Title

Soil Health in the Salad Bowl: Barriers and opportunities for building soil carbon and multifunctionality on farms in California's Central Coast region

Author

Esquivel, Kenzo Emiliano

Publication Date

2024

Peer reviewed|Thesis/dissertation

Soil Health in the Salad Bowl: Barriers and opportunities for building soil carbon and multifunctionality on farms in California's Central Coast region

By

Kenzo Emiliano Esquivel

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Environmental Science, Policy, and Management

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Timothy Bowles, Chair
Professor Céline Pallud
Professor Alastair Iles

Summer 2024

Abstract

Soil Health in the Salad Bowl: Barriers and opportunities for building soil carbon and multifunctionality on farms in California's Central Coast region

by

Kenzo Emiliano Esquivel

Doctor of Philosophy in Environmental Science, Policy, & Management

University of California, Berkeley

Professor Timothy Bowles, Chair

The relentless global pursuit of food and fiber production, often at the expense of natural ecosystems, has resulted in agricultural systems that degrade local biodiversity and environmental quality. While farmers have traditionally possessed the knowledge to maintain soil health and ecosystem balance, modern industrial agriculture has shifted towards simplistic, input-dependent practices. Organic farming offers a step towards sustainability by reducing synthetic inputs, yet it often falls short, still relying on organic substitutes and failing to address deeper ecological concerns. In contrast, soil health management practices, rooted in principles from the Natural Resource Conservation Service (NRCS), offer holistic strategies beyond mere input substitution. These practices prioritize maximizing living roots and soil cover, fostering biodiversity, and minimizing soil disturbance. However, practices that put these principles into action such as cover crops and reduced tillage remain underutilized, even among organic farmers. Understanding the barriers to the adoption of soil health management is crucial for transitioning to a more balanced agricultural paradigm that sustains productivity and environmental integrity.

Most of our current understanding of the impacts of soil health management comes from research-station trials that isolate 1-2 practices at a time, within a single edaphic and climatic context. Recent on-farm research endeavors to bridge this gap by examining how management practices impact soil health metrics in real-world settings. Rebuilding soil organic matter (SOM) is a core goal of soil health management, given its manifold benefits, including supporting soil life and enhancing structure and nutrient availability. Increasing SOM levels aligns with short- and long-term goals of bolstering soil health and combating climate change through carbon sequestration. However, it isn't clear how implementation of soil health practices, as utilized on actively managed farms, impacts these different carbon goals. Beyond carbon, soils provide many critical ecosystem services, and the impacts of soil health management on various soil-mediated ecosystem services and general multifunctionality is not well resolved. Managing farms for multiple ecosystem services beyond crop production can also present challenges, as trade-offs and conflicting priorities often arise. Understanding the intricate interplay between local soil characteristics, management practices, and various stakeholder objectives is essential for crafting effective policies.

My dissertation addresses these challenges by delving into three key areas of agricultural development: identifying barriers to adopting soil health practices, exploring the impacts of

management on soil carbon, and assessing the relationship between management practices and multiple ecosystem services. By integrating social, economic, and environmental perspectives, my dissertation informs policies that facilitate the transition to sustainable soil management practices, fostering a more resilient and environmentally sound food system. Briefly, we find that different farming models face unique and varied challenges in adopting soil health practices. On farms with higher levels of continuous living cover, reduced disturbance, and crop diversity, we observe higher carbon stocks and increased mineral-associated and particulate organic matter. We also find that management tends to be more influential on distinct carbon outcomes relative to inherent soil properties. Lately, we identified eleven beneficial relationships between various soil health practices and soil-mediated ecosystem services including yield, soil fertility, carbon sequestration, nutrient cycling, soil microbial diversity, and mitigating excess end-of-season soil nitrate. Continuous living cover in particular emerges as a key practice to enhance multiple services simultaneously (ecosystem multifunctionality). While not a panacea, improving soil management practices represents a crucial step toward achieving multifunctional and sustainable agricultural landscapes.

For the soils that give us life,
that support us,
and that give rise to me,
and to the flowers and bugs,
and to everyone, and everything I love.

For the food that nourishes our bodies,
and for every memory,
every story, every connection
made around a meal.

For the maize and chiles,
the rice and miso,
and all the tastes that connect us to our ancestors,
who, from the past, lead the way forward.

For my parents,
and everyone who believed in me,
everyone who pushed me to believe in myself.
For all my people who makes me better,
make me who I am.

Thank you.

Table of Contents

Introduction

The global drive for producing food and fiber, often the singular priority of managed agroecosystems, has created a system of agriculture that deteriorates local agrobiodiversity and degrades the quality of air, water, and soils. Farmers have known for millennia how to tend to their land to ensure sustained soil quality and well-functioning ecosystems. However, the structures and models imposed by modern industrial agriculture have shrunk the knowledge-intensive modes of sustainable agriculture and created reliance on external inputs to maintain crop productivity (Carlisle et al., 2019).

Organic farming systems mostly eliminate synthetic inputs but, in many cases, still rely on organic inputs rather than deeper systems change, thus representing a rather shallow move away from industrial agricultural practices (Gliessman, 2016). Going beyond organic, diversified farming systems (DFS) represent an alternative to industrial agriculture that relies on biodiversity and ecosystem functions at multiple temporal and spatial scales to maintain productivity (Drinkwater & Snapp, 2022; Gliessman, 2016; Kremen et al., 2012). While much of the literature on DFS initially focused on aboveground, recent shifts towards belowground biodiversity, soil health, and soil-mediated ecosystem services have gained traction. Soil health management practices premised on soil health principles popularized by the Natural Resource Conservation Service (NRCS) offer additional strategies beyond input substitution of organic production to help build soil health. These principles include maximizing continuous living roots and soil cover, increasing biodiversity through crop and non-crop plantings, and minimizing soil disturbance (NRCS, 2024).

Many diversified farming practices and the NRCS principles both aim to enhance "soil health". However, this term does not have a single definition or metric, and its measurement and interpretation are actively discussed and debated within the soil science community (Janzen et al., 2021; Lehmann et al., 2020; Wade et al., 2022). While helpful as a broad principle for communicating with farmers and non-academic communities, the vagueness of the term and the wide ways in which it is measured, monitored, and discussed creates challenges for advancing our scientific understanding of how management may increase "soil health." Additionally, much of our current understanding of management impacts on various metrics of soil health comes from research-station trials, which often only investigate one or two practices at any given time and only provide insight into a single climatic and edaphic context. Recent on-farm work has started to investigate how management practices, as implemented on working farms, might impact soil health metrics, building on the more mechanistic understanding that research trials provide (Agyei et al., 2024; Olimpi et al., 2024; Singh et al., 2024; Sprunger et al., 2021; Williams et al., 2020).

A primary metric utilized in soil health literature is Soil Organic Matter (SOM). SOM is a useful metric for soil health because of its many co-benefits, including supporting diverse soil life, increasing nutrient availability and water-holding capacity, and improving soil structure (Lehmann et al., 2020). There is also emerging interest in how working lands might be leveraged as a carbon sink to help regulate the global climate. Agricultural activity and human land use over the last 12,000 has created a "carbon debt" of ~120 Pg C, and thus there is particular interest in restoring carbon in working lands (Almaraz et al., 2023; Blanco-Canqui, 2022; Lavallee et al., 2020; Lessmann et al., 2022; Sanderman et al., 2017). While there is debate on the efficacy of this strategy as a global climate mitigation effort (Amundson et al., 2022; Moinet et al., 2024), increasing SOM is undoubtedly a good short- and long-term goal for building soil health and potentially supporting the global goal of sequestering carbon back into soils.

Soil carbon sequestration is of particular interest because of its potential to mitigate climate change, but it is just one important service that soils provide. Land managers are being asked to not only grow food but are increasingly called to maintain multi-functional systems that simultaneously help sustain agrobiodiversity and mitigate water pollution that may result from crop amendments, as just a few examples among a long list of important soil-based ecosystem services (Anikwe & Ife, 2023; Pereira et al., 2018). However, managing multiple ecosystem services can prove to be a challenge due to potential trade-offs in services, and the fact that best management practices may differ depending on the inherent soil properties of a given farm (Tamburini et al., 2016; Vazquez et al., 2021; Zwetsloot et al., 2021). Additionally, the goals prioritized by various stakeholders in agricultural landscapes including farmers, conservationists, and community members may vary. For example, collective action is necessary to make measurable landscape-level differences on issues such as groundwater nitrate pollution. However individual incentives for farmers are quite low to reduce excess nitrogen. Thus, on-farm management can have rippling effects on a landscape level where any individual farmer may not feel much responsibility (Kremen, 2020; Zhang et al., 2007). To create policies that may aid in maintaining multifunctional agricultural landscapes, we must understand the complex interplay between local soil factors, management practices, and stakeholder priorities.

My dissertation aims to investigate three key areas to support the development of agricultural systems that simultaneously achieve the goal of crop production while also providing other vital ecosystem services. In my first chapter, I ask what barriers farmers face in adopting soil health practices and what policies and structures can support farmers to transition into more agroecological management. Based on interviews with farmers in the Central Coast, we develop a typology of different types of farmers to provide a nuanced understanding of the various challenges farmers face and delve into the implications of this typology on better target policy for incentivizing movement towards soil health management.

In my second chapter, I take a closer look at soil carbon across our participating group of farms and aim to parse the impacts of inherent edaphic characteristics versus the implementation of soil health practices on farms across different forms of soil organic carbon. By looking at both bulk soil organic carbon and functionally distinct carbon fractions (free and occluded particulate organic matter and mineral-associated organic matter), we get a nuanced look into how management practices impact different components of soil organic carbon. POM fractions are critical for soil health, providing energy sources for microorganisms and aiding in building soil structure and water and nutrient holding capacity while MAOM has a longer residence time and, thus, a higher potential for long-term carbon sequestration.

Finally, my third chapter builds on my analysis of soil carbon and considers the multiple critical ecosystem services, and how these are related to management and inherent soil characteristics. In addition to building soil health and carbon stores, I consider nitrate leaching potential, yield, soil microbial biodiversity, and nutrient cycling via measured service indicators. I also assess whether there are tradeoffs and synergies amongst different ecosystem factors and consider if and how farmers might optimally manage for multifunctionality given different prioritization schemes of ecosystem services.

In this work, I bring together a look at both the social and economic landscape that creates pressures and challenges in the adoption of soil health practices and assess the impacts that these management decisions have on soil carbon and soil multifunctionality. This work aims to guide policies that may better support the transition of more farms to adopt soil health practices and provide concrete evidence and rationale for why this type of transition is critical in the context of California and global agriculture. Creating a balance between our food system and stewardship of our natural resources and environment will continue to be a challenge of paramount importance. While it is far from the only solution, creating opportunities and aiding in the transition towards better soil management practices is necessary to create a more just, resilient, regenerative food system.

References

Agyei, B., Sprunger, C. D., Anderson, E., Curell, C., & Singh, M. P. (2024). Farm-level variability in soil biological health indicators in Michigan is dependent on management and soil properties. Soil Science Society of America Journal, 88(2), 326–338. https://doi.org/10.1002/saj2.20630

Almaraz, M., Simmonds, M., Boudinot, F. G., Di Vittorio, A. V., Bingham, N., Khalsa, S. D. S., Ostoja, S., Scow, K., Jones, A., Holzer, I., Manaigo, E., Geoghegan, E., Goertzen, H., & Silver, W. L. (2023). Soil carbon sequestration in global working lands as a gateway for negative emission technologies. Global Change Biology, 29(21), 5988–5998. https://doi.org/10.1111/gcb.16884

Amundson, R., Buck, H., & Lajtha, K. (2022). Soil science in the time of climate mitigation. Biogeochemistry, 161(1), 47–58. https://doi.org/10.1007/s10533-022-00952-6

Anikwe, M. a. N., & Ife, K. (2023). The role of soil ecosystem services in the circular bioeconomy. Frontiers in Soil Science, 3. https://doi.org/10.3389/fsoil.2023.1209100

Blanco-Canqui, H. (2022). Cover crops and carbon sequestration: Lessons from U.S. studies. Soil Science Society of America Journal, 86(3), 501–519. https://doi.org/10.1002/saj2.20378

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. (2019). Transitioning to Sustainable Agriculture Requires Growing and Sustaining an Ecologically Skilled Workforce. Frontiers in Sustainable Food Systems, 3, 96. https://doi.org/10.3389/fsufs.2019.00096

Drinkwater, L. E., & Snapp, S. S. (2022). Advancing the science and practice of ecological nutrient management for smallholder farmers. Frontiers in Sustainable Food Systems, 6. https://doi.org/10.3389/fsufs.2022.921216

Gliessman, S. (2016). Transforming food systems with agroecology. Agroecology and Sustainable Food Systems, 40(3), 187–189. https://doi.org/10.1080/21683565.2015.1130765

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

Kremen, C. (2020). Ecological intensification and diversification approaches to maintain biodiversity, services and food production in a changing world. Emerging Topics in Life Sciences, 4(2), 229–240. https://doi.org/10.1042/ETLS20190205

Kremen, C., Iles, A., & Bacon, C. (2012). Diversified Farming Systems: An Agroecological, Systems-based Alternative to Modern Industrial Agriculture. Ecology and Society, 17(4). https://doi.org/10.5751/ES-05103-170444

LaRose, J., & Myers, R. (2019). Adoption of Soil Health Systems Based on Data from the 2017 U.S. Census of Agriculture. Soil Health Institute. https://soilhealthinstitute.org/app/uploads/2021/11/Soil-Health-Census-Report.pdf

Lavallee, J. M., Soong, J. L., & Cotrufo, M. F. (2020). Conceptualizing soil organic matter into particulate and mineral-associated forms to address global change in the 21st century. Global Change Biology, 26(1), 261–273. https://doi.org/10.1111/gcb.14859

Lehmann, J., Bossio, D. A., Kögel-Knabner, I., & Rillig, M. C. (2020). The concept and future prospects of soil health. Nature Reviews Earth & Environment, 1(10), Article 10. https://doi.org/10.1038/s43017-020-0080-8

Lessmann, M., Ros, G. H., Young, M. D., & de Vries, W. (2022). Global variation in soil carbon sequestration potential through improved cropland management. Global Change Biology, 28(3), 1162–1177. https://doi.org/10.1111/gcb.15954

Moinet, G. Y. K., Amundson, R., Galdos, M. V., Grace, P. R., Haefele, S. M., Hijbeek, R., Van Groenigen, J. W., Van Groenigen, K. J., & Powlson, D. S. (2024). Climate change mitigation through soil carbon sequestration in working lands: A reality check. Global Change Biology, 30(1), e17010. https://doi.org/10.1111/gcb.17010

Olimpi, E. M., Ke, A., Baur, P., Carlisle, L., Esquivel, K., Glaser, T., Snyder, W. E., Waterhouse, H., Bowles, T. M., Kremen, C., & Karp, D. S. (2024). Ungrazed seminatural habitats around farms benefit bird conservation without enhancing food borne pathogen risks. Landscape Ecology.

Pereira, P., Bogunovic, I., Muñoz-Rojas, M., & Brevik, E. C. (2018). Soil ecosystem services, sustainability, valuation and management. Current Opinion in Environmental Science & Health, 5, 7–13. https://doi.org/10.1016/j.coesh.2017.12.003

Sanderman, J., Hengl, T., & Fiske, G. J. (2017). Soil carbon debt of 12,000 years of human land use. Proceedings of the National Academy of Sciences, 114(36), 9575–9580. https://doi.org/10.1073/pnas.1706103114

Singh, P., Kawa, N. C., & Sprunger, C. D. (2024). "More questions than answers": Ohio farmers' perceptions of novel soil health data and their utility for on-farm management. Agroecology and Sustainable Food Systems, 48(1), 74–92. https://doi.org/10.1080/21683565.2023.2270928

Sprunger, C. D., Culman, S. W., Deiss, L., Brock, C., & Jackson-Smith, D. (2021). Which management practices influence soil health in Midwest organic corn systems? Agronomy Journal, 113(5), 4201–4219. https://doi.org/10.1002/agj2.20786

Tamburini, G., De Simone, S., Sigura, M., Boscutti, F., & Marini, L. (2016). Soil management shapes ecosystem service provision and trade-offs in agricultural landscapes. Proceedings of the Royal Society B: Biological Sciences, 283(1837), 20161369. https://doi.org/10.1098/rspb.2016.1369

Thompson, J. B., Symonds, J., Carlisle, L., Iles, A., Karp, D. S., Ory, J., & Bowles, T. M. (2023). Remote sensing of hedgerows, windbreaks, and winter cover crops in California's Central Coast reveals low adoption but hotspots of use. Frontiers in Sustainable Food Systems, 7. https://doi.org/10.3389/fsufs.2023.1052029

Vazquez, C., de Goede, R. G. M., Rutgers, M., de Koeijer, T. J., & Creamer, R. E. (2021). Assessing multifunctionality of agricultural soils: Reducing the biodiversity trade-off. European Journal of Soil Science, 72(4), 1624–1639. https://doi.org/10.1111/ejss.13019

Wade, J., Culman, S. W., Gasch, C. K., Lazcano, C., Maltais-Landry, G., Margenot, A. J., Martin, T. K., Potter, T. S., Roper, W. R., Ruark, M. D., Sprunger, C. D., & Wallenstein, M. D. (2022). Rigorous, empirical, and quantitative: A proposed pipeline for soil health assessments. Soil Biology and Biochemistry, 170, 108710. https://doi.org/10.1016/j.soilbio.2022.108710

Williams, H., Colombi, T., & Keller, T. (2020). The influence of soil management on soil health: An on-farm study in southern Sweden. Geoderma, 360, 114010. https://doi.org/10.1016/j.geoderma.2019.114010

Zhang, W., Ricketts, T. H., Kremen, C., Carney, K., & Swinton, S. M. (2007). Ecosystem services and dis-services to agriculture. Ecological Economics, 64(2), 253–260. https://doi.org/10.1016/j.ecolecon.2007.02.024

Zwetsloot, M. J., van Leeuwen, J., Hemerik, L., Martens, H., Simó Josa, I., Van de Broek, M., Debeljak, M., Rutgers, M., Sandén, T., Wall, D. P., Jones, A., & Creamer, R. E. (2021). Soil multifunctionality: Synergies and trade-offs across European climatic zones and land uses. European Journal of Soil Science, 72(4), 1640–1654. https://doi.org/10.1111/ejss.13051

Acknowledgments

I start by acknowledging the lands on which we sampled - now called San Benito, Santa Cruz, and Monterey counties - were, since time immemorial, stewarded by many native groups including the Esselen people (also known as Carmeleno or Monterey Band), Rumsen, Costanoan, Mutsen, and Ohlone people. Importantly, this land in this region is still tended to by active indigenous communities including the Amah Mutsun Tribal Band. The land on which I reside and on which I conducted much of this analysis and writing was done on the unceded lands of the Muwekma Ohlone people. As a researcher who studies the ground beneath us and the soils that feed us, it is essential to acknowledge that its current stewards are the beneficiaries of a system built on the dispossession of native peoples from their land. The wealth and global importance of California agriculture stems back to many generations of colonial oppression and dispossession, and little has gone back to the original stewards of this fertile land. In making this acknowledgement, I also express my ongoing commitment to Land Back movements and integrating anti-colonial and anti-racist praxis into my land-based and food systems work.

I am so grateful to have worked in the Berkeley Agroecology Lab and with Dr. Tim Bowles who supported me through this process with the utmost patience and with full faith in my abilities to take on this dissertation. Tim was not only patient with my progress when I took on organizing with our Graduate Diversity Council and graduate union, but an active ally and supporter in making our university and department a better and more hospitable place for all students, particularly for those coming from underrepresented identities and backgrounds in academia. I've learned so much from Tim's model of how to approach academia- with a healthy dose of skepticism, optimism, and willingness to push for change. I'm also grateful for how Tim was willing to learn and grow with me as I took on these non-dissertation activities and how he saw them not as extracurricular but central to our approach towards the science and research that we do.

I want to thank all of the brilliant farmers who participated in this study and enabled us to do this on-farm work. Putting up with researchers on top of what they already manage is not to be taken for granted, and I am so grateful to each of them for agreeing to work with us and helping us develop our questions, fieldwork, and research directions. They will forever be the experts, and we researchers the eager learners, hoping to be able to make some contribution by listening and observing.

This dissertation would not have been possible without the incredible team of interdisciplinary scientists that have supported the development of the Central Coast Coupled Human-Natural Systems project. In addition to Tim, I want to thank Hannah Waterhouse, Liz Carlisle, Danny Karp, Alastair Iles, Elissa Olimpi, Claire Kremen, Patrick Bauer, Jennifer Thompson, and Kait Libbey for all of their contributions to this work, and the mentorship and support they have provided over the years. Additionally, the undergraduates who have supported the countless hours of lab work, from grinding and sieving soils to running and re-running samples. In particular, I want to thank Yordi Gil-Santos, Grace Santos, Arely Ortiz, Anna Barcellos, Amiri Taylor, and Melanie Rodriguez for all of their long hours of lab time that enabled us to gather the rich dataset behind this dissertation. And Kait and Jennifer, our field team extraordinaire - thank you for your countless hours in the field and for making my trips down to Aptos amidst the pandemic a fun thing to look forward to.

Jennifer got the ball rolling on this project and made transitioning into the project so much easier - thank you for everything you did and still do.

The folks of the Berkeley Agroecology Lab over the years have created a little oasis in what could sometimes feel like an overwhelmingly chaotic department and university - thank you all for creating a space to learn, make mistakes, grow together, and advance our science. Aidee Guzman, whose example I am always trying to emulate, has been a steadfast mentor from whom I have and will continue to learn so much. Paige Stanley, my carbon compatriot, spent so many hours in the lab with me and has continued to help me troubleshoot and understand my data well past her graduation. Yvonne Socolar, who in many ways feels like the glue to our lab community - your brilliance, thoughtfulness, and kindness never cease to amaze me, and I feel so grateful for your mentorship and friendship over the years. Cole Rainey who never fails to brighten my mood, thank you for everything you do for the people around you - I feel so lucky to graduate with you. And Hannah Waterhouse, I could not have asked for a better partner in crime for this project. I have learned what feels like an impossible amount from you - from your technical knowledge to your incredible generosity with your time and energy; I am in awe of you and feel so lucky that you were the postdoc on this project with me. In the depths of the pandemic, we made things happen, and I simply could not have done it without you.

Tracing things back, my brain goes haywire to think of all the people I need to thank - all the instructors, mentors, and friends who saw more in me than I saw in myself throughout my life- thank you. Dr. Adrienne Coleman who in middle school brought me into a pre-summer program that led me to a math and science high school. I think of this as one of the critical inflection points in my life as a scientist. To see the leadership of black and brown scientists was something that I didn't fully appreciate at the time, but the importance of this type of representation is real - thank you to Drs. Anita White and Aracelys Rios for being those models. To my undergraduate mentors who supported my transition into graduate school - Drs. Cathy Pfister, Eric Larsen, Steve Pruett-Jones, Susan Kidwell, and David Archer who introduced me into the world of environmental science and ecology and the beautiful exploration of the world around us- you all forever changed how I see the world around us, and I am so grateful.

I feel so lucky for every single friend, new and old, who has been with me along this crazy journey: Ron, Peter, Bryan, Hayley, Annabelle, Nadia, Justin, Annie, Rachael, Lucy, Rosalie, Matt, Steven, Manuel, Skylar, and so many more. Thank you to my family who, for better and for worse, have made me who I am today. Thank you for instilling in me the joy of food, the love of feeding people, the simple beauty of connecting over a meal. Thank you for being my biggest cheerleaders and for always encouraging me to be the best that I could be.

And of course, Tyler, who has been with me throughout my academic trajectory. Thank you for reading and improving everything I've written over the last 9 years... from my college essays to now the pages below. I can never quite believe how time has flown so fast with you, but I am so grateful for how we continue to grow and push each other to be the best versions of ourselves. Your faith in me has fueled so much of my journey, and you constantly inspire me to be better and to keep fighting for a better world. I am so thankful for you.

Chapter 1: The 'sweet spot' in the middle: why do mid-scale farms adopt diversification practices at higher rates?[1]

Abstract

In the past few decades, farmers and researchers have firmly established that biologically diversified farming systems improve ecosystem services both on and off the farm, producing economic benefits for farmers and ecological benefits for surrounding landscapes. However, adoption of these practices has been slow, requiring a more nuanced examination of both barriers and opportunities to improve adoption rates. While previous research has demonstrated that both individual and structural factors shape farmers' decisions about whether to adopt diversification practices, this study aims to understand the interaction of these individual and structural factors, and how they relate to farm scale. Based on 20 interviews with organic lettuce growers on the Central Coast of California, as well as 8 interviews with technical assistance providers who work with these growers, we constructed a typology to help elucidate the distinct contexts that shape growers' decisions about diversification practices. This typology, which reflects the structural influence of land rent and supply chains, divides growers into three categories: limited resource, mid-scale diversified, or wholesale. In this economic context, limited resource and wholesale growers both experience significant barriers that constrain the adoption of diversification practices, while some mid-scale diversified growers have found a "sweet spot" for managing agroecosystems that can succeed in both economic and ecological terms. The key enabling factors that allow these farmers to choose diversification, however, are not directly related to their farm size, but have more to do with secure land tenure, adequate access to capital and resources, and buyers who share their values and are willing to pay a premium. By focusing on these key enabling factors with targeted policies, we believe it is possible to encourage diversification practices on farms at a variety of scales within California's Central Coast.

Introduction

In the past few decades, farmers and researchers have firmly established that biologically diversified farming systems improve ecosystem services both on and off the farm, producing economic benefits for farmers and ecological benefits for surrounding landscapes (Kremen & Miles, 2012; Tamburini et al., 2020; Tscharntke et al., 2005). Such biologically diversified farms incorporate numerous types of *planned* biodiversity, including a wide variety of cash and cover crops as well as non-crop plants such as hedgerows or floral strips to support beneficial insects. Many also incorporate *unplanned* biodiversity, by preserving some wild elements or natural areas within the farm, or attracting various species to planned elements (e.g., hedgerows). Such practices nurture biodiversity below ground, helping farmers build soil health, which directly supports crop growth while improving resilience to disease, drought, and floods (Archer et al., 2020; Bowles et al., 2020; Gaudin et al., 2013; Poeplau & Don, 2015; Smith et al., 2018; Wade et al., 2020; Weisberger et al., 2019). At the same time,

---

[1] This chapter was previously published: Esquivel, K. E., Carlisle, L., Ke, A., Olimpi, E. M., Baur, P., Ory, J., ... & Bowles, T. M. (2021). The "sweet spot" in the middle: why do mid-scale farms adopt diversification practices at higher rates?. *Frontiers in Sustainable Food Systems*, *5*, 734088.

enhancing biodiversity on the farm promotes aboveground services like pollination and pest control by providing habitat for pollinators, beneficial insects, and other wildlife (Dainese et al., 2019; Garratt et al., 2017; Kremen & Miles, 2012; Morandin et al., 2016). Given the benefits of such practices – which we will refer to throughout the paper as "diversification" practices, though many of them are also frequently referred to as regenerative or soil health practices – one might assume that they would be widespread. Yet U.S. farmers have adopted them at dismally low rates.

To understand this conundrum, researchers have turned to the extensive literature on farmer adoption of conservation practices. Starting with work that observed uneven diffusion of agricultural practices among Iowa farmers (Ryan & Gross, 1943), much of the early agricultural adoption literature focused on individual farmer-level characteristics that explained this unevenness. For example, general awareness and perception of soil erosion and other soil issues, education level, years of experience, and age have all been found to correlate positively with adoption of conservation practices (Gould et al., 1989; Napier & Camboni, 1993; Traoré et al., 1998; Warriner & Moul, 1992).

However, studies have also found negative and non-significant results for each of these same characteristics (Clay et al., 1998; Neill & Lee, 2001; Traoré et al., 1998). Indeed, recent reviews have generally found that there are no universal rules or characteristics that reliably predict adoption of diversification practices (Baumgart-Getz et al., 2012; Carlisle, 2016; Knowler & Bradshaw, 2007; Prokopy et al., 2008, 2019). Rather, it has emerged that farms and farm communities are hugely heterogeneous, and consideration of local specificity is critical. In addition to local specificity, researchers find that structural factors such as government policies, incentive programs, and supply chain requirements strongly impact farmer willingness and ability to adopt diversification practices (Baur, 2020; Liu et al., 2018; Prokopy et al., 2019; Reimer et al., 2014; Stuart & Gillon, 2013). Thus, there is a need to better understand and address the interplay between structural and individual-level factors, and specifically how structural factors differentially impact farms in various locales, and of differing scales and business structures.

We assessed these factors as part of an interdisciplinary study in California's Central Coast, a highly productive agricultural region with high land values, concentrated supply chains, a complex policy environment, and a robust alternative agriculture movement. Environmental impacts from intensive agricultural production in the region include degraded groundwater quality (Harter, 2015; Rosenstock et al., 2014) and reduced natural habitat for the region's biodiversity, which includes a major migratory bird flyway and several federally and/or state-endangered species (Gennet et al., 2013). Understanding why different types of farms do or do not adopt diversification practices, and how this in turn impacts associated biodiversity and environmental outcomes, will provide important information for regionally-specific policy interventions.

Methods

Study site

California's Central Coast, often called America's salad bowl, supplies 70% of America's leafy greens and 50% of its broccoli, with agricultural revenues of ~$7 billion annually (California Department of Food & Agriculture, 2014). Rugged ranges of coastal hills cover much of this topographically complex region, while farming concentrates along river valleys. Our study focused on the farming valleys of the Pajaro, San Juan, and Salinas rivers (located in Santa Cruz, San Benito, and Monterey Counties, respectively), at the northern end of the Central Coast (Figure 1). We also had one respondent who had recently moved to Santa Clara County.

Agricultural operations range from farms of a few acres located in the smaller, hillier valleys—which typically serve local markets -- to farms of many thousands of acres in the flatlands of the main valleys, which supply national and global outlets. Key supply chain actors include farmers, shippers (businesses that aggregate the output of many farmers), wholesale buyers, food processors, and retailers (Calvin et al., 2017). Buyers, retailers, and food processors exercise large influence in the region through their ability to set contractual production standards (e.g., for timing, volume, types of farming practices used, and product quality). Marketing has been concentrated for well over a decade. For example, in 2011, the top eight California shippers controlled ~80% of the California/Arizona iceberg lettuce volume (Cook, 2011).

Farmers in the Central Coast also operate in a policy-dense environment. A number of California state policies aim to incentivize environmentally beneficial practices--such as soil conservation or carbon capture--and regulate other practices, such as nitrate pollution. The Healthy Soils Program (HSP), effective September 2016, provides incentives for farmers to adopt practices such as cover-cropping and compost additions that may sequester carbon in soils (Clapp & Fuchs, 2009). Funded by proceeds from a greenhouse gas emissions cap and trade auctions, HSP has awarded three rounds of competitive grants to farmers as of 2021 (*CDFA - OEFI - Healthy Soils Program*, 2021). Meanwhile, the Central Coast Regional Water Quality Control Board imposes a range of water quality-related obligations on farmers, including groundwater monitoring and nitrogen application reporting (Dowd et al., 2008; Drevno, 2018b).

Qualitative interviews

Qualitative data were collected in February 2019 through semi-structured, in-depth interviews with 20 farmers across four counties: Monterey (5 interviews), San Benito (4), Santa Cruz (5), and Santa Clara (1), with 5 farmers spanning multiple of these counties. We limited the study to organic farmers who grow lettuce as their primary cash crop or as part of a diverse portfolio of crops. To identify potential interviewees, we first queried the USDA Organic Integrity Database to identify organic farms listing lettuce as a crop, with 80 results. We consulted with technical assistance providers to identify which of these operations might be willing to participate in the study and were currently growing lettuce. Because this qualitative research was carried out as part of a larger project involving on-farm ecological research, our study design was to select growers from this subset, representing a gradient of both farms and surrounding landscapes that ranged from low levels of biodiversity to relatively high ones. We further chose growers to represent different farm scales, geographical locations within the study region, and cultural backgrounds/first languages. The 20 farmers interviewed for this study account for roughly 25% percent of organic lettuce producers in this region. In addition to interviewing growers, we also interviewed 8 technical assistance providers who work with organic lettuce farmers in the region, in May 2019. Interviewing these technical assistance providers, who spoke from their knowledge of the sector as a whole, allowed us to corroborate what we learned from grower interviews about factors influencing adoption of diversification practices (such as land values, supply chain requirements, and food safety).

The interview protocols (see Supplementary Materials) focused on diversification practices, crop and non-crop diversity, and how these farm-level decisions were shaped by a variety of market and policy factors. We began by asking open-ended questions (e.g., what practices do you currently use to maintain or improve soil health on your farm?), and followed with more specific questions (e.g., could you briefly describe your tillage practices?). Interviews were digitally recorded and transcribed verbatim. Analysis of interview transcripts was conducted in Nvivo 12, using an iterative coding method following an open, axial, and selective coding procedure (Corbin & Strauss, 1990). Through an iterative coding procedure aimed at identifying key factors influencing farmer adoption of diversification practices, data were coded into thematic categories, including "Land Tenure," "Markets," and "Food Safety."

Ecological surveys

To understand how farming decisions affected unplanned, on-farm biodiversity, we surveyed birds on 23 farms, operated by 14 of the interviewed growers, using 10 minute, 50m fixed-radius point count surveys, repeated three times over consecutive days from May-July of 2019-2020. Point count locations were separated by at least 100m (Ralph et al., 1995). Thus, the number of point counts per farm varied by farm size. At least half of the survey locations on each farm were centered in lettuce crops; the other half were located within other dominant crop types (e.g., squash, broccoli, strawberry). All surveys were conducted by the same skilled observer, primarily between sunrise and 10:30am and always in the absence of rain or heavy fog. All individuals seen or heard within the survey radius were identified to species and recorded. Within each 50m radius point count, we also estimated the percent cover of each crop and then used these data to quantify crop diversity (*i.e.,* Simpson's index) within each point count radius. We also scored the percent cover of weeds within each crop type (1=0–5%; 2=5–50%; 3>50%).

Using the farm type classification that emerged from our interview data, we modeled crop diversity and weediness using generalized linear mixed models (GLMMs), followed by Tukey post-hoc tests to compare differences between farm types. We included a random effect of farmer identity to account for non-independence among management strategies. Crop diversity was square root transformed to satisfy model normality assumptions and modeled with a Gaussian distribution. Weediness was converted into a binomial variable. A point-count location was considered 'weedy' if any crop within the 50m radius had >5% weed cover.

We used an N-mixture model (see Supplemental methods) that accounts for unseen species and variation in detection probability to estimate the abundance of each bird species at each site (Kéry & Schaub, 2011; Royle & Dorazio, 2008). We extracted the modeled abundance from each iteration of the posterior (N= 3000) and then calculated the species richness, Shannon diversity, and total abundance at each location. We then extracted median values and interquartile ranges across the 3000 posteriors. Finally, we used GLMMs to assess effects of the three farm types (determined by interview data) on the species richness, Shannon diversity, and total abundance calculated from the N-mixture models, followed by Tukey post-hoc tests. We included the fraction of surrounding semi-natural habitat within 1km as a covariate to account for landscape context and farm identity as a random effect to account for spatial autocorrelation among point count locations. All variables were modeled with Gaussian distributions. Total abundance was log-transformed to satisfy model normality assumptions. To propagate error uncertainty from the N-mixture model, metrics were weighted by the inverse of their interquartile ranges, as in Karp et al. (2018). Analyses were implemented in R (R Core Team, 2014). For more information about statistical methods used, see Appendix SI.

Results

At the outset of this research, we sought to understand the factors influencing adoption of diversification practices for the organic lettuce sector of the California Central Coast *as a whole*. Indeed, several overarching trends emerged from our interviews, and we have presented these in a concurrent paper (Carlisle & Esquivel et al., 2021). However, as we analyzed interview transcripts, we began to identify a pattern: growers' approach to diversification practices seemed to fall into one of three categories. To try to get a better understanding of these three distinct adoption scenarios, we constructed a typology, stratifying our sample into three different groups (Table 1).

At first glance, this typology may appear to be based entirely on farm size. Farms in the first category are smaller than 20 acres, farms in the second category are larger than 500 acres, and farms in the third category fall somewhere in between. Yet, as we analyzed the interview responses of farmers in each of these three categories, we came to understand farm size as an emergent property of each category, rather than a defining characteristic. Moreover, we came to see these normative or ideal farm sizes for each category as highly contingent on social factors that have changed over time (and may well change again).

The central defining characteristic of each category in the typology was not farm size, then, but something we came to understand as a farming model (Table 2). Each of these farming models represented a distinct pathway through which farmers were able to navigate the structural conditions of organic lettuce farming on the California Central Coast (shaped by high land values, concentrated supply chains, and a robust alternative agriculture movement) and attempt to construct an economically viable operation. Each of these farming models integrated a business model for economic survival, an ecological model for agronomic performance, and a mental model of the farm ecosystem and how it should be managed. This integrated complex of models strongly influenced farmers' perception of diversification practices and their usefulness, their agency to apply or experiment with such practices, and the degree to which they had implemented them on their farm (Table 3).

Below, we describe the three groups in our typology – limited resource, mid-scale diversified, and large scale wholesale – as well as some grey areas that emerge between these categories. Lastly, we present results from ecological surveys across our typology.

Limited resource

Limited resource farms were shaped by several economic constraints, but also by farmers' ingenuity in adapting low-capital, low-input farming methods. The major economic constraints limiting these farms were all related to land markets. In an area where agricultural land values are particularly high (Guthman, 2004), limited resource farmers told us they could only afford to rent small parcels, typically on 1-3 year leases. Echoing Calo and DeMaster (2016), nonwhite and immigrant farmers faced particularly stiff barriers accessing quality land and negotiating leases of more than a year or two. Short-term land tenure was hence a major limitation to adopting diversification practices that only pay off after multiple years. As one of the technical assistance providers we interviewed commented, "If you're leasing, you're not going to plant perennials… .I think about one of our clients who initially leased land and then … was able to buy the land. And then as soon as she bought it, she started planting perennial borders, but it wasn't until she had that long-term land security that she started doing that." Farmers in this category also felt constant pressure to quickly intensify their production to generate cash, so as to keep up with the ever-present pressures of high lease payments. The result was often a more simplified crop rotation, with fewer (or no) cover crops. For these growers, maximizing limited acreage for production was a priority; using hedgerows and cover crops, which do not generate revenue, were in tension with this goal. One limited resource farmer explained the need to earn enough from the land to cover the cost of the lease: "We are talking 1,500, 2,000 dollars for the rent, and that is why people do not want to put coverage [cover crop], because they lose a lot of money [by not planting another cash crop]." The cost of purchasing inputs such as compost or cover crop seed, and potentially also the labor to manage these practices, was also cited as a barrier by some limited-resource farmers.

In general, limited resource farms fell somewhere in the middle of our sample with respect to both planned and unplanned biodiversity (Figure 2; Figure 3; Supplementary Table 1; Supplementary Table 2). Several of these farmers reported that they largely depended on direct markets that reward crop diversity; thus they tried to grow as many crops as they had the space and time to manage. Meanwhile, although these farmers had constrained ability to invest in hedgerows, floral strips to support beneficial insects, or other planned biodiversity beyond their crops, they frequently allowed for some degree of unplanned biodiversity. One farmer talked about the benefits of flowering plants, "either intentional plantings like that or we often let our crops go to flower …. and then things like weeds [laughter]. We have a lot of weeds as you can see."

The management strategy of these limited resource farmers could best be characterized as making do with what they had. Most limited resource farmers we spoke with were focusing their limited time and energy on high-priority tasks, which led to less intervention and landscape modification compared to other farming models. While this type of management could have ecological benefits, such as higher levels of unplanned biodiversity, it could also lead to weed and pest problems that could become difficult to control. Indeed, the probability of observing weeds growing amongst crops on limited resource farms was considerably higher than for large wholesale farms (Figure 2). Given their precarious access to necessary resources (land, labor, and capital), these farmers expressed the need to be scrappy and opportunistic, in order to cope with pervasive instability. "In general, what's planned, many times it doesn't happen," one limited resource farmer told us, in response to a question about crop rotation. "One product finishes and then I plant what I have accessible. What would be ideal is lettuce with broccoli, cauliflower, then after that, kale, but sometimes it doesn't go as planned." When asked about future plans or aspirations, however, several expressed a goal of stabilizing their business as a diversified, small-scale livelihood farm. One of our interviews with a Spanish-speaking limited resource farmer was translated by the farmer's young son, who periodically added analysis and observations of his own. "If everything goes well and he's able to pay his debt," this farmer's son said, "he hopes to get more financing, more money to be able to use the full potential that he has, that he knows he could do."

Large scale wholesale

Farmers selling into the wholesale lettuce market (mostly on contracts) must manage large acreages in order to meet their buyers' demands for large, consistent volumes of product delivered on time. Large acreages are also necessary for these farmers to earn a living on the slim margins of the wholesale market (Tourte et al., 2017). In order to meet these demands, several of these farmers were managing multiple, spatially separated parcels, sometimes across multiple counties. Given their large scale, farms in this category have an outsized influence on the sector and regional economy as a whole. The 2012 Agricultural Census, for example, found that lettuce farms in Monterey County averaged 983 crop-acres, and Calvin et al. (2017) surveyed five leafy greens grower-shippers in the region that averaged $196 million in annual fresh produce sales.

Much like the limited resource farms we visited, these large-scale wholesale farms (and their approach to diversification practices) were also strongly shaped by economic constraints. While most of these farmers had access to far more capital than limited resource farmers, the margins between their revenue and their costs were uncertain and could easily result in a loss if price or yield dipped too low (Tourte et al., 2009, 2019), leading them to express similar worries about economic vulnerability and lack of financial buffers. In terms strikingly similar to those used by the limited resource farmers we spoke with, these wholesale farmers expressed constant worries about factors beyond their control that could make their farms financially unviable. "It's pins and needles for us as growers," one of these large wholesale farmers told us. "This business is slim margins."

Again, mirroring limited resource farmers, wholesale farmers we spoke with were often renting their land on short (1-3 year) leases, which limited their interest in diversification practices that require many more years to implement and achieve a significant return on investment. However, unlike most of the limited resource farmers we interviewed, several wholesale farmers expressed a preference for short-term leases, as it gave them the flexibility to adjust quickly to changes in markets and supply chain requirements. As one grower recalled of a downturn in the lettuce market, "We found ourselves with declining contracts because of declining consumption, and we were about 1500 acres long on ground. Luckily, we had some short-term leases, so we could shed some of that ground."

In general, the picture that emerged from our conversations with large-scale wholesale growers was one in which land value still constituted a key economic constraint, as it did for limited resource farmers, but markets played an even stronger role in their decisions about whether to adopt diversification practices. For wholesale farmers, their business model revolved around the demands of their buyers, who largely determine what, when, and how they grow. "We're pretty much forced to abide by the rules that are given to us based on what your shipper is requesting," said one of these large growers, who lamented wholesalers' low tolerance for biodiversity due to stringent food safety protocols. "But we do try to give them, to try to convey a message to them to please pass that onto their customer, that realistically, there's certain things we can't mitigate. But food safety, you don't question too much. But I'd like to go back to [the idea that] we're not farming in the lab."

Wholesale farmers described minimal use of diversification practices, a choice they largely ascribed to the demands of their buyers. These farmers described rigid planting and harvest schedules that discouraged cover cropping, as well as meager wholesale markets for diverse rotation crops. As one grower explained about two crops he would ideally like to grow in rotation with each other, "[T]he demand for [romaine] hearts seems to be increasing faster than the demand for [broccoli] rabe. And, so that in the future can definitely lead to unsustainable situations." Wholesale buyers, these farmers told us, tended to discourage or even prohibit compost and hedgerows due to food safety concerns, while cover crops were considered a nuisance for harvest logistics and timing.

In the face of these supply chain constraints, both planned and unplanned biodiversity were typically minimal on these farms. In interviews, growers on these farms frequently characterized biodiversity as a liability rather than an asset, particularly in the wake of more stringent food safety audits. "We don't want to see them," one grower answered bluntly, in response to a question about experience with birds and other wildlife. "What used to be a windbreak is now a hazard," another large wholesale grower explained. "So that's why you see a lot of trees being topped."

In describing their management objectives, farmers selling into large volume wholesale markets were the polar opposite of limited resource farmers. These large-scale wholesale farmers laid out pre-planned strategies for intensive management and landscape modification to meet precise goals, scheduling farm operations well ahead of time and supplying carefully measured nutrients through external inputs. They emphasized "cleanliness" and control, keeping weeds to a bare minimum. These farmers frequently expressed the view that land can sustain productivity more or less indefinitely through rational management, and that soil can withstand and bounce back from occasional challenges such as poorly timed tillage. As one grower said, "soil has this unimaginable power. It's the most resilient thing in the world, so I hate to say it, but you can beat it up pretty bad and it's going to bounce back pretty quickly if you treat it right. At least around here because we have ideal conditions for soil to regenerate itself."

Mid-scale diversified

Distinct from these first two categories of farms, a third farming model emerged in the intermediate space between the challenges of operating a very small operation with limited resources and the stringent requirements and narrow margins of the large-scale wholesale market. We refer to these intermediate farms as "mid-scale diversified" operations, as they are characterized by highly diverse mixtures of both crops and markets, and in our study region, they tend to be larger than limited resource farms but smaller than farms that sell primarily or exclusively into wholesale markets.

Economic pressures related to land and markets were by no means absent from conversations with these mid-scale diversified farmers. As one of them put it, "farming has such a narrow margin that you're just sacrificing things all the time." However, mid-scale diversified growers tended to present these economic pressures as being moderated by the greater flexibility afforded by diverse crops and markets. "I've always felt like having a more diverse biological operation, you can reduce the ultimate loss by being able to hedge certain things that you wouldn't be able to if you didn't have that diversity in place," one mid-scale grower said. In general, these farms were well-positioned to access values-based markets that are more stable and lucrative (e.g., high-traffic farmers markets, high-end local retail). While some also sold into wholesale markets, this was typically not a primary market channel but rather a means of unloading surplus. Direct and regional markets worked well for these growers because they had a good story to tell about their ecological management strategies, and had succeeded in engaging loyal customers. As one mid-scale diversified grower expressed, “[C]hoosing clients that are understanding of what goes into achieving a certain quality, and especially understanding organic practices and ecologically supportive practices to achieve that quality, that's where I think it becomes very interesting to engage and sell.” While these diverse, values-based markets were a key source of economic stability for mid-scale diversified farms, by far their greatest source of stability was their long-term land tenure. Most of these farmers owned some or all of their land, and those who rented had long-term leases. These farmers consistently expressed that long-term land tenure was necessary in order to invest in the ecological health of their farms. “Every time I lease a piece of ground, it must be a minimum of five years,” one mid-scale grower said. “I don't do any one year, two year [leases]. I think it's a waste of time if this is what I do for a living.”

With economic pressures moderated enough to give them some flexibility to experiment, these mid-scale diversified farmers were largely designing their farming models around the goal of agroecosystem health. For example, they described crop rotations that were planned to improve soil health and provide habitat for pollinators and beneficial insects. “One of the things I'm probably the proudest of in our tenure here on this home farm is providing habitat and diversity,” said one mid-scale grower. “It was a very barren place when we first got here … and it took a lot of work to clean the place up for it first of all and then to plant various habitats in the form of hedgerows and riparian waterways.” Mid-scale diversified farmers were also more likely than farmers in either of the other two groups to characterize ecological and economic health as tightly coupled, rather than in conflict with one another. As one mid-scale diversified farmer expressed, “I'm pretty convinced that most of the things we've done over the years to have more of a biological system for our insect control, more biology in our soils, more diversity, in many levels have helped us be a profitable farm.”

In describing their management objectives, mid-scale diversified farmers tended to reference biological factors before economic factors. These farmers described (and we observed) high levels of both planned and unplanned biodiversity, from complex crop rotations to intentional plantings of alyssum (a flower that hosts beneficial insects) to native plant hedgerows to unmanaged wild areas. They also spoke in more ecological and holistic terms, about things like managing “the soil food web” rather than meeting targets for nitrogen or carbon. The degree of landscape modification on mid-scale diversified farms fell somewhere between the light touch of limited resource farmers and the precise, controlled systems on wholesale farms. In general, we found mid-scale diversified farmers practicing selective, flexible management, based on careful observation. Thus, while this farm type was in some ways less stringently managed than a wholesale-oriented farm, management of these diversified farms also seemed to require more time and knowledge. For example, one farmer said, “I think the edges of every field that has native habitats or hedgerows are inviting to animals that can have an impact on your productive, cultivated fields, and it's a matter of understanding what the cycles are. And so first, what causes the damage, of course. What organisms cause the damage? What's the extent of the damage? And then understanding whether you can either live with that interaction or if you need to really control it, then understand the cycle. And you can plant certain things by understanding those cycles so you don't have to really kind of pursue drastic measures of exclusion or other practices, trapping, or things like that.” These farmers weren’t necessarily more knowledgeable than limited resource or wholesale farmers, but they were able to stay in one place long enough to experiment and make longitudinal observations, and they were also able to devote a greater share of their mental energy to ecological (rather than strictly economic or administrative) matters.

Grey areas and transitions between farming models

By and large, limited resource farms and mid-scale diversified farms in our study were fairly consistent with the descriptions above, with clear distinctions between the two groups. We did interview one farmer who we categorized as limited resource, but who had recently secured a long-term lease and more stable markets, perhaps signaling a potential transition into the mid-scale diversified category.

The most noticeable grey areas in the typology came up in interviews with large scale wholesale growers who had been farming for a long time. Several of these farmers had retained some of the diversification practices (or at least memories and positive views of these practices) that they had used earlier in their careers. In some cases, they explained that they had shifted practices as they scaled up and became more reliant on wholesale markets. A number of them also attributed their shifting practices to changes in these wholesale markets, as markets tightened protocols, particularly around food safety. Those wholesale growers who insisted on higher levels of biodiversity than their buyers preferred were aware that they were cutting against the grain. "On the receiving side, one thing that we're trying to kind of educate on is that not every bug that they see is bad," one grower explained. "Last year, there were beneficial larvae. And so they were getting kind of scared, and they were holding up our shipments. But they didn't know that they were good beneficials."

One other notable grey area in this category was a large-scale wholesale grower who had managed to support diversified crop rotations through highly diverse wholesale markets and a small segment of direct markets. "I think the diversification is one of our biggest assets," this grower said. "Because we have so many crops, you'll never see us plant lettuce behind lettuce …. the crop rotation keeps us from getting diseases." This grower had some things in common with other wholesale growers (e.g., high percentage of leased land, large acreage, multiple parcels), but was able to incorporate many of the soil health and diversification practices utilized by mid-scale growers, including cover crops and compost. Unique among our sample, this large-scale grower had successfully negotiated long-term leases and contracts with buyers that suited this diversified farming model.

Ecological surveys

While we constructed the typology based on farmers' descriptions of their goals and practices, we also observed ecological differences in crop diversity, weediness, and avian biodiversity among farm types. These ecological data largely corroborate the distinct typologies that emerged from interviews. We identified multiple differences in plant and bird diversity between mid-scale diversified and wholesale farms, fewer differences between limited resource and wholesale farms, and no significant differences between limited resource and mid-scale diversified farms.

We found that crop diversity was significantly higher on mid-scale diversified farms than on wholesale farms ($T=4.51$, $P<0.01$), with limited resource farms hosting more intermediate levels of diversity that were marginally higher compared to wholesale farms ($T = 2.55$, $P = 0.06$; Figure 2;

Supplementary Table 1). Crop field weediness was higher on limited resource (T=3.48, P<0.01) and diversified farms (T=4.28, P<0.01) compared to wholesale farms (Figure 2; Supplementary Table 1).

Avian species richness followed the pattern found in crop diversity. Mid-scale diversified farms had higher bird species richness than wholesale farms (T = 3.95, P < 0.01; Figure 3; Supplementary Table 2) and limited resource farms had intermediate species richness that was not significantly different than the other farm types. Shannon diversity also increased from wholesale to limited resource to mid-scale diversified farms, but this trend was not significant (P > 0.05; Supplementary Table 2). Lastly, wholesale farms had lower bird abundance than limited resource (T=0.63; P = 0.01) and mid-scale diversified farms (T = 0.6, P <0.01); bird abundance was similar on limited resource and diversified farms (T=0.03, P=0.99; Figure 3; Supplementary Table 2)

Discussion

Mid-scale diversified farms lead adoption of diversification practices

Among the farms in our study, mid-scale diversified farms clearly emerged as leaders in adoption of diversification practices, which resulted in higher levels of both planned diversity (e.g., crop diversity) and unplanned diversity. This diversity may underpin high levels of avian species richness on mid-scale diversified farms which was nearly 50% higher compared to wholesale farms and 20% higher compared to limited resource farms (Figure 3). Indeed, these farms were structured around the principle of diversity, from the multitude of crops grown to the wide array of markets for which those crops were destined. Biodiversity and ecosystem services were central to the agronomic strategies of these farms, apparently creating positive feedback loops between economic and ecological dimensions of the farm operation.

Given the challenges with adopting diversification practices that we observed on both very large and very small farms in our study, and the relatively high adoption on farms with roughly intermediate acreage (20-350 acres), it would be tempting to attribute a causal relationship between farm size and adoption of diversification practices. Indeed, we could have structured our typology entirely around size. However, we suggest the stronger explanation for these mid-scale farms' adoption of diversification practices is not their size per se, but the deeper drivers of their farming model. Treating farm size as a dependent variable *alongside* diversification practice adoption allows for assessing what independent variables might drive them both. In the case of our study, the clearest causal factor underlying mid-scale farmers' adoption of diversification practices was their degree of agency.

What was perhaps most striking about our interviews with these mid-scale diversified farmers was the degree to which they spoke about making choices. They made choices about how they wanted to design their farming systems and crop rotations. They made choices about where they wanted to sell these crops. They also had the agency to value and promote forms of biodiversity that might directly benefit their farm, even in ways that are hard to measure (Kremen, 2005).

The key enabling factors that permitted these farmers to choose diversification were secure land tenure, adequate access to capital and resources, and a diverse range of buyers who shared their values and were willing to pay a premium. Supported by these three pillars, mid-scale growers had the economic security to navigate the challenges and uncertainties associated with highly biodiverse farms that are in a constant dynamic relationship with natural cycles. In a way, these mid-scale farmers had enough agency to allow their agroecosystems some agency of their own.

How other farmers could adopt more diversification practices

Researchers often look to such "lighthouse farms" or "early adopters" for clues about how other farms might transition to using more diversification practices (Nicholls et al., 2004). In the past, many such analyses have tended to focus on individual characteristics of such farms and farmers (Gould et al., 1989; Napier & Camboni, 1993; Traoré et al., 1998; Warriner & Moul, 1992). Do they take more risks? Do they have more education? In a number of cases, mid-scale diversified farmers on the California Central Coast have indeed taken significant risks or foregone short-term economic gains, based on strong commitments to an ecological model of farming and a willingness to experiment. For several in this group, commitments to biodiversity preceded their entry into agriculture, and these commitments may have even been one of the primary reasons they took up farming. However, if we want to learn how other farmers can adopt more diversification practices, we think it may be more fruitful to ask: what are the barriers to the enabling factors that have allowed these mid-scale farmers to exercise their agency in favor of diversification, and how can these barriers be overcome?

For the limited resource farmers we interviewed, the main barriers were secure access to land, capital, and other resources. For the most part, these farmers were structurally marginalized within a larger economic system that made it extremely difficult for them to access credit or build up capital. For large-scale farmers selling into wholesale markets, on the other hand, the barriers to diversification had more to do with their exposure to the demands of industrial supply chains. They lacked agency over their markets, which in turn strongly constrained their agency over their farms. Interventions aimed at helping farmers in our study area adopt diversification practices can be tailored to these two very different sets of barriers.

For small-scale farmers, policies should aim to alleviate resource limitations for adoption of practices (e.g. easier application processes for incentive programs), and work to help farmers achieve longer-term and secure land tenure (Calo & Master, 2016; Carlisle et al., 2019). In addition to land and monetary supports, policies should also prioritize secure access to water, technical assistance, and markets. These supports should not necessarily operate with the intention of helping farmers scale up and increase their farm size, as this may not be the goal for some small-scale farmers (Minkoff-Zern, 2019). Rather, the goal should be to alleviate the financial and resource limitations that prevent them from adopting more conservation practices that are often in line with their ecological values, but economically beyond their reach.

Further, expansion and streamlining of existing programs (cost-share, technical assistance, local food programs) would benefit smaller operations. Many farmers are unaware of federal and state incentive programs, and the difficulty of navigating them may create prohibitive barriers (McCann & Nunez, 2005). Even growers who are aware of such programs may not utilize them unless they hear positive feedback about conservation programs from farming peers (Prokopy et al., 2019). Thus, greater efforts should be made to publicize programs, provide enrollment assistance, and create opportunities and social structures for farmer-to-farmer sharing of personal experiences with such programs. Groups like The University of California Cooperative Extension, Kitchen Table Advisors, California FarmLink, and the Agriculture and Land-based Training Association (ALBA) provide such services for limited resource farmers in the California Central Coast region, and we know of at least one mid-scale farmer in our study who worked with these groups to build up their farm operation. These models should be expanded and better supported by public infrastructure.

Large-scale wholesale farmers, meanwhile, need help negotiating and adjusting the demands of their supply chains. Assistance is needed to build more robust alternative markets that value and encourage diversification, for example through public procurement policies for schools and other public institutions (Lo & Delwiche, 2016). Policymakers can also leverage regulations, such as water quality policies (Dowd et al., 2008; Drevno, 2018a; Harter, 2015), that force large scale wholesale buyers to utilize diversification practices to reduce pollutants on their farms. Food safety standards (particularly those enforced by third-party audits required by wholesale buyers) clearly play an important role in discouraging diversification practices on these farms, so this is also a key arena for intervention (Olimpi et al., 2019).

While direct incentives for implementing diversification practices may assist some large-scale growers, the size of incentive that would be meaningful to a small grower may not be meaningful to a large grower, who has to weigh the amount of the incentive against the expenses and potential risk involved across a highly capital-intensive operation. Our interviews with large-scale farmers selling into the wholesale market were largely consistent with interviews conducted by Medina and colleagues (2020) among a group of 10 conservation-minded Iowa farmers, mostly categorized as large-scale family farms (320 - 5000 acres). Both groups of farmers expressed that the financial incentives offered by USDA programs such as Environmental Quality Incentives Program and Conservation Stewardship Program are simply not large enough to incentivize changes in farming practices, and that greater incentives and program flexibility would benefit program adoption. Along these lines, a case study of cover cropping in Maryland showed that adoption of this practice rose as per-acre payments and program flexibility (i.e., split payment timing, extending planting deadlines) increased (Bowman & Lynch, 2019). However, these researchers also found that additional increases in incentive payments may not yield the same impact beyond a certain point and existing cost-share programs are not significant enough to drive adoption of soil conservation practices.

These findings suggest that increasing adoption of diversification practices on larger farms may require supplementing the “pull” of incentives with the “push” of regulatory mandates. Existing regulatory programs that could play a role in this process include the Irrigated Lands Regulatory Program in California, which allows for regionally-specific requirements and strategies for reducing water pollution (California Regional Water Quality Control Board: Central Coast Region, 2021). While no equivalent regulatory program exists to protect soil health, new or even existing regulatory programs could recognize the multiple benefits of diversification practices in a number of ways. Such regulatory programs could credit growers for adopting regionally appropriate conservation practices such as planting of non-crop diversity (e.g., winter cover crops to reduce nitrate leaching). These programs could work to clarify the framework surrounding food safety and allow growers more freedom to use biological inputs such as compost. Wholesalers often dictate their own food safety standards, which has dramatically decreased non-crop vegetation and use of compost and manure due to their perceived, but unsubstantiated, tie to food-borne pathogens (Baur et al., 2016; Karp et al., 2015). Previous work in this region found that food safety standards imposed by buyers impede regional sustainability outcomes (Olimpi et al., 2019). Under such conditions, it is likely that no amount of incentives will lead wholesale growers to adopt more diversification practices for fear of losing their buyers.

