Use of Yield and Soil Maps. Am J Agric Econ 2021, 1–24. https://doi.org/10.1111/ajae.12251.

Meola, A. Smart Farming in 2020: How IoT Sensors Are Creating a More Efficient Precision Agriculture Industry. Precision-Ag, 2020.

Miller, P. R.; Lighthiser, E. J.; Jones, C. A.; Holmes, J. A.; Rick, T. L.; Wraith, J. M. Pea Green Manure Management Affects Or-ganic Winter Wheat Yield and Quality in Semiarid Montana. Can. J. Plant Sci. 2011, 91 (3), 497–508. https://doi.org/10.4141/cjps10109.

Moshia, M.; Khosla, R.; Longchamps, L.; Reich, R.; Davis, J.; Westfall, D. Precision Manure Management across Site-Specific Management Zones: Grain Yield and Economic Analysis. Agron. J. 2014, 106, 2146–2156. https://doi.org/10.2134/agronj13.0400.

National Research Council. Toward Sustainable Agricultural Systems in the 21st Century; The National Academies Press: Washington, DC, 2010. https://doi.org/10.17226/12832.

Nicholson, C. C.; Emery, B. F.; Niles, M. T. Global Relationships between Crop Diversity and Nutritional Stability. Nat. Com-mun. 2021, 12 (1), 5310. https://doi.org/10.1038/s41467-021-25615-2.

Nyéléni. Declaration of the International Forum for Agroecology http://www.foodsovereignty.org/forum-agroecology-Nyéléni-2015 (accessed 2021 -01 -25).

Osterholz, W. R.; Culman, S. W.; Herms, C.; Joaquim de Oliveira, F.; Robinson, A.; Doohan, D. Knowledge Gaps in Organic Re-search: Understanding Interactions of Cover Crops and Tillage for Weed Control and Soil Health. Org. Agric. 2021, 11 (1), 13–25. https://doi.org/10.1007/s13165-020-00313-3.

Pedersen, S. M.; Lind, K. M. Precision Agriculture – From Mapping to Site-Specific Application. In Precision Agriculture: Technology and Economic Perspectives; Pedersen, S. M., Lind, K. M., Eds.; Progress in Precision Agriculture; Springer Interna-tional Publishing: Cham, 2017; pp 1–20. https://doi.org/10.1007/978-3-319-68715-5_1.

Pes, L. Z.; Amado, T. J. C.; Gebert, F. H.; Schwalbert, R. A.; Pott, L. P. Hairy Vetch Role to Mitigate Crop Yield Gap in Different Yield Environments at Field Level. Sci. Agric. 2022, 79 (5), e20200327. https://doi.org/10.1590/1678-992x-2020-0327.

Pimbert, M. Agroecology as an Alternative Vision to Conventional Development and Climate Smart Agriculture. Trans. Oph-thalmol. Soc. U. K. 2017, 58 (2–3), 286–298. https://doi.org/10.1057/s41301-016-0013-5.

Power, A. G. Ecosystem Services and Agriculture: Tradeoffs and Synergies. Philos. Trans. R. Soc. B Biol. Sci. 2010, 365 (1554), 2959–2971. https://doi.org/10.1098/rstb.2010.0143.

Relyea, R. A. The Lethal Impact of Roundup on Aquatic and Terrestrial Amphibians. Ecol. Appl. 2005, 15 (4), 1118–1124.

Robb, B.; Olsoy, P.; Mitchell, J.; Caughlin, T.; Delparte, D.; Galla, S.; Fremgen-Tarantino, M.; Nobler, J.; Rachlow, J.; Shipley, L.; Forbey, J. Near-infrared Spectroscopy Aids Ecological Restoration by Classifying Variation of Taxonomy and Phenology of a Native Shrub. Restor. Ecol. 2021. https://doi.org/10.1111/rec.13584.

Robert, P. Characterization of Soil Conditions at the Field Level for Soil Specific Management. Geoderma 1993, 60 (1), 57–72. https://doi.org/10.1016/0016-7061(93)90018-G.

Rodriguez, J. M.; Molnar, J. J.; Fazio, R. A.; Sydnor, E.; Lowe, M. J. Barriers to Adoption of Sustainable Agriculture Practices: Change Agent Perspectives. Renew. Agric. Food Syst. 2009, 24 (1), 60–71. https://doi.org/10.1017/S1742170508002421.

Rollin, O.; Benelli, G.; Benvenuti, S.; Decourtye, A.; Wratten, S. D.; Canale, A.; Desneux, N. Weed-Insect Pollinator Networks as Bio-Indicators of Ecological Sustainability in Agriculture. A Review. Agron. Sustain. Dev. 2016, 36 (1), 8. https://doi.org/10.1007/s13593-015-0342-x.

Rosset, P. M.; Altieri, M. A. Agroecology versus Input Substitution: A Fundamental Contradiction of Sustainable Agriculture. Soc. Nat. Resour. 1997, 10 (3), 283–295. https://doi.org/10.1080/08941929709381027.

Rosset, P. M.; Altieri, M. A. Agroecology: Science and Politics; Fernwood: Winnipeg, 2017.

Saiz-Rubio, V.; Rovira-Más, F. From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management. Agron-omy 2020, 10 (2), 207. https://doi.org/10.3390/agronomy10020207.

Schimmelpfennig, D.; Lowenberg-DeBoer, J. Farm Types and Precision Agriculture Adoption: Crops, Regions, Soil Variability, and Farm Size; Land, Farm & Agribusiness Management Department; United States Department of Agriculture 304070; Har-per Adams University, Land, Farm & Agribusiness Management Department, 2020.

Seufert, V.; Ramankutty, N. Many Shades of Gray—The Context-Dependent Performance of Organic Agriculture. Sci. 2017, 3 (3). https://doi.org/10.1126/sciadv.1602638.

Shava, S.; Krasny, M. E.; Tidball, K. G.; Zazu, C. Agricultural Knowledge in Urban and Resettled Communities: Applications to Social–Ecological Resilience and Environmental Education. Environ. Educ. Res. 2010, 16 (5–6), 575–589. https://doi.org/10.1080/13504622.2010.505436.

Stave, K.; Kopainsky, B. A System Dynamics Approach for Examining Mechanisms and Pathways of Food Supply Vulnera-bility. J. Environ. Stud. Sci. 2015, 5 (3), 321–336.

Stevens, D. Improving Nitrogen Use Efficiency in Sustainable Corn Production Through Use of Remote Sensors to Direct Site-Specific Nitrogen Application, 2017.

Sun, W.; Whelan, B.; McBratney, A. B.; Minasny, B. An Integrated Framework for Software to Provide Yield Data Cleaning and Estimation of an Opportunity Index for Site-Specific Crop Management - ProQuest. 2013, 14 (4), 376–391. https://doi.org/10.1007/s11119-012-9300-7.

Swinton, S.; Lupi, F.; Robertson, G.; Hamilton, S. Ecosystem Services and Agriculture: Cultivating Agricultural Ecosystems for Diverse Benefits. Ecol Econ 2007, 64 (2), 245–252. https://doi.org/10.1016/j.ecolecon.2007.09.020.

Tal, A. Making Conventional Agriculture Environmentally Friendly: Moving beyond the Glorification of Organic Agriculture and the Demonization of Conventional Agriculture. Sustainability 2018, 10 (4), 1078. https://doi.org/10.3390/su10041078.

Tilman, D.; Cassman, K. G.; Matson, P.; Naylor, R.; Polasky, S. Agricultural Sustainability and Intensive Production Practices. Nature 2002, 418 (August), 671–677. https://doi.org/DOI:10.1038/nature01014.

Tom, K. Speech at U.S. Department of Agriculture's (USDA)., 2020.

Tomich, T. P.; Brodt, S.; Ferris, H.; Galt, R.; Horwath, W. R.; Kebreab, E.; Yang, L. Agroecology: A Review from a Glob-al-Change Perspective. Annu Rev Environ Resour 2011, 36, 193–222. https://doi.org/10.1146/annurev-environ-012110-121302.

Tscharntke, T.; Clough, Y.; Wanger, T. C.; Jackson, L.; Motzke, I.; Perfecto, I.; Vandermeer, J.; Whitbread, A. Global Food Secu-rity, Biodiversity Conservation and the Future of Agricultural Intensification. Biol. Conserv. 2012, 151 (1), 53–59. https://doi.org/10.1016/j.biocon.2012.01.068.

Tscharntke, T.; Klein, A. M.; Kruess, A.; Steffan-Dewenter, I.; Thies, C. Landscape Perspectives on Agricultural Intensification and Biodiversity – Ecosystem Service Management. Ecol. Lett. 2005, 8 (8), 857–874. https://doi.org/10.1111/j.1461-0248.2005.00782.x.

Tully, K. L.; McAskill, C. Promoting Soil Health in Organically Managed Systems: A Review. Org. Agric. 2020, 10 (3), 339–358. https://doi.org/10.1007/s13165-019-00275-1.

Uphoff, N. Agroecological Innovations: Increasing Food Production with Participatory Development; Routledge: New York, NY, 2013.

USDA National Agricultural Statistics Service, 2017. 2017 Census of Agriculture.

Van Es, H.; Woodard, J. Innovation in Agricultural and Food Systems in the Digital Age. In The Global Innovation Index; 2017; Vol. Table 1, pp 97–104.

Vandermeer, J. The Ecology of Agroecosystems; Jones & Bartlett Learning: Sudbury, 2011.

Vandermeer, J.; van Noordwijk, M.; Anderson, J.; Ong, C.; Perfecto, I. Global Change and Multi-Species Agroecosystems: Concepts and Issues. Agric. Ecosyst. Environ. 1998, 67 (1), 1–22. https://doi.org/10.1016/S0167-8809(97)00150-3.

Vitousek, P. M.; Aber, J. D.; Howarth, R. W.; Likens, G. E.; Matson, P. A.; Schindler, D. W.; Schlesinger, W. H.; Tilman, D. G. Technical Report: Human Alteration of the Global Nitrogen Cycle: Sources and Consequences. Ecol. Appl. 1997, 7 (3), 737–750. https://doi.org/10.2307/2269431.

Weersink, A.; Fraser, E.; Pannell, D.; Duncan, E.; Rotz, S. Opportunities and Challenges for Big Data in Agricultural and Envi-ronmental Analysis. Annu. Rev. Resour. Econ. 2018, 10, 19–37. https://doi.org/10.1146/annurev-resource-100516-053654.

Weiner, J. Applying Plant Ecological Knowledge to Increase Agricultural Sustainability. J. Ecol. 2017, 105 (4), 856–870. https://doi.org/10.1111/1365-2745.12792.

Wezel, A.; Bellon, S.; Doré, T.; Francis, C.; Vallod, D.; David, C. Agroecology as a Science, a Movement and a Practice. In Sus-tainable Agriculture Volume 2; Lichtfouse, E., Hamelin, M., Navarrete, M., Debaeke, P., Eds.; Springer Netherlands: Dordrecht, 2011; pp 27–43. https://doi.org/10.1007/978-94-007-0394-0_3.

Wilkins, J. L. Eating Right Here: Moving from Consumer to Food Citizen. Agric. Hum. Values 2005, 22 (3), 269–273. https://doi.org/10.1007/s10460-005-6042-4.

Wolfert, S.; Ge, L.; Cor Verdouw, L. G.; Bogaardt, M. J. Big Data in Smart Farming - A Review. Agric. Syst. 153, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023.

Xu, L.; Yang, X.; Wu, L.; Chen, X.; Chen, L.; Tsai, F.-S. Consumers' Willingness to Pay for Food with Information on Animal Welfare, Lean Meat Essence Detection, and Traceability. Int. J. Environ. Res. Public. Health 2019, 16 (19), E3616. https://doi.org/10.3390/ijerph16193616.

Zuo, Y.; Zhang, F. Effect of Peanut Mixed Cropping with Gramineous Species on Micronutrient Concentrations and Iron Chlo-rosis of Peanut Plants Grown in a Calcareous Soil. Plant Soil 2008, 306, 23–26. https://doi.org/10.1007/s11104-007-9484-1.

CHAPTER THREE

OPTIMIZING ORGANIC COVER CROP SEEDING RATES AND FOLLOWING CASH CROPS TO MAXIMIZE NET RETURN IN A CONTROLLED ENVIRONMENT

Contribution of Authors and Co-authors

Manuscript in Chapter Three

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Contributions: Co-conceptualized the manuscript and provided critical interpretation of the manuscript for important intellectual content. All authors contributed critically to the drafts and gave final approval for publication.

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Abstract

A first step in enabling precision agriculture in organic grain operations is to manipulate nitrogen fixing green manure cover crop seeding rates and vary subsequent cash crop seeding rates to find optimum seeding rates that maximize net returns for farmers. As an initial step, a greenhouse experiment was conducted where rhizobially-inoculated field pea was planted at varied densities (0-140 plants m^{-2}), terminated and allowed to decompose, and then Khorasan wheat (Kamut) was planted at varied densities (100-380 plants m^{-2}) for harvest. Pea plant density of 102 pea plants m^{-2} was found to maximize pea biomass, and 66 pea plants m^{-2} maximized subsequent wheat yield. To maximize net return, given a range of economic scenarios from the last ten years, optimized pea densities ranged from 40 to 56 pea plants m^{-2}, and optimized wheat densities were found to be 100 plants m^{-2}. The rates chosen to maximize net return outcompeted other strategies including zero pea, farmer chosen rates, and literature suggested seeding rates in every economic year tested. These results provide first-principle evidence that variable seeding rates of green manure crops followed by a cereal crop can affect yields and maximize net returns for organic farmers, and thereby should be tested in in field conditions next, to determine local optima.

Keywords: Organic, Seed Rates, Kamut, Green Manure, Cover Crop, Precision Agriculture

Introduction

The primary goals of organic agriculture are twofold: sustain nutritious food production and maintain or improve environmental quality. While the primary drawback of organic production is lower yields (Seufert et al., 2012; Tal, 2018), yield can be increased without environmental damage through agroecological intensification (Garbach et al., 2017; Hunter et al., 2017). Agroecological intensification can harness new methodologies like those provided by precision agriculture to augment farmer land knowledge to achieve their goals (Duff et al., 2021; Hegedus et al., 2023; Hegedus & Maxwell, 2022); precision agriculture is defined by the International Society of Precision Agriculture as a management strategy which seeks to characterize spatial and temporal variability in agroecosystems to increase their sustainability (*International Society of Precision Agriculture*, 2021). In organic agriculture, inputs can be optimized to reduce waste while improving yields, soil health, and farmers' net return (Miller et al., 2008; Stainsby & Entz, 2022). In this way organic agriculture, which uses cover crops and manure as input resources, can achieve resilient yields, quality products, and high net returns while maximizing ecosystem services in an agricultural setting (Eyhorn et al., 2019).

One of the main limiting factors in Northern Great Plains (NGP) agriculture is nitrogen, and many organic farmers use green manure cover crops in rotation with cash crops to replace synthetic nitrogen (Morari et al., 2018; Thiessen Martens et al., 2019). Green manure crops fix atmospheric nitrogen via symbiotic rhizobacteria, provide nitrogen for fertility, increase soil organic matter, reduce erosion, and reduce weed and pest pressures (Altieri et al., 2015; Carr et al., 2020; Melander et al., 2020). Therefore, the management of these crops is crucial to improving crop quality and quantity in organic systems. Increasing the seeding rate of green manures increases biomass as well as nitrogen fixation asymptotically following the ecological law of constant final yield (Lawley & Shirtliffe, 2004; McCauley & Miller, 2011; Usukh, 2010; Weiner & Freckleton, 2010); increasing seeding rate also suppresses weed growth, and likely increases water consumption (Gan et al., 2007; Tully & McAskill, 2020). Agronomists have used plot-based research to prescribe a broad range of applicable seeding rates for green manures across the NGP, though optimum rates may perform better when developed through site-specific experimentation (Baird et al., 2009; Johnston et al., 2002; Spies, 2008). Though green manures have many benefits, little is known about how to site-specifically manage them for optimal use in organic rotations (Cherr et al., 2006). Factors including temperature and moisture influence the quantity of nitrogen fixed in the soil as well as the quantity and timing of nitrogen released by decaying plant material to the following cash crop (Miller et al., 2011; Mooleki et al., 2016). Increasing densities of crops improves their yield up to a threshold; in weedy areas increasing crop densities improves their ability to compete with weeds, again up to a threshold (Maxwell & O'Donovan, 2007). While most crop seeding rates have been developed by researchers for conventional crops under conventional conditions for maximizing yield production (Bastos et al., 2020), the seeding rates required to maximize nitrogen fixation in green manure cover crops under organic conditions have been largely overlooked and understudied.

This study sought to verify the relationship between a green manure plant density and the net return on the following season's cash crop. By determining this relationship, farmers can similarly have a starting point for determining ideal rates of both cover and cash crops for their individual operations using site-specific field experimentation to obtain the seeding rates that perform best in any particular field. Relationships between green manure and cover crop seeding rates were explored in a preliminary greenhouse study using the NGP organic grain crops field pea (*Pisum sativum*) and Khorasan wheat, (*Triticum turgidum* ssp. *turanicum*), trademarked 'Kamut' for organic production (Quinn, 1999). We predicted that an optimum pea seed rate and Kamut seed rate could be found to maximize Kamut production or net return. We specifically hypothesized that increased pea seeding rates would lead to increased pea biomass, increased plant available nitrogen after pea decomposition, increased Kamut yield, and increased Kamut net return up to an optimum seeding rate. Similarly, for Kamut we hypothesized that increased Kamut seeding rates would lead to increased yield and net returns up to a specific seeding rate. In actual field conditions both seeding rate optima are expected to have significant variation over time and sites, relating to not just changing soil conditions and weed flora, but also varied climate conditions (Pollnac et al., 2008). Accordingly, the results sought here are merely a beginning in finding site specific optimum seed rates on farmers' fields. Since this was only a greenhouse study, we cannot quantify the spatial and temporal biological variability with confidence, but we can suggest the economic variability based on recent historic costs and prices received to demonstrate probability-based outcomes. Here we demonstrate the method to identify optimized seeding rates of successive crops; the optimum seeding rates were those with the highest probability of maximizing economic net return of the Kamut when following the pea green manure crop. Considering variability in recent historic prices received for organic Kamut as well as cost of Kamut and pea seed allowed for quantifying the probability of maximized net return over the range of seeding rates.

Materials and Methods

Greenhouse

The goal of the preliminary greenhouse experiment was to determine starting points of optimum green manure and cash crop seeding rates to explore various seed optimization strategies with a focus on maximizing farmer net return. The plants were grown in the Plant Growth Center at Montana State University in Bozeman, MT. Wood boxes measuring 50 by 50 cm and 25 cm deep were lined with plastic and filled with sterilized soil mixed with 50% sand to emulate the sandy, low nitrogen conditions typical of agricultural settings in north central Montana – a hotspot of organic production in the Northern Great Plains (NGP) (Padbury et al., 2002). The green manure tested was *Arvika* green pea, a common NGP spring-planted variety, and the cash crop tested was Kamut, an organic wheat grown in the NGP (Stallknecht et al., 1996).

In order to find seeding rates that would be applicable to rainfed systems in the NGP, seeding rates encompassed a range well below and above typical farmer chosen rates and included pea rates at 0, 28, 52, and 136 seeds m^{-2} (0, 42, 78, 204 kg ha^{-1}) and Kamut rates at 100, 200, 300, and 400 seeds m^{-2} (80, 160, 240, 320 kg ha^{-1}). We conducted the following analyses using plant densities in the replicate boxes rather than seeding rates, as seeding rates in the field will vary according to the crop's thousand kernel weight and germination rate. By reporting in densities, those wishing to replicate our findings can find the appropriate rates based on their own seed masses and germination rates. The seeds we used had germination levels of 95% and 92% respectively for pea and Kamut, and thousand kernel weights of 148.4g and 72.5g for pea and Kamut respectively; results reported below are in viable seeds m^{-2}. Farmers in north central Montana attempt Kamut densities of 170 plants m^{-2}, and in Saskatchewan, which also belongs to the NGP and has similar conditions to north central Montana, 210 to 250 plants m^{-2} are recommended (Government of Saskatchewan, 2011).

Pea plants were grown for approximately eight weeks at optimal light and temperature growth conditions (Figure 3.1). The pea plants were terminated at first flowering stage, when roughly half the plants were flowering, which is the recommended termination stage to maximize nitrogen production and minimize water loss in arid conditions (McCauley et al., 2012). Pea plants were mixed into the soil and allowed to decompose over six weeks; the soil was kept moist and occasionally stirred. Kamut seed was then planted into the boxes, at the rates mentioned above, across each pea rate to create a full factorial design (4x4). Kamut was grown until maturity, which took approximately twelve weeks, then harvested. Soil samples were collected four times over the course of the experiment in order to track nitrate gain and loss in the soil. Samples of approximately 200g were taken from every box at pea planting, pea termination, Kamut planting, and following Kamut harvest. Soil samples were dried at 40 ^{o}C for 24 h, then sent away for analysis. The soil samples were analyzed by a commercial lab (Agvise Laboratories, Northwood, ND) to assess for nitrate concentration using a standard colorimetric KCl extraction, cadmium reduction method (Gelderman & Beegle, 2015). To non-destructively ascertain biomass of pea plants, peas of each non-zero density were grown in three separate boxes and assessed for both biomass and plant volume; these data were then used to establish a regression relationship between biomass and volume. The total estimated cylindrical volume of plants per box was estimated from height and width measurements of each individual plant following protocol set out in Bussler *et al* (1995).

Figure 3.1. Pea plants grown at varied densities (0 not shown) from 7, to 13, to 34 plants per box. Kamut was factorially varied across the same boxes to assess pea and Kamut seeding rate impact on Kamut yield after pea termination and decomposition.

Economics

Economic data, all reported in USD, were collected from various sources to demonstrate an economic model of net return based on seeding rates over a ten-year period from 2013-2022 (Table 3.1 and Figure 3.1). Although organic farm costs are typically more variable than conventional farm costs, the organic costs of wheat production were similar enough to Kamut to use for economic analyses (*USDA ERS - Commodity Costs and Returns*, 2022). Certain costs, classified by the USDA as operating costs, and here referred to as fixed costs, were removed from the fixed cost estimate as none of the farmers providing economic data paid for these; these removed costs included rent, irrigation, chemicals (herbicides and pesticides), and fertilizers (commercial fertilizer or manure); remaining fixed costs included: custom services, fuel, lube, electricity, repairs, straw bailing, interest on operating inputs, labor, capital recovery of machinery and equipment, taxes and insurance, and general overhead. While we attempted to emulate net returns broadly characteristic of NGP organic farming, the primary goal was to compare net returns of various seeding strategies based on greenhouse experimental results. The historic price received for Kamut was established based on personal communication with Bob Quinn (2022), the original producer and distributer of Kamut as an organic crop in the NGP. Since many organic farmers save their own seeds, Kamut seed price was estimated to be the same as Kamut price received that year plus a \$0.055 kg^{-1} charge for seed cleaning. Pea seed costs were based on USDA data, and since pea green manures are planted the year prior to the harvested cash crop, pea costs were based on the year prior to the year Kamut would be harvested and sold (*USDA ERS - Commodity Costs and Returns*, 2022).

Yield was estimated at various pea and Kamut rates based on the results of the greenhouse experiment summarized in equation 1:

$$KY = Bk_1 * K + Bp_1 * P + Bp_2 * P^2. \quad (1)$$

Where KY is Kamut grain yield (kg ha^{-1}), K is Kamut density (plants m^{-2}), P is pea density (plants m^{-2}) and Bk_i and Bp_i are fit regression parameters (Table 3.2). We then used this yield to estimate net return by subtracting seed and fixed costs (Table 3.1) from the gross income for the Kamut crop (equation 2):

$$NR_{yr} = KY * PRK_{yr} - \left(K * KC_{yr} + P * PC_{yr-1} + FC_{yr}\right). \quad (2)$$

Where NR_{yr} is the calculated net return for the given year of economic variables, PRK_{yr} is price received for Kamut (USD kg^{-1}) in the selected year, KC_{yr} is Kamut seed cost (USD kg^{-1}) in the current selected year, PC_{yr} is the cost of pea seed (USD kg^{-1}), and FC_{yr} are the year's fixed costs. The weight of pea seed is based on the number of seeds required to produce each plant density and thus relates to seeding rate. In order to display net return over time (Figure 3.2), a typical yield of 1200 kg ha^{-1} was used to estimate gross income, (Government of Saskatchewan, 2012), and typical seed rates of 75 kg ha^{-1} of pea, and 100 kg ha^{-1} of Kamut were used to estimate costs. Using the economic data found in Table 3.1 we established optimum plant densities of both pea and Kamut for every year from 2013 to 2022; these optima were compared to other seeding rate strategies including planting no pea, using farmer selected rates, and using recommended rates found in the literature. The use of recent historical data was used to examine our results considering recent economic variability, allowing us to calculate the percent of time one method outcompeted another over the ten years examined.

Table 3.1. Economic values used in modeling including seed prices of pea and Kamut, other fixed costs, and price received over ten years.

Year	Pea seed cost ($ kg^{-1})	Kamut seed cost ($ kg^{-1})	Fixed costs ($ ha^{-1})	Price received ($ kg^{-1})
2013	0.71	0.79	397.17	0.74
2014	0.71	0.86	405.71	0.81
2015	0.72	0.90	399.53	0.85
2016	0.68	0.72	388.18	0.66
2017	0.59	1.14	423.65	1.08
2018	0.65	0.94	431.02	0.88
2019	0.64	0.75	446.06	0.70
2020	0.63	0.79	441.46	0.73
2021	0.63	0.80	459.68	0.75
2022	0.63	0.82	527.00	0.77

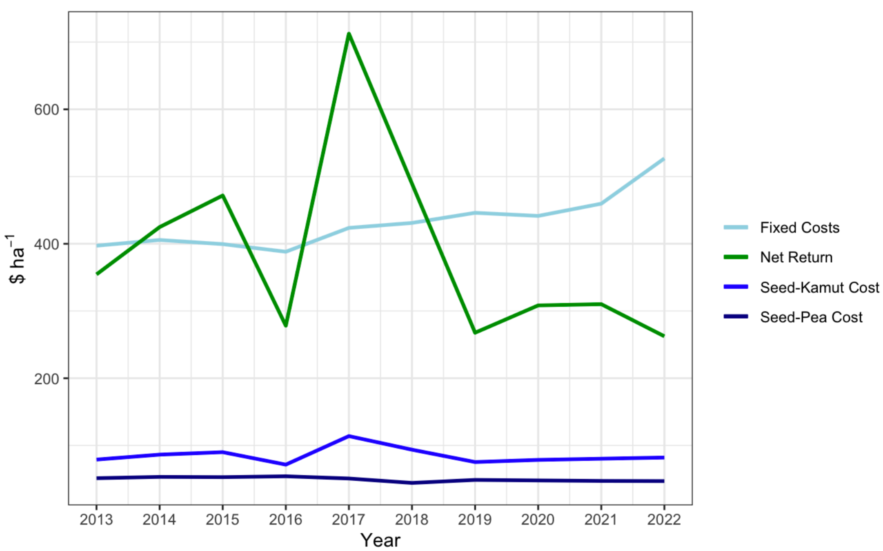


Figure 3.2. Organic economics from 2013 – 2022 showing fixed costs, net return, and costs of Kamut and pea seed. Net return was simulated based on a typical yield of 1200 kg ha^{-1} (*USDA ERS - Commodity Costs and Returns*, 2023).

Statistics and simulations

Data were analyzed with regression analysis in R (R Core Team, 2022). To identify highly influential points in the regression, Cook's distance was calculated; no values in any of the models tested had a Cook's distance greater than 0.5, and no further action was taken to remove outlying points. The first three nitrate sample groups, having met the assumptions of homogeneity of variance, were compared with an ANOVA; since data were not normally distributed a pairwise Wilcoxon test was used to determine which pairs of groups were statistically different (Figure 3.3). Soil samples were taken pre-plant, following pea incorporation, at Kamut planting, and finally at Kamut harvest. Post Kamut harvest soil nitrate levels were omitted from analysis since levels fell to nearly zero with very little variance and did not lend themselves to comparison with the other sample points (mean = 1.6 kg ha^{-1}, sd = 0.9). Generalized linear models (GLM) were applied to select parameters for inclusion in the models using AIC-selection criteria. Models with the lowest AIC value, based on standardized input variables, were chosen from a range of models, from simplest models of intercept only, to models with a quadratic response and an interaction term. Input variables were standardized to avoid estimation biases. GLMs were used to determine the existence of a relationship between pea plant density and the amount of nitrogen fixed (model 1), between pea plant density and pea biomass produced (model 2), and between both pea and Kamut plant densities and Kamut yield (model 3, Table 3.2). Assumptions of normality and homogeneity of variance were determined using Shapiro-Wilk's test and Bartlett's test respectively. Relationships between dependent and independent values were found to be non-linear, and a quadratic relationship was assessed for each. The yield of Kamut as a response to pea seed rate and Kamut seed rate was the final linear regression model we analyzed (model 3).

Four simulated management scenarios were compared to demonstrate how the models could be used to identify maximized net return for a farmer in a similar method to Hegedus et al. (2023). The net return response to pea and following year Kamut seeding rates regression models

(Eqn. 1 & Eqn. 2) were used to simulate net return outcomes given all possible pea and following year Kamut seeding rates across a range of possible economic variables experienced in previous years. Management scenarios were compared including planting no pea, using farmer reported seeding rates for pea and Kamut, or using literature-recommended seeding rates for each crop (Cherr et al., 2006; Mooleki et al., 2015); these seeding rates were input into the above model to compare economic returns. We then determined the probability using Monte Carlo sampling of distributions that one seeding rate combination approach would outperform (produce a higher net return) than each of the others from the distributions of model outcomes over the last ten years for each management approach, as seen elsewhere (Hegedus et al., 2022; Hegedus & Maxwell, 2022). We did not simply use the previous year's economic data, because we were demonstrating a more conservative approach for comparing seeding rate strategies by maximizing variation using recent economic variables. The four management scenarios were compared under the economic conditions of each of the 10 years of interest (Table 3.3). The optimized densities, yield, and net return listed in Table 3.3 show the results from the most recent year of analysis, 2022.

Results

Soil nitrogen and plant biomass

Linear and multiple linear regression models were used to assess the relationships of pea biomass, soil nitrogen, Kamut yield and Kamut net return to plant density of pea and Kamut (Table 3.2). The primary objective was to determine whether varied pea densities affected the following crop's yield success. The hypothesis was that crop yield would increase due to the increased nitrogen that more pea plants provided, and that yield would only be limited by intra-plant competition that occurred at higher densities. Therefore, soil samples were taken at multiple stages of the experiment to determine the possible process by which soil nitrogen availability may have acted as a mechanism of pea seeding rate's effect on final Kamut yield. When the peas were terminated at first flower stage, the presence of root nodules indicated that nitrogen was being fixed. When peas were planted the soil had a mean soil nitrate of 9.23 kg ha^{-1} (Figure 3.3). When the peas were terminated eight weeks later, soil nitrate levels had declined slightly to a mean of 7.30 kg ha^{-1}, indicating that soil nitrogen was possibly taken up by the pea plants. Crucially, after the pea biomass was allowed to decompose for six weeks, a significant amount of nitrogen was found to have been added to the soil, with the nitrate level having risen to 27.91 kg ha^{-1} following green manure decomposition (p-value = 0.004). Finally, at Kamut harvest, soil nitrogen levels fell to 1.57 kg ha^{-1} as the cereal crop consumed nearly all the plant available nitrogen in the soil and converted it into plant biomass and harvestable Kamut seed. These results suggested that green manure plants were feeding the soil system with plant available nitrogen that benefitted cash crop production.

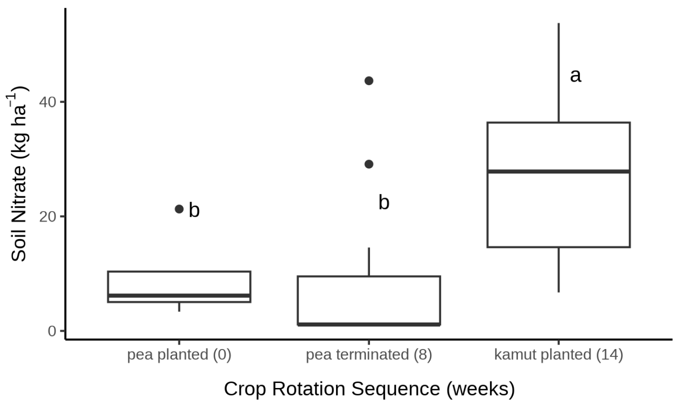


Figure 3.3. Soil nitrogen levels at each experimental point. Soil samples were taken when the peas were planted (0 weeks), when the peas were terminated (8 weeks), and when the Kamut was planted (14 weeks). Box and whiskers with different letters represent significantly different means (Wilcoxon rank sums test, $\alpha < 0.05$).

Though plant biomass is often correlated with plant nitrogen content (Biederbeck et al., 1996; Unkovich et al., 2008), we did not find evidence of a relationship between pea plant density and soil nitrate (p = 0.326 (Figure 3.4). Soil nitrate change (from pea seeding to Kamut seeding) was tracked in each individual box to assess the effect of pea seeding rate on soil plant available nitrogen. We failed to reject the null hypothesis of no nitrogen rate response (p-value = 0.326), thus, our hypothesis that nitrogen rates would rise then fall, following an increase in plant densities did not hold (Table 3.2, model 1). High variation in the zero rates may have prevented realization of this potential relationship (Figure 3.4). The visual appearance of a slight negative relationship reveals intra-plant competition at the highest rate, as these rates are well above recommended. Furthermore, to assess the effects of pea plant density we also measured pea biomass at termination of the pea plants within each replicate box. We found strong evidence to reject our null hypothesis that seeding rate had no effect on pea biomass (p-value = 0.001) (Table 3.2, model 2). As pea plant density increased, pea biomass increased up to an asymptote;

interpolating from this relationship, the maximum pea biomass was reached at a density of 102 plants m^{-2} (Figure 3.5).

Table 3.2. Results of four regression analyses for biomass nitrate yield and net return in response to seeding densities.

Model Variables	***t***	***p***	***β***	***F***	***df***	***p***	**R^2**	**Adj. R^2**
Model 1: Change in nitrate ~ pea density + pea density^2								
Overall				1.23	2, 13	0.32	0.16	0.03
Intercept	2.48	0.03	17.04					
Pea density	1.35	0.20	0.40					
Pea density^2	-1.5	0.16	-0.003					
Model 2: Pea biomass ~ pea density + pea density^2								
Overall				15.07	2, 12	< 0.01	0.72	0.67
Intercept	-1.35	< 0.01	-41.75					
Pea density	3.04	0.01	3.2					
Pea density^2	-2.48	0.03	-0.01					
Model 3: Kamut yield ~ pea density + pea density^2 + Kamut density								
Overall				3.41	3, 12	0.05	0.46	0.33
Intercept	11.87	< 0.01	803.78					
Pea density	1.74	0.11	3.31					
Pea density^2	-1.89	0.08	-0.02					
Kamut density	2.23	0.05	0.52					
Model 4: Kamut net return ~ pea density + pea density^2 + Kamut density								
Overall				10.27	3, 12	< 0.01	0.72	0.67
Intercept	-3.7	< 0.01	-87.12					
Pea density	0.57	0.58	0.38					
Pea density^2	-1.89	0.08	-0.01					
Kamut density	-1.45	0.17	-0.12					

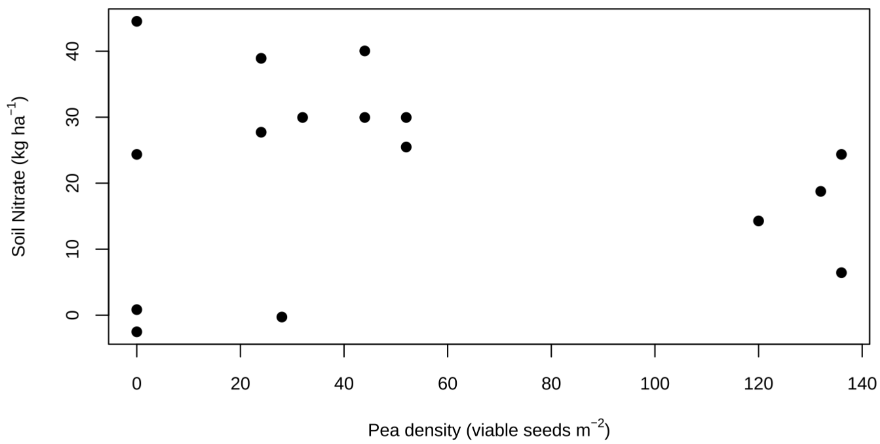


Figure 3.4. Change in soil nitrate, between pea planting and Kamut planting, as a function of pea population density where each point represents the results of one replicate box. No relationship was detected (p-value = 0.326).

