DISSERTATION

REGENERATIVE AGRICULTURE AND SOIL CARBON STORAGE IN THE UPPER CORN BELT

Submitted by

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ABSTRACT

REGENERATIVE AGRICULTURE AND SOIL CARBON STORAGE IN THE UPPER CORN BELT

Land use conversion, agricultural mismanagement, and topsoil erosion have depleted global soil organic carbon (SOC) stocks in the top two meters of soil by an estimated 133 petagrams (Pg), resulting in a significant SOC debt. Regenerative cropping practices, such as no-till and cover cropping, are recognized for their potential to enhance soil organic carbon (SOC) stocks and bolster soil health, all while allowing producers to maintain commodity crop production systems. Evaluations of these practices are typically conducted through agricultural experiments with randomized and replicated statistical designs. While these experiments are essential for understanding the mechanisms behind changes in soil properties as a function of management, they often fail to capture the complexities of diverse agricultural settings and management choices. Through an interdisciplinary, system-level study of commercial farms in the Upper Corn Belt region, I evaluated how regenerative management affects SOC storage, erosion processes, and microbial community structure. Factors such as topography, time since adoption of regenerative practices, climate, and soil texture significantly influenced SOC stocks and microbial community structure. Slope and historical erosion emerged as a key control on SOC stocks, which is largely overlooked in current process-based models. I present a method for coupling estimated soil erosion with the DayCent model to improve simulations of SOC stocks on farmland with slight slopes. I also discuss the unique challenges of simulating commercial farm scenarios using data collected from real-world farmers. The dissertation concludes with a collaborative, social science chapter on the impact of social networks on the adoption of regenerative practices in Iowa agricultural communities. In summary, this dissertation contributes to our knowledge of regenerative agriculture and its impacts on SOC storage, soil microbial diversity, and social connections in agricultural communities, including unique methods to measure, evaluate, and model these impacts.

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1. Impetus for Pursing Agricultural Management as a Negative-Emissions Strategy

Nearly 50% of the planet's land surface area is dedicated to agricultural systems, whether for crop production or pasture (FAO, 2020). Soil cultivation and grazing mismanagement has depleted global soil organic carbon (SOC) stocks in the top two meters of soil by an estimated 133 petagrams (Pg), or 8% of total global SOC stocks (Sanderman et al., 2017). Land use conversion, agricultural intensification, and erosion have contributed to the historic loss of SOC, and these activities continue to deplete SOC in some regions. For example, as grasslands and forests are converted to croplands, more than 30% of native SOC is lost to the atmosphere (Poeplau et al., 2011). Historic mismanagement of croplands, particularly through intensive tillage and bare fallow practices, contributed to significant soil erosion (averaging 1.9 mm yr^{-1} in Midwest US) (Thaler et al., 2022) and SOC loss. In areas where conservation practices are underutilized, soil erosion and SOC loss continue at unsustainable rates. Coincident global change pressures (i.e., climate change, growing populations, urban encroachment, changing diets, demand for biofuels, and soil degradation) demand more from soil systems and lead to further SOC loss in many areas (Smith et al., 2016).

Restoring SOC to depleted agricultural soils and protecting existing SOC stocks can contribute substantially to atmospheric CO_2 drawdown and efforts to stabilize the climate system (Paustian et al., 2016; Griscom et al., 2017). Climate stabilization requires both drastically reducing fossil fuel C emissions and anthropogenic emissions of non-CO_2 greenhouse gases (CH_4, N_2O) and implementing measures to remove excess CO_2 in the atmosphere. SOC sequestration, or the photosynthetic drawdown

[1] Ellis, E., Swan, A., & Paustian, K. (2023). Chapter 2: Challenges and opportunities for soil carbon sequestration on U.S. agricultural lands. In Hatfield, J., Wang, Y., Matlock, M., & Rice, C. (Eds.), *Potential for U.S. Agriculture to be Greenhouse Gas Negative* (pp. 8-20). Farmers & Ranchers in Action and the Council for Agricultural Science and Technology.

of CO_2 from the atmosphere and subsequent storage as soil organic matter, is recognized as a viable negative-emissions strategy. Even the most optimistic emissions reduction scenarios include substantial contributions from negative C technologies to keep below 2°C of warming (NASEM, 2019). This chapter will discuss the potential for agricultural best management to contribute to climate mitigation through SOC sequestration and storage in crop and grazing lands.

While soil SOC sequestration has received increased attention in the realms of research and policy, studies on the relationship between C cycling in agricultural soils and climate mitigation began in the early 1990s (Barnwell et al., 1992; Paustian et al., 1997). The impact of soil and crop management practices on soil organic matter maintenance has been of interest since soil science and agronomy emerged as scientific disciplines in the early 19th century. Scientific inquiry into the link between soil organic matter and fertility goes back to the mid-18th century (Feller et al., 2014). Many long-term field experiments (LTEs) have tracked crop yields, nutrient dynamics, and soil organic matter changes as a function of crop rotation, tillage, nutrient management and irrigation over the past several decades (Leigh & Johnston, 1994; Paul et al., 1996). The oldest field experiments still in operation, at Rothamsted, UK, date back to 1843. Data from LTEs have facilitated the development of empirical models used in the Tier 1 methodology for national reporting of greenhouse gas (GHG) emissions from soils developed by the Intergovernmental Panel on Climate Change (IPCC) (Ogle et al., 2005; IPCC, 2006). Data from LTEs are also used to establish parameters for and validate dynamic process-based models that simulate SOC turnover and soil GHG emissions as a function of management and environmental drivers (e.g., Campbell and Paustian, 2015; Basso et al., 2018). More recently, ecosystem-scale CO_2 flux measurements using eddy covariance methods have augmented the data sources available for testing and validating dynamic models (Zhang et al., 2018). Unfortunately, the U.S., unlike some other countries, does not have a measurement-based SOC stock inventory and monitoring system (van Wesemael et al., 2011), despite recommendations over a number of years by the scientific community (NRC, 2010; NASEM, 2019). Recently, USDA announced plans to evaluate the establishment of a national scale SOC and GHG

monitoring network (USDA, 2023). However, current assessments of the biophysical potential for SOC sequestration rely chiefly on existing LTEs, eddy covariance sites, and systems modeling to determine the most effective strategies for increasing SOC stocks while minimizing non-CO_2 GHG emissions and maintaining crop yields.

Because of the documented potential to increase SOC stocks, along with a multitude of soil health and ecosystem co-benefits, managing agricultural soils has become part of the global agenda to mitigate climate change. Several global initiatives, including the International "4 per 1000" Initiative (Minasny et al., 2017), the Koronivia workshops on agriculture (UNFCCC, 2021), and FAO's RECSOIL program (FAO, 2019), all emphasize increasing SOC stocks as an important tool to draw down atmospheric CO_2 and increase resilience in the face of inevitable climate change. Beyond emerging national and international policies, the connection between soil and climate change has caught the attention of the private sector, from multinational corporations to smaller, environmentally conscious companies promoting market-based CO_2 mitigation. Private, voluntary C credit markets have a vested interest in stimulating SOC accrual and recognize the untapped potential of agricultural projects to address the climate emergency, improve farmer livelihoods, and combat the degradation of arable lands worldwide. Additionally, popular documentaries like *Kiss the Ground* have brought the relationship between SOC and regenerative agriculture into homes across the country, perhaps with more optimism than is warranted (Amundson, 2021). Our role as scientists, and the purpose of this chapter, is to paint an accurate picture of how agricultural SOC sequestration can help mitigate climate change, without side-stepping the likely challenges.

2. SOC Storage: Processes and limitations

The uppermost meter of global soils contains more C (1500 Pg) than the atmosphere (750 Pg) and terrestrial biomass (560 Pg) combined (Batjes, 2014). Because most cropland soils have lost 30-50% of native SOC (Davidson & Ackerman, 1993), agricultural soils have substantial potential to sequester C

through improved soil management practices. Managing agricultural soils appropriately can accelerate the buildup of soil organic matter (SOM) by both controlling the type and frequency of organic matter additions and limiting soil disturbance that can stimulate organic matter decomposition. The amount of SOM in agricultural soils depends on a variety of climate, soil, and management factors, which vary seasonally and spatially. SOM forms through the progressive decay of plant and animal tissues, microbial biomass, manures, root exudates, and secondary compounds formed through decomposition. SOM has variable fates in the soil depending on the properties of the material, including chemical structure, C to nitrogen ratio (C:N), and solubility, as well as the properties of the surrounding soil environment. Mineralization of SOM, where organic inputs decompose or oxidize into plant available forms, is mainly driven by the synergistic activities of soil microbiota and larger soil fauna (e.g., earthworms) (Cotrufo et al., 2013; Liang et al., 2017). The soil food web and biogeochemical processes drive the progressive decomposition of SOM, as well as SOM respiration and loss.

Approximately 58% of SOM mass is C, with the remaining mass composed of hydrogen, oxygen, and other elements (e.g., nitrogen, phosphorus, and sulfur) essential to major biomolecules. Much of the C input into the soil mineralizes to CO_2 within a few years (Castellano et al., 2015). Additional C losses occur via soil system disturbance (e.g., tillage), leaching of dissolved organic C (DOC), and erosion (the latter two involve C translocation and deposition into a different location or into aquatic systems, not loss of C to the atmosphere). In general, SOC storage is guided by mass balance principles: when C inputs exceed C outputs, SOC stocks will increase, and the reverse. However, whether C additions are stabilized in the soil matrix for longer-term storage depends on many properties, such as quality of organic matter, soil type/texture and clay mineralogy, climate, and disturbance regimes. Generally, SOC accumulates more in cool, humid environments (where C inputs can be high, but cooler temperatures limit decomposition) than in hot and dry regions (Ogle et al., 2019). Additionally, SOC storage correlates with soil texture; fine-textured soils with more clay and/or silt tend to contain more SOC than coarse-textured soils.

Several proposed frameworks conceptualize the scientific understanding of SOM stabilization (Cotrufo et al., 2015; Lehmann & Kleber, 2015; Liang et al., 2017; Lehmann et al., 2020). Most research agrees that the efficiency of microbial processing of plant-derived residues, which depends on litter biochemistry, is the main control on SOM formation and stabilization over time (Cotrufo et al., 2013; Lehmann and Kleber, 2015; Liang et al., 2017; Lehmann et al., 2020; Liang & Zhu, 2021). Research supports microbial stabilization frameworks that show fungal and bacterial necromass (dead cells) are the primary constituents of stable SOM (Liang et al., 2019; Schweigert et al., 2015). Interactions between microbial byproducts, plant-litter derived compounds, and the soil mineral fraction determine the degree of SOM physical protection and persistence. At its simplest, SOM originating from microbial decomposition of organic residues can be divided into two pools with distinct pathways of formation and environmental persistence: 1) particulate organic matter (POM), composed of low density, OM fragments that are comprised of more chemically recalcitrant compounds often encapsulated within soil aggregates, or 2) mineral-associated organic matter (MAOM), composed of dissolved organic material and microbial byproducts that chemically bond with mineral particles (Lavallee et al., 2020) (Figure 1.1). The essential difference between MAOM and POM is the degree of stability: MAOM is more protected from further microbial decomposition and the effects of system disturbance, while POM is more accessible to microbes and vulnerable to disturbance. From a SOC sequestration perspective, management practices that increase MAOM stocks in soils should be prioritized because MAOM is more stable over time and less sensitive to disturbance (Haddix et al., 2020). On the other hand, MAOM is subject to saturation when colloidal mineral surfaces become increasingly occupied. The saturation capacity of a given soil depends on the physiochemical characteristics inherent to the soil (e.g., soil texture and clay mineralogy) and the ecosystem in which the soil lies (Six et al., 2002; Stewart et al., 2007;). Hence, ecosystem-specific management systems that support the formation of both MAOM and POM and prioritize the longevity of newly formed C stocks through reduced disturbance could effectively sequester C in soils and contribute to drawdown of atmospheric CO_2. An additional organic matter component in many soils, not derived from microbial-driven decomposition, is pyrogenic C (i.e., charcoal), formed from the

burning of plant residues, or added as a produced organic amendment from pyrolysis of organic waste (Lehmann et al. 2006). Depending on the combustion conditions under which it was formed, pyrogenic organic matter can be quite resistant to microbial decay and thus can be a persistent C fraction in the soil.

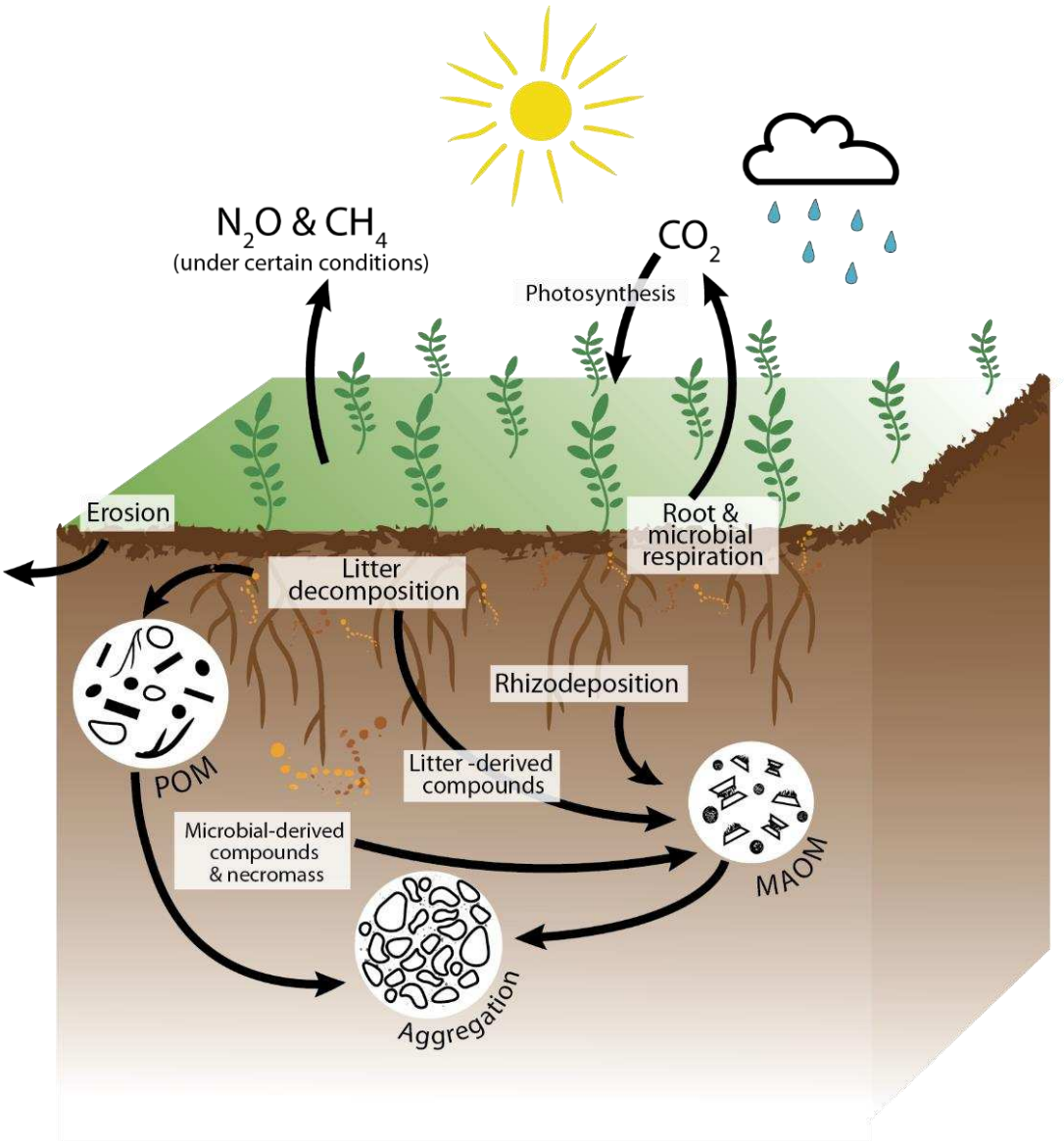

Figure 1.1 Schematic diagram of SOC cycling and stabilization mechanisms. Most SOC is lost as CO_2 through heterotrophic and autotrophic respiration. SOC can be stabilized through 1) biochemical stabilization via higher recalcitrance and 2) physical stabilization in organo-mineral complexes and aggregates.