While regulatory measures are generally less popular among growers than incentive programs, steps can be taken to build support. Growers are not homogeneous in their attitudes toward regulation, and subjective norms - farmers' belief that other farmers think a given policy is necessary - strongly influence support for regulatory measures (Niles & Wagner, 2019). This finding suggests that creating venues for farmer-to-farmer dialogue about the need for various regulatory measures may be important for driving policy support.

By focusing on these key enabling factors, we believe it is possible to encourage diversification practices on farms at a variety of scales on California's Central Coast. We do not believe that the smaller-scale farmers we spoke to necessarily need to acquire more land to achieve a diversification "sweet spot," though they typically need more secure tenure. Nor are we convinced that larger scale farmers necessarily need to scale down their operations. Under current structural conditions, roughly "mid-scale" acreages between 20 and 350 acres are clearly more conducive to farming models that emphasize biodiversity. But as we understand it, this mid-range "sweet spot" is neither an ecological nor economic first principle, but rather the highly contingent result of current opportunities to access enabling factors under existing structural conditions.

Beyond the Central Coast

We believe that our methodological process may be useful to researchers in other regions who share our interest in adoption of diversification and soil health practices, and how adoption influences ecological outcomes. We encourage researchers to ask questions that allow farmers to identify structural barriers and how they are adapting or adjusting to these barriers. We further encourage researchers to consider how farmers are differentially impacted by these structural barriers, and whether it might make sense to construct a "farming model" typology, such as the one we have built here. When analyzing qualitative data, we encourage researchers to identify groups of farmers that have more fully adopted diversification practices, and to identify the enabling factors that have made this adoption possible. We also encourage researchers to consider what interventions might extend these enabling factors to other groups of farmers whose agency to adopt diversification practices has been limited. Finally, our initial effort to integrate ecological surveys and interviews illustrates how our typology may have tangible ecological outcomes. Future work should build on this analysis to explore the extent to which the use of diversified practices may create observable environmental outcomes, and how the perception of these outcomes may shape future management decisions. Such integration of quantitative and qualitative frameworks represents an important avenue for deepening understanding of these complex socio-ecological systems.

While the specific findings of this study are particular to organic lettuce farms on California's' Central Coast, the finding that mid-scale farms are the most likely within our study region to adopt diversification practices is particularly interesting in the context of the structural shift observed in the U.S. food system over the last half-century, characterized by a bimodal distribution of very large and very small farming operations and an ever shrinking "agriculture of the middle" (Kirschenmann et al., 2008; Lyson et al., 2008). The dominant production system in U.S. agriculture currently locks many farmers on a pathway towards large scale, input-dependent systems (Anderson et al., 2019; IPES-Food, 2018; Petersen-Rockney et al., 2021). This type of agriculture is prevalent both in the conventional and organic agricultural sectors, particularly when synthetic inputs can be replaced with natural and organic-certified inputs, as in lettuce and other crops in California (Guthman, 2004; Kremen & Miles, 2012). Meanwhile, smaller farms are often limited in their ability to adopt more sustainable practices by resource constraints and insecure land tenure. In brief, the Central Coast of California is one of many U.S. agricultural regions where the demands of consolidated food supply chains have pressured farms to grow ever larger, while simultaneously spurring an alternative agriculture movement that is still actively struggling to adequately support local food systems and economically marginalized small farms. In such bimodal environments, progress toward diversification will require an understanding of the distinct challenges faced by farmers on either side of the spectrum, with particular attention to the enabling conditions that allow some farmers to choose farming models and scales that are neither too big nor too small for diversification, but just right.

Acknowledgements

We would like to thank Melanie Rodriguez for help in compiling citations and Annie Taylor for helping to create the map.

Tables

Table 1: Descriptive statistics of interviewed farmers

	Number of farmers interviewed	Acreage farmed				Percentage of land leased (not owned)				Number of years farming			
		Median	(Min - Max)	SE	n	Median	(Min - Max)	SE	n	Median	(Min - Max)	SE	n
Limited Resource	6	9.5	(4 - 20)	2.84	6	100%	(100 - 100%)	0	6	11	(9 - 40)	4.92	6
Wholesale	8	2000	(580 - >10,000)	3659.99	7[1]	88%	25% - 100%)	0.12	7*	40	(18 - >70)	6.13	7*
Mid-Scale Diversified	6	74	(20 - 350)	58.95	6	31%	(0 - 100%)	0.17	6	28	(10 - >30)	3.90	6

[1] One grower did not provide this data

Table 2: Key characteristics of the farming model typology

	Limited Resource	Large Wholesale	Mid-Scale Diversified
Size of farm	1-20 acres	500+ acres	20-350 acres
Economic pressure	High: limited resources	High: capital intensive, slim margins, high risk	Moderate: may have some economic buffer and options (e.g., multiple crops, markets)
Land tenure	Short by necessity (often only option)	Short by choice (need flexibility to adjust with markets)	Often longer-term leases and ownership
Biggest drivers of farming model	Economic (insecure access to land and other resources)	Economic (constraints from supply chain/buyers)	Ecological (health of overall farm system)
Use of diversification practices such as cover cropping, compost, complex rotations	Limited due to cost and lack of resources, insufficient land tenure to plan long term, information/knowledge barriers	Limited due to markets: lack of flexibility in cropping systems and planting schedules, food safety restrictions imposed by supply chain	Prevalent due to their importance to farming systems, availability of resources and information, and long-term tenure
Biodiversity	Some, mostly unplanned: diverse crops by necessity of opportunistic small scale marketing, natural or semi-natural components of farm often due to lack of time and resources for management	Minimal; biodiversity largely seen as a nuisance or hazard	A lot, much of it planned: due to importance to farming model, availability of resources and information, and long-term tenure
Mental model	Flexible; lack resources to set and meet precise goals	Often more mechanistic: speak of managing "carbon," "N," "nutrients"	Often ecological: speak of managing whole living systems (e.g., soil food web)

Degree of management and modification of landscape	Low, due to limited resources, time/labor, information	Total, pre-planned management of precisely controlled agroecosystem	Selective, flexible management, based on careful observation of agroecosystem with wild elements

Table 3: Key themes in the perception and implementation of diversification practices

	Number of farmers discussing			
Theme	Limited resource (N=6)	Large wholesale (N=8)	Mid-scale diversified (N=6)	Illustrative Quote
Economic pressures are a primary factor limiting my use of diversification practices	5	4	2	"We have to grow higher dollar cash crops because obviously, the price of everything is going up." (large wholesale) "We'd like to have it all covered, everything, but we don't have enough money to cover [crop] everything." (limited resource)
Short land tenure and high rent are a key factor limiting my use of diversification practices	3	2	1	"On subleased ground we're not composting because that's kind of a long-term strategy. And part of the reason we're not composting also is because we have really tight windows to work with." (large wholesale) "If the contract is extended, we should put coverage [cover crop] instead of compost, because the coverage sponges the earth very soft to work." (limited resource)

Markets are a key factor encouraging diversification practices on my farm	3	1	5	“When you're marketing the way that we do, to have a diversity of crops to market is a big benefit …. if you really wanted to look at tapping into some of the local markets, like stores, if you have a price list that you can send out with 20 items it's much easier for a store to make an order as opposed to having a price list with 4 or 5 items.” (mid-scale) “Farmers' market customers, when they see a diverse display on your table they're like, "Oh, I can probably find something I need here," versus only having only two or three things on your table.” (limited resource)
Market requirements are a key factor limiting biodiversity on my farm	0	5	0	“Going into the organic side, those standards have all changed. As more big companies, what we would consider more corporate companies and farms, whatever else is out there that's gotten into those things, the tolerance levels got closer to zero. In the old days, when I first started organic, there was a certain tolerance level for a little bit of aphid, but that's not the case today .... I mean, I would prefer to still be using compost, but there's that idea that there might be E. coli out there." (large wholesale)

Crop plan includes 20 or more crops	0	1	6	“It is a long list [laughter]. We probably do, yeah, 50 or 60 different varieties of vegetables throughout the year, and we do some tree fruits.” (mid-scale) “Oh, man. List of crops? Here. Let me grab the harvest sheet to help me.” (mid-scale)
Hesitation about using compost due to food safety concerns	0	3	0	“We used to do quite a bit of composting. But that kind of falls under the same food safety regulations that they-- [large wholesale buyers], they won't allow you to use any composting anymore because of the possibility of the E. coli.” (large wholesale)
Hedgerows are desirable	1	2	6	“We have put in hedgerows along the borders of the fields for two reasons. Not just to benefit some of the services that a hedgerow can give for the crops, pest control, but also for buffering some of the practices from intruding or damaging some of the native habitat.” (mid-scale)
Hedgerows are undesirable	0	4	0	“We've removed any hedgerows or anything because of the food safety issue.” (large wholesale)

Figures

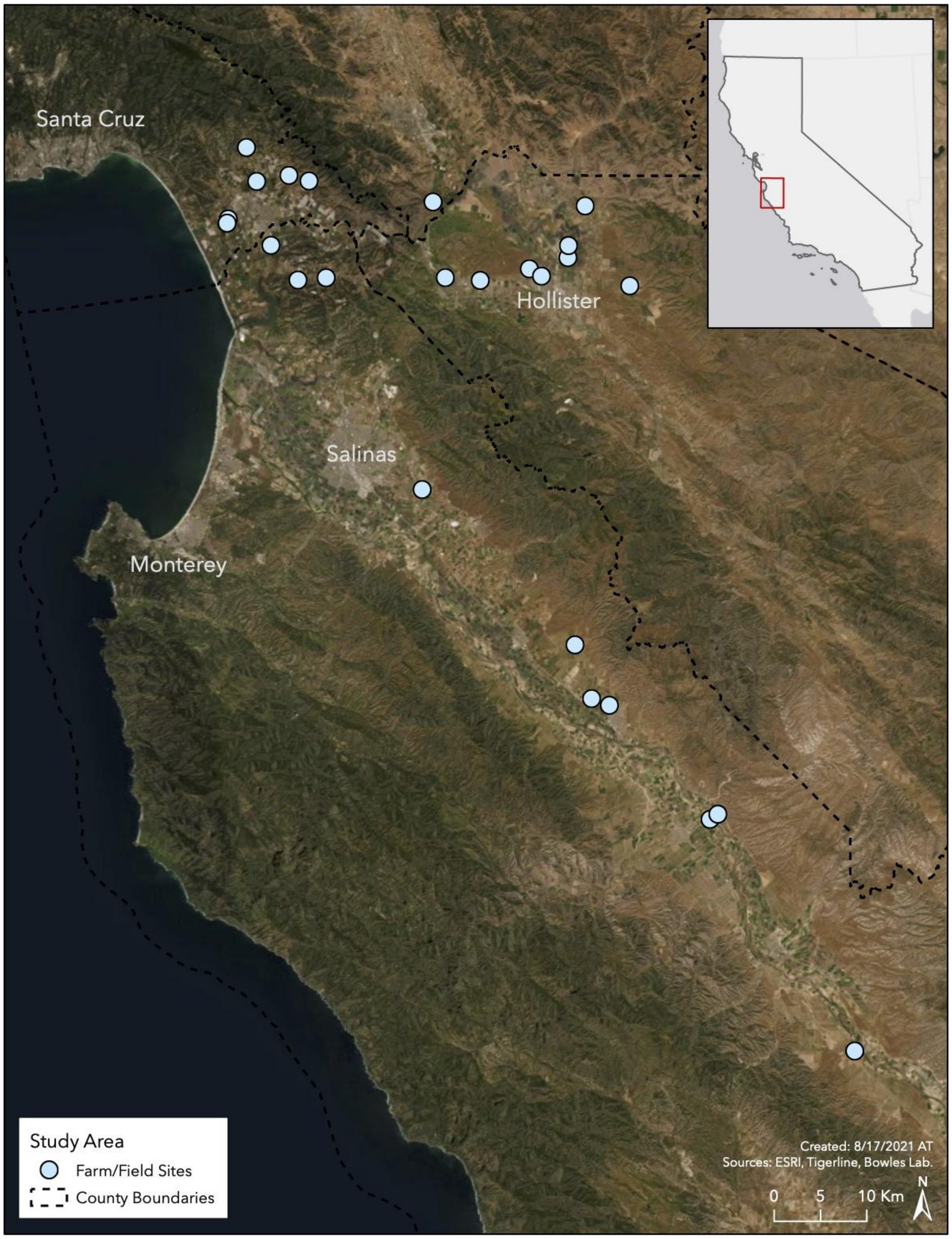


Figure 1: Map of the Central Coast Region A map of the study region showing the distribution of farm and field sites. Some farms had multiple field locations where ecological surveys were conducted, hence there are more points than number of interviews.

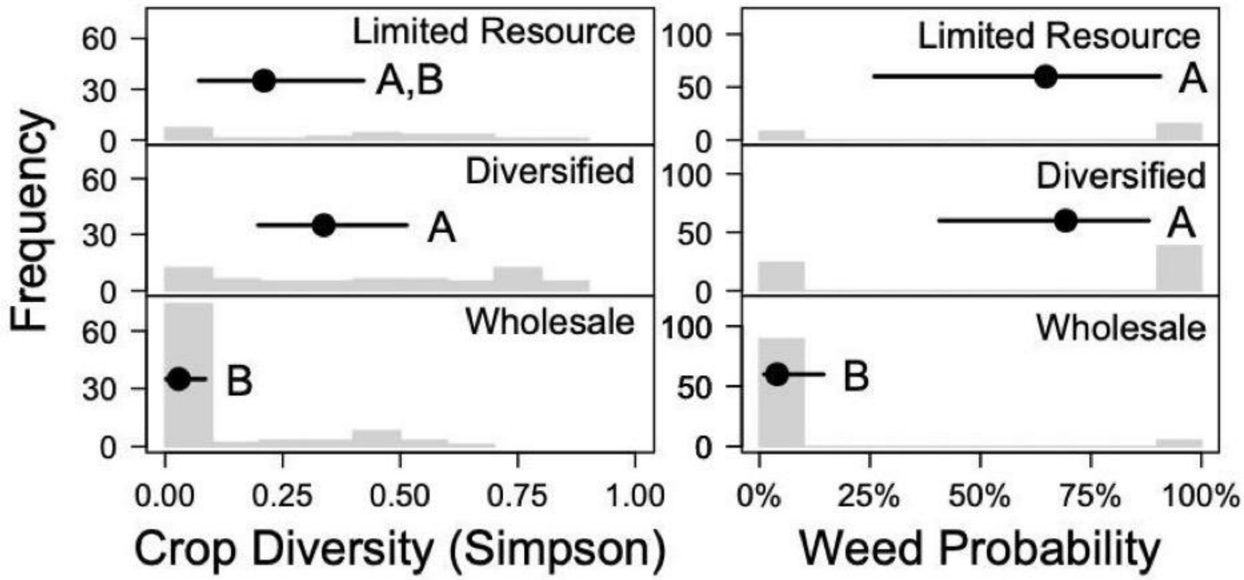


Figure 2: Effects of farm types on crop diversity and 'weediness.' *Left panels:* Crop diversity (Simpson index) was significantly higher on diversified than wholesale farms, whereas limited resource farms grew only marginally more diverse crops than wholesale farms. *Right panels:* The probability that weeds occupied >5% cover within at least one crop type was also much higher on limited resource and diversified farms than on wholesale farms. Gray histograms depict distribution of raw data. Solid black points and lines indicate estimates and 95% confidence intervals from linear mixed models; letters denote significance under Tukey posthoc tests.

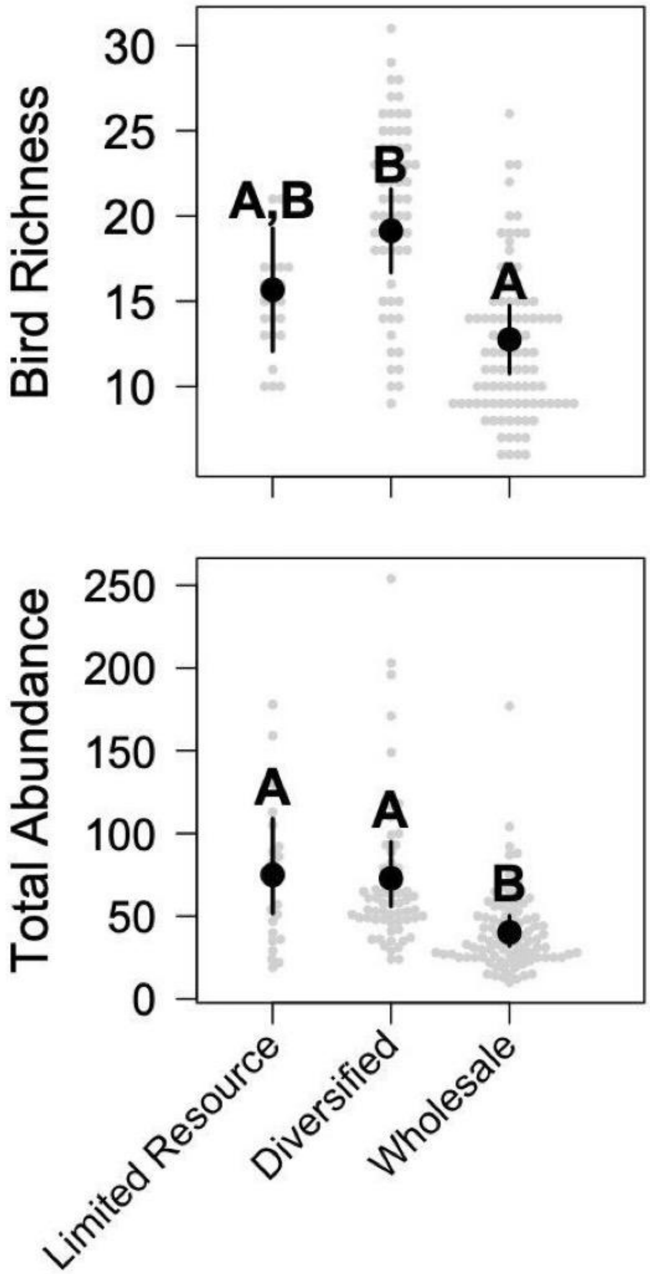


Figure 3: Effects of farm types on bird communities. Bird species richness and abundance were significantly higher on diversified than wholesale farms. Bird communities on limited resource farms had intermediate levels of diversified but high abundances, equivalent to diversified farms and significantly higher than whole farms. Gray points indicate richness (top panel) and total abundance (bottom panel) estimates at all point-count locations from N-mixture models. Solid black points and lines indicate estimates and 95% confidence intervals from linear mixed models; letters denote significance under Tukey posthoc tests.

References

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

Archer, D. W., Liebig, M. A., Tanaka, D. L., & Pokharel, K. P. (2020). Crop diversity effects on productivity and economics: A Northern Great Plains case study. Renewable Agriculture and Food Systems, 35(1), 69–76. https://doi.org/10.1017/S1742170518000261

Baumgart-Getz, A., Prokopy, L. S., & Floress, K. (2012). Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature. Journal of Environmental Management, 96(1), 17–25. https://doi.org/10.1016/j.jenvman.2011.10.006

Baur, P. (2020). When farmers are pulled in too many directions: Comparing institutional drivers of food safety and environmental sustainability in California agriculture. Agriculture and Human Values, 37(4), 1175–1194. https://doi.org/10.1007/s10460-020-10123-8

Baur, P., Driscoll, L., Gennet, S., & Karp, D. (2016). Inconsistent food safety pressures complicate environmental conservation for California produce growers. California Agriculture, 70(3), 142–151.

Bowles, T. M., Mooshammer, M., Socolar, Y., Calderón, F., Cavigelli, M. A., Culman, S. W., Deen, W., Drury, C. F., Garcia y Garcia, A., Gaudin, A. C. M., Harkcom, W. S., Lehman, R. M., Osborne, S. L., Robertson, G. P., Salerno, J., Schmer, M. R., Strock, J., & Grandy, A. S. (2020). Long- Term Evidence Shows that Crop-Rotation Diversification Increases Agricultural Resilience to Adverse Growing Conditions in North America. One Earth, 2(3), 284–293. https://doi.org/10.1016/j.oneear.2020.02.007

Bowman, M., & Lynch, L. (2019). Government Programs that Support Farmer Adoption of Soil Health Practices: A Focus on Maryland's Agricultural Water Quality Cost-Share Program. Choices, 34(2), 1–8.

California Department of Food & Agriculture. (2014). California Agricultural Statistics Review.

California Regional Water Quality Control Board: Central Coast Region. (2021). Proposed General Waste Discharge Requirements for Discharges from Irrigated Lands Order No. R3-2021-0040.

Calo, A., & Master, K. T. D. (2016). After the Incubator: Factors Impeding Land Access Along the Path from Farmworker to Proprietor. Journal of Agriculture, Food Systems, and Community Development, 6(2), 111–127. https://doi.org/10.5304/jafscd.2016.062.018

Calvin, L., Jensen, H., Klonsky, K., & Cook, R. (2017). Food Safety Practices and Costs Under the California Leafy Greens Marketing Agreement. In Economic Information Bulletin (No. 259719; Economic Information Bulletin). United States Department of Agriculture, Economic Research Service. https://ideas.repec.org/p/ags/uersib/259719.html

Carlisle, L. (2016). Factors influencing farmer adoption of soil health practices in the United States: A narrative review. Agroecology and Sustainable Food Systems, 40(6), 583–613. https://doi.org/10.1080/21683565.2016.1156596

Carlisle, L., de Wit, M. M., DeLonge, M. S., Calo, A., Getz, C., Ory, J., Munden-Dixon, K., Galt, R., Melone, B., Knox, R., Iles, A., & Press, D. (2019). Securing the future of US agriculture: The case for investing in new entry sustainable farmers. Elementa: Science of the Anthropocene, 7, 17. https://doi.org/10.1525/elementa.356

CDFA - OEFI - Healthy Soils Program. (n.d.). Retrieved June 17, 2021, from https://www.cdfa.ca.gov/oefi/healthysoils/

Clapp, J., & Fuchs, D. (2009). Agrifood Corporations, Global Governance, and Sustainability: A Framework for Analysis (pp. 1–25). https://doi.org/10.7551/mitpress/9780262012751.003.0001

Clay, D., Reardon, T., & Kangasniemi, J. (1998). Sustainable Intensification in the Highland Tropics: Rwandan Farmers' Investments in Land Conservation and Soil Fertility. Economic Development and Cultural Change, 46(2), 351–377. https://doi.org/10.1086/452342

Cook, R. L. (2011). Fundamental Forces Affecting the U.S. Fresh Berry and Lettuce/Leafy Green Subsectors. Choices, 26(4). https://www.jstor.org/stable/choices.26.4.07

Corbin, J. M., & Strauss, A. (1990). Grounded theory research: Procedures, canons, and evaluative criteria. Qualitative Sociology, 13(1), 3–21. https://doi.org/10.1007/BF00988593

Dainese, M., Martin, E. A., Aizen, M. A., Albrecht, M., Bartomeus, I., Bommarco, R., Carvalheiro, L. G., Chaplin-Kramer, R., Gagic, V., Garibaldi, L. A., Ghazoul, J., Grab, H., Jonsson, M., Karp, D. S., Kennedy, C. M., Kleijn, D., Kremen, C., Landis, D. A., Letourneau, D. K., … Steffan-Dewenter, I. (2019). A global synthesis reveals biodiversity-mediated benefits for crop production. Science Advances, 5(10), eaax0121. https://doi.org/10.1126/sciadv.aax0121

Dowd, B. M., Press, D., & Huertos, M. L. (2008). Agricultural nonpoint source water pollution policy: The case of California's Central Coast. Agriculture, Ecosystems & Environment, 128(3), 151–161. https://doi.org/10.1016/j.agee.2008.05.014

Drevno, A. (2018a). Central Coast growers' trust in water quality regulatory process needs rebuilding. California Agriculture, 72(2), 127–134. https://doi.org/10.3733/ca.2018a0015

Drevno, A. (2018b). Central Coast growers' trust in water quality regulatory process needs rebuilding. California Agriculture, 72(2), 127–134.

Garratt, M. P. D., Senapathi, D., Coston, D. J., Mortimer, S. R., & Potts, S. G. (2017). The benefits of hedgerows for pollinators and natural enemies depends on hedge quality and landscape context. Agriculture, Ecosystems & Environment, 247, 363–370. https://doi.org/10.1016/j.agee.2017.06.048

Gaudin, A. C. M., Westra, S., Loucks, C. E. S., Janovicek, K., Martin, R. C., & Deen, W. (2013). Improving Resilience of Northern Field Crop Systems Using Inter-Seeded Red Clover: A Review. Agronomy, 3(1), 148–180. https://doi.org/10.3390/agronomy3010148

Gennet, S., Howard, J., Langholz, J., Andrews, K., Reynolds, M. D., & Morrison, S. A. (2013). Farm practices for food safety: An emerging threat to floodplain and riparian ecosystems. Frontiers in Ecology and the Environment, 11(5), 236–242. https://doi.org/10.1890/120243

Gould, B. W., Saupe, W. E., & Klemme, R. M. (1989). Conservation Tillage: The Role of Farm and Operator Characteristics and the Perception of Soil Erosion. Land Economics, 65(2), 167–182. https://doi.org/10.2307/3146791

Guthman, J. (2004). Back to the Land: The Paradox of Organic Food Standards. Environment and Planning A: Economy and Space, 36(3), 511–528. https://doi.org/10.1068/a36104

Harter, T. (2015). California's agricultural regions gear up to actively manage groundwater use and protection. California Agriculture, 69(3), 193–201. https://doi.org/10.3733/ca.E.v069n03p193

IPES-Food. (2018). Breaking away from industrial food and farming systems: Seven case studies of agroecological transition.
Karp, D. S., Chaplin-Kramer, R., Meehan, T. D., Martin, E. A., DeClerck, F., Grab, H., Gratton, C., Hunt, L., Larsen, A. E., Martínez-Salinas, A., O'Rourke, M. E., Rusch, A., Poveda, K., Jonsson, M., Rosenheim, J. A., Schellhorn, N. A., Tscharntke, T., Wratten, S. D., Zhang, W., … Zou, Y. (2018). Crop pests and predators exhibit inconsistent responses to surrounding landscape composition. Proceedings of the National Academy of Sciences, 115(33), E7863–E7870. https://doi.org/10.1073/pnas.1800042115
Karp, D. S., Gennet, S., Kilonzo, C., Partyka, M., Chaumont, N., Atwill, E. R., & Kremen, C. (2015). Comanaging fresh produce for nature conservation and food safety. Proceedings of the National Academy of Sciences, 112(35), 11126–11131.
Kéry, M., & Schaub, M. (2011). Bayesian Population Analysis using WinBUGS: A Hierarchical Perspective. Academic Press.
Kirschenmann, F., Stevenson, G. W., Buttel, F., Lyson, T. A., & Duffy, M. (2008). Why Worry about the Agriculture of the Middle? In T. A. Lyson, G. W. Stevenson, & R. Welsh (Eds.), Food and the Mid-Level Farm (pp. 3–20). The MIT Press. https://doi.org/10.7551/mitpress/9780262122993.003.0001
Knowler, D., & Bradshaw, B. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research. Food Policy, 32(1), 25–48. https://doi.org/10.1016/j.foodpol.2006.01.003
Kremen, C. (2005). Managing ecosystem services: What do we need to know about their ecology? Ecology Letters, 8(5), 468–479. https://doi.org/10.1111/j.1461-0248.2005.00751.x
Kremen, C., & Miles, A. (2012). Ecosystem Services in Biologically Diversified versus Conventional Farming Systems: Benefits, Externalities, and Trade-Offs. Ecology and Society, 17(4). https://www.jstor.org/stable/26269237
Liu, T., Bruins, R. J. F., & Heberling, M. T. (2018). Factors Influencing Farmers' Adoption of Best Management Practices: A Review and Synthesis. Sustainability, 10(2), 432. https://doi.org/10.3390/su10020432
Lo, J., & Delwiche, A. (2016). The Good Food Purchasing Policy: A Tool to Intertwine Worker Justice with a Sustainable Food System. Journal of Agriculture, Food Systems, and Community Development, 6(2), 185–194. https://doi.org/10.5304/jafscd.2016.062.016
Lyson, T. A., Hendrickson, M., Stevenson, G. W., Welsh, R., Kirschenmann, F., Buttel, F. H., Duffy, M., Dahlberg, K. A., Gray, T. W., & Guptill, A. (2008). Food and the Mid-Level Farm: Renewing an Agriculture of the Middle. MIT Press. http://ebookcentral.proquest.com/lib/berkeley-ebooks/detail.action?docID=3338895
McCann, L. M. J., & Nunez, J. (2005). Who Participates in EQIP? (No. 378-2016–21394). AgEcon Search. https://doi.org/10.22004/ag.econ.19446
Medina, G., Isley, C., & Arbuckle, J. (2020). Iowa Farm Environmental Leaders' Perspectives on the U.S. Farm Bill Conservation Programs. Frontiers in Sustainable Food Systems, 4. https://doi.org/10.3389/fsufs.2020.497943
Minkoff-Zern, L.-A. (2019). The New American Farmer: Immigration, Race, and the Struggle for Sustainability. MIT Press.
Morandin, L. A., Long, R. F., & Kremen, C. (2016). Pest Control and Pollination Cost–Benefit Analysis of Hedgerow Restoration in a Simplified Agricultural Landscape. Journal of Economic Entomology, 109(3), 1020–1027. https://doi.org/10.1093/jee/tow086

Napier, T. L., & Camboni, S. M. (1993). Use of conventional and conservation practices among farmers in the Scioto River Basin of Ohio. Journal of Soil and Water Conservation, 48(3), 231–237.

Neill, S. P., & Lee, D. R. (2001). Explaining the Adoption and Disadoption of Sustainable Agriculture: The Case of Cover Crops in Northern Honduras. Economic Development and Cultural Change, 49(4), 793–820. https://doi.org/10.1086/452525

Nicholls, C. I., Altieri, M. A., Dezanet, A., Lana, M., Feistauer, D., & Ouriques, M. (n.d.). A Rapid, Farmer-Friendly Agroecological Method to Estimate Soil Quality and Crop Health in Vineyard Systems. 8.

Niles, M. T., & Wagner, C. R. H. (2019). The carrot or the stick? Drivers of California farmer support for varying groundwater management policies. Environmental Research Communications, 1(4), 045001. https://doi.org/10.1088/2515-7620/ab1778

Olimpi, E. M., Baur, P., Echeverri, A., Gonthier, D., Karp, D. S., Kremen, C., Sciligo, A., & De Master, K. T. (2019). Evolving Food Safety Pressures in California's Central Coast Region. Frontiers in Sustainable Food Systems, 3, 102. https://doi.org/10.3389/fsufs.2019.00102

Petersen-Rockney, M., Baur, P., Guzman, A., Bender, S. F., Calo, A., Castillo, F., De Master, K., Dumont, A., Esquivel, K., Kremen, C., LaChance, J., Mooshammer, M., Ory, J., Price, M. J., Socolar, Y., Stanley, P., Iles, A., & Bowles, T. (2021). Narrow and Brittle or Broad and Nimble? Comparing Adaptive Capacity in Simplifying and Diversifying Farming Systems. Frontiers in Sustainable Food Systems, 5. https://doi.org/10.3389/fsufs.2021.564900

Poeplau, C., & Don, A. (2015). Carbon sequestration in agricultural soils via cultivation of cover crops – A meta-analysis. Agriculture, Ecosystems & Environment, 200, 33–41. https://doi.org/10.1016/j.agee.2014.10.024

Prokopy, L. S., Floress, K., Arbuckle, J. G., Church, S. P., Eanes, F. R., Gao, Y., Gramig, B. M., Ranjan, P., & Singh, A. S. (2019). Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. Journal of Soil and Water Conservation, 74(5), 520–534. https://doi.org/10.2489/jswc.74.5.520

Prokopy, L. S., Floress, K., Klotthor-Weinkauf, D., & Baumgart-Getz, A. (2008). Determinants of agricultural best management practice adoption: Evidence from the literature. Journal of Soil and Water Conservation, 63(5), 300–311. https://doi.org/10.2489/jswc.63.5.300

R Core Team. (2014). R: A languange and environment for statistical computing. R Foundation for Statistical Computing. http://www.R-project.org

Ralph, C. J., Droege, S., & Sauer, J. R. (1995). Managing and Monitoring Birds Using Point Counts: Standards and Applications. In: Ralph, C. John; Sauer, John R.; Droege, Sam, Technical Editors. 1995. Monitoring Bird Populations by Point Counts. Gen. Tech. Rep. PSW-GTR-149. Albany, CA: U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station: P. 161-168, 149. https://www.fs.usda.gov/treesearch/pubs/31755

Reimer, A., Thompson, A., Prokopy, L. S., Arbuckle, J. G., Genskow, K., Jackson-Smith, D., Lynne, G., McCann, L., Morton, L. W., & Nowak, P. (2014). People, place, behavior, and context: A research agenda for expanding our understanding of what motivates farmers' conservation behaviors. Journal of Soil and Water Conservation, 69(2), 57A-61A. https://doi.org/10.2489/jswc.69.2.57A

Rosenstock, T. S., Liptzin, D., Dzurella, K., Fryjoff-Hung, A., Hollander, A., Jensen, V., King, A., Kourakos, G., McNally, A., Pettygrove, G. S., Quinn, J., Viers, J. H., Tomich, T. P., & Harter, T. (2014). Agriculture's Contribution to Nitrate Contamination of Californian

Groundwater (1945–2005). Journal of Environmental Quality, 43(3), 895–907. https://doi.org/10.2134/jeq2013.10.0411
Royle, J. A., & Dorazio, R. M. (2008). Hierarchical Modeling and Inference in Ecology: The Analysis of Data from Populations, Metapopulations and Communities. Elsevier.
Ryan, B., & Gross, N. C. (1943). The Diffusion of Hybrid Seed Corn in Two Iowa Communities. Rural Sociology, 8(1), 15–24.
Smith, E. G., Harker, K. N., O'Donovan, J. T., Turkington, T. K., Blackshaw, R. E., Lupwayi, N. Z., Johnson, E. N., Pageau, D., Shirtliffe, S. J., Gulden, R. H., Hall, L. M., & Willenborg, C. J. (2018). The profitability of diverse crop rotations and other cultural methods that reduce wild oat (Avena fatua)1. Canadian Journal of Plant Science. https://doi.org/10.1139/cjps-2018-0019
Stuart, D., & Gillon, S. (2013). Scaling up to address new challenges to conservation on US farmland. Land Use Policy, 31, 223–236. https://doi.org/10.1016/j.landusepol.2012.07.003
Tamburini, G., Bommarco, R., Wanger, T. C., Kremen, C., Heijden, M. G. A. van der, Liebman, M., & Hallin, S. (2020). Agricultural diversification promotes multiple ecosystem services without compromising yield. Science Advances, 6(45), eaba1715. https://doi.org/10.1126/sciadv.aba1715
Tourte, L., Smith, R., Klonsky, K. M., & De Moura, R. L. (2009). Sample Costs to Produce Organic Leaf Lettuce. University of California Cooperative Extension. https://coststudyfiles.ucdavis.edu/uploads/cs_public/7d/96/7d96db67-49ca-442f-9543-4482187c9cd1/lettuceleaforganiccc09.pdf
Tourte, L., Smith, R., Murdock, J., & Sumner, D. A. (2017). Costs and returns for Central Coast lettuce and broccoli examined. ANR Blogs. https://ucanr.edu/blogs/blogcore/postdetail.cfm?postnum=24599
Tourte, L., Smith, R., Murdock, J., & Sumner, D. A. (2019). Sample Costs to Produce and Harvest Romaine Hearts. UC Agriculture and Natural Resources: Cooperative Extension and Agricultural issues Center. https://coststudyfiles.ucdavis.edu/uploads/cs_public/7a/c9/7ac93a02-6ad3-439a-a74d-2bcf9e40180c/2019romainehearts-final-7-8-2019.pdf
Traoré, N., Landry, R., & Amara, N. (1998). On-Farm Adoption of Conservation Practices: The Role of Farm and Farmer Characteristics, Perceptions, and Health Hazards. Land Economics, 74(1), 114–127. https://doi.org/10.2307/3147217
Tscharntke, T., Klein, A. M., Kruess, A., Steffan-Dewenter, I., & Thies, C. (2005). Landscape perspectives on agricultural intensification and biodiversity – ecosystem service management. Ecology Letters, 8(8), 857–874. https://doi.org/10.1111/j.1461-0248.2005.00782.x
Wade, J., Culman, S. W., Logan, J. A. R., Poffenbarger, H., Demyan, M. S., Grove, J. H., Mallarino, A. P., McGrath, J. M., Ruark, M., & West, J. R. (2020). Improved soil biological health increases corn grain yield in N fertilized systems across the Corn Belt. Scientific Reports, 10(1), 3917. https://doi.org/10.1038/s41598-020-60987-3
Warriner, G. K., & Moul, T. M. (1992). Kinship and personal communication network influences on the adoption of agriculture conservation technology. Journal of Rural Studies, 8(3), 279–291. https://doi.org/10.1016/0743-0167(92)90005-Q
Weisberger, D., Nichols, V., & Liebman, M. (2019). Does diversifying crop rotations suppress weeds? A meta-analysis. PLOS ONE, 14(7), e0219847. https://doi.org/10.1371/journal.pone.0219847

Supplementary materials

Farmer interview protocol

Consent: Before we start, I need to cover a few matters of research ethics that pertain to this interview: your participation is voluntary, you can stop the interview or withdraw from the study at any time with no cost, you can pause the interview at any time for breaks, and we will keep your responses confidential. I also need to ask you explicitly for your consent to be interviewed. Do you consent? Do you consent to audio recording of this interview, which will also be kept confidential?

Demographics and Background

1. Why/How did you get involved with farming? How long have you been farming? How long have you been farming on this ground?
2. In which county (counties) is your farm or ranch located?
3. How many acres do you farm or ranch?
4. What crops (if any) do you produce? How many crops do you produce in each field per year?
5. What livestock products (if any) do you produce?
6. Is the land you farm/ranch
    a. Owned by you?
    b. Rented? How long is your lease?
    c. Split? If split, how many acres are rented?
7. What are your primary markets (e.g. wholesale, farmer's market, community supported agriculture, restaurants, other direct markets)? Approximately what share of your revenue comes from each?
8. How would you define a healthy, productive farm? What do you look for when monitoring your farm?

Soil Health

9. How do you define healthy soil? What do you look for when evaluating soil?
10. What are the biggest challenges related to managing your soil (biophysical, ecological, economic)?
11. What practices do you currently use to maintain or improve soil health on your farm?
    a. What motivates you to use these practices?
    b. What are the challenges in adopting these practices?
    c. How long has it taken to transition to these practices and see net benefits to your farm?
12. *If it doesn't come up earlier*: Do you use any inputs (either on-farm or off-farm) to maintain or improve soil health on your farm?
13. *If it doesn't come up earlier*: Could you briefly describe your tillage practices?

Crop Diversity

14. What do you think is the right amount of crop diversity for your farm and why? (Diversity could include different crops in your rotation, cover crops, or intercropping)
    a. What are the challenges in farming with this degree of diversity?
15. Do you grow any non-crop plants on your farm – such as hedgerows, buffers, or habitat for beneficial insects?
16. What kinds of pests, beneficials, or other non-crop organisms do you see regularly on your farm, and what are your management goals for them?
17. What are the biggest challenges related to managing insects, weeds, birds, and other non-crop organisms (biophysical, ecological, economic, access to information)?
18. What practices do you currently use to manage insects, weeds, birds, and other non-crop organisms?
    a. What motivates you to use these practices?
    b. What are the challenges in adopting these practices?
19. How do lands surrounding your farm impact your operation?
20. Is wildlife a problem on your farm? If so, could you please share some experiences with wildlife that you have had in the past? Think about animals that affect your crops or damage your farm in any way.
21. What have your experiences been with birds on your farm? Could you name or describe birds you have seen on your farm? Are they beneficial, harmful, or neutral?
22. If birds have been a problem on your farm, what are your preferred practices to keep them from damaging your crops?

Farm Management

23. Are there additional practices you would like to try out to improve soil health, crop diversity, or management of insects, weeds, and wildlife on your farm?
    a. What are they?
    b. Why don't you use them now?
    c. Have you tried practices in the past but stopped using them? If yes, what was making it difficult to continue?
24. *For renters only:* Does the landowner restrict the practices you can use in any way? Which of these ranges does the cost of your lease fit into:

$500-$1000/acre/year

$1001-$1500/acre/year

$1501-$2000/acre/year

$2001-$2500/acre/year

$2501-$3000/acre/year

$3001-$3500/acre/year

More than $3501/acre/year

25. In the past five years, have you participated in any federal or state programs that have influenced your soil health practices, crop diversification, or insect/weed/wildlife management?

a. *If it doesn't come up earlier:* Are there any state or federal programs that encourage you to use the practice? If yes, which ones?

b. Are there any barriers you face in using these programs? Do some programs discourage you from using soil health practices?

26. *If it doesn't come up earlier*: Does food safety play a role in what you can or can't do on your farm to improve soil health, crop diversity, or insect/weed/wildlife management?
27. *Do you think that the pressure to make margins over the short-term causes farmers to cut corners on long-term conservation?* (Prompt: For example, some farmers say that using cover crops might pay off in the long term, but the short-term risks to income seem too high to make the changes. What do you think?)
28. *If it doesn't come up earlier*: What challenges and opportunities are coming from buyers? Does contract farming affect your ability to use soil health practices, diverse crop rotations, or insect/weed management? Are buyers demanding more use of these practices?
29. Does your organic certifier or another certifier support or influence your soil health, crop diversity, or insect/weed management practices? How does growing organically differ from growing conventionally, in terms of managing soil, insects, weeds, wildlife, and crop diversity? Do you have sufficient access to markets that value soil health or crop diversity?
30. How would you describe the relationship among your farm's profitability, the health of your soil, your crop rotation, and your management of insects, weeds, and other non-crop organisms?

a. If soil health, farm diversity, or other organic practices have improved your profitability, how so (e.g. reducing input costs, increasing crop production stability)

31. Do you expect Ag Order 4.0 will impact your farming practices? Are there other water regulations that currently impact your practices or planning for the future?
32. What would encourage you to adopt more soil health improvement, crop diversity, or insect/weed/wildlife management practices?
33. How does your definition of a healthy and productive farm compare to the way your neighbors and local technical assistance providers approach farming? Do you think your soil health practices, crop diversity, and insect/weed/wildlife management practices are mainstream, or would you characterize them as more alternative or innovative? Have your neighbors or technical assistance providers influenced your approach to farming? Are there specific people or organizations who have helped you learn the soil health or diversification practices you use today? What are your primary sources of information about farming, and why do you trust these sources?
34. Do you pay hired workers to help you with some of your soil health and organic management practices? Which tasks? Does this investment in labor pay off? Do you have any concerns about access to labor? Does your need for labor relate to your level of crop diversity?

35. Have you noticed any changes in weather patterns or the severity of weather events (i.e. earlier bloom, increased droughts, heavier rains)?
    a. Are you concerned about climate resilience on-farm?
    b. Are you interested in adaptation strategies for increased climate resilience?
    c. Are you interested in learning about how to use soil health management to increase organic matter and build resistance and resilience on-farm?
36. Where are you planning to grow lettuce in 2019?
    a. Can you provide me with a map of these fields?

Technical assistance provider interview protocol

Consent: Before we start, I need to cover a few matters of research ethics that pertain to this interview: your participation is voluntary, you can stop the interview or withdraw from the study at any time with no cost, you can pause the interview at any time for breaks, and we will keep your responses confidential. I also need to ask you explicitly for your consent to be interviewed. Do you consent? Do you consent to audio recording of this interview, which will also be kept confidential?

1. What kind of work do you do with farmers, and how long have you been involved in this work?

2. Specifically, how frequently do you work with farmers growing organic lettuce in the Central Coast region?

Soil Health

1. What do you see as some of the biggest factors that impact the degree to which organic lettuce farmers you interact with use soil health practices like cover cropping, complex crop rotations, composting, or reduced tillage?

2. For farmers who transition to these practices from a more ecologically simplified farming system, how long does it take for them to realize benefits to their operation?

Biodiversity

1. What do you see as some of the biggest factors that impact the diversity of crop rotations used by organic lettuce farmers you interact with?

2. What do you see as some of the biggest factors that impact the degree to which organic lettuce farmers you interact with use non-crop vegetation, such as hedgerows or habitat for beneficial insects?

3. What have your experiences been with birds on farms? Do farmers see them as a negative or positive indicator? What, if anything, are farmers doing to mitigate bird damage and/or encourage the presence of certain birds (e.g. raptors)?

Policy

1. What has your experience been with federal or state programs that incentivize conservation practices on farms? Are these programs working well? What is preventing them from working better or preventing farmers from utilizing them?

2. What has your experience been with food safety regulations and standards?

3. Are food safety protocols interfering with soil health practices and biodiversity on the farm?

4. Do you think that pressure to make margins over the short-term causes farmers to cut corners on long-term investments in the ecological health of their farm? What factors determine how much a particular farmer might feel this pressure?

5. What challenges and opportunities are coming from buyers, in terms of whether the supply chain is pushing farmers toward soil health practices and biodiversity or toward a more ecologically simplified system?

6. How do organic certification and the certifier's interactions with farmers impact the degree to which farmers incorporate soil health practices and biodiversity on the farm?

7. What would encourage farmers to incorporate more soil health practices and biodiversity into their operations?

Bird surveys

We surveyed birds on each focal farm using 10 minute, 50m fixed-radius point count surveys, repeated three times over consecutive days from May-July of 2019-2020. Point count locations were separated by at least 100m (Ralph et al. 1993). Thus, the number of point counts per farm varied by farm size. At least half of the count locations on each farm were centered in lettuce crops; the other half were located within other dominant crop types (e.g., squash, broccoli, strawberry). All surveys were conducted by the same skilled observer, primarily between sunrise and 10:30am and always in the absence of rain or heavy fog. All individuals seen or heard within the survey radius were identified to species and recorded. Within each 50m radius point count, we also estimated the percent cover of each crop and then used these data to quantify crop diversity (*i.e.,* Simpson's index) within each point count radius. We also scored the percent cover of weeds within each crop type (1=0–5%; 2=5–50%; 3>50%).

Local diversification

We quantified local (on-farm) diversification by building a composite index from measurements of crop diversity, non-crop vegetation cover, and vegetation complexity within each 50m radius point count and then averaging across all point counts on each farm. Specifically, we estimated the percent cover of seminatural habitat (*e.g.,* trees, shrubs, grasses, weeds, and floral strips), the percent cover of weeds within crop fields (1=0–5%; 2=5–50%; 3>50%), crop diversity (Simpson's index), and the number of vegetative strata (herbaceous vegetation or row crops, understory shrubs, and trees). We then averaged vegetation measurements across all point count locations on the same farm (except for the farm with a single point count where we used raw values), scaled each vegetation measurement (subtracting the mean across all farms and dividing by the standard deviation), and then averaged the scaled vegetation measurements from each farm to create the local diversification index.

Semi-natural habitat and crop diversity

We manually digitized seminatural habitat (forest, shrubland, grassland, pasture, and wetlands) and cultivated areas from NAIP 2016 imagery ArcMap 10.3.1 (ESRI, Redlands, CA, USA) surrounding bird survey locations. We calculated the percent cover of seminatural habitat within a 1 km radius of point count locations, which is an appropriate scale for examining effects of landscape composition on bird communities (Gonthier et al., 2014). For cultivated areas, we visually surveyed crops in the field, manually digitized maps of observed crops within 500m, and then calculated crop diversity (Simpson's index).

N-mixture model

N-mixture models are frequently used to account for imperfect detection in abundance estimation (Royle, 2004; Ficetola et al., 2018; Kéry, 2008). N-mixture models estimate abundance and detection probability by using spatially and temporally replicated surveys upon which the number of individuals is counted. Populations are assumed to be closed, such that the same number of individuals are present during each visit to a site. Then, detection probability is modeled assuming that the number of individuals observed is a binomial random variable with the number of trials equal to the site-specific abundance and success probability equal to individual detection probability *P*. Site-specific abundances are modeled as a random count variable (*e.g.,* Poisson).

Here, we modeled the number of individuals observed (*Y*) of a species (*i*) at a site (*j*) and a visit (*k*) based on abundance and detection processes such that:

$$Yi, j, k \; Binomial(N_(i, j), P_(i, j, k)),$$

Where *N* is the true number of individuals and *P* is the per individual detection probability. We assumed that *N* came from a Poisson distribution based on the expected abundance that was modeled as:

$$log(_i j) = 0_i + 1_i * Seminatural_j + 2_i * Local_j + 3_i * CropDiversity_j + 0_(i, j) + 1_(i, farm[j]) + 2_(year[j])$$

Where "Seminatural" is the percent cover of seminatural habitat, "Local" is the local diversification metric, and "CropDiversity" represents the Simpson's index of crop diversity (see Methods). The detection probability of an individual was modeled as:

$$(P_(i, j, k)) \; = \; 0i + 1 * Wind_(j, k) + 2_i * Time_(j, k) + 3 * Date_(j, k) + 4 * Noise_(j, k) + 0_(i, j, k)$$

Where "Wind" is the average wind speed in miles per hour that was assessed at the beginning and end of each survey, "Time" is the start time of the survey, "Date" is the Julian date of the survey, and “Noise” is a binary variable where zero represents quiet and one represents noise during a point count (e.g. from tractors, sprinklers). All covariates were scaled and centered prior to analysis.

Parameters in the family, the β0 parameter, and the β2 parameter were estimated for each species, where each species term was drawn from a normal distribution with a mean and variance estimated from the data. The other parameters in the β family were fixed effect terms. The and terms represent random intercepts (normally distributed with mean of zero and variance estimated from the data) that were included to explain more variation for each species, site, or visit to a site that was not explained by the fixed effects.

We implemented the N-mixture model in R Version 4.0.0 using the package *rjags,* which runs Markov chain Monte Carlo (MCMC) algorithms (RC Team, 2013; Plummer et al., 2016). We ran three chains starting at random initial values with 50,000 burn-in iterations and 50,000 post burn-in iterations. We thinned chains by 50, and we used the Gelman-Rubin statistic to assess chain convergence (Gelman et al., 2004). We considered chains for abundance estimates to converge they had Gelman-Rubin statistics 1.1. Out of all abundance estimates (N = 20,657), 3.3% of them had Gelman-Rubin statistics >1.1. Most of those estimates that did not converge either (1) belonged to Cliff Swallow or (2) had over 90% of samples equal to zero but had a few samples with larger values. To deal with these issues, we eliminated Cliff Swallow from analyses and used the median and interquartile range instead of mean and standard deviation in post-hoc analyses.

We used generalized linear mixed models (GLMMs) to determine effects of the three farm types on the crop diversity and ‘weediness’ within each point-count radius, followed by Tukey post-hoc tests to compare differences between farm types. We included a random effect of farmer identity to account for non-independence among management strategies. Crop diversity was square root transformed to satisfy model normality assumptions and modeled with a Gaussian distribution. Weediness was converted into a binomial variable: a point-count location was considered ‘weedy’ if any crop within the 50m radius had >5% weed cover.

We used an N-mixture model that accounts for unseen species and variation in detection probability to estimate the abundance of each bird species at each site (Royle and Dorazio 2008, Kéry and Schaub 2011). We extracted the modeled abundance from each iteration of the posterior (N= 3000) and then calculated the species richness, Shannon diversity, and total abundance at each location. We then extracted median values and interquartile ranges across the 3000 posteriors. Finally, we used GLMMs to assess effects of farm types on species richness, Shannon diversity, and total abundance, again followed by Tukey post-hoc tests. We included the fraction of surrounding seminatural habitat within 1km as a covariate to account for landscape context and farm identity as a random effect to account for spatial autocorrelation. All variables were modeled with Gaussian distributions. Total abundance was log transformed to satisfy model normality assumptions. To propagate error uncertainty from the N-mixture model, community metrics were weighted by the inverse of their interquartile ranges (as in Karp et al. 2018). Analyses were implemented in R (R Core Team 2013).

Supplementary tables

Table S1: Effects of farm type on crop diversity (Shannon) and probability of weediness. Table depicts estimate differences between farm types, T statistics, and P values from Tukey post-hoc tests. Significant contrasts are bolded.

	Limited Resource v Mid-scale Diversified Farm			Limited Resource v Wholesale Farms			Mid-scale Diversified Farm v Wholesale Farms		
Outcome	Diff. Estimate	T	p	Diff. Estimate	T	p	Diff. Estimate	T	p
Crop Diversity	0.12	1.04	0.57	0.29	2.55	0.06	**0.41**	**4.51**	**<0.01**
Weediness	-0.21	-0.20	0.98	**3.78**	**3.48**	**<0.01**	**3.98**	**4.28**	**<0.01**

Table S2: Effects of farm type on avian richness, diversity (Shannon index), and abundance (log). Table depicts estimate differences between farm types, T statistics, and P values from Tukey post-hoc tests. Significant contrasts are bolded.

	Limited Resource v Mid-scale Diversified Farm			Limited Resource v Wholesale Farms			Mid-scale Diversified Farm v Wholesale Farms		
Outcome	Diff. Estimate	T	p	Diff. Estimate	T	p	Diff. Estimate	T	p
Species Richness	-3.46	1.55	0.27	2.91	1.41	0.35	**6.37**	**3.95**	**<0.01**
Shannon Diversity	-0.34	2.31	0.07	-0.03	0.22	0.97	0.31	2.84	0.25
Abundance (log)	0.03	0.13	0.99	**0.63**	**2.9**	**0.01**	**0.6**	**3.35**	**<0.01**

References

Ficetola, G. F., Barzaghi, B., Melotto, A., Muraro, M., Lunghi, E., Canedoli, C., Parrino, E. L., Nanni, V., Silva-Rocha, I., & Urso, A. (2018). N-mixture models reliably estimate the abundance of small vertebrates. *Scientific Reports*, *8*(1), 1–8.

Gonthier, D. J., K. K. Ennis, S. Farinas, H.-Y. Hsieh, a. L. Iverson, P. Batary, J. Rudolphi, T. Tscharntke, B. J. Cardinale, and I. Perfecto. (2014). Biodiversity conservation in agriculture requires a multi-scale approach. *Proceedings of the Royal Society of Biological Sciences, 281*:20141358– 20141358.

Kéry, Marc. (2018). Identifiability in N-mixture models: A large-scale screening test with bird data. *Ecology*, *99*(2), 281–288.

Plummer, M., Stukalov, A., Denwood, M., & Plummer, M. M. (2016). Package 'rjags'. *Vienna, Austria*.

Royle, J. A. (2004). N-mixture models for estimating population size from spatially replicated counts. *Biometrics*, *60*(1), 108–115.

Team, R. C. (2013). R: A language and environment for statistical computing.

Chapter 2: Parsing management and edaphic drivers of particulate and mineral-associated organic matter fractions on working farms

Abstract

Rebuilding soil organic carbon (SOC) on working lands is a primary goal of soil health practices. Increasing SOC has the potential to sequester carbon, mitigate the negative impacts of climate change, and create myriad co-benefits, including increased water and nutrient retention. Our current understanding of how soil health management affects SOC is primarily based on field-station research trials, often limited to a single edaphic context and one or two practices. By understanding how practices, as implemented on working farms and across variable edaphic contexts (i.e., soil texture, CEC, pH, iron phase concentrations), we can better guide on-farm best management practices for increasing soil carbon. Here, we evaluate how in-season and recent (<5 yr) implementation of soil health management systems on working farms affects SOC fractions and stocks, as well as the relative importance of such management versus edaphic properties, leveraging variation in management and edaphic conditions across 28 organic farm fields. Continuous living cover increases free particulate organic matter (fPOM) carbon and mineral-associated organic matter (MAOM) C%, and surface soil total carbon stocks, while reduced disturbance and less frequent deep tillage increase MAOM C% and fPOM. Crop diversity enhances occluded particulate organic matter (oPOM) and fPOM fractions, while organic matter amendments do not show any relationship with soil carbon. On average, management variables explain 3.7 times more variance than edaphic variables across C fractions, whereas, for carbon stocks, the opposite is true: edaphic variables explain ~2.1 times the variance compared to management. Our findings highlight that soil health practices, as implemented recently on working farms, can significantly increase soil carbon levels, including both particulate and mineral-associated organic matter fractions, across diverse soil conditions.

Introduction

Soils hold a larger carbon pool than the atmosphere and biosphere combined. However, agricultural cultivation over the last 12,000 years has resulted in the loss of 133 Pg of organic carbon worldwide (Sanderman et al., 2017). This "carbon debt" has raised interest in cropland soils' capacity to rebuild organic carbon stocks and serve as a long-term reservoir for carbon. Sustainable land management and soil health practices are of particular interest because of their potential for rebuilding soil organic carbon on cultivated lands (Abbas et al., 2020; Desjardins et al., 2005; Kopittke et al., 2022; Lal, 2016; Lessmann et al., 2022; Lorenz & Lal, 2012; Marland et al., 2003).

Along with the climate mitigation potential of soils, there is also much interest in the overall health of the world's soils - in particular, the capacity of soils to provide essential services to support plant and microbial life, continued agricultural yields, as well as many other ecological and cultural benefits (Lehmann, Bossio, et al., 2020). Increasing soil organic carbon stocks through increased soil organic matter (SOM) is crucial to restoring a given soil's overall 'health' and ability to maintain the functions underlying these services (Lal, 2016; Liptzin et al., 2022; Vendig et al., 2023).

While the loss of soil organic carbon is most acute in agricultural systems, active management on these lands can make them amenable to shifts in practices to increase SOM content. The USDA's soil health guidelines propose several key principles to promote SOM accrual and improve soil health. These include 1) maximizing continuous living roots (e.g., through crop rotations, perennial vegetation, and cover crops), 2) minimizing soil disturbance (e.g., through reducing the intensity, frequency, and depth of tillage), 3) maximizing biodiversity (e.g., through crop rotation, pollinator plantings, cover crops), and 4) maximizing soil cover (e.g., through mulching and crop residues) (NRCS, 2024). While not directly linked to one of these principles, soil amendments such as compost, green manure, and organic fertilizers are common on organic farms and have been also been studied and invested in by conservation programs such as the Healthy Soils Program in California for their potential to support increased carbon sequestration on working lands (Agarwal, 2018; California Department of Food & Agriculture, 2021; Lal, 2016; Ryals & Silver, 2013). Soil health frameworks have also begun to recognize the importance of the specific context of a given soil, including local soil forming and edaphic factors, historical management, and the inclusion of animals in production systems (Devine et al., 2021; Sprunger et al., 2021; Stavi et al., 2016).

While these principles and associated practices have garnered considerable attention and research over the past several decades, much of this research has been conducted on agricultural research stations (Maat, 2011). While crucial for developing mechanistic understanding, this work often isolates one or two practices for a single climatic and edaphic context (i.e., soil texture, CEC, pH, iron phase concentrations), seldom capturing the complexity of most actively managed farms and the mix of practices that farmers may use. Additionally, understanding how these practices interface with variable edaphic contexts and how this, in turn, relates to carbon accumulation and storage is not well resolved. Soil health research has started engaging with on-farm work to better understand how heterogeneous management, soil, climatic and crop conditions affect SOC in ways that are not possible in research station trials (Karlen et al., 2017; Olimpi et al., 2024; Singh et al., 2024; Sprunger et al., 2021; Williams et al., 2020).