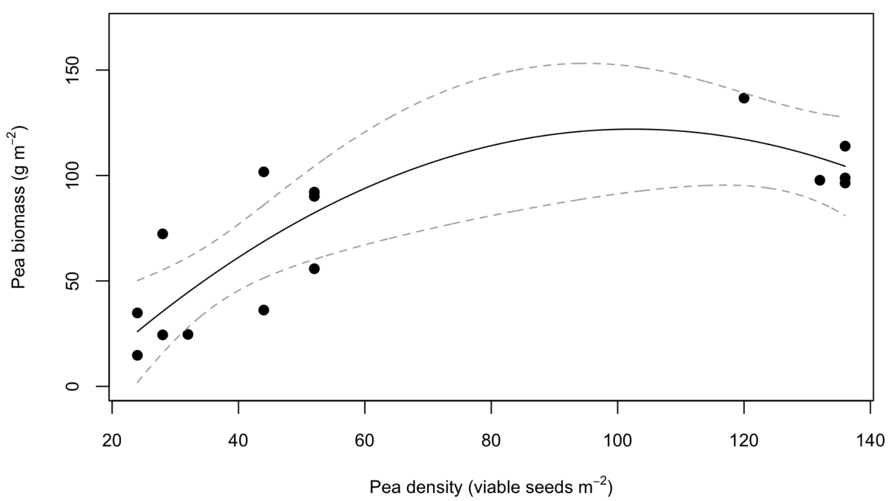
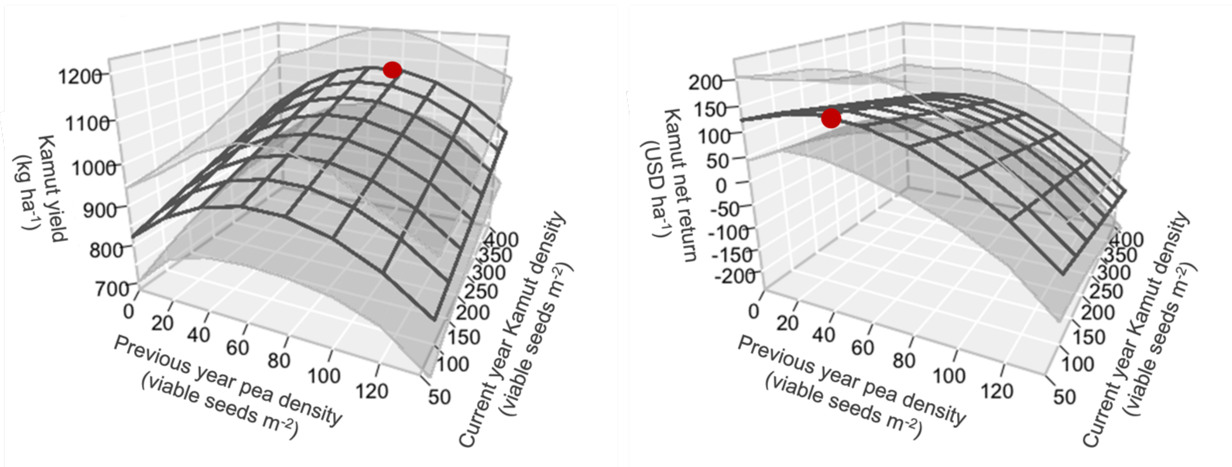


Figure 3.5. Pea biomass in grams per square meter as a function of pea plant density per square meter, where each point represents the results of one greenhouse box of varying plant density. Curved non-dashed line shows the curved relationship as found in Table 3.2; the upper and lower lines represent the 95% confidence interval.

<u>Yield and net return</u>

In the next stage of the experiment, we explored how final Kamut yield would be affected by both pea and Kamut plant densities according to multiple linear regression (Table 3.2, model 3). Yield had a quadratic relationship with pea density, reaching a maximum yield at a pea density of 66 plants m^{-2} (p-value = 0.070) (Figure 3.6a). Yield had a positive relationship with Kamut density, and since there was not strong evidence of a quadratic relationship, the optimized Kamut seeding rate for maximum yield was the maximum tested plant density of Kamut: 380 plants m^{-2} (p-value = 0.101) (Figure 3.6a). This yield model was then used to predict optimum rates for net return given a range of recent economic conditions (Equation 2). The pea plant density to net return relationship (model 4) is very similar to that found for yield (model 3), however the optimum pea density for maximized net return is always below the density for maximum yield predicted by the yield curve no matter which year is used for the economic conditions (Figure 3.6b). Since net return predictions vary year to year based on the economic conditions, the net return figure and model shown above are set to the most recent economic year, 2022. Given the cost of Kamut seed, the linear relationship of Kamut to net return is a negative relationship (p-value = 0.100). From the net return equation, we predicted the lowest tested Kamut plant density (100 plants m^{-2}) needed to maximize net return (Figure 3.6b).



(a) **(b)**

Figure 3.6. 3D plot of a) Kamut yield as a function of pea and Kamut density (F = (3, 11) 3.266, p-value = 0.0630); b) Kamut net return as a function of pea and Kamut density (F = (3, 11) 5.822, p-value = 0.0123). Grey planes represent 95% confidence intervals, red points represent maximum yield and net return respectively.

Using these models, we compared four different seeding rate management strategies for the probability that they would produce higher net returns than the other strategies, given ten years of economic variability (Table 3.3). The optimized density of pea for maximized net return in the most recent year (2022) was found to be 47 plants m^{-2}, but ranged from as low as 40 plants m^{-2} in the relatively poor economic conditions of year 2016, and as high as 56 plants m^{-2} in some of the stronger economic years: 2017 and 2018. Since the Kamut plant density to yield (and net return) relationship is linear, every year has the same predicted economic optimum density of 100 plants m^{-2}. By definition the maximum net return strategy had a higher net return than the other strategies in all ten years tested (Table 3.3). Notably, the zero rate of peas is not predicted to be the worst strategy under all economic conditions. The strategy outcompetes the literature recommended rates 40% of the time, and the farmer chosen rates 10% of the time; the farmer selected rates outperformed the literature selected rates 100% of the time. These trends may be replicable for spatially variable field locations where each specific field space will be optimizable for both green manure and cash crop plant densities. This was an important step in validating the proof of concept for future field trials with varied pea and cereal crop seeding rates.

Table 3.3. Comparison of four seeding rate management strategies for pea (PSR) followed by Kamut wheat (KSR) including the probability that the seeding rate strategy will produce a higher Kamut grain yield or associated net return than the other strategies given 10 years of historic economics generating a range of net returns.

Seeding Rate Strategy	[a]PSR (plants m^{-2})	[a]KSR (plants m^{-2})	[a]Yield (kg ha^{-1})	[a]Net Return (\$ ha^{-1})	[b]% Better than no pea	[b] % Better than farmer selected	[b] % Better than literature recommended
Max net Return	47	100	1010	107.81	100	100	100
Max net return no pea	0	100	856	67.57	-	10	40
Farmer selected rates	71	170	1126	84.12	90	-	100
Literature recommended rates	65	230	1137	72.55	60	0	-

[a]Calculated using economic variables from 2022.
[b]Calculated using all ten years of economic variables (2013-2022).

Discussion

Our results confirmed that increasing green manure density improves the following cash crop up to a threshold, and quantified the realized benefits in subsequent cash crops' net return. We presented evidence that nitrogen was fixed by pea plants, made available to the following Kamut crop, and taken up by the harvested cereal crop (Figure 3.3). We did not find the expected quadratic humped relationship between pea seeding rate and nitrate available in the soil as a response (Figure 3.4). However, we found that the Kamut crop responded positively to increasing densities of pea and that the optimum pea density for maximized Kamut yield was 66 pea plants m^{-2} and was 47 pea plants m^{-2} for maximized net return (under 2022 economic conditions) (Figure 3.6). It should be noted that under field conditions, pea cover crops do not just add nitrogen to the soil, they have other attributes such as reducing soil organic matter loss that can contribute to increasing cash crop yields (Carr et al., 2020).

These findings are consistent with McCauley et al. (2012) results from field experiments where the optimum seeding rate for maximum nitrogen fixation in pea terminated at bloom stage was 65 plants m^{-2} (92 kg/ha). This was partially a confirmation and partially surprising as we might expect higher plant densities to be healthier in the well-watered greenhouse experiment than a Montana field experiment. Stress factors, aside from water, triggered by the increased plant density may have been reducing overall plant vigor in the greenhouse, including limiting the plant's ability to fix nitrogen due to relative shallowness of the boxes. The highest Kamut densities did not limit its production. Optimum Kamut densities for yield reported by the experiment (Figure 3.6a) were the maximum tested at 380 plants m^{-2}, about double what the typical farmer would plant in north central Montana. This suggests that in the ideal greenhouse conditions we used, we could support much higher Kamut plant densities, and yet for the pea plants, optimum rates were like those tested in water limited field conditions.

Other researchers have found varied results of the correlation between biomass and nitrogen fixed by green manures. Field experiments have shown that under water stressed conditions, pea plants cease uptake of nitrogen from the soil or bacterial symbionts (Izard, 2007). Greater biomass does not necessarily mean more nitrogen fixation. Under dry field conditions, plants grown longer continued to build biomass but did not add nitrogen (McCauley et al., 2012). In that study more biomass accumulated during the reproductive stage (i.e., flower to pod) though under water stress no more nitrogen was accumulated. As noted earlier the peas we grew in the greenhouse at high densities may have been stressed in ways other than water stress (i.e., light or nutrient competition) that prevented them from fixing more nitrogen even while increasing in biomass. It is also possible that the plants did indeed fix more nitrogen but that it was outweighed by additional carbon fixation and the carbon to nitrogen ratio thus increased to a rate where the following Kamut crop was unable to access the nitrogen bound up in the decomposing pea matter. Other researchers have found the carbon to nitrogen ratio to be crucial to nitrogen release in greenhouse experiments (Watthier et al., 2020) field experiments (Miller et al., 2011; Poffenbarger et al., 2015; Ranells & Wagger, 1996), and in controlled laboratory settings (Seneviratne, 2000).

Our results indicate that even as the overall biomass of the pea plants per box increased with increased pea density, we did not see a corresponding increase in nitrogen available in the soil (at Kamut planting) (Figure 3.3 and 3.4). While we did not test the nitrogen in the plant tissue, it is possible more nitrogen was fixed in the higher pea densities, but the nitrogen was tied up in plant matter and therefore not present as nitrate in the soil after the decomposition period. Another greenhouse study found that decomposing green manure material provided mineralized nitrogen early in the subsequent crop, but fell off towards the end of the cash crop's growth, highlighting a limitation of receiving nitrogen from cover crops alone (Gatsios et al., 2021). Because the nitrogen in this case was released relatively quickly, about a month after incorporation, it reveals that nitrogen availability from green manures is not necessarily synchronized with cash crop growth. Other researchers, working on field sites, have found the timing of this release can be important for the following crop, and that the release can occur before or after peak nitrogen demand in the cash crop (Miller et al., 2011; Griffin & Hesterman, 1991; Shrestha et al., 1999). As has been noted in other field and greenhouse experiments, the timing of nitrogen release can be affected by temperature, moisture, soil microbiome, and the carbon nitrogen ratio of the decomposing plant material (Cherr et al., 2006). While our experimental setting was relatively warm and moist, it is quite possible the soil microbiome was less than that seen in field settings, given that we began the experiment with sterilized soil, and that the carbon to nitrogen ratio was relatively high in the boxes with greater pea biomass. There is evidence from field studies that plants grown in high competition areas will prioritize carbon intensive structures such as stem elongation over other areas of growth thus contributing to higher carbon to nitrogen ratios (Cobo et al., 2002). A higher carbon to nitrogen ratio could slow the decomposition of plant matter in the soil thus tying up the nitrogen in the plant material preventing its detection in soil tests and preventing the Kamut plant from taking advantage of the nitrogen fixed by the pea plants. This would explain why Kamut yield and net return had significant relationships with pea density while the tested nitrate soil levels did not.

The economic comparison of four management strategies based on the greenhouse experimental results were enlightening in several unexpected ways. While the maximized net return strategy was likely to produce the highest net return under every economic condition, the next closest were the farmer chosen rates, showing these rates are more closely aligned with maximizing net returns than the other strategies (Table 3.3). The no pea rate was the third most likely strategy to produce the highest net return, suggesting that in years with poor economic conditions the cost of pea seed can be prohibitive to generating strong net returns. While our findings suggest this as a viable option, it is unlikely a farmer would choose it since nitrogen must be added to the soil over the long term, and our experiment only considers a single two year rotation (Watson et al., 2006). We also did not assess other long term positive impacts that cover cropping can have including soil erosion minimization, weed suppression, and soil organic matter accumulation (Melander et al., 2020; Murrell et al., 2017; P. Smith, 2018; Weiner, 2017). Very interestingly, the literature-recommended rates were shown in our simulations to generate the highest yields, but only 60% of the time outcompeted the no pea option for net return, and never outperformed the other two options for net return. If only maximum yields are sought this study indicated farmer net return was reduced.

These results demonstrate how models, preferably parameterized with field experiments, could inform future farmer decision-making based on probabilistic net returns over a range of economic conditions. If a farmer had an inclination toward the type of economic conditions they were likely to face in the following year, they could use these assessments to plan their ideal plant densities of green manure and cash crop. For instance, in a year where net return for a harvested crop is predicted to be low, farmers could reduce seeding rates to save input costs. Indeed, they may even want to forgo planting peas if the cost of peas becomes prohibitive. While foregoing peas may be a logical choice in the short term, most organic farmers would not find this an adequate solution where they often have a challenge in acquiring nitrogen in their soil (Carr et al., 2020). However, if it is a rare event, it may prove to contribute to sustainability. In the water-limited areas of the NGP, this strategy could be considered and the tradeoffs associated with applying the appropriate cropping intensity should be carefully examined (Miller et al., 2018; Nielsen et al., 2005). Aside from reducing pea densities under poor economic conditions, the recommendation from our model under recent economic conditions is 47 pea plants m^{-2}; this is also well below other recommendations (McCauley et al., 2012). Literature rates are often more closely aligned with specific goals of maximizing nitrogen, yield production, or biomass. In this unique analysis we provide optima for the farmer targeting maximum net returns, and uncertainty is captured by delivering the comparative result as probabilities of higher net returns. This explicit presentation of the uncertainty of results marks a significant advancement in delivering decision support to farmers.

It is worth noting that this assessment is not an all-encompassing view of the challenges facing organic farmers. Notably absent from this experiment are weeds or water limitations. Given that our recommendation called for reduced densities, the goal of short-term net return and water savings could act synergistically. The opposite would be true for an organic farmer concerned with using crop plant density as a tool against weeds. If we took weed competition into account, crop seeding rates would likely be higher than what we recommended (Lawley & Shirtliffe, 2004; Maxwell & O'Donovan, 2007). Thus, while the analysis presented here represents a good starting point for field experiments, it offers no final prescription. Instead, the main function was to highlight the power of assessing net returns as the goal for farmers and how these scenarios may differ from other management desires given the uncertainty in economic parameters. Several limitations in this study prevented further clarity on the results. Costs prevented testing of nitrogen in pea and Kamut plant tissues, where this could have provided more clarity on the relationship of pea plant density and nitrogen added to the system. Also, the number of observations were limited by the amount of labor it took to conduct the experiment, preventing more replications.

Aside from the McCauley et al. (2012) results which ours closely match, other researchers have found optimum seeding rates for pea green manures ranging from 65 to 120 plants m^{-2} (Baird et al., 2009; Johnston et al., 2002; Lawley & Shirtliffe, 2004; Spies, 2008). These differences highlight the variability present in different experiments and highlight the likely variabilities in years and over fields which we hope to be able to match with corresponding site-specific optimum seeding rates at the within-field scale. Thus, our results confirm previous findings but critically build on them by showing the subsequent crop, to the green manure crop, benefit from the optimum pea seeding rate. These experiments were carried out using NGP organic crops pea and Kamut in organic systems. Moving forward these results provide a starting point for field seeding rate trials to provide full field and sub-field optimum rates of these crops in relation to real world conditions. We fully expect field conditions to provide a great deal of variability based on soil type, topography, and weed conditions; well-designed field experiments with varied seeding rates covering these varied spatial conditions should be capable of revealing site specific optimum rates of cover and cash crop seed for organic farmers to further optimize their agroecosystems (Tanaka et al., 2022; Trevisan et al., 2021). Put into full practice, this method of full field experimentation practiced over multiple growing seasons can account for temporal variation as well (Cook et al., 2018; Lacoste et al., 2021). In addition, we have provided analytical methods to assess economic outcomes of the seeding rate practices under historic uncertainty and using that uncertainty to quantify the probability of any one practice being superior to another. These results are the first reported example of attempting to optimize green manure seeding rates and the following season’s cash crop to maximize net return, and we intend to use the information learned here to conduct further studies under field conditions.

Conclusions

Organic agriculture is rapidly expanding in market value as well as acres farmed, and this research aims to add to this burgeoning field of agronomic interest (Willer et al., 2019). Greenhouse results confirm that varied pea plant densities contribute to the varied levels of biomass production and likely fixed variable levels of nitrogen which the following crop was able to exploit. Our results have shown that natural variability can be incorporated and built upon in farm management strategies. In the presence of precision agriculture tools these experiments easily scale to field level trials where they can enable site-specific management within fields. This mode of thinking, enabled by precision technologies, practiced with on farm experimentation, and conducted by farmers for their own net gain, can allow farmers to work in concert with local ecologies and work with variability rather than against it. These results are thus hopeful in offering potential optimization strategies that could reduce wasted inputs, increase yield, and provide more consistent net returns to organic farmers. Precision technology then can allow for holistic and agroecologically managed farms that are healthier for nature, farmers, and the broader human population, creating long term resiliency for these agroecological spaces and their interconnected surroundings.

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References

Altieri, M. A., Nicholls, C. I., Henao, A., & Lana, M. A. (2015). Agroecology and the design of climate change-resilient farming systems. *Agronomy for Sustainable Development*, *35*(3), 869–890. https://doi.org/10.1007/s13593-015-0285-2

Baird, J. M., Walley, F. L., & Shirtliffe, S. J. (2009). Optimal seeding rate for organic production of field pea in the northern Great Plains. *Canadian Journal of Plant Science*, *89*(3), 455–464. https://doi.org/10.4141/CJPS08113

Bastos, L. M., Carciochi, W., Lollato, R. P., Jaenisch, B. R., Rezende, C. R., Schwalbert, R., Vara Prasad, P. V., Zhang, G., Fritz, A. K., Foster, C., Wright, Y., Young, S., Bradley, P., & Ciampitti, I. A. (2020). Winter Wheat Yield Response to Plant Density as a Function of Yield Environment and Tillering Potential: A Review and Field Studies. *Frontiers in Plant Science*, *11*, 54. https://doi.org/10.3389/fpls.2020.00054

Biederbeck, V. O., Bouman, O. T., Campbell, C. A., Winkleman, G. E., & Bailey, L. D. (1996). Nitrogen benefits from four green-manure legumes in dryland cropping systems. *Canadian Journal of Plant Science*, *76*(2), 307–315. https://doi.org/10.4141/cjps96-053

Bussler, B. H., Maxwell, B. D., & Puettmann, K. J. (1995). Using Plant Volume to Quantify Interference in Corn (*Zea mays*) Neighborhoods. *Weed Science*, *43*(4), 586–594. https://doi.org/10.1017/S0043174500081698

Carr, P. M., Cavigelli, M. A., Darby, H., Delate, K., Eberly, J. O., Fryer, H. K., Gramig, G. G., Heckman, J. R., Mallory, E. B., Reeve, J. R., Silva, E. M., Suchoff, D. H., & Woodley, A. L. (2020). Green and animal manure use in organic field crop systems. *Agronomy Journal*, *112*(2), 648–674. https://doi.org/10.1002/agj2.20082

Cherr, C. M., Scholberg, J. M. S., & McSorley, R. (2006). Green Manure Approaches to Crop Production: A Synthesis. *Agronomy Journal*, *98*(2), 302–319. https://doi.org/10.2134/agronj2005.0035

Cobo, J. G., Barrios, E., Kass, D. C. L., & Thomas, R. J. (2002). Decomposition and nutrient release by green manures in a tropical hillside agroecosystem. *Plant and Soil*, *240*(2), 331–342. https://doi.org/10.1023/A:1015720324392

Cook, S., Lacoste, M., Evans, F., Ridout, M., Gibberd, M., & Oberthür, T. (2018). *An On-Farm Experimental philosophy for farmer-centric digital innovation*.

Duff, H., Hegedus, P. B., Loewen, S., Bass, T., & Maxwell, B. D. (2021). Precision Agroecology. *Sustainability*, *14*(1), 106. https://doi.org/10.3390/su14010106

Eyhorn, F., Muller, A., Reganold, J. P., Frison, E., Herren, H. R., Luttikholt, L., Mueller, A., Sanders, J., Scialabba, N. E.-H., Seufert, V., & Smith, P. (2019). Sustainability in global agriculture driven by organic farming. *Nature Sustainability*, *2*(4), 253–255. https://doi.org/10.1038/s41893-019-0266-6

Gan, Y. T., Wang, J., Bing, D. J., Miller, P. R., & McDonald, C. L. (2007). Water use of pulse crops at various plant densities under fallow and stubble conditions in a semiarid environment. *Canadian Journal of Plant Science*, *87*(4), 719–722. https://doi.org/10.4141/P06-117

Garbach, K., Milder, J. C., DeClerck, F. A. J., Montenegro de Wit, M., Driscoll, L., & Gemmill-Herren, B. (2017). Examining multi-functionality for crop yield and ecosystem services in five systems of agroecological intensification. *International Journal of Agricultural Sustainability*, *15*(1), 11–28. https://doi.org/10.1080/14735903.2016.1174810

Gatsios, A., Ntatsi, G., Celi, L., Said-Pullicino, D., Tampakaki, A., & Savvas, D. (2021). Legume-Based Mobile Green Manure Can Increase Soil Nitrogen Availability and Yield of Organic Greenhouse Tomatoes. *Plants*, *10*(11), Article 11. https://doi.org/10.3390/plants10112419

Gelderman, R. H., & Beegle, D. (2015). Nitrate-nitrogen (Revised January 1998). *Recommended Chemical Soil Test Procedure for the North Central Region. North Central Regional Res. Pub*, *221*, 5–1.

Griffin, T. S., & Hesterman, O. B. (1991). Potato Response to Legume and Fertilizer Nitrogen Sources. *Agronomy Journal*, *83*(6), 1004–1012. https://doi.org/10.2134/agronj1991.00021962008300060016x

Hegedus, P. B., & Maxwell, B. D. (2022). Rationale for field-specific on-farm precision experimentation. *Agriculture, Ecosystems & Environment*, *338*, 108088. https://doi.org/10.1016/j.agee.2022.108088

Hegedus, P. B., Maxwell, B., Sheppard, J., Loewen, S., Duff, H., Morales-Luna, G., & Peerlinck, A. (2023). Towards a Low-Cost Comprehensive Process for On-Farm Precision Experimentation and Analysis. *Agriculture*, *13*(3), 524. https://doi.org/10.3390/agriculture13030524

Hegedus, P., Maxwell, B., Sheppard, J., Loewen, S., Duff, H., Morales-Luna, G., & Peerlinck, A. (2022). *On-Farm Precision Experiments (OFPE) framework: Tapping local data to optimize crop sub-field scale decisions* (No. 2022120109). Preprints. https://doi.org/10.20944/preprints202212.0109.v1

Hegedus, P. & Maxwell, B.D. (2022). Constraint of Data Availability on the Predictive Ability of Crop Response Models Developed from On-farm Experimentation. *Proceedings of the 15th International Conference on Precision Agriculture*.

Hunter, M. C., Smith, R. G., Schipanski, M. E., Atwood, L. W., & Mortensen, D. A. (2017). Agriculture in 2050: Recalibrating Targets for Sustainable Intensification. *BioScience*, *67*(4), 386–391. https://doi.org/10.1093/biosci/bix010

International Society of Precision Agriculture. (2021). https://www.ispag.org/about/definition

Izard, E. J. (2007). *Seeking Sustainability For Organic Cropping Systems In The Northern Great Plains: Legume Green Manure Management Strategies*. Montana State University.

Johnston, A. M., Clayton, G. W., Lafond, G. P., Harker, K. N., Hogg, T. J., Johnson, E. N., May, W. E., & McConnell, J. T. (2002). Field pea seeding management. *Canadian Journal of Plant Science*, *82*(4), 639–644. https://doi.org/10.4141/P02-001

Lacoste, M., Cook, S., McNee, M., Gale, D., Ingram, J., Bellon-Maurel, V., MacMillan, T., Sylvester-Bradley, R., Kindred, D., Bramley, R., Tremblay, N., Longchamps, L., Thompson, L., Ruiz, J., García, F. O., Maxwell, B., Griffin, T., Oberthür, T., Huyghe, C., … Hall, A. (2021). On-Farm Experimentation to transform global agriculture. *Nature Food*, *3*(1), 11–18. https://doi.org/10.1038/s43016-021-00424-4

Lawley, Y. E., & Shirtliffe, S. J. (2004). Optimum seeding rates for three annual green manure crops: The effect of weed competition. *Soils and Crops Workshop*.

Maxwell, B.D. & O'Donovan, J. (2007). Understanding Weed–Crop Interactions to Manage Weed Problems. In U. M. K. Upadhyaya M. K. & B. R. E. Blackshaw R. E. (Eds.), *Non-chemical weed management: Principles, concepts and technology* (1st ed.). CABI. https://doi.org/10.1079/9781845932909.0000

McCauley, A. M., Jones, C. A., Miller, P. R., Burgess, M. H., & Zabinski, C. A. (2012). Nitrogen fixation by pea and lentil green manures in a semi-arid agroecoregion: Effect of planting and termination timing. *Nutrient Cycling in Agroecosystems*, *92*(3), 305–314. https://doi.org/10.1007/s10705-012-9491-3

McCauley, A., Miller, P., Holmes, J., Burgess, M., & Jones, C. (2012). Improving Annual Legume Green Manure Management by Optimizing Seeding Rate and Termination Timing. *Montana State University Extension*, *61*.

Melander, B., Rasmussen, I. A., & Olesen, J. E. (2020). Legacy effects of leguminous green manure crops on the weed seed bank in organic crop rotations. *Agriculture, Ecosystems & Environment*, *302*, 107078. https://doi.org/10.1016/j.agee.2020.107078

Miller, P., Glunk, E., Holmes, J., & Engel, R. (2018). Pea and Barley Forage as Fallow Replacement for Dryland Wheat Production. *Agronomy Journal*, *110*(3), 833–841. https://doi.org/10.2134/agronj2017.02.0087

Miller, P. R., Buschena, D. E., Jones, C. A., & Holmes, J. A. (2008). Transition from Intensive Tillage to No-Tillage and Organic Diversified Annual Cropping Systems. *Agronomy Journal*, *100*(3), 591–599. https://doi.org/10.2134/agronj2007.0190

Miller, P. R., Lighthiser, E. J., Jones, C. A., Holmes, J. A., Rick, T. L., & Wraith, J. M. (2011). Pea green manure management affects organic winter wheat yield and quality in semiarid

Montana. *Canadian Journal of Plant Science*, *91*(3), 497–508. https://doi.org/10.4141/cjps10109

Mooleki, S. P., Gan, Y., Lemke, R. L., Zentner, R. P., & Hamel, C. (2016). Effect of green manure crops, termination method, stubble crops, and fallow on soil water, available N, and exchangeable P. *Canadian Journal of Plant Science*, *96*(5), 867–886. https://doi.org/10.1139/cjps-2015-0336

Morari, F., Zanella, V., Sartori, L., Visioli, G., Berzaghi, P., & Mosca, G. (2018). Optimising durum wheat cultivation in North Italy: Understanding the effects of site-specific fertilization on yield and protein content. *Precision Agriculture*, *19*(2), 257–277. https://doi.org/10.1007/s11119-017-9515-8

Murrell, E. G., Schipanski, M. E., Finney, D. M., Hunter, M. C., Burgess, M., LaChance, J. C., Baraibar, B., White, C. M., Mortensen, D. A., & Kaye, J. P. (2017). Achieving Diverse Cover Crop Mixtures: Effects of Planting Date and Seeding Rate. *Agronomy Journal*, *109*(1), 259–271. https://doi.org/10.2134/agronj2016.03.0174

Nielsen, D. C., Unger, P. W., & Miller, P. R. (2005). Efficient Water Use in Dryland Cropping Systems in the Great Plains. *Agronomy Journal*, *97*(2), 364–372. https://doi.org/10.2134/agronj2005.0364

Padbury, G., Waltman, S., Caprio, J., Coen, G., McGinn, S., Mortensen, D., Nielsen, G., & Sinclair, R. (2002). Agroecosystems and Land Resources of the Northern Great Plains. *Agronomy Journal*, *94*(2), 251–261. https://doi.org/10.2134/agronj2002.2510

Poffenbarger, H. J., Mirsky, S. B., Weil, R. R., Kramer, M., Spargo, J. T., & Cavigelli, M. A. (2015). Legume Proportion, Poultry Litter, and Tillage Effects on Cover Crop Decomposition. *Agronomy Journal*, *107*(6), 2083–2096. https://doi.org/10.2134/agronj15.0065

Pollnac, F. W., Rew, L. J., Maxwell, B. D., & Menalled, F. D. (2008). Spatial patterns, species richness and cover in weed communities of organic and conventional no-tillage spring wheat systems. *Weed Research*, *48*(5), 398–407. https://doi.org/10.1111/j.1365-3180.2008.00631.x

Quinn, R. M. (1999). Kamut®: Ancient grain, new cereal. *Perspectives on New Crops and New Uses*, 182–183.

R Core Team. (2022). *R: A language and environment for statistical computing. R Foundation for Statistical Computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Ranells, N. N., & Wagger, M. G. (1996). Nitrogen release from grass and legume cover crop monocultures and bicultures. *Agronomy Journal*, *88*(5), 777–882.

Seneviratne, G. (2000). Litter quality and nitrogen release in tropical agriculture: A synthesis. *Biology and Fertility of Soils*, *31*(1), 60–64. https://doi.org/10.1007/s003740050624

Seufert, V., Ramankutty, N., & Foley, J. A. (2012). Comparing the yields of organic and conventional agriculture. *Nature*, *485*(7397), 229–232. https://doi.org/10.1038/nature11069

Shrestha, A., Hesterman, O. B., Copeland, L. O., Squire, J. M., Fisk, J. W., & Sheaffer, C. C. (1999). Annual legumes as green manure and forage crops in winter canola (*Brassica napus* L.) rotations. *Canadian Journal of Plant Science*, *79*(1), 19–25. https://doi.org/10.4141/P98-010

Smith, P. (2018). Managing the global land resource. *Proceedings of the Royal Society B: Biological Sciences*, *285*(1874), 20172798. https://doi.org/10.1098/rspb.2017.2798

Spies, J. M. (2008). *The Effect of Field Pea (Pisum sativum L.) Basal Branching on Optimal Plant Density and Crop Competitiveness*. University of Saskatchewan.

Stainsby, A., & Entz, M. H. (2022). Aggregate stability after 25 years of organic, conventional, and grassland management. *Canadian Journal of Soil Science*, *102*(2), 519–530. https://doi.org/10.1139/cjss-2021-0104

Stallknecht, G. F., Gilbertson, K. M., & Ranney, J. E. (1996). Alternative wheat cereals as food grains: Einkorn, emmer, spelt, kamut, and triticale. *Progress in New Crops*, *1996*, 156–170.

Tal, A. (2018). Making Conventional Agriculture Environmentally Friendly: Moving beyond the Glorification of Organic Agriculture and the Demonization of Conventional Agriculture. *Sustainability*, *10*(4), 1078. https://doi.org/10.3390/su10041078

Tanaka, T. S., Kakimoto, S., Mieno, T., & Bullock, D. S. (2022). Comparison between spatial predictor variables for machine learning in site-specific yield response modeling based on simulation study of on-farm precision experimentation. *Abstracts of Meeting of the CSSJ The 253rd Meeting of CSSJ*, 63–63.

Thiessen Martens, J. R., Lynch, D. H., & Entz, M. H. (2019). A survey of green manure productivity on dryland organic grain farms in the eastern prairie region of Canada. *Canadian Journal of Plant Science*, *99*(5), 772–776. https://doi.org/10.1139/cjps-2018-0311

Trevisan, R. G., Bullock, D. S., & Martin, N. F. (2021). Spatial variability of crop responses to agronomic inputs in on-farm precision experimentation. *Precision Agriculture*, *22*(2), 342–363. https://doi.org/10.1007/s11119-020-09720-8

Tully, K. L., & McAskill, C. (2020). Promoting soil health in organically managed systems: A review. *Organic Agriculture*, *10*(3), 339–358. https://doi.org/10.1007/s13165-019-00275-1

Unkovich, M., Herridge, D., Peoples, M., Cadisch, G., Boddey, B., Giller, K., Alves, B., & Chalk, P. (2008). *Measuring plant-associated nitrogen fixation in agricultural systems.* Australian Centre for International Agricultural Research (ACIAR).

USDA ERS - Commodity Costs and Returns. (2022). https://www.ers.usda.gov/data-products/commodity-costs-and-returns/commodity-costs-and-returns/#Cost-of-Production%20Forecasts.

Usukh, B. (2010). *The Impact Of Lentil And Field Pea Seeding Rates On Dinitrogen Fixation And Subsequent Nitrogen Benefits In An Organic Cropping System*. University of Saskatchewan.

Watson, C. A., Atkinson, D., Gosling, P., Jackson, L. R., & Rayns, F. W. (2006). Managing soil fertility in organic farming systems. *Soil Use and Management*, *18*, 239–247. https://doi.org/10.1111/j.1475-2743.2002.tb00265.x

Watthier, M., Peralta Antonio, N., Gomes, J. A., Rocha, S. B. F., & Santos, R. H. S. (2020). Decomposition of green manure with different grass: Legume ratios. *Archives of Agronomy and Soil Science*, *66*(7), 913–924. https://doi.org/10.1080/03650340.2019.1644622

Weiner, J. (2017). Applying plant ecological knowledge to increase agricultural sustainability. *Journal of Ecology*, *105*(4), 865–870. https://doi.org/10.1111/1365-2745.12792

Weiner, J., & Freckleton, R. P. (2010). Constant Final Yield. *Annual Review of Ecology, Evolution, and Systematics*, *41*(1), 173–192. https://doi.org/10.1146/annurev-ecolsys-102209-144642

Wheat: Khorasan Wheat | Cereals: Barley, Wheat, Oats, Triticale. (2012). Government of Saskatchewan. https://www.saskatchewan.ca/business/agriculture-natural-resources-and-industry/agribusiness-farmers-and-ranchers/crops-and-irrigation/field-crops/cereals-barley-wheat-oats-triticale/wheat-khorasan-wheat

Willer, E. H., Schlatter, B., Trávní, J., Kemper, L., & Lernoud, J. (n.d.). *The World of Organic Agriculture Statistics and Emerging Trends 2020*.