3. Management of Agricultural Lands for C Sequestration

Heterogeneity of organic matter inputs, microbial biomass and functional diversity, climate, soil type, time since disturbance, and management history, among other factors, drive SOC persistence, so the design of management systems to increase SOC stocks must holistically consider the context of the agroecosystem. Some agroecosystems are better suited for regeneration and C sequestration than others. Degraded soils that are substantially depleted of C have a high capacity, theoretically, to sequester C but also present the greatest challenges for regeneration if they have been degraded to the point that their primary productivity (and hence C input) has been significantly reduced (Chambers et al., 2016). The time necessary to recuperate lost SOC and improve agroecosystem functioning varies with climate, soil type, and historical and current management characteristics. Additionally, the unique C saturation potential and equilibrium point of the system limit SOC storage capacity (Stewart et al., 2007). There are no quick fixes for locking C away in soils. Instead, management should shift to a principle-based framework to improve the overall functioning of the agroecosystem, with the added benefit of improving C stocks (Paustian et al., 2016; Ogle et al., 2019).

Although the term has variable meanings depending on the context in which it is used, regenerative agriculture promotes a principles-based framework of agriculture with the goal of increasing and protecting SOC stocks, improving soil health, increasing profitability, and ensuring agricultural sustainability across the whole value chain (Newton et al., 2020). The following sections outline current best management practices for increasing SOC stocks and how these practices connect to the six principles of regenerative agriculture: 1) minimizing soil and ecological disturbance, 2) keeping soil covered, 3) maintaining living roots, 4) maximizing diversity, 5) integrating animals, and 6) understanding agroecosystem context (Eckberg and Rosenzweig, 2021; Figure 1.2).

1. Minimize disturbance: No-till, reduced tillage, and drainage management

Expanded no-till and reduced till practices in the Great Plains of the U.S. and similar agricultural regions around the world are due in part to the proven capacity of these practices to minimize erosion and

prevent further soil degradation (Derpsch et al., 2010). No-till refers to the omission of plowing (soil disturbance) traditionally used for seedbed preparation and weed control. In no-till systems, crops are directly seeded into a field, allowing surface residues from the previous crop to protect against erosion and accelerated evaporation. No-till is often used to increase and maintain soil moisture in arid and semi-

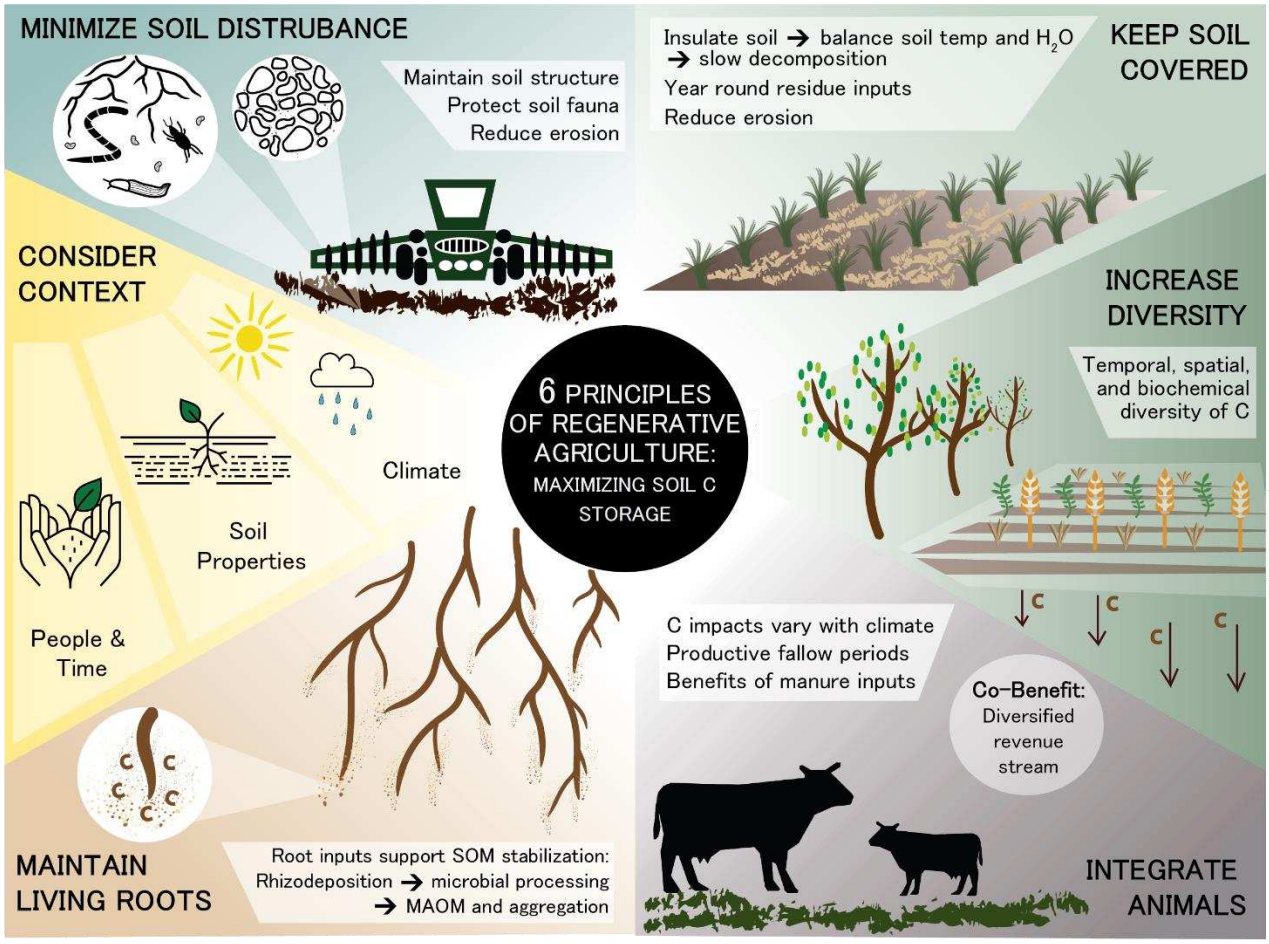

Figure 1.2 Diagram illustrating how the 6 principles of regenerative agriculture relate to SOC accumulation and stabilization mechanisms. The 6 principles of regenerative agriculture included here are 1) consider agroecosystem context, 2) minimize soil disturbance, 3) keep soil covered, 4) increase diversity, 5) maintain living roots, and 6) integrate animals. These principles can help maximize the C sequestration and general functioning of agroecosystems.

arid regions where rainfall limits crop yield (Palm et al., 2014). Additionally, no-till is a strategy to reduce atmospheric CO_2 emissions from cropland management because it protects existing SOC stocks by

reducing soil disturbance, thereby increasing the mean residence time of SOC (cf. Six et al., 2000; Six and Paustian, 2014).

Results from nearly 200 field experiments assessing how no-till management affects SOC storage (Ogle et al., 2019) show a range of responses, from substantial C gains under no-till at some locations to reduced SOC stocks (relative to conventional tillage) at others. Several meta-analyses show that, on average, more C is stored in no-till soils than soils under full tillage management, with the most significant change in the top 20 cm of soil (Bai et al., 2019; Luo et al., 2010; Ogle et al., 2005, 2019; West & Post, 2002) (Table 1). However, the potential for C storage in agricultural systems under different tillage regimes depends on agroecosystem properties, including soil type, climate, and residue management (Ogle et al., 2019; Sun et al., 2020; Yuan et al., 2020). Changes in tillage regime may not always lead to an increase in C stocks (Powlson et al., 2014). Furthermore, increased C stocks in the topsoil may be partly offset by reduced C stocks at depth (Luo et al., 2010; Ogle et al., 2019). A literature review by Ogle et al. (2019) found no-till soils generally had higher SOC stocks in the surface soil (<20 cm), while full tillage soils often had higher SOC below the plow layer (>20 cm). Further analysis of C stock dynamics in the subsoil (and how these dynamics play out over time) is needed to explain how increases in SOC in the topsoil affect SOC at depth. Theoretically, as DOC and microbial byproducts are leached from the topsoil into the subsoil, the mineral-associated fraction will likely be enhanced, leading to higher long-term storage of stable SOC (Ogle et al., 2019).

Strategic deep tillage (where OM rich topsoil is transferred to the subsoil and OM-poor subsoil is brought to surface layers, and where plant residue inputs remain high) may increase total C storage in sandy soil in cool/temperate environments (Alcantara et al., 2016; Pereira et al., 2017). However, research must assess net C sequestration benefits despite the consequences of temporary decreases in topsoil fertility and increased fuel usage associated with deep tillage (Alcántara et al., 2016; Scanlan & Davies, 2019).

An additional source of soil disturbance is artificial drainage (e.g., tile drainage) which alters the hydrology of soil systems. Drainage systems are widely used to remove excess water from fields, encouraging soil aeration and allowing heavy machinery to access fields for cultivation and harvest. Removing standing water from fields decreases CH_4 and N_2O emissions associated with anoxic soil conditions but often leads to nutrients and DOC leaching out of the system (Ruark et al., 2009).

Table 1.1 Meta-analyses reporting mean ΔSOC (C sequestration rate) in Mg C ha^{-1} yr^{-1} with mean values by climate type and soil texture (highest and lowest values reported), where available. ***** Our summary estimates assume 10 years of biochar application to derive an annual average increase.

Practice	**Reference (Author, Year)**	**Overall mean ΔSOC (Mg ha^{-1} yr^{-1})**	**Mean ΔSOC by climate type (Mg ha^{-1} yr^{-1})**	**Mean ΔSOC by soil texture (Mg ha^{-1} yr^{-1})**
Cover cropping	(Don and Poeplau, 2015)[1](Jian et al., 2020)[2]	0.32[1] ; 0.56[2]	(Tropical - 0.71 ± 0.21; Arid 0.46 ± 0.22)[2]	(Fine - 0.82 ± 0.30; Coarse - 0.43 ± 0.12)[2]
No-till	(Ogle et al., 2019)[1](Bai et al., 2019)[2]	0.38[2]	(Tropical - 0.34 to 0.54; Arid - 0.06 to 0.15)[1]	(Fine - 0.06 to 0.54; Coarse - 0.15 to 0.50) [1]
Diversified crop rotation	(McDaniel, Tiemann, and Grandy, 2014)	0.15	Not evaluated	Not evaluated
Biochar application	(Gross et al., 2021)	1.30*	(Temperate – 1.13; Tropical – 0.46)*	(Fine – 1.28 to 1.77; Coarse – 0.61)*
Manure application	(Gross and Glaser, 2021)	1.07*	(Non-tropical – 1.28; Tropical - 0.85)*	(Fine - 1.13 to 1.17; Coarse – 0.82)*

2. Maximize diversity: Crop rotations, microbial inoculum, and biochar

In unmanaged ecosystems, plant diversity increases soil microbial activity and SOC storage (Lange et al., 2015). However, the diversity of cropping systems has decreased globally in favor of monoculture

systems that rely on synthetic inputs to manage fertility and pests. Diversifying crop rotations may be an effective strategy for decreasing reliance on inputs, improving the financial resilience of the production system, and increasing SOC stocks (McDaniel et al., 2014). In a global meta-analysis, McDaniel et al. (2014) found that adding one or more crops in rotation to a monoculture system increased total C stocks by 3.6%, on average, and microbial biomass C by 20.9%, yielding a mean SOC sequestration rate of 0.15 Mg C ha^{-1} yr^{-1} (Table 1). Additional diversity may be added to the system using perennial or prairie strips, which prevent erosion, reduce nutrient leaching into waterways, and support native pollinators (Schulte et al., 2017).

In addition to maximizing the floral and faunal diversity of agroecosystems, the diversity of C inputs to the soil can be enhanced directly by applying biochar amendments (Xu et al., 2021). Biochar is a C-rich soil amendment formed through the thermochemical conversion (pyrolysis) of a biomass feedstock, which renders the residual C less decomposable by soil microbes. Biochar amendments to agricultural soils can significantly affect SOC sequestration and storage by directly increasing the pool of persistent SOC and indirectly by enhancing soil aggregation and increasing system productivity through improved nutrient availability and soil water holding capacity (Z. Du et al., 2017). Additionally, biochar may lead to a negative priming effect, where adding recalcitrant C decreases microbial decomposition of more labile C (Wang et al., 2016). Although this finding has yet to be fully confirmed, some positive priming effects have been reported. A recent meta-analysis found that applying biochar is among the most effective methods of increasing SOC content (up to 28% in field experiments), particularly over the short term (Bai et al., 2019). The costs of producing biochar, which is dependent upon the feedstock used, among other factors, may be prohibitive in some cases (Vochozka et al., 2016). In addition, the amount of waste biomass feedstock available for biochar production is a limiting factor (Schlesinger & Amundson, 2019). However, biochar may be an important tool to improve soil fertility and soil health, particularly in highly weathered acidic soils that are common in subtropical and tropical regions (Lehmann & Rondon, 2006).

3. Keep the soil covered: Residue retention and cover crops

Keeping the soil covered provides many benefits to agricultural lands, including controlling erosion, moderating soil temperature, increasing water-holding capacity, and suppressing weeds (USDA NRCS, 2017). Soil cover can be maintained by leaving crop residues on the field, mulching, or planting cover crops in rotation with annual crops. From a soil system perspective, keeping the soil covered helps maintain SOC stocks by: 1) preventing wind and water erosion, which ensures C-rich topsoil remains in place; 2) moderating soil temperature and moisture loss, which prevents accelerated microbial respiration, and 3) increasing duration of vegetative cover, which increases overall C inputs.

Crop residues can be kept on the field after crop harvest to provide the soil cover benefits listed above and to maintain C inputs to the system that might otherwise be exported (e.g., corn stover harvested for feed, bedding, or biofuel feedstock). According to a meta-analysis of residue management studies, maintaining residue cover in no-till management systems is shown to increase SOC stocks more than no-till with residue removal (13% vs 11% increase, respectively) (Li et al., 2020). It is important to note that excess residue accumulation may interfere with no-till implements or cause other site-specific management challenges (Babcook, 2008).

Several meta-analyses and review papers have evaluated global data sets of cover cropping and associated impacts on SOC stocks and climate mitigation/adaptation (Jian et al., 2020; Kaye & Quemada, 2017; McClelland et al., 2021; Poeplau & Don, 2015). Poeplau and Don (2015) used linear regression of global cover crop data from 37 experiments to derive a response function for SOC stock change in the 0 to 30 cm soil layer. They found that SOC stock increased linearly with time after introducing cover crops, with an average change rate of 0.32 ± 0.08 Mg C ha^{-1} yr^{-1}. In a more recent global meta-analysis of 131 studies, Jian et al. (2020) found a range of C accrual rates from 0.22 to 0.71 Mg C ha^{-1} yr^{-1} depending on soil texture, climate, and cropping system (Table 1). The meta-analysis also found that cover crop mixtures (particularly with legumes), as opposed to mono-species cover cropping, lead to greater increases in SOC (Jian et al., 2020). In another meta-analysis, cover crops were associated with an

average SOC stock increase of 1.11 Mg C ha^{-1} in the top 0 to 30 cm, compared to a no cover crop control (McClelland et al., 2021).

In some cases, experimental studies can show negative C stock changes after cover cropping or, alternatively, surprisingly high values of C accrual. Negative C stock changes may be due to the effects of priming, where adding low C:N crops leads to greater microbial respiration (Jian et al., 2020) or reduced productivity of the subsequent cash crop (Lobell and Villoria, 2023). The wide range in values of SOC stock change can be attributed to the heterogeneity of SOC, which is characteristic of all soil systems, along with initial C stocks, insufficient time since adopting cover crops, and sampling methods that fail to take this heterogeneity into account (Poeplau & Don, 2015).