In assessing the efficacy of soil carbon management, it is also increasingly recognized that distinct organic carbon fractions have unique dynamics and functional roles in the soil ecosystem, and partitioning them can yield greater insights relative to only the total soil carbon pool (Cotrufo & Lavallee, 2022; Lavallee et al., 2020a). Broadly, these fractions include particulate organic matter (POM) and mineral-associated organic matter (MAOM). POM is composed of partially decomposed plant fragments (Von Lützow et al., 2007), representing a less processed form of organic carbon with relatively higher C:N ratios and relatively short residence times (Bol et al., 2009). It is a popular soil health indicator as it is considered more biologically and chemically active, providing nutrients for plants and food for soil arthropods and microbial communities. Moreover, POM can contribute to desirable soil physical characteristics, including aggregate stability, increased water infiltration, and soil aeration, and function as a precursor to MAOM(Angst et al., 2023). POM can be further partitioned into free and occluded POM (fPOM and oPOM). oPOM is POM bound in physical occlusions (entrapment in soil aggregates) making it less accessible to microbial decay compared to fPOM which is unprotected. Both of these fractions play critical roles in ecological nutrient management in farming systems that do not rely on synthetic nutrient inputs (Drinkwater & Snapp, 2022). MAOM consists of smaller organic carbon compounds with lower C:N ratios, often considered to be microbially processed, that can stick, or sorb, onto mineral surfaces or protected within microaggregates (Totsche et al., 2018). Thus, this carbon is considered less accessible to soil microorganisms, making it a more stable, slower-cycling form of soil carbon, persisting in soils for hundreds to thousands of years (Lehmann, Hansel, et al., 2020), though MAOM can also cycle more rapidly (Jilling et al., 2020; Kleber et al., 2021). While inherent soil mineralogy and texture limit the total amount of MAOM in a given soil (i.e., clay soils with high-activity minerals will have more mineral surfaces for the sorption of MAOM than sandier soils), MAOM carbon concentration and saturation provide metrics that are comparable across different soil types (Georgiou et al., 2022).

With both of these OM fractions, soil biology plays a crucial role in both its formation and decomposition. Above and belowground plant inputs, and resulting microbial activity and biodiversity may both help form POM (i.e., via root fragments and exudates, fungal hyphae, aggregate formation and stabilization) and MAOM (i.e., microbial necromass and plant leachates) (Lavallee et al., 2020a; Sokol et al., 2019). Meanwhile, microbial activity is the primary mechanism for organic matter decomposition, releasing soil carbon back into the atmosphere as CO_2. Thus, it is also important to consider the ways in which management may impact these biological traits and processes that may support carbon inputs into the soil, as well as the decomposition of organic matter, and how biological traits may mediate distinct carbon fractions.

Given the distinct functions of POM and MAOM, it is useful to understand how different management practices may aid in the formation of each fraction. Recent work has shown that management practices, including cover cropping, reduced tillage, increasing the number of annual crops grown per year, and including perennial crops, have distinct implications for POM and MAOM, in most cases POM being the more responsive fraction to management on shorter timescales (Jilling et al., 2020; Prairie et al., 2023; Salonen et al., 2023; Samson et al., 2020; Yu et al., 2022; Zhang et al., 2022). However, it is unclear how farm management practices, as used on actively managed farms, impact carbon fractions and if there might be tradeoffs in management strategies for increasing POM versus MAOM.

In addition to management factors, local edaphic characteristics including mineralogy are crucial in stabilizing soil organic matter. Soil characteristics including pH, texture, and the concentration of short-range order and weathered clay and metal oxide minerals (especially aluminum and iron hydroxides) influence the capacity for a given soil to build SOM (Heckman et al., 2018; Rasmussen et al., 2018; Wagai et al., 2020). While there is recognition of extractable metal's importance in SOM stabilization, many soil health assessments and SOM studies only consider soil texture (Rasmussen et al., 2018). Thus, in considering management impacts on SOM dynamics and accrual, it is essential to also consider local edaphic characteristics. However, the relative importance of these two factors is not well resolved. Given that farmers can only control management, it is crucial to understand its impact on enhancing POM and MAOM relative to inherent edaphic factors.

Working with 15 organic vegetable growers in the Central Coast region of California, we collected detailed management information from 2015 to 2020 and measured soil physical, chemical, and biological properties across 28 actively managed fields to parse the management practices that might most contribute to increasing POM, MAOM, and surface soil organic carbon stocks. By assessing practices on working farms, we calculate a gradient of practice implementation thereby allowing us to investigate how varying degrees of utilization of a given practice impact SOC. Focusing on organic farms allowed for a widely varying application of soil health principles while avoiding the potential of synthetic fertilizers and pesticides confounding management impacts. We operationalized soil health principles into locally relevant practices used by growers and then asked:

1. if and which soil health practices drive increases in POM, MAOM, and total carbon stocks, and if key practices are consistent across fractions,
2. if any measured biological variables mediate relationships between management and carbon outcomes, and
3. if management plays an important role relative to edaphic influences on carbon fractions and overall stocks.

Based on recent meta-analyses (Blanco-Canqui, 2022; Hu et al., 2023; Prairie et al., 2023; Vendig et al., 2023), we hypothesize that cover cropping, reduced tillage, organic amendments, and crop diversity will all increase soil carbon fractions, and that POM will have larger increases than MAOM. We also hypothesize that increased microbial activity may facilitate increased MAOM concentrations but have less impact on POM. Further, we anticipate that edaphic factors will strongly influence carbon stocks via effects on MAOM but will have much less control over POM.

Methods

Study region and sampling

Study area and field sites

Our work focused on farms in San Benito, Santa Cruz, and Monterey Counties along the northern end of the California Central Coast region (Figure 1- MAP). This region experiences a relatively stable temperate Mediterranean climate with warm, dry summers, and wet winters (Köppen-Geiger Zone Csb: Warm-summer Mediterranean climate) and is characterized by a mixture of small-scale diversified farms, larger wholesale growers, and grazing lands (Olimpi et al., *in press*). This is one of the most productive and economically significant agricultural regions in California and the United States, particularly for fresh produce (CDFA, 2022). Farms range in scale from ~5000 m^2 (0.5 ha) of production to >4 km^2 (600+ ha). Participating farmers were identified using the USDA Organic Integrity Database and in consultation with local technical assistance providers and all grew organic lettuce to some extent. This crop was selected because of its economic importance in the region, with lettuce and leafy greens the most valuable crops in the region (County of Monterey Agricultural Commissioner, 2021; San Benito County Agricultural Commissioner, 2020; Santa Cruz County Agricultural Commissioner, 2021). Given that many farmers grow lettuce, this selection allowed us to sample across a wide area in the region. Lettuce has also been the focal crop along with broccoli for recent work on carbon and nitrogen dynamics in vegetable production systems in the Central Coast (White, Brennan, & Cavigelli, 2020; White, Brennan, Cavigelli, et al., 2020a). Lettuces have shallow root systems and low residue return making carbon-building management practices vital for rebuilding SOM in these systems.

Soil Sampling

The field research was designed to accommodate a broader set of questions regarding soil-based ecosystem services, in addition to the objectives of this study. At all 28 field sites, five samples were collected across a 100m transect positioned in the middle of a given lettuce field and began at least 10 m in from a field edge to get a representative sampling of soils across focal fields. Each sample was a composite of five sub-samples. All samples were collected during the 2020 growing season. Soils were collected at mid-season (defined as peak vegetative growth, approximately 3-6 weeks after transplant, depending on the lettuce variety) to best represent conditions at peak nutrient uptake and plant growth. Soils were collected from 0-15 cm, 15-30 cm, and 30-60 cm depths (for transplant and harvest samplings) and 0-15 cm for the mid-season sampling.

Soil series and order data were collected for each field location using latitude and longitude coordinates in the NRCS SSURGO database via SoilWeb (O'Geen et al., 2017). The majority of soils in this study are classified as Mollisols (20 sites), while Alfisols, Entisols, and Vertisols represent four, three, and one of our sites, respectively. Despite the constrained geographic area, California has a high level of soil heterogeneity, and our sites represented a number of different soil series, including four sites in the Sorrento series, three in the Chualar series, and two in the Placentia series. Full SSURGO data descriptions of our sites can be found in the Supplement.

Lab analyses

Basic soil characteristics

Mid-season soil samples from 0-15 cm were sent to Soiltest Labs (Moses Lake, WA, USA) for analysis of texture, pH, cation exchange capacity (CEC), and soil nutrients. pH was measured using a 1:1 soil-water slurry using a Skalar SP2000 Robotic Analyzer (Skalar, Breda, Netherlands). CEC was measured by ammonium replacement, and texture was measured by hydrometer both following protocols by Miller et al. (2013).

Bulk density for surface soils (0 - 12 cm) was measured with 2-4 replicates per site using a Hyprop cylindrical ring sampler with a sample volume of 250 mL (height = 12.34 cm, diameter = 5.08 cm). Samples were dried at 105 ºC for 3 days. Dry soil sample mass was measured and divided by the volume of the cylindrical sampler.

Extracellular enzyme potential

Soils were kept cool in an iced cooler in the field and transferred to a fridge (~4 ºC) before analysis. Within 48 hours of soil sampling, potential extracellular enzyme activities were measured fluorometrically and photometrically using a microplate assay (Bach et al., 2013; German et al., 2011). Two grams of fresh, sieved soil were added to 100mL of 50 mM sodium acetate buffer (pH=5.5) and blended for 30 seconds. For the fluorometric assays (hydrolytic enzymes), MUF (4-methylumbelliferone) and AMC (7-amino-4-methylcoumarin) labeled substrates were used. Specifically, the enzymes glucanase/1,4-β-cellobiosidase (CBH), β-glucosidase (BG), exochitinase (NAG), and phosphatase (PHO) used the substrates MUF-cellobioside, MUF-β-glucopyranoside, MUF-N-acetyl-β-D-glucosaminide, MUF-phosphate, respectively. For the enzyme leucine-amino-peptidase (LAP), the substrate L-leucine-7-amido-4methylcoumarin was used. Samples were incubated at room temperature (22°C) in the dark and measured at 1.5 h and 3 h (excitation: 365 nm, emission: 450 nm).

The oxidative enzymes peroxidase and phenoloxidase were analyzed from the same buffered soil solution. Briefly, 0.9 mL of 20 mM L-3,4-dihydroxyphenylalanine (DOPA) was added to 0.9 ml of soil suspension in triplicates for a final concentration of 10 mM DOPA, shaken on high speed for 10 min, and centrifuged for 10 min at 14,000 g. To clear microplates, paired samples for phenoloxidase and peroxidase were pipetted in triplicates with the peroxidase samples receiving an additional 10 μL of 0.3% hydrogen peroxide. Absorption was measured at 450 nm at time 0 and after incubating microplates in the dark for 20 hours. Mass-specific enzyme activities were calculated by normalizing activity levels to microbial biomass C measured using the chloroform direct extraction method (Setia et al., 2012).

Soil carbon and organic matter fractions

Bulk soil samples were dried at 35° C and sieved to 2 mm, and then ball milled for elemental analysis. Total carbon (TC%) was analyzed by combustion on an Elementar varioEL Cube (Elementar, Ronkonkoma, NY). The same samples were also analyzed by combustion with a temperature ramping procedure on an Elementar SoliTOC, which measures total inorganic carbon (TIC). TIC values were negligible (<0.1%), so we consider varioEL measurements as total organic carbon (TOC).

Mid-season 0-15 cm soil samples were fractionated by size and density into four functionally distinct pools: Dissolved organic matter (DOM), fPOM, oPOM, and MAOM. These samples were dried at 35°C and sieved but not ground prior to fractionation.

Fractionations followed the protocol described by Haddix et al. (2020) with slight modification for high-clay soils. Whereas many fractionation methods separate POM after aggregate dispersion into light and heavy fractions, this protocol separates POM before and after aggregate dispersion into fPOM and oPOM. Thus, it may provide information on how management decisions may impact soil aggregates, which offer short-term OM protection from microbial decay.

We first separated dissolved organic matter by shaking sieved, oven-dried samples with 40 mL of DI water for 15 min and centrifuging at 2520 g for 15 min. DOM is extracted as the resulting supernatant. fPOM is then fractionated by resuspending the remaining soil pellet using sodium polytungstate solution prepared at 1.85 g/cm3, and remaining oPOM and MAOM were fractionated by size (oPOM >53μm and MAOM < 53 μm) by wet sieving. High-clay soils received an additional DI rinse and centrifugation with ten additional drops of flocculants 0.25 M $CaCl_2$ and 0.25M $MgCl_2$ to help clear excess sodium polytungstate solution.

We ensured that fractions were recovered to +/- 5% of the original sample weight. Fraction samples were then dried, and ball milled. Carbon in fPOM, oPOM, and MAOM fractions was measured by combustion analysis on a varioEL cube (Elementar, Ronkonkoma, NY). fPOM and MAOM were weighed to 20mg, while oPOM, because of its lower organic content, was weighed to 100mg.

Soil iron fractions

Soil iron fractions were isolated using pyrophosphate (iron complexed with organic matter), citrate-bicarbonate-dithionite (crystalline pedogenic iron), ammonium oxalate (poorly crystalline iron), and hydroxylamine hydrochloride (poorly crystalline iron) extractants. Pyrophosphate represents iron complexed with organic matter and was extracted according to a method used by McKeague (1967). Oxalate and dithionite extractions followed protocols by Dominik & Kaupenjohann (2000) and hydroxylamine followed protocols by Lovley & Phillips (1987). The pyrophosphate, dithionite, and oxalate extractions were performed using 0.5 g of dry soil, while the hydroxylamine extraction used 1g. In brief, extractants for each fraction were added to the soils, shaken, and centrifuged, and the supernatant was diluted and measured colorimetrically using a plate reader to determine total Fe concentration. Wet extractions are not perfect in isolating their target compounds, yet in combination, they can provide meaningful insight into the different forms of iron present (Rennert, 2018).

Soil health management

Management survey

Soil health management data were collected using an in-depth survey created in Qualtrics (see supplement for abbreviated version). To ensure that questions and terms used by the survey were interpreted consistently by farmer participants, we conducted surveys in person or on the phone with farmers. This way, farmers could ask questions about our prompts, and the surveyor could provide additional context and definitions as needed. The farm management survey collected data on cover cropping, crop diversity and rotation practices, tillage, and organic inputs used by farmers. Questions about irrigation practices, barriers and incentives to soil health practices, and the impacts of COVID-19 were also conducted in the same survey but were not utilized for this portion of our study.

Remote sensing

To complement the management survey data about the historical use of cover cropping, we use satellite imagery to assess continuous living cover at each farm field site via Google Earth Engine (Gorelick et al., 2017).

We created a polygon for each of the 28 field sites to represent our field sampling locations. We computed the proportion of the year with vegetation cover from 2015 until 2019 based on an NDVI threshold approach using Landsat and Sentinel imagery. An NDVI threshold value of 0.3 was used to separate bare soil versus sparse vegetation (Sobrino et al., 2001). From 2015 through 2019, we classified the field as having or not having vegetative cover on a monthly basis, based on this threshold. For each year, we created a proportion cover by taking the number of months where the average NDVI value is above or below our threshold and dividing this by 12. We also evaluated the presence of winter cover with NDVI values in January, though we cannot distinguish winter cover versus cash crops using satellite imagery. Given that vegetation could be sparse in January, we increased the NDVI threshold to 0.5 for the 'January Average Cover' variable. This increased NDVI threshold ensures we only indicate winter cover when significant biomass is present.

Farm management standardized scores

To create interpretable management variables, we first categorized all management questions into four practice types based on NRCS soil health principles - continuous cover, crop rotational diversity, reduced disturbance, and organic amendments (Table 1). We then scaled individual management variables by creating a new variable where a value of 1 indicates the highest value of a practice within our dataset. For tillage variables such as tillage depth and frequency, we subtracted the scaled variable from 1 so that higher values indicated reduced disturbance. We then created a composite score by averaging all practices within each management category. Finally, for each category, we calculated a z-score with a mean of 0 and a standard deviation of 1 to compare different management practices on the same scale.

Statistical analysis

One primary goal was to determine relationships between management practices and soil organic carbon fractions and organic carbon stocks while considering variable edaphic conditions across sites. To do this, we used mixed-effects models for carbon fractions and stock data, using 'site' as a random effect.

Given that our dataset is observational, as opposed to manipulative, we follow an approach to statistical inference not aimed at creating a best-fit model but rather an approach of hypothesis testing wherein we look to see if management variables of interest significantly impact soil carbon fractions and stocks. This general approach is increasingly recommended in observational datasets like ours (Bradford et al., 2021; Holland, 1986; Olimpi et al., 2024). Therefore, with such modeling, we are less concerned with predictive accuracy and model comparison to maximize the variance explained. Rather, we are interested in identifying robust parameter estimates for the predictor variables of interest. Thus, we do not adhere to solely discussing model results with p-values less than 0.05 (Wasserstein et al., 2019; Wasserstein & Lazar, 2016). Even in instances where variables were not significant, they were retained to control for their potential influence.

Given that we were using composite management variables, as described above, we also used random forest variable importance analyses to assess whether there might be individual practices that have a more significant impact when considered independently rather than in a composite. For management variables found to be of high importance, we also ran mixed models that substituted those individual practices for the composite management variables. We used the 'party' package in R for these analyses (Hothorn et al., 2023).

To construct models, we first needed to select carbon variables that could reasonably be altered by management. For mineral-associated organic matter, we analyzed the %C for the MAOM fraction. This was chosen so that we could investigate how much carbon was adsorbed to mineral surfaces. While this is not equivalent to saturation, which accounts for texture and mineralogy, MAOM C% is the carbon concentration in the fine, high-density particles for a given soil (i.e., regardless of soil texture, how much carbon is present in this fraction?). This is in contrast to looking at, for example, total MAOM carbon stock, which we expect to be primarily driven by the percentage of silt and clay (though increasing MAOM C% would also increase stocks).

For the free and occluded POM fractions, we analyzed the proportional contribution of POM to the total organic carbon pool. This allows us to account for both the %C and the relative proportion, by mass, that each POM fraction represents in each sample. This was calculated as follows:

$$fPOM_{C_{prop}} = fPOM_{C\%} * mass_{fPOM}/mass_{total}$$

$$oPOM_{C_{prop}} = oPOM_{C\%} * mass_{oPOM}/mass_{total}$$

While POM stock and C_{prop} values are quite related, we also run our models with stock values to ensure that the use of C_{prop} does not change significantly from models using stocks. Indeed, there is not a significant difference and so C_{prop} values are discussed. See supplement for stock models.

These values, MAOM C%, and fPOM and oPOM C_{prop}, were subsequently transformed using a logit function as follows:

$$logit(MAOM_C) = log(MAOM_C / (1 - MAOM_C))$$

Logit transformations are useful for proportion values falling between 0 and 1, making them appropriate here (Warton & Hui, 2011). These transformations also proved helpful in improving subsequent model fit.

Stocks were calculated assuming a depth of 10 cm as follows for MAOM, fPOM, and oPOM:

$$CStock_{MAOM} = MAOM_{C\%} * \frac{mass_{MAOM}}{mass_{total}} * BD\frac{g}{cm^3} * 10cm * 10000\frac{m^2}{ha} * 10000\frac{cm^2}{m^2} * 0.000001\frac{Mg}{g}$$

We calculate stocks for surface soils, again to 10 cm as follows:

$$CStock = C\% * BD\frac{g}{cm^3} * 10cm * 10000\frac{m^2}{ha} * 10000\frac{cm^2}{m^2} * 0.000001\frac{Mg}{g}$$

Variable reduction

We used principal components analysis to reduce groups of related variables for further analysis, including soil edaphic characteristics (sand content, clay content, cation exchange capacity, and dry bulk density), soil iron phases (pyrophosphate, oxalate, hydroxylamine, and dithionite extractions, described above), and extracellular enzyme activities (phosphatase, β-glucosidase, exochitinase, leucine-aminopeptidase, glucanase/ 1,4-β-cellobiosidase, peroxidase, and phenoloxidase). The first principal component axis, which captured 85.4, 62.1 and 75.1% of variation for physical, iron, and enzyme data, respectively, was selected for further analysis. PCAs were performed using the 'ade4' package in R (Dray et al., 2023). PCA figures and variable contributions to PC1 are reported in the Supplement.

Mixed models

We constructed a set of mixed-effects models to analyze the relationship between soil carbon fractions and soil edaphic properties, soil biology (in one instance), and soil health management. Site was modeled as a random effect to account for site-level differences and to reflect our study design while avoiding pseudoreplication (Harrison et al., 2018; Zuur et al., 2009). Models followed the general structure:

$$MAOM_{C\%} = Phys_{PC1ij} + Iron_{PC1ij} + pH_{ij} + ContCover_{Zi} + Disturb_{Zi} + CropDiv_{Zi} + CInput_{Zi} + u_{ij}$$

Where subscript PC1 indicates the use of the first principal component axis, Z reflects the use of summarized practice z-scores, and *u* is the random intercept for site *i*, rep *j*. An additional model for MAOM was run with the principal component from soil enzymes. Enzymes were only included for the MAOM model because we hypothesized that enzymes, which play an important role in the breakdown of POM, might increase processed carbon products that could then sorb to mineral surfaces. While enzymes were also significantly associated with POM fractions, in this case, we believe that the directionality may be inverted and that the increase in extracellular enzymes is a function of increased POM for microbial use; thus, enzyme scores were not included in POM models (Supp figures S1; Cenini et al., 2016).

The same model structure was used for fPOM and oPOM. A second fPOM model that replaces two of the management z-scores with specific practices, continuous cover (5 yr) and deep tillage frequency, was also analyzed. These two practices were selected via random forest variable importance analysis. We also identified continuous cover (5yr) as potentially important for the C stock model - thus we utilized a similar substitution for the C-stock model wherein continuous cover (5yr) replaced the management z-score. The model using *Continuous Cover Z* is presented in the Supplement.

Model structure and results are summarized in Table 3 and visualized in Figure 4. Models were constructed using the R package 'lme4' (Bates et al., 2023). Interactions were not modeled due to our limited sample size. Model fit was assessed using the function qqnorm and plot to ensure that residuals generally follow model assumptions. We also ensured that there was no significant correlation amongst predictor variables by ensuring variance inflation factors were below 3 (see Supplement). Necessary transformations were applied to meet model assumptions including a log transformation of the fraction C Stock and a box-cox transformation for the bulk C values, and logit transformations for the fraction outcome variables to meet model assumptions.

To examine effect sizes and compare variables measured on different scales, we report standardized coefficients calculated by scaling regression inputs. This method subtracts the mean of a given variable from each observation, and then divides this value by two standard deviations (Gelman, 2008). This calculation helps account for the different units on which variables are measured.

We evaluate the variance explained by management versus edaphic and biological variables through variance partitioning. We estimate marginal R^2 values for edaphic and biological variable groupings (texture, CEC, pH, and for the MAOM 1 model, enzymes) and management variables (continuous cover, reduced disturbance, C input, crop diversity Z scores) and calculate confidence intervals using parametric bootstrapping with 1000 iterations using the 'partR2' package in R (Stoffel et al., 2024).

We evaluate the sensitivity and consistency of model results by iteratively removing variables included in the model to ensure that there are no shifts in which variables emerge as significant or major changes in coefficient estimates. These models are reported in the Supplement.

To parse potential biological influences of MAOM and POM formation and loss, we used piecewise Structural Equation Models (pSEM) to assess whether any management impacts were mediated through biological variables. Using a combination of several mixed models, pSEM allows us to evaluate both the direct and indirect paths that may influence a given variable. Here, we add microbial biomass carbon, Shannon diversity of fungal and bacterial taxa, and the abundance of 16S and ITS genes per gram (methods described in Supplemental Methods) of soil iteratively as a variable impacted by management, which can then go on to impact various carbon fractions. The model structures are detailed in the Supplement. pSEM model components were selected based on key variables from mixed models, and model fit was assessed using the Fisher-C statistic to ensure that no critical pathways were omitted.

Estimated management outcomes

Since interpreting the standardized coefficients from models on how soil health management practices affect soil carbon fractions can be challenging, we use sites with contrasting management practices to demonstrate management practices more concretely. We chose these contrasting sites based on the practices that emerge as clear drivers for a given model - in all cases these are sites that are not necessarily the highest or lowest scorers but are farm sites that have relatively high and low scores. Given that z-scores are a composite function of multiple practices, we use real farm data for these comparisons to reflect real practice implementation. We extracted the relevant coefficients, applied the necessary back-transformations, and took the difference between the two sites in the outcome variable based on the single regression coefficient. These are presented in Table 5.

Results

Site-level characteristics and bulk and fraction C%

Across the 28 field sites, we observed a diverse range of soil edaphic characteristics and implementation of practices (Fig. 2-3). Soils ranged from clays to loamy sands with mean sand, silt, and clay content of 42%, 33%, and 26%, respectively. The bulk density of topsoils (0-15 cm) ranges from 0.88 to 1.6 g/cm^3 with an average of 1.33 g/cm^3. Surface soils (0-15 cm) had an average bulk soil carbon concentration of 1.50%, ranging from 0.74 to 3.95%, again demonstrating a wide range of soil edaphic characteristics (Table 4). Mean MAOM C% was 1.73%, oPOM C% was 0.87%, and fPOM was 20.53% (Table 2). MAOM C accounts for 77.2% of the total estimated topsoil carbon stock, while fPOM and oPOM account for 13.87% and 8.93%, respectively (Fig. S2). This translates to, on average, 13.15, 2.36, and 1.52 Mg C/ha for MAOM, fPOM, and oPOM, respectively. Thus, despite the relatively constrained geographic area, with climatic conditions similar across sites, there was sufficient variation in soil physical properties and implementation of practices to identify relationships between soil health practices and SOC.

Soil health management and edaphic impacts on MAOM C%

Two soil health practices emerge as drivers of MAOM C% across the two MAOM mixed models used: reduced tillage and continuous cover. In MAOM model 1, which does not include extracellular enzymes, the positive effect of reduced disturbance on MAOM was statistically clear at $p<0.1$ (β_{std}= 0.21; p = 0.085), while continuous cover was slightly above this threshold (β_{std}= 0.20; p = 0.105).

The concentration of iron phases ($Iron_{PC1}$) and soil physical characteristics also were clearly associated with MAOM C%, with increasing amounts of poorly-crystalline (oxalate and hydroxylamine HCl -extracted) and organic complexed (pyrophosphate-extracted) iron (β_{std} = 0.13; p = 0.023) and increasing sand content (β_{std}= 0.19; p = 0.073), corresponding to higher MAOM C%. pH was negatively associated with MAOM C% (β_{std}= -0.11; p=0.064).

When extracellular enzyme activity is included in the model, continuous coverage and reduced disturbance remain the most important management factors ($\beta_{std\text{-}cover}$ = 0.2, p_{cover}= 0.073; $\beta_{std\text{-}dist}$ = 0.21, p_{dist} = 0.068, respectively). In this model, the concentration of iron phases ($Iron_{PC1}$ primarily associated with poorly crystalline and organo-mineral fractions; see supplement) remains a positively associated variable (β_{std} = 0.1; p=0.068), while the effect of pH and physical characteristics become less clear (p_{pH} = 0.21; p_{phys}= 0.18). Meanwhile, the association with enzyme activity is clear (β_{std}= 0.1; p= 0.042) with higher enzyme activities corresponding to increased MAOM C%.

Contrasting two sites with low and high z-scores for continuous cover, the model predicts that increasing cover from 28% to 90% over 5 years, and increasing winter cover from 0 to 80%, increases the absolute MAOM C concentration (C%) by ~1.85% (CI: 1.79 - 1.90). Similarly, contrasting sites for tillage practices, going from one-season beds that experience deep tillage multiple times per season, with a tillage depth of 1.07 m (42 inches), to beds that are maintained for multiple seasons, with deep tillage only used once every few years and with a tillage depth of 0.38 m (15 inches), can similarly increase absolute MAOM C% by ~1.86% (CI: 1.81 - 1.91).

Partitioned marginal R^2 values show management's relative importance: MAOM1 and MAOM2 models' management variables explain approximately double the variance observed relative to edaphic and biological variables (Table 4). Edaphic variables explain less than 10% of the variance observed in our data (6.0% and 8.1%, respectively) relative to management variables, which explain around 20% (19% and 20%, respectively). Both MAOM models explain approximately the same amount of variance (total $R^2_{marginal}$ = 0.3 and 0.32 for models 1 and 2, respectively).

Soil health management and edaphic impacts on fPOM C_{prop}

In the fPOM 1 model, using the model structure with all four management category scores, crop diversity and $Iron_{PC1}$ are statistically clear drivers of fPOM C_{prop} ($\beta_{std\text{-}crop\ div}$ = 0.34, $p_{crop\ div}$ = 0.083 ; $\beta_{std\text{-}iron}$ = 0.33; p_{iron} = 0.045).

As a result of Random Forest (RF) variable importance analysis (see Supplement), we ran a second model (fPOM 2) replacing continuous cover and reduced disturbance z-scores with the proportion of plant cover over the previous five years (hereafter $Cover_{prop\text{-}5yr}$), and the frequency of deep tillage, respectively. With this model, these two variables both clearly associate with fPOM C_{prop}, with an increased proportion of cover and decreased deep tillage corresponding to increased fPOM C_{prop} ($\beta_{std\text{-}cover5yr}$ = 0.46, $p_{cover5yr}$ = 0.017; $\beta_{std\text{-}deep\ till}$ = -0.40, $p_{deep\ till}$ =0.022). Iron's relation is less clear in this model (p=0.13).

Contrasting these individual practices across high and low implementation sites, the model predicts that a shift from 23% to 90% cover increases fPOM C stocks by ~2.76 Mg C/ha (CI: 0.67 - 11.46).

Going from using deep tillage more than once per year to never can also increase surface soil fPOM carbon stocks ~0.62 Mg C/ha (CI: 0.52 - 0.75).

The marginal R^2 value for full fPOM model 1 (0.18) was lower than that of fPOM model 2 (0.31). For the fPOM 1 model, management explains 12% of the variance, while edaphic variables explain 3.9%. When we substitute 'Continuous Cover' and 'Reduced Disturbance' management z-scores with individual practice variables, the management $R^2_{marginal}$ increases to 0.25, and edaphic variables decrease slightly to 0.03 (Table X).

Soil health management and edaphic impacts on oPOM C_{prop}

For oPOM C_{prop}, crop diversity and $Iron_{PC1}$ are the two statistically clear driving variables ($\beta_{std\text{-}crop\ div}$ = 0.36, $p_{crop\ div}$ = 0.024; $\beta_{std\text{-}iron}$ 0.40, p_{iron} = 0.001). Like fPOM, we used two individual practice variables that emerged from RF analysis ($Cover_{prop\text{-}5yr}$ and tillage depth), but this did not notably change model results (see Supplement). Contrasting a low crop diversity field with 3 cash crops, to a high diversity site with 6 cash crops and 9 species of cover crops, the oPOM C stock has a modeled increase of 4.63 Mg C/ha (CI: 4.31 - 4.97).

Marginal R^2 values show the similar trend of management variables explaining more variance than edaphic variables ($R^2_{marginal\text{-}edaphic}$ = 0.12, $R^2_{marginal\text{-}management}$ = 0.17), though the difference is not as pronounced as it is for MAOM or fPOM. The model as a whole, similar to other fractions, explains ~29% of the observed variance in our data.

C stock and management

Continuous cover and $PC1_{Phys}$ emerge as clear drivers of bulk carbon stocks ($\beta_{std\text{-}cover}$=0.015, p_{cover} =0.068; $\beta_{std\text{-}phys}$ = -0.021, p_{phys} = 0.0074). As with other models, we also substitute the continuous cover z-score with $Cover_{prop\text{-}5yr}$ which, along with $PC1_{Phys}$, remain clear drivers ($\beta_{std\text{-}cover5yr}$= 0.024, $p_{cover\text{-}5yr}$ = 0.003; $\beta_{std\text{-}phys}$ = -0.28, p_{phys} = 0.0005). The influence of $Iron_{PC1}$ is not as clear in this model (p = 0.27; see Supplement).

Contrasting sites with high and low implementation of continuous cover, increasing the cover proportion from 23 to 90% and winter cover from 0 to 80% increases topsoil C stock by ~3.57 Mg C/ha (CI: 3.55 - 3.58). The marginal R^2 value for C stocks is 0.25 for edaphic and 0.12 for management variables, and the total model R^2 is 0.34 for the bulk carbon models.

pSEM models

We used pSEM to determine whether any measured soil biological variables (microbial biomass C, Shannon diversity for fungal and bacterial taxa, and fungal and bacterial gene abundance) served as mediators between fraction outcomes and management. Ultimately, only one of the pSEM models resulted in significant pathways between soil health management and carbon fractions (Fig. 5). The fPOM model showed that the $Cover_{prop\text{-}5yr}$ was positively correlated with Shannon diversity of fungal taxa (β = 0.54; p = 0.0043) and that this fungal Shannon diversity was also positively correlated with $fPOM_{c\text{-}prop}$ (β = 0.30; p=0.0089). $fPOM_{c\text{-}prop}$ was nearly directly related to the proportion of continuous cover (β = 0.25; p = 0.063). The indirect path through Fungal Shannon diversity had a coefficient of 0.16 (0.295*.537), thus having nearly ⅔ the influence of the direct effect of this practice on fPOM.

Other portions of our pSEM model results aligned with the findings of our original mixed-effects models (i.e., deep tillage remains significantly negatively related to $fPOM_{c\text{-}prop}$), but we did not find other examples of management variables having a statistically clear indirect effect on any carbon fractions via biological variables.

Discussion

Management and edaphic impacts on soil fractions

Across the wide range of edaphic conditions and the diverse implementation of soil health management practices, we find that soil health management and practices increasing continuous living cover in particular can bolster multiple carbon fractions and increase surface soil carbon stocks. Reduced disturbance also emerges as an important driver of MAOM C% and fPOM, while crop diversity drives increases in the oPOM fraction. Interestingly, we find that management variables explain as much as four times the variance observed in our dataset across C fractions compared to edaphic variables. This means that across variable edaphic contexts, management can be crucial in increasing POM, MAOM, and surface soil carbon stocks in croplands. Surprisingly, we do not find that current season organic amendments impact any measured carbon pool. These findings have important implications for the context in which organic amendments and other soil health practices should be used to rebuild cropland soil organic carbon.

MAOM

MAOM, a slow-cycling soil carbon pool, primarily originates from smaller biopolymers formed through progressive decomposition, notably microbial processing (Lehmann & Kleber, 2015). These low molecular weight (LMW) compounds readily adsorb to mineral surfaces, making them less susceptible to microbial decay. Further protection can occur through physical occlusion in fine aggregates and the formation of stable organo-mineral complexes (Lavallee et al., 2020b; Lützow et al., 2006). Biotic pathways associated with increased microbial activity involve the processing of labile LMW plant carbon inputs by microbes. As microbes turn over, the resulting microbial necromass may sorb onto mineral surfaces to produce MAOM (Kallenbach et al., 2016; Liang et al., 2017). Non-microbial pathways can also be a source of MAOM, wherein dissolved organic matter (DOM), such as plant leachates from aboveground biomass, may be dominant in areas of bulk soil where plant inputs and microbial activity are lower (Kaiser & Kalbitz, 2012; Mikutta et al., 2019; Sokol et al., 2019).

Our results indicate that continuous living cover and reduced disturbance are key management factors associated with higher MAOM-C concentrations across soil textures. Continuous cover via cover crops can increase stable soil aggregates, generate steady belowground carbon inputs via rhizodeposition, and supply aboveground biomass often incorporated into soils (Gentsch et al., 2024; White, Brennan, Cavigelli, et al., 2020b). Thus, using cover crops (or, in some cases, winter cash crops) supports both biotic and abiotic pathways for MAOM formation. A recent meta-analysis found that relative to bare soil management (i.e. winter fallows or fallow control plots), cover crops increase mineral-associated organic carbon by 7% ((Hu et al., 2023). This effect was enhanced under longer experiments, indicating that continuous cover over extended periods may be important for MAOM accrual. Similarly, Wooliver & Jagadamma (2023) find that cover cropping treatments over 5 years increase MAOM by ~5.6% relative to fallow controls.

Another significant management practice influencing MAOM C concentration is reduced tillage. Minimizing the disruption of aggregates reduces the possibility of microbial attack on physically protected MAOM (Conceição et al., 2013; Grandy & Robertson, 2007). Similar to our findings, Samson et al. (2020) found that reduced tillage practices, in addition to crop residue management, increased so-called Fine Organic Matter (FOM), similar to the measured MAOM in our study. While Wooliver & Jagadamma (2023) did not find that conventional versus conservation tillage affected MAOM in their meta-analysis, they posit that the significant decline in total SOC due to tillage is likely a response to increased microbial decomposition of the MAOC pool.

The presence of poorly crystalline iron (oxalate and hydroxylamine HCl extracted) fractions and organo-mineral (pyrophosphate extracted) complexes also increases with MAOM C%. Although the wet extractions are not perfectly selective for these metal phases, they offer valuable insights into soil C storage and turnover times (Masiello et al., 2004; Rennert, 2018). Poorly crystalline iron and organo-mineral associations both provide important mechanisms for stabilizing LMW carbon inputs (Rasmussen et al., 2018; Wagai et al., 2020; Wu et al., 2023). Despite the known importance of iron and other minerals in associating with organic carbon, relatively few studies on agricultural soil carbon include this as a measured variable.

The pyrophosphate-extracted iron fraction has the strongest relationship with MAOM C concentration (Fig. S4). Thus, for our group of soils in the Central Coast region, organo-mineral stabilization of carbon is a critical form of metal-associated MAOM C formation. These organo-metal complexes may help form "nanocomposites" that stabilize microbially-processed OM in high-density particles and meso-density aggregates (Wagai et al., 2020).

The positive association between soil C and N enzyme activity and MAOM-C% is likely related to the breakdown of complex plant polymers and subsequent biological MAOM formation (Whalen et al., 2022). Enzyme activity has been shown to increase with SOM across ecosystems. However, the directionality of enzyme activity is usually not clear for MAOM or POM fractions, and correlations tend to be stronger for POM fractions (Cenini et al., 2016; Grandy et al., 2007). Enzyme activity in our data also strongly correlates with the fPOM fraction, but we omit enzymes as a predictor variable for POM models because of the uncertainty around directionality (Fig. S1). It is also possible for root exudates and resulting extracellular enzymes to destabilize MAOM, but given that enzymes correspond positively to MAOM C%, we do not believe this to be the directionality represented in our data (Jilling et al., 2021; H. Li et al., 2021).

Free and occluded POM

Free POM is a physically accessible OM fraction that provides an important energy source for soil microorganisms, whereas oPOM represents physically protected, hence less accessible and more stable form of less processed organic carbon (Lavallee et al., 2020b; Sokol et al., 2022).

Both fPOM model 1 and the oPOM model indicate that increased crop rotational diversity is positively related to the carbon contribution of each POM fraction. The crop diversity z-score includes the richness of cash and cover crops and the functional diversity of cover crops planted by farmers. This may be due to an increase in residue quantity and quality and increases in aggregate formation which altogether may encourage POM build-up(Liebig et al., 2014; Mikha et al., 2010). This finding aligns with a recent meta-analysis demonstrating that increasing the number of annual crops grown per year and other intensification strategies can increase POM fractions by 33% relative to control plots (Prairie et al., 2023). While this meta-analysis combines free and occluded POM fractions, other work has also shown that practices such as perennial intercropping have the potential to increase POM in both the free and occluded fractions (Drinkwater et al., 2021; Martins et al., 2015). Additionally, increased crop diversification increases the stability and size of macroaggregates that are key for oPOM (Gentsch et al., 2024; G. Li et al., 2024).

Soil iron fractions are also significant for fPOM model 1 and the oPOM model. Many of our soils are high-activity, smectitic soils, which, combined with amorphous minerals such as SRO iron minerals, can encourage greater aggregate stability and protect both POM and MAOM fractions (Six et al., 2004; Wu et al., 2023). Across ecosystems, Yu et al. (2022) found oxalate-extractable Fe predicted POM contribution to total SOC. While iron mineralogy is significantly positive for almost all models, its positive relationship is especially clear ($p = 0.001$) for oPOM, suggesting that soil iron is critical for increasing the proportion of carbon stored in the occluded fraction. This is likely due to the role that iron phases such as pyrophosphate-extractable iron play in forming stable organo-mineral associations, and the role that non-crystalline phases play in forming stable aggregates that can protect POM from microbial decay (Ren et al., 2024; Wang et al., 2019).

When $Cover_{prop\text{-}5yr}$ and deep tillage frequency are used in the model in lieu of z-score management categories, these variables replace crop rotational diversity as significant predictors of fPOM C_{prop}. With increased living cover, there are increases in the availability of aboveground and belowground biomass inputs that can become fPOM (Motta et al., 2007). Cover crops, in particular, help provide living roots when farmers might otherwise leave their fields bare. In line with our findings, several meta-analyses of cover cropping systems showed that cover crops increase POC by nearly 15% and seem primarily driven by aboveground inputs (Hu et al., 2023; Wooliver & Jagadamma, 2023).

Deep tillage may reduce the fPOM C proportion by two mechanisms. The first is the well-documented process of tillage breaking up soil structure and aerating soils, thereby promoting the decomposition of POM, particularly in the top 10 cm (Balesdent et al., 2000; Chan et al., 2002; Six et al., 1999). The other possibility is that regular deep tillage may move fPOM in topsoils down the soil profile, thus reducing the fPOM in surface soils (Angers & Eriksen-Hamel, 2008; Martins et al., 2015). Fractionations of deeper soil samples would be needed to confirm this hypothesis.

Among all pSEM models analyzed to assess biological mediation of POM and MAOM levels, the only combination of variables that came out as positive was the path between 5-year continuous cover, Shannon diversity for fungal taxa, and fPOM C_{prop}. The positive association of continuous cover and fungal diversity has been previously documented (He et al., 2023; Schmidt et al., 2019). It has also been found that changes in fungal community structure may support increases in POM when straw is added to soils (Fan & Wu, 2021). However, it is also possible that increased fPOM provides an energy source for a more diverse range of fungal taxa, though the lack of significance for the abundance of fungal taxa makes this slightly less clear.

The lack of significance of all other variables (microbial biomass C, Shannon diversity for bacterial taxa, and fungal and bacterial abundance) was somewhat unexpected, particularly for MAOM models, given the established importance of microbial pathways for MAOM formation (Klink et al., 2022; Lavallee et al., 2020b; Sokol et al., 2019; Whalen et al., 2022). Given that microbial abundance can fluctuate quite widely depending on climate and water conditions, it is possible that our sampling of sites did not capture a wide-enough window of microbial activity that could be impacted by management, or then go on to impact MAOM levels (M. C. P. e Silva et al., 2012, 2013).

Management versus edaphic impact on soil carbon

We find that management variables explain around three times the variance of edaphic and biological (in the case of enzyme activity) variables in our MAOM C% models. This finding was surprising, given the importance of soil mineralogy and texture in MAOM formation and stabilization. That said, the pH range of our samples is fairly constrained, (Table 2) and thus conclusions around pH may not hold beyond our represented range. That said, a recent meta-analysis with pH values ranging from ~4 to 8 similarly found that cover cropping impacts on POC and MAOC were not strongly influenced by soil texture and pH, (Wooliver & Jagadamma, 2023). Importantly, given the on-farm nature of our project, this means that across a range of soil textures and with management practices as implemented on real farms, agricultural soils can increase MAOM C% through cover crops and continuous living roots, as well as through reduced physical disturbance.

Like MAOM, fPOM and oPOM models also show that management variables explain more variance than edaphic characteristics by 5.7x and 1.4x for fPOM and oPOM, respectively. Given that the primary input of fPOM into soils is plant above- and below-ground biomass, the impact of management helps govern inputs, whereas edaphic variables have less influence. The edaphic and climatic environment govern the decomposition of this pool, but for our given region, management overrides edaphic conditions significantly. This trend is less robust for oPOM, where soil mineralogy is essential for forming and stabilizing POM in macro-aggregates. However, it is notable that management still explains more variation in our data than edaphic characteristics. This finding again reinforces that, despite variable edaphic conditions (clay percentage ranges from 5-60% and sand from 5-77%; Table 2) , on-farm management practices have the potential to significantly increase POM fractions in agricultural soils with benefits for soil health and fertility.

Carbon stocks and management

The carbon stock models show that continuous living cover drives C stock increases. This finding aligns with previous work showing that cover crops, perennialization, and other management practices prioritizing continual living biomass increase SOC (Jian et al., 2020; Prairie et al., 2023; Vendig et al., 2023). Fields with high levels of continuous cover (~90%) over five years show a modeled value ~3.57 Mg C/ha higher than fields with lower continuous cover (~23%; Table 5). This is very similar to results found by a recent assessment of North American long term cover crop trials which found that cover cropping, in comparison to non-cover crop trials, sequesters 3.55 Mg

C/ha (Peng et al., 2023). On average, Stevenson et al. (2024) find that agricultural soils have 33 Mg C/ha in the A horizon, and we similarly find that the average across our study is 29.25 Mg C/ha - thus a 3.57 Mg C/ha represents ~10% of this value, indicating that continuous living cover has significant potential to increase carbon stocks in C-depleted croplands.

We find increasing sandiness decreases carbon stocks. Increasing proportions of clay and silt increase the surface area of a given soil, particularly those with high-activity phyllosilicates such as smectite (Georgiou et al., 2022; Wu et al., 2023). Thus, we expected that edaphic variables would explain more variance than management variables in our variance partitioning for the carbon stock models. This result aligns with other work showing that SOM in agricultural soils is more related to soil texture than management factors (Williams et al., 2020). Interestingly, iron concentration is not quite significant for bulk soil C. This may indicate that, while important when looking at specific C fractions, that texture is the stronger edaphic factor driving C stocks.

Importantly, while soil texture is a key predictor of carbon stocks, most agricultural soils are highly undersaturated (there is a lot of remaining surface area on which carbon could sorb) relative to uncultivated soils (Georgiou et al., 2022; Rasmussen et al., 2018). Thus, agricultural management is still essential for increasing soil carbon stocks.

Implications for management and policy

Our analysis found no apparent influence of organic amendments on our carbon fractions or stocks. While non-significant, the coefficient values for all but MAOM are negative. This finding contrasts with much of the published work on increases in SOC from compost application, manures, and other organic amendments (Aguilera et al., 2013; Bian et al., 2024; Bolinder et al., 2020; Samson et al., 2020; White, Brennan, Cavigelli, et al., 2020b). Depending on how carbon enters a system via amendments, we can hypothesize different explanations for this discrepancy. One avenue for increased SOC via amendments is that they enhance plant productivity via increased nutrient provisioning and water retention (Ryals & Silver, 2013), thereby increasing aboveground and belowground inputs into the soil, primarily in the POM pool. However, our focal crop, lettuce, does not have particularly deep or long-lived roots, and most crop biomass is harvested. Thus, the potential for increased above- and belowground production from amendments to increase SOM is likely limited. Another avenue is that manures, in particular, may supply nutrient-rich compounds that stimulate microbial activity, leading to increased MAOM (Samson et al., 2020). However, our assessment focuses on carbon inputs for the current season without including long-term amendment data in our models. It is possible that the timescales and quantities required for amendments to be effective in increasing SOC via either avenue were not represented at our farm sites.

Nevertheless, we found that organic amendments correlate with standardized yield (Chapter 3), reaffirming the validity and importance of this management category. Further investigation of carbon inputs revealed negative bivariate correlations with our POM fractions, suggesting a potential priming effect, wherein adding nutrient-rich amendments may increase microbial activity, leading to increased decomposition of POM fractions. However, more specific work would be needed to corroborate this, and nitrogen variables when included in mixed models did not emerge as significant (see Supplement). Additionally, it is important to note that these findings may not hold for different crop types such as perennial or tree crops and non-vegetable systems with different rooting depths and soil residue inputs. Non-organic systems may also have different dynamics with the addition of synthetic pesticides and fertilizers, though we do see high variability even within organic systems in SOC levels. Thus, additional work should be done to understand these dynamics across different cropping systems.

There is growing interest by policymakers in the potential for organic amendments to increase the carbon sequestered in working lands. In California, the Healthy Soils Program (HSP), whose goal is explicitly tied to increasing SOC in agricultural lands, has allocated over 2/3 of its grant funding towards carbon amendments and compost application, amounting to nearly $56 million in 2021 alone (California Department of Food and Agriculture, 2022). Our study suggests that the context and timescales on which compost and amendment application may be critical in generating measurable changes in SOC and highlights the need for further research to understand the precise conditions under which amendments may be a valuable strategy for carbon sequestration on working lands. For example, it is important to note that our focal crop of lettuce may not be representative of other cropping systems such as pasture and grazing systems, where compost has been found to increase SOC (McClelland et al., 2022; Ryals & Silver, 2013).

Additionally, our findings suggest that increasing continuous living cover on working lands could significantly increase MAOM C%, POM, and overall carbon stocks. According to data from the U.S. Census of Agriculture, the percent of available cropland planted with cover crops nationally is 5.6%, and in California, it is 4.8% (LaRose & Myers, 2019). In our focal region of the Central Coast of California, a recent remote sensing analysis revealed that only ~6% of farmland had winter cover crops, and ~60% of farmers left their fields fallow through the winter (Thompson et al., 2023). The low use of continuous cover across California and the US indicates a significant opportunity for increasing cropland carbon sequestration. Policy and conservation incentive programs should focus on supporting farmers in adopting cover cropping practices while recognizing that the barriers that different groups of farmers face vary widely and that many barriers exist at structural levels beyond the farm (Carlisle et al., 2022; Esquivel et al., 2021).

Conclusion and future directions

This on-farm study examined the impact of soil health management on mineral and particulate carbon fractions and topsoil carbon stocks across 28 actively managed farms. It provides valuable insights into real-world farming practices across diverse soil textures and their effects on carbon in different functional fractions.

We found that cultivating continuous living plant cover, reducing tillage, and increasing crop diversity can enhance both the slow-cycling MAOM fraction and the more dynamic POM fraction. The dominance of the MAOM fraction in overall carbon stock suggests its potential for long-term carbon sequestration in agricultural soils. Notably, maintaining continuous cover emerged as a significant factor in increasing MAOM, fPOM, and overall soil carbon stocks in surface soils.

Furthermore, across various soil textures, management practices showed significant potential to boost carbon stored in MAOM, fPOM, and oPOM fractions. This research complements mechanistic and experimental trials, highlighting that soil health management is effective across diverse soil types and can enhance soil health while promoting long-term carbon sequestration.

This project sampled soils directly from working farms, providing a realistic view into the impacts of heterogeneous cropland management that is difficult to assess in controlled field experiments. A unique strength of this type of research is the use of our management gradient calculated as practice Z-score, thus providing a continuous measurement of the level of use of a given practice. We are also able to assess the compounding effects that multiple practices may have simultaneously. However, with our dataset, we are unable to account for interaction effects between practices. For example, simultaneous increases in tillage and continuous cover might have an especially positive impact on carbon fractions. Direct causal relationships and mechanisms between management and C outcomes are challenging to parse from this type of on-farm work.

Future studies should focus on capturing the dynamics of layered practices, including their interactions with local edaphic contexts, to better understand their effects. Additionally, repeat sampling over longer timescales would provide insights into longer-term carbon and management dynamics, offering a clearer picture of how soil health management can serve as a climate mitigation strategy.

Acknowledgements:

Thank you to Yordi Gil-Santos, Amiri Taylor, Grace Santos, Melanie Rodriguez, Arely Ortiz, and Anna Barcellos for the mountain of lab work conducted over the last several years to make this work possible. A huge thank you to the interdisciplinary team of researchers who have supported this work. I appreciate Annie Taylor, who created the site map image. This work was supported by an NSF Coupled Natural Humans Systems (#1824871) and USDA-NIFA Grant (#2019-67019-29537) funding. I also want to thank UC Berkeley's Graduate Division, the William & Lisa Liu Fellowship, the Ford Foundation, and the Switzer Foundation for providing fellowship funding throughout my graduate career.

Tables

Table 1: Management categories and included practices.

Soil health principle	Management variable	Unit/Description	Max value	Min value	Mean	Median
Maintain continuous living cover	Winter cover cropping	Average January cover crop cover over 5 years based on NDVI	1	0	0.44	0.40
	Continuous cover	Average monthly cover (cash or cover crops) over 5 years based on monthly NDVI	0.9	0.23	0.54	0.52
Organic amendments	Total carbon input	Kg/ha; calculated based on organic amendments applied during sampling season 2020	2991.11	448.74	1925.54	1786.34
Crop rotational diversity	Cash crop richness	# of crops	16	3	5.39	5
	Crop families	# of cash crop families	8	1	4.14	4
	Cover crop richness	# of cover crop types	9	0	2.96	3
	Cover crop functional richness	Number of functional groups	3	0	1.54	2
Reduced disturbance	Bed permanence	0 = one season, 1= multiple	0	1	0.14	0
	Deep tillage frequency	0= more than 1x per year, 1 = once per year, 2= once every few years, 3= never	0	3	1.07	0.5
	Tillage depth	Inches	14	42	28.05	30

Table 2: Summary statistics across 28 field sites for surface soil (0-15 cm) texture, pH, and carbon values.

Variable	Min	Median	Mean	Max
Clay (%)	5	23	26	60
Sand (%)	5	43	42	77
Silt (%)	18	32	33	49
CEC (meq/100 g)	7.4	18.8	20.3	52.1
pH	6.4	7.5	7.5	8.4
BD (g/cm^3)	0.88	1.34	1.33	1.60
TC (%)	0.74	1.39	1.50	3.95
Surface C Stock (Mg/ha)	16.88	27.01	29.25	67.69
SOM (%)	1	2.15	2.36	6.8
MAOM C%	0.79	1.57	1.73	3.69
fPOM C%	5.73	29.59	29.53	43.60
oPOM C%	0.08	0.29	0.87	10.49

Table 3: Summary of mixed-effects models. Standardized coefficient estimates with standard error are reported with p-values in parentheses. Standardization was performed following Gelman (2008) and allows for better comparison of variable effect sizes. Green and red squares indicate positive and negative coefficients respectively at significance level p<0.1. Bolded values represent values with p-values <0.05. Gray cells indicate that the variable was not included in a given model and white cells indicate that the variable was included, but non-significant. MAOM C%, and fPOM and oPOM C_{prop} were logit transformed, and C-stock was log transformed. Bulk C Stock model is Box-Cox transformed, hence the different scale of coefficients.

Variable	MAOM C (%)		free POM C (% total C)		oPOM C (% total C)	Carbon Stock (0-10cm)
Name	MAOM1	MAOM 2	fPOM1	fPOM2	oPOM	Bulk
Intercept	-4.08 ± 0.05 (1.17e-10)	-4.08 ± 0.05 (1.49e-11)	-6.48 ± 0.079 (1.19e-06)	-6.48 ± 0.067 (<2e-16)	-6.87 ± 0.063 (6.08e-4)	1.058 ± 0.0033 (5.48e-11)
Continuous coverage	0.20 ± 0.199 (0.106)	0.22 ± 0.12 (0.07)	0.18 ± 0.19 (0.37)		0.14 ± 0.15 (0.38)	0.015 ± 0.0076 (0.068)
Reduced disturbance	0.21 ± 0.117 (0.09)	0.21 ± 0.11 (0.07)	0.033 ± 0.17 (0.84)		0.10 ± 0.14 (0.47)	0.0005 ± 0.0072 (0.95)
C amendment	0.03 ± 0.013 (0.80)	0.04 ± 0.12 (0.72)	-0.26 ± 0.20 (0.21)	-0.077 ± 0.17 (0.66)	-0.189 ± 0.16 (0.24)	0.0018 ± 0.008 (0.82)
Crop diversity	0.11 ± 0.12 (0.37)	0.11 ± 0.12 (0.37)	0.34 ± 0.19 (0.083)	0.05 ± 1.84 (0.79)	**0.36 ± 0.15 (0.024)**	0.0066 ± 0.077 (0.40)
5 yr cover proportion				**0.46 ± 0.18 (0.017)**		
Deep tillage frequency				**-0.40 ± 0.16 (0.022)**		
Iron	**0.13 ± 0.05 (0.02)**	0.10 ± 0.06 (0.07)	**0.33 ± 0.16 (0.045)**	0.23 ± 0.15 (0.13)	**0.40 ± 0.11 (0.001)**	0.0061 ± 0.0043 (0.16)
pH	-0.11 ± 0.061 (0.06)	-0.07 ± 0.06 (0.21)	-0.009 ± 0.145 (0.95)	-0.014 ± 0.13 (0.92)	-0.062 ± 0.11 (0.57)	-0.0048 ± 0.0043 (0.27)
Soil physical (Clay < Sand)	0.19 ± 0.11 (0.07)	0.14 ± 0.11 (0.18)	0.29 ± 0.20 (0.17)	0.011 ± 0.098 (0.91)	0.11 ± 0.16 (0.49)	**-0.021 ± 0.0073 (0.0074)**
Enzymes		**0.10 ± 0.05 (0.04)**				

Table 4: Marginal R^2 values for edaphic variable groupings (Physical PC1 – texture, CEC, pH) and management variables (continuous cover, reduced disturbance, C input, crop diversity Z scores) with confidence intervals from bootstrapping. R^2 values and confidence intervals obtained using 'partR2' package in R. CIs estimated via parametric bootstrapping with 1000 iterations.

	MAOM (% C)		free POM C (% total C)		oPOM C (% total C)	Stock C
Model name	MAOM1	MAOM 2	fPOM1	fPOM2	oPOM	Bulk
Edaphic/Bio Variables*	0.060 (0.00 - 0.38)	0.081 (0.00 - 0.41)	0.039 (0.00 - 0.31)	0.030 (0.00 - 0.29)	0.12 (0.00 - 0.40)	0.25 (0.11 - 0.52)
Management Variables	0.19 (0.06 - 0.48)	0.20 (0.05 - 0.50)	0.12 (0.04 - 0.38)	0.25 (0.13 - 0.47)	0.17 (0.05- 0.44)	0.12 (0.00 - 0.41)
Full Model	0.30 (0.17 - 0.57)	0.32 (0.18 - 0.60)	0.18 (0.1 - 0.43)	0.31 (0.19 - 0.52)	0.29 (0.19 - 0.54)	0.34 (0.19 - 0.60)

*For all models, this includes the soil physical PC1 (soil texture, CEC), soil iron PC1, and pH. For model MAOM2 this also includes enzyme activity PC1.

Table 5: Modeled management outcomes on various carbon fractions and stocks based on untransformed mixed-effects model coefficients, comparing high- and low-adoption sites. The sites selected are not the highest or lowest sites, but rather sites that are relatively high and low for each management category.