CHAPTER FOUR

OPTIMIZING CROP SEEDING RATES ON ORGANIC GRAIN FARMS USING ON FARM PRECISION EXPERIMENTATION

Abstract

Organic agriculture is often regarded as less damaging to the environment than conventional agriculture, though at the expense of lower yields. We suggest that precision agriculture may benefit organic production practices given its inherent spatiotemporal variation relative to conventional agriculture. We addressed the question of whether on-farm precision experimentation can be used as an adaptive management methodology to maximize farmer net returns. Inputs of cash crop seed and previous-year green manure cover crop seed were experimentally varied on five different farms across the northern great plains from 2019 to 2022. Experiments provided data to model the crop yield response, and subsequently net return, to input rates plus a suite of other spatially explicit data from satellite sources. New field-specific optimum input rates were generated to maximize net return including temporal variation in economic variables. Through subsequent simulations we found that all inputs could be spatially optimized, that the spatial optimization strategies consistently outcompeted other strategies by reducing inputs and increasing yields. By adopting site specific management average increases in net return for all fields was \$46 ha^{-1}. Future data will be collected to optimize input rates with temporal variability in weather. These results showed that precision agriculture and remote sensing can be utilized with modeling to provide organic farmers powerful adaptive management tools to increase their resilience.

Introduction

Agricultural intensification calls for higher yields while minimizing ecological harm (Cassman & Grassini, 2020; Tilman et al., 2011). Fueled by the Green Revolution, farms have become larger, higher yielding and more efficient, but often at the expense of the environment (Pellegrini & Fernández, 2018; Pretty, 2018). On larger farms with more fields, less is now known about the local variation present across their management domain. This loss of knowledge exacerbates input overuse as farmers blanket the land with inputs to reduce variation and increase yields. Targeted input rates are typically provided by research sites that may not be near the farms where they are applied, and thus lose temporal and spatial relevancy (Rodriguez et al., 2019). These problems have led farmers and researchers to explore alternative farming methods, loosely assembled under the umbrella term of agroecological intensification, in which agricultural yield production is but one of many ecosystem services considered by a productive and resilient agroecosystem (Wezel et al. 2009; Wezel et al. 2015). Thus, through the lens of agroecology we can start to address some of the shortcomings of conventional agriculture and more importantly, effectively engage in accomplishing agricultural resilience and sustainability.

Some of the new or alternative farming methods being explored include organic agriculture, and precision agriculture, which each provide partial solutions to conventional agricultural intensification (Duff et al. 2022). Organic agriculture produces food without the use of synthetic chemicals, like chemical pesticides, or factory made nitrogen (Hammermeister, 2021). The advantages of this approach include less damage done to the surrounding ecosystem, better quality products, and greater net returns for the farmer due to premiums paid for organic produce (Eyhorn et al., 2019; Gomiero, 2018; Meemken & Qaim, 2018). The main detraction of organic systems is a tendency towards reduced overall crop yield (Seufert et al., 2012b; Seufert & Ramankutty, 2017). Precision agriculture, another modern agricultural practice that is not necessarily mainstream, was initially conceptualized as farming by soil variation (Robert, 1993). It has expanded its scope to enhance agricultural production by increasing efficiencies through understanding of patterns in spatial and temporal variation and their interaction present in agroecosystems (*International Society of Precision Agriculture*, 2021). Through the expansion of digital technologies precision agriculture has become both more powerful and easier to use. There is growing application of precision agriculture to place inputs in optimized quantities across farm systems, thereby reducing waste and environmental damage, and increasing farmer's net returns (Hatfield et al., 2020). Precision agriculture holds much promise for increasing production and mitigating environmental damage but, beyond yield maps and automated steering, the technology has seen only gradual uptake by farmers due to the complexities of its application, and the lack of clear economic advantage in its use (Mitchell et al., 2018). While agroecological intensification could take advantage of the research being made in organic and precision agriculture, and the modes of thinking are less antithetical than often perceived (Duff et al. 2022), a system to enable the practices in tandem has been lacking.

On Farm Precision Experimentation (OFPE) is a methodology to deploy precision agriculture, on-farm experimentation, and data science in any agricultural system to increase agronomic input efficiency and net-returns (Hegedus et al., 2023). The method seeks to utilize the reams of field data, being produced in ever growing quantities, to gain an understanding of field-specific underlying variation to optimize farm input strategies at the sub-field scale. It importantly builds upon the established notion of precision agriculture by placing an emphasis on local experimentation to empirically determine optimized input rates that are field specific, with the understanding that every individual field will have not only unique internal spatial variation but also its own unique history (Hegedus et al., 2023). In the OFPE method, farmers experimentally apply an input across their field, stratified (on previous yield maps typically) randomly across their entire field, and collect the yield data of the harvested crop to show responses to varied input rates (Hegedus et al. 2022). To augment the equipment data, other free data is collected, including from satellite data such as vegetation indexes like Normalized Difference Vegetation Index (NDVI) and Chlorophyl Index Red Edge (CIRE), and soil metrics such as pH and carbon content, amongst numerous others. By modeling these data, optimized prescription maps for the input of experimentation can be generated and used on that field in future seasons. In addition, we are building a significant calibration dataset for remote sensing of crop responses. Crucially, one year of experimentation is only the first step in the process, and to fully understand the temporal variation it is recommended to continue experimenting over multiple years, even if experimental units within the field are gradually replaced with optimized rates over the seasons. In this way crop prediction models can be updated, and farms can continuously learn about the temporal aspect of the crop responses while building ever greater optimization into their system to generate higher net returns. The concept of on farm experimentation has been around for decades (Cook and Bramley 1998; Maxwell and Luschei 2005; Ruffo et al. 2006) but has recently garnered greater traction due to improvements in digital technology and analysis techniques (Tantalaki et al., 2019; Weersink et al., 2018). OFPE is expanding rapidly in conventional agricultural systems but lacks any detailed exploration in organic systems (Bullock et al., 2019; Lacoste et al., 2021). OFPE provides an excellent method by which precision agriculture tools can be used to improve organic farm production and resilience.

Here we present the first, to our knowledge, detailed exploration of precision agriculture deployment in organic systems using OFPE. Five separate farms from across the Northern Great Plains (NGP), some with multiple fields, were involved in on farm experiments from 2019 to 2022 for a total of eleven site-years of data. The farms experimented with different inputs including annual cash crop seeding rates, as well as non-harvested previous-year nitrogen fixing green manure cover crop seeding rates. Seeding rates were thought to offer a unique application of OFPE in organic systems by offering both weed competition and optimized nitrogen levels through manipulated seeding rates (Loewen et al. 2023 *in review*; Carr et al. 2020). After collecting field-specific data to model each site-year, four different input strategies and their net returns were compared. The strategies included the actual experimental rate (AER) (i.e. cost of the experiment placed in the field), the simulated returns of the typical farmer chosen rate (FCR) defined as the rate the farmer themselves expressed as their chosen rate, the simulated returns of a single optimum uniform rate (OUR) for the entire field, and finally the simulated returns of an optimum variable rate (OVR) where rates were allowed to vary across the entire field. Each optimization strategy attempted to maximize net return, balancing input rates against economically optimum yields. To explore temporal variation, we included annual variation in input costs and prices received over the last twenty years. Our specific objectives were 1) to use OFPE to spatially optimize seeding rate inputs of cash and cover crops on organic farms on a field-specific basis. 2) To determine if variable rate strategies were consistently more profitable than the optimum uniform rate or the farmer chosen rate. Finally, 3) to quantify the economic costs and benefits of deploying OFPE. We hypothesized that OVR would be more profitable than OUR which would in turn be more profitable than FCR. We also hypothesized that there would be a cost associated with implementing the experiment, that is that AER would be less profitable than FCR.

Methods

Study Sites

To accomplish our objectives, we sought to collect and compile freely available field data, to efficiently and accurately model organic cash crop yield and subsequent net return from across farmer collaborator's fields dedicated to OFPE in the NGP. Details on employing the OFPE method, including yield monitor data accumulation and cleaning, were described by Hegedus et al. (2023). All farms involved in the study were certified organic for at least several years before experimentation began. Farm A was based in south-east Manitoba, and experiments were placed on two fields over several years comprising site-years 1-3, and 5-8, as seen in Table 4.1. On this farm various annual crop seeding rates including spring wheat, hemp, and oats were experimentally varied. The nitrogen of all fields on Farm A were sourced from uniformly applied chicken manure spread annually in the fall. Farm B was in south-east Montana, and experimented on one field in 2021 and was designated site-year 4. As opposed to all other farms, which experimented with seeding rate, this farm experimented with blood-meal as an organically approved top dress nitrogen source on uniformly seeded winter wheat. Farms C-E were in north-central Montana and experimented with the effects of annual winter wheat seeding rates as well as the nitrogen-fixing green-manure cover crop which proceeded the wheat by one season. Tilling in the green-manure crop in mid-summer provided fertility to the subsequent cash crop, a typical practice in organic grain farming (Carr et al., 2020; Miller et al., 2011). Each of these last three farms harvested a cereal crop following a pea green manure plow down in 2021 (Table 4.1). Numerous other experiments were planned over the four years of collaboration but weather conditions, including drought, wind damage, and hail storms, prevented their completion. We conducted our experiments intentionally in a field-specific manner, having encountered significant field spatial and temporal variation differences on conventional farms in the same region (Hegedus and Maxwell 2022).

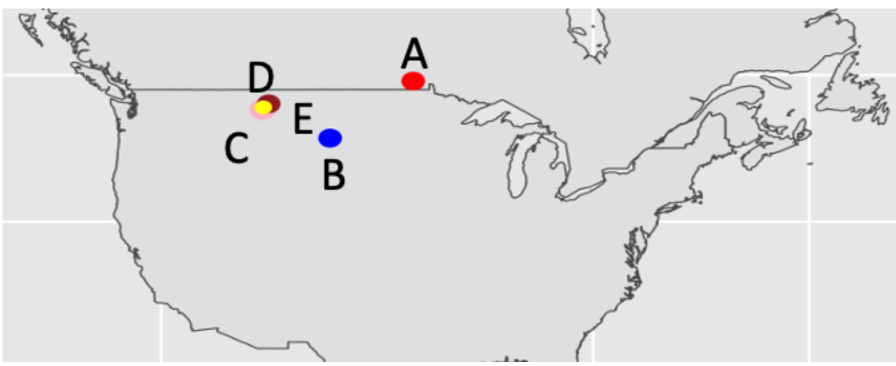


Figure 4.1. Farm locations across the Northern Great Plains (NGP) in both Canada and the USA. Farm A, in south-east Manitoba, experimented with annual crops across two fields from 2019 – 2022; Farm B, in south-east Montana, experimented with bloodmeal across one field in 2021; Farm C-E, in north-central Montana, experimented on one field each with a two-year rotation of a green-manure crop, followed by a cereal cash crop harvested in 2021.

Table 4.1. Agronomic conditions across the NGP on five farms (A-E), each with one or two fields practicing OFPE for a total of eleven site-years of data. Each unique field and year combination was treated individually for crop yield modeling purposes and was given a site-year ID. Climate anomaly were calculated from a 30-year average (1991-2021) from Daymet (Thornton et al., 2022).

Site-year ID	Year	Farm-Field	Crop	N Source	Hectares	State/ Province	Precipitation anomaly (+/- mm)	GDD anomaly (+/-C)
1	2020	A-1	Wheat*	Manure	32	Manitoba	-153.55	+48
2	2021	A-1	Hemp*	Manure	32	Manitoba	-111.44	+366
3	2022	A-1	Oat*	Manure	32	Manitoba	+151.14	-139
4	2021	B-1	Winter wheat	Bloodmeal*	130	Montana	-137.66	+412
5	2019	A-2	Wheat*	Manure	71	Manitoba	+133.94	-112
6	2020	A-2	Hemp*	Manure	71	Manitoba	-159.06	+52
7	2021	A-2	Wheat*	Manure	71	Manitoba	-115.04	+366
8	2022	A-2	Oat*	Manure	71	Manitoba	+149.52	-138
9	2021	C-1	Winter wheat*	Pea GM*	93	Montana	-156.93	+278
10	2021	D-1	Barley*	Pea GM*	32	Montana	-113.35	+287
11	2021	E-1	Winter wheat*	Pea GM*	32	Montana	-121.66	+274

*Experimentally varied input; GM = green manure; N = nitrogen; GDD = growing degree days

<u>Experimental design and data collection</u>

Experimental prescriptions were designed by increasing seeding and fertilizer rates above and below farmer chosen rates so that a standard experiment included rates at 0.6x, 0.8x, 1.0x, 1.2x, and 1.4x of the farmer stated normal rate. Unlike the seeding rate experiments, the bloodmeal experiment included a zero rate. Efforts were made to stratify the rates on previous yield maps when they existed. Under ideal experimental conditions experimental rates were placed in a checkerboard design across the field, however in several instances farmers reverted to a simpler strip trial design due to equipment failures of variable rate applicator technology. Strip design is a capable method, though less statistically optimal, and has the advantage of being able to be manually deployed by a farmer with little additional effort (Piepho et al., 2011; Pringle, McBratney, et al., 2004). These were guidelines and often farmers found themselves changing experimental rates on the fly based on field equipment constraints or weather conditions. As such, collecting the as-applied maps from the machinery, whether it was a seeder or sprayer, was integral to verifying the rates that were deployed.

Data were collected from farm machinery and satellite sources and aggregated to a 10m x 10m grid for analysis. As-applied seeding or bloodmeal rates, were collected from farmer's tractor monitors, and yield data were collected from combine mounted yield-monitors. All satellite data were collected via Google Earth Engine. Satellite data on plant information included NDVI, Normalized Difference Red Edge (NDRE), and CIRE; satellite data on soil information included Normalized Difference Water Index (NDWI), soil bulk density, sand content, clay content, pH, soil water content, and carbon content; satellite or drone collected lidar data on topographic information included slope, elevation, topographic position index (TPI), and aspect in eastness and northness following standard GIS practices (Figure 4.2)(Amatulli, 2018). Satellite data classified as "this year" were collected from January 1st of the year of harvest to March 31st. In that way future models could be updated with current information up to the point at which a decision about optimum rates for inputs must be made. To understand as much field variation as possible satellite indexes that change over time including NDVI, NDRE, CIRE, and NDWI were collected for the prior year, and two years prior to the harvest year. Previous year yield data, and previous year variable seeding rate data, were included in the analysis when they were available. Latitude and longitude were included in the full model as a standard practice to understand spatial variation not captured in the other terms in the model (Janatian 2017, Walsh 2017, Wang 2017, Hegedus & taro 2022). To remove border effects, headlands, as measured by 30 m from the field edge, were removed from analysis (Hegedus et al. (2023).

All organic farmers face weed challenges, so, variation in weed density was manually sampled. Approximately two points per hectare were sampled using a 0.25 m^2 ring. To non-destructively ascertain plant biomass, plant volume was estimated by height and width for the crop species and similarly for up to the three most dominant weed species following the method of Bussler et al. (1995). Weed data by species was too limited to present full field variation so all weed data were compiled to an “all-weeds” biomass variable and kriged across the field (Figure 4.2-14), using ordinary kriging with R packages gstat and automap (Hiemstra & Skoien, 2023; Pebesma & Graeler, 2022). All other variables included in the model are freely available, and in the future we expect weed distribution and abundance to be measured with remote sensing (Esposito et al., 2021; Mattivi et al., 2021).

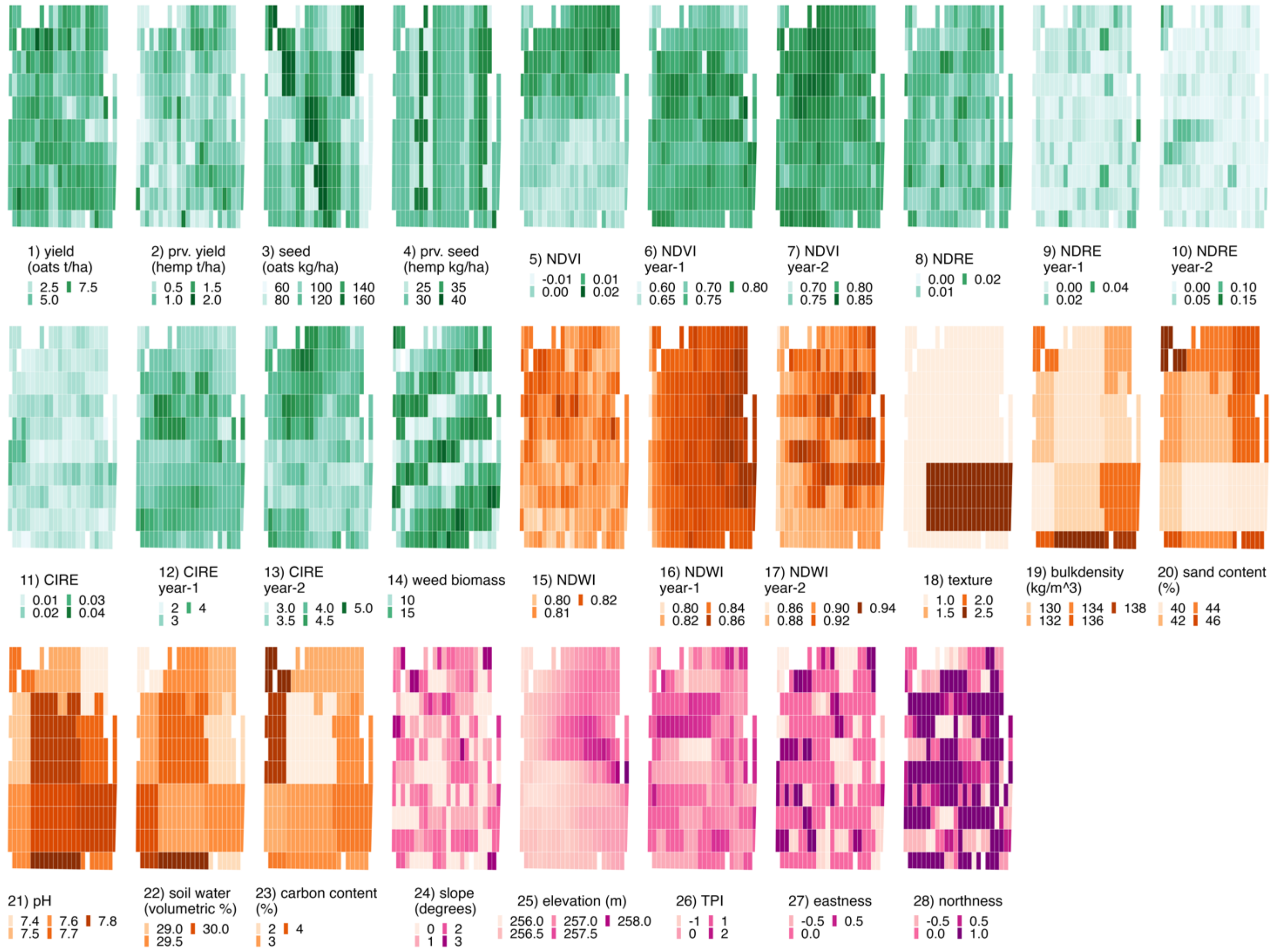


Figure 4.2. Example maps from site-year three, a 32-hectare field in south-east Manitoba planted to oats in 2022. The maps show all possible input variables in the full model, before feature selection for that site-year model. Those pictured in green (1-14) represent plant variables, those in brown (15-23) represent soil variables, and those in pink (24-28) represent topographic variables. Maps one to four are from data collected from farm machinery, the rest of the maps show data collected from satellites. Each field map shows data split into management cells of 24m wide by 120m long. Areas in the north-west and north-east of the field were not seeded due to excessive moisture (north is up). Only sand content, due to multi-collinearity, was dropped from the model for this site-year (Table 4.2).

<u>Crop Response Models</u>

We used a random forest model to predict yield across each field using a wide set of variables (Fig. 4.2). Other model types were tested but, as has been found elsewhere, based on RMSE random forest models tend to be the most accurate (Hegedus, et al. 2022). Random forest models are well designed to ignore poor model predictors added to the modeling process, nevertheless to both speed computation and aid in interpretability of the crop response models we pursued a process of feature selection. Before feature selection the full model included all variables in Equation 1 (Table 4.2); example maps of those variables are shown in Figure 4.2. Multiple variables were dropped from the various models as seen in Table 4.2 to arrive at the final models used. Unimportant variables, as determined by the Boruta package in R (Kursa & Rudnicki, 2010), were dropped from analysis; variables with a VIF over ten were also dropped from the model. Variables were dropped if more than 30% of the data were missing from a field due to machine or farmer error with farm data, or incomplete satellite data (Storey et al., 2016; Trémas et al., 2015). Following feature selection, hyperparameters of the models were tuned in R using the tidymodels and ranger packages(Kuhn et al., 2022; Wright & Ziegler, 2017). Tuning involved optimizing mtry (number of variables sampled at each node at each ensemble tree) and ntree (total number of ensemble trees) based on lowest RMSE to arrive at best models for each site-year (Table 4.2). Models were trained on the data set aggregated to 10m x 10m cells, however when building new optimized prescriptions for every field, the new rates were upscaled to a 24 m x 120 m grid cell to match field equipment size and constraints. The width is 2x a standard 12 m wide seeder, and the length used is the recommended length to get the most accurate response from combine mounted yield monitors (Guaci et al. 2022). All data analysis was conducted in R, including random forest modeling, and GIS mapping (R Core Team, 2022).

Table 4.2. Model selection on the variables used in each of the eleven site-year models, beginning with the full model each model was trimmed down through feature selection to reduce computation time, reduce multicollinearity, and reduce NAs in the datasets.

Model	Model variables
Full model	(1) $yield_y \sim yield_{y-1} + seed\ rate_y + seed\ rate_{y-1} + NDVI_y + NDVI_{y-1} + NDVI_{y-2} + NDRE_y + NDRE_{y-1} + NDRE_{y-2} + CIRE_y + CIRE_{y-1} + CIRE_{y-2}$ + weed biomass + $NDWI_y + NDWI_{y-1} + NDWI_{y-2}$ + soil texture + bulkdensity + sand content + pH + soil water content + carbon content + slope + elevation + TPI + eastness + northness + latitude + longitude
	Model variables removed by field:
Site-year 1	seed $rate_{y-1}$, $CIRE_{y-1}$, sand content
Site-year 2	$CIRE_{y-1}$, sand content
Site-year 3	$yield_{y-1}$, sand content
Site-year 4	$yield_{y-1}$, seed $rate_{y-1}$, longitude, weed biomass
Site-year 5	$yield_{y-1}$, seed $rate_{y-1}$, sand content, longitude, $NDRE_{y-1}$, X
Site-year 6	sand content, longitude, $NDRE_{y-1}$
Site-year 7	sand content, longitude
Site-year 8	sand content, longitude
Site-year 9	$yield_{y-1}$, longitude, carbon content
Site-year 10	$yield_{y-1}$, latitude, weed biomass, $NDRE_{y-1}$, $CIRE_y$, $CIRE_{y-1}$
Site-year 11	$yield_{y-1}$, sand content, latitude, bulkdensity, $NDWI_{y-1}$, weed biomass, carbon content, $CIRE_y$, $CIRE_{y-1}$

Economic Optimization

Economic data were collected from a range of sources encompassing the years 1998-2022 to estimate net return based on predicted yields (Bertramsen and Dobbs, 2002; USDA, 2022; Würriehausen et al. 2015; Personal communication: Manitoba Harvest). Data included price received for winter wheat, spring wheat, oats, hemp, and barley, the seed costs for each of these crops, and their associated fixed costs over the course of those years. From these data we established the net return formula found in equation 2.

$$NR = Y * PR - (IR_1 * IC_1 + \cdots + IR_x * IC_x + FC) \qquad \text{Equation (2)}$$

Where NR was the net return received by that farmer in a given year; Y was the yield of the harvested crop in the given year, PR was the price received for the crop in the given year and FC was the fixed costs. When seeding rates or bloodmeal rates were experimented with, they were represented with the first input rate (IR_1) and input cost (IC_1). Not all fields had a second input, but when pea seeding rates as green manures were experimented with, $x = 2$, and the pea seeding rate and input cost from the year pea was seeded, were represented with (IR_2) and input cost (IC_2). If bloodmeal was the value varied, seed costs were included in the fixed costs. Price received as well as costs of seed were measured in USD kg^{-1}, and fixed costs and net return were measured in USD ha^{-1}. Full economic data found in supplemental material (Supplemental Table 4.1).

Objective one was accomplished by using the crop response models to find economically optimum seeding rates in every cell across the field thereby spatially optimizing inputs. Economically optimum seeding rates were generated for each site-year for the year of harvest, and also generated for each of the previous twenty years based on historical economic data described above. By including this series of possible net return outcomes, we could present an estimated range of outcomes based on past economic variability and accomplish objective two by stating how often one seeding rate strategy outcompetes another. Finally, we accomplished objective three by quantifying the specific average amount ($) by which the optimized (profit maximized) rate strategies, OVR and OUR, outcompeted FCR on a field specific basis.

Results

Spatial optimization using field specific models

Through experimentation and simulation we found that inputs could be spatially optimized on all fields. The exception was the bloodmeal application on site-year 4, where the OVR and OUR were both zero with negligible crop response across bloodmeal rates. Of the eleven site-years tested two are highlighted below to exemplify the two-year rotation of green manure seeding rates followed by cash crop seeding rates (Figure 4.3 & 4.4). Spatial variation of inputs could be large and obvious, as in OVR for site-year 5 (Figure 4.3), or subtle like the OVR strategy in site-year 10 (Figure 4.4). The resultant calculated changes in yields and net return using the crop response models appear minor on the generated maps, however the cumulative changes in net return were meaningful at the field scale. For example, site-year five was a single year rotation in non-drought conditions and demonstrated substantial changes in net return between strategies (OVR, OUR and FCR) and between seeding rates (Table 4.3). The AER on field site-year 5 had a net return \$25.04 ha^{-1} less than FCR; this was the estimated cost of the experiment for this site-year. The FCR for the wheat crop planted in site-year five was 187 kg ha^{-1}, the OUR was calculated to be 154 kg ha^{-1}. The reduction in seeding rate did not have a large effect on yield using the OUR strategy, so primarily offered the farmer savings through reduced seed costs. The OVR was also able to reduce seed input overall, thus saving costs. However, the OVR model also found areas on the field where increased plant density offered an economically significant yield advantage, thus offering an economic incentive for an optimized prescription for variable seeding rates (Fig. 4.3). Calculated net return for OVR increased by \$44.22 ha^{-1} over the FCR management on this site-year (Table 4.3).

Site-year 10 represented a two-year rotation, which occurred during a drought in 2020 and 2021 (-113 mm precipitation anomaly, Table 4.1). In this instance the seeding rate changes were less obvious than site-year 5, and net return gains from FCR to OUR were \$27.92 ha^{-1} (Fig. 4.4, Table 4.4). There was very little difference between the OUR and OVR, the net return increase to OUR was only \$0.25 ha^{-1}; which is likely the response to drought. Despite the low crop response to seeding rates in low precipitation years the calculated optima did identify areas where seeding rates could increase, thus enabling slightly better chances of increasing net return. The specific examples illustrated here demonstrated the specifics of where and how input rates could be spatially optimized to provide an advantage to the farmer.

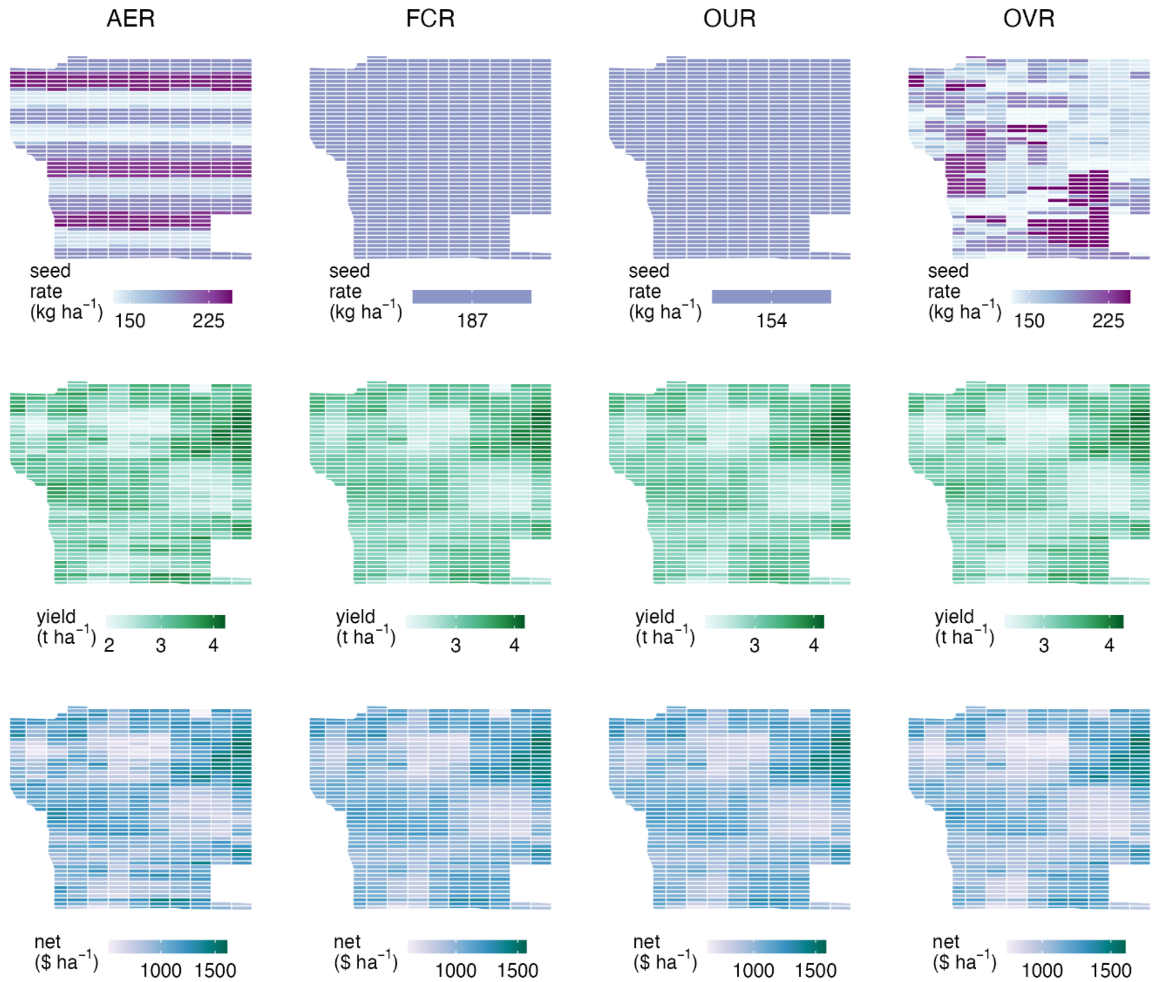


Figure 4.3. Visualizations of the seed rates (top row) and resulting yields (middle row) and net-returns (bottom row) to the four management strategies in site-year 5. This experiment featured variable spring wheat seeding in south-east Manitoba from 2021 on a 71-hectare field. The management strategies were the actual experimental rate (AER), farmer chosen rate (FCR), optimum uniform rate (OUR), and optimum variable rate (OVR).

Table 4.3. Quantified results from site-year 5 indicating rate, yield, and net return of the four strategies averaged across all field cells and all economic years.

	AER	FCR	OUR	OVR
Avg seed rate (kg ha^{-1})	187	187	154	174
Avg yield (t ha^{-1})	3.01	3.06	3.05	3.16
Avg net return ($ ha^{-1})	990.59	1015.63	1023.06	1067.28

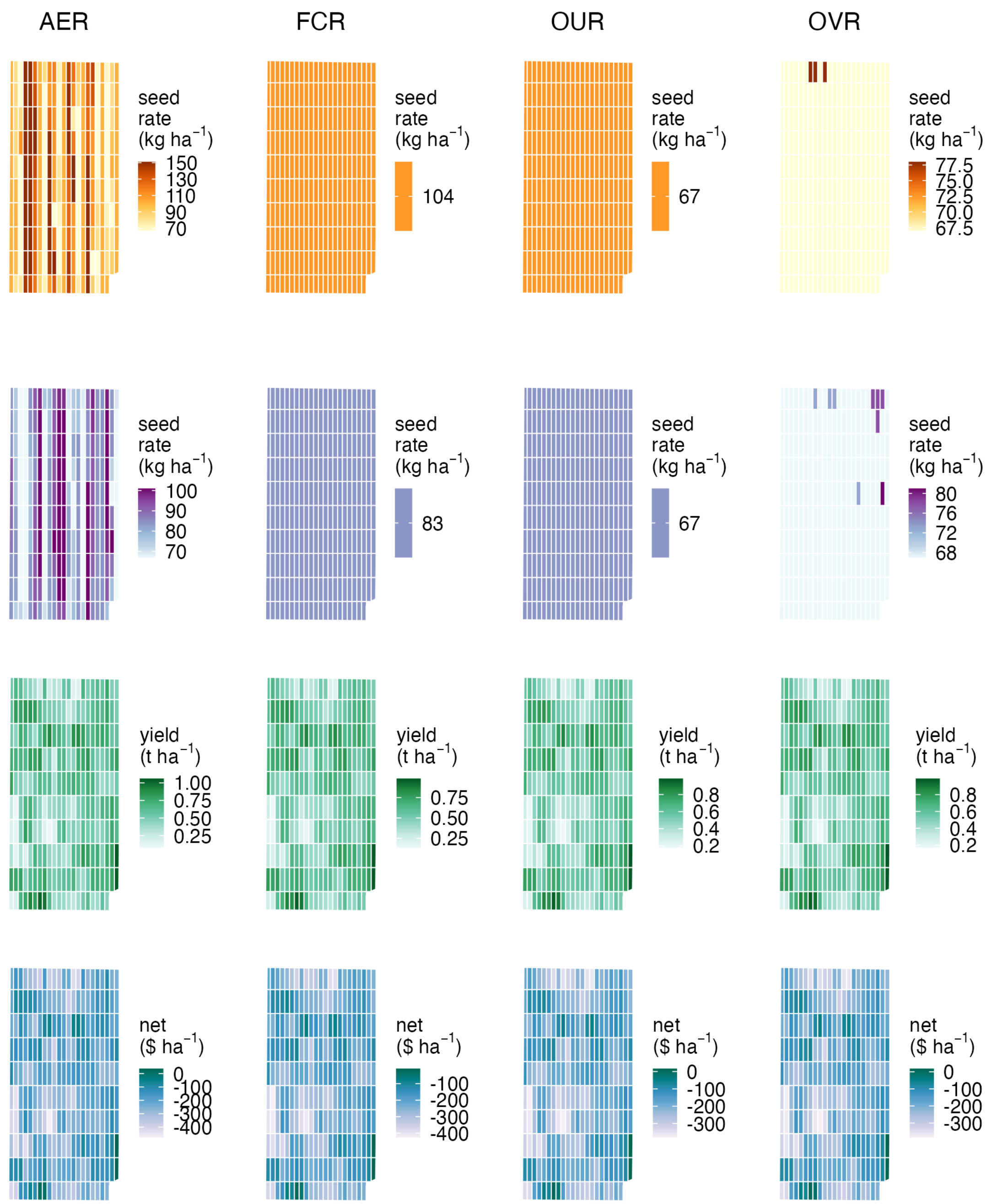


Figure 4.4. Results from site-year 10, a green manure and barley rotation on a 32 ha piece in north-central Montana, pea green manure seed rate (top row), the subsequent barley cash crop seed rate (second row), their respective simulated yields (third row), and calculated net returns (bottom row), for each of four seeding rate strategies (columns), including the actual experimental rate (AER), farmer chosen rate (FCR), optimum uniform rate (OUR), and optimum variable rate (OVR).