4. Maintain living roots: Agroforestry and perennial crops

Increasing the perenniality of agricultural systems by maintaining above and below ground C inputs across space and time through cover crops and crop rotations is an effective strategy for increasing SOC in agricultural systems (King & Blesh, 2018). Conceptual models of SOM dynamics, root exudates and root biomass are hypothesized to be more important to the formation of stable SOM (in both the MAOM and POM fractions) than aboveground plant material (Cotrufo et al., 2013; Sokol et al., 2019). This is likely because root deposits can be directly absorbed to mineral surfaces and can bolster microbial biomass growth in the rhizosphere (McDaniel et al., 2014). The expansion of agroforestry and perennial staple crops offers an opportunity to greatly increase SOC sequestration in agricultural soils (Toensmeier, 2016). When we account for both above and belowground C sequestration, agroforestry systems often offer the most benefit per hectare C storage rates (De Stefano & Jacobson, 2018). While developing perennial grains may offer significant SOC and water use efficiency benefits (de Oliveira et al., 2020), the challenges of achieving economically viable yields (compared to conventional annual crops) should not be overlooked. Finally, protecting C stocks in existing native perennial grasslands, wetlands, and forests is essential to avoid further SOC losses from these terrestrial systems (De Stefano & Jacobson, 2018; Bossio et al., 2020).

5. Integrate livestock: Integrated crop & livestock systems and grazing management

While the main focus of this chapter is cropland management for SOC storage, pastures and rangelands account for nearly 70% of global agricultural land and are of critical importance to C storage. Livestock grazing has the potential to increase SOC storage, but the appropriate grazing practices (e.g., rotation and intensity) to support C gains and avoid losses are dependent on climate, soil type, and other environmental factors. Prolonged high-intensity grazing (overgrazing) frequently decreases SOC stocks (Zhou et al., 2017), however, short-duration, intensive (rotational) grazing may increase SOC, particularly in moist, warm climates (Abdalla et al., 2019). In some dry environments, SOC stocks may increase by reducing grazing pressure (G. Zhou et al., 2017). However, SOC responses to grazing intensity can vary strongly as a function of grass species/ecotypes (Milchunas & Lauenroth, 1993). While grazing removes aboveground biomass and heavy grazing can decrease net primary productivity (NPP), grazing may also lead to increased fungal dominance belowground, contributing to more SOC storage and resilience to changing moisture regimes (Abdalla et al., 2019). In addition to controlled grazing intensity, pastures managed with adaptive multi-paddock grazing (AMP), or short duration, high stock density grazing rotations, had 13% more SOC (9 Mg C ha^{-1}) in the top 1 m of soil than neighboring conventionally grazed sites (Mosier et al., 2021).

Additionally, integrated livestock and annual cropping systems, where livestock graze cover crops or crop residues, may improve SOC storage and soil health while reducing system GHG emissions (Salton et al., 2014). Furthermore, grazing livestock on non-cash crops provides an additional revenue stream that may improve the financial resilience of the farm system, particularly as annual crop yields become less stable with climate change (Peterson et al., 2020). Particularly in semi-arid systems where C inputs from annual crops are low, crop rotations that include intermittent grazed forage crops increase C inputs to soil and accrual of SOC (Brewer and Gaudin, 2020). In the absence of grazing animals, animal manures may be broadcasted on or injected into cropland fields to derive some of the benefits of an integrated animal livestock system. Manure application provides fertility benefits that may otherwise be

provided solely be synthetic fertilizers, generating use value out of an otherwise difficult to manage waste product. Manure application is shown to increase SOC stocks but associated increases in field GHG emissions (namely N2O) must also be considered. A full accounting of the potential benefits of integrated crop livestock versus decoupled crop and livestock production requires a comprehensive life cycle analysis of all components of each system (Liebig et al., 2021).

6. Understanding context: Agroecosystem specificity and co-benefits

The sixth principle is not always included in descriptions of regenerative agriculture, but it is perhaps the most important. There are no one-size-fits-all solutions for soil management to maximize C storage; management must instead be adapted to unique soil types, climate, and production needs of the agroecosystem. Ideally, the combined effects of regenerative practices work synergistically to confer the greatest benefits to the soil system, leading to high rates of C accumulation (Bai et al., 2019). However, with so few established long-term experiments, relative to the diversity of potential systems, assessing the impact of many different combinations of regenerative practices is difficult. In the absence of established experiments, recent observational studies have worked in collaboration with dedicated producers to evaluate the impact of their regenerative management systems (e.g., Ellis & Paustian, 2024; LaCanne & Lundgren, 2018; Luján Soto et al., 2021; Mosier et al., 2021; van der Pol et al., 2022) and meta-analyses provide information about the impact of integrating several best management practices simultaneously (Bai et al., 2019; Yuan et al., 2020).

The effects of regenerative practices should be viewed from a systems level, looking beyond CO_2 inputs and outputs to other GHGs. For example, producing and applying N-fertilizers is the primary source of N_2O emissions, a greenhouse gas with ~300 times the global warming potential of CO_2. Therefore, practices that increase SOC and reduce emissions from all GHGs sources across the agricultural value chain should be favored.

Reducing N_2O emissions from fertilizers is an important co-benefit of implementing regenerative practices that increase organic N availability by increasing SOM. Practices that maintain soil cover and

living roots are another example of systems that increase agroecosystem resilience to changing and unpredictable climate conditions. Protecting bare soil reduces soil erosion, maintains C in topsoil, and insulates soil to reduce evapotranspiration and soil temperatures. Furthermore, increasing crop diversity protects against pathogens and disease outbreaks, represses undesirable weed species, and diversifies producer revenue streams. Once the initial costs of transition (e.g., new equipment, potential yield reductions) are recovered, regenerative agriculture has the potential to decrease production costs through reduced input costs, fewer passes with farm machinery, and less yield loss due to extreme weather and pests (Liu et al., 2018; K. M. Singh & Meena, 2013).

4. Biophysical potential for soil C sequestration/negative emissions on U.S. cropland

As part of a recent U.S. national decarbonization analysis (Larson et al., 2020), we estimated the potential to increase soil C stocks on managed croplands in the U.S. A recent National Academies report (NASEM, 2019) classified soil C sequestration technologies into two main categories: existing conservation practices and frontier technologies. Frontier technologies include advances such as crop varieties with enhanced root phenotypes (i.e., larger, deeper root systems), perennial grains, widespread use of biochar amendments, and other technologies still in the research phase but not yet ready for widespread deployment in U.S. agricultural systems (NASEM, 2019). In contrast, existing conservation practices (described as regenerative earlier in this paper) are relatively well understood and have been deployed to varying degrees in production agriculture (e.g., cover crops, intensified rotations, no-till or reduced tillage, and integrated crop-livestock systems). U.S. cropland acres planted to cover crops increased 17% from 2017 to 2022, but this still only amounts to 4.7% of total cropland (USDA NASS, 2022). Conservation tillage practices were used on approximately 75% of corn/soybean, 68% of wheat, and 43% of cotton acres in the U.S. in 2021. Conservation tillage includes both no-till and mulch tillage (using a chisel plow or disk) (USDA NASS, 2022). Only half of the reported conservation tillage acres utilize no-till, and tillage practices may vary with point in the crop rotation (i.e., periodic tillage in

corn/soybean systems) or management challenges (i.e., compaction or residue accumulation). For example, many corn/soybean acres in the Midwest are managed using periodic no-till, usually meaning no-till practices are used during soybean years while conventional tillage is used during corn years. Even a one-time tillage event may lead to the loss of 1-10% of SOC (Conant et al., 2007), negating the potential SOC storage benefits of conservation tillage and other complementary practices. The main challenge in implementing these existing practices for C drawdown is increasing their level of continuous adoption on the greatest number of acres possible.

For the current estimate of negative emissions potential, we considered only existing conservation management practices, not frontier technologies. While many studies report significant potential for increasing soil C stocks on grazing lands (e.g., Conant et al., 2017; Mosier et al., 2021), field data are sparser than for annual cropping systems, and current (baseline) grazing management systems are not well documented. Thus, our estimates here are limited to agricultural land presently used as annual cropland. The potential C drawdown from all agricultural lands, including grazing lands, and the potential for widespread adoption of new agronomic technologies could have significantly more impact than the results presented here.

Our estimates for the cropland SOC sink and potential for reducing net GHG emissions in the U.S. are derived from 1) annual croplands, 2) cropland purposed for bioenergy crop production systems, and 3) land set aside from crop production for conservation. To estimate potential agricultural land negative emissions in 2050, we considered the total land area available within each land use category, selecting one of two scenarios for bioenergy production developed for a broader cross-sectoral/cross-technology negative emissions assessment (see Larson et al., 2020). We chose the delimited bioenergy scenario, which included only the conversion of corn grain ethanol croplands to perennial biomass energy crops (6.9% of annual cropland area) and did not include any conversion of marginal croplands to biomass energy crops, as in the high bioenergy scenario (U.S. DOE, 2016). Two mitigation sub-scenarios (called ‘moderate’ and ‘widespread’ below, based on the percent of annual cropland converted to

perennial grass conservation cover) were applied only on annual croplands not converted to perennial biomass energy crop production (Table 2).

Table 1.2 Summary of mitigation scenarios by land use category and the USDA/NRCS Conservation Practice Standards (CPS) applied (USDA-NRCS, 2022). The two right columns are percent of total cropland area to which the standards are applied.

Land Use	**USDA/NRCS Conservation Practice Standard**	**Moderate Adoption**	**Widespread Adoption**
		Percent Land Area	
Croplands remaining under crops	*Humid Climates*: No-Till (CPS 329) + Cover Crops (CPS 340) *Dry Climates*: No-Till on Irrigated Croplands (CPS 329); Conservation Crop Rotation (CPS 328) on Non-Irrigated Croplands	44.4%	85%
Croplands Converted to Permanent Herbaceous Cover	Conservation Cover (CPS 327)	3.8%	8.1%
Corn Ethanol Area Converted to Biomass Energy Crops	Forage and Biomass Plantings (CPS 512)	6.9%	6.9%

Total baseline areas of cropland were extracted at the county-scale from the 2017 U.S. Agricultural Census (USDA-NASS, 2017). The agricultural land areas that could contribute to potential SOC stock increases were grouped into three categories: 1) land currently used for corn grain ethanol production that could be converted to perennial grass biomass crops, 2) marginal cropland area converted to perennial vegetation for conservation, and 3) cropland remaining in annual crop production using soil conservation management practices (Table 3). We conservatively estimated a small portion (5% and 10% in moderate and widespread adoption scenarios, respectively) of current annual cropland would be available to convert to permanent herbaceous cover for conservation within cropland, including field borders, filter strips, grass waterways, and riparian buffers. Recent estimates suggest that more than 20% of cropland in an average field in the Midwest has much lower productivity than other parts of the field and may even

produce negative net revenues (Basso et al., 2019). Thus, consistently low productivity areas could be more profitably set aside as an in-field conservation area.

Table 1.3 Total land areas affected by land use conversions and adoption of conservation management practices; resulting total net CO_2-eq emission changes (as negative emissions).

Moderate Adoption Scenario	10^6 hectares	MMT CO_2-eq/yr
Corn ethanol converted to herbaceous biomass crops	11	-23
Marginal cropland area converted to perennial cover	6	-4
Conservation practices on annual cropland	71	-106
Total	**88**	**-133**

Widespread Adoption Scenario	10^6 hectares	MMT CO_2-eq/yr
Corn ethanol converted to herbaceous biomass crops	11	-23
Marginal cropland area converted to perennial cover	13	-7
Conservation practices on annual cropland	136	-204
Total	**160**	**-234**

Once current and future agricultural land bases were established (Table 3), areas were determined for the adoption of moderate scenarios of conservation practices that could sequester atmospheric C or widespread adoption scenarios using conservation practices that could reduce GHG emissions (see Table 2). Practices were chosen based on the potential to reduce emissions and the practical scalability of implementation (see Table 2). Emission reduction coefficients associated with adopting USDA-Natural Resource Conservation Service Conservation Practices Standards (USDA-NRCS, 2022) were derived from the COMET-Planner Tool (Swan et al., 2020). Values in COMET-Planner represent regionally-averaged SOC and GHG emissions computed with the DayCent biogeochemical simulation model within

the COMET-Farm platform for completing field-scale C and GHG inventories (Paustian et al., 2018). The COMET-Planner tool reports net changes in SOC stocks and soil nitrous oxide emissions (as CO_2 equivalents) from implementing soil conservation management. Negative values indicate a net reduction of GHG emissions relative to baseline agricultural management. Emission reductions due to increases in SOC under consistent management should continue for approximately 20-30 years on average before approaching a new state of equilibrium (Paustian, 2014). Soil nitrous oxide emission reductions would continue indefinitely, assuming consistent management over time in baseline and conservation scenarios.

To avoid double counting emission reductions on lands currently practicing conservation management, we removed those land areas from future projections to the extent possible. The 2017 Agricultural Census provides data on the current use of no-till and cover crops but does not provide data on areas under both no-till and cover crops. Because no-till has been adopted on more acres than cover crops, we conservatively removed all land area already under no-till management from future projections. Similarly, we did not estimate future reductions in emissions for lands currently enrolled in the Conservation Reserve Program (CRP), which pays farmers to temporarily convert annual crop to perennial grass or tree cover.

Under the widespread conservation management adoption scenario, we estimated an overall net GHG emission decrease of approximately 234 million metric tons (MMT) CO_2-eq yr^{-1} (Table 3). Across the U.S., we estimated an average per ha GHG emission decrease on current cropland area of 1.47 Mg CO_2-eq ha^{-1} yr^{-1} relative to current agricultural management. With a moderate level of conservation practice adoption, we estimated a reduction in total net emissions of 133 MMT CO_2-eq yr^{-1} , approximately 57% of the decrease projected for the widespread adoption level.

The geographic patterns of C sequestration and net GHG reductions on a per unit area basis generally reflect climate patterns in the U.S., with higher sequestration rates predicted for humid climates or irrigated systems (more than 2-3 Mg CO_2-eq ha^{-1} yr^{-1}) and lower rates predicted in drier climates under rainfed conditions (< 1 Mg CO_2-eq ha^{-1} yr^{-1}) (Figure 1.3). When these rates were applied to the area of

agricultural lands, the highest potential for C sequestration and GHG emission reductions are in the rainfed (largely non-irrigated) croplands of the northern Great Plains, Midwest, and Mississippi Delta regions and irrigated croplands in the West (Figure 1.4).

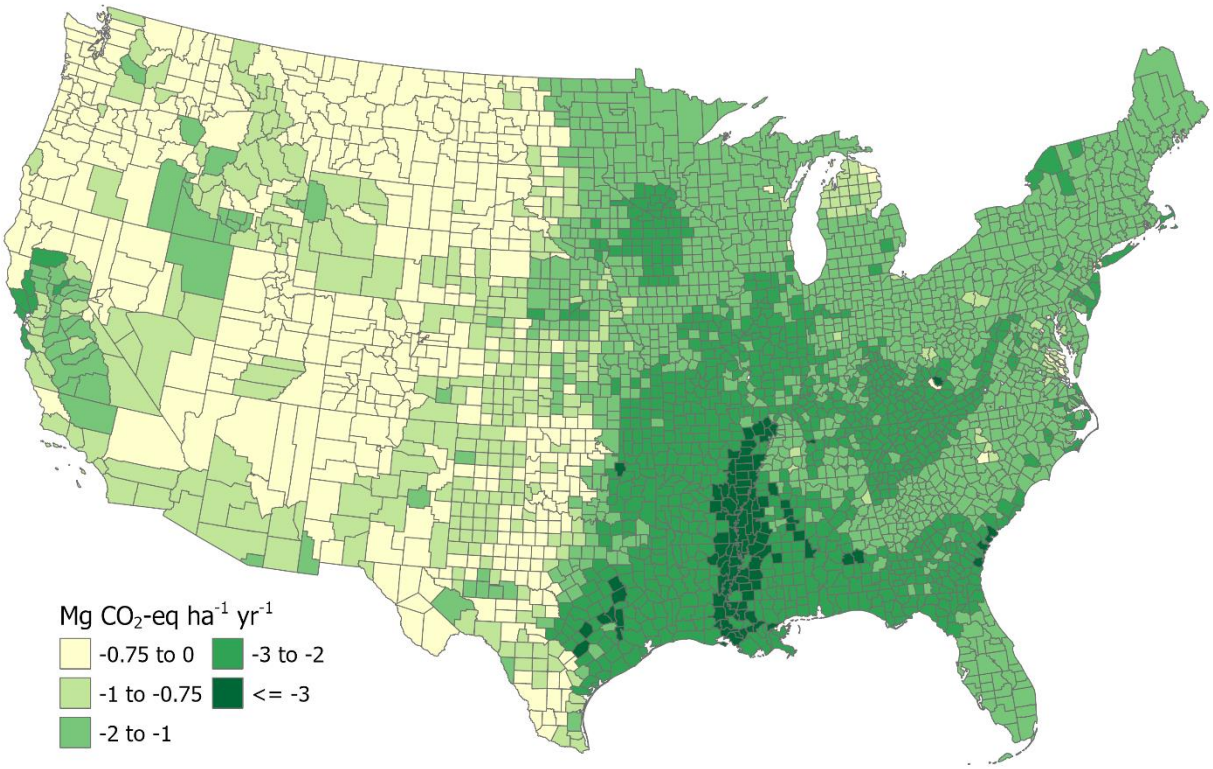

Figure 1.3 Per unit area rates of net negative emissions (in Mg CO_2-eq ha^{-1} yr^{-1}) for all cropland uses at the county scale for the widespread adoption scenario. Negative emissions are relative to the baseline emission/removals.