	Low Score Site	High Score Site	Modeled Increase
MAOM C%			
Continuous cover	28% cover over 5 years 0% January cover	90% cover over 5 years 80% January Cover	MAOM1 (no enzyme): 1.85% C (1.79 - 1.90) MAOM2 (Enzyme): 1.86% C (1.80 - 1.91)
Reduced Disturbance	One season beds Deep till 1x/yr Tillage depth = 1.07 m (42 in)	Multiple season beds Deep till 1x/ few years Tillage depth = 0.38 m (15 in)	MAOM1: 1.86% C (1.81 - 1.91) MAOM2: 1.86% C (1.77 - 1.95)
fPOM stock			
Continuous cover	23% cover over 5 yrs	90% cover over 5 years	2.76 Mg C/ha (0.67 - 11.46)
Deep tillage frequency	More than 1x/year	Never	0.62Mg C/ha (0.52 - 0.75)
oPOM Stock			
Crop Diversity	3 cash crops, no cover crops	6 cash crops, 9 species cover crop mix w/ 3 functional groups	4.63 Mg C/ha (4.31 - 4.97)
C Bulk Stock			
Continuous cover	28% cover over 5 years 0% January cover	90% cover over 5 years 80% January Cover	3.57 Mg C/ha (3.55 - 3.58)

Figures

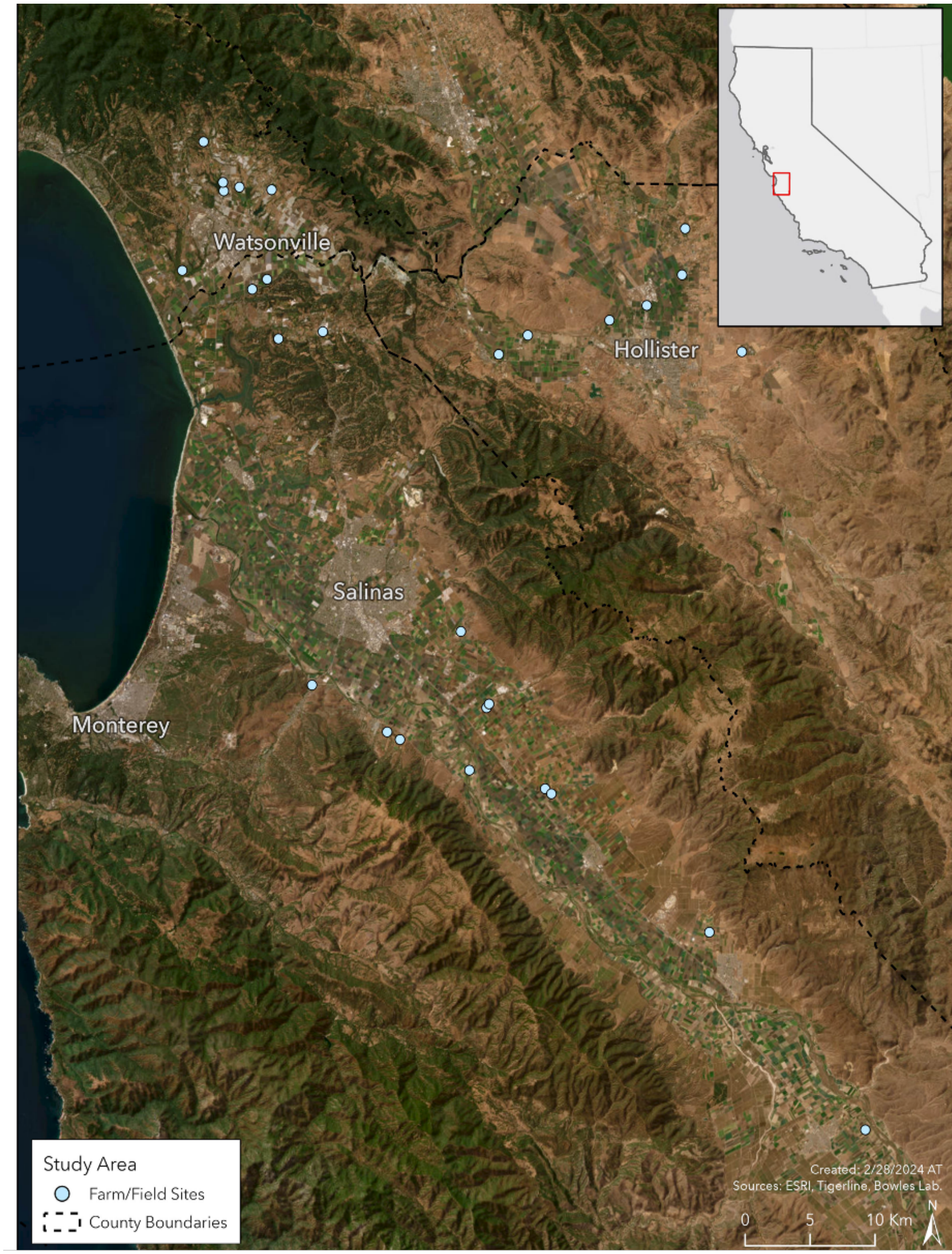


Figure 1: Map of soil sampling locations. 28 field sites span Santa Cruz, Monterey, and San Benito Counties (Map created by Annie Taylor).

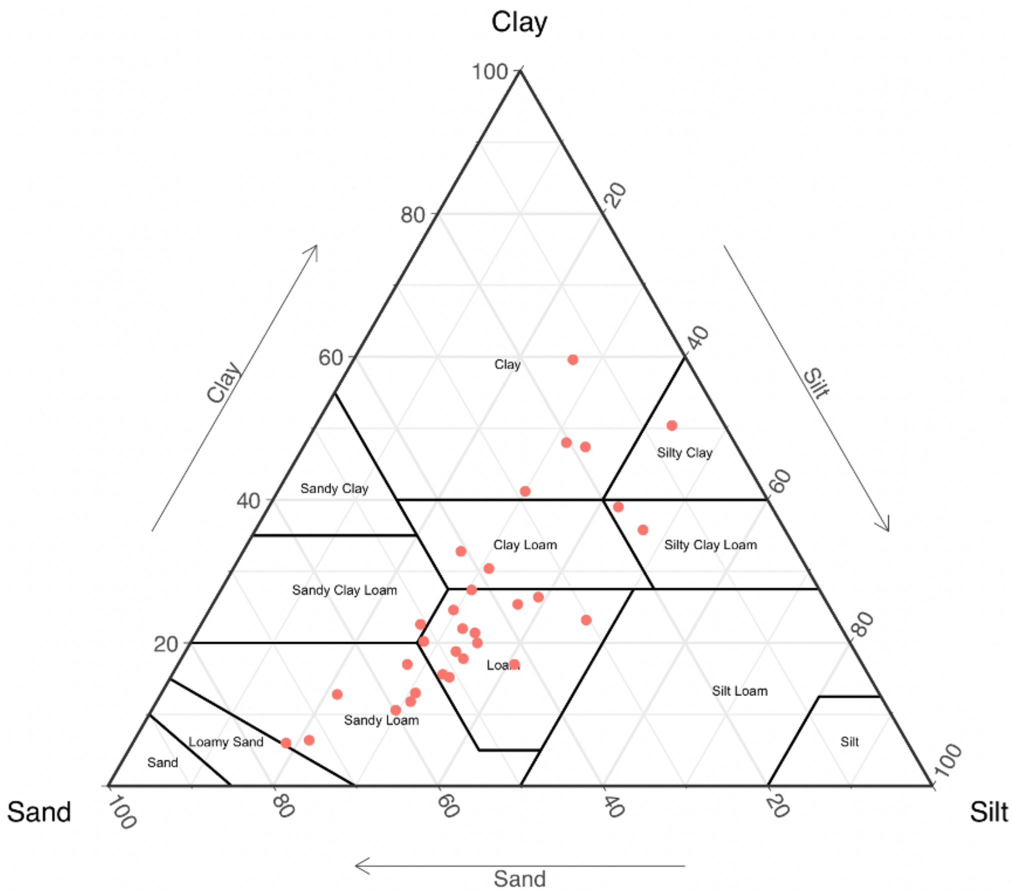


Figure 2: Soil texture across the 28 field sites (red circles).

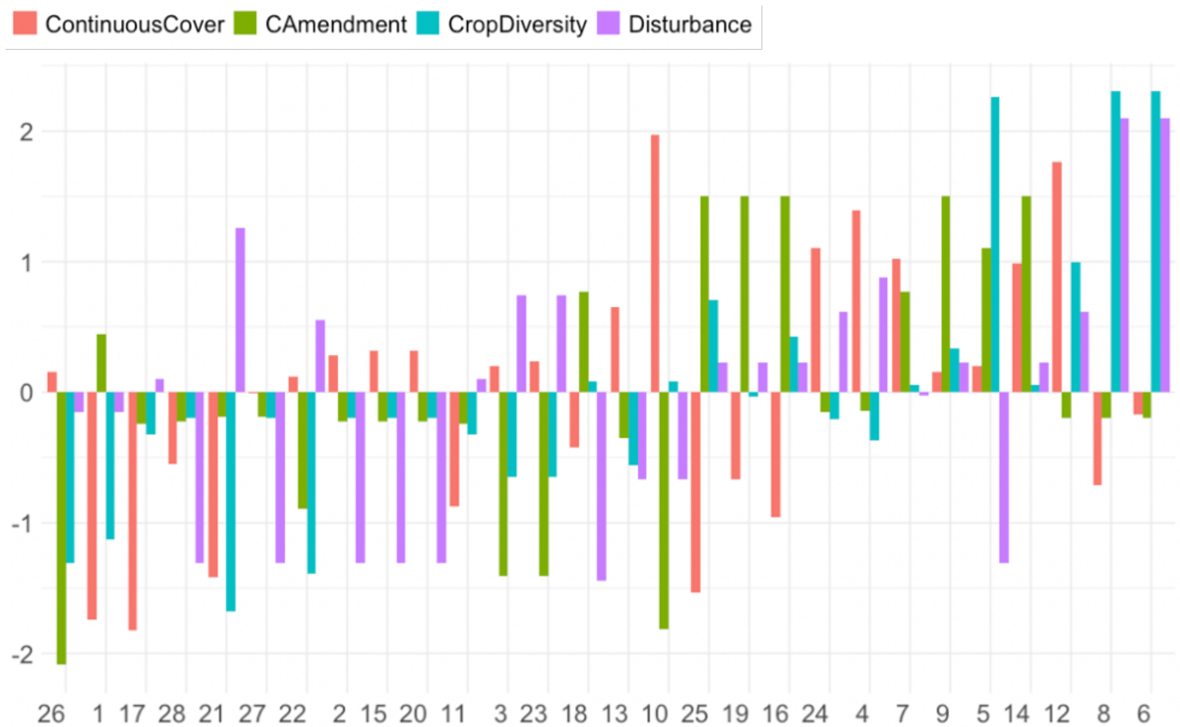


Figure 3: Scaled management Z-scores across 28 field sites, ordered by degree of soil health practice utilization. Higher values indicate higher utilization of a given practice.

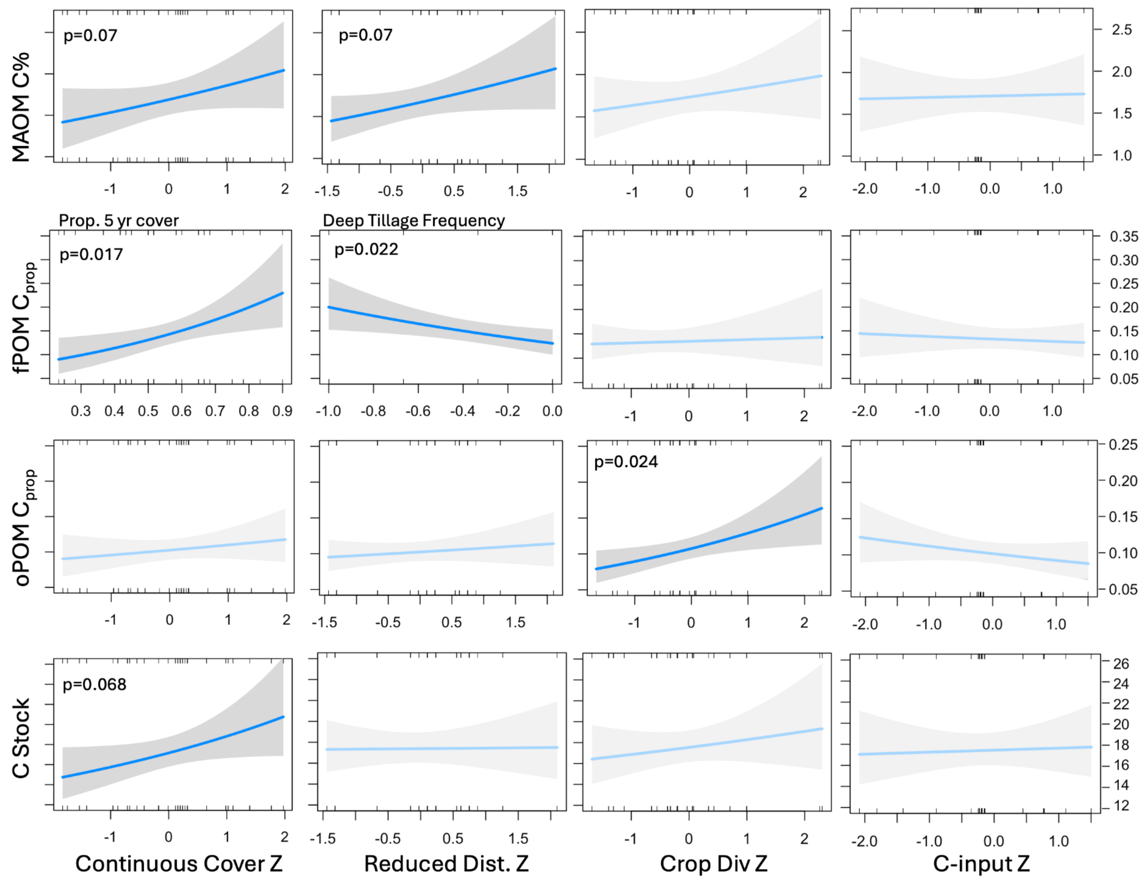


Figure 4: Modeled regressions for carbon fraction and stock models holding all other variables constant at mean values. Significant relationships are darker with p-values listed. Unless otherwise indicated, x-axis uses z–scores for each management category.

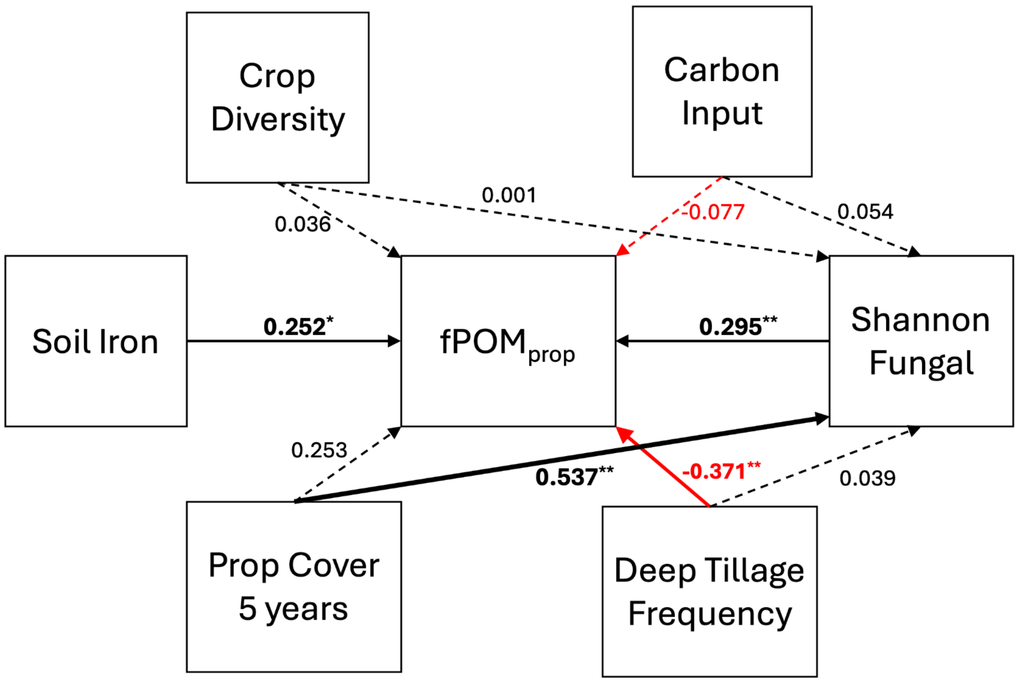


Figure 5: Structural equation model diagram for $fPOM_{prop}$ and Shannon Fungal. Dotted lines indicate non-significant paths, and solid lines represent significant paths. Thickness of the arrow represents the strength of the relationship. One asterisk represents statistical significance at $p<0.05$ and two represents $p<0.01$.

References

Abbas, F., Hammad, H. M., Ishaq, W., Farooque, A. A., Bakhat, H. F., Zia, Z., Fahad, S., Farhad, W., & Cerdà, A. (2020). A review of soil carbon dynamics resulting from agricultural practices. Journal of Environmental Management, 268, 110319. https://doi.org/10.1016/j.jenvman.2020.110319

Agarwal, R. K. (2018). Carbon Capture, Utilization and Sequestration. BoD – Books on Demand.

Aguilera, E., Lassaletta, L., Gattinger, A., & Gimeno, B. S. (2013). Managing soil carbon for climate change mitigation and adaptation in Mediterranean cropping systems: A meta-analysis. Agriculture, Ecosystems & Environment, 168, 25–36. https://doi.org/10.1016/j.agee.2013.02.003

Angers, D. A., & Eriksen-Hamel, N. S. (2008). Full-Inversion Tillage and Organic Carbon Distribution in Soil Profiles: A Meta-Analysis. Soil Science Society of America Journal, 72(5), 1370–1374. https://doi.org/10.2136/sssaj2007.0342

Angst, G., Mueller, K. E., Castellano, M. J., Vogel, C., Wiesmeier, M., & Mueller, C. W. (2023). Unlocking complex soil systems as carbon sinks: Multi-pool management as the key. Nature Communications, 14(1), 2967. https://doi.org/10.1038/s41467-023-38700-5

Bach, C. E., Warnock, D. D., Van Horn, D. J., Weintraub, M. N., Sinsabaugh, R. L., Allison, S. D., & German, D. P. (2013). Measuring phenol oxidase and peroxidase activities with pyrogallol, l-DOPA, and ABTS: Effect of assay conditions and soil type. Soil Biology and Biochemistry, 67, 183–191. https://doi.org/10.1016/j.soilbio.2013.08.022

Balesdent, J., Chenu, C., & Balabane, M. (2000). Relationship of soil organic matter dynamics to physical protection and tillage. Soil and Tillage Research, 53(3), 215–230. https://doi.org/10.1016/S0167-1987(99)00107-5

Bates, D., Maechler, M., Bolker [aut, B., cre, Walker, S., Christensen, R. H. B., Singmann, H., Dai, B., Scheipl, F., Grothendieck, G., Green, P., Fox, J., Bauer, A., simulate.formula), P. N. K. (shared copyright on, & Tanaka, E. (2023). lme4: Linear Mixed-Effects Models using "Eigen" and S4 (1.1-35.1) [Computer software]. https://cran.r-project.org/web/packages/lme4/index.html

Bian, Q., Zhao, L., Cheng, K., Jiang, Y., Li, D., Xie, Z., Sun, B., & Wang, X. (2024). Divergent accumulation of microbe- and plant-derived carbon in different soil organic matter fractions in paddy soils under long-term organic amendments. Agriculture, Ecosystems & Environment, 366, 108934. https://doi.org/10.1016/j.agee.2024.108934

Blanco-Canqui, H. (2022). Cover crops and carbon sequestration: Lessons from U.S. studies. Soil Science Society of America Journal, 86(3), 501–519. https://doi.org/10.1002/saj2.20378

Bol, R., Poirier, N., Balesdent, J., & Gleixner, G. (2009). Molecular turnover time of soil organic matter in particle-size fractions of an arable soil. Rapid Communications in Mass Spectrometry, 23(16), 2551–2558. https://doi.org/10.1002/rcm.4124

Bolinder, M. A., Crotty, F., Elsen, A., Frac, M., Kismányoky, T., Lipiec, J., Tits, M., Tóth, Z., & Kätterer, T. (2020). The effect of crop residues, cover crops, manures and nitrogen fertilization on soil organic carbon changes in agroecosystems: A synthesis of reviews. Mitigation and Adaptation Strategies for Global Change, 25(6), 929–952. https://doi.org/10.1007/s11027-020-09916-3

Bradford, M. A., Wood, S. A., Addicott, E. T., Fenichel, E. P., Fields, N., González-Rivero, J., Jevon, F. V., Maynard, D. S., Oldfield, E. E., Polussa, A., Ward, E. B., & Wieder, W. R.

(2021). Quantifying microbial control of soil organic matter dynamics at macrosystem scales. Biogeochemistry, 156(1), 19–40. https://doi.org/10.1007/s10533-021-00789-5
Bramble, D. S. E., Ulrich, S., Schöning, I., Mikutta, R., Brandt, L., Poll, C., Kandeler, E., Mikutta, C., Konrad, A., Siemens, J., Yang, Y., Polle, A., Schall, P., Ammer, C., Kaiser, K., & Schrumpf, M. (2024). Formation of mineral-associated organic matter in temperate soils is primarily controlled by mineral type and modified by land use and management intensity. Global Change Biology, 30(1), e17024. https://doi.org/10.1111/gcb.17024
California Department of Food & Agriculture. (2021). Healthy Soils Program. https://www.cdfa.ca.gov/oefi/healthysoils/
California Department of Food & Agriculture. (2022). California Agricultural Statistics Review 2021-2022 (Agricultural Statistics Review).
California Department of Food and Agriculture. (2022). 2021 Healthy Soils Program—Incentives Program: Applications Selected For Award. https://www.cdfa.ca.gov/oefi/healthysoils/docs/2021-HSPIncentive-SelectedProjects.pdf
Carlisle, L., Esquivel, K., Baur, P., Ichikawa, N. F., Olimpi, E. M., Ory, J., Waterhouse, H., Iles, A., Karp, D. S., Kremen, C., & Bowles, T. M. (2022). Organic farmers face persistent barriers to adopting diversification practices in California's Central Coast. Agroecology and Sustainable Food Systems, 46(8), 1145–1172. https://doi.org/10.1080/21683565.2022.2104420
Cenini, V. L., Fornara, D. A., McMullan, G., Ternan, N., Carolan, R., Crawley, M. J., Clément, J.-C., & Lavorel, S. (2016). Linkages between extracellular enzyme activities and the carbon and nitrogen content of grassland soils. Soil Biology and Biochemistry, 96, 198–206. https://doi.org/10.1016/j.soilbio.2016.02.015
Chan, K. Y., Heenan, D. P., & Oates, A. (2002). Soil carbon fractions and relationship to soil quality under different tillage and stubble management. Soil and Tillage Research, 63(3), 133–139. https://doi.org/10.1016/S0167-1987(01)00239-2
Conceição, P. C., Dieckow, J., & Bayer, C. (2013). Combined role of no-tillage and cropping systems in soil carbon stocks and stabilization. Soil and Tillage Research, 129, 40–47. https://doi.org/10.1016/j.still.2013.01.006
Cotrufo, M. F., & Lavallee, J. M. (2022). Chapter One - Soil organic matter formation, persistence, and functioning: A synthesis of current understanding to inform its conservation and regeneration. In D. L. Sparks (Ed.), Advances in Agronomy (Vol. 172, pp. 1–66). Academic Press. https://doi.org/10.1016/bs.agron.2021.11.002
County of Monterey Agricultural Commissioner. (2021). Monterey County Crop & Livestock Report: Salad bowl of the world.
Desjardins, R. L., Smith, W., Grant, B., Campbell, C., & Riznek, R. (2005). Management Strategies to Sequester Carbon in Agricultural Soils and to Mitigate Greenhouse Gas Emissions. In J. Salinger, M. V. K. Sivakumar, & R. P. Motha (Eds.), Increasing Climate Variability and Change: Reducing the Vulnerability of Agriculture and Forestry (pp. 283–297). Springer Netherlands. https://doi.org/10.1007/1-4020-4166-7_14
Devine, S. M., Steenwerth, K. L., & O'Geen, A. T. (2021). A regional soil classification framework to improve soil health diagnosis and management. Soil Science Society of America Journal, 85(2), 361–378. https://doi.org/10.1002/saj2.20200
Dominik, P., & Kaupenjohann, M. (2000). Simple spectrophotometric determination of Fe in oxalate and HCl soil extracts. Talanta, 51(4), 701–707. https://doi.org/10.1016/s0039-9140(99)00324-0

Dray, S., Dufour, A.-B., Thioulouse, and J., Jombart, with contributions from T., Pavoine, S., Lobry, J. R., Ollier, S., Borcard, D., Legendre, P., & Chessel, S. B. and A. S. B. on earlier work by D. (2023). ade4: Analysis of Ecological Data: Exploratory and Euclidean Methods in Environmental Sciences (1.7-22) [Computer software]. https://cran.r-project.org/web/packages/ade4/index.html

Drinkwater, L. E., Midega, C. A. O., Awuor, R., Nyagol, D., & Khan, Z. R. (2021). Perennial legume intercrops provide multiple belowground ecosystem services in smallholder farming systems. Agriculture, Ecosystems & Environment, 320, 107566. https://doi.org/10.1016/j.agee.2021.107566

Drinkwater, L. E., & Snapp, S. S. (2022). Advancing the science and practice of ecological nutrient management for smallholder farmers. Frontiers in Sustainable Food Systems, 6. https://doi.org/10.3389/fsufs.2022.921216

Emde, D., Hannam, K. D., Midwood, A. J., & Jones, M. D. (2022). Estimating Mineral-Associated Organic Carbon Deficits in Soils of the Okanagan Valley: A Regional Study With Broader Implications. Frontiers in Soil Science, 2. https://doi.org/10.3389/fsoil.2022.812249

Esquivel, K., Carlisle, L., Ke, A., Olimpi, E., Baur, P., Ory, J., Waterhouse, H., Iles, A., Karp, D. S., Kremen, C., & Bowles, T. M. (2021). The "sweet spot" in the middle: Why do mid-scale farms adopt diversification practices at higher rates? Frontiers in Sustainable Food Systems. https://doi.org/10.3389/fsufs.2021.734088

Fan, W., & Wu, J. (2021). Changes in soil fungal community on SOC and POM accumulation under different straw return modes in dryland farming. Ecosystem Health and Sustainability, 7(1), 1935326. https://doi.org/10.1080/20964129.2021.1935326

Gelman, A. (2008). Scaling regression inputs by dividing by two standard deviations. Statistics in Medicine, 27(15), 2865–2873. https://doi.org/10.1002/sim.3107

Gentsch, N., Riechers, F. L., Boy, J., Schweneker, D., Feuerstein, U., Heuermann, D., & Guggenberger, G. (2024). Cover crops improve soil structure and change organic carbon distribution in macroaggregate fractions. SOIL, 10(1), 139–150. https://doi.org/10.5194/soil-10-139-2024

Georgiou, K., Jackson, R. B., Vindušková, O., Abramoff, R. Z., Ahlström, A., Feng, W., Harden, J. W., Pellegrini, A. F. A., Polley, H. W., Soong, J. L., Riley, W. J., & Torn, M. S. (2022). Global stocks and capacity of mineral-associated soil organic carbon. Nature Communications, 13(1), 3797. https://doi.org/10.1038/s41467-022-31540-9

German, D. P., Weintraub, M. N., Grandy, A. S., Lauber, C. L., Rinkes, Z. L., & Allison, S. D. (2011). Optimization of hydrolytic and oxidative enzyme methods for ecosystem studies. Soil Biology and Biochemistry, 43(7), 1387–1397. https://doi.org/10.1016/j.soilbio.2011.03.017

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

Grandy, A. S., Neff, J. C., & Weintraub, M. N. (2007). Carbon structure and enzyme activities in alpine and forest ecosystems. Soil Biology and Biochemistry, 39(11), 2701–2711. https://doi.org/10.1016/j.soilbio.2007.05.009

Grandy, A. S., & Robertson, G. P. (2007). Land-Use Intensity Effects on Soil Organic Carbon Accumulation Rates and Mechanisms. Ecosystems, 10(1), 59–74. https://doi.org/10.1007/s10021-006-9010-y

Haddix, M. L., Gregorich, E. G., Helgason, B. L., Janzen, H., Ellert, B. H., & Francesca Cotrufo, M. (2020). Climate, carbon content, and soil texture control the independent formation and persistence of particulate and mineral-associated organic matter in soil. Geoderma, 363, 114160. https://doi.org/10.1016/j.geoderma.2019.114160

Harrison, X. A., Donaldson, L., Correa-Cano, M. E., Evans, J., Fisher, D. N., Goodwin, C. E. D., Robinson, B. S., Hodgson, D. J., & Inger, R. (2018). A brief introduction to mixed effects modelling and multi-model inference in ecology. PeerJ, 6, e4794. https://doi.org/10.7717/peerj.4794

He, D., Yao, X., Zhang, P., Liu, W., Huang, J., Sun, H., Wang, N., Zhang, X., Wang, H., Zhang, H., Ao, X., & Xie, F. (2023). Effects of continuous cropping on fungal community diversity and soil metabolites in soybean roots. Microbiology Spectrum, 11(6), e01786-23. https://doi.org/10.1128/spectrum.01786-23

Heckman, K., Lawrence, C. R., & Harden, J. W. (2018). A sequential selective dissolution method to quantify storage and stability of organic carbon associated with Al and Fe hydroxide phases. Geoderma, 312, 24–35. https://doi.org/10.1016/j.geoderma.2017.09.043

Holland, P. W. (1986). Statistics and Causal Inference. Journal of the American Statistical Association, 81(396), 945–960. https://doi.org/10.1080/01621459.1986.10478354

Hothorn, T., Hornik, K., Strobl, C., & Zeileis, A. (2023). party: A Laboratory for Recursive Partytioning (1.3-14) [Computer software]. https://cran.r-project.org/web/packages/party/index.html

Hu, Q., Thomas, B. W., Powlson, D., Hu, Y., Zhang, Y., Jun, X., Shi, X., & Zhang, Y. (2023). Soil organic carbon fractions in response to soil, environmental and agronomic factors under cover cropping systems: A global meta-analysis. Agriculture, Ecosystems & Environment, 355, 108591. https://doi.org/10.1016/j.agee.2023.108591

Jian, J., Du, X., Reiter, M. S., & Stewart, R. D. (2020). A meta-analysis of global cropland soil carbon changes due to cover cropping. Soil Biology and Biochemistry, 143, 107735. https://doi.org/10.1016/j.soilbio.2020.107735

Jilling, A., Kane, D., Williams, A., Yannarell, A. C., Davis, A., Jordan, N. R., Koide, R. T., Mortensen, D. A., Smith, R. G., Snapp, S. S., Spokas, K. A., & Stuart Grandy, A. (2020). Rapid and distinct responses of particulate and mineral-associated organic nitrogen to conservation tillage and cover crops. Geoderma, 359, 114001. https://doi.org/10.1016/j.geoderma.2019.114001

Jilling, A., Keiluweit, M., Gutknecht, J. L. M., & Grandy, A. S. (2021). Priming mechanisms providing plants and microbes access to mineral-associated organic matter. Soil Biology and Biochemistry, 158, 108265. https://doi.org/10.1016/j.soilbio.2021.108265

Kaiser, K., & Kalbitz, K. (2012). Cycling downwards – dissolved organic matter in soils. Soil Biology and Biochemistry, 52, 29–32. https://doi.org/10.1016/j.soilbio.2012.04.002

Kallenbach, C. M., Frey, S. D., & Grandy, A. S. (2016). Direct evidence for microbial-derived soil organic matter formation and its ecophysiological controls. Nature Communications, 7(1), Article 1. https://doi.org/10.1038/ncomms13630

Karlen, D. L., Goeser, N. J., Veum, K. S., & Yost, M. A. (2017). On-farm soil health evaluations: Challenges and opportunities. Journal of Soil and Water Conservation, 72(2), 26A-31A. https://doi.org/10.2489/jswc.72.2.26A

Kleber, M., Bourg, I. C., Coward, E. K., Hansel, C. M., Myneni, S. C. B., & Nunan, N. (2021). Dynamic interactions at the mineral–organic matter interface. Nature Reviews Earth &

Environment, 2(6), 402–421. https://doi.org/10.1038/s43017-021-00162-y
Klink, S., Keller, A. B., Wild, A. J., Baumert, V. L., Gube, M., Lehndorff, E., Meyer, N., Mueller, C. W., Phillips, R. P., & Pausch, J. (2022). Stable isotopes reveal that fungal residues contribute more to mineral-associated organic matter pools than plant residues. Soil Biology and Biochemistry, 168, 108634. https://doi.org/10.1016/j.soilbio.2022.108634
Kopittke, P. M., Berhe, A. A., Carrillo, Y., Cavagnaro, T. R., Chen, D., Chen, Q.-L., Román Dobarco, M., Dijkstra, F. A., Field, D. J., Grundy, M. J., He, J.-Z., Hoyle, F. C., Kögel-Knabner, I., Lam, S. K., Marschner, P., Martinez, C., McBratney, A. B., McDonald-Madden, E., Menzies, N. W., … Minasny, B. (2022). Ensuring planetary survival: The centrality of organic carbon in balancing the multifunctional nature of soils. Critical Reviews in Environmental Science and Technology, 52(23), 4308–4324. https://doi.org/10.1080/10643389.2021.2024484
Lal, R. (2016). Soil health and carbon management. Food and Energy Security, 5(4), 212–222. https://doi.org/10.1002/fes3.96
LaRose, J., & Myers, R. (2019). Adoption of Soil Health Systems Based on Data from the 2017 U.S. Census of Agriculture. Soil Health Institute. https://soilhealthinstitute.org/app/uploads/2021/11/Soil-Health-Census-Report.pdf
Lavallee, J. M., Soong, J. L., & Cotrufo, M. F. (2020a). Conceptualizing soil organic matter into particulate and mineral-associated forms to address global change in the 21st century. Global Change Biology, 26(1), 261–273. https://doi.org/10.1111/gcb.14859
Lavallee, J. M., Soong, J. L., & Cotrufo, M. F. (2020b). Conceptualizing soil organic matter into particulate and mineral-associated forms to address global change in the 21st century. Global Change Biology, 26(1), 261–273. https://doi.org/10.1111/gcb.14859
Lehmann, J., Bossio, D. A., Kögel-Knabner, I., & Rillig, M. C. (2020). The concept and future prospects of soil health. Nature Reviews Earth & Environment, 1(10), Article 10. https://doi.org/10.1038/s43017-020-0080-8
Lehmann, J., Hansel, C. M., Kaiser, C., Kleber, M., Maher, K., Manzoni, S., Nunan, N., Reichstein, M., Schimel, J. P., Torn, M. S., Wieder, W. R., & Kögel-Knabner, I. (2020). Persistence of soil organic carbon caused by functional complexity. Nature Geoscience, 13(8), 529–534. https://doi.org/10.1038/s41561-020-0612-3
Lehmann, J., & Kleber, M. (2015). The contentious nature of soil organic matter. Nature, 528(7580), 60–68. https://doi.org/10.1038/nature16069
Lessmann, M., Ros, G. H., Young, M. D., & de Vries, W. (2022). Global variation in soil carbon sequestration potential through improved cropland management. Global Change Biology, 28(3), 1162–1177. https://doi.org/10.1111/gcb.15954
Li, G., Yu, C., Shen, P., Hou, Y., Ren, Z., Li, N., Liao, Y., Li, T., & Wen, X. (2024). Crop diversification promotes soil aggregation and carbon accumulation in global agroecosystems: A meta-analysis. Journal of Environmental Management, 350, 119661. https://doi.org/10.1016/j.jenvman.2023.119661
Li, H., Bölscher, T., Winnick, M., Tfaily, M. M., Cardon, Z. G., & Keiluweit, M. (2021). Simple Plant and Microbial Exudates Destabilize Mineral-Associated Organic Matter via Multiple Pathways. Environmental Science & Technology, 55(5), 3389–3398. https://doi.org/10.1021/acs.est.0c04592
Liang, C., Schimel, J. P., & Jastrow, J. D. (2017). The importance of anabolism in microbial control over soil carbon storage. Nature Microbiology, 2(8), 1–6.

https://doi.org/10.1038/nmicrobiol.2017.105
Liebig, M. A., Archer, D. W., & Tanaka, D. L. (2014). Crop Diversity Effects on Near-Surface Soil Condition under Dryland Agriculture. Applied and Environmental Soil Science, 2014(1), 703460. https://doi.org/10.1155/2014/703460
Lorenz, K., & Lal, R. (2012). Cropland Soil Carbon Dynamics. In R. Lal, K. Lorenz, R. F. Hüttl, B. U. Schneider, & J. von Braun (Eds.), Recarbonization of the Biosphere: Ecosystems and the Global Carbon Cycle (pp. 303–346). Springer Netherlands. https://doi.org/10.1007/978-94-007-4159-1_14
Lovley, D. R., & Phillips, E. J. P. (1987). Rapid Assay for Microbially Reducible Ferric Iron in Aquatic Sediments. Applied and Environmental Microbiology, 53(7), 1536–1540. https://doi.org/10.1128/aem.53.7.1536-1540.1987
Lützow, M. V., Kögel-Knabner, I., Ekschmitt, K., Matzner, E., Guggenberger, G., Marschner, B., & Flessa, H. (2006). Stabilization of organic matter in temperate soils: Mechanisms and their relevance under different soil conditions – a review. European Journal of Soil Science, 57(4), 426–445. https://doi.org/10.1111/j.1365-2389.2006.00809.x
Maat, H. (2011). The history and future of agricultural experiments. NJAS: Wageningen Journal of Life Sciences, 57(3–4), 187–195. https://doi.org/10.1016/j.njas.2010.11.001
Marland, G., West, T. O., Schlamadinger, B., & Canella, L. (2003). Managing soil organic carbon in agriculture: The net effect on greenhouse gas emissions. Tellus B: Chemical and Physical Meteorology, 55(2), 613–621. https://doi.org/10.3402/tellusb.v55i2.17042
Martins, B. H., Cavigelli, M. A., Buyer, J. S., Maul, J. E., Reeves III, J. B., & Martin-Neto, L. (2015). Chemical Evaluation of Soil Organic Matter Structure in Diverse Cropping Systems. In Labile Organic Matter—Chemical Compositions, Function, and Significance in Soil and the Environment (pp. 195–217). John Wiley & Sons, Ltd. https://doi.org/10.2136/sssaspecpub62.2014.0041
Masiello, C. A., Chadwick, O. A., Southon, J., Torn, M. S., & Harden, J. W. (2004). Weathering controls on mechanisms of carbon storage in grassland soils. Global Biogeochemical Cycles, 18(4). https://doi.org/10.1029/2004GB002219
McClelland, S. C., Cotrufo, M. F., Haddix, M. L., Paustian, K., & Schipanski, M. E. (2022). Infrequent compost applications increased plant productivity and soil organic carbon in irrigated pasture but not degraded rangeland. Agriculture, Ecosystems & Environment, 333, 107969. https://doi.org/10.1016/j.agee.2022.107969
McKeague, J. A. (1967). An evaluation of 0.1 m pyrophosphate and pyrophosphate-dithionite in comparison with oxalate as extractants of the accumulation products in podzols and some other soils. Canadian Journal of Soil Science, 47(2), 95–99. https://doi.org/10.4141/cjss67-017
Mikha, M. M., Benjamin, J. G., Vigil, M. F., & Nielson, D. C. (2010). Cropping Intensity Impacts on Soil Aggregation and Carbon Sequestration in the Central Great Plains. Soil Science Society of America Journal, 74(5), 1712–1719. https://doi.org/10.2136/sssaj2009.0335
Mikutta, R., Turner, S., Schippers, A., Gentsch, N., Meyer-Stüve, S., Condron, L. M., Peltzer, D. A., Richardson, S. J., Eger, A., Hempel, G., Kaiser, K., Klotzbücher, T., & Guggenberger, G. (2019). Microbial and abiotic controls on mineral-associated organic matter in soil profiles along an ecosystem gradient. Scientific Reports, 9(1), 10294. https://doi.org/10.1038/s41598-019-46501-4
Miller, R. O., Gavlak, R., & Horneck, D. (2013). Soil, Plant and Water Reference Methods for the

Western Region (4th Edition). https://www.naptprogram.org/files/napt/publications/method-papers/western-states-methods-manual-2013.pdf
Motta, A. C. V., Wayne Reeves, D., Burmester, C., & Feng, Y. (2007). Conservation Tillage, Rotations, and Cover Crop Affecting Soil Quality in the Tennessee Valley: Particulate Organic Matter, Organic Matter, and Microbial Biomass. Communications in Soil Science and Plant Analysis, 38(19–20), 2831–2847. https://doi.org/10.1080/00103620701663065
O'Geen, A., Walkinshaw, M., & Beaudette, D. (2017). SoilWeb: A Multifaceted Interface to Soil Survey Information. Soil Science Society of America Journal, 81(4), 853–862. https://doi.org/10.2136/sssaj2016.11.0386n
Olimpi, E. M., Ke, A., Baur, P., Carlisle, L., Esquivel, K., Glaser, T., Snyder, W. E., Waterhouse, H., Bowles, T. M., Kremen, C., & Karp, D. S. (2024). Ungrazed seminatural habitats around farms benefit bird conservation without enhancing food borne pathogen risks. Landscape Ecology.
Peng, Y., Rieke, E. L., Chahal, I., Norris, C. E., Janovicek, K., Mitchell, J. P., Roozeboom, K. L., Hayden, Z. D., Strock, J. S., Machado, S., Sykes, V. R., Deen, B., Tavarez, O. B., Gamble, A. V., Scow, K. M., Brainard, D. C., Millar, N., Johnson, G. A., Schindelbeck, R. R., … Van Eerd, L. L. (2023). Maximizing soil organic carbon stocks under cover cropping: Insights from long-term agricultural experiments in North America. Agriculture, Ecosystems & Environment, 356, 108599. https://doi.org/10.1016/j.agee.2023.108599
Prairie, A. M., King, A. E., & Cotrufo, M. F. (2023). Restoring particulate and mineral-associated organic carbon through regenerative agriculture. Proceedings of the National Academy of Sciences, 120(21), e2217481120. https://doi.org/10.1073/pnas.2217481120
Rasmussen, C., Heckman, K., Wieder, W. R., Keiluweit, M., Lawrence, C. R., Berhe, A. A., Blankinship, J. C., Crow, S. E., Druhan, J. L., Hicks Pries, C. E., Marin-Spiotta, E., Plante, A. F., Schädel, C., Schimel, J. P., Sierra, C. A., Thompson, A., & Wagai, R. (2018). Beyond clay: Towards an improved set of variables for predicting soil organic matter content. Biogeochemistry, 137(3), 297–306. https://doi.org/10.1007/s10533-018-0424-3
Ren, L., Yang, H., Li, J., Zhang, N., Han, Y., Zou, H., & Zhang, Y. (2024). Organic fertilizer enhances soil aggregate stability by altering greenhouse soil content of iron oxide and organic carbon. Journal of Integrative Agriculture, S209531192400217X. https://doi.org/10.1016/j.jia.2024.05.026
Rennert, T. (2018). Wet-chemical extractions to characterise pedogenic Al and Fe species – a critical review. Soil Research, 57(1), 1–16. https://doi.org/10.1071/SR18299
Ryals, R., & Silver, W. L. (2013). Effects of organic matter amendments on net primary productivity and greenhouse gas emissions in annual grasslands. Ecological Applications, 23(1), 46–59. https://doi.org/10.1890/12-0620.1
Salonen, A. R., Soinne, H., Creamer, R., Lemola, R., Ruoho, N., Uhlgren, O., Goede, R. de, & Heinonsalo, J. (2023). Assessing the effect of arable management practices on carbon storage and fractions after 24 years in boreal conditions of Finland. Geoderma Regional, 34, e00678. https://doi.org/10.1016/j.geodrs.2023.e00678
Samson, M.-E., Chantigny, M. H., Vanasse, A., Menasseri-Aubry, S., Royer, I., & Angers, D. A. (2020). Management practices differently affect particulate and mineral-associated organic matter and their precursors in arable soils. Soil Biology and Biochemistry, 148, 107867. https://doi.org/10.1016/j.soilbio.2020.107867

San Benito County Agricultural Commissioner. (2020). San Benito County Crop & Livestock Report.
Sanderman, J., Hengl, T., & Fiske, G. J. (2017). Soil carbon debt of 12,000 years of human land use. Proceedings of the National Academy of Sciences, 114(36), 9575–9580. https://doi.org/10.1073/pnas.1706103114
Santa Cruz County Agricultural Commissioner. (2021). Santa Cruz County Agricultural Crop and Livestock Report.
Schmidt, R., Mitchell, J., & Scow, K. (2019). Cover cropping and no-till increase diversity and symbiotroph:saprotroph ratios of soil fungal communities. Soil Biology and Biochemistry, 129, 99–109. https://doi.org/10.1016/j.soilbio.2018.11.010
Setia, R., Verma, S. L., & Marschner, P. (2012). Measuring microbial biomass carbon by direct extraction – Comparison with chloroform fumigation-extraction. European Journal of Soil Biology, 53, 103–106. https://doi.org/10.1016/j.ejsobi.2012.09.005
Silva, M. C. P. e, Dias, A. C. F., Elsas, J. D. van, & Salles, J. F. (2012). Spatial and Temporal Variation of Archaeal, Bacterial and Fungal Communities in Agricultural Soils. PLOS ONE, 7(12), e51554. https://doi.org/10.1371/journal.pone.0051554
Silva, M. C. P. e, Schloter-Hai, B., Schloter, M., Elsas, J. D. van, & Salles, J. F. (2013). Temporal Dynamics of Abundance and Composition of Nitrogen-Fixing Communities across Agricultural Soils. PLOS ONE, 8(9), e74500. https://doi.org/10.1371/journal.pone.0074500
Silva, L. C. R., Doane, T. A., Corrêa, R. S., Valverde, V., Pereira, E. I. P., & Horwath, W. R. (2015). Iron-mediated stabilization of soil carbon amplifies the benefits of ecological restoration in degraded lands. Ecological Applications, 25(5), 1226–1234. https://doi.org/10.1890/14-2151.1
Singh, P., Kawa, N. C., & Sprunger, C. D. (2024). "More questions than answers": Ohio farmers' perceptions of novel soil health data and their utility for on-farm management. Agroecology and Sustainable Food Systems, 48(1), 74–92. https://doi.org/10.1080/21683565.2023.2270928
Six, J., Bossuyt, H., Degryze, S., & Denef, K. (2004). A history of research on the link between (micro)aggregates, soil biota, and soil organic matter dynamics. Soil and Tillage Research, 79(1), 7–31. https://doi.org/10.1016/j.still.2004.03.008
Six, J., Elliott, E. T., & Paustian, K. (1999). Aggregate and Soil Organic Matter Dynamics under Conventional and No-Tillage Systems. Soil Science Society of America Journal, 63(5), 1350–1358. https://doi.org/10.2136/sssaj1999.6351350x
Sobrino, J. A., Raissouni, N., & Li, Z.-L. (2001). A Comparative Study of Land Surface Emissivity Retrieval from NOAA Data. Remote Sensing of Environment, 75(2), 256–266. https://doi.org/10.1016/S0034-4257(00)00171-1
Soil Health | Natural Resources Conservation Service. (2024, April 1). https://www.nrcs.usda.gov/conservation-basics/natural-resource-concerns/soils/soil-health
Sokol, N. W., Sanderman, J., & Bradford, M. A. (2019). Pathways of mineral-associated soil organic matter formation: Integrating the role of plant carbon source, chemistry, and point of entry. Global Change Biology, 25(1), 12–24. https://doi.org/10.1111/gcb.14482
Sokol, N. W., Whalen, E. D., Jilling, A., Kallenbach, C., Pett-Ridge, J., & Georgiou, K. (2022). Global distribution, formation and fate of mineral-associated soil organic matter under a changing climate: A trait-based perspective. Functional Ecology, 36(6), 1411–1429. https://doi.org/10.1111/1365-2435.14040

Sprunger, C. D., Culman, S. W., Deiss, L., Brock, C., & Jackson-Smith, D. (2021). Which management practices influence soil health in Midwest organic corn systems? Agronomy Journal, 113(5), 4201–4219. https://doi.org/10.1002/agj2.20786

Stavi, I., Bel, G., & Zaady, E. (2016). Soil functions and ecosystem services in conventional, conservation, and integrated agricultural systems. A review. Agronomy for Sustainable Development, 36(2), 32. https://doi.org/10.1007/s13593-016-0368-8

Stoffel, M. A., Nakagawa, S., & Schielzeth, H. (2024). partR2: Partitioning R2 in GLMMs (0.9.2) [Computer software]. https://cran.r-project.org/web/packages/partR2/index.html

Thompson, J. B., Symonds, J., Carlisle, L., Iles, A., Karp, D. S., Ory, J., & Bowles, T. M. (2023). Remote sensing of hedgerows, windbreaks, and winter cover crops in California's Central Coast reveals low adoption but hotspots of use. Frontiers in Sustainable Food Systems, 7. https://doi.org/10.3389/fsufs.2023.1052029

Totsche, K. U., Amelung, W., Gerzabek, M. H., Guggenberger, G., Klumpp, E., Knief, C., Lehndorff, E., Mikutta, R., Peth, S., Prechtel, A., Ray, N., & Kögel-Knabner, I. (2018). Microaggregates in soils. Journal of Plant Nutrition and Soil Science, 181(1), 104–136. https://doi.org/10.1002/jpln.201600451

Vendig, I., Guzman, A., De La Cerda, G., Esquivel, K., Mayer, A. C., Ponisio, L., & Bowles, T. M. (2023). Quantifying direct yield benefits of soil carbon increases from cover cropping. Nature Sustainability, 6(9), Article 9. https://doi.org/10.1038/s41893-023-01131-7

Von Lützow, M., Kögel-Knabner, I., Ekschmitt, K., Flessa, H., Guggenberger, G., Matzner, E., & Marschner, B. (2007). SOM fractionation methods: Relevance to functional pools and to stabilization mechanisms. Soil Biology and Biochemistry, 39(9), 2183–2207. https://doi.org/10.1016/j.soilbio.2007.03.007

Wagai, R., Kajiura, M., & Asano, M. (2020). Iron and aluminum association with microbially processed organic matter via meso-density aggregate formation across soils: Organo-metallic glue hypothesis. SOIL, 6(2), 597–627. https://doi.org/10.5194/soil-6-597-2020

Wang, P., Wang, J., Zhang, H., Dong, Y., & Zhang, Y. (2019). The role of iron oxides in the preservation of soil organic matter under long-term fertilization. Journal of Soils and Sediments, 19(2), 588–598. https://doi.org/10.1007/s11368-018-2085-1

Warton, D. I., & Hui, F. K. C. (2011). The arcsine is asinine: The analysis of proportions in ecology. Ecology, 92(1), 3–10. https://doi.org/10.1890/10-0340.1

Wasserstein, R. L., & Lazar, N. A. (2016). The ASA Statement on p-Values: Context, Process, and Purpose. The American Statistician, 70(2), 129–133. https://doi.org/10.1080/00031305.2016.1154108

Wasserstein, R. L., Schirm, A. L., & Lazar, N. A. (2019). Moving to a World Beyond "$p < 0.05$." The American Statistician, 73(sup1), 1–19. https://doi.org/10.1080/00031305.2019.1583913

Whalen, E. D., Grandy, A. S., Sokol, N. W., Keiluweit, M., Ernakovich, J., Smith, R. G., & Frey, S. D. (2022). Clarifying the evidence for microbial- and plant-derived soil organic matter, and the path toward a more quantitative understanding. Global Change Biology, 28(24), 7167–7185. https://doi.org/10.1111/gcb.16413

White, K. E., Brennan, E. B., & Cavigelli, M. A. (2020). Soil carbon and nitrogen data during eight years of cover crop and compost treatments in organic vegetable production. Data in Brief, 33, 106481. https://doi.org/10.1016/j.dib.2020.106481

White, K. E., Brennan, E. B., Cavigelli, M. A., & Smith, R. F. (2020a). Winter cover crops increase readily decomposable soil carbon, but compost drives total soil carbon during eight years of

intensive, organic vegetable production in California. PLOS ONE, 15(2), e0228677. https://doi.org/10.1371/journal.pone.0228677
White, K. E., Brennan, E. B., Cavigelli, M. A., & Smith, R. F. (2020b). Winter cover crops increase readily decomposable soil carbon, but compost drives total soil carbon during eight years of intensive, organic vegetable production in California. PLOS ONE, 15(2), e0228677. https://doi.org/10.1371/journal.pone.0228677
Williams, H., Colombi, T., & Keller, T. (2020). The influence of soil management on soil health: An on-farm study in southern Sweden. Geoderma, 360, 114010. https://doi.org/10.1016/j.geoderma.2019.114010
Wooliver, R., & Jagadamma, S. (2023). Response of soil organic carbon fractions to cover cropping: A meta-analysis of agroecosystems. Agriculture, Ecosystems & Environment, 351, 108497. https://doi.org/10.1016/j.agee.2023.108497
Wu, S., Konhauser, K. O., Chen, B., & Huang, L. (2023). "Reactive Mineral Sink" drives soil organic matter dynamics and stabilization. Npj Materials Sustainability, 1(1), Article 1. https://doi.org/10.1038/s44296-023-00003-7
Ye, C., Huang, W., Hall, S. J., & Hu, S. (2022). Association of Organic Carbon With Reactive Iron Oxides Driven by Soil pH at the Global Scale. Global Biogeochemical Cycles, 36(1), e2021GB007128. https://doi.org/10.1029/2021GB007128
Yu, W., Huang, W., Weintraub-Leff, S. R., & Hall, S. J. (2022). Where and why do particulate organic matter (POM) and mineral-associated organic matter (MAOM) differ among diverse soils? Soil Biology and Biochemistry, 172, 108756. https://doi.org/10.1016/j.soilbio.2022.108756
Zhang, Z., Kaye, J. P., Bradley, B. A., Amsili, J. P., & Suseela, V. (2022). Cover crop functional types differentially alter the content and composition of soil organic carbon in particulate and mineral-associated fractions. Global Change Biology, 28(19), 5831–5848. https://doi.org/10.1111/gcb.16296
Zuur, A. F., Ieno, E. N., Walker, N. J., Saveliev, A. A., & Smith, G. M. (2009). Mixed Effects Modelling for Nested Data. In A. F. Zuur, E. N. Ieno, N. Walker, A. A. Saveliev, & G. M. Smith (Eds.), Mixed effects models and extensions in ecology with R (pp. 101–142). Springer. https://doi.org/10.1007/978-0-387-87458-6_5

Supplemental materials

Supplemental tables

Table S1: Site-level texture, CEC, pH, order and series data from lab analysis and SSURGO

Site ID	Series	Sand (%)	Clay (%)	Silt (%)	CEC (Meq/100g)	pH	Dominant Order
1	Sorrento	6.4	50.4	43.2	32.6	7.44	Mollisol
2	Salinas	40.8	32.8	26.4	27.3	7.52	Mollisol
3	Riverwash	37.6	25.4	37	20.38	7.74	Mollisol
4	Sorrento	30.4	23.2	46.4	23.36	8.24	Mollisol
5	Sorrento	20.4	48	31.6	43.52	7.8	Mollisol
6	Chualar	55.2	17	27.8	11.06	7.82	Mollisol
7	Chualar	72.4	6.4	21.2	12.06	7.68	Mollisol
8	Sorrento	18.4	47.4	34.2	36.64	7.44	Mollisol
9	Arnold	34.6	26.4	39	21.08	6.98	Entisol
10	Pinto	48	17.8	34.2	14.7	7.32	Mollisol
11	Danville	45.8	24.6	29.6	24.12	6.72	Mollisol
12	Tierra-Watsonville	38.6	30.4	31	26.82	7.52	Alfisol
13	Clear Lake	13.8	59.6	26.6	43.04	6.96	Vertisol
14	Chualar	56.2	13	30.8	10.2	7.7	Mollisol
15	Corducci-Typic Xerofluvents	51	15.2	33.8	13.24	7.72	Entisol
16	Watsonville	42.2	27.4	30.4	19.04	7.54	Mollisol
17	Pacheco	28.8	41.2	30	28.78	7.86	Mollisol
18	Conejo	46	22	32	19.5	7.1	Mollisol
19	Chualar	65.8	12.8	21.4	8.34	8.06	Mollisol
20	Placentia	44.8	21.4	33.8	16.1	7.42	Alfisol
21	Pinto	51.6	20.2	28.2	11.28	6.54	Mollisol
22	Mocho	17.2	35.8	47	25.2	8.26	Mollisol
23	Gloria	42.2	17	40.8	12.44	7.34	Alfisol
24	Placentia	45.2	20	34.8	15.02	7.08	Alfisol
25	Sorrento	18.6	39	42.4	25	8.06	Mollisol
26	Elder	57.4	11.8	30.8	11.84	6.68	Mollisol
27	San Andreas-Santa Ynez	59.8	10.6	29.6	8.44	7.7	Mollisol
28	Hanford	75.4	6	18.6	8.1	7.8	Entisol

Table S2: Summary of mixed-effects models. Coefficient estimates with standard error are reported with p-values in parentheses. Green and red squares indicate positive and negative coefficients respectively at significance level $p<0.1$. Gray cells indicate that the variable was not included in a given model and white cells indicate that the variable was included, but non-significant. MAOM C%, and fPOM and oPOM C_{prop} were logit transformed, and C-stock was log transformed. Bulk C Stock model is Box-Cox transformed, hence the different scale of coefficients

Variable	MAOM C (%)		free POM C (% total C)		oPOM C (% total C)	Carbon Stock (0-10 cm)
Model	MAOM1	MAOM 2	fPOM1	fPOM2	oPOM	Bulk
Intercept	-3.23 ± 0.46 (1.17e-10)	-3.501 ± 0.47 (1.49e-11)	-6.476 ± 0.079 (1.19e-06)	-6.48 ± 0.067 (<2e-16)	-6.87 ± 0.064 (0.000608)	1.97 ± 0.47 (5.48e-11)
Continuous Coverage	0.103 ± 0.061 (0.105)	0.11 ± 0.06 (0.073)	0.087 ± 0.095 (0.37)		0.067 ± 0.075 (0.38)	0.0073 ± 0.0038 (0.068)
Reduced Disturbance	0.103 ± 0.057 (0.085)	0.11 ± 0.056 (0.068)	0.017 ± 0.087 (0.85)		0.051 ± 0.069 (0.47)	0.0002 ± 0.036 (0.95)
C amendment	0.017 ± 0.064 (0.80)	0.022 ± 0.062 (0.72)	-0.13 ± 0.1 (0.21)	-0.039 ± 0.087 (0.66)	-0.095 ± 0.079 (0.24)	0.0009 ± 0.0040 (0.82)
Crop Diversity	0.057 ± 0.061 (0.37)	0.055 ± 0.060 (0.37)	0.17 ± 0.094 (0.083)	0.025 ± 0.092 (0.79)	**0.18 ± 0.074 (0.024)**	0.0033 ± 0.0038 (0.40)
5 yr Cover Proportion				**0.23 ± 0.09 (0.017)**		
Deep Tillage Frequency				**-0.20 ± 0.08 (0.022)**		
Iron	**0.04 ± 0.029 (0.023)**	0.032 ± 0.017 (0.068)	**0.16 ±0.08 (0.045)**	0.12 ± 0.076 (0.13)	**0.20 ± 0.059 (0.001)**	0.0030 ± 0.0021 (0.16)
pH	-0.11 ± 0.061 (0.064)	-0.078 ± 0.062 (0.21)	-0.004 ±0.072 (0.95)	-0.007 ± 0.064 (0.92)	-0.031 ± 0.053 (0.57)	-0.0024 ± 0.0022 (0.27)
Soil Physical (Clay < Sand)	0.053 ± 0.029 (0.073)	0.039 ± 0.029 (0.18)	0.14 ± 0.102 (0.17)	0.011 ± 0.098 (0.91)	0.05 ± 0.078 (0.49)	**-0.010 ± 0.0036 (0.0074)**
Enzymes		**0.025 ± 0.012 (0.042)**				

Supplemental figures

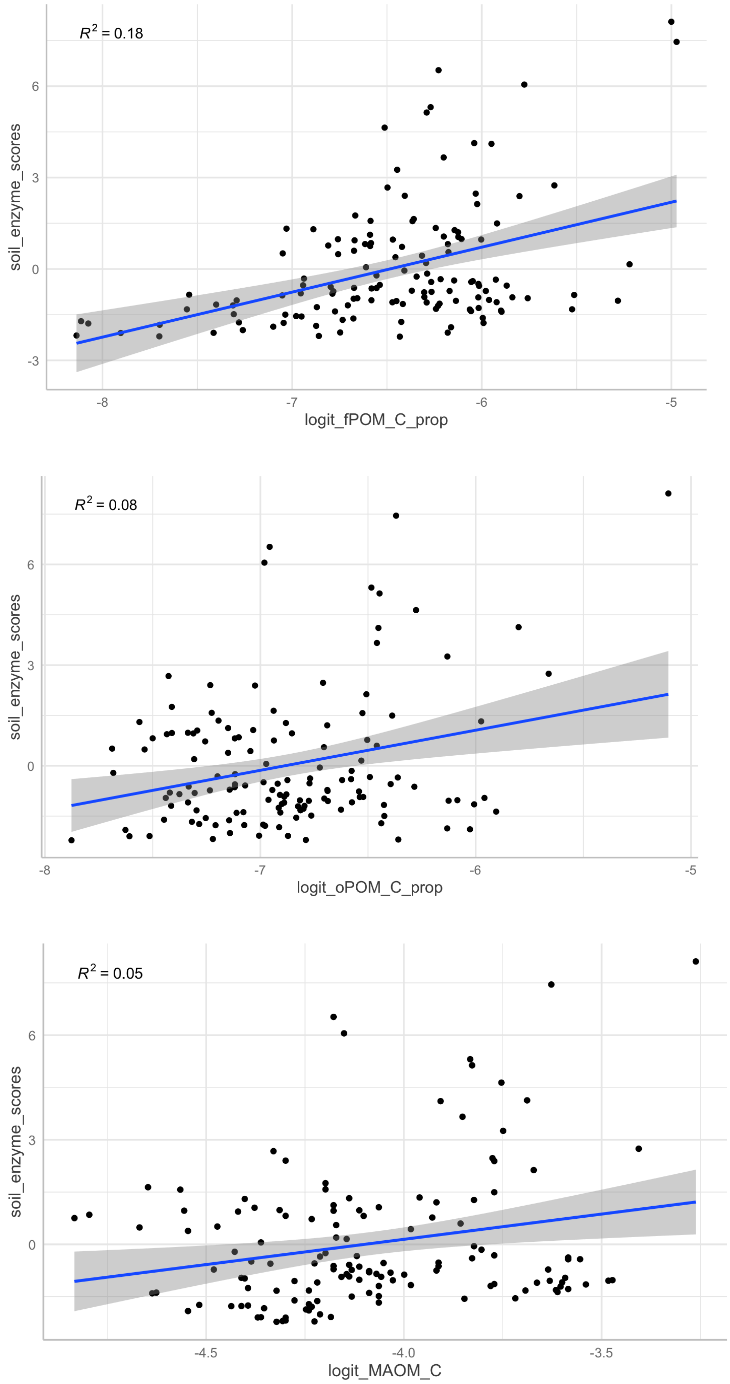


Figure S1: Bivariate relationships between fraction variables and soil enzyme scores (PC1 - Hydrolytic enzymes PHO, BG, NAG have largest contributions). Positive correlation is clearest for fPOM, while oPOM and MAOM are less clear.