Table 4.4 Quantified results from site-year 10 indicating rate, yield, and net return of the four strategies averaged across all field cells and all economic years.

	AER	FCR	OUR	OVR
Avg seed rate (kg ha^{-1})	104	104	67	67
Avg seed rate (kg ha^{-1})	83	83	67	67
Avg yield (t ha^{-1})	0.57	0.57	0.58	0.58
Avg net return ($ ha^{-1})	-237.89	-238.93	-211.01	-210.76

The random forest models to predict subfield cash crop yield used in this study were field and year specific. Through model variable selection field-specific models were developed that included different variables than the initial full model (Supplemental Table 4.3). The input variables, and their importance to crop yield prediction were quite different field to field and year to year (Fig. 4.5). This exemplified the variability we saw between the fields examined, and emphasized the requirement to estimate optimization and compare strategies using field specific models (Hegedus and Maxwell 2022). The variable importance plots were useful in visualizing the differences among model years, and were also a starting point for unpacking potential driving variables in the models. For example, in site-year 5 seeding rate was a very important driver of the model, however in site-year 10 seeding rate is near the bottom of the list. The variable importance plots were useful for understanding which variables were driving the sub-field scale patterns in crop yield (Fig. 4.5).

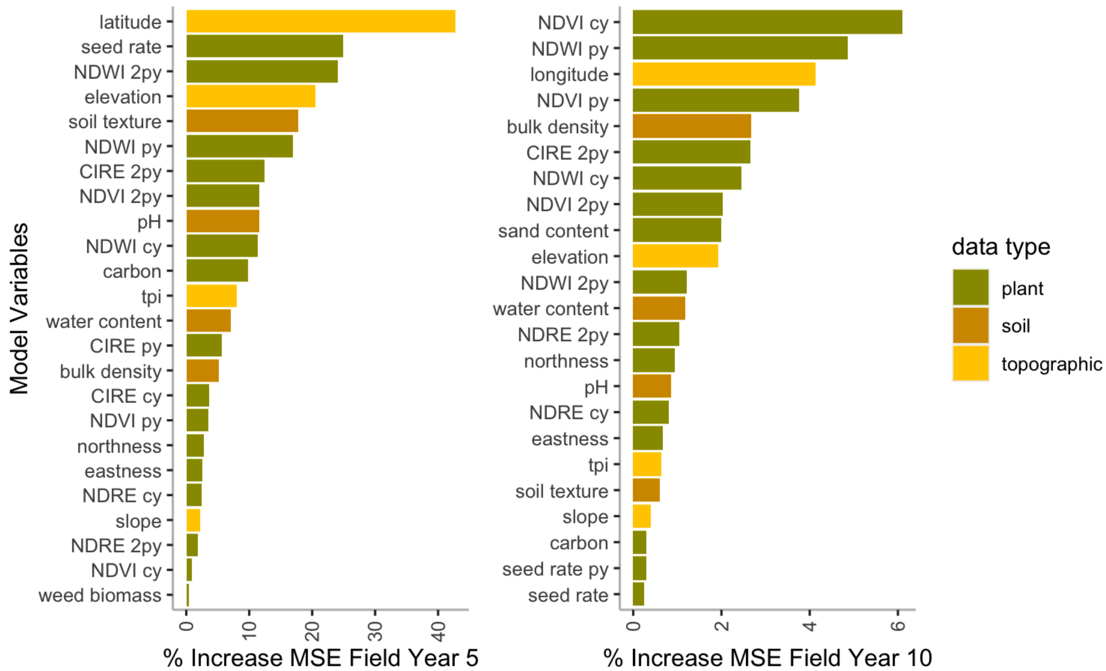


Figure 4.5. Variable importance plot derived from the random forest model for site-year five and site-year ten, where every variable was measured based on the increase in MSE if that variable was randomly permuted within the modeling process. The greater the increase in MSE for a variable, the more important it was to accurate predictions of crop yield. Each model for each site-year had a different variable importance plot and we used this as an example tied to the results in Figure 4.3, where we showed the predictions of the model on differing optimization strategies. By looking at this plot we could start to predict which factors across the field were the most important in predicting yield. The variables were broken down into sub-categories of plant, soil, and topographic variables.

Comparison of Management Strategies

Input optimization strategies were compared for profitability within fields, and across fields by simulating temporal variability in outcomes using the variability in cost of seed and different prices received for the cash crop (Fig. 4.6). Simulated site-specific optimum seeding rates and subsequent yields were assumed to be constant over time (2002-2022) and based on the OFPE we conducted, yields were also compared within fields and across fields (Fig. 4.7). Based on these observations it was possible to describe how OVR compared in profitability to OUR, FCR, and AER (Fig. 4.8). Averaged optimum (profit maximized) input rates tended to be lower when compared with the FCR strategy (Fig. 4.6); this was particularly evident under drought conditions in 2021 (site-years 2, 4, 7, 9, 10, and 11) (Table 4.1: precipitation anomalies). All optimum green manure seeding rates were found to be lower than the FCR (Fig. 4.6: 9.1-9.3). In a few instances however, input rates increased when optimized, such as in site-year 8, an oat rate experiment in above average precipitation conditions (+150 mm precipitation anomaly) in Manitoba (Table 4.1). Optimized uniform seeding rates of oats on site-year 8, called for increased seeding rates, and the increased oat rates resulted in higher net return by increasing yields, which we saw in the corresponding yield figure for site-year 8 (Fig. 4.7). Site-year 8 OUR and site-year 2 were the exceptions, and generally optimum seeding rates, either uniform or variable, were reduced, relative to the FCR.

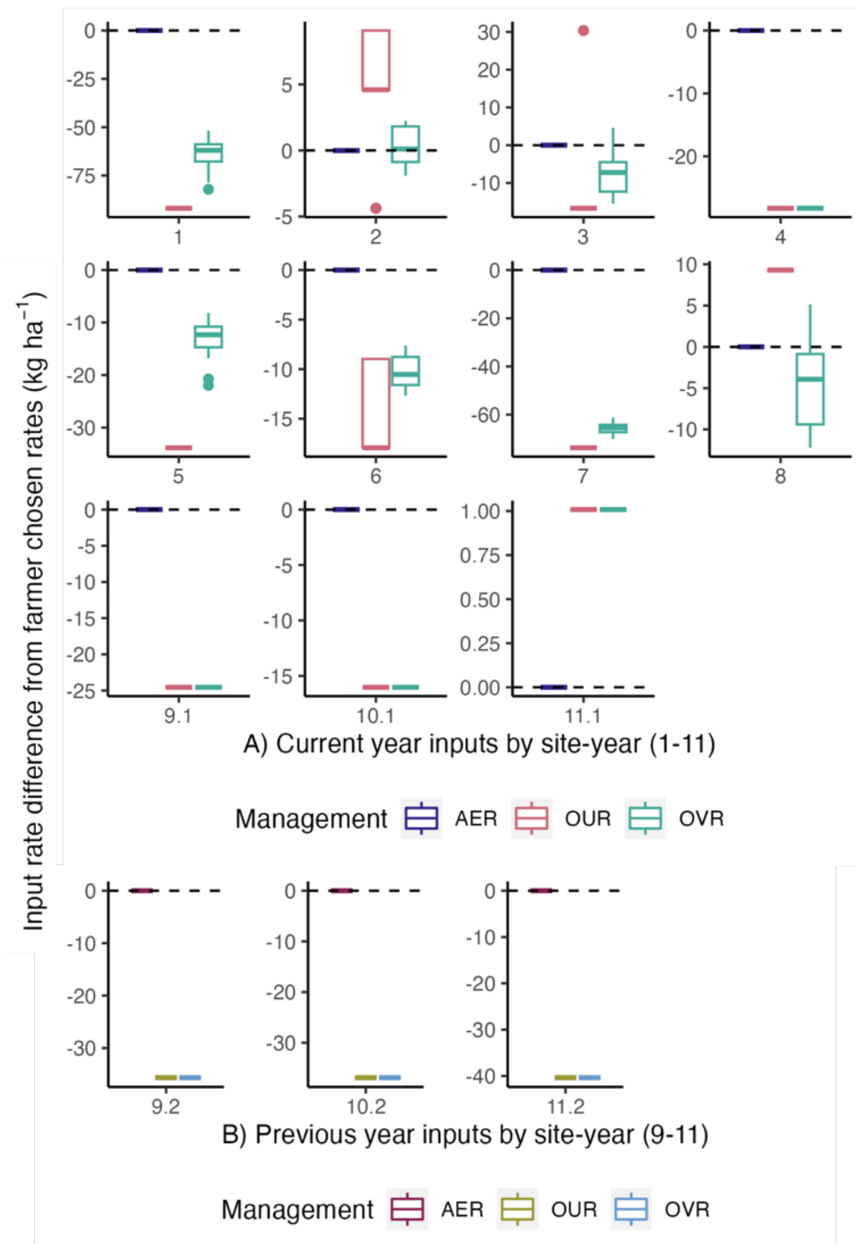


Figure 4.6. A) The current year input rates of three different management strategies on site-years 1-11, and B) the previous year input rates for pea green manure for site-years 9-11. Management strategies included actual experimental rates (AER), farmer chosen rates (FCR), optimum uniform rates (OUR), and optimum variable rates (OVR). All were shown here relative to the FCR, which here was 0, and shown as a horizontal black dashed line. Each box represented a range of outcomes given our experimental or optimized rates on 20 years of historical economic data.

Yield was always highest under the OVR management strategy (Fig. 4.7) regardless of whether input rates were higher or lower (Fig. 4.6). Yields were typically shown to increase when moving from the FCR to the OUR to the OVR strategy (Fig. 4.6). Though in some instances yield gains were negligible, such as in site-year 5 where moving from FCR to OUR showed no improvement in yield. In this instance, only reductions in seeding rate allowed the net return to increase. In some cases the OUR strategy had reduced crop yield and net return relative to the FCR strategy;. For example, in site-year 6, a hemp experiment in Manitoba, which had a relatively high cost for hemp seed (Supplemental Table 4.1). Under the AER conditions yields were usually lower than FCR, though not always. Occasionally, due to random chance, AER was shown to produce more yield than FCR such as site-years two and ten. Optimization was set to maximize net return which often resulted in either reduced inputs, or increased yields, and typically both occurred.

In net return, OVR tended to outcompete OUR, which tended to outcompete FCR, which tended to outcompete AER as hypothesized (Fig. 4.8). The dollar spread between OUR and OVR was less when wheat was the cash crop (site-years 1, 4, 5, 7, 9, 11) than the other cash crops tested. The spread between OUR and OVR was less under drought conditions (Table 4.1 & Figure 4.7); drought conditions included site-years 2, 4, 7, 9, 10, and 11. Despite very different moisture conditions, the hemp crops (site-years 2 and 6) showed large gaps between management strategies, highlighting the potential of this crop for variable rate management.

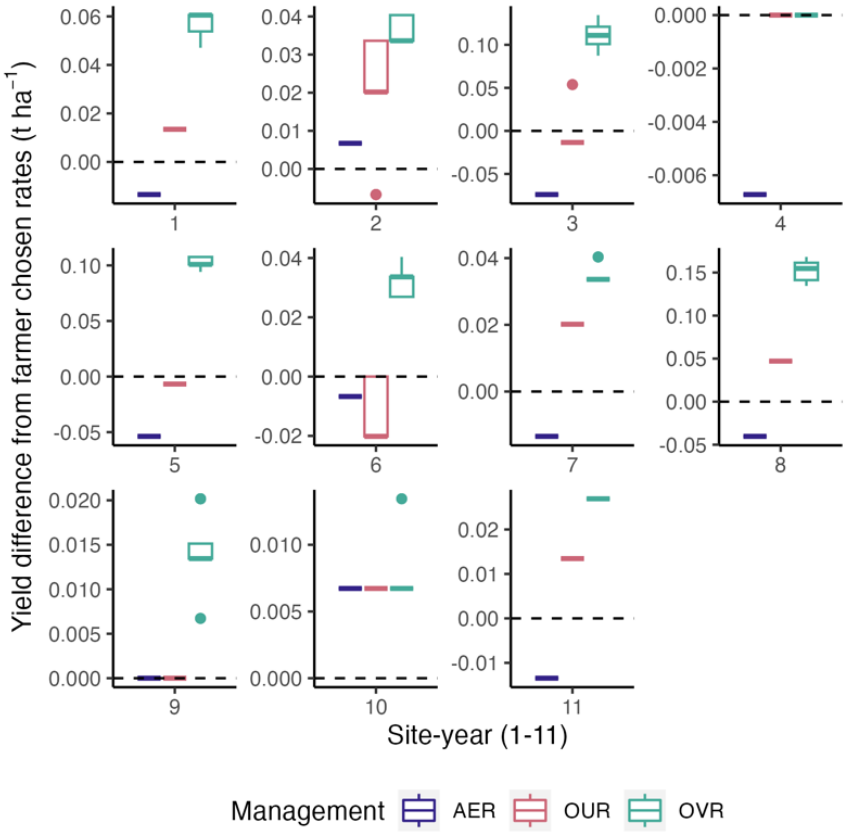


Figure 4.7. The cash crop yields for three different management strategies. Management strategies included actual experimental rates (AER), farmer chosen rates (FCR), optimum uniform rates (OUR), and optimum variable rates (OVR). All were shown here relative to the FCR strategy, which here was set to 0, and shown as a horizontal black dashed line. Each box represented a range of outcomes given our experimental or optimized rates over 20 years of historical economic variables.

Quantification of net return differences

Net returns were always shown to improve relative to FCR when inputs were optimized under either the OVR or OUR strategy. We compared each strategy against a baseline of the FCR to clarify the net return results and make them more telling to farmers (Fig. 4.8). The results demonstrated and quantified what improvement could be gained in adopting the profit maximizing strategy, and if the gain in profit represented enough economic advantage to offset the costs and time required to employ OFPE. Depending on the site-year, average improvements (across all 20 years of economic variation) were as low as \$5.28 ha^{-1} in site-year 8 under OUR management (an oat experiment in Manitoba), to as high as \$85.58 ha^{-1}, in site-year 6 under OVR management (a hemp experiment in Manitoba) (Fig. 4.8, Supplemental Table 4.2). While results were field specific, the average increase across all site years when adopting OVR management, over FCR, was \$45.82 ha^{-1}. Implementing OFPE usually cost the farmer on average across all site-years \$5.91 ha^{-1}. In site-years 2 and 10 the farmer actually made money from running the experiment(Supplemental Table 4.2).

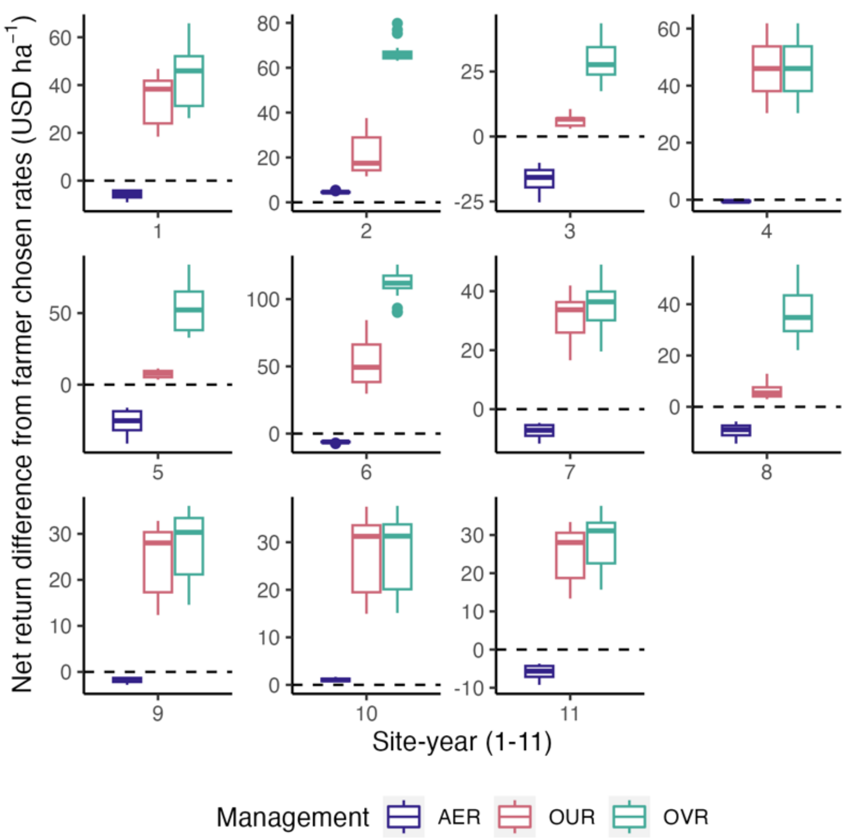


Figure 4.8. The average net returns for four different management strategies including actual experimental rates (AER), farmer chosen rates (FCR), optimum uniform rates (OUR), and optimum variable rates (OVR). All were shown relative to the FCR strategy, which here was set at \$0.00, and shown as a horizontal black dashed line. Each box represented a range of outcomes given our experimental or optimized rates on 20 years of historical economic data.

Discussion

Precision agriculture is underused in organic agriculture despite its strong potential to inform and refine crop management (Maxwell & Luschei, 2005a; McFadden et al., 2022; Schimmelpfennig & Lowenberg-DeBoer, 2020). Organic farmers do not have the advantage of variation suppressing chemicals in their toolbox, and this disadvantage leads to lower yields than conventional agriculture. Yet awareness of spatial variation in organic agroecosystems will allow precision agriculture technology and resultant data to uniquely benefit organic farms by helping to manage heterogeneity. While conventional farmers have seen relatively small gains in variable rate technology (Bullock et al., 2020; Lawrence et al., 2015; Pedersen & Lind, 2017), we find here substantial possibilities for increased net returns for organic farmers using PA. In conventional systems optimized input rates, such as soybean seed or nitrogen fertilizer, have been inconsistent, showing both increases and decreases of input rates when optimized (Hegedus, Ewing, et al., 2022; Rothrock et al., 2022). In our study optimized variable rate treatments (OVR) provided the greatest increase in net return over the optimized uniform (OUR) strategy, but both were more profitable than the farmer chosen rates. These results largely confirm our hypothesis and findings from conventional systems (Bullock et al., 2020; Hegedus & Maxwell, 2022), that the OFPE method is applicable in organic systems. Average increases across our study sites found an average increase across all tested fields and all tested years of \$45.82 ha^{-1}. Despite low adoption rates, organic farmers may benefit the most from precision agriculture.

Organic agriculture is predicated on the farm manager understanding the complex bioeconomic interactions in the agroecosystem. To gain agroecosystem understanding farmers rely on generational knowledge and personal experience about their land to make informed decisions. OFPE is the basis for bringing objectivity (science) into the decision process associated with applying inputs in these complex agroecosystems. The OFPE method encourages learning, and is not solely a decision making device (Bramley et al., 2022; Cook et al., 2018; Toffolini & Jeuffroy, 2022). To highlight the importance of the farmer we presented results that include the value of outcomes using, or not, using the OFPE approach, and how often one approach outperforms another. Additionally, we calculate the increased gain or loss in net return using the OFPE approach over the standard approach the farmer had arrived at on their own. Given all this information the farmer can decide whether to utilize the newly designed precision agriculture approach or not. There is considerable skepticism in the farm community regarding black box modeling and prescriptive software (Altieri & Nicholls, 2020; Daum, 2021). We therefore envisage future decision support tools which delineate possible outcome strategies, given known economic and climatic variability, in response to different input management strategies. A decision support tool which encouraged experimentation and attempted to augment farmer knowledge, rather than replace the farmer with an automated prescription, will be more successful in helping to create more sustainable organic farms (Prost et al., 2023). Ideally these tools would leave the management decisions up to the farmer but provide extra data and support that a farmer could use to improve decision making. The OFPE method encourages learning, not decision making in and of itself.

The primary drawback of this study and analysis was a lack of consistently repeated experiments over time. While organic farming has been found to have greater yield stability over time than conventional (Schrama et al., 2018), we nevertheless expect more data collection over time to improve the applicability of these models (Hegedus, Maxwell, et al., 2022). The models developed are time and site specific, though designed with enough flexibility to be updated to future conditions based on future remotely sensed variables (Hegedus et al., 2023). In this manner updated models ought to be able to make predictions based on real-time up to date field conditions, an important consideration in light of climate change (Lawrence et al., 2018). Nevertheless, the models are only trained on one season of climate data each and therefore in the future we expect to find greater variation in their outputs as they adjust to changing weather years. The point is exemplified in this study from fields experimented on during drought. Under drought conditions the lowest input rates were selected by the model as optimum, yet this was under anomalous conditions, and it would be expected to see higher rates as optima in wetter conditions. We could only effectively address temporal variability in this study by incorporating economic changes from year-to-year, and that alone was instructive to a decision maker, but climate data will add crucial information moving forward. Key to future research will be reproduction of these rainfed field-specific experiments to engage with temporal variability in yield in response to variable precipitation over years.

Another component of future work will be examining weeds in greater detail. Weeds are an important factor in organic production, and integrated weed management is becoming ever more important in conventional agriculture as well due to the negative effects of chemicals on the environment, and the rise of herbicide resistant weeds (Heap & Duke, 2018; MacLaren et al., 2020b; Monteiro & Santos, 2022). In this study weeds were treated as a prediction variable in the models but were not the focus of analysis. We maintained a focus of seeding rate’s impact directly on net return, however we recognize that organic farmers make other choices when conducting their operations that may favor long-term management of soil and weed seed banks and treat these with greater importance than short term net return. Indeed, we often found that reducing seeding rates led to higher net returns, but an organic farmer may in fact wish to maintain higher seeding rates than necessary across their fields to increase competition with weeds and reduction of weed seed production that can increase future weed densities (Merfield, 2019). Future projects could therefore examine weed abundance as a response variable as well as crop yield to minimize the tradeoff between reduced crop yield and long-term benefit of reduced weed seed production.

Conclusion

By experimenting with varied input rates across individual organic fields, optimized rates different than the FCR were found to maximize net return. The OFPE approach resulted in increased economic returns for organic farmers. In addition, our study demonstrated how farmers can decide if precision agriculture technology is a good investment for them and is useful for researchers to form the basis for development and deployment of new decision support tools designed specifically for organic farmers. The primary limitation in this study was a lack of repetition over time, but future work will repeat experiments and generate understanding of temporal variability. By optimizing organic agricultural inputs with precision agriculture tools we are enabling decision making that responds to field-specific spatial and temporal variability. Where uncertainty in economics and climate are becoming increasingly intense, an adaptive management tool like OFPE can provide up-to-date information that can empower organic farmers managing large scale farms to continue high levels of quality production under uncertain conditions. Agroecological practitioners can harness the power of precision agricultural tools to lead the way in both sustainable and high-tech farming.

References

Altieri, M. A., & Nicholls, C. I. (2020). Agroecology and the reconstruction of a post-COVID-19 agriculture. *The Journal of Peasant Studies*, *47*(5), 881–898. https://doi.org/10.1080/03066150.2020.1782891

Bertramsen, S. K., & Dobbs, T. L. (2002). An Update on prices of Organic Crops in Comparison to Conventional Crops.

Bramley, R. G. V., Song, X., Colaço, A. F., Evans, K. J., & Cook, S. E. (2022). Did someone say "farmer-centric"? Digital tools for spatially distributed on-farm experimentation. *Agronomy for Sustainable Development*, *42*(6), 105. https://doi.org/10.1007/s13593-022-00836-x

Bullock, D. S., Boerngen, M., Tao, H., Maxwell, B., Luck, J. D., Shiratsuchi, L., et al. (2019). The Data-Intensive Farm Management Project: Changing Agronomic Research Through On-Farm Precision Experimentation. *Agronomy Journal*, *111*(6), 2736–2746. https://doi.org/10.2134/agronj2019.03.0165

Bullock, D. S., Mieno, T., & Hwang, J. (2020). The value of conducting on-farm field trials using precision agriculture technology: a theory and simulations. *Precision Agriculture*, *21*(5), 1027–1044. https://doi.org/10.1007/s11119-019-09706-1

Carr, P. M., Cavigelli, M. A., Darby, H., Delate, K., Eberly, J. O., Fryer, H. K., et al. (2020). Green and animal manure use in organic field crop systems. *Agronomy Journal*, *112*(2), 648–674. https://doi.org/10.1002/agj2.20082

Cassman, K. G., & Grassini, P. (2020). A global perspective on sustainable intensification research. *Nature Sustainability*, *3*(4), 262–268. https://doi.org/10.1038/s41893-020-0507-8

Cook, S. E., & Bramley, R. G. V. (1998). Precision agriculture — opportunities, benefits and pitfalls of site-specific crop management in Australia. *Australian Journal of Experimental Agriculture*, *38*(7), 753. https://doi.org/10.1071/EA97156

Cook, S., Lacoste, M., Evans, F., Ridout, M., Gibberd, M., & Oberthür, T. (2018). An On-Farm Experimental philosophy for farmer-centric digital innovation.

Daum, T. (2021). Farm robots: ecological utopia or dystopia? *Trends in Ecology & Evolution*, *36*(9), 774–777. https://doi.org/10.1016/j.tree.2021.06.002

Duff, H., Hegedus, P. B., Loewen, S., Bass, T., & Maxwell, B. D. (2021). Precision Agroecology. *Sustainability*, *14*(1), 106. https://doi.org/10.3390/su14010106

Esposito, M., Crimaldi, M., Cirillo, V., Sarghini, F., & Maggio, A. (2021). Drone and sensor technology for sustainable weed management: a review. *Chemical and Biological Technologies in Agriculture*, *8*(1), 18. https://doi.org/10.1186/s40538-021-00217-8

Eyhorn, F., Muller, A., Reganold, J. P., Frison, E., Herren, H. R., Luttikholt, L., et al. (2019). Sustainability in global agriculture driven by organic farming. *Nature Sustainability*, *2*(4), 253–255. https://doi.org/10.1038/s41893-019-0266-6

Gomiero, T. (2018). Food quality assessment in organic vs. conventional agricultural produce: Findings and issues. *Applied Soil Ecology*, *123*, 714–728. https://doi.org/10.1016/j.apsoil.2017.10.014

Guaci, A., Fulton, J. P., Lindsey, A., Shearer, S., Barker, D., & Hawkins, E. (2022). Limitations of Yield Monitor Data to Support Field-scale Research. In *Proceedings of the 15th International Conference on Precision Agriculture, Minneapolis, USA* (Vol. 28).

Hatfield, J. L., Cryder, M., & Basso, B. (2020). Remote Sensing: Advancing the Science and the Applications to Transform Agriculture. *IT Professional*, *22*(3), 42–45. Presented at the IT Professional. https://doi.org/10.1109/MITP.2020.2986102

Heap, I., & Duke, S. O. (2018). Overview of glyphosate-resistant weeds worldwide: Overview of glyphosate-resistant weeds. *Pest Management Science*, *74*(5), 1040–1049. https://doi.org/10.1002/ps.4760

Hegedus, P. B., Ewing, S., Jones, C., & Maxwell, B. D. (2022). *Using spatially variable nitrogen application and crop responses to evaluate crop nitrogen use efficiency* (preprint). In Review. https://doi.org/10.21203/rs.3.rs-2126328/v1

Hegedus, P. B., & Maxwell, B. D. (2022). Rationale for field-specific on-farm precision experimentation. *Agriculture, Ecosystems & Environment*, *338*, 108088. https://doi.org/10.1016/j.agee.2022.108088

Hegedus, P. B., Maxwell, B. D., & Mieno, T. (2022). Assessing performance of empirical models for forecasting crop responses to variable fertilizer rates using on-farm precision experimentation. *Precision Agriculture*. https://doi.org/10.1007/s11119-022-09968-2

Hegedus, P. B., Maxwell, B., Sheppard, J., Loewen, S., Duff, H., Morales-Luna, G., & Peerlinck, A. (2023). Towards a Low-Cost Comprehensive Process for On-Farm Precision Experimentation and Analysis. *Agriculture*, *13*(3), 524. https://doi.org/10.3390/agriculture13030524

Hiemstra, P., & Skoien, J. O. (2023). automap: Automatic Interpolation Package. https://CRAN.R-project.org/package=automap. Accessed 7 March 2023

International Society of Precision Agriculture. (2021). https://www.ispag.org/about/definition. Accessed 29 January 2023

Kuhn M., cre, Wickham, H., & RStudio. (2022). tidymodels: Easily Install and Load the "Tidymodels" Packages. https://CRAN.R-project.org/package=tidymodels. Accessed 7 March 2023

Kursa, M. B., & Rudnicki, W. R. (2010). Feature Selection with the **Boruta** Package. *Journal of Statistical Software*, *36*(11). https://doi.org/10.18637/jss.v036.i11

Lacoste, M., Cook, S., McNee, M., Gale, D., Ingram, J., Bellon-Maurel, V., et al. (2021). On-Farm Experimentation to transform global agriculture. *Nature Food*, *3*(1), 11–18. https://doi.org/10.1038/s43016-021-00424-4

Lawrence, P. G., Maxwell, B. D., Rew, L. J., Ellis, C., & Bekkerman, A. (2018). Vulnerability of dryland agricultural regimes to economic and climatic change. *Ecology and Society*, *23*(1), art34. https://doi.org/10.5751/ES-09983-230134

Lawrence, P. G., Rew, L. J., & Maxwell, B. D. (2015). A probabilistic Bayesian framework for progressively updating site-specific recommendations. *Precision Agriculture*, *16*(3), 275–296. https://doi.org/10.1007/s11119-014-9375-4

Loewen, S., Maxwell, B. D. (2023). *Optimizing organic cover crop seeding rates and following cash crops to maximize net return in a controlled environment*. Manuscript submitted for publication.

MacLaren, C., Storkey, J., Menegat, A., Metcalfe, H., & Dehnen-Schmutz, K. (2020). An ecological future for weed science to sustain crop production and the environment. A review. *Agronomy for Sustainable Development*, *40*(4), 24. https://doi.org/10.1007/s13593-020-00631-6

Mattivi, P., Pappalardo, S. E., Nikolić, N., Mandolesi, L., Persichetti, A., De Marchi, M., & Masin, R. (2021). Can Commercial Low-Cost Drones and Open-Source GIS Technologies Be Suitable for Semi-Automatic Weed Mapping for Smart Farming? A Case Study in NE Italy. *Remote Sensing*, *13*(10), 1869. https://doi.org/10.3390/rs13101869

Maxwell, B. D., & Luschei, E. C. (2005). Justification for site-specific weed management based on ecology and economics. *Weed Science*, *53*(2), 221–227. https://doi.org/10.1614/WS-04-071R2

McFadden, J. R., Rosburg, A., & Njuki, E. (2022). Information inputs and technical efficiency in midwest corn production: evidence from farmers' use of yield and soil maps. *American Journal of Agricultural Economics*, *104*(2), 589–612. https://doi.org/10.1111/ajae.12251

Meemken, E.-M., & Qaim, M. (2018). Organic Agriculture, Food Security, and the Environment. *Annual Review of Resource Economics*, *10*(1), 39–63. https://doi.org/10.1146/annurev-resource-100517-023252

Merfield, C. N. (2019). Chapter 5 - Integrated Weed Management in Organic Farming. In S. Chandran, M. R. Unni, & S. Thomas (Eds.), *Organic Farming* (pp. 117–180). Woodhead Publishing. https://doi.org/10.1016/B978-0-12-813272-2.00005-7

Miller, P. R., Lighthiser, E. J., Jones, C. A., Holmes, J. A., Rick, T. L., & Wraith, J. M. (2011). Pea green manure management affects organic winter wheat yield and quality in semiarid Montana. *Canadian Journal of Plant Science*, *91*(3), 497–508. https://doi.org/10.4141/cjps10109

Mitchell, S., Weersink, A., & Erickson, B. (2018). Adoption of precision agriculture technologies in Ontario crop production. *Canadian Journal of Plant Science*, *98*(6), 1384–1388. https://doi.org/10.1139/cjps-2017-0342

Monteiro, A., & Santos, S. (2022). Sustainable Approach to Weed Management: The Role of Precision Weed Management. *Agronomy*, *12*(1), 118. https://doi.org/10.3390/agronomy12010118

Pebesma, E., & Graeler, B. (2022, October 19). gstat: Spatial and Spatio-Temporal Geostatistical Modelling, Prediction and Simulation. https://CRAN.R-project.org/package=gstat. Accessed 7 March 2023

Pedersen, S. M., & Lind, K. M. (Eds.). (2017). *Precision Agriculture: Technology and Economic Perspectives*. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-68715-5

Pellegrini, P., & Fernández, R. J. (2018). Crop intensification, land use, and on-farm energy-use efficiency during the worldwide spread of the green revolution. *Proceedings of the National Academy of Sciences*, *115*(10), 2335–2340. https://doi.org/10.1073/pnas.1717072115

Piepho, H.-P., Richter, C., Spilke, J., Hartung, K., Kunick, A., Thöle, H., et al. (2011). Statistical aspects of on-farm experimentation. *Crop and Pasture Science*, *62*(9), 721–735. https://doi.org/10.1071/CP11175

Pollnac, F. W., Maxwell, B. D., & Menalled, F. D. (2009). Using Species-Area Curves to Examine Weed Communities in Organic and Conventional Spring Wheat Systems. *Weed Science*, *57*(3), 241–247. https://doi.org/10.1614/WS-08-159.1

Pretty, J. (2018). Intensification for redesigned and sustainable agricultural systems. *Science*, *362*(6417), eaav0294. https://doi.org/10.1126/science.aav0294

Pringle, M. J., McBratney, A. B., & Cook, S. E. (2004). Field-Scale Experiments for Site-Specific Crop Management. Part II: A Geostatistical Analysis. *Precision Agriculture*, *5*(6), 625–645. https://doi.org/10.1007/s11119-004-6347-0

Prost, L., Martin, G., Ballot, R., Benoit, M., Bergez, J.-E., Bockstaller, C., et al. (2023). Key research challenges to supporting farm transitions to agroecology in advanced economies. A review. *Agronomy for Sustainable Development*, *43*(1), 11. https://doi.org/10.1007/s13593-022-00855-8

R Core Team. (2022). R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/

Robert, P. (1993). Characterization of soil conditions at the field level for soil specific management. *Geoderma*, *60*(1–4), 57–72. https://doi.org/10.1016/0016-7061(93)90018-G

Rodriguez, D. G. P., Bullock, D. S., & Boerngen, M. A. (2019). The Origins, Implications, and Consequences of Yield-Based Nitrogen Fertilizer Management. *Agronomy Journal*, *111*(2), 725–735. https://doi.org/10.2134/agronj2018.07.0479

Rothrock, G. P., Sears, E. L., Poncet, A. M., Ross, W. J., & France, O. W. (2022). Drivers of Yield Variability in a Variable-Rate Seeding Experiment. *Agronomy*, 31–37.