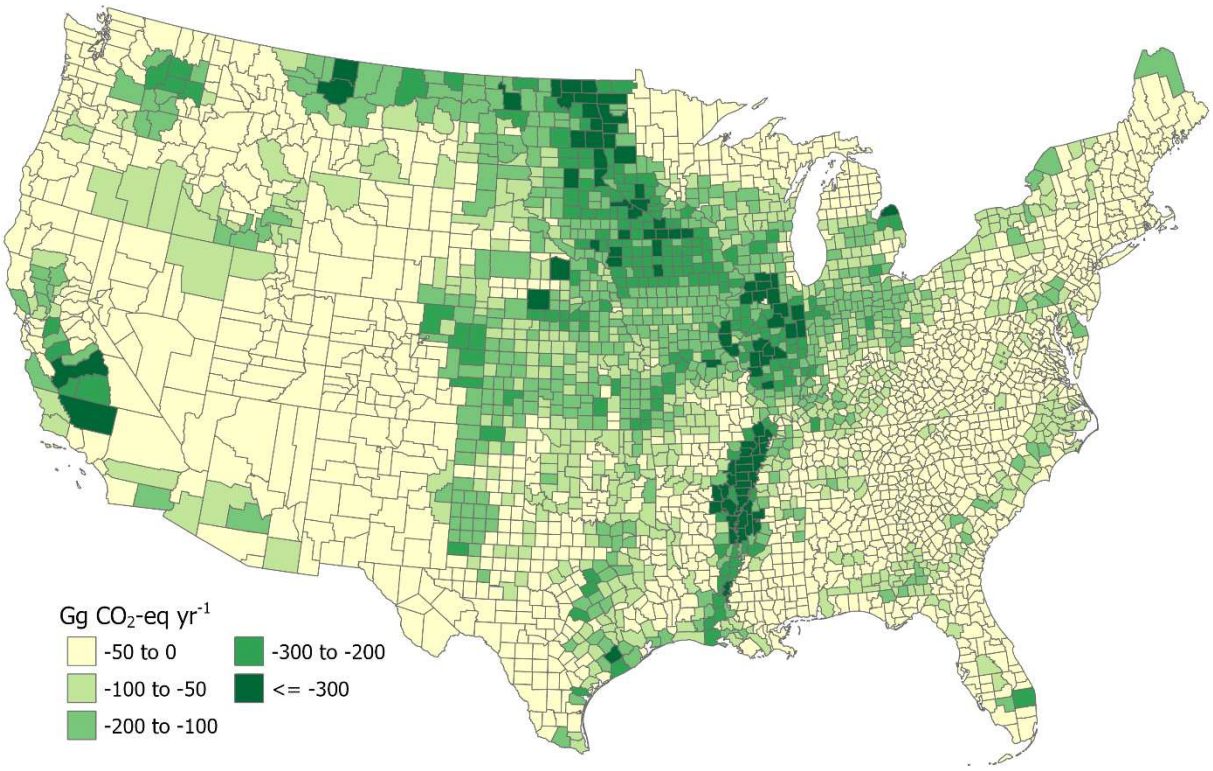

Figure 1.4 Total net negative emissions at county-scale applied to agricultural lands (in Gg CO_2-eq yr^{-1} or 10^3 Mg CO_2-eq yr^{-1}) for all cropland uses for the widespread adoption scenario. Negative emissions are relative to the baseline emission/removals.

According to our analysis, converting corn grain ethanol to perennial energy grasses and using perennial grass conservation set asides could reduce emissions by 30 MMT CO_2-eq yr^{-1}, representing about 15% of total emission reductions under the high bioenergy/widespread conservation adoption scenario. Geographically, most conversion of corn grain ethanol to perennial energy grass would be in the Midwest, with smaller areas spread throughout the eastern U.S. (Figure 1.5). The potential for increased SOC sequestration following the conversion of annual crops (including corn) to perennial grass biomass feedstocks such as switchgrass is well established from field and model-based studies (Field et al., 2020).

Our estimates of the potential for removing CO_2 from the atmosphere using widespread adoption of conservation practices on U.S. croplands align with several other estimates ranging between 170 to 290 MMT CO_2-eq yr^{-1} (Lal, 2003; Morgan et al., 2010; Sperow, 2016, 2020). In a recent analysis, Robertson

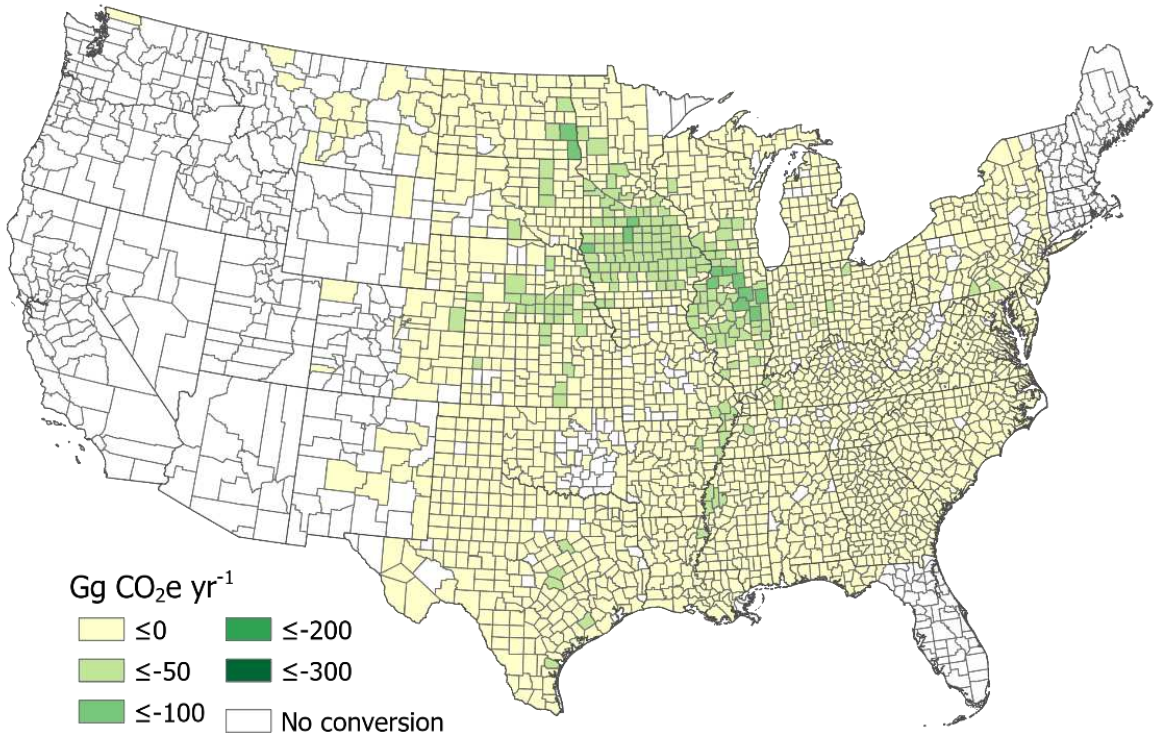

Figure 1.5 Total GHG changes (in Gg CO_2-eq yr^{-1} or 10^3 Mg CO_2-eq yr^{-1}) due to conversion of corn grain ethanol to perennial energy grasses at the county scale for the widespread adoption scenario. Negative emissions are relative to the baseline emission/removals.

et al. (2022) estimated CO_2 removal and GHG emission reduction for US annual cropland as well as land conversions to perennial biomass production for bioenergy. Based on empirical models derived from LTE data, they estimated potential SOC gains of 208 MMT CO_2-eq yr^{-1} on annual cropland employing a similar suite of conservation practices for which we estimated 204 MMT CO_2-eq yr^{-1}. Robertson et al. (2022) estimated an additional net emission reduction of 99 MMT CO_2-eq yr^{-1} on annual cropland from N_2O and rice CH_4 reductions, and avoided CO_2 emissions from industrial fertilizer use and rewetting of peat soils, which were not included in our analysis. Their study also included a more in-depth look at the potential for perennial biomass feedstocks (e.g., switchgrass) on marginal lands and land used for corn ethanol production. They estimated a total SOC increase potential on available land (i.e., 10 million ha (Mha) currently used for corn ethanol, 5 Mha from Conservation Reserve Program land, 41 Mha of non-

forested abandoned agricultural land), if converted to switchgrass, could yield an additional increase of 101 MMT CO_2-eq yr^{-1}. Our total assumed cropland area available for conversion to perennial grass (24 Mha; Table 2) was much less and hence our total SOC gain from conversion on perennial grass (30 MMT CO_2-eq yr^{-1}) was less.

The degree of convergence between our estimates and others recent estimates, including those above, is not surprising, given that the major determining factors (available cropland area and rates of SOC accrual after adopting conservation practices) are well defined and widely used by different analysts. The greatest variable in estimating potential C removal by cropland soils is estimating the proportion of total land area where conservation practices may be adopted. If low rates of adoption are assumed, then accordingly the potential for SOC sequestration will appear to be low. Adoption, of course, depends largely on economic and policy conditions that may incentivize or inadvertently discourage farmers from adopting SOC sequestering practices, as well as increased outreach, training, and technological innovation.

The US national greenhouse gas inventory (EPA, 2023) currently estimates an annual increase of 15 MMT CO_2-eq yr^{-1} in baseline SOC stocks for cropland remaining under cropland management, with cropland converted to perennial grass (e.g., pasture) accounting for an additional SOC stock increase of 23 MMT CO_2-eq yr^{-1}. Both would add up to almost 50 MMT CO_2-eq yr^{-1}. These baseline increases are based on the current modest adoption rates of conservation practices, including reduced tillage and no-till, conservation plantings on marginal lands (i.e., CRP), field buffers, and grassed waterways. Thus, if more farmers adopt C sequestration practices (particularly cover crops), achieving an additional 100-200 MMT CO_2-eq yr^{-1} would be feasible. However, note that the U.S. GHG inventory also estimates a loss of about 50 MMT CO_2-eq yr^{-1} from converting grassland and forest into annual cropland, effectively canceling out current estimated SOC gains for other land uses. Such SOC losses associated with land use change underline the importance of avoiding the conversion of perennial vegetation, including grasslands and forests, to cropland.

5. Concluding Remarks

The scientific community has progressed toward a robust understanding of the mechanisms controlling SOC stabilization and storage, as well as the key role of SOC in ecosystem services. Aggregate data from LTEs and biogeochemical modeling provide estimates of the potential for existing conservation management practices to reduce agricultural GHG emissions and contribute to drawdown of excess atmospheric CO_2.

Without underselling the potential benefits of regenerative agriculture (stabilizing the climate system and improving agroecosystem functioning), we must remain aware of likely challenges. As demonstrated in our analysis, the reduction of potential emissions and removal of existing atmospheric CO_2 associated with management changes differ greatly across diverse ecoregions and soil conditions in the U.S. Furthermore, the potential impacts of climate change on SOC stocks will vary by region and will require region-specific management responses (i.e., shifts to warmer and/or wetter climates, intensified droughts, impacts of large precipitation events, etc.). Coordinated efforts to model county-level C sequestration potentials, accounting for soil type, climate, current/historic land use, and future climate scenarios should guide land use conversion and promote conservation management. Further research recommendations, including nation-wide measurements and monitoring, systems-level research, and technological developments are outlined in Table 4.

Table 1.4 Research recommendations for the development, expansion, and implementation of negative C agriculture practices, technologies, and monitoring (References: 1. Middendorf et al., 2020; 2. NASEM, 2019; 3. Rumpel et al., 2020; 4. Smith et al., 2021)

Research need	Recommended Research Action	Description and Justification

Expanding monitoring & measurement	National on-farm monitoring system and integrated model data platform[1,2,3,4]	• Development of national system for measuring and modeling regional on-farm C sequestration accounting for soil type, climate, current/historic land use, and socio-economic factors impacting transition to negative C practices • National standards for sampling, analysis, modeling, and data reporting • Systems-level analysis of ecosystem services and effects beyond productivity, including emissions of all pertinent GHGs across the production system (ex. Sustainable Intensification Assessment Framework) • National assessment of alignment to and delivery on UN Sustainable Development Goals
Interdisciplinary systems-research	Agricultural systems field experiment network[1,2,3]	• Expand upon existing network of long-term agricultural experiments and collaborative on-farm research endeavors to evaluate region-specific best management practices and effects of integrating multiple practices simultaneously • Emphasize understanding C stock dynamics in the subsoil (below 30 cm) • Measure changes in SOM fractions, with implications for stability, permanence, and sensitivity to system disturbance. Effect of integrating multiple regenerative management practices simultaneously
	Socio-economic barriers to increasing landowner adoption of negative C practices, quantifying economic benefits of increasing SOC[2,3]	• Interdisciplinary research to understand socio-economic barriers to adopting negative C agriculture practices and opportunities for co-benefits • Research to inform development of economic and policy structures as incentives to adopting negative C practices • Co-development of knowledge with producers to inform research, understand barriers to adoption, and provide effective technical support and training
Frontier research and technology development	High throughput, low-cost methods to monitor changes in SOC stocks	• Reducing cost and time associated with SOC monitoring through robustly calibrated and verified technologies that measure SOC and bulk density in the field (e.g., advances in field spectroscopy, non-invasive bulk density measurement)
	High C input crop phenotypes and perennial staple crops[2]	• Developing high C input crop phenotypes with altered root morphology and biomass • Using perennial staple grain and oilseed crops

		• Analysis of the soil and ecosystem C effects of on-farm perennial strips, agroforestry systems, etc.
	Innovative soil amendments for improved C sequestration and soil function[2]	• Microbial inoculants, seed coatings, and genetic engineering for novel plant-microbe associations • Full LCA of biochar production system (including various feedstocks) and effects on nutrient cycling and non-CO_2 GHG emissions

Although SOC was depleted from agricultural soils in a geologic instant, it will take time and coordinated effort to replenish C stocks across the range of generally C-depleted U.S. cropland soils. Biophysical/technical potential provides strong evidence that we can achieve GHG reductions and C drawdown of 100-200 MMT CO_2-eq yr^{-1} (over two to three decades) on U.S. cropland if the adoption of regenerative management continues and is widespread. However, the socio-economic and political challenges associated with the change of this scale should not be downplayed. Effective economic incentives, technical guidance, and social support structures are needed to meet the urgency of this challenge.

With widespread adoption of regenerative management, cropland soils can contribute 17 to 33% of the 600 MMT CO_2-eq yr-1 needed to offset U.S. agricultural emissions, as proposed in Chapter 1. Given the urgent need to stabilize the climate system, agricultural management to prevent further GHG emissions and increase SOC storage should be employed as one of many diverse strategies to mitigate atmospheric C and protect terrestrial C stores.