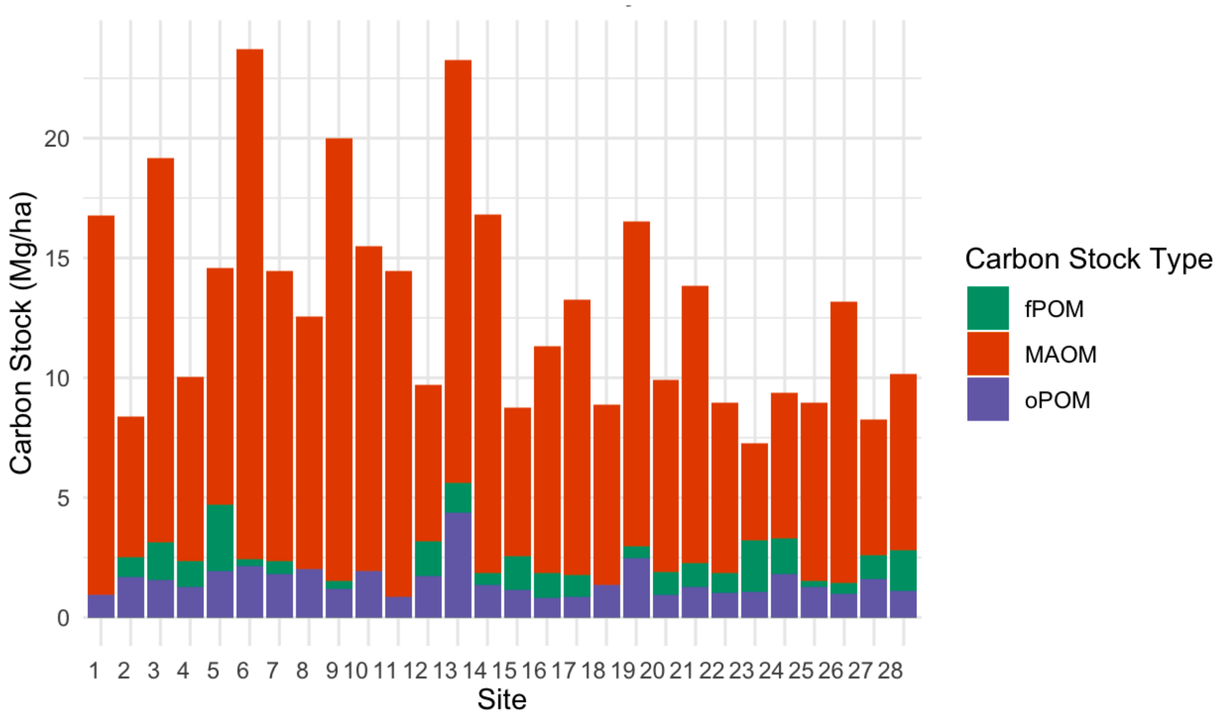


Figure S2: Fraction Contributions to C Stocks by site. Relative contributions of fPOM, oPOM, and MAOM to total carbon stock, estimated to 10 cm depth across one hectare.

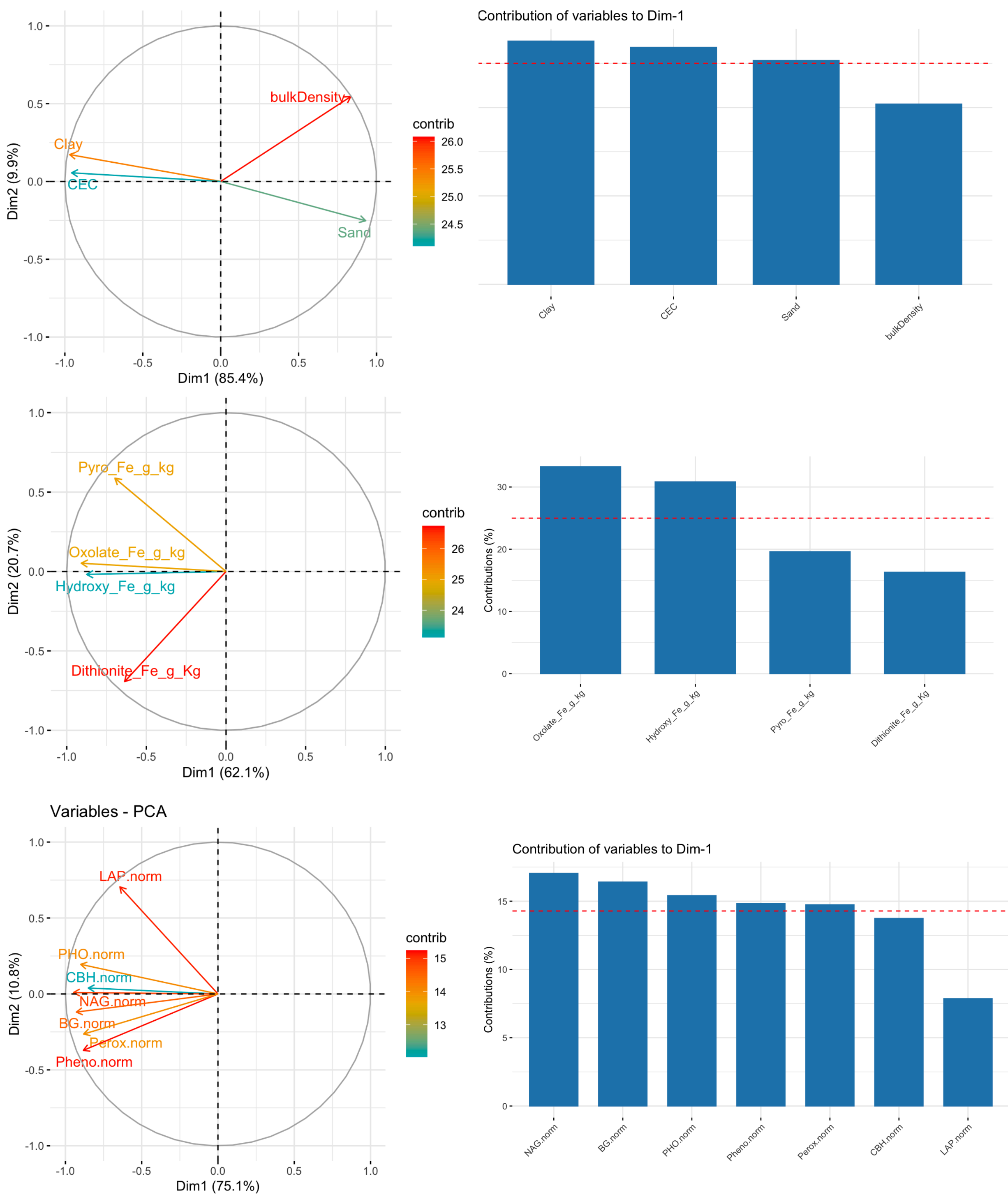


Figure S3: Principal component axes utilized for mixed models: physical edaphic characteristics, iron phases, and extracellular enzyme variable reduction.

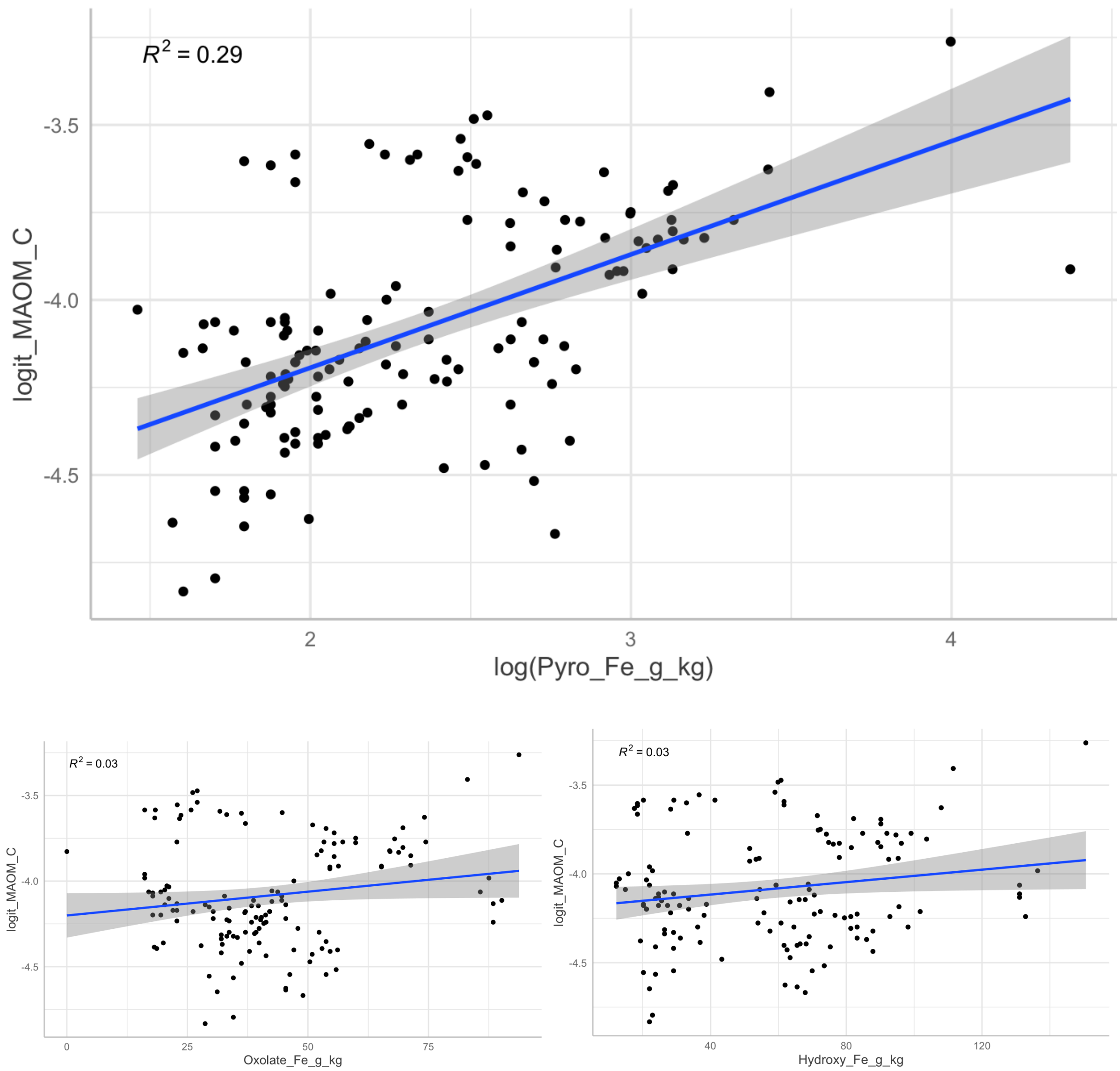


Figure S4: Soil Iron Fractions and MAOM C% (logit transformed). Pyrophosphate is log transformed to better display relationships given a larger spread of values.

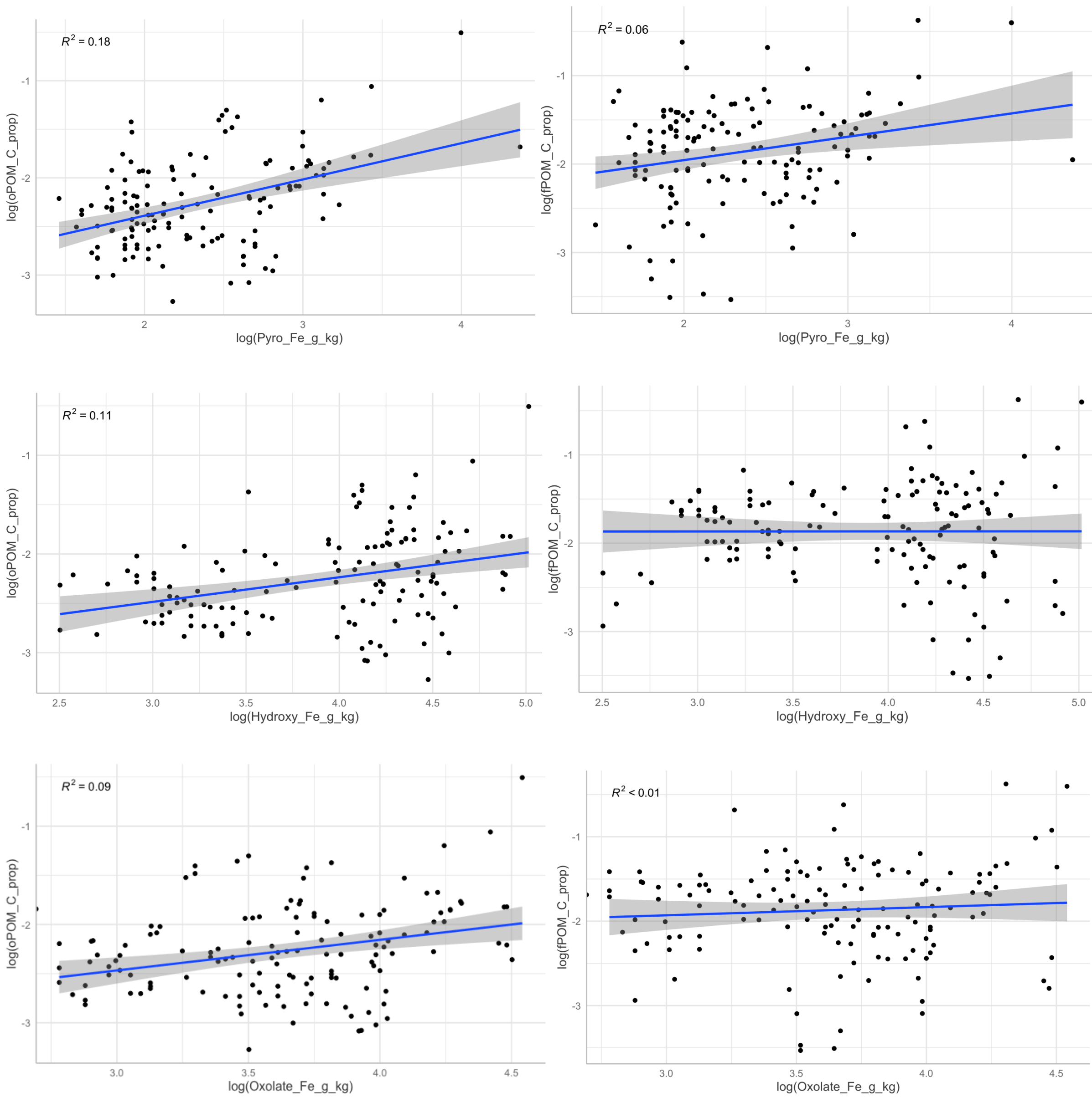


Figure S5: oPOM and fPOM versus distinct iron phase fractions. Strongest correlations with pyrophosphate extracted iron, and only oPOM has positive trends with the hydroxy and oxalate-extracted phases.

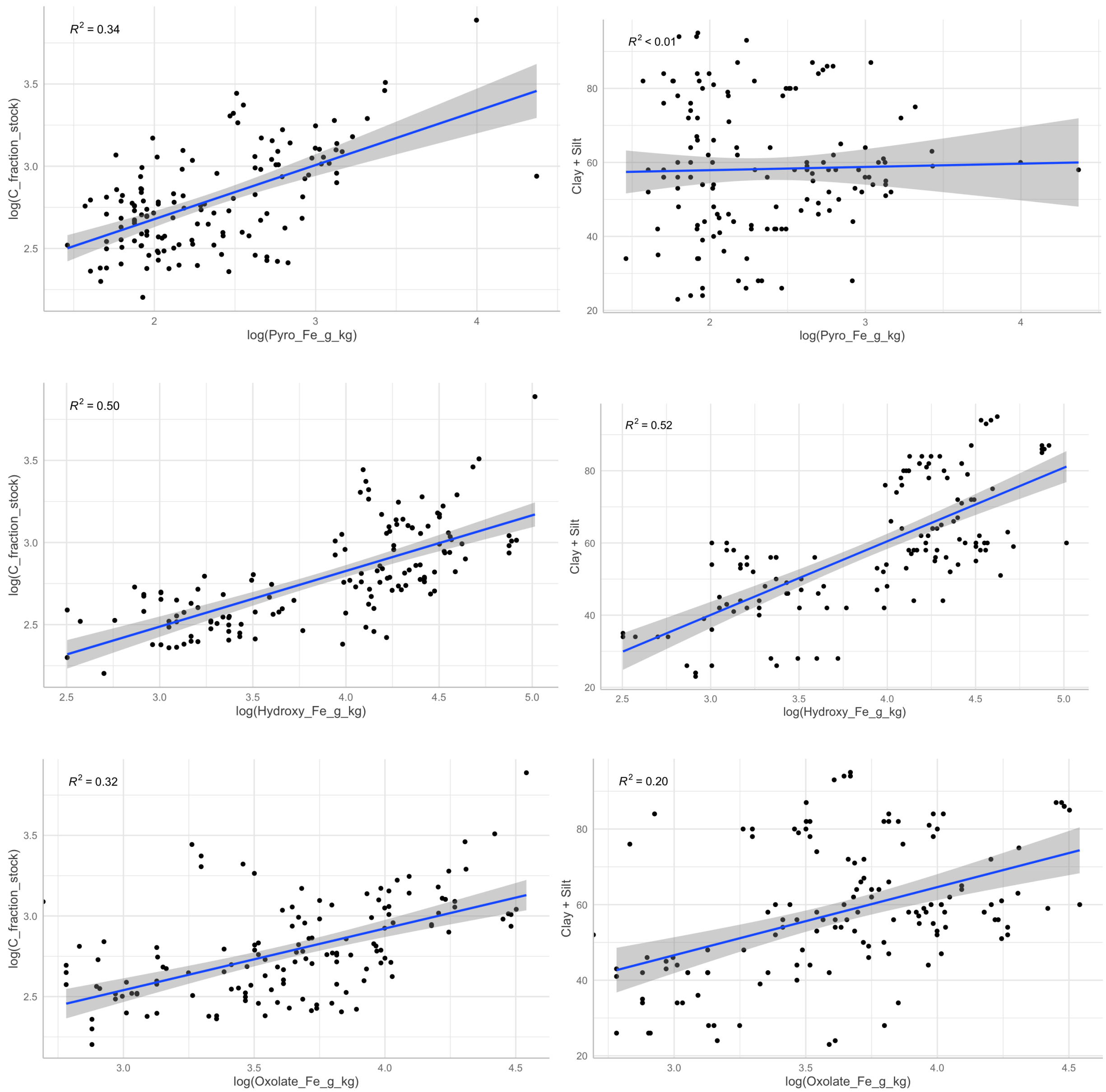


Figure S6: Carbon stocks and Clay + Silt versus three iron extractions. Clear positive trends for most relationships except for pyrophosphate-extracted iron and soil texture, where there is no clear trend.

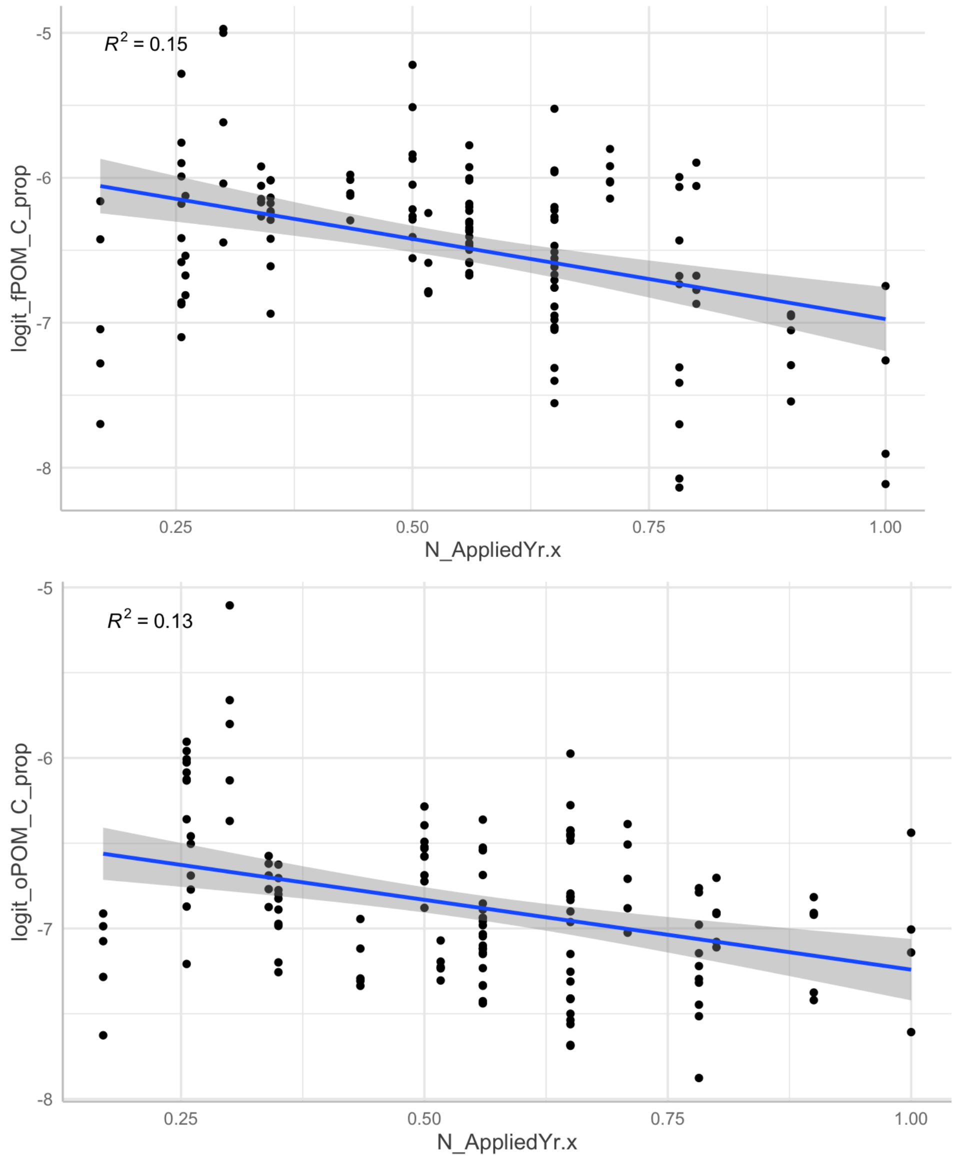


Figure S7: Decreasing fPOM and oPOM proportion with increased nitrogen application indicates potential priming effect.

Supplemental methods:

DNA extractions and sequencing

Soil was frozen at -80°C after sampling for subsequent DNA sequencing. DNA was extracted from 0.25g of soil using DNeasy PowerLyzer PowerSoil Kits (Qiagen) according to the manufacturer protocol. 3 replicate DNA extractions were performed for each sample. DNA was quantified using Quant-iT PicoGreen dsDNA Assay-Kit (Invitrogen) and equal amounts of DNA from the 3 replicates was pooled to create 1 composite DNA sample per soil sample.

Library prep and ITS2 and 16sV4 amplicon sequencing was done by the University of Minnesota Genomics Center. Template DNA was diluted to 1:8 and 1:64 and subjected to qPCR to assess template DNA quality. The primers V4_515F and V4_806R targeted the V4 locus in the 16S rRNA gene. For fungal amplicons we used ITS2 amplicons 5.8SFun (forward) and ITS4Fun (reverse) primers from Taylor et al (2016) as they match well with *Glomeromycotina* lineages. If necessary, samples were diluted with water and then amplicons were created using the same primers. Thermocycler conditions for qPCR were as follows: 95°C for 5 minutes then 35 cycles of: 98°C for 20 seconds, 55°C for 15 seconds, 72°C for 1 minute and 72°C for 5 minutes. Subsequent PCR products were diluted 1:100 in water. A second, 10-cycle PCR cycle was run to attach Illumina sequencing primer regions and individual barcodes for each sample. Samples were all uniquely dual-indexed, as detailed in Gohl, et al. (Gohl, et al., 2016). Final PCR products were normalized using SequalPrep kits (Invitrogen), pooled into sequencing libraries, and cleaned with AMPure XP mag beads (Beckman Coulter). Samples were normalized to 167,000 molecules/µl for paired-end sequencing on an Illumina MiSeq using a 2x300 v3 flow cell (Illumina, San Diego,CA).

Microbial biomass carbon and nitrogen

Microbial biomass C and N were determined via the direct fumigation method as described in Setia et al. (2012). Briefly, two subsamples per were divided into two falcon tubes with 16.67g soil. To one of the falcon tubes, 2.08 ml of ethanol free chloroform was added and to both falcon tubes, 40 ml of 0.5M K_2SO_4 was added. Samples were shaken for 30 minutes, centrifuged, filtered and the supernatant was bubbled for one hour to remove chloroform. Samples were analyzed for C and N on an elemental analyzer (VarioTOC Cube©, Elementar).

UC Berkeley soil management survey

Please fill out this survey referencing practices used at field [name/block] for the lettuce crop grown between [dates]. If you are unsure which field we sampled, please let us know so we can clarify.

Soil amendments and fertilizers:

Please fill out the table below indicating what type of fertilizers and soil amendments you use on your lettuce field.

Type of organic amendment or organic fertilizer applied	Rate of application (e.g. lbs N/acre) - please include units	When is it applied?	How is it applied? (e.g. broadcast)	What is the name or brand? Or please list NPK or C:N ratio
EXAMPLE: Pelleted chicken manure	100 lbs N /acre	2 weeks before transplant	Banded down the bed	True Organics

Cover crops:

If your operation uses cover crops, please fill out the following tables about the cover crop species planted at the specified field over the last few years.

2016 cover crop	2017 cover crop	2018 cover crop	2019 cover crop
EXAMPLE: Fava bean	None	Mustard	Winter wheat and rye

If you use cover crops, please fill out the following table:

When did you plant the 2019/2020 winter cover crop?	When did you terminate & incorporate this cover crop?	Will you plant a cover crop this winter (2020/2021)?	Did you plant a 2020 summer cover crop? If so, when
EXAMPLE: December 2019	March	No	Yes, in June

About how much of your lettuce field acreage is planted with a cover crop each season? *(ex. 40%)*

Cash crop rotation:

What cash crops were planted in the specified field over the past five years? (include fallow periods). If you grew multiple crops per year, please list them in the order they were planted

2015	2016	2017	2018	2019	2020
EXAMPLE: 1. Romaine Lettuce 2. Broccoli	1. Straw-berries	1. Straw-berries	1. Kale 2. Butter Lettuce	1. Butter lettuce 2. Broccoli	1. Romaine Lettuce 2. Summer cover crop

Tillage:

If you practice deep tillage (greater than 12 inches) of any kind (e.g. ripping) in your lettuce fields, please fill in the following table.

How deep do you till?	How often do you use deep tillage?	What was the last year deep tillage was used on this field	What month do you normally do this?	What percent of the field is tilled during deep tillage
EXAMPLE: 14 in	Before every crop	2020	March	100

Please describe your tillage and/or cultivation practices (other than deep ripping). **Please include** What implement, how often, how deep, and when you till, and how you prepare the beds.

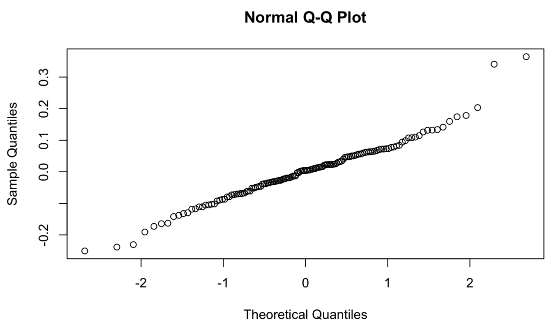
Irrigation: Please fill in the following table about your irrigation practices on the specified lettuce field.

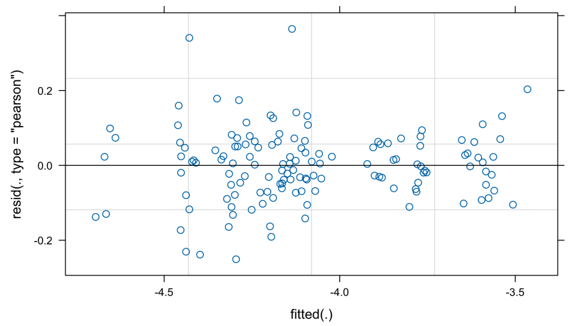
How many inches of water did you apply before planting lettuce in this field (in total)?	What type of preseason/transplant irrigation system do you use	What type of growing season irrigation system do you use?	How many inches of water did you apply during the 2020 lettuce crop (after planting) in total?
EXAMPLE: 3	sprinkler	sprinkler	12

Do you add chlorine to the water? Yes or No
If yes, to the preseason or production water or both?
If you answered yes, why do you use chlorine?
If you answered yes, for how many years have you used chlorine?

Model fit checks

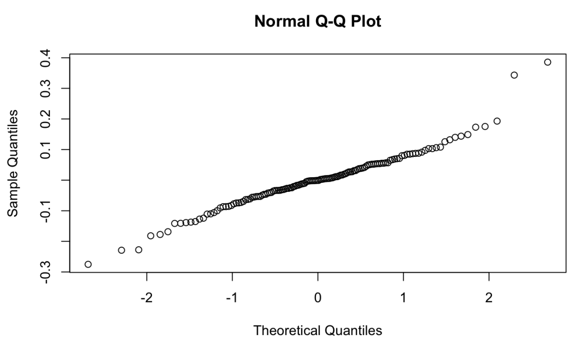
MAOM 1:

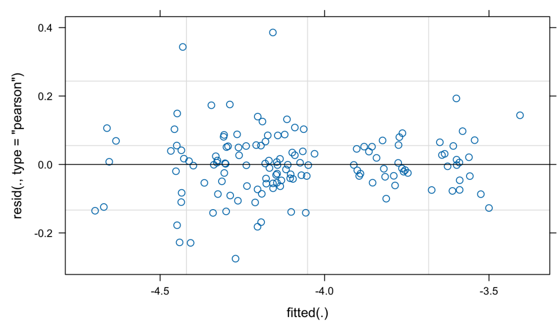





```
VIF:
soil_phys_scores soil_iron_scores               pH  CoverCrop_Z_rem    Disturbance_Z
        1.360383         1.194374         1.063132         1.338636         1.162723
       CropDiv_Z         Cinput_Z
        1.338195         1.450155
```

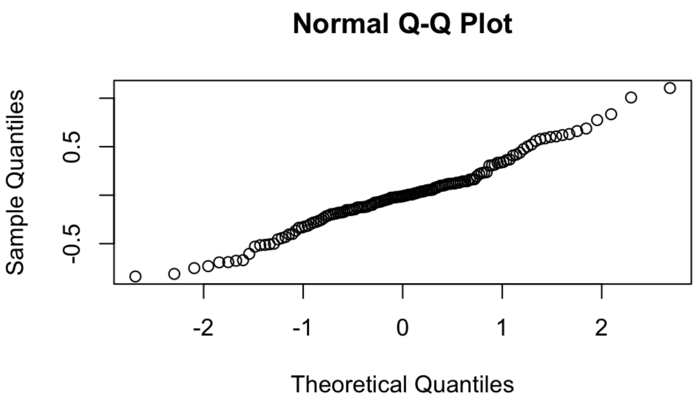
MAOM 2:

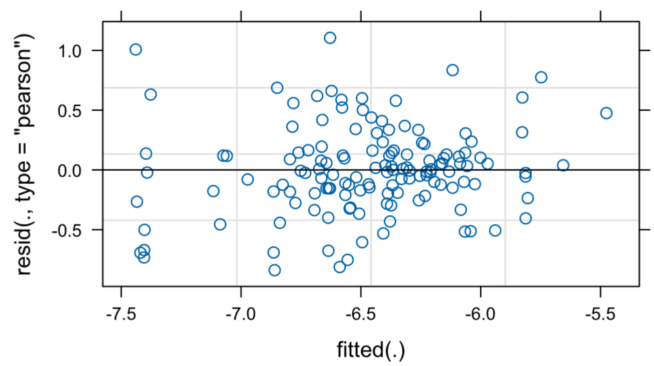





```
VIF:
soil_phys_scores   soil_iron_scores     soil_enzyme_scores          pH
        1.434775           1.252872               1.160380    1.152377
CoverCrop_Z_rem    Disturbance_Z         CropDiv_Z             Cinput_Z
1.348097             1.165278             1.339506             1.455429
```

fPOM 1:



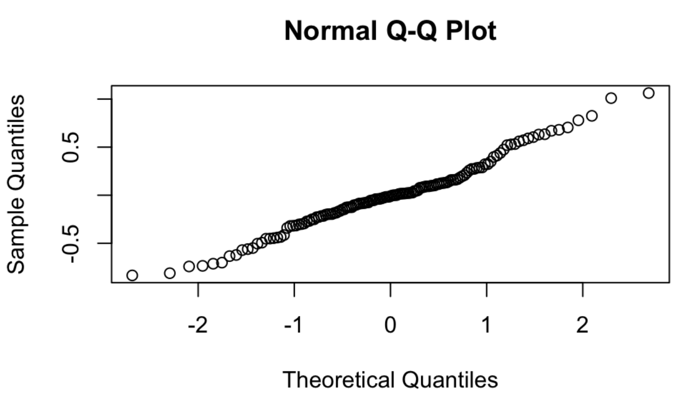


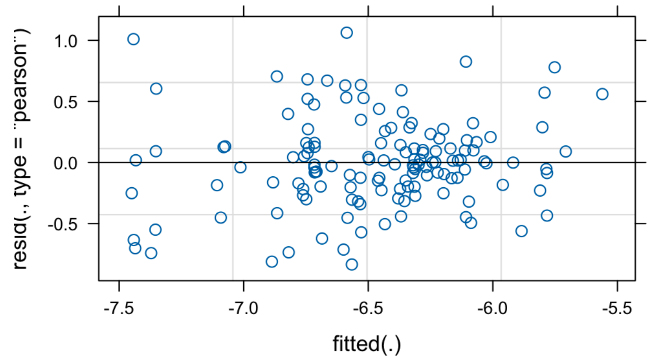
VIF:

Soil_phys_scores	soil_iron_scores	pH	CoverCrop_Z_rem	Disturbance_Z
1.732324	1.493375	1.116042	1.478738	1.189019

CropDiv_Z	Cinput_Z
1.395103	1.598201

fPOM 2:



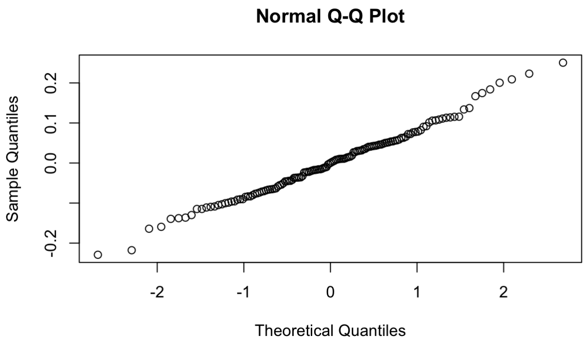


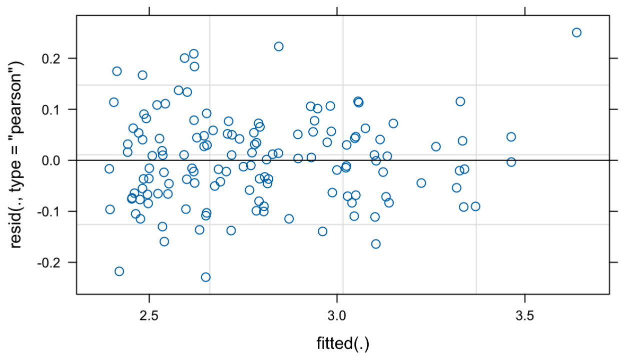
VIF:

soil_phys_scores	soil_iron_scores	pH	Prop5yr	DeepTillageFreq
2.222199	1.681237	1.115935	1.824689	1.397168

CropDiv_Z	Cinput_Z
1.868738	1.679382

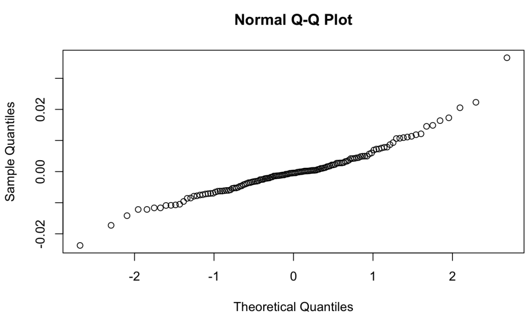
oPOM:

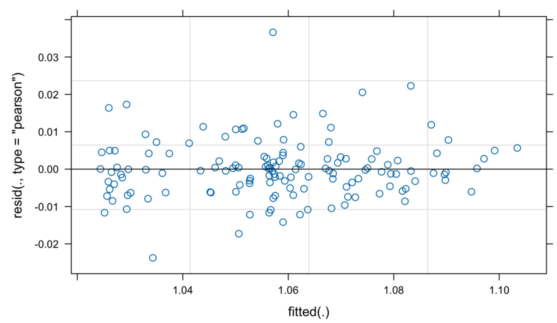





```
VIF:
soil_phys_scores soil_iron_scores               pH          Prop5yr    Disturbance_Z
        1.830358         1.295353         1.052876         1.596217         1.232987
      CropDiv_Z          Cinput_Z
       1.396249         1.326742
```

C stock (bulk):






```
soil_phys_scores soil_iron_scores               pH  CoverCrop_Z_rem        CropDiv_Z
        1.449288         1.246023         1.068774         1.379489         1.353208
   Disturbance_Z         Cinput_Z
        1.172728         1.488132
```

Carbon Stock model results with standard management z-scores:

```
log(C_fraction_stock) ~ soil_phys_scores + soil_iron_scores + pH
                  + CoverCrop_Z_rem + Disturbance_Z + CropDiv_Z + Cinput_Z
                  + (1 | Site)
------------------------------------------------------------------
                          Est.   S.E.   t val.     d.f.       p
---------------------- ------- ------ -------- -------- ----------
(Intercept)               3.41   0.39     8.81   103.69   3.14e-14
soil_phys_scores         -0.05   0.02    -2.33    40.58   0.03
soil_iron_scores          0.07   0.02     4.95   129.00   2.29e-06
pH                       -0.08   0.05    -1.61   105.06   0.11
CoverCrop_Z_rem           0.05   0.04     1.03    23.54   0.31
Disturbance_Z             0.04   0.04     0.88    21.41   0.39
CropDiv_Z                 0.06   0.04     1.44    21.77   0.16
Cinput_Z                 -0.03   0.05    -0.71    23.22   0.49
------------------------------------------------------------------
```

fPOM RF Variable Importance (root MSE of predicted versus permuted):

```
fPOM_C_stock                     fPOM_N_stock               soil_enzyme_scores
   0.195                            0.171                             0.095
  poxC                       N_AvailabilityMax          N_AvailabilityAverage
  0.092                            0.090                           0.086
ProportionCovercroppedOperation     CBH                          Prop5yr
            0.084                                                   0.078
0.078
N_AvailabilityMin                 N_fraction_stock          Prop_Cover2017
   0.076                               0.075                    0.075
soil_nitrogen_scores             N_AppliedYr              Pres_AbsJan2018
       0.072                        0.071                    0.067
  DeepTillageFreq
       0.063
```

oPOM model with specific variables:

```
logit_oPOM_C_prop ~ soil_phys_scores + soil_iron_scores + Prop5yr +
    TillageDepth + CropDiv_Z + Cinput_Z + (1 | Site)
```

FIXED EFFECTS:

	Est.	S.E.	t val.	d.f.	p
(Intercept)	-6.90	0.31	-22.24	25.70	4.21e-10
soil_phys_scores	0.01	0.04	0.34	36.02	0.73
soil_iron_scores	0.13	0.04	3.60	104.53	0.000678
Prop5yr	0.40	0.46	0.86	25.64	0.40
TillageDepth	0.32	0.29	1.10	22.05	0.28
CropDiv_Z	0.16	0.08	2.07	22.20	0.05
Cinput_Z	-0.10	0.07	-1.47	23.63	0.15

Bulk C model w/ Prop5yr:

FIXED EFFECTS:

	Est.	S.E.	t val.	d.f.	p
(Intercept)	1.0580	0.0030	358.0558	21.5634	0.0000
soil_phys_scores	-0.0281	0.0075	-3.7329	46.2097	0.0005
soil_iron_scores	0.0047	0.0042	1.1133	128.6745	0.2676
pH	-0.0053	0.0041	-1.2935	92.6334	0.1990
Prop5yr	0.0242	0.0075	3.2469	27.3039	0.0031
CropDiv_Z	0.0033	0.0070	0.4653	22.7899	0.6461
Disturbance_Z	-0.0053	0.0066	-0.8017	23.3423	0.4308
Cinput_Z	0.0005	0.0068	0.0788	23.6054	0.9379

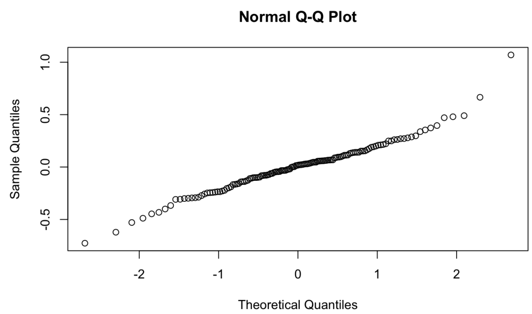
POM fractions with N_applied:

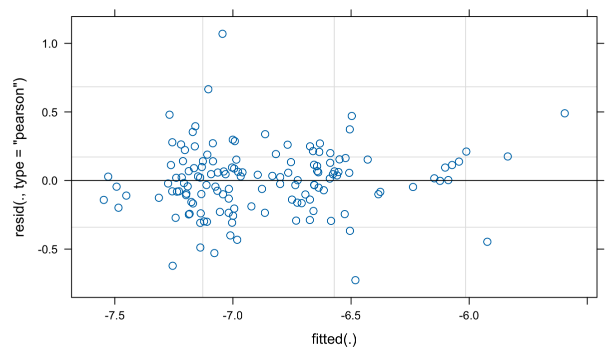
```
logit_oPOM_C_prop ~ soil_phys_scores + soil_iron_scores + lm_df$N_AppliedYr.x +
    CoverCrop_Z_rem + Disturbance_Z + CropDiv_Z + Cinput_Z +      (1 | Site)
```

FIXED EFFECTS:

	Est.	S.E.	t val.	d.f.	p
(Intercept)	-6.75	0.31	-21.87	20.89	0.00
soil_phys_scores	0.03	0.04	0.61	33.52	0.54

soil_iron_scores	0.12	0.04	3.42	100.92	0.00
N_AppliedYr	-0.21	0.56	-0.38	20.95	0.71
CoverCrop_Z_rem	0.06	0.09	0.62	21.12	0.54
Disturbance_Z	0.04	0.07	0.56	20.83	0.58
CropDiv_Z	0.16	0.09	1.75	21.47	0.09
Cinput_Z	-0.06	0.10	-0.67	23.12	0.51

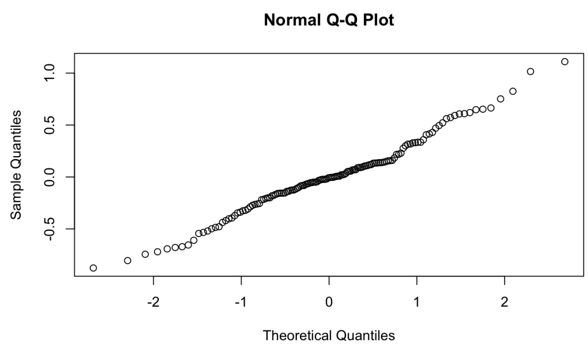


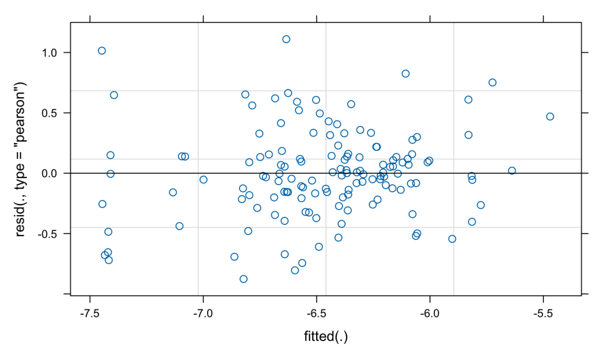



```
logit_fPOM_C_prop ~ soil_phys_scores + soil_iron_scores + N_AppliedYr.x +
    CoverCrop_Z_rem + Disturbance_Z + CropDiv_Z + Cinput_Z +      (1 | Site)
```

FIXED EFFECTS:

	Est.	S.E.	t val.	d.f.	p
(Intercept)	-6.14	0.39	-15.78	20.89	0.00
soil_phys_scores	0.07	0.06	1.26	31.77	0.22
soil_iron_scores	0.10	0.05	1.88	81.13	0.06
N_AppliedYr	-0.62	0.70	-0.89	20.96	0.38
CoverCrop_Z_rem	0.03	0.12	0.30	21.09	0.76
Disturbance_Z	-0.01	0.09	-0.10	20.72	0.93
CropDiv_Z	0.11	0.11	1.02	21.53	0.32
Cinput_Z	-0.07	0.12	-0.55	23.32	0.59





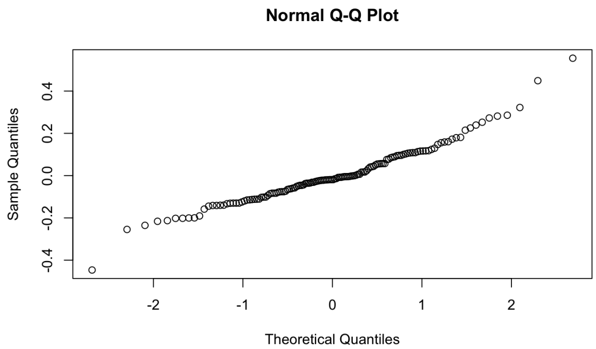
Yield verification:

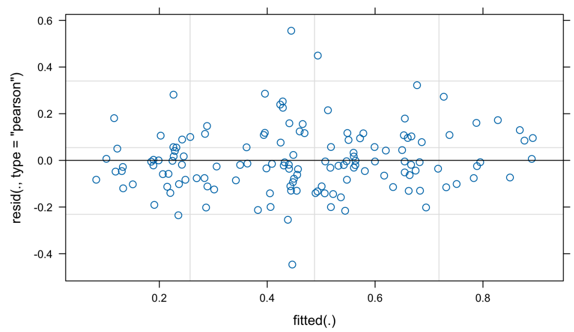
```
standardized_yield ~ soil_phys_scores + soil_iron_scores + CoverCrop_Z_rem +
    Disturbance_Z + CropDiv_Z + Cinput_Z + (1 | Site)
```

FIXED EFFECTS:

	Est.	S.E.	t val.	d.f.	p

(Intercept)	0.46	0.03	13.52	21.70	4.82e-12
soil_phys_scores	0.01	0.02	0.37	34.17	0.71
soil_iron_scores	-0.05	0.02	-2.63	95.94	0.01004
CoverCrop_Z_rem	0.05	0.04	1.14	24.36	0.27
Disturbance_Z	-0.01	0.04	-0.28	21.95	0.78
CropDiv_Z	-0.10	0.04	-2.57	22.31	0.02
Cinput_Z	0.15	0.04	3.62	24.03	0.00138



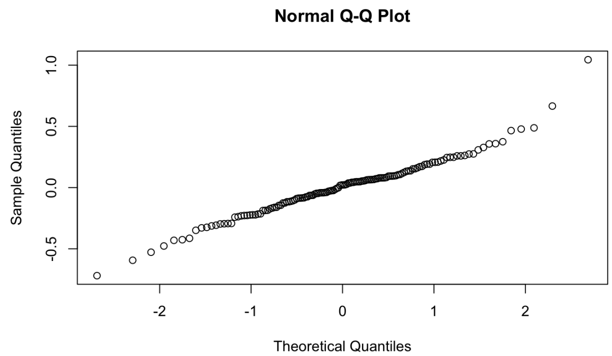


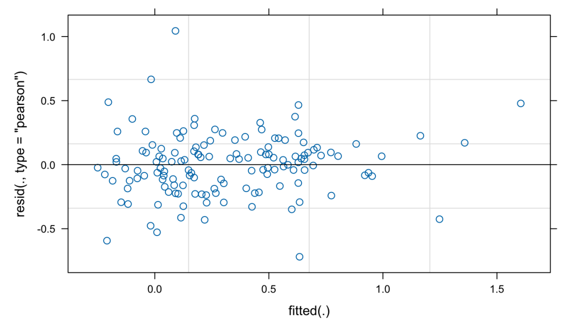
oPOM and fPOM stock models:

When we run the same model structures for fPOM and oPOM stocks rather than carbon proportion values, the results for oPOM differ slightly in that soil physical characteristics are significant. fPOM results remain unchanged in terms of which variables are significant. In the case of oPOM, we find that the oPOM stock increases slightly with sandier soils because they will have less carbon in the MAOM fraction, which dominates the overall carbon stock across all samples.

```
log(oPOM_C_stock) ~ soil_phys_scores + soil_iron_scores + pH +
    CoverCrop_Z_rem + Disturbance_Z + CropDiv_Z + Cinput_Z + (1 | Site)
FIXED EFFECTS:
```

	Est.	S.E.	t val.	d.f.	p
(Intercept)	0.55	0.82	0.67	55.66	0.51
soil_phys_scores	0.09	0.04	2.13	31.94	0.04
soil_iron_scores	0.14	0.04	3.86	94.38	0.0002
pH	-0.03	0.11	-0.28	56.00	0.78
CoverCrop_Z_rem	0.07	0.07	0.96	22.62	0.35
Disturbance_Z	0.04	0.07	0.56	20.42	0.58
CropDiv_Z	0.15	0.07	2.13	21.08	0.04
Cinput_Z	-0.07	0.08	-0.95	22.63	0.35



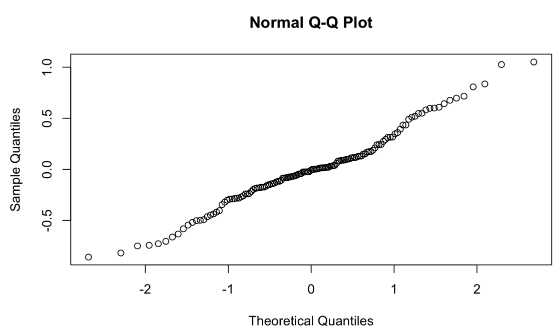


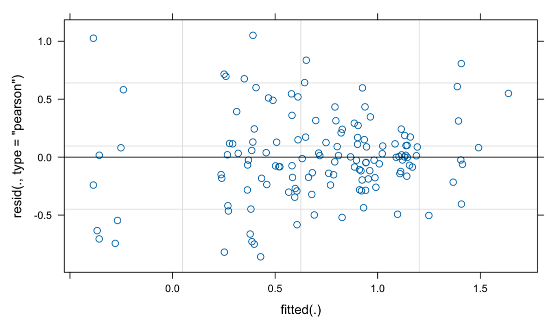

```
soil_phys_scores soil_iron_scores                pH   CoverCrop_Z_rem    Disturbance_Z
        1.667712         1.427696          1.102020          1.460060         1.186524
       CropDiv_Z          Cinput_Z
        1.386764         1.575725
```

```
log(fPOM_C_stock) ~ soil_phys_scores + soil_iron_scores + pH +
    Prop5yr + DeepTillageFreq + CropDiv_Z + Cinput_Z + (1 | Site)
```

FIXED EFFECTS:

	Est.	S.E.	t val.	d.f.	p
(Intercept)	-0.39	1.02	-0.38	35.68	0.71
soil_phys_scores	0.07	0.05	1.39	32.81	0.17
soil_iron_scores	0.09	0.05	1.84	70.27	0.07
pH	0.02	0.13	0.16	40.35	0.87
Prop5yr	1.42	0.52	2.75	24.65	0.01
DeepTillageFreq	-0.48	0.18	-2.61	20.83	0.02
CropDiv_Z	-0.01	0.09	-0.10	22.11	0.92
Cinput_Z	-0.01	0.08	-0.16	23.04	0.88






```
soil_phys_scores soil_iron_scores                pH           Prop5yr  DeepTillageFreq
        2.275531         1.730738          1.125883          1.844375         1.398467
       CropDiv_Z          Cinput_Z
        1.877561         1.690550
```

Model sensitivity

	MAOM			fPOM			oPOM		
Test	1	2	3	1	2	3	1	2	3
Intercept	-4.08 ± 0.05	-4.085 ± 0.049	-4.08 ± 0.050	-7.59081 ± 0.27848	-7.41 ± 0.324	-7.39 ± 0.99	-6.87 ± 0.06	-6.45 ± 0.83	-6.87 ± 0.06
Continuous Coverage	0.12 ± 0.06	0.11 ± 0.054	0.12 ± 0.054	Not Included	Not included	Not included	0.11 ± 0.07	0.08 ± 0.07	0.11 ± 0.07
Reduced Disturbance	0.1 ± 0.057	0.10 ± 0.052	0.11 ± 0.05	Not Included	Not included	Not included	0.06 ±0.07	REMOVED	REMOVED
C amendment	0.039 ± 0.0.06	REMOVED	REMOVED	REMOVED	-0.037 ± 0.085	-0.025 ± 0.07	REMOVED	-0.097 ± 0.07	REMOVED
Crop Diversity	0.04 ± 0.06	0.2529	REMOVED	-0.0087 ± 0.074	0.024 ± 0.09	REMOVED	0.14 ± 0.06	0.19 ± 0.07	0.14 ± 0.06
5 yr Cover Proportion	Not included	Not included	Not included	1.724 ± 0.469	1.40 ± 0.54	1.479 ± 0.42	Not included	Not included	Not included
Deep Tillage Frequency	Not included	Not included	Not included	-0.495 ± 0.172	-0.48 ± 0.19	-0.51 ± 0.16	Not included	Not included	Not included
Iron	0.35 ± 0.017	0.030 ± 0.17	0.029 ± 0.017	REMOVED	0.07 ± 0.05	0.069 ± 0.038	0.12 ± 0.03	0.12 ± 0.03	0.11 ± 0.03
pH	REMOVED	REMOVED	REMOVED	REMOVED	REMOVED	-0.009 ± 0.13	REMOVED	-0.05 ± 0.11	REMOVED
Soil Physical	0.05175 ± 0.03	0.036 ± 0.028	0.035 ± 0.028	-0.040 ± 0.0412	0.007 ±0.05	REMOVED	0.022 ± 0.04	REMOVED	0.01 ± 0.04
Enzymes	Not included	0.030 ±0.012	REMOVED	Not Included	Not included	Not included	Not included	Not included	Not included

Model sensitivity tests removing variables to ensure stable outcomes.

pSEM results

MAOM & Microbial Biomass Carbon:

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_MAOM_C	CoverCrop_Z_rem	0.1144	0.0540	23.9657	2.1187	0.0447	0.3470	*
logit_MAOM_C	Disturbance_Z	0.1112	0.0529	23.2798	2.1013	0.0466	0.3536	*
logit_MAOM_C	pH	-0.0647	0.0636	118.8553	-1.0165	0.3115	-0.0923	
logit_MAOM_C	soil_enzyme_scores	0.0226	0.0126	122.7239	1.8037	0.0737	0.1452	
logit_MAOM_C	MBC	0.0002	0.0003	125.3500	0.7496	0.4549	0.0561	
logit_MAOM_C	soil_iron_scores	0.0456	0.0199	124.8858	2.2922	0.0236	0.2217	*
logit_MAOM_C	soil_phys_scores	0.0418	0.0293	50.5113	1.4272	0.1597	0.2477	
soil_enzyme_scores	MBC	0.0031	0.0018	127.0971	1.7135	0.0891	0.1372	
soil_enzyme_scores	pH	-1.3621	0.4098	101.2567	-3.3242	0.0012	-0.3030	**
soil_enzyme_scores	soil_phys_scores	0.5475	0.1565	40.9055	3.4991	0.0011	0.5058	**
soil_enzyme_scores	soil_iron_scores	0.4071	0.1328	124.8524	3.0654	0.0027	0.3083	**
MBC	CoverCrop_Z_rem	-13.6058	16.0947	25.2210	-0.8454	0.4059	-0.1459	
MBC	Disturbance_Z	18.0085	16.0516	24.9582	1.1219	0.2726	0.2023	

16S & MAOM

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_MAOM_C	CoverCrop_Z_rem	0.1083	0.0537	24.0558	2.0156	0.0551	0.3287	
logit_MAOM_C	Disturbance_Z	0.1137	0.0522	22.6642	2.1774	0.0401	0.3616	
logit_MAOM_C	pH	-0.0678	0.0637	118.7033	-1.0646	0.2892	-0.0967	*
logit_MAOM_C	soil_enzyme_scores	0.0231	0.0125	122.8029	1.8549	0.0660	0.1483	

logit_MAOM_C	B16_log	0.0305	0.0343	119.0952	0.8874	0.3766	0.0554	
logit_MAOM_C	soil_iron_scores	0.0422	0.0196	125.7209	2.1544	0.0331	0.2049	
logit_MAOM_C	soil_phys_scores	0.0370	0.0290	49.2999	1.2765	0.2077	0.2192	*
soil_enzyme_scores	B16_log	0.2266	0.2427	128.1326	0.9335	0.3523	0.0642	
soil_enzyme_scores	pH	–1.3787	0.4141	102.7174	-3.3291	0.0012	-0.3067	
soil_enzyme_scores	soil_phys_scores	0.4848	0.1583	42.0048	3.0636	0.0038	0.4479	**
soil_enzyme_scores	soil_iron_scores	0.3552	0.1319	122.9742	2.6938	0.0081	0.2690	**
B16_log	CoverCrop_Z_rem	0.2027	0.0966	25.3094	2.0982	0.0460	0.3385	**
B16_log	Disturbance_Z	–0.0239	0.0962	24.8691	-0.2480	0.8061	-0.0417	*

MAOM & ITS abundance:

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_MAOM_C	CoverCrop_Z_rem	0.1080	0.0535	24.6302	2.0197	0.0544	0.3278	
logit_MAOM_C	Disturbance_Z	0.1109	0.0522	23.2550	2.1259	0.0443	0.3525	*
logit_MAOM_C	pH	–0.0602	0.0634	117.5670	-0.9486	0.3448	-0.0858	
logit_MAOM_C	soil_enzyme_scores	0.0249	0.0124	123.3279	2.0077	0.0469	0.1598	*
logit_MAOM_C	ITS_log	0.0319	0.0275	116.2837	1.1614	0.2479	0.0656	
logit_MAOM_C	soil_iron_scores	0.0417	0.0196	125.7717	2.1324	0.0349	0.2025	*
logit_MAOM_C	soil_phys_scores	0.0338	0.0292	49.4838	1.1583	0.2523	0.2001	
soil_enzyme_scores	ITS_log	–0.1239	0.1965	125.4181	-0.6304	0.5296	-0.0397	
soil_enzyme_scores	pH	–1.3561	0.4149	102.2765	-3.2688	0.0015	-0.3017	**
soil_enzyme_scores	soil_phys_scores	0.5255	0.1600	41.0807	3.2854	0.0021	0.4855	**
soil_enzyme_scores	soil_iron_scores	0.3659	0.1320	123.2098	2.7719	0.0064	0.2771	**
ITS_log	CoverCrop_Z_rem	0.2702	0.1002	25.5846	2.6970	0.0122	0.3989	*

ITS_log	Disturbance_Z	0.0264	0.0995	24.9409	0.2654	0.7929	0.0408	

MAOM and Shannon bacteria

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_MAOM_C	CoverCrop_Z_rem	0.1125	0.0548	24.5112	2.0552	0.0507	0.3415	
logit_MAOM_C	Disturbance_Z	0.1148	0.0536	23.6998	2.1411	0.0428	0.3650	*
logit_MAOM_C	pH	-0.0642	0.0639	119.9536	-1.0036	0.3176	-0.0916	
logit_MAOM_C	soil_enzyme_scores	0.0239	0.0125	122.6480	1.9218	0.0569	0.1536	
logit_MAOM_C	Shannon_bacteria	-0.0009	0.0380	108.2277	-0.0227	0.9819	-0.0011	
logit_MAOM_C	soil_iron_scores	0.0430	0.0197	125.4875	2.1876	0.0306	0.2091	*
logit_MAOM_C	soil_phys_scores	0.0403	0.0298	52.6617	1.3532	0.1818	0.2387	
soil_enzyme_scores	Shannon_bacteria	-0.1869	0.2767	113.9133	-0.6754	0.5008	-0.0356	
soil_enzyme_scores	pH	-1.3269	0.4161	103.0512	-3.1888	0.0019	-0.2952	**
soil_enzyme_scores	soil_phys_scores	0.5265	0.1595	41.8553	3.3002	0.0020	0.4864	**
soil_enzyme_scores	soil_iron_scores	0.3544	0.1324	122.9871	2.6766	0.0085	0.2684	**
Shannon_bacteria	CoverCrop_Z_rem	-0.0042	0.0522	22.2259	-0.0803	0.9367	-0.0104	
Shannon_bacteria	Disturbance_Z	0.0698	0.0498	20.7007	1.4012	0.1760	0.1816	
Shannon_bacteria	soil_iron_scores	-0.0308	0.0328	49.3115	-0.9389	0.3523	-0.1224	
Shannon_bacteria	soil_phys_scores	0.1057	0.0332	27.8744	3.1889	0.0035	0.5130	**

MAOM and Shannon fungal

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_MAOM_C	CoverCrop_Z_rem	0.1115	0.0548	24.3545	2.0328	0.0531	0.3383	
logit_MAOM_C	Disturbance_Z	0.1127	0.0539	24.2067	2.0903	0.0473	0.3582	*

logit_MAOM_C	pH	–0.0659	0.0640	118.5698	-1.0297	0.3053	-0.0940	
logit_MAOM_C	soil_enzyme_scores	0.0242	0.0124	122.6763	1.9430	0.0543	0.1550	
logit_MAOM_C	Shannon_fungal	0.0232	0.0626	121.4875	0.3698	0.7122	0.0293	
logit_MAOM_C	soil_iron_scores	0.0419	0.0199	124.6993	2.1108	0.0368	0.2036	*
logit_MAOM_C	soil_phys_scores	0.0371	0.0306	61.8933	1.2122	0.2300	0.2198	
soil_enzyme_scores	Shannon_fungal	–0.1950	0.4412	128.9109	-0.4419	0.6593	-0.0385	
soil_enzyme_scores	pH	–1.3428	0.4156	100.6068	-3.2310	0.0017	-0.2987	**
soil_enzyme_scores	soil_phys_scores	0.5347	0.1688	52.2791	3.1681	0.0026	0.4940	**
soil_enzyme_scores	soil_iron_scores	0.3730	0.1341	125.2254	2.7824	0.0062	0.2825	**
Shannon_fungal	CoverCrop_Z_rem	0.0519	0.0602	24.7611	0.8613	0.3973	0.1242	
Shannon_fungal	Disturbance_Z	0.0942	0.0589	24.1229	1.5997	0.1227	0.2364	
Shannon_fungal	soil_phys_scores	0.1177	0.0312	32.6639	3.7775	0.0006	0.5503	***

fPOM & MBC

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_fPOM_C_prop	Prop5yr	1.5657	0.3802	23.0825	4.1185	0.0004	0.4486	***
logit_fPOM_C_prop	DeepTillageFreq	–0.5043	0.1549	22.5727	-3.2549	0.0035	-0.3620	**
logit_fPOM_C_prop	MBC	0.0008	0.0006	51.1553	1.2044	0.2340	0.1187	
logit_fPOM_C_prop	soil_iron_scores	0.0891	0.0387	38.9818	2.3006	0.0269	0.2363	*
MBC	Prop5yr	–98.9779	96.0952	25.0609	-1.0300	0.3128	-0.1835	
MBC	DeepTillageFreq	–31.2854	38.9585	24.9794	-0.8030	0.4295	-0.1453	

fPOM & 16S

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_fPOM_C_prop	Prop5yr	1.3896	0.4069	26.0220	3.4149	0.0021	0.3982	**

logit_fPOM_C_prop	DeepTillageFreq	–0.4870	0.1655	25.1930	-2.9433	0.0069	-0.3497	**
logit_fPOM_C_prop	B16_log	0.0778	0.1005	90.3089	0.7738	0.4411	0.0772	
logit_fPOM_C_prop	soil_iron_scores	0.0830	0.0389	40.5353	2.1314	0.0392	0.2201	*
B16_log	Prop5yr	1.2812	0.5096	24.8533	2.5144	0.0188	0.3698	*
B16_log	DeepTillageFreq	–0.4614	0.2064	24.6796	-2.2357	0.0347	-0.3337	*

fPOM & ITS

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_fPOM_C_prop	Prop5yr	1.6642	0.4290	25.5665	3.8789	0.0007	0.4769	***
logit_fPOM_C_prop	DeepTillageFreq	–0.5775	0.1720	23.7094	-3.3572	0.0026	-0.4146	**
logit_fPOM_C_prop	ITS_log	–0.1084	0.0865	116.8168	-1.2529	0.2127	-0.1217	
logit_fPOM_C_prop	soil_iron_scores	0.0821	0.0403	41.5117	2.0372	0.0480	0.2177	*
ITS_log	Prop5yr	1.6185	0.5230	25.1386	3.0949	0.0048	0.4131	**
ITS_log	DeepTillageFreq	–0.5064	0.2116	24.8774	-2.3931	0.0246	-0.3238	*

fPOM & Shannon Fungal

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_fPOM_C_prop	Prop5yr	0.8825	0.4548	26.1651	1.9406	0.0632	0.2529	
logit_fPOM_C_prop	CropDiv_Z	0.0209	0.0796	21.0744	0.2625	0.7955	0.0361	
logit_fPOM_C_prop	DeepTillageFreq	–0.5162	0.1756	21.2317	-2.9402	0.0078	-0.3706	**
logit_fPOM_C_prop	Cinput_Z	–0.0456	0.0780	22.0996	-0.5850	0.5645	-0.0771	
logit_fPOM_C_prop	soil_iron_scores	0.0952	0.0394	39.5084	2.4149	0.0205	0.2525	*
logit_fPOM_C_prop	Shannon_fungal	0.4262	0.1578	60.7308	2.7020	0.0089	0.2950	**
Shannon_fungal	Prop5yr	1.2976	0.4089	22.8852	3.1732	0.0043	0.5373	**
Shannon_fungal	CropDiv_Z	0.0004	0.0807	22.8444	0.0048	0.9962	0.0010	

Shannon_fungal	DeepTillageFreq	0.0374	0.1767	22.8251	0.2118	0.8342	0.0388	
Shannon_fungal	Cinput_Z	0.0221	0.0771	22.9571	0.2871	0.7766	0.0541	

fPOM & Shannon Bacteria

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_fPOM_C_prop	Prop5yr	1.4255	0.4008	26.2693	3.5564	0.0015	0.4085	**
logit_fPOM_C_prop	DeepTillageFreq	–0.5146	0.1598	23.5918	-3.2196	0.0037	-0.3694	**
logit_fPOM_C_prop	Shannon_bacteria	0.0763	0.1263	128.7979	0.6040	0.5469	0.0509	
logit_fPOM_C_prop	soil_iron_scores	0.0887	0.0404	44.5856	2.1967	0.0333	0.2354	*
Shannon_bacteria	Prop5yr	0.8279	0.2811	21.5139	2.9454	0.0076	0.3556	**
Shannon_bacteria	DeepTillageFreq	–0.1043	0.1157	21.5554	-0.9016	0.3772	-0.1123	
Shannon_bacteria	soil_iron_scores	–0.0837	0.0279	40.1171	-2.9995	0.0046	-0.3329	**

oPOM & MBC

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_oPOM_C_prop	CoverCrop_Z_rem	0.1590	0.0556	25.1756	2.8624	0.0083	0.3338	**
logit_oPOM_C_prop	CropDiv_Z	0.1376	0.0546	23.8867	2.5202	0.0188	0.3011	*
logit_oPOM_C_prop	soil_iron_scores	0.1273	0.0294	59.9709	4.3314	0.0001	0.4275	***
logit_oPOM_C_prop	MBC	0.0016	0.0005	85.1490	3.3599	0.0012	0.3072	**
MBC	CoverCrop_Z_rem	–15.3880	16.4744	25.2102	-0.9341	0.3591	-0.1650	
MBC	CropDiv_Z	0.0265	16.4359	24.9810	0.0016	0.9987	0.0003	

oPOM & 16S

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate
logit_oPOM_C_prop	CoverCrop_Z_rem	0.1204	0.0618	24.6161	1.9486	0.0628	0.2527

logit_oPOM_C_prop	CropDiv_Z	0.1252	0.0611	23.7968	2.0490	0.0516	0.2741	
logit_oPOM_C_prop	soil_iron_scores	0.1107	0.0309	61.1952	3.5878	0.0007	0.3720	***
logit_oPOM_C_prop	B16_log	0.0725	0.0702	122.5531	1.0320	0.3041	0.0911	
B16_log	CoverCrop_Z_rem	0.1899	0.0903	25.3094	2.1042	0.0455	0.3171	*
B16_log	CropDiv_Z	0.1719	0.0898	24.8549	1.9134	0.0673	0.2992	

oPOM & ITS

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_oPOM_C_prop	CoverCrop_Z_rem	0.1213	0.0627	25.7799	1.9336	0.0642	0.2545	
logit_oPOM_C_prop	CropDiv_Z	0.1276	0.0616	24.3017	2.0710	0.0491	0.2793	*
logit_oPOM_C_prop	soil_iron_scores	0.1117	0.0311	63.9080	3.5911	0.0006	0.3752	***
logit_oPOM_C_prop	ITS_log	0.0513	0.0584	128.9924	0.8791	0.3810	0.0729	
ITS_log	CoverCrop_Z_rem	0.2507	0.0922	25.6272	2.7192	0.0116	0.3700	*
ITS_log	CropDiv_Z	0.1960	0.0915	24.9482	2.1418	0.0422	0.3017	*

oPOM & Shannon Bacteria

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_oPOM_C_prop	CoverCrop_Z_rem	0.1363	0.0629	25.4492	2.1663	0.0398	0.2861	*
logit_oPOM_C_prop	CropDiv_Z	0.1416	0.0628	25.1178	2.2561	0.0330	0.3098	*
logit_oPOM_C_prop	soil_iron_scores	0.1059	0.0322	73.0033	3.2827	0.0016	0.3556	**
logit_oPOM_C_prop	Shannon_bacteria	-0.0458	0.0817	125.2638	-0.5607	0.5760	-0.0387	
Shannon_bacteria	CoverCrop_Z_rem	0.0519	0.0530	22.9979	0.9790	0.3378	0.1290	
Shannon_bacteria	CropDiv_Z	0.0840	0.0524	22.0279	1.6038	0.1230	0.2177	
Shannon_bacteria	soil_iron_scores	-0.0880	0.0295	45.0625	-2.9881	0.0045	-0.3501	**

oPOM & Shannon Fungal

Response	Predictor	Estimate	Std.Error	DF	Crit.Value	P.Value	Std.Estimate	
logit_oPOM_C_prop	CoverCrop_Z_rem	0.1554	0.0646	26.3639	2.4071	0.0234	0.3261	*
logit_oPOM_C_prop	CropDiv_Z	0.1456	0.0629	24.5225	2.3159	0.0292	0.3187	*
logit_oPOM_C_prop	soil_iron_scores	0.1093	0.0314	69.0858	3.4782	0.0009	0.3671	***
logit_oPOM_C_prop	Shannon_fungal	-0.1780	0.1135	96.0813	-1.5675	0.1203	-0.1560	
Shannon_fungal	CoverCrop_Z_rem	0.1184	0.0729	24.4936	1.6239	0.1172	0.2836	
Shannon_fungal	CropDiv_Z	0.0450	0.0728	24.2832	0.6186	0.5419	0.1124	
Shannon_fungal	soil_iron_scores	0.0145	0.0260	122.9732	0.5567	0.5788	0.0555	

Chapter 3: Cultivating multifunctional soils: Enhancing ecosystem services through soil health management on organic vegetable farms

Abstract

Agroecosystems can provide a range of essential ecosystem services. Yet, a singular focus on crop production has often overshadowed and even imperiled other critical services. Management practices promoting soil health, such as continuous crop cover, reduced disturbance, increased crop diversity, and organic amendments, are known to enhance the soil-mediated ecosystem services including carbon sequestration, nutrient cycling, and maintenance of water quality. Yet how farmers can best manage agroecosystems to deliver diverse soil-based ecosystem services while maintaining crop production across varying edaphic conditions remains unclear, particularly in the context of working farms. We evaluated six ecosystem service indicators across 28 active organic lettuce fields in California's Central Coast, characterized by diverse edaphic and management conditions. Using mixed-effects models, we find that the proportion of continuous cover over 5 years increases soil fertility, while the proportion of cover over the previous year corresponds to increases in nutrient cycling capacity, microbial diversity, and may reduce residual end-of-season nitrate. Increased crop diversity also supports reduced residual nitrate and increased soil fertility. We find a potential trade-off between carbon sequestration and yield, but only for fields with low continuous cover and high disturbance. Furthermore, our analysis suggests that management practices exert more influence on ecosystem service provision than edaphic variables including texture, CEC, and pH. Finally, our findings reveal that continuous living cover over the previous 5 years fosters agroecosystem multifunctionality across different prioritization schemes of ecosystem services. Altogether, we demonstrate that growers can enhance individual service provision, reduce trade-offs between services, and improve ecosystem multifunctionality through the implementation of soil health practices across diverse edaphic conditions. This study underscores the importance of policy measures supporting the increased adoption of soil health management to enhance vital ecosystem services and multifunctionality to benefit on-farm production and improve overall environmental quality on the landscape level.

Introduction

Over the past century, industrial agriculture has driven a model of farming that has prioritized crop production, often at the expense of other vital soil-based ecosystem services. Beyond crop provision, soils support rich micro and macro biodiversity (Anthony et al., 2023), help regulate the global climate (Lal et al., 2021), and aid in maintaining water quality (Lehmann et al., 2020; Smith et al., 2015; Smukler et al., 2012). However, a singular focus on crop production has, in most cases, eroded soil health and other vital soil functions (Schulte et al., 2014). For example, intensive agricultural production has compromised agrobiodiversity (Dainese et al., 2019), depleted soil organic matter and carbon stores (Sanderman et al., 2017), and created poor water quality through run-off of excess nitrates and other pollutants (Abdalla et al., 2019; Almasri & Kaluarachchi, 2004; Hamilton & Helsel, 1995).

Determining how to best balance these functions is challenging, particularly given the need for farmers to maintain production levels for economic viability, at least in the dominant capitalist political economy. Over the last decade, diversified farming systems (DFS) have emerged as an alternative to the extractive model of industrial agriculture, building on agroecological principles prioritizing agro-biodiversity and ecosystem processes at multiple spatial and temporal scales (Kremen et al., 2012). DFS leverages agroecosystem biodiversity and ecosystem processes to create productive and ecologically sustainable farming systems. Initially, much of this literature focused on aboveground diversification, prioritizing practices including crop diversification, planting of hedgerows and non-crop vegetation, and livestock integration, all of which benefit a range of ecosystem services including enhanced soil fertility, pest, weed, and disease control, and pollination services. Gradually, belowground biodiversity and soil-mediated ecosystem services beyond 'fertility' have become more explicitly integrated into the DFS framework (Isbell et al., 2017; Rosa-Schleich et al., 2019; Tamburini et al., 2016).

Parallel to the development and spread of DFS research, the USDA-Natural Resources Conservation Service popularized a set of principles, in many ways overlapping with the principles of DFS, to help guide land managers and farmers in improving the health of their soils. These principles include maximizing continuous living roots (e.g., cover crops, perennial vegetation), minimizing soil disturbance (e.g., reducing the intensity, frequency, and depth of tillage), maximizing biodiversity (e.g., crop rotation, pollinator plantings), and maximizing soil cover (e.g., mulching and crop residues) (NRCS, 2024). While not explicitly included in these principles, green manures and other organic soil amendments are common in organic farming systems. These practices help build soil structure, reduce erosion, and contribute energy and food sources for soil life that underpin soil-mediated ecosystem services (Abdalla et al., 2019; Beillouin et al., 2021; De Gryze et al., 2011; Lal, 2014; Paustian et al., 2016; Six et al., 1999).

The DFS framework and soil health guidelines both have a particular focus on building soil organic matter as a primary goal and metric for building soil health. Within the soil science community, there continues to be a robust discussion of the meaning of 'soil health' and its appropriate indicators (Janzen et al., 2021; Lehmann et al., 2020a; Wade et al., 2022). However, in the broader literature on ecosystem services, soil organic carbon is often a catch-all indicator of soil health and fertility (Beillouin et al., 2021; Tamburini et al., 2020), despite functional differences in the various components of SOC (e.g., particulate and mineral-associated organic matter; Chapter 2). While SOC is a very important aspect of soil health (relating to increased water-holding capacity, nutrient provision, and improved soil structure), it alone can only tell us so much about the functioning and health of soils.

Complementary to the vast literature on ecosystem services, research into an ecosystem's capacity to provide multiple services simultaneously – known as ecosystem multifunctionality (EMF)– has also become widespread. This term is now widely applied across a wide range of ecological, soil, and management research, with disparate measurements and protocols around its use (Garland, Banerjee, et al., 2021; Hölting et al., 2019; Manning et al., 2018). For example, much of the literature on soil multifunctionality focuses largely on the capacity for soils to cycle different nutrients through the soil system (Delgado-Baquerizo et al., 2016; Wagg et al., 2019), and the role of microbial diversity in supporting multifunctionality (Delgado-Baquerizo et al., 2016, 2017). At the landscape level, multifunctionality has the potential to meet the diverse needs of society (Kremen & Merenlender, 2018) but different stakeholders in a region may stand to benefit differentially from various services (Turkelboom et al., 2018). For example, farmers are likely to prioritize crop production, though those with ecological goals may also be interested in simultaneously increasing soil fertility and soil carbon stocks (particularly in light of carbon market opportunities for large growers). Meanwhile, regional water boards and environmental groups may prioritize regional water quality outcomes. Thus, it is increasingly recognized that in a land management context, multifunctionality assessments benefit from consideration of the priorities of multiple stakeholders (Hölting et al., 2020; Manning et al., 2018).

Beyond these stakeholder considerations, assessing the multifunctionality of soils is also challenged by the fact that soil biogeochemical dynamics are strongly influenced by local climatic and inherent qualities of a given region, alongside land management factors. Climatic conditions and edaphic characteristics such as texture, cation exchange capacity, pH, and local mineralogy can drive changes in water holding capacity, nutrient cycling dynamics, and microbial activity and diversity, all of which influence soil multifunctionality (W. Hu et al., 2021; Nazaries et al., 2021; Zheng et al., 2019). If inherent soil properties are the primary driver of soil ecosystem services, then implementing soil health management systems may not exert much influence. However, parsing the relative impact of local edaphic factors and land management practices on multiple ecosystem services has not been widely studied in agricultural systems. Thus, an important knowledge gap is how soil health practices affect ecosystem services important to different stakeholders while accounting for variable edaphic conditions (Schulte et al., 2014; Vazquez et al., 2021; Zwetsloot et al., 2021). Understanding these relationships could inform the development of policies that support the maintenance of crop production along with prioritization of specific ecosystem services, and multifunctionality generally.

In this study, we take an on-farm approach to evaluate the impact of multiple soil health management practices on crop provisioning, carbon sequestration, maintenance of water quality, nutrient cycling capacity, efficiency of microbial nutrient cycling, soil fertility, and soil biodiversity (Table 1). Specifically, we ask:

1. How do edaphic and management factors impact various ecosystem services, and what is the relative influence of management versus edaphic variables?
2. What tradeoffs and synergies exist between our suite of ecosystem services? and,
3. What soil health management practices, if any, are important for soil multifunctionality? How might this change for varying prioritizations of soil services (production vs. environmental quality vs. soil microbial diversity and activity)?

We anticipate that continuous cover and reduced disturbance will increase carbon inputs and stability, and thus support carbon sequestration, microbial diversity, and nutrient cycling capacity, and also help support water quality by retaining nutrients. Crop diversification may also support increased microbial diversity by providing varied inputs (D'Acunto et al., 2018; Wooliver et al., 2022). We also expect that organic amendments will increase crop production and provide an energy source for microbial communities, potentially impacting microbial diversity and nutrient cycling capacity. But trade-offs between yield and water quality may occur when such amendments increase yields and also the potential for excess nutrients at the end of the season. Finally, yield and soil fertility are expected to positively correlate (Oldfield et al., 2019; Wood et al., 2016), though this relationship may depend on edaphic characteristics (Schjønning et al., 2018).

Leveraging in-depth management surveys of farmers, soil bacterial and fungal diversity assays, and a range of soil physicochemical metrics from 28 farms across the Central Coast region of California, we parse the impacts of management and edaphic variables on individual ecosystem services and multifunctionality using mixed-effects models and assess synergies and tradeoffs. The Central Coast region is characterized by widespread intensive agriculture that has depleted SOC and faces several major environmental challenges including the quality and quantity of groundwater (Rosenstock et al., 2014). Research in this region has found that soil health practices such as cover cropping can promote efficient nitrogen use and increase soil organic carbon in organic vegetable systems, while compost applications dramatically increases the total soil N and nitrate levels, much of which is thought to leach out of the system (White, Brennan, & Cavigelli, 2020; White, Brennan, Cavigelli, et al., 2020a; White et al., 2022). However, a comprehensive assessment of multiple practices and services has not been conducted.

Ultimately, we find that at least one of the four soil health practices evaluated positively relates to each of the ecosystem services considered and that only one negative relationship exists. These soil health practices also support composite multifunctionality (considering all services at once) across multiple prioritization weightings and a range of inherent soil characteristics. Thus, soil health management has the potential to support a range of individual ecosystem services, as well as multifunctionality across agroecosystems.

Methods

Study region and sampling

Study area and field sites

Our study centered on farms in San Benito, Santa Cruz, and Monterey Counties at the northern end of California's Central Coast region (Chapter 2, Figure 1). This area has a stable temperate Mediterranean climate, with warm, dry summers and wet winters (Köppen-Geiger Zone Csb). It is characterized by a diverse mix of small-scale farms, larger wholesale growers, and grazing lands (Olimpi, in review). The region is among the most productive and economically significant agricultural areas in the US, particularly for fresh produce (CDFA, 2022). Farms in this region vary in scale from 0.5 ha of production to 600+ ha. All participating farmers cultivated organic lettuce to some degree. We chose this crop because it is one of the most valuable crops in the region (County of Monterey Agricultural Commissioner, 2021; San Benito County Agricultural Commissioner, 2020; Santa Cruz County Agricultural Commissioner, 2021). We identified participating farmers using the USDA Organic Integrity Database and in collaboration with local technical assistance providers.

Field sampling

We designed field sampling to collect information on key ecosystem services (see below) at times during the growing season most relevant to each service. All samples were gathered during the 2020 growing season. At each of the 28 field sites, we collected five soil samples along a 100 m transect positioned centrally within each lettuce field, beginning at least 10 m away from the field edge. Each sample consisted of a composite of five sub-samples. Soil collection occurred at three distinct time points: during transplant, mid-season (approximately 3-6 weeks post-transplant, depending on lettuce variety), and at harvest (1-7 days before lettuce harvest). Soil samples were obtained from depths of 0-15 cm, 15-30 cm, and 30-60 cm (for transplant and harvest sampling), and from 0-15 cm depth for mid-season sampling. At harvest (1-7 days prior to lettuce harvest), we collected 5 heads of lettuce at each field replicate location.

Soil series and order data were collected for each field location using latitude and longitude coordinates from the NRCS SSURGO database via SoilWeb (O'Geen et al., 2017). Most soils are classified as Mollisols (20 sites), with Alfisols, Entisols, and Vertisols representing four, three, and one site, respectively. Despite the limited geographic area, California exhibits a high degree of soil heterogeneity, with our sites encompassing various soil series, including four sites in the Sorrento series, three in the Chualar series, and two in the Placentia series. Detailed SSURGO data descriptions for our sites can be found in the supplement.

Selection of ecosystem services and indicators

We selected six ecosystem services of economic and environmental importance for the Central Coast region to assess and related measurable indicators for each service (Table 1): crop provisioning (measured as normalized yield), climate regulation/soil carbon sequestration (measured as soil organic carbon stocks from 0 - 60 cm depth), nitrate leaching risk (measured as end-of-season residual soil nitrate), soil nutrient cycling capacity and efficiency (measured as absolute and mass-specific enzyme activity, respectively), soil fertility (measured as particulate organic matter stock), and lastly soil habitat provisioning (measured as fungal and bacterial Shannon diversity). Services and their indicators were selected based on available data, feasibility of data collection, and using criteria including stakeholder legibility and scientific credibility, as outlined by van Oudenhoven et al. (2018). Most indicators positively relate to the service they represent (e.g. normalized yield with crop production service). For nitrate leaching risk, we used an inverse metric such that higher values correspond to risk mitigation (e.g. higher end-of-season nitrate corresponds to low service score). For some metrics, the indicator is a direct measure of a given service (e.g. crop production in terms of yield or Shannon diversity for soil biodiversity), whereas others are indirect measures of ecosystem characteristics that underpin a given service (e.g. particulate organic matter for soil fertility). Methods for gathering different proxies are outlined below.

Indicator measurements

Crop provisioning

Crop provisioning was measured using normalized yields. Lettuce samples were dried at 65°C. To obtain yield per unit area, a harvest density in heads/m^2 was measured for each field. We then multiplied the average dry biomass per head by the harvest density to get a yield estimate in kg/ha. Because different farms grew different varieties of lettuce (romaine, butter, iceberg, leaf mix), we normalized yields to create a comparable yield metric across lettuce varieties. The normalized yield for each lettuce type was calculated as follows:

$$Yield_{norm} = (Yield_i - Yield_{min})/(Yield_{max} - Yield_{min})$$

Where $Yield_{min}$ and $Yield_{max}$ correspond to minimum and maximum yields for a particular lettuce variety across all fields growing this lettuce variety, and $Yield_i$ corresponds to each replicate sample for that same lettuce variety.

Nutrient cycling capacity and efficiency

Nutrient cycling capacity and efficiency were estimated using absolute and mass-specific extracellular enzyme potentials, respectively. Soils were kept cool in an iced cooler in the field and transferred to a fridge (~4 ºC) before analysis. Within 48 hours of soil sampling, potential extracellular enzyme activities were measured fluorometrically and photometrically using a microplate assay (Bach et al., 2013; German et al., 2011). Two grams of fresh, sieved soil were added to 100mL of 50 mM sodium acetate buffer (pH=5.5) and blended for 30 seconds. For the fluorometric assays (hydrolytic enzymes), MUF (4-methylumbelliferone) and AMC (7-amino-4-methylcoumarin) labeled substrates were used. Specifically, the enzymes glucanase/1,4-β-cellobiosidase (CBH), β-glucosidase (BG), exochitinase (NAG), and phosphatase (PHO) used the substrates MUF-cellobioside, MUF-β-glucopyranoside, MUF-N-acetyl-β-D-glucosaminide, MUF-phosphate, respectively. For the enzyme leucine-amino-peptidase (LAP), the substrate L-leucine-7-amido-4methylcoumarin was used. Samples were incubated at room temperature (22°C) in the dark and measured at 1.5 h and 3 h (excitation: 365 nm, emission: 450 nm).

The oxidative enzymes peroxidase and phenoloxidase were analyzed from the same buffered soil solution. Briefly, 0.9 mL of 20 mM L-3,4-dihydroxyphenylalanine (DOPA) was added to 0.9 ml of soil suspension in triplicates for a final concentration of 10 mM DOPA, shaken on high speed for 10 min, and centrifuged for 10 min at 14,000 g. To clear microplates, paired samples for phenoloxidase and peroxidase were pipetted in triplicates with the peroxidase samples receiving an additional 10 µL of 0.3% hydrogen peroxide. Absorption was measured at 450 nm at time 0 and after incubating microplates in the dark for 20 hours. Mass-specific enzyme activities were calculated by normalizing activity levels to microbial biomass C measured using the chloroform direct extraction method (Setia et al., 2012).

We report both absolute and mass-specific enzyme activities, as they provide distinct insights into microbial community dynamics, with mass-specific activities often being more responsive to management (Raiesi & Beheshti, 2014). Mass-specific enzyme activities were calculated by normalizing activity levels to microbial biomass C measured using the chloroform direct extraction method (Setia et al., 2012). Subsequently, soil enzyme activities were scaled using a z-score calculation and averaged to generate a composite enzyme activity score for analysis.

Carbon sequestration

Carbon sequestration was estimated via carbon stocks down to 60 cm. Bulk soil samples were dried at 35ºC, sieved to 2 mm and then ball milled for elemental analysis. Total carbon (TC%) was analyzed by combustion on an Elementar varioEL Cube (Elementar, Ronkonkoma, NY). The same samples were also analyzed by combustion with a temperature ramping procedure on an Elementar SoliTOC, which measures inorganic carbon. TIC values were negligible (<0.1%), so we consider varioEL measurements as total organic carbon (TOC).

Carbon stocks were calculated by multiplying C concentrations, depth increments (0.15 m for 0-15 cm and 15-30 cm depths and 0.3 m for 30-60 cm depth), bulk density (BD) estimates, and unit area (per hectare), resulting in kg C/ha. At the 0-15 cm depth BD was measured using a cylindrical ring (height = 12.34 cm, diameter = 5.08 cm). Samples were dried at 105 °C for 3 days. Dry soil weight was measured and divided by the volume of the cylinder. Bulk density at deeper depths relied on a pedotransfer function that was determined to have the best fit for measured 0-15 cm BD values ($R^2 = 0.12$). The function from Hollis et al., (2012) is as follows:

$$BD = 0.69794 + 0.750636 * e^{-0.230355 * SOC} + 0.0008687 * Sand - 0.0005164 * Clay$$

Soil fertility

Soil fertility was measured using particulate organic matter stocks. Mid-season 0-15 cm soil samples were fractionated by size and density into four functionally distinct pools: Dissolved organic matter (DOM), free particulate organic matter (fPOM), occluded particulate organic matter (oPOM), and mineral-associated organic matter (MAOM). These samples were dried at 35°C and sieved but not ground prior to fractionation. Reported POM values add fPOM and oPOM together. The following protocol is also described in Chapter 2.

Fractionations followed the protocol described by Haddix et al. (2020) with slight modification for high-clay soils. Whereas many fractionation methods separate particulate organic matter (POM) after aggregate dispersion into light and heavy fractions, this protocol separates POM before and after aggregate dispersion into fPOM and oPOM. Thus, it may provide information on how management decisions may impact soil aggregates, which offer short-term OM protection from microbial decay.

We first separated dissolved organic matter by shaking sieved, oven-dried samples with 40 mL of DI water for 15 min and centrifuging at 2520 g for 15 min. DOM is extracted as the resulting supernatant. fPOM is then fractionated by resuspending the remaining soil pellet using sodium polytungstate solution prepared at 1.85 g/cm3, and remaining oPOM and MAOM were fractionated by size (oPOM >53µm and MAOM < 53 µm) by wet sieving. High-clay soils received an additional DI rinse and centrifugation with ten additional drops of flocculants 0.25 M CaCl2 and 0.25M MgCl2 to help clear excess sodium polytungstate solution.

We ensured that fractions were recovered to +/- 5% of the original sample weight. Fraction samples were then dried, and ball milled. Carbon in fPOM, oPOM, and MAOM fractions was measured by combustion analysis on a varioEL cube (Elementar, Ronkonkoma, NY). fPOM and MAOM were weighed to 20mg, while oPOM, because of its lower organic content, was weighed to 100mg.

Nitrate leaching risk

While nitrate leaching depends on many factors including irrigation volumes, subsequent crops or cover crops, CEC, OM content, and soil texture, we take residual soil nitrate levels at lettuce harvest as an indicator of nitrate leaching potential (Khakural & Robert, 1993). Soil nitrate was measured at all depths (0-15, 15-30, 30-60 cm) using 2M KCl soil extracts with a 2.5:1 ratio of KCl to soil followed by colorimetry. Extracts were measured in triplicate with a saturated solution of VCl_3 in 1 M HCl after 12-16 hours (540 nm) following a modified protocol from Miranda et al. (2001). Nitrate stock was calculated by multiplying concentrations by the relevant depth increments (.15 m for 0-15 cm, and 15-30 cm depths and .3 m for 30-60 cm depth), bulk density estimates, and unit area (calculated per hectare) resulting in kg NO_3^--N/ha. Harvest sampling times varied from April to August depending on the planting date and lettuce development across farms.

Soil habitat provisioning

We measured soil habitat provisioning by assessing Shannon diversity of both fungal and bacterial taxa. We then scaled fungal and bacterial Shannon diversity independently using a z-score calculation and take their average to arrive at a single value for soil microbial diversity.

DNA extractions and sequencing

Methods for DNA extraction and sequencing have also been described in Khondoker et al. (*in prep*). Soil samples were frozen at -80°C after sampling for subsequent DNA sequencing. DNA was extracted from 0.25 g of soil using DNeasy PowerLyzer PowerSoil Kits (Qiagen) according to the manufacturer's protocol. 3 replicate DNA extractions were performed for each sample. DNA was quantified using Quant-iT PicoGreen dsDNA Assay-Kit (Invitrogen) and equal amounts of DNA from the 3 replicates were pooled to create one composite DNA sample per soil sample.

Library prep and ITS2 and 16sV4 amplicon sequencing were done by the University of Minnesota Genomics Center. Template DNA was diluted to 1:8 and 1:64 and subjected to qPCR to assess template DNA quality. The primers V4_515F and V4_806R targeted the V4 locus in the 16S rRNA gene. For fungal amplicons, we used ITS2 amplicons 5.8SFun (forward) and ITS4Fun (reverse) primers from Taylor et al. (2016) as they match well with *Glomeromycotina* lineages. If necessary, samples were diluted with water and then amplicons were created using the same primers. Thermocycler conditions for qPCR were as follows: 95°C for 5 min then 35 cycles of: 98°C for 20 seconds, 55°C for 15 seconds, 72°C for 1 minute, and 72°C for 5 min. Subsequent PCR products were diluted 1:100 in water. A second, 10-cycle PCR cycle was run to attach Illumina sequencing primer regions and individual barcodes for each sample. Samples were all uniquely dual-indexed, as detailed in Gohl, et al. (Gohl, et al., 2016). Final PCR products were normalized using SequalPrep kits (Invitrogen), pooled into sequencing libraries, and cleaned with AMPure XP mag beads (Beckman Coulter). Samples were normalized to 167,000 molecules/µl for paired-end sequencing on an Illumina MiSeq using a 2x300 v3 flow cell (Illumina, San Diego, CA).

Sequencing data processing and identification of amplicon sequence variants (ASVs):

Microbiome bioinformatics was performed using QIIME2 2022.2 (Bolyen et al., 2019). Amplicon sequence variants (ASVs) were utilized instead of operational taxonomic units (OTUs) because of recent benchmark studies that compared the two sequence inference methods (Callahan et al., 2016; Joos et al., 2020). Raw reads were processed using q2-cutadapt (version 2022.2.0) to remove adapter and primer sequences (Martin, 2011). Demultiplexing was performed using the q2-demux plugin followed by quality control, length trimming, denoising, chimera removal, and feature table construction using DADA2 with default settings, except for "–ptrunc-len-f" and "–p-trunc-len-r", which were set at 245 and 185, respectively, for 16S data and at 251 and 193, respectively, for ITS data (via q2-dada2) (Callahan et al., 2016). The resulting ASVs were aligned with MAFFT (Katoh et al., 2002), and phylogenetic trees were constructed using FastTree2 (Price et al., 2010). Taxonomy was assigned to ASVs using the QIIME feature-classifier classify-sklearn (Bokulich et al., 2018), with the pre-trained naïve Bayes SILVA classifier v138 trimmed to the V4 region of the 16S rDNA gene (Quast et al., 2013) for bacteria and a pre-trained UNITE ver8 dynamic classifier (Põlme et al., 2020), trained on full reference sequences without any extraction for fungi, using the same primers as mentioned above. Non-bacterial and fungal reads were removed from the ASV table. We normalized the library using scaling with ranked subsampling using the 'SRS'-function in the 'SRS' with 'qiime srs SRS', using the Cmin values of 14300 and 16400 for bacteria and fungi, respectively (Beule & Karlovsky, 2020). Using these normalized data, we obtained Shannon diversity values using QIIME2.

Edaphic properties

Many of the following sections are also described in Chapter 2.

Basic soil characteristics

Mid-season soil samples from 0-15 cm were sent to Soiltest Labs (Moses Lake, WA, USA) for analysis of texture, pH, cation exchange capacity (CEC), and soil nutrients. pH was measured using a 1:1 soil-water slurry using a Skalar SP2000 Robotic Analyzer (Skalar, Breda, Netherlands). CEC was measured by ammonium replacement, and texture was measured by hydrometer both following protocols by Miller et al. (2013).

Soil iron fractions

Soil iron fractions were isolated using pyrophosphate (iron complexed with organic matter), citrate-bicarbonate-dithionite (crystalline pedogenic iron), ammonium oxalate (poorly crystalline iron), and hydroxylamine hydrochloride (poorly crystalline iron) extractants. Pyrophosphate extractable iron represents iron complexed with organic matter and was extracted according to a method used by McKeague (1967). Oxalate and dithionite extractions followed protocols by Dominik & Kaupenjohann (2000) and hydroxylamine followed protocols by Lovley & Phillips (1987). The pyrophosphate, dithionite, and oxalate extractions were performed using 0.5 g of dry soil, while the hydroxylamine extraction used 1g. In brief, extractants for each fraction were added to the soils, shaken, and centrifuged, and the supernatant was diluted and measured colorimetrically using a plate reader to determine total Fe concentration. Wet extractions are not perfect in isolating their target compounds, yet in combination, they can provide meaningful insight into the different forms of iron present (Rennert, 2018).

Soil health management

Management survey

Soil health management data were collected using an in-depth survey created in Qualtrics (see Chapter 2 supplement). To ensure that questions and terms used by the survey were interpreted consistently by farmer participants, we conducted surveys in person or on the phone with farmers. This way, farmers could ask questions about our prompts, and the surveyor could provide additional context and definitions as needed. The farm management survey collected data on cover cropping, crop diversity and rotation practices, tillage, and organic inputs used by farmers. Questions about irrigation practices, barriers and incentives to soil health practices, and the impacts of COVID-19 were also conducted in the same survey but were not utilized for this portion of our study.

Remote sensing

To complement the management survey data about the historical use of cover cropping, we used satellite imagery to assess continuous living cover at each farm field site via Google Earth Engine (Gorelick et al., 2017). We created a polygon for each of the 28 field sites to represent our field sampling locations. We computed the proportion of the year with vegetation cover from 2015 through 2019 based on an NDVI threshold approach using Landsat and Sentinel imagery. An NDVI threshold value of 0.3 was used to separate bare soil versus sparse vegetation (Sobrino et al., 2001). From 2015 through 2019, we classified the field as having or not having vegetative cover on a monthly basis, based on this threshold. For each year, we created a proportion cover by taking the number of months where the average NDVI value is above or below our threshold and dividing this by 12. We also evaluated the presence of winter cover with NDVI values in January, though we cannot distinguish winter cover versus cash crops using satellite imagery. Given that vegetation could be sparse in January, we increased the NDVI threshold to 0.5 for the 'January Average Cover' variable. This increased NDVI threshold ensures we only indicate winter cover when significant biomass is present.

Farm management standardized scores

To create interpretable management variables, we first categorized all management questions into four practice types based on NRCS soil health principles – continuous cover, crop rotational diversity, reduced disturbance, and organic amendments. We then scaled individual management variables by creating a new variable where a value of 1 indicates the highest value of a practice within our dataset. For tillage variables such as tillage depth and frequency, we subtracted the scaled variable from 1 so that higher values indicated reduced disturbance. We then created a composite score by averaging all practices within each management category. Finally, for each category, we calculated a z-score with a mean of 0 and a standard deviation of 1 to compare different management practices on the same scale.

Statistical analysis

A primary goal of this project was to determine relationships between management practices and different ecosystem services while taking variable edaphic conditions into account. To do this, we used mixed-effects models for various ecosystem services using 'site' as a random effect.

As our dataset is observational, as opposed to manipulative, our statistical inference approach focuses on hypothesis testing to determine if management variables significantly affect the measured ecosystem service indicators, rather than creating a best-fit model. This approach is increasingly used for observational datasets like ours (Bradford et al., 2021; Holland, 1986; Olimpi et al., 2024). Consequently, our modeling prioritizes robust parameter estimates for the predictor variables of interest, rather than model comparison to maximize the variance explained. Hence, we do not solely rely on discussing model results with p-values below 0.05 (Wasserstein et al., 2019; Wasserstein & Lazar, 2016). Non-significant variables were retained to control for their potential influence.

Given our use of composite management variables, as described above, we also used random forest variable importance analyses to determine if certain individual practices have a more significant impact when considered independently rather than as part of a composite. For management variables identified as highly important, we conducted mixed models replacing these individual practices for the composite management variables. These analyses were performed using the 'party' package in R (Hothorn et al., 2023).

Variable reduction

We conducted principal components analysis (PCA) to condense groups of related variables for further analysis. These groups included soil edaphic characteristics (such as sand, clay, cation exchange capacity, and bulk density), soil iron mineralogy (including pyrophosphate, oxalate, hydroxylamine, and dithionite extractions, as described earlier), and extracellular enzyme activities (phosphatase, beta-glucosidase, exochitinase, leucine-aminopeptidase, glucanase/1,4-β-cellobiosidase, peroxidase, and phenoloxidase). We selected the first principal component axis, which accounted for 85.4%, 62.1%, and 75.1% of the variation in physical, iron, and enzyme data, respectively, for further analysis. PCA was performed using the 'ade4' package in R (Dray et al., 2023). PCA figures and variable contributions to PC1 are reported in the supplement.

Mixed models

We constructed a set of mixed-effects models to analyze the relationship between ecosystem service provisioning, soil edaphic properties, and soil health management. Site was modeled as a random effect to account for site-level differences and to reflect our study design while avoiding pseudoreplication (Harrison et al., 2018; Zuur et al., 2009). Models followed the general structure:

$$ES\ Indicator_{ij} = Phys_{PC1ij} + Iron_{PC1ij} + pH_{ij} + ContCover_{Zi} + Disturb_{Zi} + CropDiv_{Zi} + CInput_{Zi} + u_i + \varepsilon_{ij}$$

Where *i* denotes site, *j* denotes one of five site replicates, subscript *PC1* indicates the use of the first principal component axis, subscript *Z* reflects the use of summarized practice z-scores, and *u* is the random intercept for site *i*.

For each ES proxy, we also analyzed variables that emerged as potentially important from the random forest analysis. For various service models, this resulted in replacing the z-scores with practices including the proportion of continuous cover in 2019 (for continuous cover Z), the depth of tillage (for reduced disturbance Z), and number of crop varieties grown in previous seasons (for crop diversity Z). The models without significant results are presented in the supplement.

Model structure and results are summarized in Table 2 and visualized in Figure 1. Models were constructed using the R package 'lme4' (Bates et al., 2023). Interactions were not modeled due to our limited sample size. Model fit was assessed using the function qqnorm and plot to ensure that residuals generally follow model assumptions, and we also ensured that there was no significant correlation amongst predictor variables by ensuring variance inflation factors were below 3 (Supplemental Materials).

To examine effect sizes and compare variables measured on different scales, we report standardized coefficients calculated by scaling regression inputs. This method subtracts the mean of a given variable from each observation and then divides this value by two standard deviations (Gelman, 2008). This calculation helps account for the different units on which variables are measured.

We assessed the influence of management factors compared to soil properties in our models through variance partitioning. Marginal R^2 values were estimated for edaphic variables, including texture, cation exchange capacity (CEC), and pH, and, for the MAOM 1 model, enzymes, and management (continuous cover, reduced disturbance, carbon input, and crop diversity Z scores or substitute practices). Confidence intervals were determined using parametric bootstrapping with 1000 iterations with the 'partR2' package in R (Stoffel et al., 2024).

ES trade-off and synergy

To evaluate the monotonic relationships between ESs, we calculated Spearman's rank correlations between the different ES indicators. This type of correlation analysis is common for assessing synergies and tradeoffs between different ESs (Hölting et al., 2020; Lee & Lautenbach, 2016; Tamburini et al., 2016). To evaluate management impacts on the relationships between ESs, we subset data used for rank correlations by the level of use of different practices. This split the dataset by z-scores greater than, or less than zero. We then evaluated changes in the trade-offs and synergies between higher- and lower-adoption field sites. Due to our sample size, we evaluated each management practice independently. We also ensured that practices were roughly equally distributed between low- and high-scoring sites. Due to z-score asymmetry, carbon amendments were not evaluated as a part of this analysis.

Multifunctionality index and function prioritization models

In addition to individual ES models, we also modeled a composite multifunctionality score (MF_Z) calculated as the average of the scaled ES indicator variables. The default MF_Z evenly weighs all six ES indicators. Additionally, following an approach laid out by Manning et al., (2018), we compared service weightings that consider different potential priorities for various stakeholders. While these are hypothetical weightings, we tried to construct weightings that prioritize different sets of services. Evaluated weightings include production, environmental, and biodiversity prioritizations (Table 4). The first prioritized yield and soil fertility, a stated goal of many farmers we worked with (Carlisle et al., 2022; Esquivel et al., 2021). The environmental weighting prioritized carbon sequestration and nitrate risk mitigation, the regulating services with the broadest off-farm environmental impact. Finally, soil biodiversity prioritized soil microbial diversity and absolute enzyme activity (to reflect microbial activity), and to a lesser extent soil fertility as POM is an important food source for microbes. These weightings were then used to create a modified MF_Z for each prioritization category.

Following the protocols above, we re-applied the mixed-effects model structure to see what practices emerge as important for different multifunctionality indices. We used the proportion of continuous living cover over 5 years in place of the continuous cover z-score.

Results

Soil health management and edaphic impacts on soil-mediated ecosystem services

Across our six ES models, we find that there are 11 cases of positive relationships between soil health management practices and individual ecosystem services, while there is only one instance of a negative relationship.

Continuous cover

Metrics of continuous cover including the proportion of months with living cover in 2019 (2019 cover) and the 5-year proportion of living cover (prop5yr), positively correlate with three out of six services: absolute microbial activity ($\beta_{std\text{-}2019\ cover}$ = 0.52 ± 0.23, p=0.033), soil fertility ($\beta_{std\text{-}prop5yr}$ = 0.69 ± 0.34, p= 0.054), and soil habitat ($\beta_{std\text{-}2019\ cover}$ = 0.72 ± 0.36, p= 0.055). It is also nearly significant for nitrate leaching risk mitigation ($\beta_{std\text{-}2019\ cover}$ = 0.41 ± 0.25, p= 0.12). While harvest nitrate stocks are presented for our analysis, we also evaluated transplant (beginning of the growing season) nitrate stocks to see how management from the previous growing season impacted starting levels of soil nutrients, before. With nitrate at transplant, continuous cover has a clearer significant correlation ($\beta_{std\text{-}CC\text{-}Z}$ = 0.60 ± 0.33, p= 0.08; see supplement). For carbon sequestration, continuous cover is positively correlated to the C stock in the 0-15 cm depth ($\beta_{std\text{-}prop5yr}$ = 0.31 ± 0.10, p= 0.004; see supplement), but is not related to carbon stock across the entire depth profile (0-60 cm).

Reduced disturbance

Reducing soil disturbance primarily influences the risk of nitrate leaching, where deeper tillage significantly reduces nitrate stocks in 0-60 cm($\beta_{std\text{-}tillage\ depth}$ = 0.91 ± 0.22, p= 0.00074). Our metric for nitrate risk is based on remaining nitrate at the end of the season, thus deeper tillage emerges as a positive factor in reducing the nitrate risk. While not statistically significant, reduced disturbance also appears to correlate with carbon sequestration down to 60 cm ($\beta_{std\text{-}\ Disturbance\ Z}$ =0.41 ± 0.25, p= 0.12), and this association is statistically clearer for deep carbon stocks (30-60 cm; $\beta_{std\text{-}\ Disturbance\ Z}$ = 0.274 ± 0.12, p = 0.027, see supplement).

Crop diversity

Higher diversity of cash and cover crops increased soil fertility ($\beta_{std\text{-}\ Crop\ Div.\ Z}$ =0.59 ± 0.32, p=0.08) and reduced nitrate leaching risk ($\beta_{std\text{-}\ 5yr\ crop\ div.}$ = 0.70 ± 0.25, p= 0.0050), but decreased lettuce yields ($\beta_{std\text{-}\ Crop\ Div.\ Z}$ = -0.10 ± 0.041, p=0.019). Because our measure of crop diversity includes cash and cover crops, we also investigated a model that included both 2019 cover and the continuous cover z-score. This ensures that the observed effect of crop diversity was from diversification itself and not the use of cover crops that might be confounded in the diversification metric. Including the continuous cover z-score did not change which variables are significant (see supplement).

Organic amendments

Carbon-inputs from organic amendments clearly increased lettuce yields (β_{std} = 0.15 ± 0.044, p = 0.0019), mass-specific enzyme activity (β_{std} = 0.75 ± 0.41, p = 0.079), and reduced nitrate leaching risk (β_{std} = 0.47 ± 0.23, p = 0.05). No alternative variables were used for this management category.

Edaphic variables:

Soil iron influenced almost all services except for nitrate leaching risk. For crop provisioning and soil habitat, soil iron was significantly negatively associated ($\beta_{std\text{-}yield}$ = -0.053 ± 0.020, p_{yield} = 0.011; $\beta_{std\text{-}habitat}$ = - 0.84 ± 0.33, $p_{habitat}$ = 0.014). Soil iron was positively correlated with climate regulation (β_{std} = 0.46 ± 0.18, p= 0.0091), absolute (β_{std} = 0.20 ± 0.12, p = 0.083) and mass-specific enzyme activity (β_{std} = 0.39 ± 0.24, p = 0.10), and soil fertility (β_{std} = 0.83 ± 0.22, p = 0.0002).

pH was a positively associated with nitrate risk mitigation (β_{std} = 0.51 ± 0.19; p = 0.01), wherein more alkaline soils have less residual nitrate, and negatively associated with absolute enzyme activity (β_{std} = -0.42 ± 0.12, p = 0.001).

Soil physical properties ($Phys_{PC1}$) also clearly relate to several of the soil-based ecosystem services. Sandier soils (corresponding to higher values on $Phys_{PC1}$) were significantly correlated with absolute (β_{std} = 0.59 ± 0.22, p = 0.010) and mass-specific enzyme activity (β_{std} = 0.81 ± 0.38, p = 0.040), soil fertility (β_{std} = 0.62 ± 0.36, p = 0.09), and soil biodiversity (β_{std} = 0.79 ± 0.41, p = 0.061). Meanwhile, clayier soil textures (corresponding to lower values on our $PC1_{Phys}$) correlated with increased climate regulation (β_{std} = -1.07 ± 0.27, p = 0.00027). Nitrate leaching risk was also nearly significant (β_{std} = 0.43 ± 0.26, p = 0.11), with sandier soils associated with decreasing end-of-season nitrate levels.

Contribution of edaphic vs. management variables to ES provision

We used variance partitioning to assess the relative strength of edaphic and management controls on individual ESs (Table 3). Marginal R^2 values include only the variance explained by these fixed-effect variables, which varies from 30% (Yield) to 56% (C-stock and nitrate stock). Edaphic variables explained more variance than management for the carbon-stock and microbial diversity models ($R^2_{edaphic}$ = 0.40 and 0.27, respectively). For the rest of the ecosystem services, management variables explained more variance than edaphic variables: yield ($R^2_{management}$ = 0.20), nitrate stocks ($R^2_{management}$ = 0.51), absolute and mass-specific enzyme activity ($R^2_{management}$ = 0.17 and 0.15, respectively), POM ($R^2_{management}$ = 0.22), and our evenly weighted multifunctionality model ($R^2_{management}$ = 0.30).

Synergy and trade-off analysis

The Spearman rank correlation offers a non-parametric estimate of the monotonic correlation (positive, negative, or neutral) between pairwise combinations of our indicator variables. With the full dataset, a weak tradeoff occurred between yield and carbon sequestration (ϱ= -0.15, p = 0.0016), and there was a stronger trade-off between carbon sequestration and soil biodiversity (ϱ= -0.46, p = 3.29e-05; Figure 2). Two synergies also emerged between yield and soil biodiversity (ϱ= 0.26, p = 0.0018) and microbial activity and soil fertility (ϱ= 0.22, p = 0.0053; Figure 2).

A few key changes emerged when we compared fields with high vs. low scores of soil health practices (continuous cover, reducing soil disturbance, and crop diversity). First, the trade-off between carbon sequestration and yield found in the full dataset is only apparent for low-continuous cover and high-disturbance fields (Figure 3). Fields with high continuous cover exhibit a positive correlation between soil fertility and reduced nitrate leaching risk. Conversely, this relationship transforms into a tradeoff for sites with low cover. With higher tillage and lower crop diversity, the tradeoff between yield and nitrate risk mitigation intensified. Lastly, for high-diversity fields, there was a clear synergy between microbial diversity and nitrate risk mitigation, which was neutral for low-diversity fields.

Multifunctionality index and service prioritization analysis

Across all four ecosystem multifunctionality weighting scenarios (even, production, environmental, and biodiversity), 5-year proportion of living cover emerged as a significant, positive correlate for MF_Z ($\beta_{std\text{-}even} = 0.45 \pm 0.17$ p_{even}=0.015; $\beta_{std\text{-}prod.} = 0.73 \pm 0.35$, $p_{prod.}$ =0.045; $\beta_{std\text{-}env.} = 0.71 \pm 0.37$, p_{env} =0.091; $\beta_{std\text{-}bio} = 0.76 \pm 0.38$, $p_{bio} = 0.05$; Table 5). Carbon amendments were also important for even and production-weighted MF_Z scores ($\beta_{std\text{-}even} = 0.43 \pm 0.15$, $p_{even} = 0.01$; $\beta_{std\text{-}prod} = 1.02 \pm 0.31$, $p_{prod.} = 0.0031$; Figure 4, Table 5). Among edaphic variables, iron was important for the environmental MF_Z weighting ($\beta_{std} = 0.59 \pm 0.21$, $p = 0.0047$; Table 5) and soil texture for soil biodiversity ($\beta_{std} = 0.91 \pm 0.40$, $p = 0.031$).

Discussion

In this study, we find that in-season and recent (<5 yrs) use of soil health management can significantly shape the provision of multiple ecosystem services across working farms in the Central Coast region of California. Bringing together management interview data, remotely sensed metrics of continuous cover, and a wide array of biological, chemical, and physical soil property data, we find that soil health practices can support individual ecosystem services to varying degrees and also mitigate trade-offs between services. Further, our on-farm approach enabled sampling across a wide gradient of both soil texture and utilization of soil health practices. Analysis of these gradients show that soil health practices have a greater influence on the provision of four out of six ecosystem services considered. This means that across the range of soil types observed in our study, targeted management can significantly improve the provision of specific ESs. Finally, we identify one principle in particular, continuous living cover, as a key driver of soil multifunctionality across three different prioritization schemes for multifunctionality (production, environmental, and microbial biodiversity).

Soil health management and edaphic factors shape ecosystem service delivery

Continuous cover

Across the four soil health management practices, continuous cover is associated with increasing the most individual ecosystem services. While many studies only assess the use of cover crops, by using remotely sensed continuous living cover, our metric is inclusive of all forms of living cover that may be used by farmers.

Continuous living cover provides vital inputs of carbon and nutrients into the soil ecosystem (e.g., plant above- and belowground biomass and root exudates) when fields may otherwise be fallow. Following our findings, cover crops have been found to support greater microbial abundance and diversity (Kim et al., 2020; Tosi et al., 2022; Vukicevich et al., 2016), and soil extracellular enzyme activity (Bandick & Dick, 1999; Chavarría et al., 2016). Increases in POM may similarly be attributed to the sustained input of organic matter from cash and cover crops (Q. Hu et al., 2023; Prairie et al., 2023).

Cover crops are a key part of organic nutrient management systems to retain nitrate and other nutrients in the soil in between cash crop plantings (Drinkwater & Snapp, 2022). Without uptake by living plants, nutrients are otherwise liable to leach with irrigation or rainfall (Nouri et al., 2022). Conventionally, the relationship between cover crops and nitrate movement might be evaluated with soil or leachate samplings at several timepoints and/or across control and treatment plots (G. Singh et al., 2018; White et al., 2022), whereas, given our sampling design, we assess the impact of previous season's utilization of cover cropping on in-season nitrate levels. While the statistical evidence is less clear, we find that the higher levels of continuous cover in 2019 may also support reduced nitrate remaining at harvest ($p=0.12$). The benefits of this continuous cover in 2019 is clearer for nitrate levels at the beginning of the season, where living cover absorbs excess nitrate and reduces excess nitrate levels in the bulk soil (transplant timepoint – see supplement). This means that the use of cover crops or winter cash crops can reduce the residual nitrate levels at transplant and that this impact is sustained through the growing season. Nitrate pollution in groundwater is a large concern in the Central Coast region (California Regional Water Quality Control Board, 2021), and ongoing work is needed to hone how farmers may best use cover crops to mitigate the risk of nitrate pollution. Notably, we do not find any negative implications of continuous cover on yields (Table 2; Figure 1).

Reduced disturbance

Tillage has long played a role in agricultural systems, but finding ways of minimizing disturbance to soils is of growing interest to improve soil structure and reduce erosion, compaction, and disruption of stable aggregates that could hold organic carbon (Carr et al., 2012; Lal, 1991; Lal et al., 1990; Six et al., 1999). The effect of reduced disturbance on reductions in soil nitrate at the end of the season ($p= 0.00074$) could have several explanations. One is that deeper tillage encourages deeper rooting depths, thus allowing for increased plant nitrate uptake, and decreasing residual nitrate (Varsa et al., 1997). It is also possible that deeper tillage increases water infiltration rates and disrupts soil structure to greater depths, thus increasing the potential for nitrate to move to deeper depths. This is consistent with other findings on the impact of tillage on decreased residual nitrate (Al-Kaisi & Licht, 2004; Bakhsh et al., 2000).