Ruffo, M. L., Bollero, G. A., Bullock, D. S., & Bullock, D. G. (2006). Site-specific production functions for variable rate corn nitrogen fertilization. *Precision Agriculture*, *7*(5), 327–342. https://doi.org/10.1007/s11119-006-9016-7

Schimmelpfennig, D., & Lowenberg-DeBoer, J. (2020). Farm Types and Precision Agriculture Adoption: Crops, Regions, Soil Variability, and Farm Size. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3689311

Schrama, M., de Haan, J. J., Kroonen, M., Verstegen, H., & Van der Putten, W. H. (2018). Crop yield gap and stability in organic and conventional farming systems. *Agriculture, Ecosystems & Environment*, *256*, 123–130. https://doi.org/10.1016/j.agee.2017.12.023

Seufert, V., & Ramankutty, N. (2017). Many shades of gray—The context-dependent performance of organic agriculture. *Science Advances*, *3*(3), e1602638. https://doi.org/10.1126/sciadv.1602638

Seufert, V., Ramankutty, N., & Foley, J. A. (2012). Comparing the yields of organic and conventional agriculture. *Nature*, *485*(7397), 229–232. https://doi.org/10.1038/nature11069

Storey, J., Roy, D. P., Masek, J., Gascon, F., Dwyer, J., & Choate, M. (2016). A note on the temporary misregistration of Landsat-8 Operational Land Imager (OLI) and Sentinel-2 Multi Spectral Instrument (MSI) imagery. *Remote Sensing of Environment*, *186*, 121–122. https://doi.org/10.1016/j.rse.2016.08.025

Tantalaki, N., Souravlas, S., & Roumeliotis, M. (2019). Data-Driven Decision Making in Precision Agriculture: The Rise of Big Data in Agricultural Systems. *Journal of Agricultural & Food Information*, *20*(4), 344–380. https://doi.org/10.1080/10496505.2019.1638264

Thornton, M. M., Shrestha, R., Wei, Y., Thornton, P. E., Kao, S.-C., & Wilson, B. E. (2022). Daymet: Annual Climate Summaries on a 1-km Grid for North America, Version 4 R1. *ORNL DAAC*. https://doi.org/10.3334/ORNLDAAC/2130

Tilman, D., Balzer, C., Hill, J., & Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences*, *108*(50), 20260–20264. https://doi.org/10.1073/pnas.1116437108

Toffolini, Q., & Jeuffroy, M.-H. (2022). On-farm experimentation practices and associated farmer-researcher relationships: a systematic literature review. *Agronomy for Sustainable Development*, *42*(6), 114. https://doi.org/10.1007/s13593-022-00845-w

Trémas, T. L., Déchoz, C., Lacherade, S., Nosavan, J., & Petrucci, B. (2015). Sentinel-2: presentation of the CAL/VAL commissioning phase. In *Image and Signal Processing for Remote Sensing XXI* (Vol. 9643, pp. 94–106). Presented at the Image and Signal Processing for Remote Sensing XXI, SPIE. https://doi.org/10.1117/12.2194847

USDA ERS - Commodity Costs and Returns. (2022). https://www.ers.usda.gov/data-products/commodity-costs-and-returns/commodity-costs-and-returns/#Cost-of-Production%20Forecasts. Accessed 29 January 2023

Weersink, A., Fraser, E., Pannell, D., Duncan, E., & Rotz, S. (2018). Opportunities and Challenges for Big Data in Agricultural and Environmental Analysis. *Annual Review of Resource Economics*, *10*(1), 19–37. https://doi.org/10.1146/annurev-resource-100516-053654

Wezel, A., Bellon, S., Doré, T., Francis, C., Vallod, D., & David, C. (2009). Agroecology as a science, a movement and a practice. A review. *Agronomy for Sustainable Development*, *29*(4), 503–515. https://doi.org/10.1051/agro/2009004

Wezel, Alexander, Soboksa, G., McClelland, S., Delespesse, F., & Boissau, A. (2015). The blurred boundaries of ecological, sustainable, and agroecological intensification: a review. *Agronomy for Sustainable Development*, *35*(4), 1283–1295. https://doi.org/10.1007/s13593-015-0333-y

Wright, M. N., & Ziegler, A. (2017). ranger: A Fast Implementation of Random Forests for High Dimensional Data in C++ and R. *Journal of Statistical Software*, *77*, 1–17. https://doi.org/10.18637/jss.v077.i01

Würriehausen, N., Ihle, R., & Lakner, S. (2015). Price relationships between qualitatively differentiated agricultural products: organic and conventional wheat in Germany. *Agricultural Economics*, *46*(2), 195–209. https://doi.org/10.1111/agec.12151

Appendix A

Supplemental Table 4.1. Economic variables for each crop over time.

Year	Crop	Seed Price (kg ha^{-1})	Fixed Costs (\$ ha^{-1})	Price Received (\$ kg^{-1})
2022	Spring Wheat	0.35	527.00	0.56
2021	Spring Wheat	0.35	459.68	0.42
2020	Spring Wheat	0.35	441.46	0.43
2019	Spring Wheat	0.36	446.06	0.46
2018	Spring Wheat	0.37	431.02	0.59
2017	Spring Wheat	0.33	423.65	0.59
2016	Spring Wheat	0.38	388.18	0.60
2015	Spring Wheat	0.41	399.53	0.64
2014	Spring Wheat	0.40	405.71	0.50
2013	Spring Wheat	0.40	397.17	0.39
2012	Spring Wheat	0.38	386.40	0.35
2011	Spring Wheat	0.33	366.84	0.58
2010	Spring Wheat	0.28	335.81	0.46
2009	Spring Wheat	0.34	336.67	0.47
2008	Spring Wheat	0.40	325.41	0.75
2007	Spring Wheat	0.25	285.97	0.54
2006	Spring Wheat	0.21	268.25	0.34
2005	Spring Wheat	0.21	258.53	0.30
2004	Spring Wheat	0.20	236.56	0.34
2003	Spring Wheat	0.19	238.46	0.34
2002	Spring Wheat	0.15	218.32	0.31
2001	Spring Wheat	0.16	228.80	0.30
2000	Spring Wheat	0.15	221.08	0.29
1999	Spring Wheat	0.16	206.32	0.33
1998	Spring Wheat	0.19	199.49	0.31
2022	Barley	0.59	604.54	0.59
2021	Barley	0.46	431.95	0.45
2020	Barley	0.46	410.20	0.46
2019	Barley	0.47	415.53	0.49
2018	Barley	0.55	436.57	0.63
2017	Barley	0.56	428.94	0.62

2016	Barley	0.56	427.16	0.64
2015	Barley	0.58	438.38	0.68
2014	Barley	0.53	448.99	0.53
2013	Barley	0.53	440.04	0.42
2012	Barley	0.50	429.73	0.37
2011	Barley	0.39	409.98	0.62
2010	Barley	0.31	404.14	0.49
2009	Barley	0.36	404.08	0.50
2008	Barley	0.37	394.36	0.80
2007	Barley	0.26	343.75	0.57
2006	Barley	0.24	315.21	0.36
2005	Barley	0.24	301.99	0.32
2004	Barley	0.24	275.81	0.36
2003	Barley	0.25	267.07	0.36
2002	Barley	0.24	143.71	0.33
2001	Barley	0.25	154.34	0.32
2000	Barley	0.24	143.39	0.31
1999	Barley	0.24	138.20	0.35
1998	Barley	0.26	136.60	0.33
2022	Oat	0.83	663.60	0.48
2021	Oat	0.58	519.24	0.36
2020	Oat	0.58	496.76	0.37
2019	Oat	0.59	502.11	0.39
2018	Oat	0.60	485.10	0.50
2017	Oat	0.61	475.84	0.50
2016	Oat	0.62	473.16	0.51
2015	Oat	0.63	487.46	0.55
2014	Oat	0.55	393.45	0.42
2013	Oat	0.54	383.83	0.34
2012	Oat	0.52	370.82	0.30
2011	Oat	0.43	350.63	0.49
2010	Oat	0.40	320.61	0.39
2009	Oat	0.42	315.91	0.40
2008	Oat	0.42	308.69	0.64
2007	Oat	0.35	279.64	0.46
2006	Oat	0.30	261.35	0.29
2005	Oat	0.28	250.23	0.26

2004	Oat	0.41	104.70	0.29
2003	Oat	0.42	98.42	0.29
2002	Oat	0.34	94.89	0.26
2001	Oat	0.34	102.14	0.26
2000	Oat	0.33	96.48	0.25
1999	Oat	0.34	90.22	0.28
1998	Oat	0.36	92.23	0.27
2022	Winter Wheat	0.34	455.94	0.39
2021	Winter Wheat	0.34	397.70	0.29
2020	Winter Wheat	0.34	381.94	0.30
2019	Winter Wheat	0.35	385.92	0.32
2018	Winter Wheat	0.35	372.91	0.41
2017	Winter Wheat	0.32	366.53	0.41
2016	Winter Wheat	0.37	335.84	0.42
2015	Winter Wheat	0.39	345.66	0.45
2014	Winter Wheat	0.38	351.00	0.35
2013	Winter Wheat	0.38	343.62	0.27
2012	Winter Wheat	0.37	334.30	0.25
2011	Winter Wheat	0.32	317.38	0.40
2010	Winter Wheat	0.27	290.53	0.32
2009	Winter Wheat	0.33	291.28	0.33
2008	Winter Wheat	0.38	281.53	0.52
2007	Winter Wheat	0.24	247.41	0.37
2006	Winter Wheat	0.21	232.08	0.23
2005	Winter Wheat	0.20	223.67	0.21
2004	Winter Wheat	0.19	204.67	0.24
2003	Winter Wheat	0.19	206.31	0.24
2002	Winter Wheat	0.15	188.88	0.21
2001	Winter Wheat	0.15	197.95	0.21
2000	Winter Wheat	0.15	191.27	0.20
1999	Winter Wheat	0.15	178.50	0.23
1998	Winter Wheat	0.18	172.59	0.22
2022	Pea	0.63	498.12	NA
2021	Pea	0.63	434.49	NA
2020	Pea	0.63	417.27	NA
2019	Pea	0.64	421.62	NA
2018	Pea	0.65	407.40	NA

2017	Pea	0.59	400.44	NA
2016	Pea	0.68	366.91	NA
2015	Pea	0.72	377.63	NA
2014	Pea	0.71	383.47	NA
2013	Pea	0.71	375.40	NA
2012	Pea	0.68	365.23	NA
2011	Pea	0.58	346.74	NA
2010	Pea	0.49	317.41	NA
2009	Pea	0.61	318.22	NA
2008	Pea	0.71	307.57	NA
2007	Pea	0.45	270.30	NA
2006	Pea	0.38	253.55	NA
2005	Pea	0.37	244.36	NA
2004	Pea	0.35	223.60	NA
2003	Pea	0.34	225.39	NA
2002	Pea	0.28	206.36	NA
2001	Pea	0.28	216.26	NA
2000	Pea	0.27	208.96	NA
1999	Pea	0.28	195.02	NA
1998	Pea	0.33	188.56	NA
2022	Winter Wheat Bloodmeal*	0.47	484.42	0.39
2021	Winter Wheat Bloodmeal*	0.45	426.23	0.29
2020	Winter Wheat Bloodmeal*	0.44	410.60	0.30
2019	Winter Wheat Bloodmeal*	0.43	415.05	0.32
2018	Winter Wheat Bloodmeal*	0.42	402.51	0.41
2017	Winter Wheat Bloodmeal*	0.41	393.42	0.41
2016	Winter Wheat Bloodmeal*	0.39	366.71	0.42
2015	Winter Wheat Bloodmeal*	0.38	378.53	0.45
2014	Winter Wheat Bloodmeal*	0.37	383.10	0.35
2013	Winter Wheat Bloodmeal*	0.36	375.95	0.27
2012	Winter Wheat Bloodmeal*	0.34	365.45	0.25
2011	Winter Wheat Bloodmeal*	0.33	343.97	0.40
2010	Winter Wheat Bloodmeal*	0.32	313.03	0.32
2009	Winter Wheat Bloodmeal*	0.31	319.16	0.33
2008	Winter Wheat Bloodmeal*	0.30	313.63	0.52
2007	Winter Wheat Bloodmeal*	0.28	267.67	0.37
2006	Winter Wheat Bloodmeal*	0.27	249.35	0.23

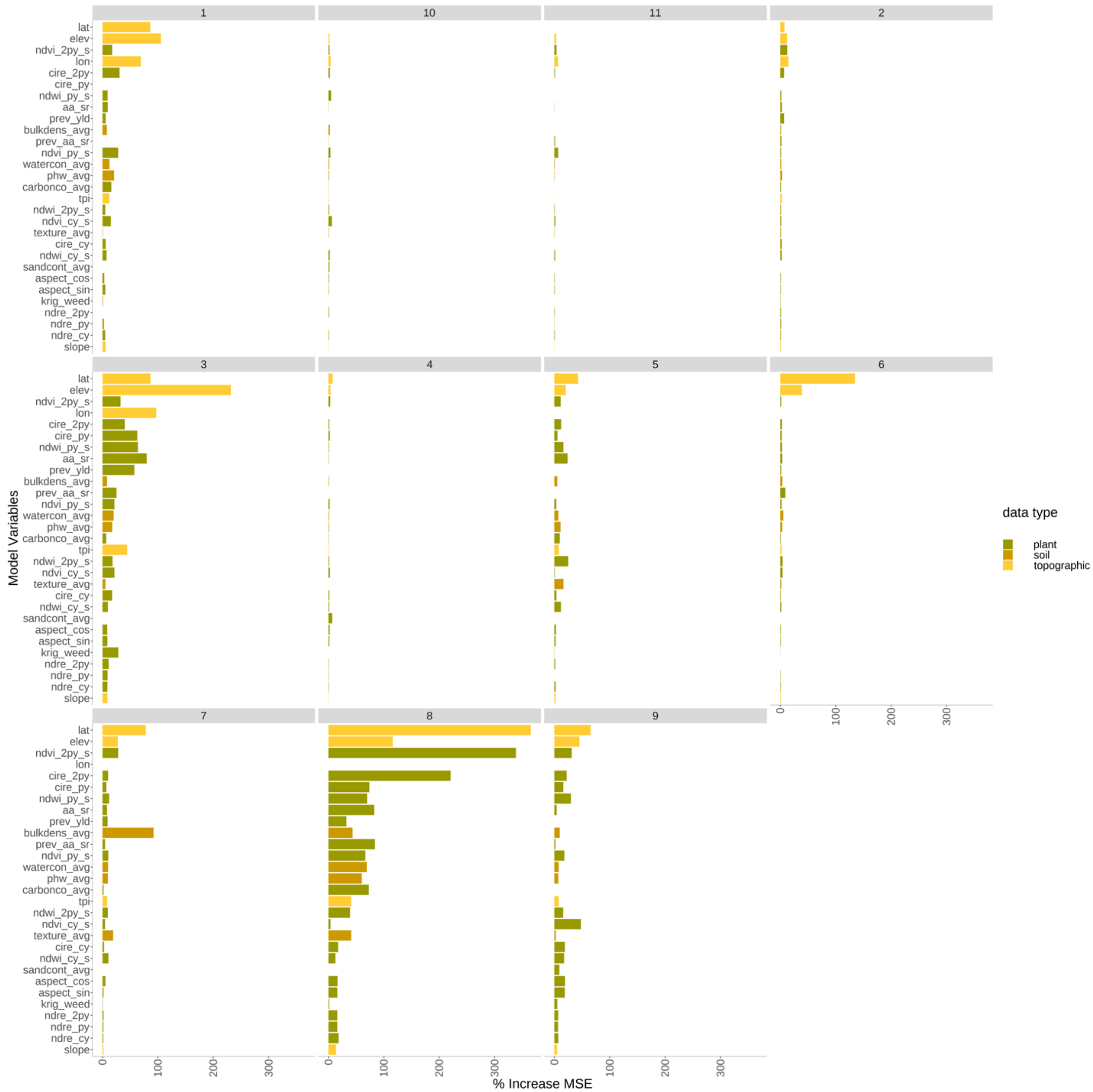
2005	Winter Wheat Bloodmeal*	0.26	240.46	0.21
2004	Winter Wheat Bloodmeal*	0.25	220.65	0.24
2003	Winter Wheat Bloodmeal*	0.24	221.95	0.24
2002	Winter Wheat Bloodmeal*	0.22	201.43	0.21
2001	Winter Wheat Bloodmeal*	0.21	210.52	0.21
2000	Winter Wheat Bloodmeal*	0.20	203.54	0.20
1999	Winter Wheat Bloodmeal*	0.19	191.11	0.23
1998	Winter Wheat Bloodmeal*	0.18	187.74	0.22
2022	Hemp	3.28	534.67	3.59
2021	Hemp	3.25	466.37	2.59
2020	Hemp	3.21	447.89	2.55
2019	Hemp	2.99	452.56	2.52
2018	Hemp	3.18	437.30	2.44
2017	Hemp	3.72	429.82	3.04
2016	Hemp	3.51	393.83	2.87
2015	Hemp	3.99	405.35	2.67
2014	Hemp	4.66	411.61	2.99
2013	Hemp	5.00	402.95	2.57
2012	Hemp	5.00	402.95	2.57
2011	Hemp	4.92	360.82	1.92
2010	Hemp	5.11	348.91	1.90
2009	Hemp	5.30	337.00	1.88
2008	Hemp	5.49	325.09	1.87
2007	Hemp	5.68	313.18	1.85
2006	Hemp	5.87	301.27	1.83
2005	Hemp	6.06	289.36	1.81
2004	Hemp	6.25	277.45	1.79
2003	Hemp	6.44	265.54	1.77
2002	Hemp	6.63	253.63	1.76
2001	Hemp	6.82	241.72	1.74
2000	Hemp	7.01	229.81	1.72
1999	Hemp	7.20	217.90	1.70
1998	Hemp	7.39	205.99	1.68

*Shows cost of bloodmeal rather than seed

Supplemental Table 4.2. Predicted net returns from four management strategies including actual experimental rate (AER), farmer chosen rate (FCR), optimum uniform rate (OUR), and optimum variable rate (OVR), each shown here for the economic data from the harvest year of that crop. Also shown are the average yields and average seeding rates across each site-year in each management strategy.

Site-year	Management	Predicted Yield	Predicted Net Return	Seed Rate Previous Year	Seed Rate Current Year
1	AER	3.48355	1208.2736	NA	236.5099
1	FCR	3.497	1213.88285	NA	236.5099
1	OUR	3.51045	1248.27731	NA	144.5961
1	OVR	3.55449875	1258.08453	NA	173.027729
2	AER	0.598525	622.761987	NA	30.15221
2	FCR	0.5918	618.168562	NA	30.15221
2	OUR	0.611975	639.620613	NA	34.7479
2	OVR	0.62845125	685.355907	NA	30.477271
3	AER	5.7835	832.585269	NA	115.34061
3	FCR	5.857475	848.858131	NA	115.34061
3	OUR	5.85075	854.757785	NA	103.34698
3	OVR	5.96742875	877.516065	NA	107.757722
4	AER	1.082725	-21.570687	NA	28.24668
4	FCR	1.08945	-21.024469	NA	28.24668
4	OUR	1.08945	24.982699	NA	0
4	OVR	1.08945	24.9925853	NA	0
5	AER	3.006075	990.590707	NA	187.41448
5	FCR	3.059875	1015.63025	NA	187.41448
5	OUR	3.05315	1023.05981	NA	153.5633
5	OVR	3.1627675	1067.27879	NA	174.29995
6	AER	0.948225	1257.48764	NA	38.1106
6	FCR	0.95495	1263.78028	NA	38.1106
6	OUR	0.942845	1317.03658	NA	23.76308
6	OVR	0.98689375	1374.67746	NA	27.831947
7	AER	3.0935	1048.14385	NA	182.48252
7	FCR	3.10695	1055.43623	NA	182.48252
7	OUR	3.127125	1086.58304	NA	108.7273
7	OVR	3.14158375	1090.27187	NA	116.837012
8	AER	5.93145	860.975037	NA	124.08363
8	FCR	5.9718	870.186604	NA	124.08363
8	OUR	6.018875	876.277805	NA	133.3871
8	OVR	6.12244	906.303757	NA	119.471127

9	AER	3.48355	748.210578	114.10762	79.47181
9	FCR	3.48355	749.971577	114.10762	79.47181
9	OUR	3.48355	774.981463	78.463	54.9241
9	OVR	3.49800875	777.724913	78.463	54.9241
10	AER	0.57835	-237.89298	104.13161	83.28287
10	FCR	0.571625	-238.93969	104.13161	83.28287
10	OUR	0.57835	-211.01705	67.254	67.254
10	OVR	0.5790225	-210.75877	67.254	67.254
11	AER	1.81575	187.238013	143.13893	78.57509
11	FCR	1.8292	193.012852	143.13893	78.57509
11	OUR	1.84265	218.234058	102.78653	79.5839
11	OVR	1.8561	221.583045	102.78653	79.5839



Supplemental Figure 4.1. Variable importance plots for all eleven site-year models.

CHAPTER FIVE

ORGANIC WEED MANAGEMENT USING PRECISION SEEDING RATES

Abstract

Integrated weed management is integral to organic farming, with increased crop seeding rates as one effective weed suppression tactic. Precision agriculture, uses guidance and sensor technologies to direct site-specific management, could allow for targeted weed management using variable seeding rates. On farm precision experimentation (OFPE) can be used to predict sub-field weed biomass response to a range of varied seed rates across whole fields. We used OFPE to compare five simulated precision seeding strategies based on maximizing net returns, minimizing weed biomass, and compared them to farmer-chosen rates. Five site-years of OFPE data were collected from organic farms in Manitoba, Canada and Montana, USA. Seeding rate, weed biomass, crop yield, topographic variables and other remotely sensed data were collected on a 10 m superimposed grid for each field to model site-specific and full-field uniform seeding rates for each field. Site-specific variable seeding rate net returns improved farmer chosen uniform seeding rate net returns on average by \$115 ha^{-1}. When variable seeding rates were set to minimize weed biomass, weeds were reduced on average by nearly 10 kg ha^{-1} compared to the farmer chosen uniform seed rates. An optimized site-specific seeding strategy to balance net return and weed minimization improved net return and weed suppression compared to farmer-chosen seeding rates in every site-year. We present these results as a list of options for farmers to consider as result of OFPE implementation to increase their field-scale ecological knowledge and of sub-field specific, optimized planting rates.

Introduction

Organic agriculture is expanding in acreage across the world to meet rising consumer demand and achieve environmental conservation goals (Eyhorn et al., 2019). Organic management practices forgo the use of synthetic chemical inputs, and instead rely on knowledge of biological interactions to manage complex agroecosystems (Hammermeister, 2020). One of the most important yet contentious interactions in organic systems is weed and crop plant interactions, as weeds are often cited as the primary reason for lower organic crop yields compared to conventional high input agroecosystems (Benaragama et al., 2016). Therefore, studying crop-weed interactions, and how to best manage them without herbicide inputs, is of prime research importance to improve organic production. Precision agriculture represents a new set of technologically advanced tools that are under-utilized in organic systems (Duff et al., 2021). We envision precision agriculture technology as a tool to collect and analyze novel data sets to improve understanding of variability within organic crop systems, thereby improving management by working with the variability. While technology advances have often been shunned by organic farmers, there are potential benefits to employing the precision agriculture technology in organic systems, particularly to assess and manage weed populations.

Organic farmers rely on integrated weed management (IWM) to reduce weed pressures and produce crops. IWM began as a concept to help conventional farmers reduce their reliance on chemical herbicides, and relies on two fundamental principles: understanding the underlying agroecological system, and deploying multiple tactics to manage weeds (Liebman et al., 1997). IWM is not a one-size fits all approach, and rather seeks understanding of local ecosystem function in order to reduce weed growth and reproduction where necessary (Buhler et al., 2000).

Through this knowledge a farmer can sustainably manage weeds with a variety of resources including well-timed mechanical operations, increased cropping diversity, cover cropping, and increased seeding rates (Lemerle, 2004). In these ways, the farmer can also learn where and when weed management is ineffective, unnecessary, or even counter to their primary goal of crop production (Maxwell, 2017). Weeds have been shown to reduce worldwide crop production by 34% (Oerke, 2006), but the effect of weeds on crops is highly variable on a site-by-site basis, as it is influenced by many genetic, environment and management effects (MacLaren et al., 2020). Thus, a core tenet of IWM is knowledge of these interactions to improve management. One way to improve this process is to automate precision agricultural data collection and analysis so that farmers can utilize readily available data sources to augment their knowledge of local ecosystems and plan their IWM strategies accordingly (Korres et al., 2019; van Evert et al., 2017).

Over the last several decades the field of precision agriculture has seen vast increases in technology, accuracy, and data collection (Weersink et al., 2018). Yet farmers are reticent to fully adopt the technology. Yield maps and autosteer have been widely adopted by Western farmers (McFadden et al., 2022), but the revolutionary aspects of precision agriculture, notably variable rate application (Robert, 1993), have seen only mild implementation. The primary failure has been a lack of effective decision support tools that work in local environments (Hegedus et al., 2023). General input recommendations are typically provided by agronomic research stations that may be over a hundred miles from the fields where they are to be applied (Rodriguez et al., 2019). One solution to this issue is a process known as On Farm Precision Experimentation (OFPE), where experiments are conducted in the very fields where inputs are to be applied, using multiple years of experiments to improve site-specific recommendations (Hegedus et al., 2023). Formal on farm experimentation has been around for decades (Cook & Bramley, 1998; Ruffo et al., 2006) but broader uptake of the practice is recently gaining traction due to more affordable and user-friendly technology (Lacoste et al., 2021). Precision agriculture equipment, now owned and under-utilized by many farmers, allows for experimental prescription rates to be deployed, and harvest data collected with very little additional effort by the farmer. Thus, a farmer can experiment on their fields, understanding that every field has its own unique history, and develop field-specific input rates for specific goals such as maximum net return or minimizing weed pressure.

IWM can use the OFPE method to develop greater ecosystem understanding of site-specific biological relationships present in organic agriculture. Through OFPE a farmer can develop IWM in a site-specific nature leading to precision weed management (PWM) (Maxwell & Luschei, 2005; Pollnac et al., 2008; Somerville et al., 2020). Weeds are heterogenous across fields and respond to soil variation and topographic variation similar to crops, lending themselves to the potential of site-specific management (Gerhards et al., 2022). PWM is often thought of as a method to spray herbicides only where weeds are detected to reduce ecosystem contamination and slow herbicide resistance (Partel et al., 2019). More broadly it is any method of weed management that functions in a site-specific manner, for example through mechanical weed control like precision guided inter-row cultivation, or patch-mowing perennial weeds. Organic agriculture tends to use increased seeding rates of cover crop and cash crops as a method of IWM. It is often true, and generally assumed by organic farmers, that increased seeding rates will suppress weeds (Cherr et al., 2006; Lemerle et al., 2004). However, organic weeds respond to seeding densities in a site-specific manner (Weiner, 2023), and it is our aim to provide a method to farmers to explore and understand the spatial and temporal relationships between weeds and their environment using OFPE.

We compared several seeding rate optimization strategies based on managing for maximized net return or managing for minimized weed biomass. Our hypothesis is that spatial variability can be found across each field, tested such that seeding rates can have an impact on weeds and net return, and that certain strategies will result in multiple optima, depending on a farmer's preferred management strategy. Our objectives are 1) to develop variable seeding rate prescriptions for every site-year using a variety of hypothetical strategies, 2) to quantify and compare each strategy in terms of weed biomass, and 3) net return (as an economic function of crop yield) to determine how often one strategy might outcompete another given historic economic variability. Through this process we aim to provide a method for organic farmers to harness the power of PA through OFPE to augment their ecological knowledge and determine their own field-specific, or sub-field specific, optimized planting rates.

Materials And Methods

OFPE Study Sites

On Farm Precision Experimentation (OFPE) was conducted across three fields in the Northern Great Plains (NGP) from 2019 to 2022 for a total of five site-years of individually analyzed field data. Objectives were to estimate and compare the net return and weed biomass in each field and year where variable crop seeding rates were applied as treatments to experimentally parameterize weed biomass and crop grain yield predictive models. The experimental approach followed the OFPE design (Hegedus et al. 2023). Each field was certified organic and managed by a farmer who collaborated in experimental design and data sharing with our research team. Fields A and B were part of the same farm in south-east Manitoba, and Field C was from a separate farm in north central Montana. Farmers chose the crops they would normally plant, including hemp (*Cannabis sativa*), spring and winter wheat (*Triticum aestivum*), oats (*Avena sativa*), and pea (*Pisum sativum*). The pea was grown as a cover crop green manure plow down on Field C, whereas all other crops were harvested. Fields A and B received plant available nitrogen from chicken manure, spread uniformly each fall across each field; field C relied exclusively on green manure crops for nitrogen. Growing conditions on all fields were generally warm and dry in 2020 and 2021, and cool and wet in 2022 (Table 5.1).

Table 5.1. Field locations and relevant agronomic information where full field varied seeding rate experiments were carried out. Climate anomaly were calculated from a 30-year average (1991-2021) from Daymet (Thornton et al., 2022).

Site-year	Field	Year	CY Crop*	PY Crop**	Field Size (ha)	State / Province	Precipitation Anomaly (+/- mm)	GDD*** Anomaly (+/-C)
1	A	2021	Hemp	Spring Wheat	32	Manitoba	-111	+366
2	A	2022	Oat	Hemp	32	Manitoba	+151	-139
3	B	2020	Hemp	Spring Wheat	71	Manitoba	-159	+52
4	B	2021	Spring Wheat	Hemp	71	Manitoba	-115	+366
5	C	2021	Winter Wheat	Pea	93	Montana	-157	+278

* CY = current year; **PY = previous year; ***GDD = growing degree days base

Experimental Design and Data Collection

Each farmer selected the crop type and normal uniform application seeding rate for each field and experiments bracketed the farmer selected seeding rates (Loewen et al. *in review*). Prescription maps, readable by each farmers seeder machine and software, randomly placed varied seeding rates across the fields at 0.6x, 0.8x, 1.0x, 1.2x and 1.4x of the farmer’s stated normal seeding rate (x) in a checkerboard design (Fig. 5.1 panel A and B). Checkerboard designs were the preferred method of rate distribution however due to equipment or software malfunction in some instances farmers reverted to strip trials in which whole strips were planted at a single rate. In the event of machine or software failure, experiments could still be conducted manually using the full strip method, without a significant time burden on the farmer and still hold statistical significance when analyzed with regression (Piepho et al., 2011; Pringle et al., 2004).

Data were collected from machinery, and satellites, and aggregated to a 10 x 10m grid across each field with a 30m buffer to reduce impact of headlands and edge effects. As-applied maps were collected from the seeder application monitors to determine the actual input seed rates as they often varied in some way from prescription maps. Yield data were collected from combine mounted yield monitors. Satellite data were also collected for each field including topographic information and soil and plant indexes. Topographic information included elevation, slope, topographic position index (TPI), and aspect measured in eastness and northness (Amatulli et al., 2018). Satellite plant indexes included normalized difference vegetation index (NDVI), normalized difference red edge (NDRE), and chlorophyl index red edge (CIRE). Satellite soil indexes included normalized difference water index (NDWI), soil texture, bulk density, sand content, pH, soil water, and carbon content, and were collected from Google Earth Engine (GEE)(Supplemental Table 5.1)(Gorelick et al., 2017). The results of the analysis (i.e. strategy prescriptions as medians) were upscaled to a 24m x 120m cell, which represented the scale at which farm equipment can optimally deploy and collect results (Hegedus et al., 2023). These larger cell sizes are represented as rectangles in maps (Figure 5.1). Further details on OFPE including data collection and cleaning are described in Hegedus et al. (2023).

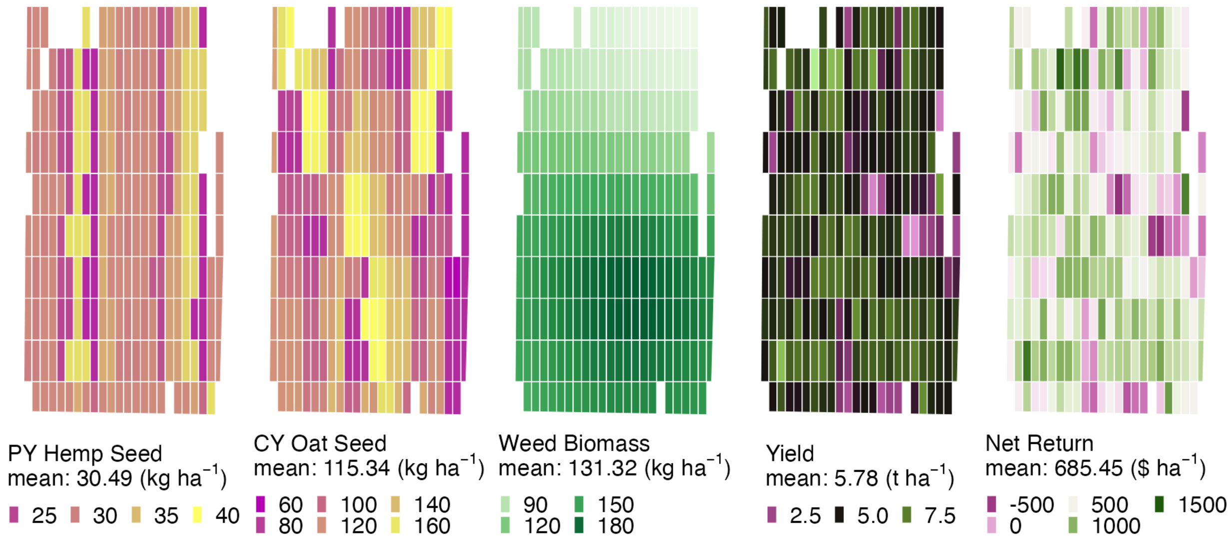


Figure 5.1. Experimental layout and data collection map of the OFPE method representing field A in 2021-2022. As-applied seeding rates of hemp and oat in 2021 and 2022, the resulting weed biomass collected mid-growing season, the yield collected by the combine harvester yield monitor at harvest, and the net return calculated based on these variables and USDA data (USDA ERS - Commodity Costs and Returns, 2023). Other data (not shown), including topographic information and satellite soil and plant indexes, were collected for every point on the field. PY = previous year; CY = current year.

Weed and crop biomass samples were collected from across every field approximately four weeks after crop emergence. Sample points included approximately two quadrat samples per hectare stratified randomly on underlying current-year seeding rate (Fig. 5.2). A 0.25m^2 circular quadrat was placed at each location, and the volumes of both the crop species and the top three most dominant weed species at that specific point were estimated following the method of Bussler et al. (1995). Researchers stood on either side of the quadrat and estimated the percent cover of the plant species within the circle, an average of these values was recorded, and the median height of the species was recorded. A cylindrical volume was thus attained from the plant height and area for each species in each quadrat. Additionally, the plants from a dozen random locations on a field were cut, collected, dried, and weighed to create a reliable relationship between plant volume and dried biomass (R^2 = 0.95, $p < 0.001$) (Supplemental Fig. 5.1). Any plant that was not intended for harvest that year was assessed as a weed (i.e. volunteer crops like wheat and sweet clover were included as weeds). As there were insufficient species-specific data points to spatially interpolate the values of each species across a whole field, weed values were summed to create one ‘all-weed species’ value for each point across each field. See supplemental for a complete list of weeds per field (Supplemental Fig. 5.1).

Sampled plant populations are typically related through spatial autocorrelation (Mathur, 2015). Moran’s I, a standard measurement of spatial autocorrelation, was calculated for the ‘all-weed species’ sample values from each field using the package “ape” in R (Paradis et al., 2023; R Core Team, 2022). Two site-years were dropped from further analysis as their weed values failed to show spatial correlation according to the Moran’s I criteria (alpha = 0.05) (Data not shown). Weed samples from the five remaining site-years (Fig. 5.2) were determined to have sufficient spatial structure to use ordinary kriging to interpolate weed values on all 10 x 10m grid points across each field. Kriging was conducted in R using package ‘automap’ to find the semi-variogram and ‘gstat’ to krige (Hiemstra & Skoien, 2023; Pebesma & Graeler, 2022).