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IMPORTANCE OF ON-FARM RESEARCH FOR VALIDATING PROCESS-BASED MODELS OF CLIMATE SMART AGRICULTURE[2]

1. Introduction

While agriculture is a major source of GHG emissions, agriculture can also contribute to climate mitigation through avoided emissions and carbon sequestration by following conservation management principles (Amelung et al., 2020; Bossio et al., 2020; Bradford et al., 2019; Paustian et al., 2016). The United States agricultural sector contributes approximately 10% of total US greenhouse gas (GHG) emissions. While only a small proportion of total agricultural emissions (< 1%) currently come from the conversion of grassland and forest to croplands (US EPA, 2023), creation of new agricultural land and the release of soil organic carbon (SOC) as CO_2 was a significant historical source of emissions to the atmosphere (Spawn et al., 2019). Thus, a significant C 'deficit' remains in most US cropland soils due to historical land use change, generated through lower rates of plant C inputs to soil compared to native ecosystems, along with decades of intensive tillage and extended bare fallow periods (Jackson & Schlesinger, 2004; Sanderman et al., 2017). Restoring SOC lost from cropland soils can contribute to climate mitigation, reduce GHG emissions associated with agricultural activities, and regenerate degraded land (Amelung et al., 2020; Bossio et al., 2020; Paustian et al., 2019).

Practices that rebuild SOC stocks have the added benefits of restoring soil fertility, reducing emissions associated with field activities, and increasing agroecosystem resilience to climate stressors, such as drought, flooding, and pest pressures (Bossio et al., 2020; Bradford et al., 2019; Kane et al., 2021). Thus, these practices fall under the umbrella of "climate-smart agriculture," indicating they are tools to both mitigate atmospheric C and adapt to the pressures of climate change (Chandra et al., 2018;

[2] Ellis, E., & Paustian, K. (2024). Importance of on-farm research for validating process-based models of climate-smart agriculture. *Carbon Balance and Management*, *19*(1), 16. https://doi.org/10.1186/s13021-024-00260-6

Paustian et al., 2016). SOC stocks can be replenished over time by managing the balance between photosynthesis (C gain) and biological decomposition (C loss). During decomposition, the majority of plant residue C is lost as CO_2 to the atmosphere while a portion is stabilized in soil organic matter (SOM) as soil organic matter carbon (SOM-C or SOC). If the amount of C added to the SOC pool exceeds the amount lost as CO_2 during decomposition, cropland soils act as a net sink for atmospheric C. This can occur with changes in management practices that induce greater plant C inputs and/or reduce SOM decomposition rates, although there is likely a finite capacity or 'saturation' limit to the attainable size of SOC stocks in agricultural soils (Cotrufo et al., 2023; Six et al., 2024; Stewart et al., 2007). There are several climate-smart practices that can positively impact the SOC balance, such as no-till, cover crops, diversified crop rotations, integrating animals into crop systems, or a combination of multiple synergistic practices (Bai et al., 2019; Bossio et al., 2020; Griscom et al., 2017; Paustian et al., 2016, 2019).

With recent national and international commitments to agriculture as a climate mitigation strategy (Minasny et al., 2017; Wiese et al., 2021), there is demand for reliable methods to measure and estimate changes in SOC stocks and GHG fluxes under agricultural management change. Ecosystem process-based models are increasingly used to estimate SOC stocks and GHG fluxes at the field and regional level. The applicability of models is dependent on the degree to which they are parameterized, calibrated, and validated to reflect the environmental and management characteristics of the unique land use settings and soil characteristics encountered across the country (Ogle et al., 2019). Thus, to accurately quantify or estimate the climate mitigation potential of climate-smart practices, it's important that measurements and models reflect the variety of soil types, topography, and management systems encountered on cropland across the country. Here, we make the case for increased sampling and activity data collection on commercial farms to test conclusions from long-term field experiments (LTEs), improve process-based models, and support the successful adoption of climate-smart practices at scale. We describe challenges in process-based modeling associated with data availability, summarize recent studies of SOC stock change

in commercial farm settings, and propose a method for integrating on-farm measurements and activity data to improve model simulations.

2. The US is committed to agriculture as a climate-mitigation strategy, but available quantification tools need improvement.

The US agricultural sector declared its commitment to agriculture as a climate-mitigation strategy with the announcement of USDA's Partnerships for Climate Smart Commodities project (USDA, 2021) and the significant allocation of Inflation Reduction Act funds for currently oversubscribed agriculture conservation programs, like CSP and EQIP (USDA, 2023). Collectively, these two initiatives appropriated $22.6 billion towards the creation of markets for climate-smart commodities and to support agricultural producers in the adoption of climate-smart practices to both mitigate and adapt to the pressures of climate change. If climate-smart practices are adopted on all possible US agricultural land, it is estimated that 0.17 Gt CO_2e yr^{-1} could be sequestered over the following 20 years (Sperow, 2020). By the end of the century, a total mitigation of 110 Gt CO_2e might be achieved in the US through a range of nature-based climate mitigation practices on managed lands, including C sequestration in soils and biomass and bioenergy with carbon capture and storage (Robertson et al., 2022). However, catalyzing wide-spread management changes on millions of farms and ranches across the US continues to be a major challenge (Roesch-McNally et al., 2018; Schlesinger & Amundson, 2019). Technical assistance, social change, and economic incentives are needed across scales and sectors to spread the use of climate-smart practices (Luxton & Ellis, et al., 2024; Prokopy et al., 2019). One such incentive is the creation of markets for agriculturally-generated carbon credits that pay producers for C stored in their soil and/or reduced GHG emissions (Oldfield et al., 2022), an otherwise unrewarded ecosystem service (Ribaudo et al., 2010).

A common goal of private carbon credit markets and other climate-smart initiatives, such as 'low-carbon' supply chains, is to improve methods for monitoring, reporting, and verification (MRV) of the GHG emission reductions or C sequestration benefits of climate-smart practices. Most MRV protocols

require a combination of direct soil measurements, modeling, and/or remote sensing, but there are no industry or governmental standards to ensure the comparability of offsets generated through different protocols (Oldfield et al., 2021). With current methods and technologies, laboratory measurement of SOC is too costly and time-intensive to be used on all desired fields and with the large sample sizes needed to detect small changes in carbon stocks (Bradford et al., 2023; Stanley et al., 2023). Thus, a combination of direct measurement and process-based biogeochemical modeling represents the "gold standard" for voluntary carbon-market MRV protocols (Conant et al., 2011; Paustian et al., 2019; Smith et al., 2020).

Nearly all process-based model development processes are carried out using field activity data and SOC and/or GHG flux measurements from LTEs with controlled and repeated management. Although LTEs are essential for basic agricultural research and model parameterization, they are limited in their extent and representation of soil, climate, topography, field size, and management combinations, and therefore do not include the full range of activities, outcomes, and production challenges encountered on real commercial farms (Blanco-Canqui & Lal, 2008; de Oliveira Ferreira et al., 2021; Dupla et al., 2022). There is need for greater collaboration between researchers, agricultural producers, and various entities developing MRV protocols to improve process based models using on-farm measurements and activity data (Bradford et al., 2023; Oldfield & Lavallee, et al., 2022).

3. Model-based simulations of SOC stocks could be improved with further on-farm measurements.

Simulation of ecosystem processes for estimation of changes in SOC stock and GHG emissions are, and will continue to be, an essential aspect of climate-smart agriculture MRV protocols. Process-based biogeochemical models, such as DayCent (Parton et al., 1998), DNDC (Giltrap et al., 2010), and RothC (Coleman & Jenkinson, 1996), rely on measurement data to improve simulations of agroecosystem processes occurring above and belowground and their subsequent impacts on biogeochemical stocks and fluxes, including SOC stocks and GHG emissions. SOM models and modeling approaches incorporate

new experimental data to reflect the latest understanding of SOM dynamics, such as saturation kinetics, permanence, priming, measurable SOM fractions, subsoil SOM, and specific microbial processes (Berardi et al., 2020; Campbell & Paustian, 2015; Castellano et al., 2015; Schimel, 2023; Zhang et al., 2021). Despite improvements in the ability of process-based models to simulate observed SOC dynamics, uncertainties remain high when estimating SOC stock change at the field and regional scale. For example, uncertainties for simulating past SOC stock change in the Century model were as high as +/- 118% and +/-739% at subregional and site scales, respectively (Ogle et al., 2010). Bayesian model analysis frameworks and intermodal comparisons have proven useful for reducing uncertainty (Gurung et al., 2020; Sulman et al., 2018), but the limited amount of measured data for model calibration and validation remain the largest bottle-neck for further reducing uncertainty in quantifying SOC stock changes (Bernardini et al., 2024; Campbell & Paustian, 2015; Conant et al., 2011; Gurung et al., 2020; Pierson et al., 2022).

New modeling techniques incorporating artificial intelligence and multi-model ensembles may improve simulation accuracy and uncertainty estimations if the necessary data are available. For example, machine learning (ML) algorithms have the potential to incorporate large quantities of data to model ecological processes with superior performance to traditional process-based models (Bernardini et al., 2024). Furthermore, multi-model ensembles that incorporate the strengths of several models simultaneously are shown to improve C flux simulations and are currently being pursued by collaborative groups throughout the process-based modeling community (Riggers et al., 2019; Sándor et al., 2020; Sulman et al., 2018). Even more so than traditional process-based models, the performance of ML algorithms and multi-model ensembles is strongly dependent on the quantity and quality of measurement data used for training, calibration, and validation.

Most data available for model development are generated at LTEs and LTE networks representing a narrow range of agricultural regions, crop production systems, climate-smart practices, topographical settings, and soil types (Rasmussen et al., 1998). While LTE data are essential for generating high-control,

low-variability, time series data for model parameterization, applicability of experimental results to the broader range of commercial farm settings is uncertain. When modeling outcomes on commercial farms, accurately simulating biomass input (crop yields), impacts of historical land use, and baseline SOC stocks are important (Mathers et al., 2023). Furthermore, available data must represent the full range of pedo-climatic and landscape-level variables (including topography and soil erodibility) that affect SOC baseline stocks, SOC accrual, and SOC stability in commercial farms settings (Brilli et al., 2017; Thaler et al., 2021; Zhang et al., 2021). In the following sections, we provide examples of on-farm studies that help to address the lack of data from commercial farm settings. We then outline how on-farm direct and remotely-sensed measurements could be incorporated into a secure data platform to facilitate further model improvements.

4. Observational experimental techniques popular in other subfields of ecology can be used to generate on-farm measurement data.

To effectively use process-based models and decision support tools to quantify SOC stock change and GHG emissions on commercial farms, we need more measured soil data from real farms using a variety of management systems to supplement LTE data. On-farm monitoring data (i.e., measurements across multiple time points, ideally including baseline measurements) are essential to improve model calibration and validation, particularly as process-based model results are increasingly used in voluntary C market MRV protocols.

While LTEs enable us to quantify the impacts of specific management variables in comparison to a no-treatment control, the application of experimental results to real-world agronomic conditions has limitations (de Oliveira Ferreira et al., 2021; Dupla et al., 2022). First, the agricultural inputs of LTEs (such as biocides, fertilizers, and organic amendments) are often held consistent from year to year, while commercial farms vary their management based on input prices, weather, success of previous years management, and personal agronomic goals (Govaerts et al., 2009). Further, LTEs prioritize management

consistency over maximizing yields, so yields of LTE plots often do not reflect yields on nearby commercial farms (Leigh and Johnson 1994). This discrepancy may impact the biomass input calibrations in process-based models. Perhaps most importantly, there are few existing LTEs that measure the impacts of multiple synergistic management practices applied to the same field. For example, a Midwest farmer dedicated to soil regeneration may use no-till in combination with winter cover crops, manure injection, diversified rotations, and reduced synthetic N inputs. LTEs are not designed to fully reflect the real-world complexity of annual crop production under various economic, social, and ecological pressures.

Establishing new LTEs that reflect region-specific climate-smart management changes at the systems-level (i.e., multi-practices used simultaneously) would allow us to understand the synergistic outcomes of complex management systems (NASEM, 2019), but in the absence of such experiments in the short term, we can adopt observational experiment techniques popular in other subfields of ecology, such as space-for-time substitution and paired field studies (Pickett, 1989). For example, space-for-time substitution experiments can be used to generate chronosequences of SOC stocks and/or GHG flux measurements from adjacent farms using contrasting management systems (Leigh & Johnston, 1994; Machmuller et al., 2015; Pickett, 1989). Additionally, recent studies have worked collaboratively with agricultural producers across select regions to sample commercial fields representing a broader range of climate-smart practices than are currently established in LTEs or to compare LTE results to on-farm realities (Blanco-Canqui & Lal, 2008; de Oliveira Ferreira et al., 2021; Dupla et al., 2022; Mosier et al., 2021; Rosenzweig et al., 2018; van der Pol et al., 2022). Table 1 summarizes several studies using one of the following approaches to generating and evaluating on-farm data: 1) space-for-time substitution, 2) paired fields, 3) comparison between commercial farms and LTEs, or 4) diversity of commercial farm management across a region.

Of course, the greatest limitation of paired farm comparisons and chronosequence designs is that they are *not* randomized, controlled experiments and thus, are associated with a high degree of variability, unpredictability, and study design challenges. Common challenges noted in the studies presented in Table 1 include accounting for spatial variability in SOC stocks at the field-level, identifying producers willing

to allow access to their farms, obtaining reliable and complete activity data, and site selection to control for variability between sites. On-farm studies rely on the implicit assumption that differences between paired-fields or categorically grouped farms are attributable primarily to management system differences, and that the variables of interest (i.e., SOC stocks) were similar before the management change occurred, but this assumption is difficult to verify. Careful site selection can be used to ensure sampled fields have similar soil types, topographic position, and long-term management histories, but some uncertainty about the influence of non-management induced differences in SOC stocks often remains.

While on-farm analyses are essential for understanding the impact of management change as it is applied at the commercial farm scale, evaluating more than one management practices simultaneously, along with environmental co-variates that also impact SOC stocks, makes it difficult to determine which practice (i.e., cover cropping, tillage regime, manure additions, or fertilizer reduction) is driving the results. Thus, there is still great value in controlled experiments that manipulate one management variable at a time. On-farm measurement data should be used in combination with measurements from LTEs to evaluate the extent to which LTEs reflect on-farm outcomes and whether process-based models are biased to LTE measurements.

In the following section, we describe our personal experience designing and executing an on-farm study of SOC stock differences between conventional and climate-smart farms across a portion of the Upper Corn Belt region (Iowa and Southern Minnesota). In addition to the studies cited in Table 1, we hope our experience can serve as a case study of the benefits and challenges of on-farm research and provide a road map for further on-farm data collection efforts.

5. On-farm SOC stock measurement and activity data collection is challenging, yet necessary.

To help address the paucity of SOC stock data from commercial farms, we conducted on-farm sampling and collected detailed management activity data from 22 farms across Iowa and Southern

Table 2.1 Description of recent studies employing various observational methods for on-farm data collection.

	Type of study or purpose	Management system	Field selection method	Number of farms/fields	Variables of interest	Activity data collection methods
Blanco-Canqui and Lal, 2008	Paired on-farm study; Regional variability in practice use and soil, topography, climate variables; Comparison to LTE	No-till vs. conventional tillage; Comparison to undisturbed control; Range of cropping systems	Adjacent pairs only; Duration of no-till management, crops produced, and soil type varied widely across study pairs	11 MLRAs, one farm pair per MLRA; Compiled data from 16 published, paired LTEs for comparison	Whole profile (0-60 cm) SOC stocks, BD, C/N	Report years of current tillage practice and N fertilization rate; Method of data collection unknown
de Oliviera Ferreira et al., 2021	Paired on-farm study; Outcomes on commercial farms under a range of management; Comparison to native ecosystem SOC stocks; Comparison to LTE measurements	Conservation tillage, no-till, cropping intensification	Sites with long-term conservation practice use (20-30 years); Neighboring LTEs; Each agricultural site paired to a natural vegetation site	Nine paired sites (agriculture vs. natural vegetation); Four LTEs and five commercial farms	SOC stock; SOC recovery (to native ecosystem)	Report years of current and historic tillage practices, biomass input, and crop rotation; Method of data collection unknown
Dupla et al., 2022	Comparison of commercial farms to LTEs; Outcomes on commercial farms under a range of management systems (not represented in LTEs)	Broad range of cropping systems across select region of Switzerland	Randomly selected from regional farm directory, randomly selected one field per farm	120 farms, one composite sample per farm	Change in topsoil (0-20 cm) SOC stock; SOC:clay	Pulled from records (record keeping mandatory in Switzerland to participate in subsidy programs); interviews with selected producers to gap fill and confirm
Machmueller et al., 2015	Chronosequence of land use change	Transitioning cropland to management-intensive grazing	Similar row crop management and tillage histories	Three farms representing a seven-year period of land use change	SOC stocks; CEC; root mass; $\delta^{13}C$	Report tillage history, forage crops seeded, cattle stocking rates, and rotation frequency; Method of data collection unknown
Mosier et al., 2021	Paired on-farm study of grazing systems	Adaptive multi-paddock (AMP) grazing vs. conventional grazing	Survey to identify AMP grazers in the region, selected 25 for in person visits, identified conventional grazing neighbor, selected 5 best pairs based on soil type, management history, etc.	Ten farms (five pairs); sampled two catenas per farm	SOC and N stocks; root C; SOM fractions	Surveys and site visits/interviews
Rosenzweig et al., 2018	Outcomes on commercial farms under a range of management systems (not represented in LTEs)	Dryland cropping system intensification	Producers identified through "snowball" sampling; sample represents a range of mangement conditions, soil types, PET rates, and crop rotations	96 fields (54 commercial farms, 42 LTEs, 6 CRP sites)	SOC stocks, microbial activity, aggregation	Five years of activity data collected direct from producer or LTE manager

Minnesota. We describe our study design and activity data acquisition efforts, along with unexpected challenges encountered, to facilitate future on-farm sampling and activity data collection. A more comprehensive discussion of the measured data results and model simulations is currently in preparation and will be published in future papers (see Chapter 3).