While the statistical evidence is not as clear, we also find that reducing disturbance may aid in building soil carbon stocks ($p = 0.12$) – in particular at deeper depths (30 - 60 cm; $p = 0.027$; supplement). This is slightly counter to previous work which has found that reduced tillage can increase subsoil carbon by moving soil organic matter deeper into the soil profile, while surface carbon levels may decrease due to increased decomposition of otherwise protected organic matter in soils (Bongiorno et al., 2019; Conceição et al., 2013; Six et al., 1999). Several system and study-specific points may explain this discrepancy. First, there is relatively little crop residue associated with lettuce. Thus, there may not be a significant pool of SOM to move deeper into the soil, thus the potential input of SOC into the subsoil may be outweighed by increased SOM access and microbial respiration. We also incorporate a metric of bed permanence, where higher scoring fields maintain a bed for several plantings. However, on these maintained beds, there could still be highly intensive cultivation and multiple plantings, which we know to be typical practices in this region, that reduces surface carbon levels. Together, these may influence the weaker association between SOC in surface soils with decreased disturbance, relative to deeper soils.

Crop diversification

Lower yields with higher cash and cover crop diversity may be an indirect relationship, driven by aspects of the organic industry. Growers with lower crop diversity tend to be lettuce and leafy green specialists with industrial-scale operations (Carlisle et al., 2022; Esquivel et al., 2021). This specialization may increase lettuce yields, while more diversified operations that grow a wide array of other crops may not focus on maximization of individual crop yields. This would explain the contrast with work showing how crop diversification strategies such as intercropping and crop rotations often increase yields (Beillouin et al., 2019, 2021; Bowles et al., 2020; Burchfield et al., 2019; Tamburini et al., 2020), including by increasing soil fertility. We did find a relationship between diversification and soil fertility (POM), which could be a result of a wider array of POM inputs (e.g. in terms of size, nutrient composition, and structural complexity) that can lead to slower decomposition and thus higher POM accumulation (though decomposition is necessary to be a source of soil fertility; Wood et al., 2018).

Our finding that diversity decreases residual nitrates may be explained by a number of factors. Increased carbon from POM, as discussed above, may increase microbial activity and N-mineralization for plant uptake, therefore reducing excess N accumulation and supporting tighter N cycling (Bowles et al., 2015). Varied rooting depths and nitrogen requirements of different crops may also support more efficient overall nitrogen use (Malhi et al., 2009; Szumigalski & Van Acker, 2006).

Carbon input

(228 words) Organic amendments are a key practice for organic operations. We find that higher carbon inputs correspond to increased crop yields ($p=0.0019$), likely via the provision of essential nutrients, stimulation of microbial activity, and increased water holding capacity provided by composts and fertilizers (Brown & Cotton, 2011; Ros et al., 2006). Organic amendments also correlate to higher mass-specific enzyme activity ($p=0.079$), reflecting increased microbial efficiency or metabolically more active microbial communities (Raiesi & Beheshti, 2014). However, we do not find increased absolute enzyme activity or diversity as a result of carbon inputs.

While organic amendments such as manures and composts can be sources of nitrate and other nutrients that harm water quality (Y. C. Li et al., 1997; White, Brennan, Cavigelli, et al., 2020b), we find that higher carbon inputs are associated with reduced residual in-field nitrate at the end of the season ($p=0.05$). This may be due to heightened microbial activity and carbon inputs increasing the rate and efficiency of microbial denitrification, converting nitrate to N_2 and N_2O gas (Kramer et al., 2006). Further, organic amendments have relatively high C:N ratios compared to synthetic fertilizers which can increase microbial nitrogen use efficiency, and encourage overall tighter nitrogen cycling (Bowles et al., 2014; Mooshammer et al., 2014; Zhang et al., 2023).

Management versus edaphic influence on services

Understanding the relative contribution of management versus inherent edaphic factors can help guide recommendations to land managers and policy makers interested in enhancing specific ecosystem services or multifunctionality more generally. However, this type of analysis is relatively unexplored by existing literature. Here, we find that management variables explain more variance in our ES indicators for crop provisioning, microbial nutrient cycling, mitigation of nitrate leaching, soil fertility, and overall multifunctionality (Table 3). This means that soil health management can significantly improve the provision of these services across a wide range of inherent soil properties. Meanwhile, only carbon sequestration and soil biodiversity are principally governed by edaphic variables. While it is well established that a given soil's carbon sequestration capacity is limited by inherent soil physical properties, other work on the same farming system found that management can still strongly influence increases in specific soil organic carbon fractions with functional implications on long-term carbon storage (Chapter 2; Esquivel et al., *in prep*). Further, while pH and texture often drive soil microbial community composition (Xia et al., 2020), management has still been found to influence microbial diversity (Gajda et al., 2018; Zu-Cong et al., 2004).

Synergies and trade-offs between services

Critical to understanding the dynamics of ES provision in working landscapes is how management may shape or alter the relationships between services. Understanding these synergies and trade-offs between services is important for managing complex ecosystems where we rely on multiple ecosystem functions (Manning et al., 2018; Raudsepp-Hearne et al., 2010). Existing research in soil management and services has found that management including fertilizer and pesticide use can increase negative trade-offs between services (Tamburini et al., 2016; Vazquez et al., 2021). However, Tamburini et al. (2016) primarily track aboveground ESs (i.e., weed, pest, and disease incidence, yield), while Vazquez et al. (2021) only consider three services (primary productivity, nutrient cycling, and biodiversity) categorized by low, medium, and high provisioning. Here, our consideration of six different services allows us to take a more comprehensive look at a range of potential synergies and trade-offs between soil-mediated ESs, and our gradient approach allows us to parse the influence of high or low adoption of specific management practices.

Microbial diversity increases yield but decreases carbon sequestration

Looking at our full dataset across sites, we find that soil microbial diversity correlates positively with yield but negatively with carbon sequestration (Figure 2). Carbon sequestration is notably the only trade-off with yield, meaning that all other services can be delivered simultaneously without compromising yield. The synergy between microbial diversity and yield could be driven by the presence of plant growth-supporting microbes (Stefan et al., 2021), while this may simultaneously mediate increased SOM decomposition resulting in lower carbon stocks (Schimel & Schaeffer, 2012; Zhou et al., 2022).

Trade-offs are driven by low-adoption sites

When we compare fields with high use of soil health management practices against those with low use, the dynamics of these trade-offs change. For instance, we observe that the trade-off between carbon sequestration and yield is driven by fields with low continuous cover ($Z_{\text{cont. Cover}} < 0$) and high disturbance ($Z_{Disturbance} < 0$). This might mean that farmers could eliminate this trade-off by reducing soil disturbance and increasing continuous cover.

In fields with high crop diversity ($Z_{Crop\ Div} > 0$), there is a synergy between microbial diversity and nitrate risk mitigation. Conversely, in fields with higher tillage and lower crop diversity, there is a clearer trade-off between yield and nitrate risk, suggesting the importance of these management practices in enabling farmers to boost yields through organic nutrient inputs without escalating the risk of nitrate pollution. This could be due to reduced plant-based carbon inputs from continuous cover or increased decomposition from tillage.

The nature of this correlation analysis limits our ability to make causal associations, though future work on the mechanistic underpinnings would benefit management recommendations. In particular, it may be of interest to investigate thresholds of management implementation that influence the dynamics of multiple service provision. However, there are clear differences in the configuration of synergies and trade-offs for fields using high versus low levels of soil health practices. Specifically, higher adoption of continuous cover and reduced disturbance could mitigate observed trade-offs between yield and carbon sequestration, and increased diversity and reduced disturbance could mitigate trade-offs between water quality and yield.

Continuous cover is vital for effective multifunctionality

Cultivating multifunctional landscapes is a crucial goal of agroecological management (Kremen & Merenlender, 2018). In the Central Coast, where threats of groundwater depletion and contamination (California Regional Water Quality Control Board, 2021; Rosenstock et al., 2014) and a warming climate (Pathak et al., 2018) loom, along with acute economic and supply chain pressures to sustain crop production (Guthman, 2004), finding land management solutions to simultaneously enhance multiple ESs is particularly crucial. First, we take the average of all ESs to create a baseline multifunctionality index that reflects even prioritization across all ESs. Collapsing all of our functions into a single metric necessarily eliminates some nuance but can provide useful insights into what management practices might be key for simultaneously promoting multiple ESs. We then use weighting factors (Table 4) to create three additional multifunctionality indices - one prioritizing crop production and soil fertility to reflect farmer priorities, one prioritizing carbon storage and nitrate leaching mitigation to reflect landscape-level environmental priorities, and a final weighting prioritizing soil microbial biodiversity and activity. Using these multifunctionality indices, we apply the same mixed-modeling strategy to determine the management practices that may be most important for achieving each multifunctionality scheme.

Using our evenly weighted MF alongside weighting schemes prioritizing production, environmental protection, and soil microbial biodiversity, we find that the average proportion of continuous cover over 5-years before sampling is a clear driver for all ecosystem multifunctionality indices. While continuous cover emerged as significant for just a handful of individual service models, it may support several key mechanisms that indirectly support all of the different services when considered in aggregate. Continuous living cover critically maintains a consistent carbon and nutrient source for soils and soil microbial life. A recent meta-analysis found that the continuous living cover offered by perennial cropping systems yielded the greatest gains in particulate and mineral-associated organic carbon relative to annual systems (Prairie et al., 2023), which are crucial for soil life, structure, and nutrient provision (Lehmann et al., 2020b). While their metric for multifunctionality is calculated slightly differently, Garland et al., (2021) also find that, across European agricultural systems, the proportion of time with a cover crop over 10 years drives multifunctionality more than other factors such as crop diversity. Currently, the California Healthy Soils program invests the majority of its funding into defraying compost and amendment costs, which we find supports evenly- and production-weighted MF indices. Finding additional policy and outreach mechanisms to increase continuous living cover on farms (e.g., encouraging combinations of perennial crops, cover crops, and winter cash crop rotations), may be a crucial strategy to support broadly multifunctional agricultural soils.

Conclusions

Here, we have shown that a suite of soil health management practices are crucial in creating and maintaining multifunctional agroecosystems. While balancing the many needs that society demands of these landscapes, we find that continuous living cover, in particular, may support overall multifunctionality, while other practices such as reduced tillage or increased crop diversity may better support individual functions like increasing soil carbon stocks and reducing nitrate leaching risk, respectively. While a few ESs are primarily controlled by inherent edaphic conditions, we find that in general, management plays an important role in the provision of the majority of services evaluated and overall multifunctionality. We also find that higher use of soil health management practices can reduce negative trade-offs between ecosystem services without undermining yield. All together, these results demonstrate the potential for soil health management to aid in addressing multiple environmental challenges facing the Central Coast of California while sustaining crop production and underscore the need for policy mechanisms that encourage greater adoption of soil health management. While the barriers that farmers face in adopting these practice vary widely (Chapter 1; Esquivel et al., 2021), policy makers and farmer advocates should strive to support farmers in implementing soil health practices on the ground, while also pushing to dismantle technical and structural policy barriers faced by farmers (Carlisle et al., 2022).

Acknowledgments

Thank you to Yordi Gil-Santos, Amiri Taylor, Grace Santos, Melanie Rodriguez, Arely Ortiz, and Anna Barcellos for the mountain of lab work conducted over the last several years to make this work possible. A huge thank you to the interdisciplinary team of researchers who have supported this work. I appreciate Annie Taylor, who created the site map image. This work was supported by an NSF Coupled Natural Humans Systems (#1824871) and USDA-NIFA Grant (#2019-67019-29537) funding. I also want to thank UC Berkeley's Graduate Division, the William & Lisa Liu Fellowship, the Ford Foundation, and the Switzer Foundation for providing fellowship funding throughout my graduate career.

Tables

Table 1: Summary of ecosystem services, indicator variables, and relevant notes for their interpretation and calculation.

ES Type	Ecosystem Service	Indicator Variable	Notes/calculation
Provisioning	Crop provisioning	Normalized Yield	$Yield_{normalized}$ = $(Yield_i - Yield_{Min}) / (Yield_{Max} - Yield_{Min})$ Where min and max are for each specific crop variety for the i^{th} sample in each species-specific group
Regulating	Climate regulation/ Carbon sequestration	Carbon stock from 0-60 cm at harvest (Mg C / ha)	C stock = $\Sigma(C\% * \text{Bulk Density})_{0\text{-}15,\ 15\text{-}30,\ 30\text{-}60}$
Regulating	Potential nitrate leaching risk	-NO_3 stock from 0 to 60 cm at harvest (Mg NO_3^--N/ ha)	NO_3 stock = $\Sigma(NO_3 * BD)_{0\text{-}15,\ 15\text{-}30,\ 30\text{-}60}$
Supporting	Nutrient cycling capacity	-Hydrolytic enzyme activity -Oxidative enzyme activity	$Z_{enzyme\text{-}absolute}$ = mean $(Z_{BG}, Z_{PHO}, Z_{NAG}, Z_{LAP}, Z_{Phenoloxidase}, Z_{Peroxidase})$
	Efficiency of microbial nutrient and SOM cycling	-Hydrolytic enzyme activity -Oxidative enzyme activity - Molecular biomass carbon	$Z_{enzyme\text{-}mass\ specific}$ = mean $(Z_{BG/MBC}, Z_{PHO/MBC}, Z_{NAG/MBC}, Z_{LAP/MBC}, Z_{Phenoloxidase/MBC}, Z_{Peroxidase/MBC})$
Supporting	Soil fertility	-POM stock in surface soils (gC/kg)	POM = $C\%_{fPOM} * prop_{oPOM} + C\%_{fPOM} * prop_{fPOM}$
Supporting	Soil habitat provisioning / Microbial biodiversity	-Fungal and bacterial Shannon Diversity	$Z_{microbial} = (Z_{Bacterial\ Shannon} + Z_{Fungal\ Shannon})/2$ Obtained using normalized sequence data in QIIME2.

Table 2: Summary of mixed-effects models for single ecosystem services. Standardized coefficients with standard error are reported with p-values in parentheses. Standardization was performed following Gelman (2008) and allows for comparison across variable effect sizes. Green and red squares indicate positive and negative coefficients, respectively, at a significance level of $p < 0.1$. Light yellow-green indicates values just above this threshold. Bolded values represent values with p-values <0.05. Gray cells indicate that the variable was not included in a given model and white cells indicate that the variable was included, but non-significant.

Service model	Crop provisioning	Climate regulation	Nitrate risk mitigation	SOM turnover/Microbial activity		Soil fertility	Soil habitat
Indicator	Normalized yield	Carbon stock (0-60cm)	Inverse harvest NO_3 stock (0-60cm)	Absolute enzyme activity	Mass-specific enzyme activity	Particulate organic matter stock (0-15 cm)	Microbial Shannon diversity
Intercept	0.39 ± 0.47 (0.4)	-0.0001.1 ± 0.11 (0.999)	0.00 ± 0.10 (0.98)	**-0.33 ± 0.10 (0.005)**	-1.10 ± 0.17 (0.55)	-0.01 ± 0.13 (0.95)	**7.86 ± 0.15 (<0.0001)**
Continuous cover	0.048 ± 0.042 (0.27)	0.30 ± 0.27 (0.27)			0.48 ± 0.39 (0.23)		
Reduced disturbance	-0.011 ± 0.038 (0.78)	0.41 ± 0.25 (0.12)		-0.25 ± 0.23 (0.28)	-0.30 ± 0.37 (0.43)	-0.09 ± 0.30 (0.76)	0.11 ± 0.34 (0.74)
Carbon amendment	**0.15 ± 0.044 (0.0019)**	0.16 ± 0.28 (0.57)	**0.47 ± 0.23 (0.05)**	-0.02 ± 0.23 (0.95)	0.75 ± 0.41 (0.079)	-0.45 ± 0.31 (0.16)	0.25 ± 0.34 (0.48)
Crop diversity	**-0.10 ± 0.041 (0.019)**	0.14 ± 0.27 (0.61)		-0.13 ± 0.24 (0.59)	-0.10 ± 0.39 (0.80)	0.59 ± 0.32 (0.08)	0.37 ± 0.34 (0.29)
Prop. 5-year cont. cover						0.69 ± 0.34 (0.054)	
Prop. 2019 cont. cover			0.41 ± 0.25 (0.12)	**0.52 ± 0.23 (0.033)**			0.72 ± 0.36 (0.055)
Deep tillage depth			**0.91 ± 0.22 (0.00074)**				
5-year crop diversity			**0.70 ± 0.25 (0.0050)**				

Iron	**-0.053 ± 0.020 (0.011)**	**0.46 ± 0.18 (0.0091)**	0.24 ± 0.20 (0.22)	0.20 ± 0.12 (0.083)	0.39 ± 0.24 (0.10)	**0.83 ± 0.22 (0.0002)**	**- 0.84 ± 0.33 (0.014)**
pH	0.0088 ± 0.063 (0.89)	-0.20 ± 0.17 (0.24)	**0.51 ± 0.19 (0.01)**	**-0.42 ± 0.12 (0.001)**	-0.28 ± 0.24 (0.24)	-0.10 ± 0.20 (0.63)	0.43 ± 0.29 (0.15)
Soil physical (Clay < Sand)	0.0086 ± 0.023 (0.71)	**-1.07 ± 0.27 (0.00027)**	0.43 ± 0.26 (0.11)	**0.59 ± 0.22 (0.010)**	**0.81 ± 0.38 (0.040)**	0.62 ± 0.36 (0.09)	**0.79 ± 0.41 (0.061)**

Table 3: Marginal R^2 values for edaphic variable groupings (Physical PC1 – texture, CEC, pH) and management variables (continuous cover, reduced disturbance, C input, crop diversity Z scores OR individual practices, as reported in Table 2) with confidence intervals from parametric bootstrapping. Bolded values indicate the variable grouping with the higher marginal R^2 value.

Indicator	Management	Edaphic	Total
Normalized Yield	**0.20 (0.07 - 0.47)**	0.11 (0.00 - 0.41)	0.30 (0.19 - 0.56)
Carbon Stock (0-60 cm)	0.07 (0.00 - 0.38)	**0.40 (0.27 - 0.61)**	0.56 (0.43 - 0.73)
Harvest NO_3 stock (0-60 cm)	**0.51 (0.37 - 0.64)**	0.069 (0.00 - 0.29)	0.56 (0.43 - 0.68)
Absolute Enzyme Activity	**0.17 (0.00 - 0.46)**	0.12 (0.00 - 0.41)	0.48 (0.32 - 0.68)
Mass-specific enzyme activity	**0.15 (0.00 - 0.47)**	0.06 (0.00 - 0.42)	0.33 (0.21 - 0.62)
Particulate Organic Matter Stock (0-15 cm)	**0.22 (0.076 - 0.64)**	0.076 (0.00 - 0.38)	0.40 (0.25 - 0.64)
Microbial Shannon Diversity	0.089 (0.01 - 0.21)	**0.27 (0.16 - 0.37)**	0.39 (0.28 - 0.47)
Multifunctionality (Even weighting)	**0.30 (0.28 - 0.65)**	0.0099 (0.00 - 0.32)	0.43 (0.28 - 0.65)

Table 4: Multifunctionality index weighting coefficients.

Service	Even	Production	Environmental	Biodiversity
Yield	0.16	0.45	0	0
Soil Microbial Diversity	0.16	0.1	0.05	0.4
Absolute Microbial Activity	0.16	0.15	0.05	0.3
Carbon Sequestration	0.16	0.05	0.40	0.05
NO_3 Mitigation	0.16	0.05	0.40	0.05
Soil Fertility (POM)	0.16	0.2	0.10	0.2

Table 5: Standardized coefficient estimates, standard errors, and p-values from multifunctionality mixed-models. Each column represents a different multifunctionality weighting calculation. Green cells indicate a positive coefficient estimate.

MF Weighting	Even	Production	Environmental	Biodiversity
Intercept	-0.20 ± 0.07 (0.007)	-0.30 ± 0.13 (0.036)	-0.12 ± 0.15 (0.87)	-0.57 ± 0.14 (0.001)
Reduced disturbance	-0.05 ± 0.15 (0.73)	-0.28 ± 0.30 (0.37)	0.24 ± 0.33 (0.42)	-0.18 ± 0.33 (0.586)
C amendment	0.43 ± 0.15 (0.01)	1.02 ± 0.31 (0.0031)	0.51 ± 0.33 (0.20)	0.52 ± 0.34 (0.134)
Crop diversity	0.02 ± 0.16 (0.91)	-0.36 ± 0.32 (0.26)	0.21 ± 0.35 (0.53)	0.34 ± 0.34 (0.333)
Prop. 5-year Cover	0.45 ± 0.17 (0.015)	0.73 ± 0.35 (0.045)	0.71 ± 0.37 (0.091)	0.76 ± 0.38 (0.050)
Iron	0.09 ± 0.11 (0.44)	-0.22 ± 0.25 (0.38)	0.59 ± 0.21 (0.005)	0.063 ± 0.26 (0.808)
pH	0.03 ± 0.11 (0.81)	-0.01 ± 0.23 (0.97)	0.10 ± 0.20 (0.67)	-0.012 ± 0.24 (0.959)
Soil physical (Clay < Sand)	0.19 ± 0.18 (0.30)	0.45 ± 0.38 (0.25)	-0.35 ± 0.37 (0.37)	0.91 ± 0.40 (0.031)

Figures

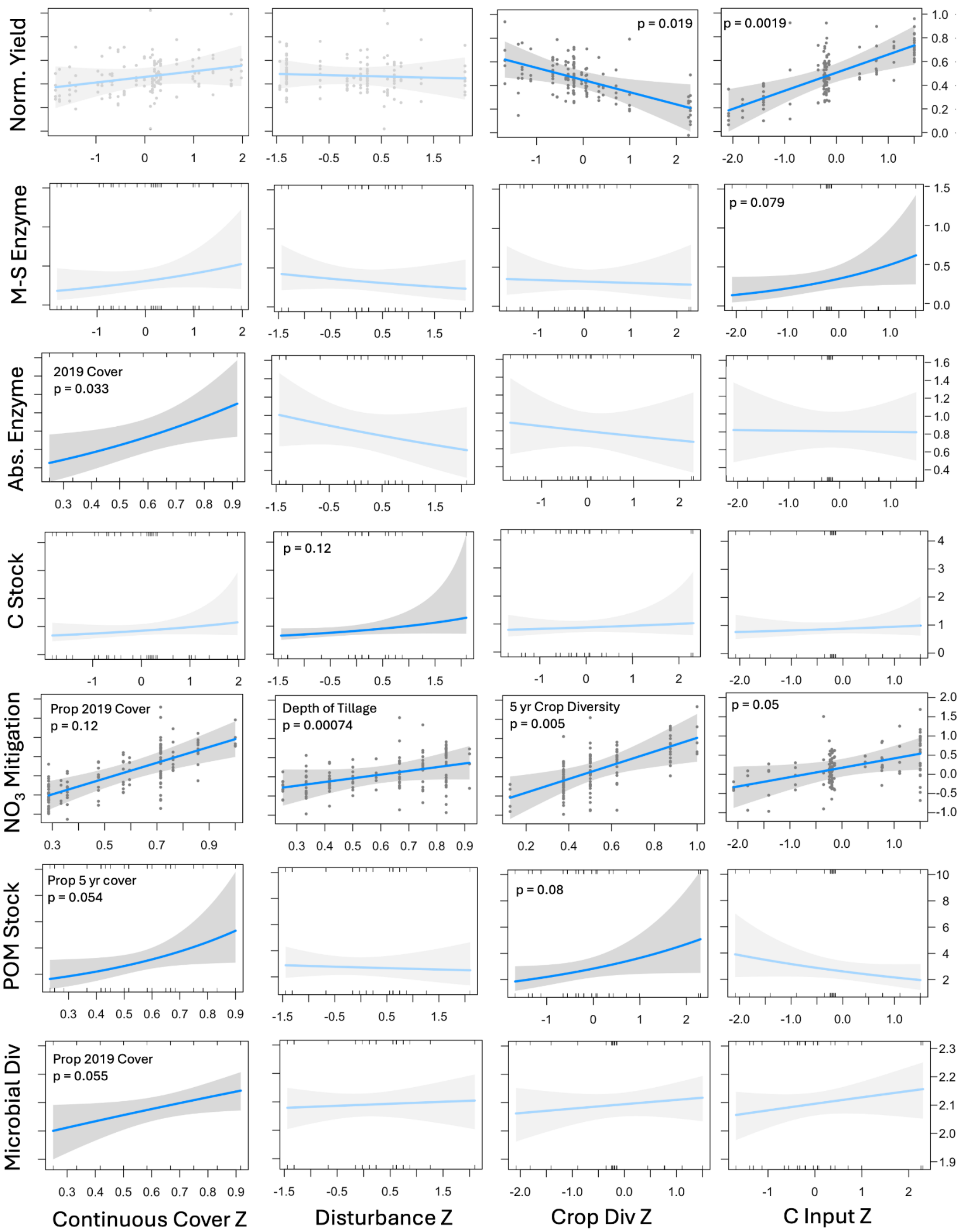


Figure 1: Modeled relationships between each ecosystem service indicator and soil health management practice, holding all other variables in the models constant at mean values. Significant and near-significant relationships are darker with p-values. Unless otherwise indicated, x-axis uses z–scores for each management category. Back-transformed plots display tick mark rug along the x-axis.

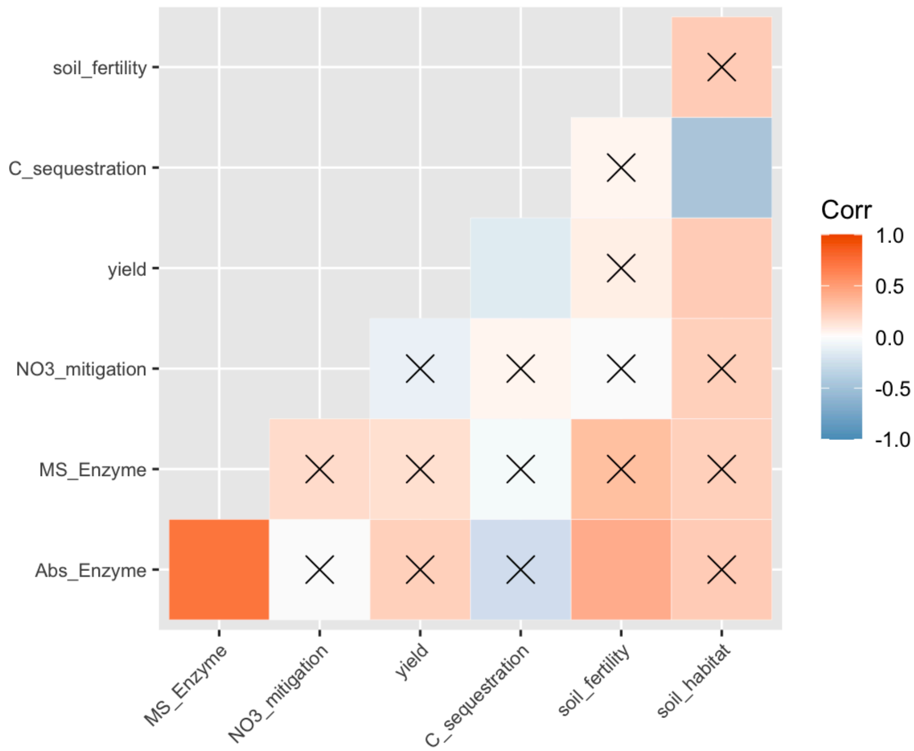


Figure 2: Spearman's correlation plot of ecosystem services. "X" indicates that the relationship is non-significant (p>0.05). Positive correlations are shaded in red, and negative correlations are shaded in blue. MS Enzyme is mass-specific enzyme activity, and Abs is absolute enzyme activity.

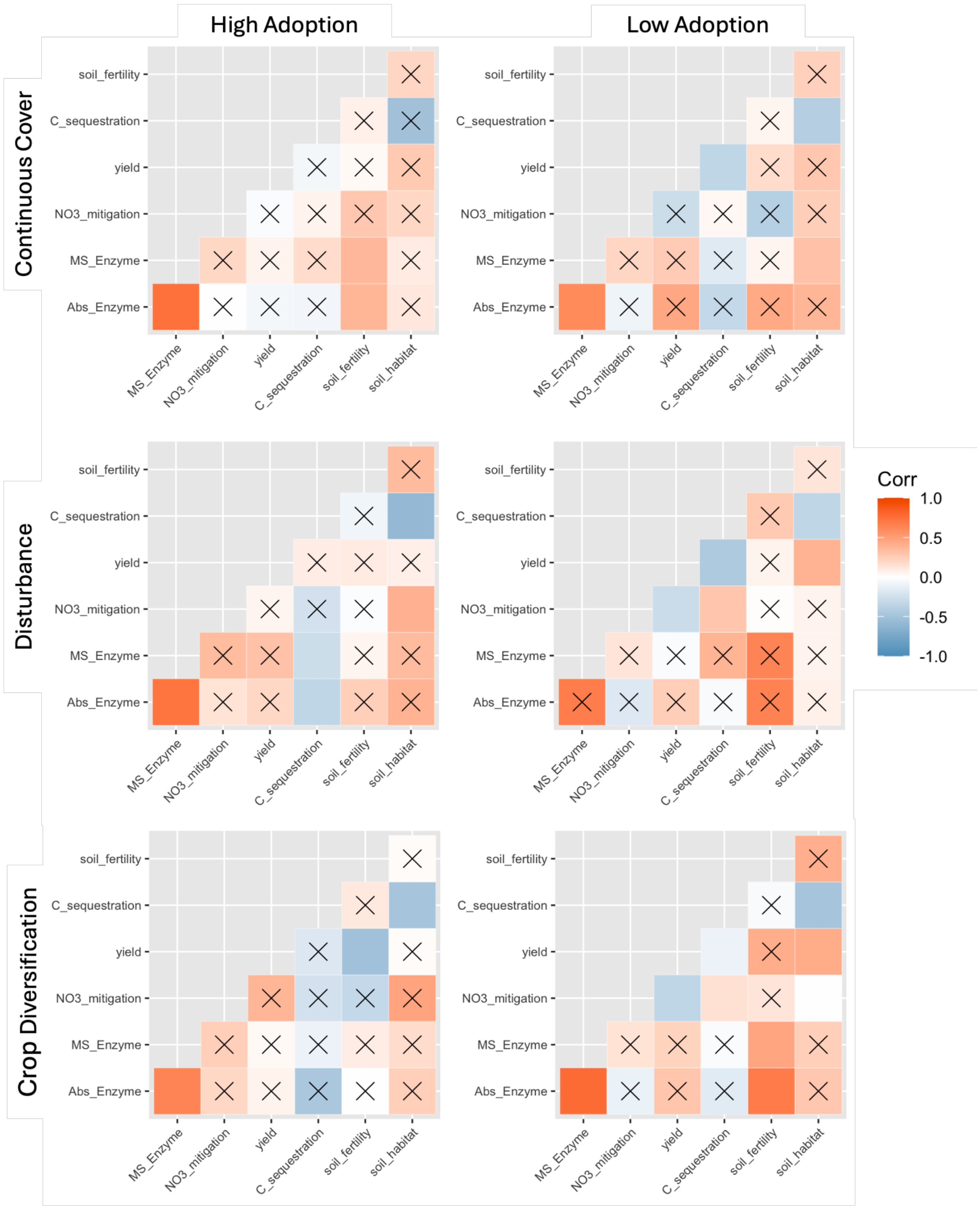


Figure 3: Spearman's correlation plot of ecosystem services partitioned by high adoption (z score > 0) in the left column and low adoption (z score < 0) on the right column for respective practices by row. "X" indicates that the relationship is non-significant (p>0.05). Positive correlations are shaded in red, and negative correlations are shaded in blue.

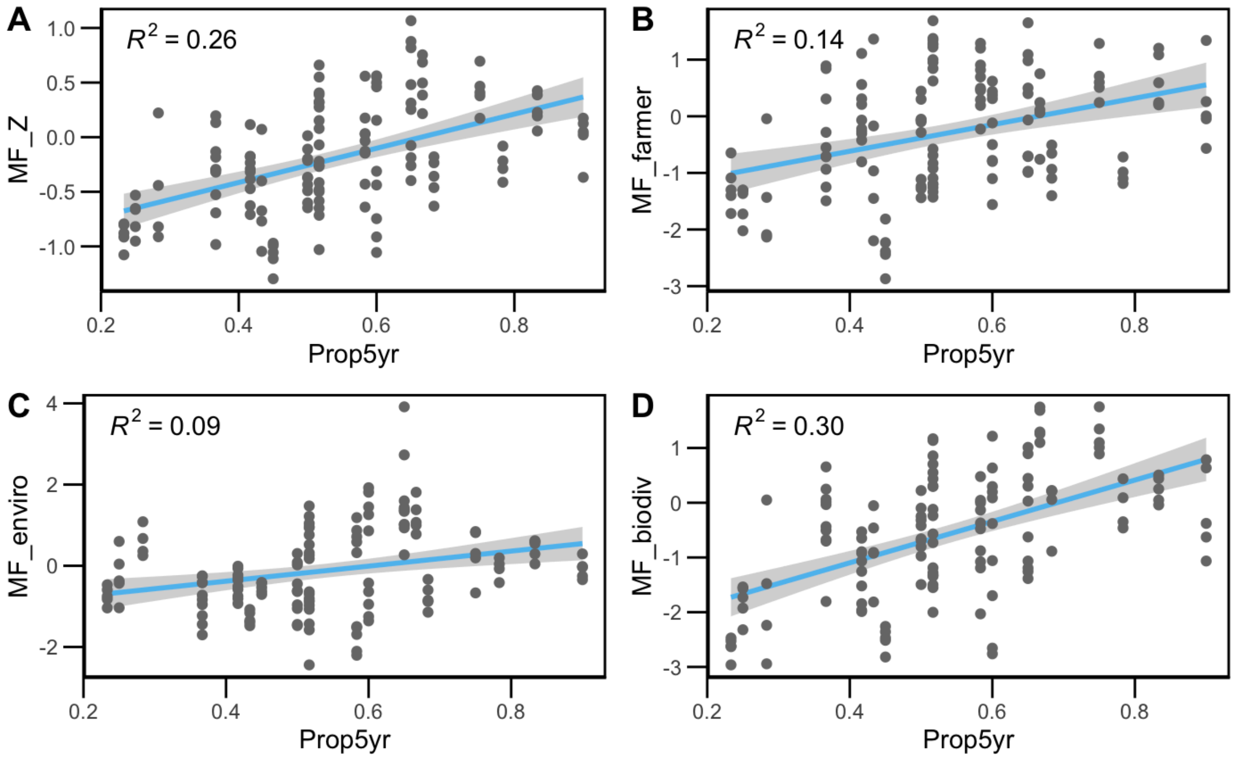


Figure 4: Bivariate plots of multifunctionality scores based on even (A), farmer or production (B), environmental (C), and soil microbial diversity (D) prioritization schemes and the proportion of continuous coverage over 5 years.

References

Abdalla, M., Hastings, A., Cheng, K., Yue, Q., Chadwick, D., Espenberg, M., Truu, J., Rees, R. M., & Smith, P. (2019). A critical review of the impacts of cover crops on nitrogen leaching, net greenhouse gas balance and crop productivity. *Global Change Biology*, *25*(8), 2530–2543. https://doi.org/10.1111/gcb.14644

Al-Kaisi, M., & Licht, M. A. (2004). Effect of Strip Tillage on Corn Nitrogen Uptake and Residual Soil Nitrate Accumulation Compared with No-Tillage and Chisel Plow. *Agronomy Journal*, *96*(4), 1164–1171. https://doi.org/10.2134/agronj2004.1164

Almasri, M. N., & Kaluarachchi, J. J. (2004). Assessment and management of long-term nitrate pollution of ground water in agriculture-dominated watersheds. *Journal of Hydrology*, *295*(1), 225–245. https://doi.org/10.1016/j.jhydrol.2004.03.013

Anthony, M. A., Bender, S. F., & van der Heijden, M. G. A. (2023). Enumerating soil biodiversity. *Proceedings of the National Academy of Sciences*, *120*(33), e2304663120. https://doi.org/10.1073/pnas.2304663120

Bach, C. E., Warnock, D. D., Van Horn, D. J., Weintraub, M. N., Sinsabaugh, R. L., Allison, S. D., & German, D. P. (2013). Measuring phenol oxidase and peroxidase activities with pyrogallol, l-DOPA, and ABTS: Effect of assay conditions and soil type. *Soil Biology and Biochemistry*, *67*, 183–191. https://doi.org/10.1016/j.soilbio.2013.08.022

Bakhsh, A., Kanwar, R. S., Karlen, D. L., Cambardella, C. A., Colvin, T. S., Moorman, T. B., & Bailey, T. B. (2000). TILLAGE AND NITROGEN MANAGEMENT EFFECTS ON CROP YIELD AND RESIDUAL SOIL NITRATE. *Transactions of the ASAE*, *43*(6), 1589–1595. https://doi.org/10.13031/2013.3059

Bandick, A. K., & Dick, R. P. (1999). Field management effects on soil enzyme activities. *Soil Biology and Biochemistry*, *31*(11), 1471–1479. https://doi.org/10.1016/S0038-0717(99)00051-6

Bates, D., Maechler, M., Bolker [aut, B., cre, Walker, S., Christensen, R. H. B., Singmann, H., Dai, B., Scheipl, F., Grothendieck, G., Green, P., Fox, J., Bauer, A., simulate.formula), P. N. K. (shared copyright on, & Tanaka, E. (2023). *lme4: Linear Mixed-Effects Models using "Eigen" and S4* (1.1-35.1) [Computer software]. https://cran.r-project.org/web/packages/lme4/index.html

Beillouin, D., Ben-Ari, T., & Makowski, D. (2019). Evidence map of crop diversification strategies at the global scale. *Environmental Research Letters*, *14*(12), 123001. https://doi.org/10.1088/1748-9326/ab4449

Beillouin, D., Ben-Ari, T., Malézieux, E., Seufert, V., & Makowski, D. (2021). Positive but variable effects of crop diversification on biodiversity and ecosystem services. *Global Change Biology*, *27*(19), 4697–4710. https://doi.org/10.1111/gcb.15747

Beule, L., & Karlovsky, P. (2020). Improved normalization of species count data in ecology by scaling with ranked subsampling (SRS): Application to microbial communities. *PeerJ*, *8*, e9593. https://doi.org/10.7717/peerj.9593

Bokulich, N. A., Kaehler, B. D., Rideout, J. R., Dillon, M., Bolyen, E., Knight, R., Huttley, G. A., & Gregory Caporaso, J. (2018). Optimizing taxonomic classification of marker-gene amplicon sequences with QIIME 2's q2-feature-classifier plugin. *Microbiome*, *6*(1), 90. https://doi.org/10.1186/s40168-018-0470-z

Bolyen, E., Rideout, J. R., Dillon, M. R., Bokulich, N. A., Abnet, C. C., Al-Ghalith, G. A., Alexander, H., Alm, E. J., Arumugam, M., Asnicar, F., Bai, Y., Bisanz, J. E., Bittinger, K., Brejnrod, A., Brislawn, C. J., Brown, C. T., Callahan, B. J., Caraballo-Rodríguez, A. M., Chase, J., … Caporaso, J. G. (2019). Reproducible, interactive, scalable and extensible microbiome data science using QIIME 2. *Nature Biotechnology*, *37*(8), 852–857. https://doi.org/10.1038/s41587-019-0209-9

Bongiorno, G., Bünemann, E. K., Oguejiofor, C. U., Meier, J., Gort, G., Comans, R., Mäder, P., Brussaard, L., & de Goede, R. (2019). Sensitivity of labile carbon fractions to tillage and organic matter management and their potential as comprehensive soil quality indicators across pedoclimatic conditions in Europe. *Ecological Indicators*, *99*, 38–50. https://doi.org/10.1016/j.ecolind.2018.12.008

Bowles, T. M., Acosta-Martínez, V., Calderón, F., & Jackson, L. E. (2014). Soil enzyme activities, microbial communities, and carbon and nitrogen availability in organic agroecosystems across an intensively-managed agricultural landscape. *Soil Biology and Biochemistry*, *68*, 252–262. https://doi.org/10.1016/j.soilbio.2013.10.004

Bowles, T. M., Hollander, A. D., Steenwerth, K., & Jackson, L. E. (2015). Tightly-Coupled Plant-Soil Nitrogen Cycling: Comparison of Organic Farms across an Agricultural Landscape. *PLOS ONE*, *10*(6), e0131888. https://doi.org/10.1371/journal.pone.0131888

Bowles, T. M., Mooshammer, M., Socolar, Y., Calderón, F., Cavigelli, M. A., Culman, S. W., Deen, W., Drury, C. F., Garcia y Garcia, A., Gaudin, A. C. M., Harkcom, W. S., Lehman, R. M., Osborne, S. L., Robertson, G. P., Salerno, J., Schmer, M. R., Strock, J., & Grandy, A. S. (2020). Long-Term Evidence Shows that Crop-Rotation Diversification Increases Agricultural Resilience to Adverse Growing Conditions in North America. *One Earth*, *2*(3), 284–293. https://doi.org/10.1016/j.oneear.2020.02.007

Bradford, M. A., Wood, S. A., Addicott, E. T., Fenichel, E. P., Fields, N., González-Rivero, J., Jevon, F. V., Maynard, D. S., Oldfield, E. E., Polussa, A., Ward, E. B., & Wieder, W. R. (2021). Quantifying microbial control of soil organic matter dynamics at macrosystem scales. *Biogeochemistry*, *156*(1), 19–40. https://doi.org/10.1007/s10533-021-00789-5

Brown, S., & Cotton, M. (2011). Changes in Soil Properties and Carbon Content Following Compost Application: Results of On-farm Sampling. *Compost Science & Utilization*, *19*(2), 87–96. https://doi.org/10.1080/1065657X.2011.10736983

Burchfield, E. K., Nelson, K. S., & Spangler, K. (2019). The impact of agricultural landscape diversification on U.S. crop production. *Agriculture, Ecosystems & Environment*, *285*, 106615. https://doi.org/10.1016/j.agee.2019.106615

California Department of Food & Agriculture. (2022). *California Agriultural Statistics Review 2021-2022* (Agricultural Statistics Review).

California Regional Water Quality Control Board, C. C. R. (2021). *GENERAL WASTE DISCHARGE REQUIREMENTS FOR DISCHARGES FROM IRRIGATED LANDS ORDER NO. R3-2021-0040*.

Callahan, B. J., McMurdie, P. J., Rosen, M. J., Han, A. W., Johnson, A. J. A., & Holmes, S. P. (2016). DADA2: High-resolution sample inference from Illumina amplicon data. *Nature Methods*, *13*(7), 581–583. https://doi.org/10.1038/nmeth.3869

Carlisle, L., Esquivel, K., Baur, P., Ichikawa, N. F., Olimpi, E. M., Ory, J., Waterhouse, H., Iles, A., Karp, D. S., Kremen, C., & Bowles, T. M. (2022). Organic farmers face persistent barriers to adopting diversification practices in California's Central Coast. *Agroecology and Sustainable Food Systems*, *46*(8), 1145–1172. https://doi.org/10.1080/21683565.2022.2104420

Carr, P. M., Mäder, P., Creamer, N. G., & Beeby, J. S. (2012). Editorial: Overview and comparison of conservation tillage practices and organic farming in Europe and North America. *Renewable Agriculture and Food Systems*, *27*(1), 2–6. https://doi.org/10.1017/S1742170511000536

Chavarría, D. N., Verdenelli, R. A., Serri, D. L., Restovich, S. B., Andriulo, A. E., Meriles, J. M., & Vargas-Gil, S. (2016). Effect of cover crops on microbial community structure and related enzyme activities and macronutrient availability. *European Journal of Soil Biology*, *76*, 74–82. https://doi.org/10.1016/j.ejsobi.2016.07.002

Conceição, P. C., Dieckow, J., & Bayer, C. (2013). Combined role of no-tillage and cropping systems in soil carbon stocks and stabilization. *Soil and Tillage Research*, *129*, 40–47. https://doi.org/10.1016/j.still.2013.01.006

County of Monterey Agricultural Commissioner. (2021). *Monterey County Crop & Livestock Report: Salad bowld of the world.*

D'Acunto, L., Andrade, J. F., Poggio, S. L., & Semmartin, M. (2018). Diversifying crop rotation increased metabolic soil diversity and activity of the microbial community. *Agriculture, Ecosystems & Environment*, *257*, 159–164. https://doi.org/10.1016/j.agee.2018.02.011

Delgado-Baquerizo, M., Maestre, F. T., Reich, P. B., Jeffries, T. C., Gaitan, J. J., Encinar, D., Berdugo, M., Campbell, C. D., & Singh, B. K. (2016). Microbial diversity drives multifunctionality in terrestrial ecosystems. *Nature Communications*, *7*(1), Article 1. https://doi.org/10.1038/ncomms10541

Delgado-Baquerizo, M., Trivedi, P., Trivedi, C., Eldridge, D. J., Reich, P. B., Jeffries, T. C., & Singh, B. K. (2017). Microbial richness and composition independently drive soil multifunctionality. *Functional Ecology*, *31*(12), 2330–2343. https://doi.org/10.1111/1365-2435.12924

Devine, S. M., Steenwerth, K. L., & O'Geen, A. T. (2021). A regional soil classification framework to improve soil health diagnosis and management. *Soil Science Society of America Journal*, *85*(2), 361–378. https://doi.org/10.1002/saj2.20200

Dominik, P., & Kaupenjohann, M. (2000). Simple spectrophotometric determination of Fe in oxalate and HCl soil extracts. *Talanta*, *51*(4), 701–707. https://doi.org/10.1016/s0039-9140(99)00324-0

Dray, S., Dufour, A.-B., Thioulouse, and J., Jombart, with contributions from T., Pavoine, S., Lobry, J. R., Ollier, S., Borcard, D., Legendre, P., & Chessel, S. B. and A. S. B. on earlier work by D. (2023). *ade4: Analysis of Ecological Data: Exploratory and Euclidean Methods in Environmental Sciences* (1.7-22) [Computer software]. https://cran.r-project.org/web/packages/ade4/index.html

Drinkwater, L. E., & Snapp, S. S. (2022). Advancing the science and practice of ecological nutrient management for smallholder farmers. *Frontiers in Sustainable Food Systems*, *6*. https://doi.org/10.3389/fsufs.2022.921216

Esquivel, K., Carlisle, L., Ke, A., Olimpi, E., Baur, P., Ory, J., Waterhouse, H., Iles, A., Karp, D. S., Kremen, C., & Bowles, T. M. (2021). The "sweet spot" in the middle: Why do mid-scale farms adopt diversification practices at higher rates? *Frontiers in Sustainable Food Systems*. https://doi.org/10.3389/fsufs.2021.734088

Gajda, A. M., Czyż, E. A., Dexter, A. R., Furtak, K. M., Grządziel, J., & Stanek-Tarkowska, J. (2018). Effects of different soil management practices on soil properties and microbial diversity. *International Agrophysics*, *32*(1), 81–91. https://doi.org/10.1515/intag-2016-0089

Garland, G., Banerjee, S., Edlinger, A., Miranda Oliveira, E., Herzog, C., Wittwer, R., Philippot, L., Maestre, F. T., & Van Der Heijden, M. G. A. (2021). A closer look at the functions behind ecosystem multifunctionality: A review. *Journal of Ecology*, *109*(2), 600–613. https://doi.org/10.1111/1365-2745.13511

Garland, G., Edlinger, A., Banerjee, S., Degrune, F., García-Palacios, P., Pescador, D. S., Herzog, C., Romdhane, S., Saghai, A., Spor, A., Wagg, C., Hallin, S., Maestre, F. T., Philippot, L., Rillig, M. C., & van der Heijden, M. G. A. (2021). Crop cover is more important than rotational diversity for soil multifunctionality and cereal yields in European cropping systems. *Nature Food*, *2*(1), 28–37. https://doi.org/10.1038/s43016-020-00210-8

Gelman, A. (2008). Scaling regression inputs by dividing by two standard deviations. *Statistics in Medicine*, *27*(15), 2865–2873. https://doi.org/10.1002/sim.3107

German, D. P., Weintraub, M. N., Grandy, A. S., Lauber, C. L., Rinkes, Z. L., & Allison, S. D. (2011). Optimization of hydrolytic and oxidative enzyme methods for ecosystem studies. *Soil Biology and Biochemistry*, *43*(7), 1387–1397. https://doi.org/10.1016/j.soilbio.2011.03.017

Guthman, J. (2004). *Agrarian dreams: The paradox of organic farming in California*. University of California Press.

Hamilton, P. A., & Helsel, D. R. (1995). Effects of Agriculture on Ground-Water Quality in Five Regions of the United States. *Groundwater*, *33*(2), 217–226. https://doi.org/10.1111/j.1745-6584.1995.tb00276.x

Harrison, X. A., Donaldson, L., Correa-Cano, M. E., Evans, J., Fisher, D. N., Goodwin, C. E. D., Robinson, B. S., Hodgson, D. J., & Inger, R. (2018). A brief introduction to mixed effects modelling and multi-model inference in ecology. *PeerJ*, *6*, e4794. https://doi.org/10.7717/peerj.4794

Holland, P. W. (1986). Statistics and Causal Inference. *Journal of the American Statistical Association*, *81*(396), 945–960. https://doi.org/10.1080/01621459.1986.10478354

Hollis, J. M., Hannam, J., & Bellamy, P. H. (2012). Empirically-derived pedotransfer functions for predicting bulk density in European soils. *European Journal of Soil Science*, *63*(1), 96–109. https://doi.org/10.1111/j.1365-2389.2011.01412.x

Hölting, L., Beckmann, M., Volk, M., & Cord, A. F. (2019). Multifunctionality assessments – More than assessing multiple ecosystem functions and services? A quantitative literature review. *Ecological Indicators*, *103*, 226–235. https://doi.org/10.1016/j.ecolind.2019.04.009

Hölting, L., Komossa, F., Filyushkina, A., Gastinger, M.-M., Verburg, P. H., Beckmann, M., Volk, M., & Cord, A. F. (2020). Including stakeholders' perspectives on ecosystem services in multifunctionality assessments. *Ecosystems and People*, *16*(1), 354–368. https://doi.org/10.1080/26395916.2020.1833986

Hothorn, T., Hornik, K., Strobl, C., & Zeileis, A. (2023). *party: A Laboratory for Recursive Partytioning* (1.3-14) [Computer software]. https://cran.r-project.org/web/packages/party/index.html

Hu, Q., Thomas, B. W., Powlson, D., Hu, Y., Zhang, Y., Jun, X., Shi, X., & Zhang, Y. (2023). Soil organic carbon fractions in response to soil, environmental and agronomic factors under cover cropping systems: A global meta-analysis. *Agriculture, Ecosystems & Environment*, *355*, 108591. https://doi.org/10.1016/j.agee.2023.108591

Hu, W., Ran, J., Dong, L., Du, Q., Ji, M., Yao, S., Sun, Y., Gong, C., Hou, Q., Gong, H., Chen, R., Lu, J., Xie, S., Wang, Z., Huang, H., Li, X., Xiong, J., Xia, R., Wei, M., … Deng, J. (2021). Aridity-driven shift in biodiversity–soil multifunctionality relationships. *Nature Communications*, *12*(1), 5350. https://doi.org/10.1038/s41467-021-25641-0

Isbell, F., Adler, P. R., Eisenhauer, N., Fornara, D., Kimmel, K., Kremen, C., Letourneau, D. K., Liebman, M., Polley, H. W., Quijas, S., & Scherer-Lorenzen, M. (2017). Benefits of increasing plant diversity in sustainable agroecosystems. *Journal of Ecology*, *105*(4), 871–879. https://doi.org/10.1111/1365-2745.12789

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

Joos, L., Beirinckx, S., Haegeman, A., Debode, J., Vandecasteele, B., Baeyen, S., Goormachtig, S., Clement, L., & De Tender, C. (2020). Daring to be differential: Metabarcoding analysis of soil and plant-related microbial communities using amplicon sequence variants and operational taxonomical units. *BMC Genomics*, *21*(1), 733. https://doi.org/10.1186/s12864-020-07126-4

Katoh, K., Misawa, K., Kuma, K., & Miyata, T. (2002). MAFFT: A novel method for rapid multiple sequence alignment based on fast Fourier transform. *Nucleic Acids Research*, *30*(14), 3059–3066. https://doi.org/10.1093/nar/gkf436

Khakural, B. R., & Robert, P. C. (1993). Soil Nitrate Leaching Potential Indices: Using a Simulation Model as a Screening System. *Journal of Environmental Quality*, *22*(4), 839–845. https://doi.org/10.2134/jeq1993.00472425002200040029x

Kim, N., Zabaloy, M. C., Guan, K., & Villamil, M. B. (2020). Do cover crops benefit soil microbiome? A meta-analysis of current research. *Soil Biology and Biochemistry*, *142*, 107701. https://doi.org/10.1016/j.soilbio.2019.107701

Kramer, S. B., Reganold, J. P., Glover, J. D., Bohannan, B. J. M., & Mooney, H. A. (2006). Reduced nitrate leaching and enhanced denitrifier activity and efficiency in organically fertilized soils. *Proceedings of the National Academy of Sciences*, *103*(12), 4522–4527. https://doi.org/10.1073/pnas.0600359103

Kremen, C., Iles, A., & Bacon, C. (2012). Diversified Farming Systems: An Agroecological, Systems-based Alternative to Modern Industrial Agriculture. *Ecology and Society*, *17*(4). https://doi.org/10.5751/ES-05103-170444

Kremen, C., & Merenlender, A. M. (2018). Landscapes that work for biodiversity and people. *Science*, *362*(6412), eaau6020. https://doi.org/10.1126/science.aau6020

Kremen, C., & Miles, A. (2012). Ecosystem Services in Biologically Diversified versus Conventional Farming Systems: Benefits, Externalities, and Trade-Offs. *Ecology and Society*, *17*(4). https://www.jstor.org/stable/26269237

Lal, R. (1991). Tillage and agricultural sustainability. *Soil and Tillage Research*, *20*(2), 133–146. https://doi.org/10.1016/0167-1987(91)90036-W

Lal, R., Eckert, D. J., Fausey, N. R., & Edwards, W. M. (1990). Conservation Tillage in Sustainable Agriculture. In *Sustainable Agricultural Systems*. CRC Press.

Lal, R., Monger, C., Nave, L., & Smith, P. (2021). The role of soil in regulation of climate. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *376*(1834), 20210084. https://doi.org/10.1098/rstb.2021.0084

Lee, H., & Lautenbach, S. (2016). A quantitative review of relationships between ecosystem services. *Ecological Indicators*, *66*, 340–351. https://doi.org/10.1016/j.ecolind.2016.02.004

Lehmann, J., Bossio, D. A., Kögel-Knabner, I., & Rillig, M. C. (2020a). The concept and future prospects of soil health. *Nature Reviews Earth & Environment*, *1*(10), 544–553. https://doi.org/10.1038/s43017-020-0080-8

Lehmann, J., Bossio, D. A., Kögel-Knabner, I., & Rillig, M. C. (2020b). The concept and future prospects of soil health. *Nature Reviews Earth & Environment*, *1*(10), Article 10. https://doi.org/10.1038/s43017-020-0080-8

Li, J., Yuan, X., Ge, L., Li, Q., Li, Z., Wang, L., & Liu, Y. (2020). Rhizosphere effects promote soil aggregate stability and associated organic carbon sequestration in rocky areas of desertification. *Agriculture, Ecosystems & Environment*, *304*, 107126. https://doi.org/10.1016/j.agee.2020.107126

Li, Y. C., Stoffella, P. J., Alva, A. K., Calvert, D. V., & Graetz, D. A. (1997). Leaching of Nitrate, Ammonium, and Phosphate From Compost Amended Soil Columns. *Compost Science & Utilization*, *5*(2), 63–67. https://doi.org/10.1080/1065657X.1997.10701875

Lovley, D. R., & Phillips, E. J. P. (1987). Rapid Assay for Microbially Reducible Ferric Iron in Aquatic Sediments. *Applied and Environmental Microbiology*, *53*(7), 1536–1540. https://doi.org/10.1128/aem.53.7.1536-1540.1987

Malhi, S. S., Brandt, S. A., Lemke, R., Moulin, A. P., & Zentner, R. P. (2009). Effects of input level and crop diversity on soil nitrate-N, extractable P, aggregation, organic C and N, and nutrient balance in the Canadian Prairie. *Nutrient Cycling in Agroecosystems*, *84*(1), 1–22. https://doi.org/10.1007/s10705-008-9220-0

Manning, P., van der Plas, F., Soliveres, S., Allan, E., Maestre, F. T., Mace, G., Whittingham, M. J., & Fischer, M. (2018). Redefining ecosystem multifunctionality. *Nature Ecology & Evolution*, *2*(3), Article 3. https://doi.org/10.1038/s41559-017-0461-7

Martin, M. (2011). Cutadapt removes adapter sequences from high-throughput sequencing reads. *EMBnet.Journal*, *17*(1), Article 1. https://doi.org/10.14806/ej.17.1.200

McKeague, J. A. (1967). An evaluation of 0.1 m pyrophosphate and pyrophosphate-dithionite in comparison with oxalate as extractants of the accumulation products in podzols and some other soils. *Canadian Journal of Soil Science*, *47*(2), 95–99. https://doi.org/10.4141/cjss67-017

Miller, R. O., Gavlak, R., & Horneck, D. (2013). *Soil, Plant and Water Reference Methods for the Western Region* (4th Edition). https://www.naptprogram.org/files/napt/publications/method-papers/western-states-methods-manual-2013.pdf

Miranda, K. M., Espey, M. G., & Wink, D. A. (2001). A Rapid, Simple Spectrophotometric Method for Simultaneous Detection of Nitrate and Nitrite. *Nitric Oxide*, *5*(1), 62–71. https://doi.org/10.1006/niox.2000.0319

Moebius-Clune, B. N. (2016). *Comprehensive assessment of soil health: The Cornell framework manual* (Third edition). Cornell University.

Mooshammer, M., Wanek, W., Hämmerle, I., Fuchslueger, L., Hofhansl, F., Knoltsch, A., Schnecker, J., Takriti, M., Watzka, M., Wild, B., Keiblinger, K. M., Zechmeister-Boltenstern, S., & Richter, A. (2014). Adjustment of microbial nitrogen use efficiency to carbon:nitrogen imbalances regulates soil nitrogen cycling. *Nature Communications*, *5*(1), 3694. https://doi.org/10.1038/ncomms4694

Nazaries, L., Singh, B. P., Sarker, J. R., Fang, Y., Klein, M., & Singh, B. K. (2021). The response of soil multi-functionality to agricultural management practices can be predicted by key soil abiotic and biotic properties. *Agriculture, Ecosystems & Environment*, *307*, 107206. https://doi.org/10.1016/j.agee.2020.107206

Nouri, A., Lukas, S., Singh, S., Singh, S., & Machado, S. (2022). When do cover crops reduce nitrate leaching? A global meta-analysis. *Global Change Biology*, *28*(15), 4736–4749. https://doi.org/10.1111/gcb.16269

O'Geen, A., Walkinshaw, M., & Beaudette, D. (2017). SoilWeb: A Multifaceted Interface to Soil Survey Information. *Soil Science Society of America Journal*, *81*(4), 853–862. https://doi.org/10.2136/sssaj2016.11.0386n

Oldfield, E. E., Bradford, M. A., & Wood, S. A. (2019). Global meta-analysis of the relationship between soil organic matter and crop yields. *SOIL*, *5*(1), 15–32. https://doi.org/10.5194/soil-5-15-2019

Olimpi, E. M., Ke, A., Baur, P., Carlisle, L., Esquivel, K., Glaser, T., Snyder, W. E., Waterhouse, H., Bowles, T. M., Kremen, C., & Karp, D. S. (2024). Ungrazed seminatural habitats around farms benefit bird conservation without enhancing food borne pathogen risks. *Landscape Ecology*.