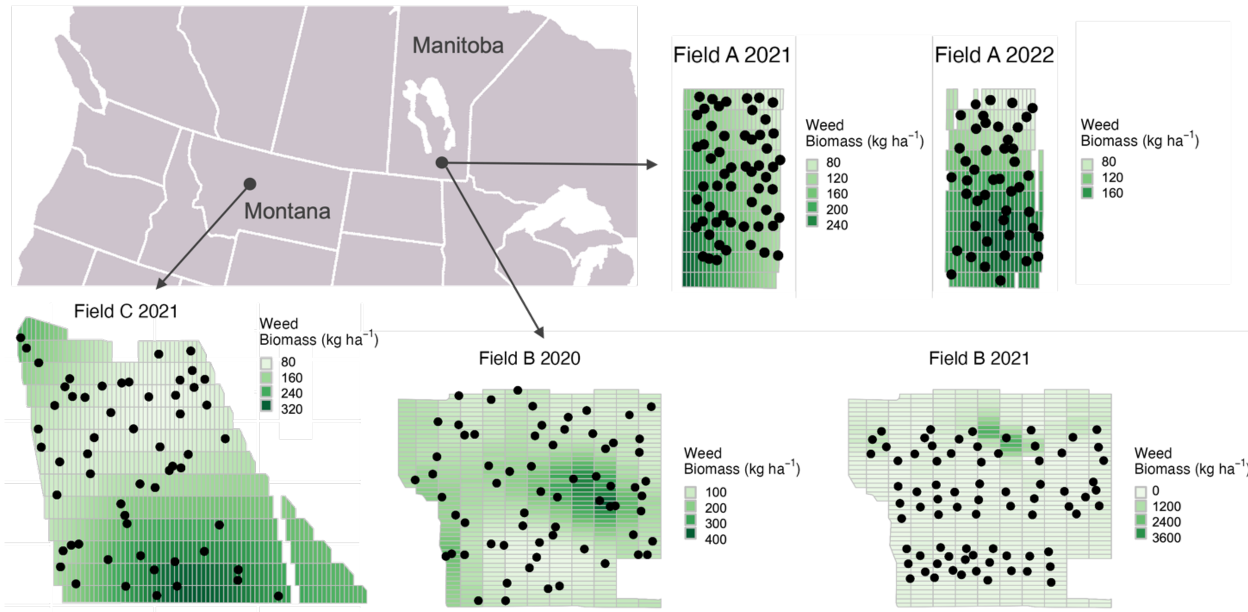


Figure 5.2. All five site-years of weed sample data are shown from across the NGP, including sites in Manitoba, Canada, and Montana, USA. Kriged weed biomass values are shown underlying weed sample points across each field. Field A was 32 ha, field B was 71 ha, and field C was 93 ha; rectangular cells on each field are 120m by 24m.

Crop and Weed Response Models

Random forest models were created for each site-year to predict crop yield and weed biomass as response variables to crop seeding rate and other GEE downloaded variables. Random forest modeling approach for crop yield with OFPE data was generally found to be best (lowest RMSE), relative to a number of other modeling techniques (Hegedus et al., 2022). The harvest year, referred to as 'current year', and previous year seeding rate data were used as predictors in both models. Initial variables in each model included all variables listed in data collection above. Random forest models were made with R package 'Rangers', and the hyperparameters were tuned with 'Tidymodels' (Kuhn & Wickham, 2022; Wright & Ziegler, 2017). The tuned values of 'mtry', the number of variables sampled at each node at each ensemble tree, ranged from nine to thirteen. The tuned values of 'ntree', the total number of trees in the ensemble, ranged from 100-500 depending on the site-year. To decrease computational time for the random forest to run and increase model interpretability, variables were identified to be removed from the models. Variables were selected for removal if they were found to be unimportant as classified by the random forest feature selection package 'Boruta' (Kursa & Rudnicki, 2010), if they had a VIF greater than 10, or if they were missing more than 30% of the data from across the field aggregation points. Each model was able to predict how previous year and current year seeding rates would affect the current year's yield, and the current year's weed biomass specific to each 10 x 10m grid cell across the field. The relationship of crop yield to seed rate, and weed biomass to seed rate, therefore varied for every grid cell across the field, allowing for site specific (each grid cell) optimization (Supplemental Fig. 5.3). Thus, a model was built to predict mean crop yield and mean weed biomass in each 10m x 10m grid cell across each field for each site-year's current and previous year's seeding rates.

Economic predictions

Net return (NR) was calculated from yield to determine the economic benefit of one strategy over another. The net return was calculated using the formula in equation 1 using economic information compiled from USDA and other sources (Würriehausen *et al.*, 2015; "USDA ERS - Commodity Costs and Returns," 2022; Bertramsen & Dobbs, 2002; Personal communication: Manitoba Harvest, 2022).

$$NR = Y * PR - (SR_1 * SC_1 + SR_2 * SC_2 + FC) \qquad \text{Equation (1)}$$

Where NR was the net return (USD ha^{-1}); Y was the predicted marketable yield (t ha^{-1}) of the harvested crop; PR was the price received for the crop (USD ha^{-1}) in the year of interest; SR_1 was the seed rate of the crop (kg ha^{-1}) in the harvest year and SC_1 was the cost of that crop's seed (USD ha^{-1}); SR_2 was the seed rate of the crop (kg ha^{-1}) in the year prior to harvest and SC_2 was the cost of that crop's seed (USD ha^{-1}); FC was the fixed cost associated with the harvest year's production (USD ha^{-1}) representing all other costs except planted seed. Net returns were calculated based on harvest year information, but were also estimated for the ten previous years to provide a distribution of economic outcomes a farmer might expect given economic variability in all the variables in Eqn. 1.

Optimization Strategies

Five seeding rate strategies were compared in this study based on full-field net returns ($ per field) to provide the probability that one would outcompete another given a range of historic economic prices received for crop and costs of seeds planted. All five simulated strategies were also compared to the realized ('actual') net return with the experiment in the field, which allowed determining the cost of obtaining the data to make all other comparisons and was not simulated and included the random varied experimental rates (Fig. 5.1). Strategies 1-5 represent simulated outcomes of both yield and weed biomass based on hypothetical seed rate strategies. Strategy 1 was based on each individual farmer-chosen seed rates ('farmer-chosen'). This strategy formed a baseline to compare to the other strategies. Strategy 2 was the seeding rate strategy a farmer would choose to maximize their NR using one uniform seed rate for each year across their full field based on the outcomes of OFPE ('max NR uniform'). Strategy 3 was the seeding rate strategy a farmer would choose to maximize their net return using site specific variable rates at a sub-field scale ('max NR variable'). Strategy 4 represented the site-specific crop seeding rates a farmer would choose to minimize weed biomass ('min weed'), rather than maximizing net return. Organic farmers might perceive strategy 3 as missing a weed management opportunity and therefore strategy 5 combined strategies 3 and 4 to capture strengths of each. Strategy 5 represented a hybrid approach between 3 and 4, where the field was split into managing the 80% containing the lowest weed biomass using the maximum net return strategy, and managing the 20% containing the most weed biomass using the minimum weed strategy. Strategy 5 targeted only the weediest areas of the field with variable seeding rates ('targeted').

Results

Site specific predictions

Relationships between seed rate and yield, seed rate and weed biomass, and yield and weed biomass, varied greatly across the field, highlighting the random forest's versatility in predicting varied outcomes based on complex driving variables. The abundance of data, and complexity in underlying relationships revealed relationships in response variables which could be predictable or unexpected. A standard agronomic model would predict a negative relationship between yield and weed biomass, and in certain points on the field this is what the model predicted, and yet on other sites on the field the opposite relationship was found (Fig. 5.4). Overall, the variable predictions of crop yield resulted in varied optimum seeding rates to maximize farmer profits or minimize weed biomass across each site-year.

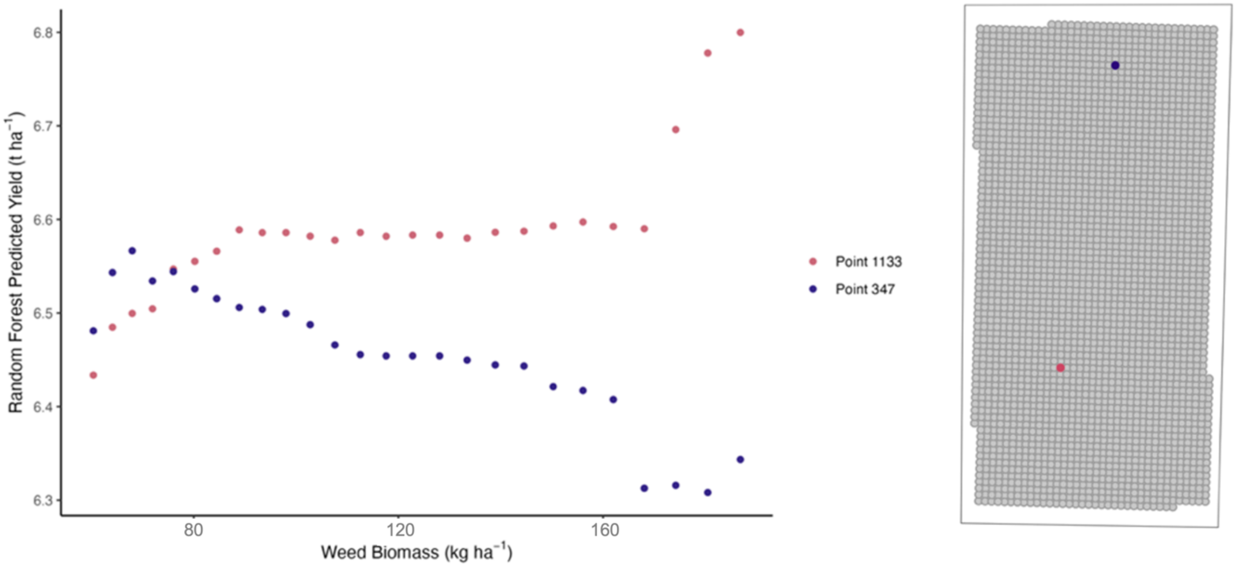


Figure 5.4. Predicted crop yield in response to weed biomass from the random forest model from two randomly chosen grid cells on field A (32 ha oat field) in 2022 demonstrating the variability in response to weed biomass.

Site-year 2 represented a range of predicted optimum seeding rates and resulting weed, yield, and net return outcomes under different seeding rate application strategies (Fig. 5.5 & 5.6). Using the max NR uniform rate strategy across site-year 2, predicted seeding rates were lower than the farmer-chosen rates. To achieve the max NR uniform rate strategy, the farmer was recommended to reduce previous year's hemp rates from 31 to 21 kg ha^{-1}, and the current year's oat rates from 115 kg ha^{-1} to 100 kg ha^{-1}. This change would result in a very small decline in weed biomass by 0.12 kg ha^{-1} and a small decline in crop yield of 0.01 t ha^{-1}. However, mean net return was shown to increase by \$49.91 ha^{-1} (Fig. 5.5, row 2). Results indicated that the max NR variable seeding rate strategy could further improve NR from the max NR uniform strategy by a mean of \$20.80 ha^{-1} (Fig. 5.6, row 1). The min weed seeding rate strategy (Fig. 5.6 row 2) increased seeding rates for the previous year, and decreased seeding rates for the current year relative to the farmer-chosen rates, and followed slightly different spatial patterns across the field than the max NR variable strategy. Weed biomass was reduced on average by 1.08 kg ha^{-1} under the min weed strategy on Field A and the NR would decline by \$73.94 ha^{-1}from the max NR variable strategy. Finally, the targeted approach, where min weed was incorporated into the max NR variable strategy, where weed biomass was in the 80th percentile and above, resulted in a mean NR of \$726.84 ha^{-1} compared to \$774.04 ha^{-1} for the max NR variable strategy and \$629.42 for the min weed strategy (Fig. 5.5). The targeted approach highlighted the divergence of the max NR variable strategy and the min weed strategy as the targeted areas show maximum seeding rates in the previous year, and minimum seeding rates in the current year to reduce weed biomass in the current year most effectively. The targeted approach was the second most effective strategy for minimizing weeds, and the third most effective strategy for generating maximum net return on site-year 2 (Figure 5.5 & 5.6).

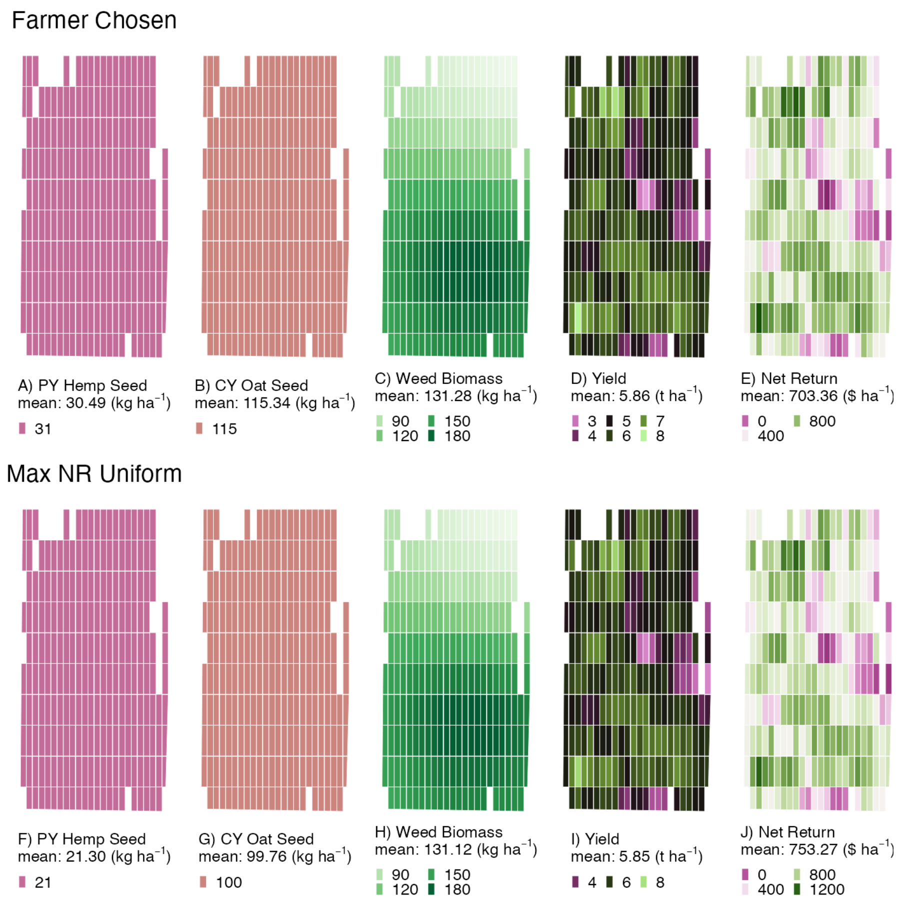


Figure 5.5. Site-year 2, illustrating the two simulated uniform seeding rate strategies: 'farmer chosen', and 'max NR uniform'. Columns one through five show previous year's hemp seed rate, current year's oat seed rate, estimated weed biomass, oat yield, and net return respectively. The random forest predicted mean value per hectare is listed above the legend.

Figure 5.6. Site-year 2, illustrating the three simulated variable seeding rate strategies. Columns one to five show previous year's hemp seed rate, current year's oat seed rate, estimated weed biomass, oat yield, and net return respectively. The predicted mean value per hectare is listed above the legend. The weediest 20% of the field is outlined in pink on the weed biomass map for the targeted strategy.

Comparison of weed minimization and net return maximization strategies

Weed biomass estimates were assessed for each management strategy for each site year. (Fig. 5.7). The weed biomass in most fields and years was decreased by each seeding rate strategy relative to the farmer chosen strategy. Using the min weed strategy, weed biomass reduction from farmer chosen strategy ranged from 0.80 kg ha^{-1} in site-year 5, to 28.80 kg ha^{-1} in site-year 4. Farmer chosen rates had the highest or second highest weed biomasses of all strategies assessed in three of five years (Figure 5.7 site-year 1,2 or 4). The max NR uniform rate had the highest weed biomass in two site-years (Figure 5.7 site-year 3 & 5), and the actual experiment had the highest weed biomass in two site-years (Figure 5.7 site-year 1 & 2). The targeted approach fell between the maximum NR strategy and the min weed strategy for decreasing weed biomass (Figure 5.7).

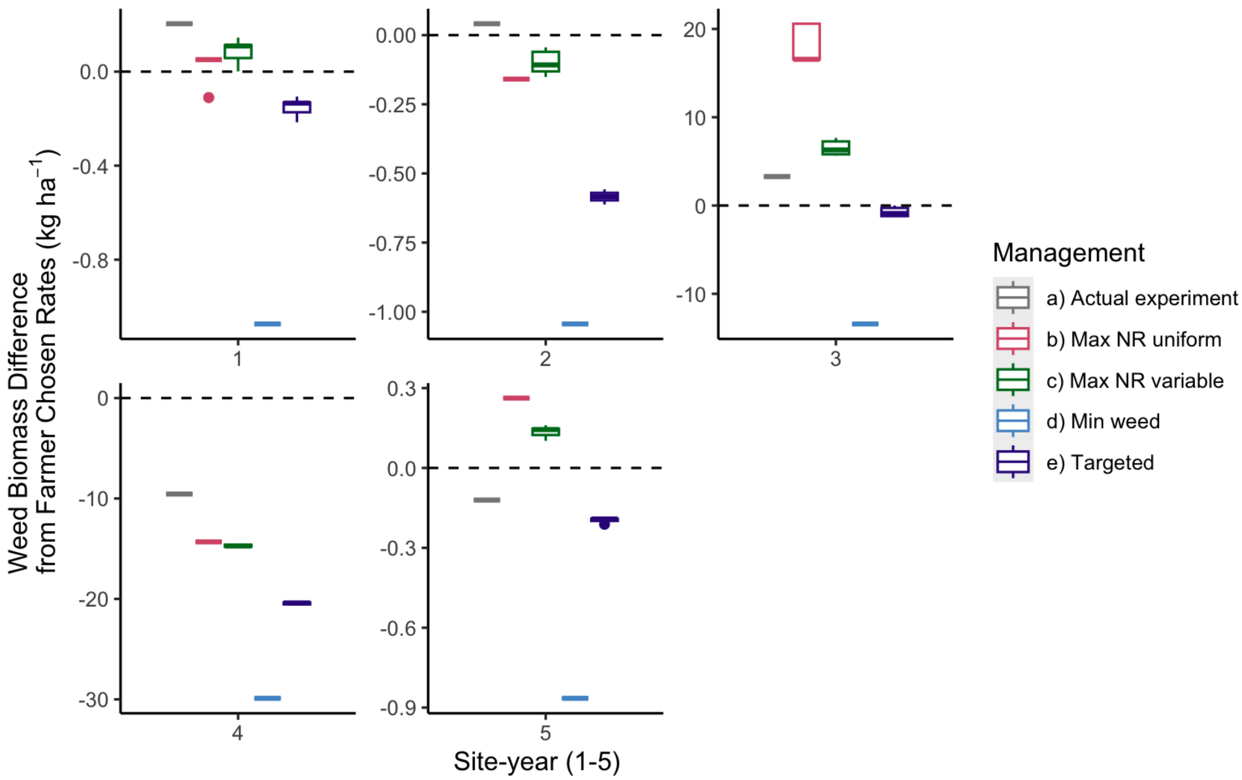


Figure 5.7. Mean weed biomass resulting from each seeding rate strategy across five site-years, compared to the farmer-chosen rates denoted as black dashed line at 0 biomass on the y-axis.

In place of a weed minimization strategy, farmers may choose to pursue a net return maximization strategy. The farmer chosen seeding rate strategy was shown to generate net returns as high as \$185.32 ha^{-1}, and as low as \$27.45 ha^{-1}, and the net return was improved from the farmer chosen strategy by an average of \$114.97 ha^{-1} over all fields using the maximum NR variable strategy (Fig. 5.8). The max NR uniform rate was often the second-highest mean NR strategy, however the targeted strategy was at times the second highest depending on which historic economic conditions were used to calculate NR. The net return from the actual experiment was typically just below the farmer chosen rate net return. The experimental cost ranged from -\$32.98 ha^{-1} on site-year 3, and -\$1.79 ha^{-1} on site-year 5, to making the farmer a slight amount of money, 12.36^{-1}, on site-year 1. The min weed strategy performed poorly relative to the other strategies in net return, falling near or below the actual experiment levels across all site-years. Over these experimental study sites and years, pursuing the min weed strategy came at an expense to the farmer's current year NR.

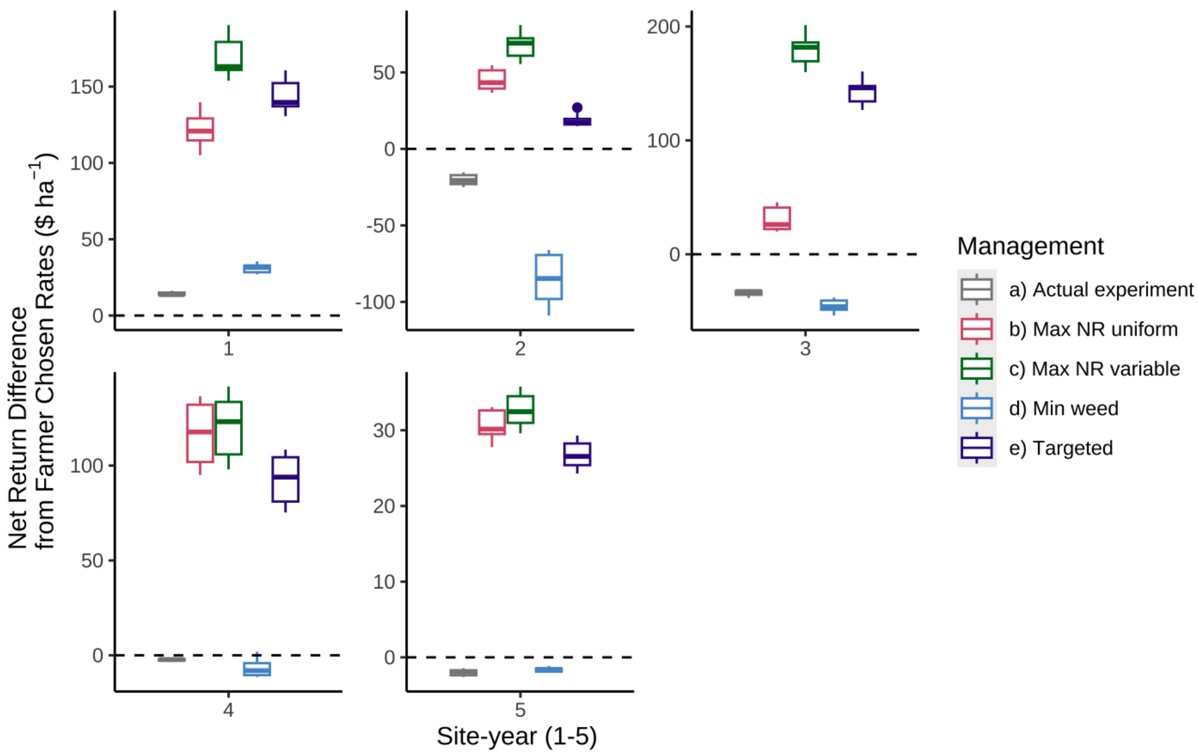


Figure 5.8. Net return difference between the farmer chosen strategy and all other strategies, including the actual experiment, tested across five site-years, where the farmer-chosen rates indicated as a black dashed line at 0 NR on the y-axis.

Recommended profit maximizing seeding rates were field and year specific, though some trends were seen consistently across site-years, and some management strategies were clearly improvements over others. The results indicated that the farmer chosen rate strategy, was more closely aligned with net return maximization than weed management (Figure 5.7). Compared to the other strategies, the farmer chosen rates were not effective for weed management, and NR could be improved from this baseline strategy, by reducing overall seed rates across each site-year (Table 5.3). Averaged across all site years the max NR variable strategy resulted in reduced estimated weed biomass of 2.20 kg ha^{-1}, or a 0.71% reduction (Table 5.3). The max NR variable strategy also gained the farmer an average increase in NR of $114.97, or a 14.69% increase. These results were driven partially by decreasing the current year's SR by 18.80% and the previous year's seeding rates by an average of 26.71% (Table 5.3).

Table 5.3 – Mean previous year (PY) seeding rate, current year (CY) seeding rate, weed biomass, crop yield and net return averaged across all five site-years as a percent of the farmer chosen rates.

Strategy	PY Seed Rate (%)	CY Seed Rate (%)	Weed Biomass (%)	Mean crop yield (%)	Mean net return (%)
Farmer-Chosen	100.00	100.00	100.00	100.00	100.00
Actual Experiment	100.00	100.00	99.46	99.49	99.33
Max NR Uniform	71.95	81.69	101.33	101.78	109.79
Max NR Variable	73.29	81.20	99.29	104.87	114.69
Min Weed	98.70	90.17	93.80	97.78	97.87
Targeted	78.31	80.89	97.27	103.21	111.01

Discussion

Spatial variability

We used random forest models to spatially predict crop yield and weed biomass across fields using a controlled variable of crop seeding rate and a suite of other potential driving variables under real production conditions. The models were then used to assess different seeding rate strategies, some full-field uniform and some site-specific variable, based on how well they produced profits for the farmer and affected weeds. In some instances, findings were predictable, such as when prescriptions called for increased seeding rate to reduce weed biomass (Lemerle et al. 2004). In other instances, prescriptions unexpectedly called for decreased seeding rates to reduce weed biomass (Fig. 5.6 & Table 5.3). There are competitive and symbiotic biological reasons for both recommendations (Lemerle, 2004; Weiner, 2023), and site-specific findings can clarify these types of relationships so that a farmer can make informed management decisions.

The benefit of a random forest machine learning model is its ability to ingest as much information as possible about a particular space and define spatially-explicit relationships (Hegedus et al., 2022). High volumes of data allow for flexibility in the model to find divergent relationships across fields. While it is typically assumed that weed presence harms crop yield (Zimdahl, 2007), weeds can be neutral, or even beneficial by increasing crop yield (Moonen & Bàrberi, 2008). The general relationship between weeds and net return using all data acquired in this study was inconclusive on whether weeds reduce overall net return (supplemental Fig. 5.4). But there were areas of fields where weeds were positively correlated with yield, evident in random forest outputs (Fig. 5.5). This could indicate a beneficial impact of weeds, or that these areas provide suitable conditions for both crop and weed growth. Regardless, attempting to control for weeds in these instances reduced net return in our study. As weeds are patchy, and responded variably to seed rate, weeds may be most effectively managed with crop seeding rates using a site-specific approach. Thus, clarifying the site-specific weed and crop interaction using precision agriculture technology can provide effective decision support for farmers.

Weed management

Although site-specific weed management using variable seeding rates is possible in organic systems, there are short-term economic disincentives. Economic performance of the min weed strategy typically had the lowest net returns (Fig. 5.6). The strategy of increased seeding rates, encompassed in the farmer-chosen rate strategy, did not perform very well economically, nor in terms of weed management (Table 5.3). Three factors may describe this trend. One, the unique management of organic systems led to a reduction in crop-weed competition. This can be as a result of greater overall plant diversity (Smith et al., 2010), a more abundant soil microbiome (Johnson et al., 2017), or evolution of weeds to reduce their interactions with crops (Maxwell, 2017). Two, increased crop seed rates can harm the crop itself through intraspecific competition (Lu et al., 2020). Three, the economic impact of weeds on the crop can be minimal (Benaragama et al., 2016), therefore attempts to control them with crop seeding rate changes resulted in wasted inputs which could otherwise be directed towards improving net return. Thus, a uniform increase of seeding rates to manage weeds was ineffective. Instead, farmers can use OFPE to target areas where increased seeding rates have the greatest impact on weed suppression or economic improvement.

Net return management

Economically optimum variable seed rate strategies are site-specific, time-specific, and highly dependent on crop selection. While the max NR variable seeding rate strategy produced the highest net returns amongst all simulated strategies, the max NR uniform rate was often a close second (Fig. 5.6). In this sense, a farmer could still opt for uniform rate management, an economically improved approach with only a slight reduction across all fields from the max NR variable rate (Table 5.3). Indeed, farmers that lack variable rate seeding equipment but have access to a yield monitor can apply the OFPE method, albeit more laboriously. In three of the five site-years tested, the max NR uniform rate was very close to the max NR variable rate, and in each of those years a cereal crop (either winter wheat or oats) was harvested. The years in which the max NR variable rate had the largest improvements over the max NR uniform rate were years where hemp was the harvested crop. These results underscore the biological nature of these experiments, where crop species affect outcomes. A tillering cereal crop such as oats or wheat will have a more plastic response to resource availability, than a broad-leaf crop like hemp, and therefore the latter may lend itself more to a variable rate approach.

While the max NR variable strategy performed the best economically, it is important to note that the experiment itself had a cost, and that the farmer lost money by conducting the OFPE experiment (Table 5.3). While the value of the site-specific knowledge may be worth the simulated net return improvement, that is up to the farmer to decide. The presented costs enable farmers to decide whether to continue experimenting, whether to invest further in variable rate technology, and whether to adapt future management decisions based on the simulated outcomes of their farmer-chosen rates and the quantified local response.

Alternative Strategies

Net return was maximized through variable rate input of seed rate over the course of a two-year farm operation. It is understood that farmers, particularly organic farmers, may have long term goals which differ from immediate net return. Notably, organic agriculture states ‘soil health’ as one of its key foundations (Hammermeister, 2020). While ‘soil health’ is a nebulous term (Janzen et al., 2021), goals such as long-term reduction of weed seed bank, or increased soil organic matter, could be regarded as important values of the farm operation, and rank them higher than a single year’s net return. In such instances the model could be adjusted to reflect these desires. Given many more years of experimentation, such aspirations could be built into the models to achieve various goals in a multi-objective optimization approach. Such goals could also be pursued where different parts of a field could be targeted to different optimization strategies such as the one simplified example that we presented.

The targeted weed management strategy developed here was a first step in the direction of multi-objective optimization. The targeted weed strategy captures the notion that short term net return is not necessarily a farmer's only goal. While max NR variable did out-compete every other strategy in economic terms (across recent economic historical values and across all five site-years), in several instances (site years 1,2,4) it was less effective at weed biomass suppression than the farmer chosen rates. Conversely, the min weed strategy always reduced more weed biomass (albeit a small amount) of any strategy tested in every site-year, but almost always preformed more poorly economically than the farmer chosen rates with only one exception (site-year 1). The benefit of the targeted approach then was that it always outperformed the default farmer chosen rates economically as well as for weed suppression. Thus, a farmer with multiple objectives may find alternative management strategies to accommodate these field-specific OFPE approaches. Indeed, the targeted approach in this sense may be regarded as the most risk averse strategy, as it attempts to generate net returns here and now, while also hedging bets and attempting to reduce weed pressures over the long term in persistent patches.

Assumptions

Weed biomass maps across whole fields were interpolated from a limited weed survey. Although weed data have been interpolated like this in other studies, it is a considerable assumption to impute spatially autocorrelated data in this manner. This weed collection technique was both labor intensive and added uncertainty to the data set not reflected in the weed biomass predictions used as a response variable. Weed surveys, however, provide an increasingly improved basis for calibrating remote sensing of weeds which will reduce the cost in capturing their distribution and abundance (Mattivi et al., 2021). Since all other variables included in the random forest models in this study were freely available to the farmer, it would be greatly beneficial to harness the powers of drones or satellites to automate weed data collection.

A second major assumption made in this study was that the data collected form a complete representation of the area under study. In reality the data represented a snapshot of growing conditions, and omitted crucial long term data such as variable weather patterns. While the data here were collected over the same field for a maximum of four consecutive years, many organic farms have rotations of up to 10 years. Thus, a continuation of this study, one which focuses on variation over time, and how spatial variation may interact with those changes, would provide a more comprehensive understanding of the potential use of crop seeding rates to maximize net returns and minimize weeds in organic systems.

Conclusion

IWM using variable seeding rates typically recommends increasing seeding rates to suppress weeds (Lemerle et al., 2004). However, this study produced results with the opposite effect in some instances, possibly by reducing crop biomass through intra-crop competition, which can result in increased weeds and reduced net return. Therefore, it is key to clarify how these relationships differ in a site-specific manner. Precision agriculture technology can be used to determine when and where weeds can be suppressed or tolerated to ultimately optimize farmer net return and other ecological/long-term management goals. OFPE can be used to build and refine weed response models to organic inputs and improve PWM in organic crop production. Here we demonstrated variable weed responses to varied seed inputs, identified areas where crop and seed rates were effective at suppressing weeds, and provided circumstances in which there were no weed benefits. Thus, optimizing farmer net return can be achieved using the “many little hammers” approach that organic farmers rely on for long-term weed management. By employing the OFPE process over time farmers can learn to deploy precision tools together with their own ecological understanding with multiple objectives in mind to effectively manage complex agroecosystems.

References

Amatulli, G., Domisch, S., Tuanmu, M.-N., Parmentier, B., Ranipeta, A., Malczyk, J., & Jetz, W. (2018). A suite of global, cross-scale topographic variables for environmental and biodiversity modeling. *Scientific Data*, *5*(1), Article 1. https://doi.org/10.1038/sdata.2018.40

Benaragama, D., Shirtliffe, S. J., Gossen, B. D., Brandt, S. A., Lemke, R., Johnson, E. N., Zentner, R. P., Olfert, O., Leeson, J., Moulin, A., & Stevenson, C. (2016). Long-term weed dynamics and crop yields under diverse crop rotations in organic and conventional cropping systems in the Canadian prairies. *Field Crops Research*, *196*, 357–367. https://doi.org/10.1016/j.fcr.2016.07.010

Bertramsen, S. K., & Dobbs, T. L. (2002). *An Update on prices of Organic Crops in Comparison to Conventional Crops*.

Buhler, D. D., Liebman, M., & Obrycki, J. J. (2000). Theoretical and practical challenges to an IPM approach to weed management. *Weed Science*, *48*(3), 274–280. https://doi.org/10.1614/0043-1745(2000)048[0274:TAPCTA]2.0.CO;2

Bussler, B. H., Maxwell, B. D., & Puettmann, K. J. (1995). Using Plant Volume to Quantify Interference in Corn (*Zea mays*) Neighborhoods. *Weed Science*, *43*(4), 586–594. https://doi.org/10.1017/S0043174500081698

Cherr, C. M., Scholberg, J. M. S., & McSorley, R. (2006). Green Manure Approaches to Crop Production: A Synthesis. *Agronomy Journal*, *98*(2), 302–319. https://doi.org/10.2134/agronj2005.0035

Cook, S. E., & Bramley, R. G. V. (1998). Precision agriculture—Opportunities, benefits and pitfalls of site-specific crop management in Australia. *Australian Journal of Experimental Agriculture*, *38*(7), 753. https://doi.org/10.1071/EA97156

Duff, H., Hegedus, P. B., Loewen, S., Bass, T., & Maxwell, B. D. (2021). Precision Agroecology. *Sustainability*, *14*(1), 106. https://doi.org/10.3390/su14010106

Eyhorn, F., Muller, A., Reganold, J. P., Frison, E., Herren, H. R., Luttikholt, L., Mueller, A., Sanders, J., Scialabba, N. E.-H., Seufert, V., & Smith, P. (2019). Sustainability in global agriculture driven by organic farming. *Nature Sustainability*, *2*(4), 253–255. https://doi.org/10.1038/s41893-019-0266-6

Gerhards, R., Andújar Sanchez, D., Hamouz, P., Peteinatos, G. G., Christensen, S., & Fernandez-Quintanilla, C. (2022). Advances in site-specific weed management in agriculture—A review. *Weed Research*, *62*(2), 123–133. https://doi.org/10.1111/wre.12526

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Hammermeister, A. M. (2020). Organic Agriculture: A Model for Sustainability. In C. D. Caldwell & S. Wang (Eds.), *Introduction to Agroecology* (pp. 279–299). Springer. https://doi.org/10.1007/978-981-15-8836-5_20

Hegedus, P. B., Maxwell, B. D., & Mieno, T. (2022). Assessing performance of empirical models for forecasting crop responses to variable fertilizer rates using on-farm precision experimentation. *Precision Agriculture*. https://doi.org/10.1007/s11119-022-09968-2

Hegedus, P. B., Maxwell, B., Sheppard, J., Loewen, S., Duff, H., Morales-Luna, G., & Peerlinck, A. (2023). Towards a Low-Cost Comprehensive Process for On-Farm Precision Experimentation and Analysis. *Agriculture*, *13*(3), 524. https://doi.org/10.3390/agriculture13030524

Hiemstra, P., & Skoien, J. O. (2023). *automap: Automatic Interpolation Package* (1.1-1). https://CRAN.R-project.org/package=automap

Janzen, H. H., Janzen, D. W., & Gregorich, E. G. (2021). The ‘soil health’ metaphor: Illuminating or illusory? *Soil Biology and Biochemistry*, *159*, 108167. https://doi.org/10.1016/j.soilbio.2021.108167

Johnson, S. P., Miller, Z. J., Lehnhoff, E. A., Miller, P. R., & Menalled, F. D. (2017). Cropping systems modify soil biota effects on wheat (*Triticum aestivum*) growth and competitive ability. *Weed Research*, *57*(1), 6–15. https://doi.org/10.1111/wre.12231

Korres, N. E., Burgos, N. R., Travlos, I., Vurro, M., Gitsopoulos, T. K., Varanasi, V. K., Duke, S. O., Kudsk, P., Brabham, C., Rouse, C. E., & Salas-Perez, R. (2019). Chapter Six - New directions for integrated weed management: Modern technologies, tools and knowledge discovery. In D. L. Sparks (Ed.), *Advances in Agronomy* (Vol. 155, pp. 243–319). Academic Press. https://doi.org/10.1016/bs.agron.2019.01.006

Kuhn, M., & Wickham, H. (2022). *tidymodels: Easily Install and Load the “Tidymodels” Packages* (1.0.0). https://CRAN.R-project.org/package=tidymodels

Kursa, M. B., & Rudnicki, W. R. (2010). Feature Selection with the **Boruta** Package. *Journal of Statistical Software*, *36*(11). https://doi.org/10.18637/jss.v036.i11

Lacoste, M., Cook, S., McNee, M., Gale, D., Ingram, J., Bellon-Maurel, V., MacMillan, T., Sylvester-Bradley, R., Kindred, D., Bramley, R., Tremblay, N., Longchamps, L., Thompson, L., Ruiz, J., García, F. O., Maxwell, B., Griffin, T., Oberthür, T., Huyghe, C., … Hall, A. (2021). On-Farm Experimentation to transform global agriculture. *Nature Food*, *3*(1), 11–18. https://doi.org/10.1038/s43016-021-00424-4

Lemerle, D., Cousens, R. D., Gill, G. S., Peltzer, S. J., Moerkerk, M., Murphy, C. E., Collins, D., & Cullis, B. R. (2004). Reliability of higher seeding rates of wheat for increased competitiveness with weeds in low rainfall environments. *The Journal of Agricultural Science*, *142*(4), 395–409. https://doi.org/10.1017/S002185960400454X

Liebman, M., Gallandt, E. R., & Jackson, L. E. (1997). Many little hammers: Ecological management of crop-weed interactions. *Ecology in Agriculture*, *1*, 291–343.