Spatial variability in management systems allowed us to design a paired, space-for-time substitution experiment, where we identified neighboring producers using different management practices on the same soil type for "across-the-fence" comparisons of the SOC and N stocks and agronomic impacts of different management systems with a range of years since practice adoption. Despite a recent relative increase in cover crop adoption across the Midwest (Q. Zhou et al., 2022), there is still a high degree of variability in management systems across regions and between neighboring farms. Cover crops are used on about 4.2% of acres and no-till on 30% of acres in Iowa (NASS, 2018), indicating that climate-smart management is still far from the norm. Given the heterogeneity in regional practice use, it was possible to identify neighboring producers using contrasting management systems for a paired comparison of outcomes.

After harvest in the fall of 2022, we sampled 22 paired corn and soybean farms throughout Iowa and Southern Minnesota using one of two management systems: 1) "climate-smart" (defined as greater than 8 years of no-till and at least 4 years of cover crop use, along with other best management practices), or 2) "conventional" (defined as annual or biannual tillage and winter bare fallow, which is typical of most row crop production systems in Iowa). All farms were planted in a corn and soybeans rotation, while some also raised livestock and used manure as an input. To reduce variability associated with crop-year, all fields selected for sampling were planted to soybeans in 2022. Rather than isolating one management practice as the study "treatment", such as tillage or cover crops, the study design allows us to evaluate the impact of common management systems that use complementary practices simultaneously and vary management from year to year. For each of the 22 farms we obtained a series of soil cores for four depth increments (0-15, 15-30, 30-60, and 60-100 cm) to enable direct measurements of SOC and total N and other soil properties (including bulk density, pH, textural class, inorganic C content, and microbial

community composition). Our paired, across-the-fence approach used space-for-time substitution to measure and model the impact of management change, where the conventional farms represent soil conditions pre-management change. The climate-smart farms adopted conservation practices at different times, allowing us to generate a chronosequence of measurements representing different times since practice adoption (while accounting for management differences and regional variability in soil properties and climate). We buried ball markers at each sampling location to enable precise resampling at the same location at a future time (Conant & Paustian, 2002). Long-term monitoring of each farm will be used to establish a time series of measurements documenting the impact of long-term practice use (i.e., SOC change with 5 vs. 15 years of cover crop use). Additionally, we asked each farmer to voluntarily provide year-by-year management information (going back to 2013 or further, if available) needed to schedule events in the DayCent model and the COMET-Farm decision support tool (Table 2).

It is important to note the tradeoffs and challenges associated with an on-farm study of this kind: First, it is challenging to attribute differences in measurements between farms to a particular soil characteristic or management practice used. Lack of experimental control leads to other challenges such as a higher degree of variability across a single field and between pseudo-replicates, making it difficult to quantify effect size. While we did our best to control for variations in soil type, topography, and land use history at the study design phase there were often uncontrolled differences between the pairs that were not identified until after SOC stock and activity data were analyzed. For example, after receiving unexpectedly low SOC stock measurements from a regenerative farm field, we learned from the producer that that field was highly degraded and low yielding when he transitioned it to no-till 30 years ago. In this case, the conventional *vs* regenerative pair had quite different management and erosive histories, violating the assumption that the baseline SOC stocks were similar. This issue could have been avoided through more careful field selection, perhaps through in-depth farmer interviews or remote sensing of historic land use.

Connecting with willing farmer participants was an additional unforeseen challenge of our study and may prove difficult for future research aiming to collect on-farm data. We identified farms using "snowball" sampling techniques, where each producer who agreed to participate in the study recommended nearby producers who might be willing to participate as well. Connecting with farmer networks such as Practical Farmers of Iowa, attending local field days, and gaining connections through agronomic consultants were helpful strategies in the participant recruitment process. Identifying neighboring producers with the same soil type, topography, and management history was challenging when connections could only be provided to specific neighbors.

Reaching a level of trust with each participant (in most cases, by visiting their farms before data collection began) or gaining an introduction through a trusted organization or individual was a necessary element of the recruitment process. When asking participants to divulge detailed management information and to talk openly about their farming expertise, it was important that participants knew how the data collected would be used and kept secure. Institutional Review Board (IRB) approval was required to collect this information and was used to establish structures for data security and confidentiality.

Beyond data security concerns, our data collection experience brought to light other difficulties associated with collecting management data from producers for process-based modeling. Process-based modeling at the field level requires detailed yearly activity data (ideally going back 20 or more years) and knowledge of historic land use practices, which must be provided by the land managers or ascertained through remote sensing. For example, scheduling management events in the DayCent model and the COMET-Farm decision support tool requires data on tillage practices, fertilization rates, crop cultivars, organic matter addition, grazing events, among other field activities, including the dates of each management action. Even with substantial efforts to build relationships and trust, obtaining detailed activity data from the producers involved in our study was still difficult. Commonly unreported or incompletely reported data included historic management practices, planting/harvest dates, tillage dates, tillage implement/intensity, fertilizer application dates, and detailed liming practices. Only one producer

was able to provide activity data for all ten years and all applicable management categories, and this producer owns an agronomic consulting business that helps producers collate their management data for carbon crediting programs, among other applications. In most cases, a lack of detailed yearly record keeping or unwillingness to spend the time required to collate data from multiple sources prevented farmer participants from providing the requested data, rather than data security concerns. It is possible that many producers do not maintain management records with the level of detail required for process-based modeling, or the effort required to collate management data from various sources puts an undue burden on producers. As stipulated by our IRB, reporting data was voluntary, thus whether unreported categories were due to lack of records, data privacy concerns, or the time/efforts required to collate records is unknown. In the absence of farmer-reported activity data, default management assumptions based on county- or regional-averages or agronomic recommendations can be used to specify model inputs. In some cases, use of default activity data such as planting or fertilizer application dates may not affect model outcomes, but missing management data for sensitive variables such as fertilizer application rates or manure amendments will result in greater uncertainty in model results.

According to previous studies, producers express concern about data security when there is a lack of trust between the agricultural community and the entity asking for the data, which may deter producers from participating in C crediting programs or research efforts (Niles & Han, 2022). To overcome this challenge, we recommend initiating collaborations between C accounting projects and data management software commonly used by producers, such as John Deere's farm management software (APEX™). There is potential to align the data recorded automatically by advanced agricultural equipment software and the data needed to accurately and precisely model biogeochemical fluxes from cropland management. As precision agriculture and AI continue to expand, the viability of this option will increase. Further, the use of remote sensing tools to remotely monitor field activities and estimate soil properties using hyperspectral imagery can help overcome both soil measurement and management data challenges (Smith

et al., 2020). With these emerging technologies, data privacy and security to protect producer's anonymity should be prioritized.

Furthermore, data that are timely and relevant to farmer's management choices, such as potential profitability changes or fertilizer demand changes, should be provided to farmer participants whenever possible. On-farm research has the potential to benefit all parties involved when the data production process becomes more collaborative and reciprocal. For example, farmer participants should be consulted in the study design phase to ensure the study is evaluating production systems most relevant to the region. Additionally, farmer participants should be provided with timely data reports describing the research findings relevant to their management decisions, including SOM and N stocks, water holding capacity, or profitability estimates. We propose the term "reciprocal research" to describe studies that are designed with the farmer participant's interests in mind, rather than extracting information from agricultural communities without considering how the research can benefit the participants in the short-term. Reciprocal research, following principles of participatory action research common in the social sciences, has the potential to motivate system change by involving groups often excluded from the research process in the creation of new knowledge (Cuéllar-Padilla & Calle-Collado, 2011; Luján Soto, Cuéllar Padilla, et al., 2021).

6. On-farm measurements can be assembled into a database to facilitate model improvement

We propose a framework for integrating on-farm measurements and activity data into a secure, anonymized database to facilitate process-based model validation and improvements. As more on-farm studies are conducted, likely by private sector companies and research institutions, these data could be curated into an open-source database. This database could facilitate model intercomparisons, multi-model ensembles, and systematic comparisons of LTE results to on-farm studies. Further, this database could provide a data source for model testing of decision support tools designed to easily quantify the benefits of climate-smart practice adoption, such as COMET-Farm and COMET-Planner. COMET-Farm was

developed as a decision support tool that includes the DayCent process-based biogeochemical model, as well as a number of other greenhouse gas emission models and databases, to provide everyday users the ability to estimate agricultural GHG emission and SOC sequestration through a web-based tool that does not require any modeling or other technical expertise (Paustian et al., 2017). Like most process-based models, DayCent and the associated COMET tools were developed mostly using data from LTEs. With improved sources of on-farm data process-based models and decision support tools could be improved to better serve the end users and ensure the platform represents the range of agricultural management systems in use across the country.

A key element of the proposed data platform should be providing the information needed to incentivize and facilitate the adoption of climate-smart practices on as many acres as possible. This means ensuring a diversity of cropping systems are represented, the model results are easy to interpret, and the information provided is relevant to the producer. As the diversity and complexity of agricultural practices evaluated using these simple tools increases, there will be continual need to parameterize new practices and validate model results against measured data. Further, models that integrate socio-economic variables and environmental outcomes are needed to assess the system-level outcomes of management change (Wei et al., 2009). Following the idea of reciprocal research, practice outcomes that are more relevant to management decision making, such as profitability, resilience to weather extremes, or fertilizer requirements, should be provided to support adoption of new practices more effectively. Additionally, the burden of reporting data should be alleviated from the producer. Integrated data acquisition through farm data management software or remote sensing of field activities could be used to reduce the reporting and survey burden on producers (Mandal et al., 2022). Data privacy, security, and anonymization will continue to be challenges under this framework, as this is a top concern for many producers interested in participating in carbon markets and related programs (Niles & Han, 2022).

Table 2.2 Yearly management data needed to schedule events in the DayCent process-based model and the COMET-Farm GHG accounting tool, along with the number of producers who were able/willing to provide data for each requested data point in our on-farm study. * = assumed only to be applicable to specific farms and years. **Bold text** = properties that can be remotely-sensed given current technologies.

Period data are needed for	Data category	Specific activity data needed to schedule model events	# of producers reporting ≥10 years activity data	# of producers reporting ≥ 5 years activity data
Pre 1980 and 1980-2000s	Historic management	• **Pre-1980s land use (grazing, cropland, upland vs. lowland)** • Pre 2000 enrollment in CRP (yes or no) • **1980 – 2000 management: irrigated vs. non-irrigated, crop type vs. grazing, tillage practices**	• 0/22 • 0/22 • 0/22	• 0/22 • 0/22 • 0/22
Baseline (2000 to start of management change scenario)	Crop planting and harvest	• **Cash crop type/rotation** • **Planting date** • **Harvest date** • **Yields** • Residue removal (% dry matter)	• 15/22 • 10/22 • 8/22 • 10/22 • 1/2*	• 19/22 • 19/22 • 19/22 • 19/22 • 2/2*
	Cover crops	• **Presence of cover crop** • Cover crop type or mixture • Seed population • Planting date • Planting equipment • Termination/harvest date	• 11/11 • 9/11 • 6/11 • 6/11 • 7/11 • 6/11	• 11/11 • 9/11 • 8/11 • 8/11 • 8/11 • 7/11
	Grazing practices	• **Start and end date** • **Rest period (days)** • **Daily utilization %**	• 1/2* • 0/2 • 0/2	• 1/2* • 0/2 • 0/2
	Tillage and other implement passes	• Date of each implement pass • **Tillage intensity (intensive, reduced, no-till)** • Other implement passes (roller crimping, mowing, herbicide application)	• 8/22 • 12/22 • 0/22	• 11/22 • 19/22 • 3/22
	Irrigation	• **Presence of irrigation** • Irrigation start and end date • Irrigation amount (inches per application) • Days between irrigation events	NA	NA
	Manure application	• **Presence of manure** • Date applied • Manure type and form (solid, slurry) • Manure application rate • Moisture % (if known) • Total N and C/N ratio (if known)	• 0/5* • 4/5 • 3/5 • 0/5 • 0/5	• 0/5* • 4/5 • 3/5 • 0/5 • 0/5
	Fertilization	• Date applied • Fertilizer type applied • Total N applied (kg/ha) per event	• 2/22 • 12/22 • 11/22	• 9/22 • 15/22 • 14/22
	Liming	• Liming date • Liming material and amount applied	• 2/5* • 0/5	• 4/5* • 2/5
	Burning	• **If burning occurred, did it occur before planting or after harvest?**	NA	NA

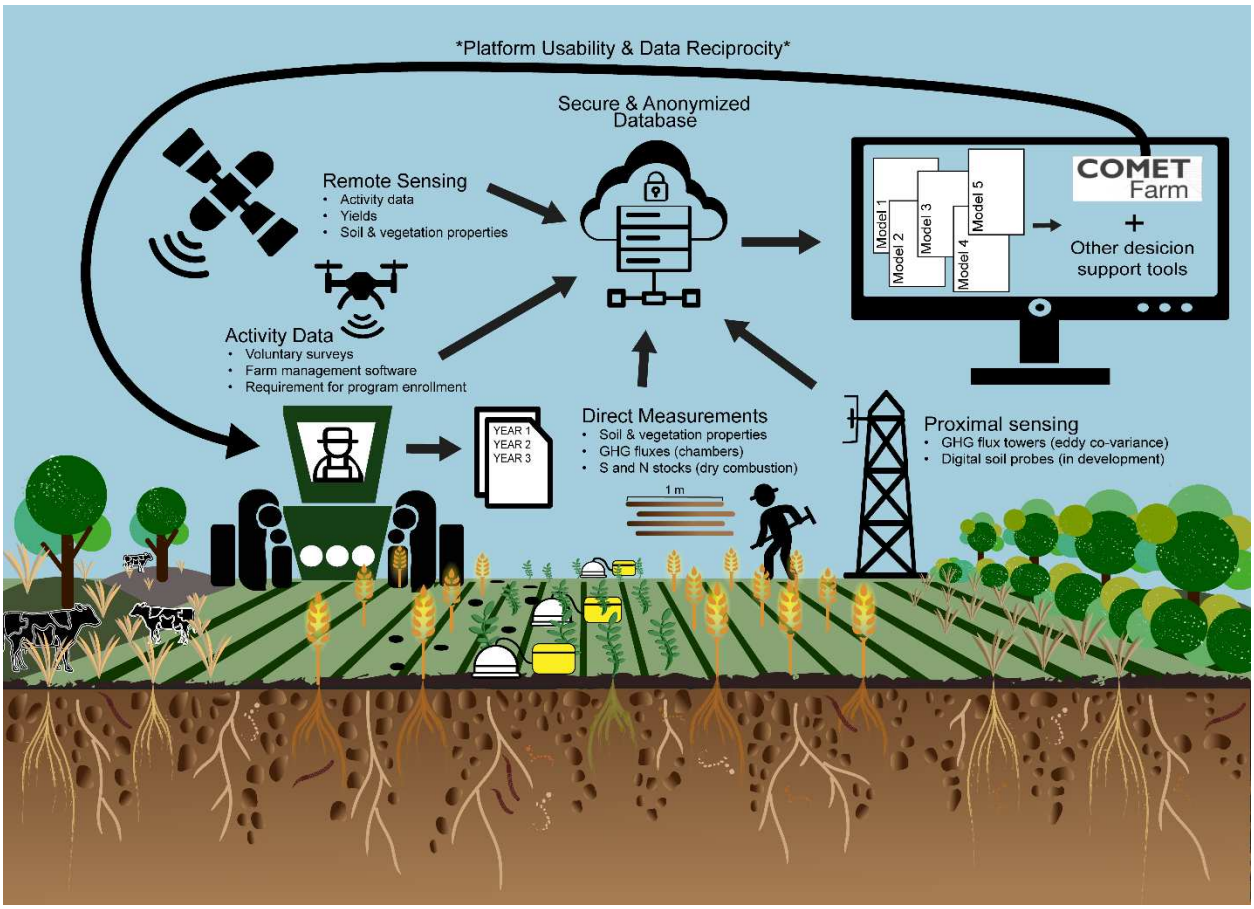

Figure 2.1 System framework for integrating on-farm measurements (directly measured, proximally sensed, and remotely sensed) into a secure and anonymized database that can be used for model improvements. Activity data is obtained from producers when readily available and remotely sensed whenever possible. Activity and measurement data are used simultaneously to improve existing model performance, conduct model intercomparisons, and build new models/ multi-model ensembles using artificial intelligence. Improved models can support decision support tools like COMET-Farm, which are expanded to include data of immediate relevancy to the producer following the principle of "reciprocal research."