Pathak, T. B., Maskey, M. L., Dahlberg, J. A., Kearns, F., Bali, K. M., & Zaccaria, D. (2018). Climate Change Trends and Impacts on California Agriculture: A Detailed Review. *Agronomy*, *8*(3), Article 3. https://doi.org/10.3390/agronomy8030025

Põlme, S., Abarenkov, K., Henrik Nilsson, R., Lindahl, B. D., Clemmensen, K. E., Kauserud, H., Nguyen, N., Kjøller, R., Bates, S. T., Baldrian, P., Frøslev, T. G., Adojaan, K., Vizzini, A., Suija, A., Pfister, D., Baral, H.-O., Järv, H., Madrid, H., Nordén, J., … Tedersoo, L. (2020). FungalTraits: A user-friendly traits database of fungi and fungus-like stramenopiles. *Fungal Diversity*, *105*(1), 1–16. https://doi.org/10.1007/s13225-020-00466-2

Prairie, A. M., King, A. E., & Cotrufo, M. F. (2023). Restoring particulate and mineral-associated organic carbon through regenerative agriculture. *Proceedings of the National Academy of Sciences*, *120*(21), e2217481120. https://doi.org/10.1073/pnas.2217481120

Price, M. N., Dehal, P. S., & Arkin, A. P. (2010). FastTree 2 – Approximately Maximum-Likelihood Trees for Large Alignments. *PLOS ONE*, *5*(3), e9490. https://doi.org/10.1371/journal.pone.0009490

Quast, C., Pruesse, E., Yilmaz, P., Gerken, J., Schweer, T., Yarza, P., Peplies, J., & Glöckner, F. O. (2013). The SILVA ribosomal RNA gene database project: Improved data processing and web-based tools. *Nucleic Acids Research*, *41*(Database issue), D590–D596. https://doi.org/10.1093/nar/gks1219

Raiesi, F., & Beheshti, A. (2014). Soil specific enzyme activity shows more clearly soil responses to paddy rice cultivation than absolute enzyme activity in primary forests of northwest Iran. *Applied Soil Ecology*, *75*, 63–70. https://doi.org/10.1016/j.apsoil.2013.10.012

Raudsepp-Hearne, C., Peterson, G. D., & Bennett, E. M. (2010). Ecosystem service bundles for analyzing tradeoffs in diverse landscapes. *Proceedings of the National Academy of Sciences*, *107*(11), 5242–5247. https://doi.org/10.1073/pnas.0907284107

Rennert, T. (2018). Wet-chemical extractions to characterise pedogenic Al and Fe species – a critical review. *Soil Research*, *57*(1), 1–16. https://doi.org/10.1071/SR18299

Ros, M., Klammer, S., Knapp, B., Aichberger, K., & Insam, H. (2006). Long-term effects of compost amendment of soil on functional and structural diversity and microbial activity. *Soil Use and Management*, *22*(2), 209–218. https://doi.org/10.1111/j.1475-2743.2006.00027.x

Rosa-Schleich, J., Loos, J., Mußhoff, O., & Tscharntke, T. (2019). Ecological-economic trade-offs of Diversified Farming Systems – A review. *Ecological Economics*, *160*, 251–263. https://doi.org/10.1016/j.ecolecon.2019.03.002

Rosenstock, T. S., Liptzin, D., Dzurella, K., Fryjoff-Hung, A., Hollander, A., Jensen, V., King, A., Kourakos, G., McNally, A., Pettygrove, G. S., Quinn, J., Viers, J. H., Tomich, T. P., & Harter, T. (2014). Agriculture's Contribution to Nitrate Contamination of Californian

Groundwater (1945–2005). *Journal of Environmental Quality*, *43*(3), 895–907. https://doi.org/10.2134/jeq2013.10.0411
San Benito County Agricultural Commissioner. (2020). *San Benito County Crop & Livestock Report*.
Santa Cruz County Agricultural Commissioner. (2021). *Santa Cruz County Agricultural Crop and Livestock Report*.
Schimel, J., & Schaeffer, S. M. (2012). Microbial control over carbon cycling in soil. *Frontiers in Microbiology*, *3*. https://doi.org/10.3389/fmicb.2012.00348
Schjønning, P., Jensen, J. L., Bruun, S., Jensen, L. S., Christensen, B. T., Munkholm, L. J., Oelofse, M., Baby, S., & Knudsen, L. (2018). The Role of Soil Organic Matter for Maintaining Crop Yields: Evidence for a Renewed Conceptual Basis. In *Advances in Agronomy* (Vol. 150, pp. 35–79). Elsevier. https://doi.org/10.1016/bs.agron.2018.03.001
Schulte, R. P. O., Creamer, R. E., Donnellan, T., Farrelly, N., Fealy, R., O'Donoghue, C., & O'hUallachain, D. (2014). Functional land management: A framework for managing soil-based ecosystem services for the sustainable intensification of agriculture. *Environmental Science & Policy*, *38*, 45–58. https://doi.org/10.1016/j.envsci.2013.10.002
Setia, R., Verma, S. L., & Marschner, P. (2012). Measuring microbial biomass carbon by direct extraction – Comparison with chloroform fumigation-extraction. *European Journal of Soil Biology*, *53*, 103–106. https://doi.org/10.1016/j.ejsobi.2012.09.005
Singh, G., Williard, K. W. J., & Schoonover, J. E. (2018). Cover Crops and Tillage Influence on Nitrogen Dynamics in Plant-Soil-Water Pools. *Soil Science Society of America Journal*, *82*(6), 1572–1582. https://doi.org/10.2136/sssaj2018.03.0111
Singh, P., Kawa, N. C., & Sprunger, C. D. (2024). "More questions than answers": Ohio farmers' perceptions of novel soil health data and their utility for on-farm management. *Agroecology and Sustainable Food Systems*, *48*(1), 74–92. https://doi.org/10.1080/21683565.2023.2270928
Six, J., Elliott, E. T., & Paustian, K. (1999). Aggregate and Soil Organic Matter Dynamics under Conventional and No-Tillage Systems. *Soil Science Society of America Journal*, *63*(5), 1350–1358. https://doi.org/10.2136/sssaj1999.6351350x
Soil Health | Natural Resources Conservation Service. (2024, April 1). https://www.nrcs.usda.gov/conservation-basics/natural-resource-concerns/soils/soil-health
Sprunger, C. D., Culman, S. W., Deiss, L., Brock, C., & Jackson-Smith, D. (2021). Which management practices influence soil health in Midwest organic corn systems? *Agronomy Journal*, *113*(5), 4201–4219. https://doi.org/10.1002/agj2.20786
Stefan, L., Hartmann, M., Engbersen, N., Six, J., & Schöb, C. (2021). Positive Effects of Crop Diversity on Productivity Driven by Changes in Soil Microbial Composition. *Frontiers in Microbiology*, *12*. https://doi.org/10.3389/fmicb.2021.660749
Stoffel, M. A., Nakagawa, S., & Schielzeth, H. (2024). *partR2: Partitioning R2 in GLMMs* (0.9.2) [Computer software]. https://cran.r-project.org/web/packages/partR2/index.html
Szumigalski, A. R., & Van Acker, R. C. (2006). Nitrogen Yield and Land Use Efficiency in Annual Sole Crops and Intercrops. *Agronomy Journal*, *98*(4), 1030–1040. https://doi.org/10.2134/agronj2005.0277
Tamburini, G., Bommarco, R., Wanger, T. C., Kremen, C., van der Heijden, M. G. A., Liebman, M., & Hallin, S. (2020). Agricultural diversification promotes multiple ecosystem services without compromising yield. *Science Advances*, *6*(45), eaba1715. https://doi.org/10.1126/sciadv.aba1715

Tamburini, G., De Simone, S., Sigura, M., Boscutti, F., & Marini, L. (2016). Soil management shapes ecosystem service provision and trade-offs in agricultural landscapes. *Proceedings of the Royal Society B: Biological Sciences*, *283*(1837), 20161369. https://doi.org/10.1098/rspb.2016.1369

Taylor, D. L., Walters, W. A., Lennon, N. J., Bochicchio, J., Krohn, A., Caporaso, J. G., & Pennanen, T. (2016). Accurate Estimation of Fungal Diversity and Abundance through Improved Lineage-Specific Primers Optimized for Illumina Amplicon Sequencing. *Applied and Environmental Microbiology*, *82*(24), 7217–7226. https://doi.org/10.1128/AEM.02576-16

Tosi, M., Drummelsmith, J., Obregón, D., Chahal, I., Van Eerd, L. L., & Dunfield, K. E. (2022). Cover crop-driven shifts in soil microbial communities could modulate early tomato biomass via plant-soil feedbacks. *Scientific Reports*, *12*(1), 9140. https://doi.org/10.1038/s41598-022-11845-x

Turkelboom, F., Leone, M., Jacobs, S., Kelemen, E., García-Llorente, M., Baró, F., Termansen, M., Barton, D. N., Berry, P., Stange, E., Thoonen, M., Kalóczkai, Á., Vadineanu, A., Castro, A. J., Czúcz, B., Röckmann, C., Wurbs, D., Odee, D., Preda, E., … Rusch, V. (2018). When we cannot have it all: Ecosystem services trade-offs in the context of spatial planning. *Ecosystem Services*, *29*, 566–578. https://doi.org/10.1016/j.ecoser.2017.10.011

van Oudenhoven, A. P. E., Schröter, M., Drakou, E. G., Geijzendorffer, I. R., Jacobs, S., van Bodegom, P. M., Chazee, L., Czúcz, B., Grunewald, K., Lillebø, A. I., Mononen, L., Nogueira, A. J. A., Pacheco-Romero, M., Perennou, C., Remme, R. P., Rova, S., Syrbe, R.-U., Tratalos, J. A., Vallejos, M., & Albert, C. (2018). Key criteria for developing ecosystem service indicators to inform decision making. *Ecological Indicators*, *95*, 417–426. https://doi.org/10.1016/j.ecolind.2018.06.020

Varsa, E. C., Chong, S. K., Abolaji, J. O., Farquhar, D. A., & Olsen, F. J. (1997). Effect of deep tillage on soil physical characteristics and corn (*Zea mays* L.) root growth and production. *Soil and Tillage Research*, *43*(3), 219–228. https://doi.org/10.1016/S0167-1987(97)00041-X

Vazquez, C., de Goede, R. G. M., Rutgers, M., de Koeijer, T. J., & Creamer, R. E. (2021). Assessing multifunctionality of agricultural soils: Reducing the biodiversity trade-off. *European Journal of Soil Science*, *72*(4), 1624–1639. https://doi.org/10.1111/ejss.13019

Villarino, S. H., Pinto, P., Jackson, R. B., & Piñeiro, G. (2021). Plant rhizodeposition: A key factor for soil organic matter formation in stable fractions. *Science Advances*, *7*(16), eabd3176. https://doi.org/10.1126/sciadv.abd3176

Vukicevich, E., Lowery, T., Bowen, P., Úrbez-Torres, J. R., & Hart, M. (2016). Cover crops to increase soil microbial diversity and mitigate decline in perennial agriculture. A review. *Agronomy for Sustainable Development*, *36*(3), 48. https://doi.org/10.1007/s13593-016-0385-7

Wade, J., Culman, S. W., Gasch, C. K., Lazcano, C., Maltais-Landry, G., Margenot, A. J., Martin, T. K., Potter, T. S., Roper, W. R., Ruark, M. D., Sprunger, C. D., & Wallenstein, M. D. (2022). Rigorous, empirical, and quantitative: A proposed pipeline for soil health assessments. *Soil Biology and Biochemistry*, *170*, 108710. https://doi.org/10.1016/j.soilbio.2022.108710

Wagg, C., Schlaeppi, K., Banerjee, S., Kuramae, E. E., & van der Heijden, M. G. A. (2019). Fungal-bacterial diversity and microbiome complexity predict ecosystem functioning. *Nature Communications*, *10*(1), 4841. https://doi.org/10.1038/s41467-019-12798-y

Wasserstein, R. L., & Lazar, N. A. (2016). The ASA Statement on p-Values: Context, Process, and Purpose. *The American Statistician*, *70*(2), 129–133. https://doi.org/10.1080/00031305.2016.1154108

Wasserstein, R. L., Schirm, A. L., & Lazar, N. A. (2019). Moving to a World Beyond "p < 0.05." *The American Statistician*, *73*(sup1), 1–19. https://doi.org/10.1080/00031305.2019.1583913
White, K. E., Brennan, E. B., & Cavigelli, M. A. (2020). Soil carbon and nitrogen data during eight years of cover crop and compost treatments in organic vegetable production. *Data in Brief*, *33*, 106481. https://doi.org/10.1016/j.dib.2020.106481
White, K. E., Brennan, E. B., Cavigelli, M. A., & Smith, R. F. (2020a). Winter cover crops increase readily decomposable soil carbon, but compost drives total soil carbon during eight years of intensive, organic vegetable production in California. *PLOS ONE*, *15*(2), e0228677. https://doi.org/10.1371/journal.pone.0228677
White, K. E., Brennan, E. B., Cavigelli, M. A., & Smith, R. F. (2020b). Winter cover crops increase readily decomposable soil carbon, but compost drives total soil carbon during eight years of intensive, organic vegetable production in California. *PLOS ONE*, *15*(2), e0228677. https://doi.org/10.1371/journal.pone.0228677
White, K. E., Brennan, E. B., Cavigelli, M. A., & Smith, R. F. (2022). Winter cover crops increased nitrogen availability and efficient use during eight years of intensive organic vegetable production. *PLOS ONE*, *17*(4), e0267757. https://doi.org/10.1371/journal.pone.0267757
Williams, A., & Hedlund, K. (2013). Indicators of soil ecosystem services in conventional and organic arable fields along a gradient of landscape heterogeneity in southern Sweden. *Applied Soil Ecology*, *65*, 1–7. https://doi.org/10.1016/j.apsoil.2012.12.019
Wood, S. A., Sokol, N., Bell, C. W., Bradford, M. A., Naeem, S., Wallenstein, M. D., & Palm, C. A. (2016). Opposing effects of different soil organic matter fractions on crop yields. *Ecological Applications*, *26*(7), 2072–2085. https://doi.org/10.1890/16-0024.1
Wood, S. A., Tirfessa, D., & Baudron, F. (2018). Soil organic matter underlies crop nutritional quality and productivity in smallholder agriculture. *Agriculture, Ecosystems & Environment*, *266*, 100–108. https://doi.org/10.1016/j.agee.2018.07.025
Wooliver, R., Kivlin, S. N., & Jagadamma, S. (2022). Links Among Crop Diversification, Microbial Diversity, and Soil Organic Carbon: Mini Review and Case Studies. *Frontiers in Microbiology*, *13*, 854247. https://doi.org/10.3389/fmicb.2022.854247
Xia, Q., Rufty, T., & Shi, W. (2020). Soil microbial diversity and composition: Links to soil texture and associated properties. *Soil Biology and Biochemistry*, *149*, 107953. https://doi.org/10.1016/j.soilbio.2020.107953
Zhang, X., Zhang, X., Li, X., Zhu, Y., Lv, H., Zhou, W., & Liang, B. (2023). Microbial mechanism of crop residues addition in nitrogen leaching loss retention and soil ecosystem stability maintenance. *Environmental Technology & Innovation*, *31*, 103194. https://doi.org/10.1016/j.eti.2023.103194
Zheng, Q., Hu, Y., Zhang, S., Noll, L., Böckle, T., Dietrich, M., Herbold, C. W., Eichorst, S. A., Woebken, D., Richter, A., & Wanek, W. (2019). Soil multifunctionality is affected by the soil environment and by microbial community composition and diversity. *Soil Biology and Biochemistry*, *136*, 107521. https://doi.org/10.1016/j.soilbio.2019.107521
Zhou, X., Sun, H., Heinonsalo, J., Pumpanen, J., & Berninger, F. (2022). Microbial biodiversity contributes to soil carbon release: A case study on fire disturbed boreal forests. *FEMS Microbiology Ecology*, *98*(8), fiac074. https://doi.org/10.1093/femsec/fiac074
Zu-Cong, C., Wen-Hui, Z., & 1 State Key Laboratory of Soil and Sustainable Agriculture, Institute of Soil Sciences, Chinese Academy of Sciences, Nanjing 210008</br>2 College of Chemistry and Enivio

nmental Sciences,Nanjing Normal University,Nanjing 210097. (2004). Effect of soil management practices and environmental factors on soil microbial diversity: A review. *Biodiversity Science*, *12*(4), 456–465. https://doi.org/10.17520/biods.2004056

Zuur, A. F., Ieno, E. N., Walker, N. J., Saveliev, A. A., & Smith, G. M. (2009). Mixed Effects Modelling for Nested Data. In A. F. Zuur, E. N. Ieno, N. Walker, A. A. Saveliev, & G. M. Smith (Eds.), *Mixed effects models and extensions in ecology with R* (pp. 101–142). Springer. https://doi.org/10.1007/978-0-387-87458-6_5

Zwetsloot, M. J., van Leeuwen, J., Hemerik, L., Martens, H., Simó Josa, I., Van de Broek, M., Debeljak, M., Rutgers, M., Sandén, T., Wall, D. P., Jones, A., & Creamer, R. E. (2021). Soil multifunctionality: Synergies and trade-offs across European climatic zones and land uses. *European Journal of Soil Science*, *72*(4), 1640–1654. https://doi.org/10.1111/ejss.13051

Supplementary materials

Supplemental tables

Table S1: Site-level texture, CEC, pH, order and series data from lab analysis and SSURGO

Site ID	Series	Sand (%)	Clay (%)	Silt (%)	CEC (Meq/100g)	pH	Dominant Order
1	Sorrento	6.4	50.4	43.2	32.6	7.44	Mollisol
2	Salinas	40.8	32.8	26.4	27.3	7.52	Mollisol
3	Riverwash	37.6	25.4	37	20.38	7.74	Mollisol
4	Sorrento	30.4	23.2	46.4	23.36	8.24	Mollisol
5	Sorrento	20.4	48	31.6	43.52	7.8	Mollisol
6	Chualar	55.2	17	27.8	11.06	7.82	Mollisol
7	Chualar	72.4	6.4	21.2	12.06	7.68	Mollisol
8	Sorrento	18.4	47.4	34.2	36.64	7.44	Mollisol
9	Arnold	34.6	26.4	39	21.08	6.98	Entisol
10	Pinto	48	17.8	34.2	14.7	7.32	Mollisol
11	Danville	45.8	24.6	29.6	24.12	6.72	Mollisol
12	Tierra-Watsonville	38.6	30.4	31	26.82	7.52	Alfisol
13	Clear Lake	13.8	59.6	26.6	43.04	6.96	Vertisol
14	Chualar	56.2	13	30.8	10.2	7.7	Mollisol
15	Corducci-Typic Xerofluvents	51	15.2	33.8	13.24	7.72	Entisol
16	Watsonville	42.2	27.4	30.4	19.04	7.54	Mollisol
17	Pacheco	28.8	41.2	30	28.78	7.86	Mollisol
18	Conejo	46	22	32	19.5	7.1	Mollisol
19	Chualar	65.8	12.8	21.4	8.34	8.06	Mollisol
20	Placentia	44.8	21.4	33.8	16.1	7.42	Alfisol
21	Pinto	51.6	20.2	28.2	11.28	6.54	Mollisol
22	Mocho	17.2	35.8	47	25.2	8.26	Mollisol
23	Gloria	42.2	17	40.8	12.44	7.34	Alfisol
24	Placentia	45.2	20	34.8	15.02	7.08	Alfisol
25	Sorrento	18.6	39	42.4	25	8.06	Mollisol
26	Elder	57.4	11.8	30.8	11.84	6.68	Mollisol
27	San Andreas - Santa Ynez	59.8	10.6	29.6	8.44	7.7	Mollisol
28	Hanford	75.4	6	18.6	8.1	7.8	Entisol

Table S2: Summary of mixed-effects models for single ecosystem services. Unstandardized coefficients with standard error are reported with p-values in parentheses. Green and red squares indicate positive and negative coefficients, respectively, at a significance level of $p < 0.1$. Light yellow-green indicates values just above this threshold. Gray cells indicate that the variable was not included in a given model and white cells indicate that the variable was included, but non-significant.

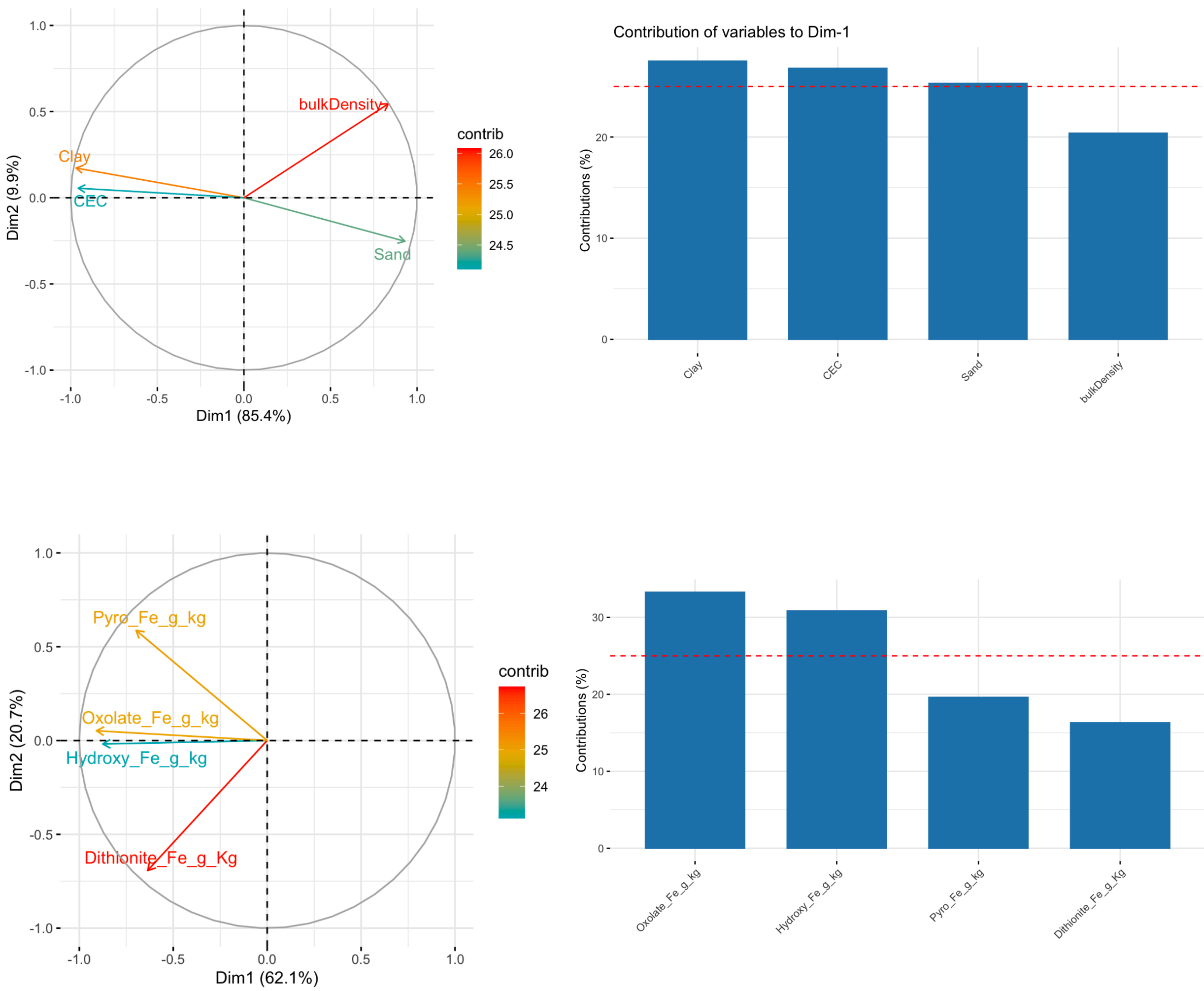
Service model	Crop provisioning	Climate regulation	NO_3 leaching mitigation	SOM turnover/ Microbial activity		Soil fertility	Soil habitat / Biodiversity
Indicator	Normalized yield	Carbon stock (0-60 cm)	Harvest NO_3 stock (0-60 cm)	Absolute enzyme activity	Mass-specific enzyme activity	Particulate organic matter stock (0-15 cm)	Microbial Shannon diversity
Intercept	0.46 ± 0.034 (9.64e-12)	1.63 ± 1.37 (0.24)	-6.78 ± 1.56 (6.21e-5)	2.30 ± 1.07 (0.033)	1.14 ± 1.90 (0.55)	-0.36 ± 1.74 (0.84)	3.43 ± 2.45 (0.17)
Continuous coverage	0.092 ± 0.081 (0.27)	0.15 ± 0.14 (0.27)			0.25 ± 0.20 (0.23)		
Reduced disturbance	-0.021 ± 0.075 (0.78)	0.21 ± 0.13 (0.12)		-0.13 ± 0.12 (0.28)	-0.15 ± 0.18 (0.43)	-0.05 ± 0.15 (0.76)	.057 ± 0.17 (0.74)
C amendment	0.30 ± 0.086 (0.0019)	0.08 ± 0.14 (0.57)	0.24 ± 0.12 (0.052)	-0.01 ± 0.12 (0.95)	0.38 ± 0.21 (0.079)	-0.23 ± 0.16 (0.16)	0.13 ± 0.18 (0.48)
Crop diversity	-0.20 ± 0.081 (0.019)	0.07 ± 0.14 (0.61)		-0.06 ± 0.12 (0.59)	-0.05 ± 0.20 (0.80)	0.30 ± 0.16 (0.08)	0.19 ± 0.17 (0.29)
Prop. 5-year cont. cover						2.1 ± 1.04 (0.054)	
2019 prop. cont. cover			0.97 ± 0.61 (0.12)	1.22 ± 0.54 (0.033)			1.69 ± 0.84 (0.055)
Deep tillage depth			2.05 ± 0.49 (0.00053)				
No. of crop families			1.79 ± 0.63 (0.009)				
Iron	-0.167 ± 0.064 (0.011)	0.15 ± 0.06 (0.0091)	0.08 ± 0.06 (0.22)	0.06 ± 0.04 (0.083)	0.12 ± 0.08 (0.10)	0.26 ± 0.07 (0.0002)	-0.27 ± 0.11 (0.014)

pH	0.008 ± 0.059 (0.89)	-0.22 ± 0.18 (0.24)	0.54 ± 0.20 (0.009)	-0.45 ± 0.13 (0.001)	0.30 ± 0.25 (0.24)	-0.10 ± 0.22 (0.63)	0.45 ± 0.31 (0.15)
Soil physical (Clay < Sand)	0.032 ± 0.034 (0.712)	-0.29 ± 0.07 (0.00027)	0.12 ± 0.07 (0.11)	0.16 ± 0.06 (0.010)	0.22 ± 0.10 (0.040)	0.17 ± 0.10 (0.09)	0.21 ± 0.11 (0.061)

Table S3: Unstandardized coefficient estimates, standard errors, and p-values from multifunctionality mixed-models. Each column represents a different multifunctionality weighting calculation. Green cells indicate a positive coefficient estimate.

Raw values	Even	Production	Environmental	Biodiversity
Intercept	-1.14 ± 0.89 (0.20)	-1.46 ± 1.91, (0.45)	-0.18 ± 0.18 (0.31)	-0.18 ± 0.20 (0.38)
Reduced disturbance	-0.03 ± 0.074 (0.73)	-0.14 ± 0.15, (0.37)	0.01 ± 0.02 (0.42)	-0.009 ± 0.016 (0.59)
C amendment	0.22 ± 0.079 (0.0099)	0.53 ± 0.16, (0.0031)	0.02 ± 0.02 (0.19)	0.027 ± 0.018 (0.13)
Crop diversity	0.0088 ± 0.078 (0.91)	-0.18 ± 0.16, (0.26)	0.01 ± 0.02 (0.53)	0.017 ± 0.017 (0.33)
Prop. 5-year Cover	1.34 ± 0.51 (0.015)	2.21 ± 1.05, (0.045)	0.20 ± 0.11 (0.091)	0.23 ± 0.11 (0.050)
Iron	0.027 ± 0.036 (0.44)	-0.07 ± 0.08, (0.38)	0.02 ± 0.01 (0.0047)	0.002 ± 0.008 (0.81)
pH	0.028 ± 0.11 (0.81)	-0.01 ± 0.24, (0.97)	0.01 ± 0.02 (0.67)	-0.0013 ± 0.025 (0.96)
Soil physical (Clay < Sand)	0.051 ± 0.048 (0.30)	0.12 ± 0.10, (0.25)	-0.01 ± 0.01 (0.37)	0.024 ± 0.011 (0.031)

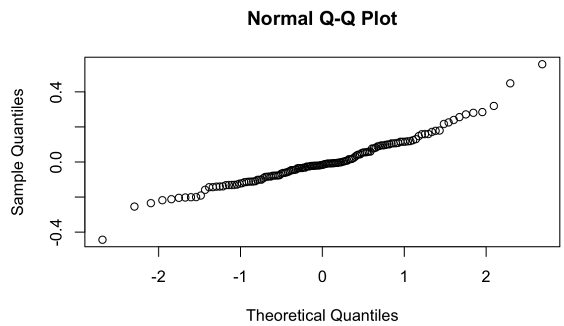
Supplemental figure

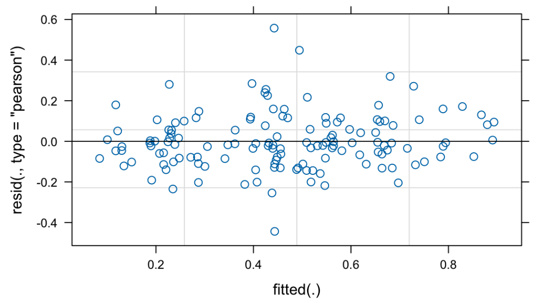


Supplemental Figure 1: Principal component axes utilized for mixed models. Physical and iron characteristics. The first principal component describes 85.4% and 62.1% of variance for physical and iron PCAs, respectively.

Model assumption checks

Yield



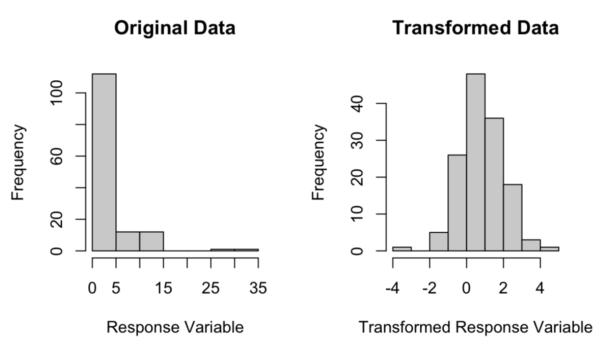



```
soil_phys_scores soil_iron_scores               pH  CoverCrop_Z_rem
        1.667592         1.427579         1.101996         1.460023
   Disturbance_Z        CropDiv_Z         Cinput_Z
        1.186519         1.386748         1.575682
```

Enzyme activities:

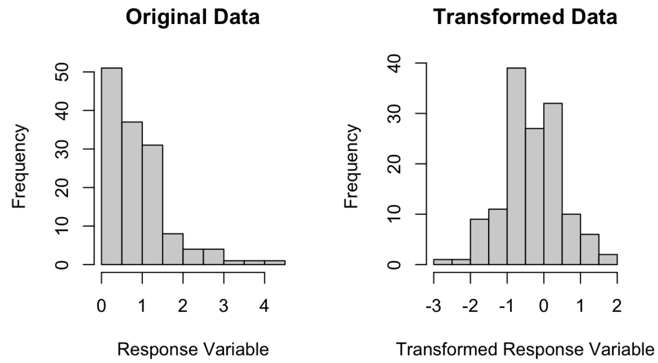
Box-cox transformation of Enzyme scores:

Mass-specific:



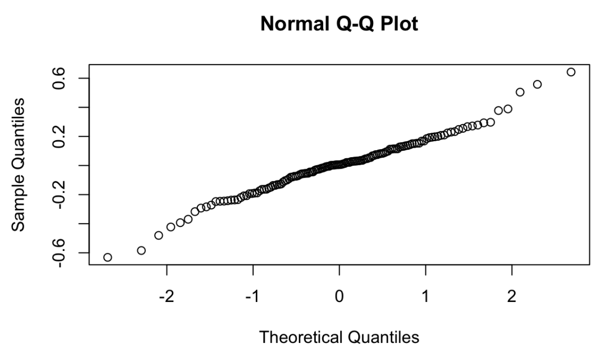

```
lambda = 0.1010101
```

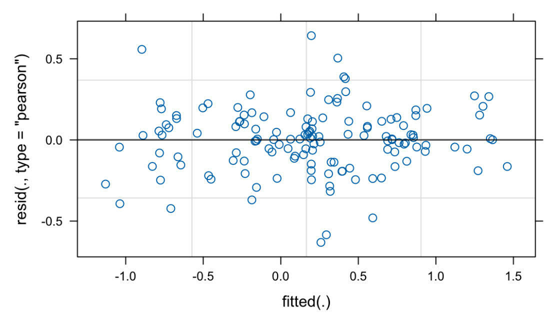
Absolute:




```
lambda = 0.2626263
```

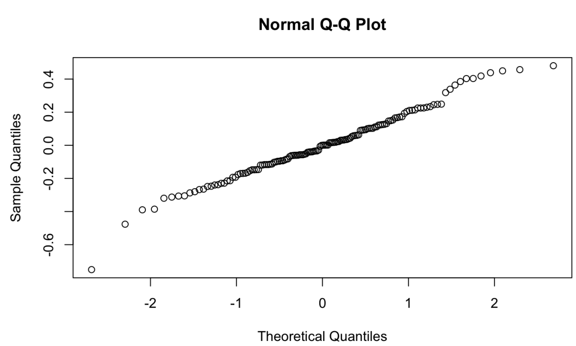
Absolute Enzyme Activity:

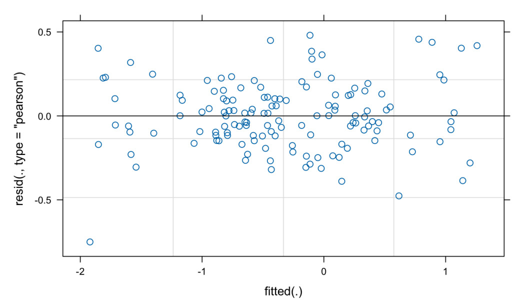





```
soil_phys_scores soil_iron_scores               pH    Prop_Cover2019
        1.514724         1.273710         1.087963          1.286120
   Disturbance_Z        CropDiv_Z        Cinput_Z
        1.227546         1.274365         1.265071
```

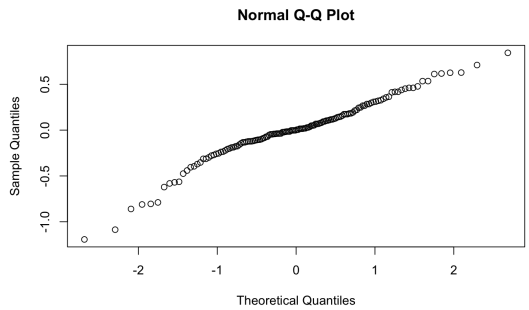
Mass-specific enzyme activity:

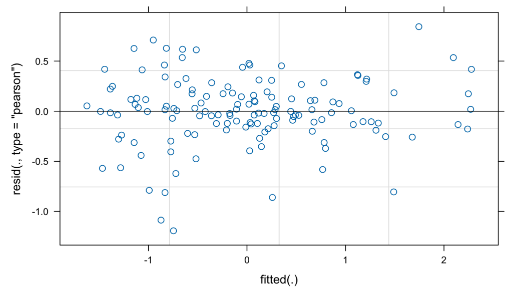





```
soil_phys_scores soil_iron_scores               pH    Prop_Cover2019     Disturbance_Z
        1.427369         1.222385         1.077721          1.240096          1.207476
       CropDiv_Z         Cinput_Z
        1.264776         1.249389
```

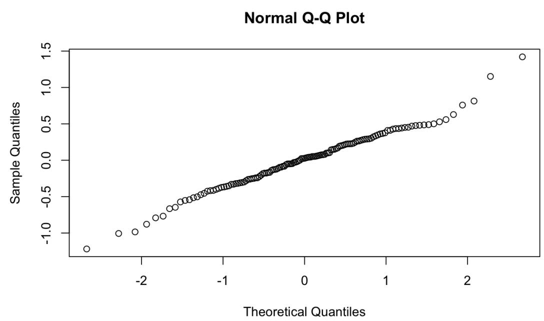
C-stock

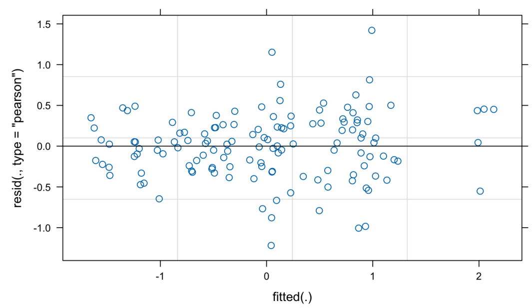





```
soil_iron_scores soil_phys_scores               pH  CoverCrop_Z_rem    Disturbance_Z
        1.307653         1.533450         1.078623         1.413827         1.179375
       CropDiv_Z         Cinput_Z
        1.367049         1.523747
```

NO_3 risk mitigation

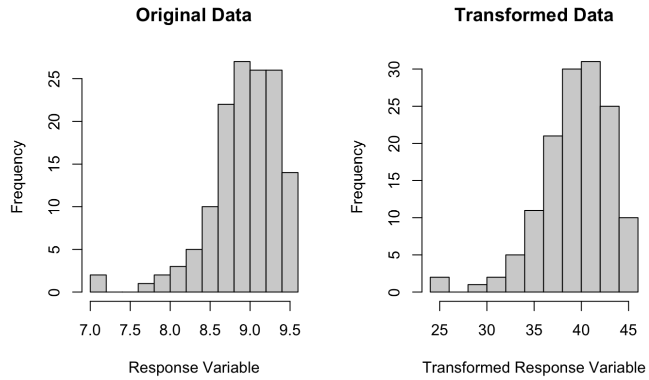




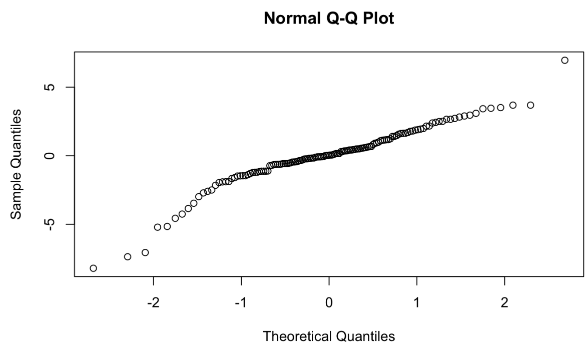

```
  soil_phys_scores   soil_iron_scores                 pH     Prop_Cover2019
          1.645860           1.441267           1.253497           1.492306
        Till_depth NumberCropFamilies           Cinput_Z
          1.073098           1.382302           1.180744
```

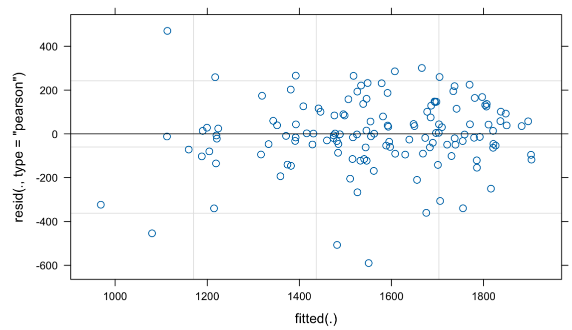
Shannon bacteria

Box-cox transformation



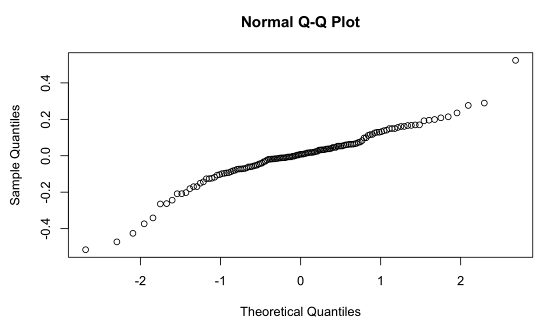

```
lambda = 2
```

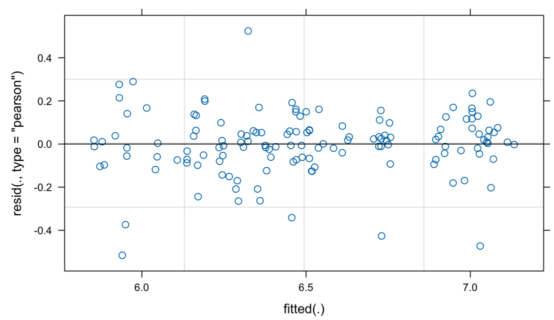





```
soil_iron_scores soil_phys_scores               pH   Prop_Cover2019    Disturbance_Z
        1.626176         1.926002         1.164632         1.460065         1.286336
      CropDiv_Z          Cinput_Z
        1.314132         1.326922
```

Shannon fungi

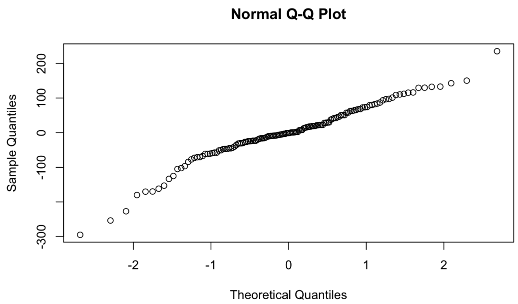


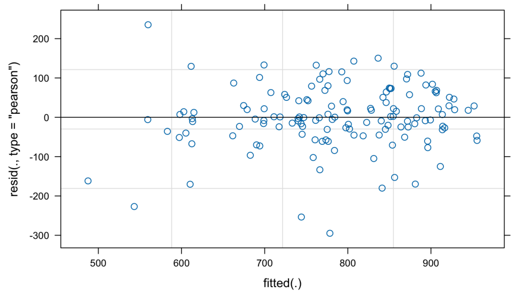



```
soil_iron_scores soil_phys_scores               pH   Prop_Cover2019    Disturbance_Z

        1.325917         1.590304         1.099115         1.323458         1.241933

       CropDiv_Z         Cinput_Z

        1.282565         1.277911
```

Shannon microbial

```
Shannon_microbial = mean(Shannon_bacteria^2 + Shannon_fungal)/100
```



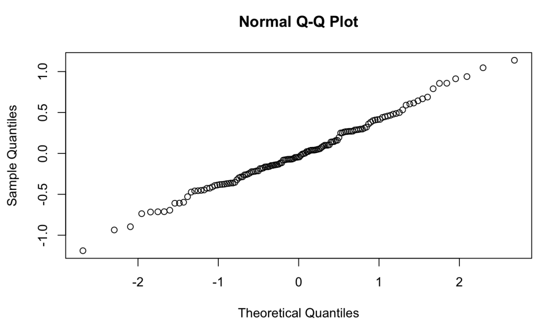


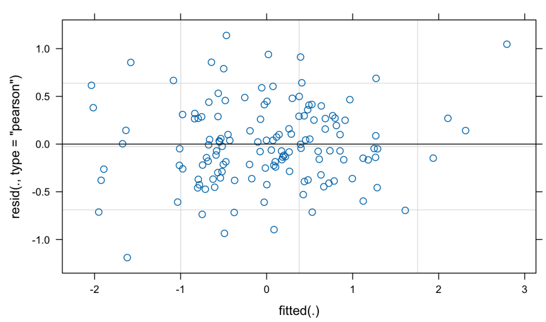

```
soil_iron_scores soil_phys_scores               pH   Prop_Cover2019    Disturbance_Z
        1.625781         1.925618         1.164547         1.459935         1.286297
       CropDiv_Z         Cinput_Z
        1.314100         1.326870
```

FIXED EFFECTS:

	Est.	S.E.	t val.	d.f.	p
(Intercept)	3.43	2.48	1.38	40.81	0.17
soil_iron_scores	-0.27	0.10	-2.53	72.03	0.01
soil_phys_scores	0.21	0.11	1.94	32.08	0.06
pH	0.45	0.31	1.47	43.43	0.15
Prop_Cover2019	1.69	0.84	2.01	24.56	0.06
Disturbance_Z	0.06	0.17	0.34	22.10	0.74
CropDiv_Z	0.19	0.17	1.08	21.96	0.29
Cinput_Z	0.13	0.18	0.72	22.67	0.48

Particulate Organic Matter






```
soil_phys_scores soil_iron_scores               pH          Prop5yr    Disturbance_Z
        1.997165         1.385707         1.060922         1.675962         1.254104
       CropDiv_Z         Cinput_Z
        1.413624         1.352888
```

Transplant (beginning of season) NO_3 stock model standardized coefficient estimates:

FIXED EFFECTS:

	Est.	S.E.	t val.	d.f.	p
(Intercept)	0.009	0.142	0.067	20.127	0.948
soil_phys_scores	0.412	0.321	1.285	34.324	0.207
soil_iron_scores	-0.242	0.208	-1.161	122.286	0.248
pH	0.205	0.210	0.977	99.909	0.331
CoverCrop_Z_rem	0.599	0.328	1.824	23.486	0.081
Till_depth	0.771	0.294	2.625	20.778	0.016
NumberCropFamilies	0.987	0.311	3.172	23.098	0.004
Cinput_Z	0.214	0.319	0.670	24.176	0.509

0-15 cm C-stock model standardized coefficient estimates:

FIXED EFFECTS:

	Est.	S.E.	t val.	d.f.	p
(Intercept)	3.333	0.039	86.094	21.302	0.000
soil_iron_scores	0.102	0.058	1.754	127.237	0.082
soil_phys_scores	-0.338	0.101	-3.359	44.492	0.002
pH	-0.076	0.056	-1.366	86.459	0.175
Prop5yr	0.310	0.098	3.148	26.978	0.004
Disturbance_Z	-0.056	0.087	-0.645	23.006	0.525
CropDiv_Z	0.043	0.092	0.464	22.537	0.647
Cinput_Z	-0.002	0.089	-0.026	23.376	0.980

30-60cm C-stock model standardized coefficient estimates:

FIXED EFFECTS:

	Est.	S.E.	t val.	d.f.	p
(Intercept)	3.592	0.052	68.715	21.178	0.000
soil_iron_scores	0.269	0.112	2.391	73.480	0.019
soil_phys_scores	-0.444	0.138	-3.227	31.258	0.003
pH	-0.039	0.099	-0.396	44.846	0.694
CoverCrop_Z_rem	0.012	0.126	0.092	23.437	0.927
Disturbance_Z	0.274	0.115	2.380	21.336	0.027
CropDiv_Z	-0.013	0.124	-0.102	22.015	0.919
Cinput_Z	0.142	0.133	1.073	23.522	0.294

Harvest NO_3 stock model w/ 2019 Cover Crop & Continuous Cover Z standardized coefficient estimates:

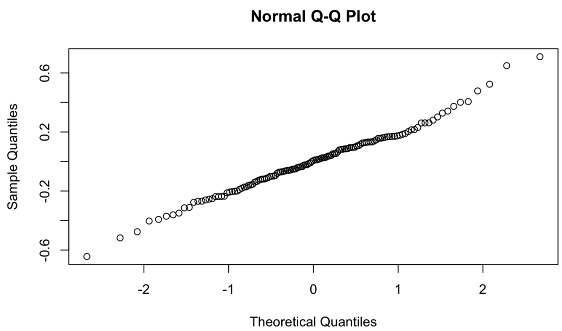
FIXED EFFECTS:

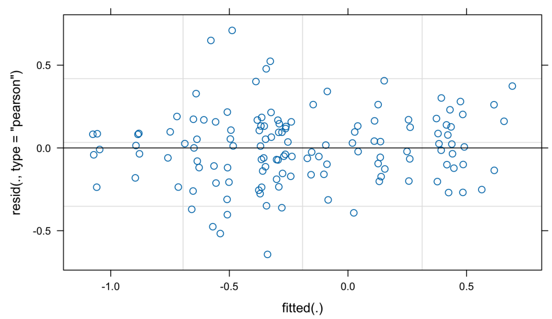
	Est.	S.E.	t val.	d.f.	p
(Intercept)	0.002	0.107	0.021	17.497	0.983
soil_phys_scores	0.467	0.277	1.684	29.543	0.103
soil_iron_scores	0.266	0.203	1.311	98.638	0.193
pH	0.489	0.195	2.512	63.383	0.015

```
CoverCrop_Z_rem          -0.107   0.272  -0.394   18.894   0.698
Prop_Cover2019            0.440   0.279   1.578   18.733   0.131
Till_depth                0.886   0.228   3.888   18.011   0.001
NumberCropFamilies        0.716   0.254   2.814   21.072   0.010
Cinput_Z                  0.420   0.256   1.639   20.151   0.117
-----------------------------------------------------------------
```

MF model assumption check

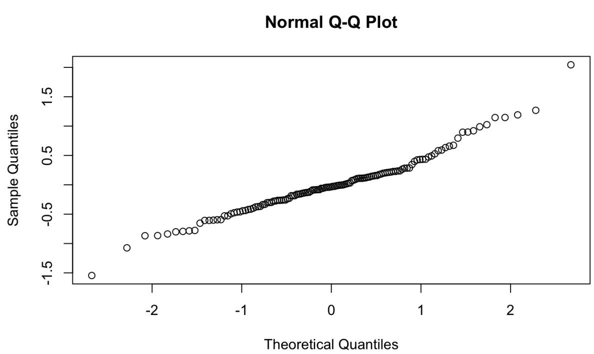
MF-even weights:

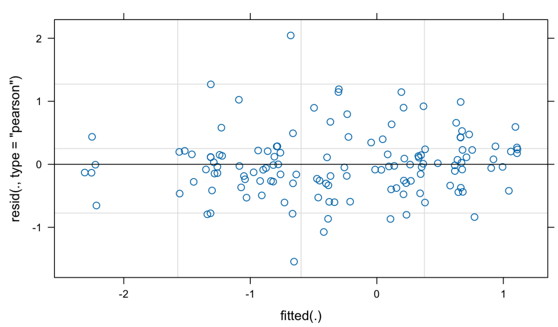





```
soil_phys_scores soil_iron_scores               pH          Prop5yr    Disturbance_Z
        2.053962         1.410876         1.098069         1.705130         1.255679
       CropDiv_Z         Cinput_Z
        1.401805         1.364406
```

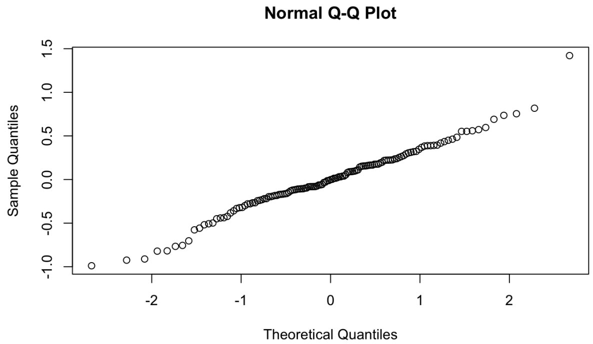
MF-production:

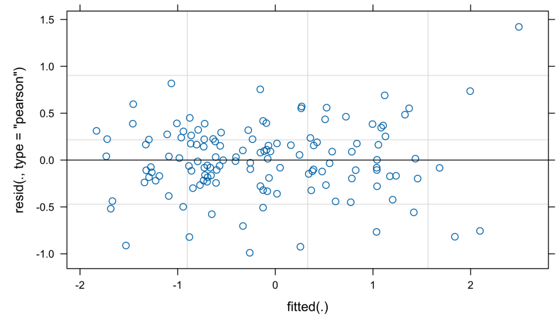





```
soil_phys_scores soil_iron_scores               pH          Prop5yr    Disturbance_Z
        2.173760         1.493064         1.111502         1.752556         1.267620
       CropDiv_Z         Cinput_Z
        1.411910         1.388538
```

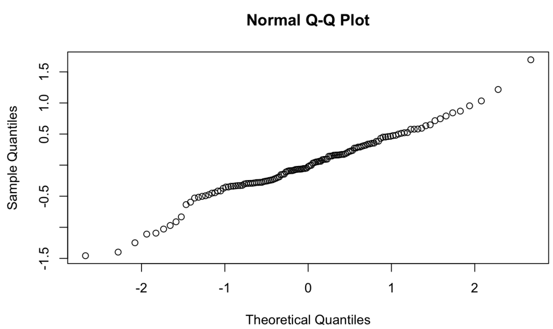
MF-environmental:

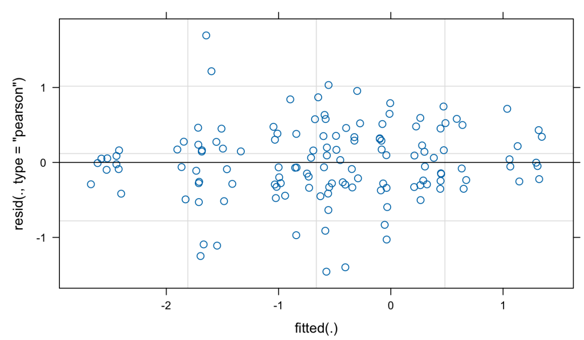





```
soil_phys_scores soil_iron_scores               pH          Prop5yr    Disturbance_Z
        1.858279         1.291980         1.080154         1.621180         1.232415
      CropDiv_Z         Cinput_Z
        1.383965         1.321797
```

MF- biodiversity:






```
soil_phys_scores soil_iron_scores               pH          Prop5yr    Disturbance_Z
        2.078251         1.427041         1.100659         1.714948         1.258220
      CropDiv_Z         Cinput_Z
        1.403905         1.369429
```

Conclusion

Through my dissertation, I demonstrate that soil health management practices as implemented on working farms build the overall health and functional capacity of soils, but that farmers face an uphill battle in implementing these practices. The barriers they face are varied, depending on their model of farming operations, and are largely structured at levels that go far beyond the farm. In Chapter 1, I sought to understand the nuances of the challenges that face farmers in adopting soil health management practices, and in Chapters 2 and 3, I dive into the consequent impacts that these practices have on soil organic carbon levels and their capacity to provide essential ecosystem services. I aimed to answer questions that were relevant and timely for the farmers we worked with and to generate research that could guide policy to better support the broader adoption of soil health management.

In Chapter 1, we find that the barriers to soil health management are structured largely by the farming model of a given operation. Three groups of farms emerge from our participating growers in the Central Coast - limited resource, mid-size diversified, and wholesale growers - based not on the scale of a farm, but on their economic and ecological approach and model of farming. While the size of the farms largely falls along our typology, importantly, this is an emergent property in our model and not a defining feature of the categorization. For almost all of the participating farmers, implementation of soil health practices is still limited, but for the mid-scale diversified group, we find that they manage to find a sense of autonomy and freedom to experiment and live out an ecological ethos of farming. This is enabled by secure land tenure and steady access to premium markets that create financial stability.

Agroecological management of farms is knowledge-intensive, and the industrial model of farming that, since colonization, has come to dominate Californian agriculture devalues and diminishes the place-based knowledge of diversified and ecological farming. We find that this mid-scale diversified group of farmers is at the forefront of experimenting with ways of managing their systems in response to their local climate and soils. I anticipate that they will also be at the forefront of finding ways to adapt to a changing climate.

Meanwhile, larger wholesale growers largely operate at the whim of their buyers, limiting their flexibility to experiment or make big changes to their operations. From the timing of their crops to the use of non-crop vegetation, their autonomy is hampered by misguided food safety regulations. At the same time, limited-resource farmers, some of whom are beginning farmers, face the challenge of limited labor and monetary resources. Organic cultivation already requires more labor, and going above the organic standards to adopt soil health practices requires even more effort, intention, time, and resources. Despite many farmers in this group hoping to implement more soil health practices, many indicated that their insecure land tenure made the already financially challenging proposition of soil health management a non-starter. To fundamentally shift the landscape of soil health management, policies must recognize these different challenges that are faced by farms.

Since publishing Chapter 1, its reception among the organic farming communities in California and beyond has demonstrated that our findings are mirrored in systems across the state, and further afield. From British Columbia to southern California, we have heard from farmers and researchers that this typology and framework for thinking about their local farming systems has been useful in particular for framing policy that could support a transition towards soil health management at a broader scale.

In our management survey with farmers participating in the soils component of our research project, over half of our participating farmers indicated interest in the "role of soils in climate change mitigation," and even more were interested in the relationship between cover cropping, crop rotation, and compost application on soil health. This, alongside growing interest in agricultural carbon credit schemes, motivated my second chapter. I wanted to dive deeper into the carbon response to soil health management on the participating farms, looking at functional fractions of soil organic carbon. Excitingly, we found that soil health practices do indeed have significant benefits for building several of these functional pools as well as overall organic carbon stocks and that in particular, continuous living cover emerges as a key practice for building soil carbon. While inherent soil characteristics may limit carbon sequestration capacity, the undersaturation of agricultural soils and our finding that management can significantly outweigh the influence of inherent edaphic variables in explaining our observed changes to soil carbon fractions point to a large opportunity for farmers to rebuild soil organic carbon stocks in their soils via management changes. While I remain skeptical about the overall prospect of soil carbon markets, partially because of the difficulty in reliable monitoring of soil carbon levels and the inherent structural preference that these markets have for large operations, it is clear that soil health management has the potential for rebuilding functional fractions of soil carbon, and overall C stocks in surface soils.

Finally, I wanted to broaden my scope of soil responses beyond carbon to capture a more holistic look at the many services that soils provide. Using the rich dataset collected by the team of researchers on this project, I aimed to investigate soil multifunctionality. I brought together data on soil nitrate levels to capture potential impacts on regional water quality, soil microbial diversity to represent the capacity of soils to serve as habitat for microbes, soil enzyme activities to capture the microbial activity and nutrient cycling capacity of a soil, POM to investigate the fertility of a given soil and its capacity to support microbial life, bulk carbon data down to 60 cm to capture climate mitigation potential, and crop yield data, to see if and how soil health practices change the productive capacity of these farms. Looking at this range of services, we find that soil health management overwhelmingly supports these individual functions (11 instances), and only poses one trade-off between yield with higher crop diversity. We also find, similar to Chapter 2, that continuous crop cover emerges as a key variable explaining multifunctionality, when we consider all of the ecosystem services simultaneously. These final two chapters underscore the importance and potential for soil health management to create agricultural systems that rebuild soil organic carbon and the functional capacity of agricultural soils.

Throughout this work, I have been struck by the ingenuity, creativity, humbleness, and brilliance of the farmers we worked with. They are the real scientists of the land, always observing, noting changes, and tinkering to find better ways to manage their systems. I see my role as an agroecological researcher as but a tool for them to get a different look into their soils (i.e., providing measurements of soil carbon and nutrients), helping them contextualize their farm amongst others that may be comparable (which they are always curious about), and to provide validation that the things they are doing on their land are making a measurable difference. I hope that with this work, I have provided a bit of reassurance for them that they can indeed make a remarkable difference in how they manage their lands.

I began my PhD because I believe deeply in the importance of the food system as a central node for how we, as a society, can rebuild our relationship with nature and with each other. I remain steadfast in my belief that food systems transition must be at the core of any climate change agenda and that without fundamentally questioning our societal relationship to food and where it comes from, we cannot create change at the level needed to avert the climate crisis. As our climate continues to warm, resilient agricultural systems will only become more important. I know that farmers will do their darndest to keep us fed, and so the question that feels critical for me is what we will do to support them in this moment. The forces of extraction and greed that control our economy and society are so deeply entrenched it makes system change seem nearly impossible. I leave this PhD process with far more questions about what my role can be in changing our food system for the better, but also knowing just how many brilliant people are out there tackling this issue. So, I remain hopeful. In community, we can do what is needed to create a more ecological, just, and resilient food system.