Loewen, S., Maxwell, B. D. (2023). *Optimizing organic cover crop seeding rates and following cash crops to maximize net return in a controlled environment*. Manuscript submitted for publication.

Lu, P., Jiang, B., & Weiner, J. (2020). Chapter Three—Crop spatial uniformity, yield and weed suppression. In D. L. Sparks (Ed.), *Advances in Agronomy* (Vol. 161, pp. 117–178). Academic Press. https://doi.org/10.1016/bs.agron.2019.12.003

MacLaren, C., Storkey, J., Menegat, A., Metcalfe, H., & Dehnen-Schmutz, K. (2020). An ecological future for weed science to sustain crop production and the environment. A review. *Agronomy for Sustainable Development*, *40*(4), 24. https://doi.org/10.1007/s13593-020-00631-6

Mathur, M. (2015). Spatial autocorrelation analysis in plant population: An overview. *Journal of Applied and Natural Science*, *7*(1), Article 1. https://doi.org/10.31018/jans.v7i1.639

Mattivi, P., Pappalardo, S. E., Nikolić, N., Mandolesi, L., Persichetti, A., De Marchi, M., & Masin, R. (2021). Can Commercial Low-Cost Drones and Open-Source GIS Technologies Be Suitable for Semi-Automatic Weed Mapping for Smart Farming? A Case Study in NE Italy. *Remote Sensing*, *13*(10), 1869. https://doi.org/10.3390/rs13101869

Maxwell, B. (2017). Weed-plant interactions. In Colorado State University, USA & R. Zimdahl (Eds.), *Integrated weed management for sustainable agriculture* (pp. 29–42). Burleigh Dodds Science Publishing. https://doi.org/10.19103/AS.2017.0025.02

Maxwell, B. D., & Luschei, E. C. (2005). Justification for site-specific weed management based on ecology and economics. *Weed Science*, *53*(2), 221–227. https://doi.org/10.1614/WS-04-071R2

McFadden, J. R., Rosburg, A., & Njuki, E. (2022). Information inputs and technical efficiency in midwest corn production: Evidence from farmers' use of yield and soil maps. *American Journal of Agricultural Economics*, *104*(2), 589–612. https://doi.org/10.1111/ajae.12251

Moonen, A.-C., & Bàrberi, P. (2008). Functional biodiversity: An agroecosystem approach. *Agriculture, Ecosystems & Environment*, *127*(1), 7–21. https://doi.org/10.1016/j.agee.2008.02.013

Oerke, E.-C. (2006). Crop losses to pests. *The Journal of Agricultural Science*, *144*(1), 31–43. https://doi.org/10.1017/S0021859605005708

Paradis, E., Blomberg, S., Bolker [aut, B., cph, Brown, J., Claramunt, S., Claude, J., Cuong, H. S., Desper, R., Didier, G., Durand, B., Dutheil, J., Ewing, R. J., Gascuel, O., Guillerme, T., Heibl, C., Ives, A., Jones, B., Krah [aut, F., … Vienne, D. de. (2023). *ape: Analyses of Phylogenetics and Evolution* (5.7-1). https://CRAN.R-project.org/package=ape

Partel, V., Charan Kakarla, S., & Ampatzidis, Y. (2019). Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. *Computers and Electronics in Agriculture*, *157*, 339–350. https://doi.org/10.1016/j.compag.2018.12.048

Pebesma, E., & Graeler, B. (2022). *gstat: Spatial and Spatio-Temporal Geostatistical Modelling, Prediction and Simulation* (2.1-0). https://CRAN.R-project.org/package=gstat

Piepho, H.-P., Richter, C., Spilke, J., Hartung, K., Kunick, A., Thöle, H., Piepho, H.-P., Richter, C., Spilke, J., Hartung, K., Kunick, A., & Thöle, H. (2011). Statistical aspects of on-farm experimentation. *Crop and Pasture Science*, *62*(9), 721–735. https://doi.org/10.1071/CP11175

Pollnac, F. W., Rew, L. J., Maxwell, B. D., & Menalled, F. D. (2008). Spatial patterns, species richness and cover in weed communities of organic and conventional no-tillage spring wheat systems. *Weed Research*, *48*(5), 398–407. https://doi.org/10.1111/j.1365-3180.2008.00631.x

Pringle, M. J., Cook, S. E., & McBratney, A. B. (2004). Field-Scale Experiments for Site-Specific Crop Management. Part I: Design Considerations. *Precision Agriculture*, *5*(6), 617–624. https://doi.org/10.1007/s11119-004-6346-1

R Core Team. (2022). *R: A language and environment for statistical computing. R Foundation for Statistical Computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Robert, P. (1993). Characterization of soil conditions at the field level for soil specific management. *Geoderma*, *60*(1–4), 57–72. https://doi.org/10.1016/0016-7061(93)90018-G

Rodriguez, D. G. P., Bullock, D. S., & Boerngen, M. A. (2019). The Origins, Implications, and Consequences of Yield-Based Nitrogen Fertilizer Management. *Agronomy Journal*, *111*(2), 725–735. https://doi.org/10.2134/agronj2018.07.0479

Ruffo, M. L., Bollero, G. A., Bullock, D. S., & Bullock, D. G. (2006). Site-specific production functions for variable rate corn nitrogen fertilization. *Precision Agriculture*, *7*(5), 327–342. https://doi.org/10.1007/s11119-006-9016-7

Smith, R. G., Mortensen, D. A., & Ryan, M. R. (2010). A new hypothesis for the functional role of diversity in mediating resource pools and weed–crop competition in agroecosystems. *Weed Research*, *50*(1), 37–48. https://doi.org/10.1111/j.1365-3180.2009.00745.x

Somerville, G. J., Sønderskov, M., Mathiassen, S. K., & Metcalfe, H. (2020). Spatial Modelling of Within-Field Weed Populations; a Review. *Agronomy*, *10*(7), 1044. https://doi.org/10.3390/agronomy10071044

Thornton, M. M., Shrestha, R., Wei, Y., Thornton, P. E., Kao, S.-C., & Wilson, B. E. (2022). Daymet: Annual Climate Summaries on a 1-km Grid for North America, Version 4 R1. *ORNL DAAC*. https://doi.org/10.3334/ORNLDAAC/2130

USDA ERS - Commodity Costs and Returns. (2022). Retrieved January 29, 2023, from https://www.ers.usda.gov/data-products/commodity-costs-and-returns/commodity-costs-and-returns/#Cost-of-Production%20Forecasts.

van Evert, F. K., Fountas, S., Jakovetic, D., Crnojevic, V., Travlos, I., & Kempenaar, C. (2017). Big Data for weed control and crop protection. *Weed Research*, *57*(4), 218–233. https://doi.org/10.1111/wre.12255

Weiner, J. (2023). Weed suppression by cereals: Beyond 'competitive ability.' *Weed Research*, 1–6. https://doi.org/10.1111/wre.12572

Weersink, A., Fraser, E., Pannell, D., Duncan, E., & Rotz, S. (2018). Opportunities and Challenges for Big Data in Agricultural and Environmental Analysis. *Annual Review of Resource Economics*, *10*(1), 19–37. https://doi.org/10.1146/annurev-resource-100516-053654

Wright, M. N., & Ziegler, A. (2017). ranger: A Fast Implementation of Random Forests for High Dimensional Data in C++ and R. *Journal of Statistical Software*, *77*, 1–17. https://doi.org/10.18637/jss.v077.i01

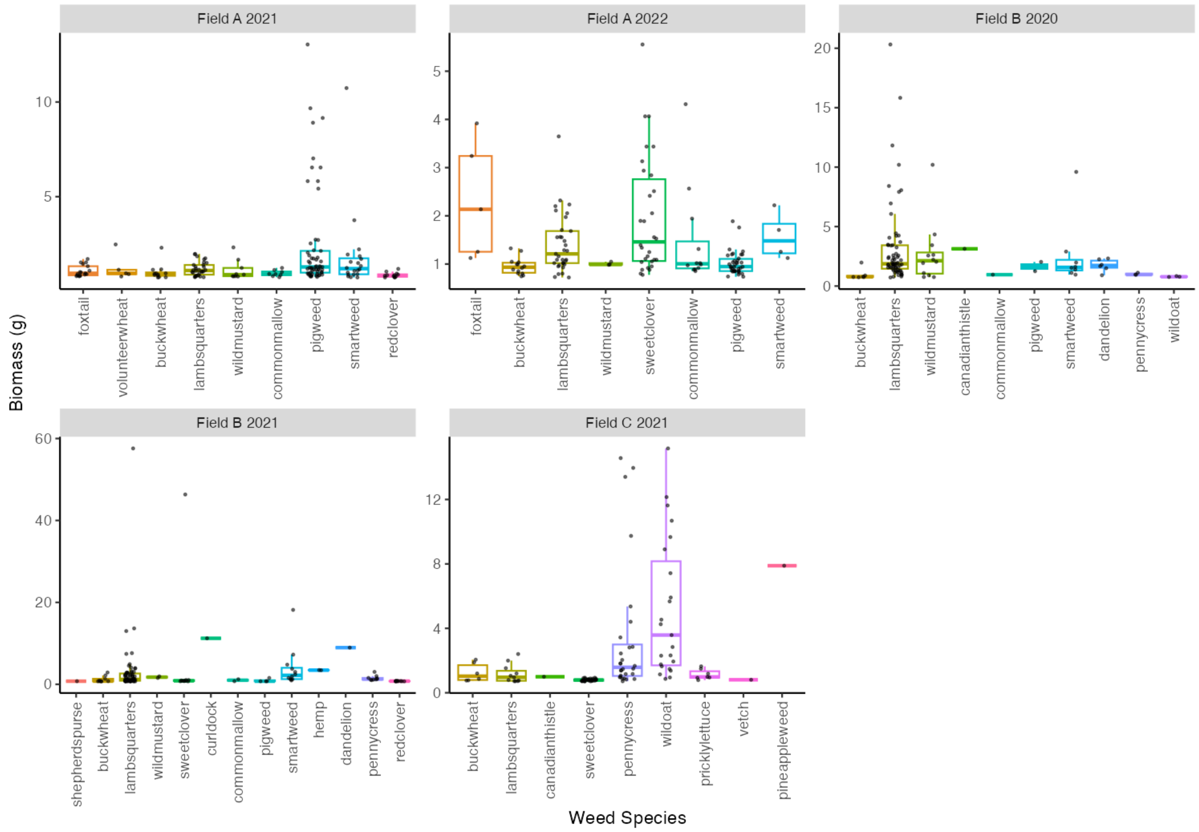
Würriehausen, N., Ihle, R., & Lakner, S. (2015). Price relationships between qualitatively differentiated agricultural products: Organic and conventional wheat in Germany. *Agricultural Economics*, *46*(2), 195–209. https://doi.org/10.1111/agec.12151

Zimdahl, R. L. (2007). *Weed-Crop Competition: A Review*. John Wiley & Sons.

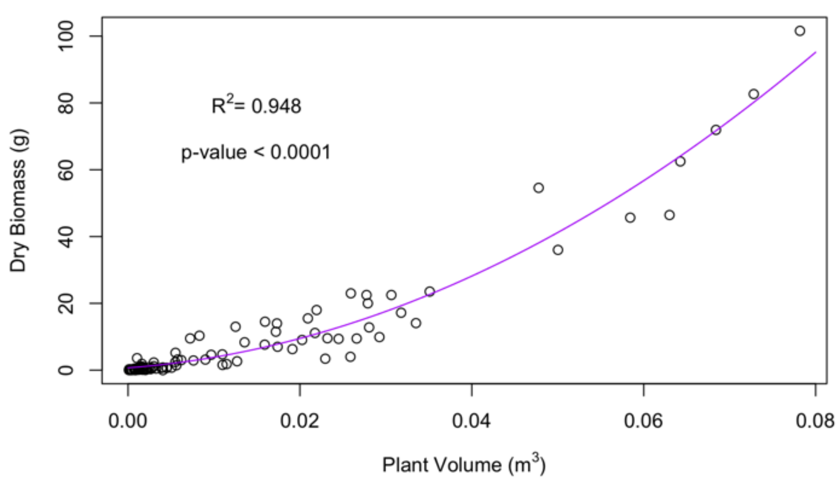
Appendix B

Supplemental Table 5.1. Covariate data types gathered from Google Earth Engine to create predictive models of yield and weed data gathered from on farms (Adjusted from (Hegedus et al., 2023)).

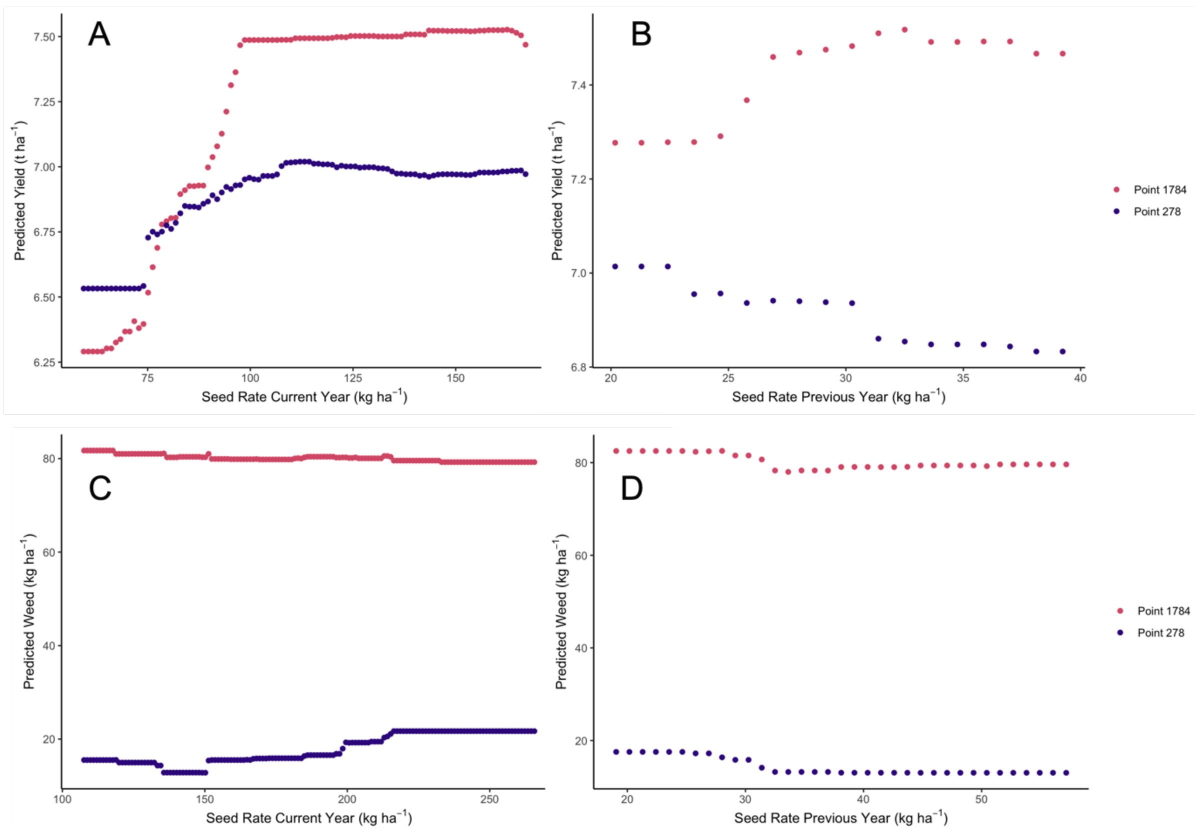
Data Type	Data Sources	Resolution	Description
Normalized Difference Vegetation Index (NDVI)	Sentinel 2	10 m	Sentinel is a European Space Agency Mission. Bands: B8 (NIR) and B4 (red)
Normalized Difference Water Index (NDWI)	Sentinel 2	20 m	Sentinel is a European Space Agency Mission. Bands: B8 (NIR) and B12 (MIR)
Elevation	USGS NED	~10 m (1/3 arc second), ~23 m (3/4 arc second)	USGS National Elevation Dataset. Measured in meters.
Aspect	USGS NED	~10 m (1/3 arc second), 30 m	Direction the surface faces, function of neighboring elevations, in radians, and also calculated for each E/W and N/S direction as cosine and sine.
Slope	USGS NED	~10 m (1/3 arc second), 30 m	Rate of change in height from neighboring cells. Measured in degrees.
Topographic Position Index (TPI)	USGS NED	~10 m (1/3 arc second), 30 m	Measure of divots and low spots as a function of neighboring elevation.
Precipitation	DaymetV3	1 km	Estimates from the NASA Oak Ridge National Laboratory (ORNL). Measured in mm.
Growing Degree Days (GDDs)	DaymetV3	1 km	Estimates from the NASA Oak Ridge National Laboratory (ORNL).
Bulk Density	OpenLandMap	250 m	Soil bulk density (fine earth) 10 × kg/m_3 averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1, and 2 m).
Clay Content	OpenLandMap	250 m	Clay content in % (kg/kg) averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1, and 2 m).
Sand Content	OpenLandMap	250 m	Sand content in % (kg/kg) averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1, and 2 m).
pH (phw)	OpenLandMap	250 m	Soil pH in H_2O averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1, and 2 m).
Water Content	OpenLandMap	250 m	Soil water content (volumetric %) for 33 kPa and 1500 kPa suctions predicted and averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1, and 2 m).
Carbon Content	OpenLandMap	250 m	Soil organic carbon content in × 5 g/kg averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1, and 2 m).



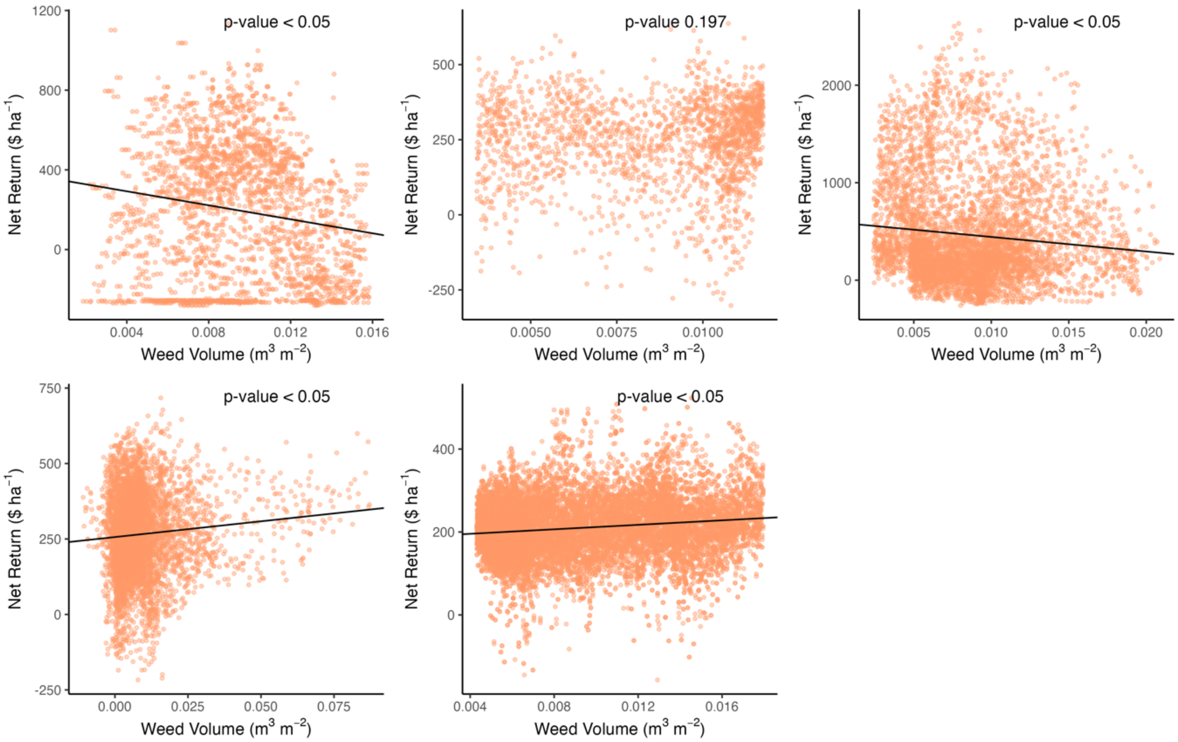
Supplemental Figure 5.1. Weed species in frequency and size at each sample point across each field and year.



Supplemental Figure 5.2. Weighed dry biomass values as a function of estimated plant volume. The sampled weed positions across the fields were estimated by volume (Bussler, 1995), and a sub-sample of these were cut, collected, and dried to ascertain a relationship to biomass, shown here.



Supplemental Figure 5.3. Example of various relationships found through random forest modelling at two random points across site-year 2 for A) predicted yield in response to current year seed rate; B) predicted yield in response to previous year seed rate; C) predicted weed biomass in response to current year seed rate; D) predicted weed biomass in response to previous year seed rate.



Supplemental Figure 5.4. Net return as a response to weed volume across each of five site-years.

CHAPTER SIX

EPILOGUE

"Surely there could be a more indigenous life than we have. There could be a consciousness that would establish itself on a place by understanding its nature and learning what is potential in it. A man ought to study the wilderness of a place before applying to it the ways he learned in another place."

-Wendell Berry

General Summary

This dissertation is an exploration of the use of modern farm technologies and precision agriculture in organic farm systems. The primary methodology used was on farm precision experimentation (OFPE). OFPE combines the expertise of researchers in statistical analysis with farmers' own equipment and land, to answer site specific agronomic questions, with spatially explicit input rates optimized to maximize net return. In the prologue, I traced the rise of intensification throughout the practice of agriculture, historically, and concluded that a paradigm shift needs to occur, one in which technology is merged with sustainable farming practices – like organic agriculture – to manage for the ecosystem services provided by agroecosystems, rather than focusing purely on crop yield. In chapter two, I worked with my lab mates to outline how precision agriculture can unify and satisfy each of the five levels of agroecology, from fields to farms to landscapes to human networks and the globe. In chapter three I then narrowed my scope and, using first principles, found the relationship between organic green manure cover crop seed rates and subsequent cash crop seeding rates and a farmer's net return, thereby highlighting a specific use case of precision agriculture in organic field settings. In chapter four, I showed how farmers could use precision seeding rates of cover crops and cash crops in field settings to maximize net return. Net returns could be increased by as much as \$46 ha^{-1} using spatially optimized rates, and farmers could optimize green manure cover crop seed rates as well as cash crop seed rates like wheat, oat, or hemp. Finally, in chapter five, I compared seeding rate management strategies as weed suppression tactics. I found that a farmer could focus on net return maximization and that this, in itself, presented a better weed management strategy than attempting to use high seeding rates across fields generally. A targeted approach, where only the weediest parts of the field were managed for weed suppressions, was the only management strategy which outperformed the farmer-chosen rates for both increased net return and reduced weed, highlighting the potential of using multi-objective optimization in the future as a low-risk organic farming strategy.

Future work

It has been found in both my work and others (Bullock et al., 2019; Hegedus & Maxwell, 2022) that spatial variability can be quickly revealed through on-farm precision experimentation. The primary limitation of a relatively short study like mine is the inability to analyze these systems over a long-time frame and thus learn about temporal variability. In farming, ever-changing weather is a preeminent feature of crop output; this represents a large source of unknown variation and is a serious drawback to precision management. Thus, to truly understand agroecosystems, experiments should be continued so that an understanding of temporal variability can be found and added to the models that predict the potential distribution of agronomic outcomes. The distribution can then be tapped through simulation to run different weather scenarios that would provide a farmer a quantification of the uncertainty in agronomic outcomes caused by highly influential weather variables like precipitation and growing degree days. Another highly important factor to follow up on is the automation on the process of gaining knowledge using OFPE, including subsequent analysis and resulting predictive models. All of the data used in this project were freely available from either public databases or farmers' equipment. Weed data were the exception to this and were collected through manual labor. A promising line of future work, highly relevant to both chemical and organic agriculture, is automating weed species and biomass collection across fields using remote sensing. Many researchers are currently exploring this possibility (Mattivi et al., 2021), and these data sets would enable more practical precision weed management using the OFPE method.

What would Wendell Berry say?

Wendell Berry is a longtime opponent of new farm technology (Filipiak, 2011). Berry saw that technology only served to make farms larger, and thus removed the most important prerequisites of being a farmer, namely, to know the land and to be a student of it. Technology has indeed provided farmers with the ability to manage increasingly large farms through increased mechanization, and knowledge has been lost of the unique spaces they manage. Current farm practices are to blanket thousands of acres with homogeneous doses of seed and chemical inputs aiming for quantity over quality. In direct contrast, Berry calls us to "study the wilderness of a place," and we proffer that one can encourage this process and find truth (i.e. site specific natural functions) through experimentation (Wendell Berry, 2017). While observation reveals a great deal about a place, to speed up the process of knowing would be to systematically experiment over that space and thereby increase discovery of optimal practices. In this dissertation I have presented a unique view, shared by my lab group, that modern technology can actually reverse this trend of *unknowing* places and, instead, use experimentation and remote sensing techniques to help us remember and re-learn how to manage variability. Some would say that technological solutions to the problems caused by previous technological solutions are nothing more than band-aid solutions – covering up the underlying problems. A more optimistic view is that we are providing a steppingstone toward a new model of farming, a model in which local knowledge is prioritized over distant recommendations and in which empiricism through experimentation is practiced by default, and one in which new technologies enable a paradigm shift to farming with nature rather than against it.

References

Bullock, D. S., Boerngen, M., Tao, H., Maxwell, B., Luck, J. D., Shiratsuchi, L., Puntel, L., & Martin, N. F. (2019). The Data-Intensive Farm Management Project: Changing Agronomic Research Through On-Farm Precision Experimentation. *Agronomy Journal*, *111*(6), 2736–2746. https://doi.org/10.2134/agronj2019.03.0165

Filipiak, J. (2011). The Work of Local Culture: Wendell Berry and Communities as the Source of Farming Knowledge. *Agricultural History*, *85*(2), 174–194. https://doi.org/10.3098/ah.2011.85.2.174

Hegedus, P. B., & Maxwell, B. D. (2022). Rationale for field-specific on-farm precision experimentation. *Agriculture, Ecosystems & Environment*, *338*, 108088. https://doi.org/10.1016/j.agee.2022.108088

Mattivi, P., Pappalardo, S. E., Nikolić, N., Mandolesi, L., Persichetti, A., De Marchi, M., & Masin, R. (2021). Can Commercial Low-Cost Drones and Open-Source GIS Technologies Be Suitable for Semi-Automatic Weed Mapping for Smart Farming? A Case Study in NE Italy. *Remote Sensing*, *13*(10), 1869. https://doi.org/10.3390/rs13101869

Wendell Berry. (2017). *The World-Ending Fire; The Essential Wendell Berry*. Counterpoint.

CUMULATIVE REFERENCES CITED

Altieri, M. A. (1999). Applying Agroecology to Enhance the Productivity of Peasant Farming Systems in Latin America. *Environment, Development and Sustainability*, *1*, 197–217.

Altieri, M. A., & Nicholls, C. I. (2020). Agroecology and the reconstruction of a post-COVID-19 agriculture. *The Journal of Peasant Studies*, *47*(5), 881–898. https://doi.org/10.1080/03066150.2020.1782891

Altieri, M. A., Nicholls, C. I., Henao, A., & Lana, M. A. (2015). Agroecology and the design of climate change-resilient farming systems. *Agronomy for Sustainable Development*, *35*(3), 869–890. https://doi.org/10.1007/s13593-015-0285-2

Amatulli, G., Domisch, S., Tuanmu, M.-N., Parmentier, B., Ranipeta, A., Malczyk, J., & Jetz, W. (2018). A suite of global, cross-scale topographic variables for environmental and biodiversity modeling. *Scientific Data*, *5*(1), Article 1. https://doi.org/10.1038/sdata.2018.40

Anderson, C. R., Bruil, J., Chappell, M. J., Kiss, C., & Pimbert, M. P. (2019). From Transition to Domains of Transformation: Getting to Sustainable and Just Food Systems through Agroecology. *Sustainability*, *11*(19), 5272. https://doi.org/10.3390/su11195272

Baird, J. M., Walley, F. L., & Shirtliffe, S. J. (2009). Optimal seeding rate for organic production of field pea in the northern Great Plains. *Canadian Journal of Plant Science*, *89*(3), 455–464. https://doi.org/10.4141/CJPS08113

Barański, M., Średnicka-Tober, D., Volakakis, N., Seal, C., Sanderson, R., Stewart, G. B., Benbrook, C., Biavati, B., Markellou, E., Giotis, C., Gromadzka-Ostrowska, J., Rembiałkowska, E., Skwarło-Sońta, K., Tahvonen, R., Janovská, D., Niggli, U., Nicot, P., & Leifert, C. (2014). Higher antioxidant and lower cadmium concentrations and lower incidence of pesticide residues in organically grown crops: A systematic literature review and meta-analyses. *British Journal of Nutrition*, *112*(5), 794–811. https://doi.org/10.1017/S0007114514001366

Bastos, L. M., Carciochi, W., Lollato, R. P., Jaenisch, B. R., Rezende, C. R., Schwalbert, R., Vara Prasad, P. V., Zhang, G., Fritz, A. K., Foster, C., Wright, Y., Young, S., Bradley, P., & Ciampitti, I. A. (2020). Winter Wheat Yield Response to Plant Density as a Function of Yield Environment and Tillering Potential: A Review and Field Studies. *Frontiers in Plant Science*, *11*, 54. https://doi.org/10.3389/fpls.2020.00054

Benaragama, D., Shirtliffe, S. J., Gossen, B. D., Brandt, S. A., Lemke, R., Johnson, E. N., Zentner, R. P., Olfert, O., Leeson, J., Moulin, A., & Stevenson, C. (2016). Long-term weed dynamics and crop yields under diverse crop rotations in organic and conventional cropping systems in the Canadian prairies. *Field Crops Research*, *196*, 357–367. https://doi.org/10.1016/j.fcr.2016.07.010

Bertramsen, S. K., & Dobbs, T. L. (2002). An Update on prices of Organic Crops in Comparison to Conventional Crops. *Economics Commentator*.

Biederbeck, V. O., Bouman, O. T., Campbell, C. A., Winkleman, G. E., & Bailey, L. D. (1996). Nitrogen benefits from four green-manure legumes in dryland cropping systems. *Canadian Journal of Plant Science*, *76*(2), 307–315. https://doi.org/10.4141/cjps96-053

Bramley, R. G. V., Song, X., Colaço, A. F., Evans, K. J., & Cook, S. E. (2022). Did someone say "farmer-centric"? Digital tools for spatially distributed on-farm experimentation. *Agronomy for Sustainable Development*, *42*(6), 105. https://doi.org/10.1007/s13593-022-00836-x

Buhler, D. D., Liebman, M., & Obrycki, J. J. (2000). Theoretical and practical challenges to an IPM approach to weed management. *Weed Science*, *48*(3), 274–280. https://doi.org/10.1614/0043-1745(2000)048[0274:TAPCTA]2.0.CO;2

Bullock, D. S., Boerngen, M., Tao, H., Maxwell, B., Luck, J. D., Shiratsuchi, L., Puntel, L., & Martin, N. F. (2019). The Data-Intensive Farm Management Project: Changing Agronomic Research Through On-Farm Precision Experimentation. *Agronomy Journal*, *111*(6), 2736–2746. https://doi.org/10.2134/agronj2019.03.0165

Bullock, D. S., Mieno, T., & Hwang, J. (2020). The value of conducting on-farm field trials using precision agriculture technology: A theory and simulations. *Precision Agriculture*, *21*(5), 1027–1044. https://doi.org/10.1007/s11119-019-09706-1

Bussler, B. H., Maxwell, B. D., & Puettmann, K. J. (1995). Using Plant Volume to Quantify Interference in Corn (*Zea mays*) Neighborhoods. *Weed Science*, *43*(4), 586–594. https://doi.org/10.1017/S0043174500081698

Carr, P. M., Cavigelli, M. A., Darby, H., Delate, K., Eberly, J. O., Fryer, H. K., Gramig, G. G., Heckman, J. R., Mallory, E. B., Reeve, J. R., Silva, E. M., Suchoff, D. H., & Woodley, A. L. (2020). Green and animal manure use in organic field crop systems. *Agronomy Journal*, *112*(2), 648–674. https://doi.org/10.1002/agj2.20082

Cassman, K. G., & Grassini, P. (2020). A global perspective on sustainable intensification research. *Nature Sustainability*, *3*(4), 262–268. https://doi.org/10.1038/s41893-020-0507-8

Cherr, C. M., Scholberg, J. M. S., & McSorley, R. (2006). Green Manure Approaches to Crop Production: A Synthesis. *Agronomy Journal*, *98*(2), 302–319. https://doi.org/10.2134/agronj2005.0035

Cobo, J. G., Barrios, E., Kass, D. C. L., & Thomas, R. J. (2002). Decomposition and nutrient release by green manures in a tropical hillside agroecosystem. *Plant and Soil*, *240*(2), 331–342. https://doi.org/10.1023/A:1015720324392

Cook, S. E., & Bramley, R. G. V. (1998a). Precision agriculture—Opportunities, benefits and pitfalls of site-specific crop management in Australia. *Australian Journal of Experimental Agriculture*, *38*(7), 753. https://doi.org/10.1071/EA97156

Cook, S., Lacoste, M., Evans, F., Ridout, M., Gibberd, M., & Oberthür, T. (2018). *An On-Farm Experimental philosophy for farmer-centric digital innovation*.