7. Conclusion

Improved management of cropland soils has the potential to be a significant climate mitigation and adaptation tool, one that private markets and federal programs are heavily investing in. Measuring and modeling changes in cropland SOC stocks and GHG emissions associated with adoption of climate-smart practices is a challenging, yet necessary, aspect of agriculture GHG accounting or carbon offset generation. To test, validate, and improve process-based models and decision support tools, more direct

soil measurements from commercial farms can complement data from LTEs while providing management-relevant data to facilitate scaled adoption. Detailed management data (obtained from producers or remotely sensed) paired with direct field measurements can support model-readiness for the diverse management scenarios encountered on diverse agricultural lands, which is of particular importance as interest in modeling SOC stocks on commercial farms continues to proliferate. We suggest the creation of a secure and anonymized database of on-farm measurements and activity data to facilitate model improvements and our understanding of what drives the successful adoption of climate-smart practices.

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IMPACT OF REGENERATIVE AGRICULTURE ON SOIL CARBON STORAGE AND MICROBIAL COMMUNITY STRUCTURE IN THE UPPER CORN BELT: AN ON-FARM ASSESSMENT[3]

1. Introduction

Regenerative agriculture is an approach to farming and land management that aims to restore and enhance the health of agroecosystems while continuing to produce food, fuel, and fiber (Brown, 2018; Lal, 2020; O'Donoghue et al., 2022; Schreefel et al., 2020). Practices that fall under the umbrella of regenerative agriculture include cover cropping, reduced tillage or no-till, diversified crop rotations, and integrating animals into cropping systems, all while maintaining or enhancing the productive outcomes of the farm system. Management systems that incorporate several complementary regenerative practices can confer a multitude of benefits at the farm and ecosystem level (Bai et al., 2019), including reduced erosion (Jacobs et al., 2022), beneficial shifts in microbial community structure (Singh et al., 2023), and increased soil organic carbon (SOC) stocks (Bai et al., 2019; Franzluebbers, 2010; Paustian et al., 2016). Regenerative agricultural has received increasing attention for its potential to contribute to climate change mitigation through C sequestration and mitigation of farm-level greenhouse gas (GHG) emissions (Lal, 2020; Toensmeier, 2016). Regenerative practices that decrease C losses through soil organic matter (SOM) mineralization while simultaneously enhancing the quality/quantity of C inputs can increase SOC stocks and contribute to atmospheric CO_2 mitigation. It is likely that the inter-relationship between microbial community composition, agricultural management, and inherent soil and landscape properties plays an important role in SOC turnover processes (Bhattacharyya et al., 2022; Liang & Zhu, 2021; Trivedi et al., 2018).

Several long-term field experiments in the U.S. Upper Corn Belt region (including in Iowa and Minnesota) demonstrate that practices such as no-till, reduced tillage, cover crops, and diversified

[3] Ellis, E., Mason, L., Eagle., A., Wrighton, K.C., Paustian, K., impact of regenerative agriculture on soil carbon storage and microbial community structure in the upper corn belt: an on-farm assessment. [In prep].

rotations can increase SOC stocks on the order of 0.25-0.43 Mg C ha^{-1} yr^{-1} (Al-Kaisi & Kwaw-Mensah, 2020; Jordahl et al., 2023; Poffenbarger et al., 2020; Qin et al., 2023), but it is unclear to what extent experimental findings fully represent the complexity of commercial farm settings (Bradford et al., 2023; Dupla et al., 2022). Evaluations of these practices are typically conducted through agricultural experiments with randomized and replicated statistical designs with a limited (typically 1-3) set of treatment variables. While controlled experiments are essential to identify mechanisms and variables driving SOC stock changes associated with a given practice, these experiments often do not fully reflect the agroecosystem variability present on commercial farms. Moreover, the cost of maintaining such experiments strongly limits their number and hence their representation of the diversity of climate, soil and management systems within any agricultural region. Further, few long-term experiments evaluate the impact of multiple regenerative management practices applied on the same field, as is typical on many commercial regenerative farms. Indeed, complementary row crop management practices, such as planting cover crops and/or applying manure in no-till systems, may synergistically improve soil health and bolster the potential to increase SOC stocks (Blanco-Canqui et al., 2011; Huang et al., 2020). Given the diverse combinations of soils, climates, topographies, and management systems in this region, there is need for further observational measurements of SOC and associated properties. Observational studies of commercial farms systems may provide insights into the agroecological controls on SOC stock change, beyond what could be gleaned from controlled agricultural experiments (Ellis & Paustian, 2024).

Here, we present results from an observational study conducted on pairs of neighboring farms across Iowa and Southern Minnesota using one of two management systems: 1) Regenerative (fields managed with at least seven years continuous no-till and at least four years winter cover crops), and 2) Conventional (fields managed with full width tillage and bare winter fallow). We hypothesize that a suite of system-level agroecological factors and management properties will be associated with differences in SOC stocks between regenerative and conventional farms. Further, we hypothesize differences in SOM-C fractions as well as soil microbial community structure, diversity, and network topology may serve as indicators of SOC dynamics. In summary, our system-level analysis provides multiple lenses through

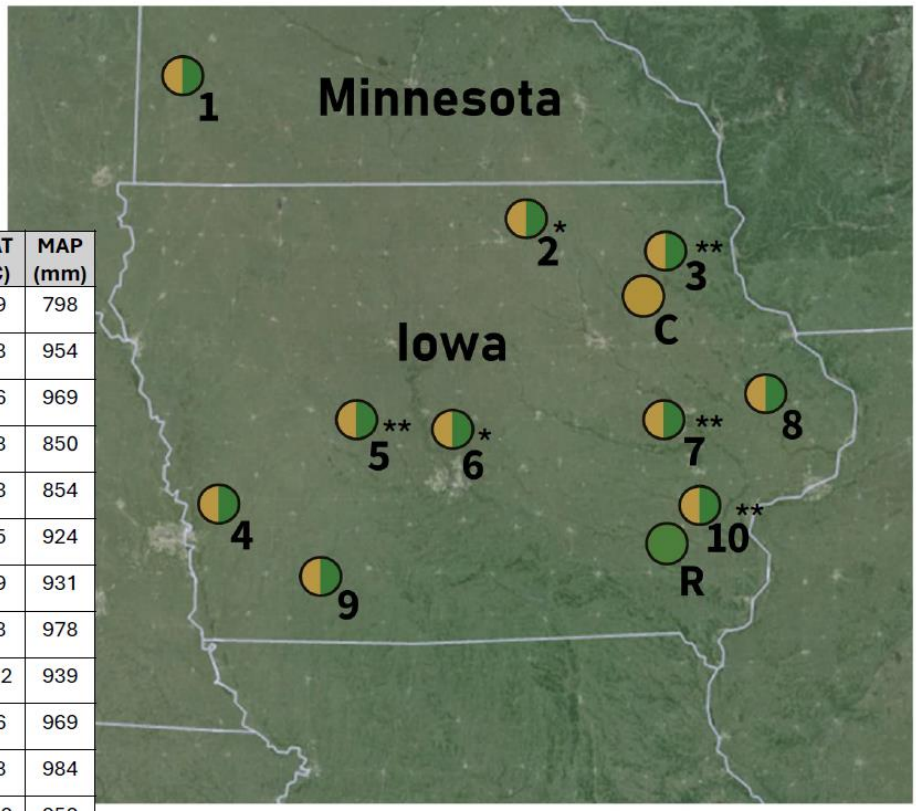
which to view the drivers and impacts of SOC stock differences under different management systems, as they are applied by real-world producers.

2. Methods

2.1 Study sites

We selected 22 producers across Iowa and Southern Minnesota who were amenable to sample collection on their farms and able to provide ~10 years of management activity data. In the summer of 2022, we recruited interested producers through in-person meetups (i.e., field days and farm visits) and/or interpersonal connections (i.e., via agronomic consultants, extension agents, and neighbors). Participants were recruited from across the region to account for the range of climates, soil types, and management systems present. An informal screening process was used to determine if the interested producer fit into one of two management groups (regenerative vs. conventional) and to identify a field on each farm with the desired management characteristics for the study (i.e., no-till and cover crops vs. annual tillage and bare winter fallow). Further recruitment was conducted through "snowball sampling," where producers who agreed to participate in the study recommended several neighbors using the opposite production system. To the extent possible, neighboring farm pairs were selected based on proximity, presence of matching soil units, and similarity in topography and land use history. USDA NRCS soil maps were used to identify areas of matching or similar soil units between each farm pair. The final sample consisted of ten neighboring farm pairs and two unpaired farms (where a suitable neighbor could not be identified) (Figure 3.1). The unpaired farms are included in analyses that include all farms, but not in pairwise comparisons. We prioritized across-the-fence farm pairs where available (n=7 of 10 pairs); otherwise, the paired farms were located within 5 km of each other (n = 3).

Selected fields were managed using one of two management systems: 1) Regenerative (REGEN), defined as fields managed with at least seven years continuous no-till and four years of winter cover crops, and 2) Conventional (CONV), defined as fields managed primarily with full-width tillage and bare winter fallow. The exact management details vary from farm to farm but represent management practices



Pair #	MAT (°C)	MAP (mm)
1	6.9	798
2	7.8	954
3	7.6	969
4	9.8	850
5	9.3	854
6	9.5	924
7	9.9	931
8	8.8	978
9	10.2	939
10	7.6	969
NP-C	7.8	984
NP-R	10.2	952

Figure 3.1 Map of approximate sampled pair locations across Iowa and Southern Minnesota, along with climate data for each pair (table to the right). Green/yellow circles indicate REGEN/CONV farm pairs, while single-colored circles mark the two unpaired farms sampled (green = REGEN, yellow = CONV). Single or double asterisks (*, **) indicate farm pairs where soil was fractionated by size and density (farm pairs 2, 3, 5, 6, 7, and 10). Double asterisks (**) indicate samples that were fractionated by size and density and additional samples were collected for amplicon-based microbiome analyses (farm pairs 3, 5, 7, 10). Fractionation was performed on top two depth layers (0-15 and 15-30 cm) only).

typical of the region (detailed management practices for each farm are provided in SI Table 1). The minimum practice adoption time periods for the REGEN fields are based on the knowledge that it takes significant time (on the order of 5-10 years) for soil carbon stocks to accrue enough carbon following a significant management change to detect a difference at reasonable sample sizes (Necpalova et al., 2014; Smith, 2004; Stanley et al., 2023). Selected fields were planted to predominately corn (*Zea mays* L.) and soybeans (*Glycine max* L.) in rotation and all had been planted to soybeans in 2022, which helped to reduce variability in SOC associated with phase in the crop rotation. Some fields had short (<4 yr) periods of continuous corn, continuous soybeans, or alfalfa (see SI Table 1). In some cases, the conventional

control was converted to no-till and cover cropped for the first time in the 2021 or 2022 growing season, one to two years before we sampled. We assume that one or two years of practice implementation is not enough time to cause a detectable change in SOC and thus our measurements were reflective of long-term management history (Necpalova et al., 2014; Smith, 2004). Further, this study design offers the opportunity to generate a time series of SOC change through future resampling at the geolocated sample locations, particularly on the farms recently converted to regenerative management.

2.2 Soil and biomass sampling for biochemical and biophysical analyses

All sampling took place in October and November of 2022 after soybean harvest. Nine random sampling points within the areas of matching soil units between the paired farms were generated using QGIS (QGIS Development Team, 2024). At each of the nine randomized sampling points, three cores were collected at the corners of a north-oriented isosceles triangle with a height of 100 cm, a base width of 60 cm, with the length equivalent to the swing width of the hydraulic probe (SI Figure 3.1). Cores were collected using a truck-mounted, 5.4 cm (inside) diameter hydraulic probe (Giddings Machine Company, Inc., Windsor, Colorado). A 100 cm deep soil core was collected from the north apex of the triangle, and two 30 cm cores were collected from the bottom two corners of the triangle. To enable resampling, a geolocator ball was buried ~150 cm deep at each of the sampling locations on each farm to provide precise locations for potential future resampling. During and after sample collection, cores were carefully inspected for signs of compaction, and only non-compacted cores were kept. Cores were cut along four depth layers (0-15, 15-30, 30-60, and 60-100 cm) and composited by depth. We noted the actual sampling depth for bulk density calculations for cores that could not be taken to the full depth of 100 cm. There were a total of 10 sampling sites from six of the farms where no soil was collected from the 60-100 cm depth layer due to compaction or impenetrable layers. At three farms (R8, C8, and R10), only eight locations were sampled due to time and weather constraints (SI Table 2). Prior to taking soil cores, a crop residue sample was collected from the north apex of each sampling triangle by collecting all surface residues present in a 15 cm diameter ring. A total of 770 soil samples and 195 crop litter samples were collected from the 22 farms. All samples were temporarily stored in insulated boxes or coolers and

shipped back to Colorado State University within three days of sample collection. Soil samples for non-microbiome analysis were stored at 5°C until processed.

2.3 Soil sampling for microbial community characterization

At four farm pairs (3, 6, 7, and 10), an additional 100 cm core was collected ~10 cm to the left of the apex of the triangle for DNA extraction and microbial community characterization. We selected these four pairs based on similarity in soil types, topography, land use history, and consistency in management practices from year to year. After removal from the ground, the core for microbiome sampling was separated at the same four depth layers (0-15, 15-30, 30-60, and 60-100 cm), with soil aseptically processed using sterilized tables and extraction materials. Several grams of soil were collected from the interior of the core to avoid areas contaminated through contact with the core tube or the table. The samples were placed in a sterilized soil sample bag. Samples were kept on ice until shipped back to Colorado State University, where they were stored at -20°C until DNA extraction.

Table 3.1 Select management data, regen score (Eq 1), and average field/ soil properties for paired-farms. Regen score and adoption group are used to evaluate the influence of time since regenerative practice adoption on SOC and related properties. Mean BD of fine soil fraction, pH, clay %, and sand % (obtained via laboratory measurements) are reported for the 0-15 cm soil depth layer. Average slope is the average slope of the sampled points, determined via three-meter DEM (See Methods 2.9). Management data, including years no-till, years cover cropping, sum 2-year N fertilization, and mean soybean yield were obtained via voluntary farmer reporting. NR = not reported. NP-C and NP-R are unpaired conventional (C) and regenerative (R) farms. Additional site characteristics are given in Table S1.