Daum, T. (2021). Farm robots: Ecological utopia or dystopia? *Trends in Ecology & Evolution*, *36*(9), 774–777. https://doi.org/10.1016/j.tree.2021.06.002

Díaz, S., Fargione, J., Chapin, F. S., & Tilman, D. (2006). Biodiversity Loss Threatens Human Well-Being. *PLoS Biology*, *4*(8), e277. https://doi.org/10.1371/journal.pbio.0040277

Drugova, T., Pozo, V. F., Curtis, K. R., & Randall Fortenbery, T. (2019). Organic wheat prices and premium uncertainty: Can cross hedging and forecasting play a role? *Journal of Agricultural and Resource Economics*, *44*(3), 551–570. https://doi.org/10.22004/ag.econ.292331

Duff, H., Hegedus, P. B., Loewen, S., Bass, T., & Maxwell, B. D. (2021). Precision Agroecology. *Sustainability*, *14*(1), 106. https://doi.org/10.3390/su14010106

Duke, S. O. (2018). The history and current status of glyphosate. *Pest Management Science*, *74*(5), 1027–1034. https://doi.org/10.1002/ps.4652

Durham, Ti. C., & Mizik, T. (2021). Comparative Economics of Conventional, Organic, and Alternative Agricultural Production Systems. *Economies*, *9*(64), 1–22.

Esposito, M., Crimaldi, M., Cirillo, V., Sarghini, F., & Maggio, A. (2021). Drone and sensor technology for sustainable weed management: A review. *Chemical and Biological Technologies in Agriculture*, *8*(1), 18. https://doi.org/10.1186/s40538-021-00217-8

Eyhorn, F., Muller, A., Reganold, J. P., Frison, E., Herren, H. R., Luttikholt, L., Mueller, A., Sanders, J., Scialabba, N. E.-H., Seufert, V., & Smith, P. (2019). Sustainability in global agriculture driven by organic farming. *Nature Sustainability*, *2*(4), 253–255. https://doi.org/10.1038/s41893-019-0266-6

Filipiak, J. (2011). The Work of Local Culture: Wendell Berry and Communities as the Source of Farming Knowledge. *Agricultural History*, *85*(2), 174–194. https://doi.org/10.3098/ah.2011.85.2.174

Gan, Y. T., Wang, J., Bing, D. J., Miller, P. R., & McDonald, C. L. (2007). Water use of pulse crops at various plant densities under fallow and stubble conditions in a semiarid environment. *Canadian Journal of Plant Science*, *87*(4), 719–722. https://doi.org/10.4141/P06-117

Garbach, K., Milder, J. C., DeClerck, F. A. J., Montenegro de Wit, M., Driscoll, L., & Gemmill-Herren, B. (2017). Examining multi-functionality for crop yield and ecosystem services in five systems of agroecological intensification. *International Journal of Agricultural Sustainability*, *15*(1), 11–28. https://doi.org/10.1080/14735903.2016.1174810

Gatsios, A., Ntatsi, G., Celi, L., Said-Pullicino, D., Tampakaki, A., & Savvas, D. (2021). Legume-Based Mobile Green Manure Can Increase Soil Nitrogen Availability and Yield of Organic Greenhouse Tomatoes. *Plants*, *10*(11), Article 11. https://doi.org/10.3390/plants10112419

Gelderman, R. H., & Beegle, D. (2015). Nitrate-nitrogen (Revised January 1998). *Recommended Chemical Soil Test Procedure for the North Central Region. North Central Regional Res. Pub*, *221*, 5–1.

Gemmill-Herren, B. (2020). Closing the circle: An agroecological response to covid-19. *Agriculture and Human Values*, *37*(3), 613–614. https://doi.org/10.1007/s10460-020-10097-7

Gerhards, R., Andújar Sanchez, D., Hamouz, P., Peteinatos, G. G., Christensen, S., & Fernandez-Quintanilla, C. (2022). Advances in site-specific weed management in agriculture—A review. *Weed Research*, *62*(2), 123–133. https://doi.org/10.1111/wre.12526

Gomiero, T. (2018). Food quality assessment in organic vs. conventional agricultural produce: Findings and issues. *Applied Soil Ecology*, *123*, 714–728. https://doi.org/10.1016/j.apsoil.2017.10.014

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Griffin, T. S., & Hesterman, O. B. (1991). Potato Response to Legume and Fertilizer Nitrogen Sources. *Agronomy Journal*, *83*(6), 1004–1012. https://doi.org/10.2134/agronj1991.00021962008300060016x

Guaci, A., Fulton, J. P., Lindsey, A., Shearer, S., Barker, D., & Hawkins, E. (2022). Limitations of Yield Monitor Data to Support Field-scale Research. *Proceedings of the 15th International Conference on Precision Agriculture, Minneapolis, USA*, *28*.

Hammermeister, A. M. (2020). Organic Agriculture: A Model for Sustainability. In C. D. Caldwell & S. Wang (Eds.), *Introduction to Agroecology* (pp. 279–299). Springer. https://doi.org/10.1007/978-981-15-8836-5_20

Hatfield, J. L., Cryder, M., & Basso, B. (2020). Remote Sensing: Advancing the Science and the Applications to Transform Agriculture. *IT Professional*, *22*(3), 42–45. https://doi.org/10.1109/MITP.2020.2986102

Heap, I., & Duke, S. O. (2018). Overview of glyphosate-resistant weeds worldwide: Overview of glyphosate-resistant weeds. *Pest Management Science*, *74*(5), 1040–1049. https://doi.org/10.1002/ps.4760

Hegedus, P. B., Ewing, S., Jones, C., & Maxwell, B. D. (2022). *Using spatially variable nitrogen application and crop responses to evaluate crop nitrogen use efficiency* [Preprint]. In Review. https://doi.org/10.21203/rs.3.rs-2126328/v1

Hegedus, P. B., & Maxwell, B. D. (2022). Rationale for field-specific on-farm precision experimentation. *Agriculture, Ecosystems & Environment*, *338*, 108088. https://doi.org/10.1016/j.agee.2022.108088

Hegedus, P. B., Maxwell, B. D., & Mieno, T. (2022). Assessing performance of empirical models for forecasting crop responses to variable fertilizer rates using on-farm precision experimentation. *Precision Agriculture*. https://doi.org/10.1007/s11119-022-09968-2

Hegedus, P. B., Maxwell, B., Sheppard, J., Loewen, S., Duff, H., Morales-Luna, G., & Peerlinck, A. (2023). Towards a Low-Cost Comprehensive Process for On-Farm Precision Experimentation and Analysis. *Agriculture*, *13*(3), 524. https://doi.org/10.3390/agriculture13030524

Hegedus, P. & Maxwell, B.D. (2022). Constraint of Data Availability on the Predictive Ability of Crop Response Models Developed from On-farm Experimentation. *Proceedings of the 15th International Conference on Precision Agriculture*.

Hiemstra, P., & Skoien, J. O. (2023). *automap: Automatic Interpolation Package* (1.1-1). https://CRAN.R-project.org/package=automap

Holleman, H. (2018). *Dust bowls of empire: Imperialism, environmental politics, and the injustice of "green" capitalism*. Yale University Press.

Hunter, M. C., Smith, R. G., Schipanski, M. E., Atwood, L. W., & Mortensen, D. A. (2017). Agriculture in 2050: Recalibrating Targets for Sustainable Intensification. *BioScience*, *67*(4), 386–391. https://doi.org/10.1093/biosci/bix010

International Society of Precision Agriculture. (2021). https://www.ispag.org/about/definition

Izard, E. J. (2007). *SEEKING SUSTAINABILITY FOR ORGANIC CROPPING SYSTEMS IN THE NORTHERN GREAT PLAINS: LEGUME GREEN MANURE MANAGEMENT STRATEGIES*. Montana State University.

Janzen, H. H., Janzen, D. W., & Gregorich, E. G. (2021). The 'soil health' metaphor: Illuminating or illusory? *Soil Biology and Biochemistry*, *159*, 108167. https://doi.org/10.1016/j.soilbio.2021.108167

Johnson, S. P., Miller, Z. J., Lehnhoff, E. A., Miller, P. R., & Menalled, F. D. (2017). Cropping systems modify soil biota effects on wheat (*Triticum aestivum*) growth and competitive ability. *Weed Research*, *57*(1), 6–15. https://doi.org/10.1111/wre.12231

Johnston, A. M., Clayton, G. W., Lafond, G. P., Harker, K. N., Hogg, T. J., Johnson, E. N., May, W. E., & McConnell, J. T. (2002). Field pea seeding management. *Canadian Journal of Plant Science*, *82*(4), 639–644. https://doi.org/10.4141/P02-001

Korres, N. E., Burgos, N. R., Travlos, I., Vurro, M., Gitsopoulos, T. K., Varanasi, V. K., Duke, S. O., Kudsk, P., Brabham, C., Rouse, C. E., & Salas-Perez, R. (2019). Chapter Six - New directions for integrated weed management: Modern technologies, tools and knowledge discovery. In D. L. Sparks (Ed.), *Advances in Agronomy* (Vol. 155, pp. 243–319). Academic Press. https://doi.org/10.1016/bs.agron.2019.01.006

Kuhn, M., & Wickham, H. (2022). *tidymodels: Easily Install and Load the "Tidymodels" Packages* (1.0.0). https://CRAN.R-project.org/package=tidymodels

Kumar, K., Gambhir, G., Dass, A., Tripathi, A. K., Singh, A., Jha, A. K., Yadava, P., Choudhary, M., & Rakshit, S. (2020). Genetically modified crops: Current status and future prospects. *Planta*, *251*(4), 1–27. https://doi.org/10.1007/s00425-020-03372-8

Kursa, M. B., & Rudnicki, W. R. (2010). Feature Selection with the **Boruta** Package. *Journal of Statistical Software*, *36*(11). https://doi.org/10.18637/jss.v036.i11

Kyveryga, P. M. (2019). On-Farm Research: Experimental Approaches, Analytical Frameworks, Case Studies, and Impact. *Agronomy Journal*, *111*(6), 2633–2635. https://doi.org/10.2134/agronj2019.11.0001

Lacoste, M., Cook, S., McNee, M., Gale, D., Ingram, J., Bellon-Maurel, V., MacMillan, T., Sylvester-Bradley, R., Kindred, D., Bramley, R., Tremblay, N., Longchamps, L., Thompson, L., Ruiz, J., García, F. O., Maxwell, B., Griffin, T., Oberthür, T., Huyghe, C., … Hall, A. (2021). On-Farm Experimentation to transform global agriculture. *Nature Food*, *3*(1), 11–18. https://doi.org/10.1038/s43016-021-00424-4

Lawley, Y. E., & Shirtliffe, S. J. (2004). Optimum seeding rates for three annual green manure crops: The effect of weed competition. *Soils and Crops Workshop*.

Lawrence, P. G., Maxwell, B. D., Rew, L. J., Ellis, C., & Bekkerman, A. (2018). Vulnerability of dryland agricultural regimes to economic and climatic change. *Ecology and Society*, *23*(1), art34. https://doi.org/10.5751/ES-09983-230134

Lawrence, P. G., Rew, L. J., & Maxwell, B. D. (2015). A probabilistic Bayesian framework for progressively updating site-specific recommendations. *Precision Agriculture*, *16*(3), 275–296. https://doi.org/10.1007/s11119-014-9375-4

Lemerle, D., Cousens, R. D., Gill, G. S., Peltzer, S. J., Moerkerk, M., Murphy, C. E., Collins, D., & Cullis, B. R. (2004). Reliability of higher seeding rates of wheat for increased competitiveness with weeds in low rainfall environments. *The Journal of Agricultural Science*, *142*(4), 395–409. https://doi.org/10.1017/S002185960400454X

Liebman, M., Gallandt, E. R., & Jackson, L. E. (1997). Many little hammers: Ecological management of crop-weed interactions. *Ecology in Agriculture*, *1*, 291–343.

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

Loewen, S., Maxwell, B. D. (2023). *Optimizing organic cover crop seeding rates and following cash crops to maximize net return in a controlled environment*. Manuscript submitted for publication.

Lu, P., Jiang, B., & Weiner, J. (2020). Chapter Three—Crop spatial uniformity, yield and weed suppression. In D. L. Sparks (Ed.), *Advances in Agronomy* (Vol. 161, pp. 117–178). Academic Press. https://doi.org/10.1016/bs.agron.2019.12.003

MacLaren, C., Storkey, J., Menegat, A., Metcalfe, H., & Dehnen-Schmutz, K. (2020a). An ecological future for weed science to sustain crop production and the environment. A review. *Agronomy for Sustainable Development*, *40*(4), 24. https://doi.org/10.1007/s13593-020-00631-6

MacLaren, C., Storkey, J., Menegat, A., Metcalfe, H., & Dehnen-Schmutz, K. (2020b). An ecological future for weed science to sustain crop production and the environment. A review. *Agronomy for Sustainable Development*, *40*(4), 24. https://doi.org/10.1007/s13593-020-00631-6

Mathur, M. (2015). Spatial autocorrelation analysis in plant population: An overview. *Journal of Applied and Natural Science*, *7*(1), Article 1. https://doi.org/10.31018/jans.v7i1.639

Mattivi, P., Pappalardo, S. E., Nikolić, N., Mandolesi, L., Persichetti, A., De Marchi, M., & Masin, R. (2021). Can Commercial Low-Cost Drones and Open-Source GIS Technologies Be Suitable for Semi-Automatic Weed Mapping for Smart Farming? A Case Study in NE Italy. *Remote Sensing*, *13*(10), 1869. https://doi.org/10.3390/rs13101869

Maxwell, B. (2017). Weed-plant interactions. In Colorado State University, USA & R. Zimdahl (Eds.), *Integrated weed management for sustainable agriculture* (pp. 29–42). Burleigh Dodds Science Publishing. https://doi.org/10.19103/AS.2017.0025.02

Maxwell, B. D., & Luschei, E. C. (2005a). Justification for site-specific weed management based on ecology and economics. *Weed Science*, *53*(2), 221–227. https://doi.org/10.1614/WS-04-071R2

Maxwell, B.D. & O'Donovan, J. (2007). Understanding Weed–Crop Interactions to Manage Weed Problems. In U. M. K. Upadhyaya M. K. & B. R. E. Blackshaw R. E. (Eds.), *Non-chemical weed management: Principles, concepts and technology* (1st ed.). CABI. https://doi.org/10.1079/9781845932909.0000

McBratney, A., Whelan, B., & Ancev, T. (2005). Future Directions of Precision Agriculture. *Precision Agriculture*, *6*, 7–23.

McCauley, A. M., Jones, C. A., Miller, P. R., Burgess, M. H., & Zabinski, C. A. (2012). Nitrogen fixation by pea and lentil green manures in a semi-arid agroecoregion: Effect of planting and termination timing. *Nutrient Cycling in Agroecosystems*, *92*(3), 305–314. https://doi.org/10.1007/s10705-012-9491-3

McCauley, A., Miller, P., Holmes, J., Burgess, M., & Jones, C. (2012). Improving Annual Legume Green Manure Management by Optimizing Seeding Rate and Termination Timing. *Montana State University Extension*, *61*.

McFadden, J. R., Rosburg, A., & Njuki, E. (2022). Information inputs and technical efficiency in midwest corn production: Evidence from farmers' use of yield and soil maps. *American Journal of Agricultural Economics*, *104*(2), 589–612. https://doi.org/10.1111/ajae.12251

Meemken, E.-M., & Qaim, M. (2018). Organic Agriculture, Food Security, and the Environment. *Annual Review of Resource Economics*, *10*(1), 39–63. https://doi.org/10.1146/annurev-resource-100517-023252

Melander, B., Rasmussen, I. A., & Olesen, J. E. (2020). Legacy effects of leguminous green manure crops on the weed seed bank in organic crop rotations. *Agriculture, Ecosystems & Environment*, *302*, 107078. https://doi.org/10.1016/j.agee.2020.107078

Merfield, C. N. (2019). Chapter 5—Integrated Weed Management in Organic Farming. In S. Chandran, M. R. Unni, & S. Thomas (Eds.), *Organic Farming* (pp. 117–180). Woodhead Publishing. https://doi.org/10.1016/B978-0-12-813272-2.00005-7

Miller, P., Glunk, E., Holmes, J., & Engel, R. (2018). Pea and Barley Forage as Fallow Replacement for Dryland Wheat Production. *Agronomy Journal*, *110*(3), 833–841. https://doi.org/10.2134/agronj2017.02.0087

Miller, P. R., Buschena, D. E., Jones, C. A., & Holmes, J. A. (2008). Transition from Intensive Tillage to No-Tillage and Organic Diversified Annual Cropping Systems. *Agronomy Journal*, *100*(3), 591–599. https://doi.org/10.2134/agronj2007.0190

Miller, P. R., Lighthiser, E. J., Jones, C. A., Holmes, J. A., Rick, T. L., & Wraith, J. M. (2011). Pea green manure management affects organic winter wheat yield and quality in semiarid Montana. *Canadian Journal of Plant Science*, *91*(3), 497–508. https://doi.org/10.4141/cjps10109

Mitchell, S., Weersink, A., & Erickson, B. (2018). Adoption of precision agriculture technologies in Ontario crop production. *Canadian Journal of Plant Science*, *98*(6), 1384–1388. https://doi.org/10.1139/cjps-2017-0342

Monteiro, A., & Santos, S. (2022). Sustainable Approach to Weed Management: The Role of Precision Weed Management. *Agronomy*, *12*(1), Article 1. https://doi.org/10.3390/agronomy12010118

Mooleki, S. P., Gan, Y., Lemke, R. L., Zentner, R. P., & Hamel, C. (2016). Effect of green manure crops, termination method, stubble crops, and fallow on soil water, available N, and exchangeable P. *Canadian Journal of Plant Science*, *96*(5), 867–886. https://doi.org/10.1139/cjps-2015-0336

Moonen, A.-C., & Bàrberi, P. (2008). Functional biodiversity: An agroecosystem approach. *Agriculture, Ecosystems & Environment*, *127*(1), 7–21. https://doi.org/10.1016/j.agee.2008.02.013

Morari, F., Zanella, V., Sartori, L., Visioli, G., Berzaghi, P., & Mosca, G. (2018). Optimising durum wheat cultivation in North Italy: Understanding the effects of site-specific fertilization on yield and protein content. *Precision Agriculture*, *19*(2), 257–277. https://doi.org/10.1007/s11119-017-9515-8

Murrell, E. G., Schipanski, M. E., Finney, D. M., Hunter, M. C., Burgess, M., LaChance, J. C., Baraibar, B., White, C. M., Mortensen, D. A., & Kaye, J. P. (2017). Achieving Diverse Cover Crop Mixtures: Effects of Planting Date and Seeding Rate. *Agronomy Journal*, *109*(1), 259–271. https://doi.org/10.2134/agronj2016.03.0174

Nielsen, D. C., Unger, P. W., & Miller, P. R. (2005). Efficient Water Use in Dryland Cropping Systems in the Great Plains. *Agronomy Journal*, *97*(2), 364–372. https://doi.org/10.2134/agronj2005.0364

Oerke, E.-C. (2006). Crop losses to pests. *The Journal of Agricultural Science*, *144*(1), 31–43. https://doi.org/10.1017/S0021859605005708

Padbury, G., Waltman, S., Caprio, J., Coen, G., McGinn, S., Mortensen, D., Nielsen, G., & Sinclair, R. (2002). Agroecosystems and Land Resources of the Northern Great Plains. *Agronomy Journal*, *94*(2), 251–261. https://doi.org/10.2134/agronj2002.2510

Paradis, E., Blomberg, S., Bolker [aut, B., cph, Brown, J., Claramunt, S., Claude, J., Cuong, H. S., Desper, R., Didier, G., Durand, B., Dutheil, J., Ewing, R. J., Gascuel, O., Guillerme, T., Heibl, C., Ives, A., Jones, B., Krah [aut, F., … Vienne, D. de. (2023). *ape: Analyses of Phylogenetics and Evolution* (5.7-1). https://CRAN.R-project.org/package=ape

Partel, V., Charan Kakarla, S., & Ampatzidis, Y. (2019). Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence.

Computers and Electronics in Agriculture, *157*, 339–350. https://doi.org/10.1016/j.compag.2018.12.048

Pebesma, E., & Graeler, B. (2022). *gstat: Spatial and Spatio-Temporal Geostatistical Modelling, Prediction and Simulation* (2.1-0). https://CRAN.R-project.org/package=gstat

Pedersen, S. M., & Lind, K. M. (2017a). Precision Agriculture – From Mapping to Site-Specific Application. In S. M. Pedersen & K. M. Lind (Eds.), *Precision Agriculture: Technology and Economic Perspectives* (pp. 1–20). Springer International Publishing. https://doi.org/10.1007/978-3-319-68715-5_1

Pellegrini, P., & Fernández, R. J. (2018). Crop intensification, land use, and on-farm energy-use efficiency during the worldwide spread of the green revolution. *Proceedings of the National Academy of Sciences*, *115*(10), 2335–2340. https://doi.org/10.1073/pnas.1717072115

Piepho, H.-P., Richter, C., Spilke, J., Hartung, K., Kunick, A., Thöle, H., Piepho, H.-P., Richter, C., Spilke, J., Hartung, K., Kunick, A., & Thöle, H. (2011). Statistical aspects of on-farm experimentation. *Crop and Pasture Science*, *62*(9), 721–735. https://doi.org/10.1071/CP11175

Poffenbarger, H. J., Mirsky, S. B., Weil, R. R., Kramer, M., Spargo, J. T., & Cavigelli, M. A. (2015). Legume Proportion, Poultry Litter, and Tillage Effects on Cover Crop Decomposition. *Agronomy Journal*, *107*(6), 2083–2096. https://doi.org/10.2134/agronj15.0065

Pollnac, F. W., Rew, L. J., Maxwell, B. D., & Menalled, F. D. (2008). Spatial patterns, species richness and cover in weed communities of organic and conventional no-tillage spring wheat systems. *Weed Research*, *48*(5), 398–407. https://doi.org/10.1111/j.1365-3180.2008.00631.x

Pretty, J. (2018). Intensification for redesigned and sustainable agricultural systems. *Science*, *362*(6417), eaav0294. https://doi.org/10.1126/science.aav0294

Pringle, M. J., Cook, S. E., & McBratney, A. B. (2004). Field-Scale Experiments for Site-Specific Crop Management. Part I: Design Considerations. *Precision Agriculture*, *5*(6), 617–624. https://doi.org/10.1007/s11119-004-6346-1

Pringle, M. J., McBratney, A. B., & Cook, S. E. (2004). Field-Scale Experiments for Site-Specific Crop Management. Part II: A Geostatistical Analysis. *Precision Agriculture*, *5*(6), 625–645. https://doi.org/10.1007/s11119-004-6347-0

Prost, L., Martin, G., Ballot, R., Benoit, M., Bergez, J.-E., Bockstaller, C., Cerf, M., Deytieux, V., Hossard, L., Jeuffroy, M.-H., Leclère, M., Le Bail, M., Le Gal, P.-Y., Loyce, C., Merot, A., Meynard, J.-M., Mignolet, C., Munier-Jolain, N., Novak, S., … van der Werf, H. (2023). Key research challenges to supporting farm transitions to agroecology in advanced economies. A review. *Agronomy for Sustainable Development*, *43*(1), 11. https://doi.org/10.1007/s13593-022-00855-8

Provenza, F. D., Anderson, C., & Gregorini, P. (2021). We Are the Earth and the Earth Is Us: How Palates Link Foodscapes, Landscapes, Heartscapes, and Thoughtscapes. *Frontiers in Sustainable Food Systems*, *5*, 547822. https://doi.org/10.3389/fsufs.2021.547822

Quinn, R. M. (1999). Kamut®: Ancient grain, new cereal. *Perspectives on New Crops and New Uses*, 182–183.

R Core Team. (2022). *R: A language and environment for statistical computing. R Foundation for Statistical Computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Ranells, N. N., & Wagger, M. G. (1996). Nitrogen release from grass and legume cover crop monocultures and bicultures. *Agronomy Journal*, *88*(5), 777–882.

Riedo, J., Wettstein, F. E., Rosch, A., Herzog, C., Banerjee, S., Buchi, L., Charles, R., Wachter, D., Martin-Laurent, F., Bucheli, T. D., Walder, F., & Van Der Heijden, M. G. A. (2021). Widespread occurrence of pesticides in organically managed agricultural soils-The ghost of a conventional agricultural past? *Environmental Science and Technology*, *55*(5), 2919–2928. https://doi.org/10.1021/acs.est.0c06405

Robert, P. (1993). Characterization of soil conditions at the field level for soil specific management. *Geoderma*, *60*(1–4), 57–72. https://doi.org/10.1016/0016-7061(93)90018-G

Rodriguez, D. G. P., Bullock, D. S., & Boerngen, M. A. (2019a). The Origins, Implications, and Consequences of Yield-Based Nitrogen Fertilizer Management. *Agronomy Journal*, *111*(2), 725–735. https://doi.org/10.2134/agronj2018.07.0479

Rosset, P. M., & Altieri, M. A. (1997). Agroecology versus input substitution: A fundamental contradiction of sustainable agriculture. *Society & Natural Resources*, *10*(3), 283–295. https://doi.org/10.1080/08941929709381027

Rothrock, G. P., Sears, E. L., Poncet, A. M., Ross, W. J., & France, O. W. (2022). Drivers of Yield Variability in a Variable-Rate Seeding Experiment. *Agronomy*, 31–37.

Ruffo, M. L., Bollero, G. A., Bullock, D. S., & Bullock, D. G. (2006). Site-specific production functions for variable rate corn nitrogen fertilization. *Precision Agriculture*, *7*(5), 327–342. https://doi.org/10.1007/s11119-006-9016-7

Schimmelpfennig, D., & Lowenberg-DeBoer, J. (2020). Farm Types and Precision Agriculture Adoption: Crops, Regions, Soil Variability, and Farm Size. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3689311

Schrama, M., de Haan, J. J., Kroonen, M., Verstegen, H., & Van der Putten, W. H. (2018). Crop yield gap and stability in organic and conventional farming systems. *Agriculture, Ecosystems & Environment*, *256*, 123–130. https://doi.org/10.1016/j.agee.2017.12.023

Seneviratne, G. (2000). Litter quality and nitrogen release in tropical agriculture: A synthesis. *Biology and Fertility of Soils*, *31*(1), 60–64. https://doi.org/10.1007/s003740050624

Seufert, V., & Ramankutty, N. (2017). Many shades of gray—The context-dependent performance of organic agriculture. *Science Advances*, *3*(3), e1602638. https://doi.org/10.1126/sciadv.1602638

Seufert, V., Ramankutty, N., & Foley, J. A. (2012a). Comparing the yields of organic and conventional agriculture. *Nature*, *485*(7397), 229–232. https://doi.org/10.1038/nature11069

Shrestha, A., Hesterman, O. B., Copeland, L. O., Squire, J. M., Fisk, J. W., & Sheaffer, C. C. (1999). Annual legumes as green manure and forage crops in winter canola (*Brassica napus* L.) rotations. *Canadian Journal of Plant Science*, *79*(1), 19–25. https://doi.org/10.4141/P98-010

Smith, C., Hill, A. K., & Torrente-Murciano, L. (2020). Current and future role of Haber–Bosch ammonia in a carbon-free energy landscape. *Energy & Environmental Science*, *13*(2), 331–344. https://doi.org/10.1039/C9EE02873K

Smith, P. (2018). Managing the global land resource. *Proceedings of the Royal Society B: Biological Sciences*, *285*(1874), 20172798. https://doi.org/10.1098/rspb.2017.2798

Smith, R. G., Mortensen, D. A., & Ryan, M. R. (2010). A new hypothesis for the functional role of diversity in mediating resource pools and weed–crop competition in agroecosystems. *Weed Research*, *50*(1), 37–48. https://doi.org/10.1111/j.1365-3180.2009.00745.x

Somerville, G. J., Sønderskov, M., Mathiassen, S. K., & Metcalfe, H. (2020). Spatial Modelling of Within-Field Weed Populations; a Review. *Agronomy*, *10*(7), 1044. https://doi.org/10.3390/agronomy10071044

Spies, J. M. (2008). *The Effect of Field Pea (Pisum sativum L.) Basal Branching on Optimal Plant Density and Crop Competitiveness*. University of Saskatchewan.

Stainsby, A., & Entz, M. H. (2022). Aggregate stability after 25 years of organic, conventional, and grassland management. *Canadian Journal of Soil Science*, *102*(2), 519–530. https://doi.org/10.1139/cjss-2021-0104

Stallknecht, G. F., Gilbertson, K. M., & Ranney, J. E. (1996). Alternative wheat cereals as food grains: Einkorn, emmer, spelt, kamut, and triticale. *Progress in New Crops*, *1996*, 156–170.

Storey, J., Roy, D. P., Masek, J., Gascon, F., Dwyer, J., & Choate, M. (2016). A note on the temporary misregistration of Landsat-8 Operational Land Imager (OLI) and Sentinel-2 Multi Spectral Instrument (MSI) imagery. *Remote Sensing of Environment*, *186*, 121–122. https://doi.org/10.1016/j.rse.2016.08.025

Tal, A. (2018). Making Conventional Agriculture Environmentally Friendly: Moving beyond the Glorification of Organic Agriculture and the Demonization of Conventional Agriculture. *Sustainability*, *10*(4), 1078. https://doi.org/10.3390/su10041078

Tanaka, T. S., Kakimoto, S., Mieno, T., & Bullock, D. S. (2022). Comparison between spatial predictor variables for machine learning in site-specific yield response modeling based on simulation study of on-farm precision experimentation. *Abstracts of Meeting of the CSSJ The 253rd Meeting of CSSJ*, 63–63.

Tantalaki, N., Souravlas, S., & Roumeliotis, M. (2019). Data-Driven Decision Making in Precision Agriculture: The Rise of Big Data in Agricultural Systems. *Journal of Agricultural & Food Information*, *20*(4), 344–380. https://doi.org/10.1080/10496505.2019.1638264

Thiessen Martens, J. R., Lynch, D. H., & Entz, M. H. (2019). A survey of green manure productivity on dryland organic grain farms in the eastern prairie region of Canada. *Canadian Journal of Plant Science*, *99*(5), 772–776. https://doi.org/10.1139/cjps-2018-0311

Thornton, M. M., Shrestha, R., Wei, Y., Thornton, P. E., Kao, S.-C., & Wilson, B. E. (2022). Daymet: Annual Climate Summaries on a 1-km Grid for North America, Version 4 R1. *ORNL DAAC*. https://doi.org/10.3334/ORNLDAAC/2130

Tilman, D., Balzer, C., Hill, J., & Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences*, *108*(50), 20260–20264. https://doi.org/10.1073/pnas.1116437108

Toffolini, Q., & Jeuffroy, M.-H. (2022). On-farm experimentation practices and associated farmer-researcher relationships: A systematic literature review. *Agronomy for Sustainable Development*, *42*(6), 114. https://doi.org/10.1007/s13593-022-00845-w

Trémas, T. L., Déchoz, C., Lacherade, S., Nosavan, J., & Petrucci, B. (2015). Sentinel-2: Presentation of the CAL/VAL commissioning phase. *Image and Signal Processing for Remote Sensing XXI*, *9643*, 94–106. https://doi.org/10.1117/12.2194847

Trevisan, R. G., Bullock, D. S., & Martin, N. F. (2021). Spatial variability of crop responses to agronomic inputs in on-farm precision experimentation. *Precision Agriculture*, *22*(2), 342–363. https://doi.org/10.1007/s11119-020-09720-8

Tully, K. L., & McAskill, C. (2020). Promoting soil health in organically managed systems: A review. *Organic Agriculture*, *10*(3), 339–358. https://doi.org/10.1007/s13165-019-00275-1

Unkovich, M., Herridge, D., Peoples, M., Cadisch, G., Boddey, B., Giller, K., Alves, B., & Chalk, P. (2008). *Measuring plant-associated nitrogen fixation in agricultural systems.* Australian Centre for International Agricultural Research (ACIAR).

USDA ERS - Commodity Costs and Returns. (2022). https://www.ers.usda.gov/data-products/commodity-costs-and-returns/commodity-costs-and-returns/#Cost-of-Production%20Forecasts.

Usukh, B. (2010). *THE IMPACT OF LENTIL AND FIELD PEA SEEDING RATES ON DINITROGEN FIXATION AND SUBSEQUENT NITROGEN BENEFITS IN AN ORGANIC CROPPING SYSTEM*. University of Saskatchewan.

van Evert, F. K., Fountas, S., Jakovetic, D., Crnojevic, V., Travlos, I., & Kempenaar, C. (2017). Big Data for weed control and crop protection. *Weed Research*, *57*(4), 218–233. https://doi.org/10.1111/wre.12255

Watson, C. A., Atkinson, D., Gosling, P., Jackson, L. R., & Rayns, F. W. (2006). Managing soil fertility in organic farming systems. *Soil Use and Management*, *18*, 239–247. https://doi.org/10.1111/j.1475-2743.2002.tb00265.x

Watthier, M., Peralta Antonio, N., Gomes, J. A., Rocha, S. B. F., & Santos, R. H. S. (2020). Decomposition of green manure with different grass: Legume ratios. *Archives of Agronomy and Soil Science*, *66*(7), 913–924. https://doi.org/10.1080/03650340.2019.1644622

Weersink, A., Fraser, E., Pannell, D., Duncan, E., & Rotz, S. (2018). Opportunities and Challenges for Big Data in Agricultural and Environmental Analysis. *Annual Review of Resource Economics*, *10*(1), 19–37. https://doi.org/10.1146/annurev-resource-100516-053654

Weiner, J. (2017). Applying plant ecological knowledge to increase agricultural sustainability. *Journal of Ecology*, *105*(4), 865–870. https://doi.org/10.1111/1365-2745.12792

Weiner, J., & Freckleton, R. P. (2010). Constant Final Yield. *Annual Review of Ecology, Evolution, and Systematics*, *41*(1), 173–192. https://doi.org/10.1146/annurev-ecolsys-102209-144642

Wendell Berry. (2017). *The World-Ending Fire; The Essential Wendell Berry*. Counterpoint.

Wezel, A., Bellon, S., Doré, T., Francis, C., Vallod, D., & David, C. (2009). Agroecology as a science, a movement and a practice. A review. *Agronomy for Sustainable Development*, *29*(4), 503–515. https://doi.org/10.1051/agro/2009004

Wezel, A., Soboksa, G., McClelland, S., Delespesse, F., & Boissau, A. (2015). The blurred boundaries of ecological, sustainable, and agroecological intensification: A review. *Agronomy for Sustainable Development*, *35*(4), 1283–1295. https://doi.org/10.1007/s13593-015-0333-y

Wheat: Khorasan Wheat | Cereals: Barley, Wheat, Oats, Triticale. (2012). Government of Saskatchewan. Retrieved January 29, 2023, from https://www.saskatchewan.ca/business/agriculture-natural-resources-and-industry/agribusiness-farmers-and-ranchers/crops-and-irrigation/field-crops/cereals-barley-wheat-oats-triticale/wheat-khorasan-wheat

Willer, E. H., & Lernoud, J. (2019). *The World of Organic Agriculture Statistics and Emerging Trends 2019*.

Wright, M. N., & Ziegler, A. (2017). ranger: A Fast Implementation of Random Forests for High Dimensional Data in C++ and R. *Journal of Statistical Software*, *77*, 1–17. https://doi.org/10.18637/jss.v077.i01

Würriehausen, N., Ihle, R., & Lakner, S. (2015). Price relationships between qualitatively differentiated agricultural products: Organic and conventional wheat in Germany. *Agricultural Economics*, *46*(2), 195–209. https://doi.org/10.1111/agec.12151

Zabinski, C. (2020). *Amber waves: The extraordinary biography of wheat, from wild grass to world megacrop*. The University of Chicago Press.

Zimdahl, R. L. (2007). *Weed-Crop Competition: A Review*. John Wiley & Sons.