Pair #	Regen Score (Eq 1)	Management System/Adoption Group	Years no-till	Years cover crops	Sum 2-year N fert (kg ha^{-1})	Mean soybean yield (Mg ha^{-1})	BD of fine soil (g cm^{-3})	pH	Clay %	Sand %	Average slope (°)
1	0.0	CONV	0	0	NR	3.2	1.17	6.40	28.0	33.7	1.9
	3.1	REGEN-recent	8	7	68	3.3	1.27	6.63	27.6	32.9	1.9
2	0.0	CONV	0	0	NR	NR	1.33	6.07	20.6	31.6	0.7
	5.1	REGEN-long	30	8	68	4.6	1.28	5.72	23.0	26.4	1.0
3	0.0	CONV	1	1	73	3.2	1.38	6.17	18.0	31.6	1.9
	9.4	REGEN-long	30	20	54	3.7	1.32	6.46	18.3	42.6	2.4
4	0.0	CONV	0	0	75	3.8	1.26	5.23	29.2	3.8	1.3
	3.8	REGEN-recent	30	5	54	4.1	1.27	5.71	29.0	4.4	4.0

5	0.0	CONV	0	0	69	3.2	1.25	5.50	25.0	36.0	1.3
	6.1	REGEN-long	14	14	69	3.6	1.28	5.33	26.9	33.0	0.8
6	0.0	CONV	0	0	86	4.7	1.25	5.43	23.8	39.5	1.3
	4.9	REGEN-long	12	11	68	3.0	1.25	6.73	24.1	32.2	0.9
7	0.0	CONV	0	0	NR	2.0	1.27	7.44	28.1	20.5	2.8
	3.4	REGEN-recent	30	4	73	4.7	1.26	6.14	26.3	12.5	2.7
8	0.0	CONV	1	0	98	3.9	1.20	5.36	21.8	9.3	1.1
	2.4	REGEN-recent	8	5	NR	NR	1.32	5.71	23.2	11.6	2.9
9	0.8	CONV	3	2	77	3.8	1.23	5.74	33.5	2.8	1.4
	6.4	REGEN-long	30	12	83	4.0	1.24	6.05	33.8	3.0	3.7
10	0.0	CONV	2	0	22	4.6	1.24	6.07	28.0	3.5	1.4
	4.5	REGEN-long	30	7	27	4.4	1.22	5.67	29.9	3.0	0.6
NP-C	0.0	CONV	0	0	79	4.6	1.21	5.67	22.6	42.2	2.0
NP-R	8.1	REGEN-long	40	15	NR	NR	1.26	5.93	30.0	4.7	2.4

2.4 Soil processing and elemental analysis

Soil processing and laboratory analyses of gravimetric soil water content, bulk density, soil texture, root biomass C, and total C and N were conducted in the EcoCore Facilities and Soil Innovation Laboratory at Colorado State University. After weighing each field-moist soil sample, a representative subsample was collected to determine gravimetric water content. The remainder of the sample was passed through an 8 mm sieve and roots and rocks > 8 mm were separated. After air drying for ~72 hours, a ~200 g subsample was further sieved to 2 mm. Any remaining rocks and roots > 2mm were removed. Roots and rocks were dried at 60 °C for 24 hours before weighing. For soil texture, % sand was determined from wet sieving of 2 mm sieved soil on a 53 µm sieve, % clay was determined by the hydrometer method (Gee & Bauder, 1986) and % silt by difference. Soil pH was measured using a pH probe in a 1:2 soil to DI water slurry. Bulk density of the fine soil fraction (particles <2mm) was determined using oven-dry sample mass and volume, subtracting the weight and volume of coarse fragment > 2 mm. A subsample of 2 mm sieved soil was collected in a square glass vial for grinding on a roller table with steel roller bars. The ground sample was analyzed for total C and N through dry combustion on an elemental

analyzer (Elementar vario ISOTOPE CUBE - Langenselbold, Germany). All samples were tested for presence of carbonates using an HCl acid fizz test procedure. In samples with a positive fizz test, carbonates were quantified using the pressure transducer method (Sherrod et al., 2002). SOC concentration was estimated as the difference between total C and inorganic C content.

To calculate SOC stocks, we used the equivalent soil mass approach rather than a fixed-depth approach to better account for changes in soil volume due to management (i.e., tillage) (von Haden et al., 2020). We used the SimpleESM R script provided in van Haden et al., 2020, which facilitates the calculation of SOC and N stocks based on multiple soil mass layers using a cubic spline model. The average bulk density of the conventionally tilled fields was used to determine the reference soil mass. Soil carbon stocks were calculated on an oven-dry soil basis.

2.5 Root and litter processing and analysis

Organic matter content of roots collected for each depth layer was determined by loss-on-ignition (LOI). Roots and litter were dried at 60°C for ~24 hours and weighed. Root samples were placed in a clean and oven-dried crucible and the sample weight was collected before and after ashing in a muffle furnace at 600°C for 5 hours. The root organic matter fraction was calculated using the total dry root weight minus the ash weight, and the C percentage of that fraction was assumed to be 45%. The C content of the aboveground litter samples was also measured via LOI, assuming C content of 45%. There was a significant amount of adhering soil incorporated with the litter samples, so to separately measure the C contents of the residual soil and the crop litter, the litter was washed, and the soil and litter fractions were separated through a simple density floatation in DI water. After air drying, the litter sample was ground in a Wiley mill and a subsample was ashed using the LOI procedures outlined for roots. The soil fraction separated from the litter was also dried and ashed to determine organic matter and estimate C content using the van Bemmelen factor (SOM = 58% C).

2.6 Soil organic matter fractionation

To further characterize soil organic carbon stocks, the six farm pairs with the greatest positive differences between bulk SOC stocks (pairs 2, 3, 5, 6, 7, and 10) were selected for soil organic matter

(SOM) fractionation. SOM was fractionated by size and density to quantify the C and N stocks in three functionally distinct soil organic matter pools: light particulate organic matter (LPOM), coarse heavy organic matter (CHOM), and mineral-associated organic matter (MAOM) (Leuthold et al., 2023; Mosier et al., 2021; Sollins et al., 2009). All nine pseudo-replicates were fractionated to capture variability across the field and to allow for sample removal from the dataset if recoveries were low. Following methods outlined in Mosier et al, 2021, about 10 g of 2 mm sieved soil was added to sodium polytungstate (SPT) solution at a density of 1.85 g cm^{-3} and shaken with glass beads on a reciprocal shaker for 18 hours. After centrifugation at 3400 g for 27 minutes, the suspended LPOM particles were aspirated using a filter vacuum. The heavy fraction was rinsed in DI and centrifuged three times to remove remaining SPT. The heavy fraction was further separated by size into CHOM (>53 μm) and MAOM (<53 μm) through wet sieving. Dry weights of each fraction were collected to evaluate sample mass recovery. All samples with recoveries +/- 5% of the original sub-sample weight were dried and ground for analyses on the elemental analyzer for C and N concentrations, while samples with lower or higher recoveries were re-fractionated until they met the recovery cutoff. Mean SOC recovery was calculated by comparing the sum of the C concentrations of each fraction to the bulk SOC concentration of each sample. Any samples with a C recovery less than 60% were not used in fraction calculations, which led to the removal of 24 out of 188 fraction C measurements. The mean SOC and N recoveries were 77% and 89%, respectively.

2.7 Soil bacterial & fungal DNA extraction and sequencing

Microbial DNA was isolated from 0.5 g of soil at Colorado State University using the Zymo Research Quick-DNA fecal/soil microbe Microprep Kit (cat no: D6012). Genomic DNA was amplified with primers 515F (GTGYCAGCMGCCGCGGTAA) and 806R (GGACTACNVGGGTWTCTAAT) to amplify the 16S rRNA gene V3 - V4 of the bacterial and archaeal community, and the primers ITS1f (CTTGGTCATTTAGAGGAAGTAA) and ITS2 (GCTGCGTTCTTCATCGATGC) to amplify the ITS gene in the fungal community. PCR consisted of 12.5 μL PCR-grade water, 10.5 μL Platinum II Hot-Start PCR Master Mix (Invitrogen #14000014), 0.5 μL of each primer, and 1 μL template DNA, with cycling

conditions of 94 °C for 2 min, followed by 35 cycles (94°C for 15 s, 60°C for 15 s, 68°C for 1 min), and a final elongation at 68°C for 10 min. DNA libraries were normalized using the Invitrogen SequalPrep Normalization kit (Invitrogen A150510-010) and sequenced with an Illumina MiSeq 250 x 250 PE kit at the University of Colorado, Boulder.

Sequencing reads were demultiplexed and analyzed in QIIME2 (2023.9, Boylen et al., 2019) using the DADA2 pipeline (Callahan et al., 2016) for trimming, denoising, and clustering into amplicon sequence variants (ASVs) at 100% identity. Forward and reverse bacterial and archaeal reads were trimmed at 240 base pairs. Reverse fungal reads were removed, and forward reads were trimmed at 28 base pairs and truncated at 150 base pairs. Bacterial and archaeal taxonomy was classified with a naive Bayes classifier trained on GTDB-Tk species genomes (release 214 (Chaumeil et al., 2019)) and reclassified using Silva nr 138 (Quast et al., 2013) to remove eukaryotic sequences. Fungal taxonomy was classified using the naive Bayes sklearn classifier trained with the UNITE fungal reference database (v9; Abarenkov et al., 2023). ASVs appearing less than three times were excluded and ASVs were converted to relative abundance within each sample based on the number of filtered and quality-controlled reads per ASV divided by the total filtered and quality-controlled reads in each sample.

2.8 Time and practice based regenerative score calculation

To account for differences in years of practice use amongst the 22 farms, we formulated an index scoring scheme to separate the farms into three "adoption groups": 1) conventional (CONV), 2) recent adopters of regenerative practices (REGEN-recent), and 3) long-term users of regenerative practices (REGEN-long). It should be noted that this index score is intended to facilitate categorical comparison amongst the paired farms and is not used as a quantitative measure of SOC accrual potential. We used the following equation to group farms based on the number of years regenerative practices have been used, creating a score between 0 and 10 to compare farms within the sample set:

$$Regen\ Index = \left(\frac{Years\ no\ till\ (i)}{Max\ years\ no\ till\ for\ all\ farms} * 0.25\right) + \left(\frac{Years\ cover\ crops\ (i)}{Max\ years\ cover\ crops\ for\ all\ farms} * 0.75\right) * 10 \quad \textbf{(Eq 3.1)}$$

Cover crop use was weighted more heavily in Eq 1 because it is likely that extended cover crop usage will have more of an impact on SOC stocks than no-till alone (Bai et al., 2019; Blanco-Canqui et al., 2011). Previous studies in the Corn Belt region suggest that continuous cover crop use in fine textured soils has the potential to increase SOC by 0.82 Mg C ha^{-1} yr^{-1} (Jian et al., 2020), while continuous no-till can increase SOC by 0.36 Mg C ha^{-1} yr^{-1} (Al-Kaisi & Kwah-Mensah, 2020). Farms with a regenerative score between 0 and 1 are considered CONV, scores between 1 and 5 are considered REGEN-recent, and scores > 5 are considered REGEN-long. CONV fields have been no-till 0-3 years, and cover cropped between 0-2 years, REGEN-recent have been no-till 8-30 years, and cover cropped 4-7 years. REGEN-long fields have been no-till 12-40 years and cover cropped 7-20 years.

2.9 Slope estimation and erosion modeling

Field slope was estimated at each of the sampled points using a three-meter resolution digital elevation model (DEM) obtained using the *elevatr* package (Hollister & Shah, 2017). The *terrain* function in the *raster* R package was used to calculate the average slope at each sampled point and the average slope of the entire field extent (Hijmans, 2021). For select farm pairs with differences in slope greater than 2° where historical erosion is hypothesized to be a driver of differences in SOC stock (pairs 4, 8, and 9), we used the Revised Universal Soil Loss Equation, Version 2 (RUSLE2) model and database to compare potential erosion rates between the paired fields under historic and modern management practices (USDA, 2008). The model was parameterized using county level climate data available in the RUSLE2 database, soil textural class, organic matter content, estimated soil permeability, and average corn/soybean yields for each field. We used the average field slope obtained through the geospatial calculations described above and assumed a horizontal slope length of 1000 ft for each field. To estimate the SOC loss from the RUSLE2 estimated erosion rate, we used the following equation:

$$Est.C\ loss\ (Mg\ C\ ha^{-1}\ yr^{-1}) = Est.erosion\ rate\ (Mg\ C\ ha^{-1}\ yr^{-1}) * \frac{SOC\ stock\ (Mg\ ha^{-1})}{BD\ (cm^{-3}) * 15\ cm * 100} \quad \textbf{(Eq 2)}$$

Assuming the CONV field represents baseline management conditions and SOC stocks, we used the average SOC stock and BD measurements from the CONV field to estimate annual SOC loss from both the REGEN and CONV fields.

2.10 Statistical analyses

2.10.1 Statistical analysis of soil biochemical and biophysical properties

All statistical analyses were performed using R software (R version 4.3.2). Before analysis, we identified and removed outlier SOC and N stock values, defined as those more than 2.5 standard deviations from the sample mean. 21 out of 770 samples were identified as outliers and were removed from the dataset (SI Table 2). We used the *lme4* package (Bates et al., 2015) to generate a linear mixed-effect model to test the effect of the management system and soil depth layer on SOC percent, SOC stocks (Mg ha^{-1}), total N stocks (Mg ha^{-1}), BD (g cm^{-3}), root C stocks (Mg ha^{-1}), litter C stocks (Mg ha^{-1}), and soil organic matter fraction C (Mg ha^{-1}). Adoption group (CONV, REGEN-recent, REGEN-long), soil depth layer, and the interaction between adoption group and depth layer are treated as fixed effects. For analyses where only a subset of paired farm (or depth) samples was used (microbial community diversity and SOM fractionation), we used a simple two-level REGEN vs. CONV management system grouping due to the smaller sample size. Pair number and field number are included as random effects in the model to account for unmeasured variability. Corrected Akaike information criterion (AIC) values were generated using the *MuMIn* package to select relevant covariates. Covariates evaluated for inclusion in the model included percent clay, percent sand, mean annual precipitation (MAP), mean annual temperature (MAT), and average field slope, where climate variables were obtained using the PRISM database (PRISM Climate Group, 2023). Sand percent, slope, and MAP were retained in the model and the same model was used to evaluate all response variables. Response variables with unequal variance or non-normal distributions were log-transformed. Given the highly variable nature of the data, we considered p-values < 0.1 significant.

2.10.2 Statistical analysis of soil microbial community structure and diversity

Total microbial biomass was determined using DNA (Semenov et al., 2018) and alpha and beta diversity were calculated with the *vegan* (v2.6-4) package (Oksanen et al., 2024) in R v4.3.2. Before statistical analysis, we used the Shapiro-Wilk's test and Levene's test to assess for normality and homogeneity of variance, respectively. Alpha diversity differences were estimated via Kruskal-Wallis and pairwise Wilcoxon tests with a Bonferroni correction. For all, the level of significance was set to $p < 0.1$. Data were relative abundance transformed, and beta diversity was calculated using Bray-Curtis distances. PERMANOVA (*adonis2*) quantified whether the microbial compositions varied by soil and management groups on a Bray-Curtis distance matrix. Selected variables included farm pair, soil depth layer, interaction between farm pair and soil depth layer, management system, and soil chemical and climate data with field-level pseudo-replicates as strata. Non-metric Multi-Dimensional Scaling (NMDS, *vegan* (v2.6-4) package (Oksanen et al., 2024)) was used to visualize the clustering of samples by management and depth at each site. Due to the limited effect of environmental parameters on community composition, Mantel tests were then used to identify pairwise correlations between soil biochemical and biophysical properties and community composition.

Differential ASV enrichment by REGEN vs CONV was calculated using the *MAasLin2* package (Malick et al., 2021) in R with management type as the main effect and depth and site as random effects. Core ASVs were identified as those detected across at least 70% of samples within a management type and depth (Neu, et al., 2021). We applied sparse Partial Least Squares (sPLS) regression (Guidi et al., 2016; Shen & Huang, 2008) using the R package mixOmics (Lê Cao et al., 2008). This method allowed us to model the relationship between microbial relative abundances and environmental parameters, with a focus on SOM-C fraction variables (i.e., CHOM-C, MAOM-C, LPOM-C). The analysis computes Variable Importance in Projection (VIP) scores, which quantify the contribution of each ASV (Amplicon Sequence Variant) to the PLS model. ASVs with high VIP scores are considered key predictors, indicating their strong influence on the model's response variable. Lastly, we attempted to assign bacterial ASVs to a relevant agricultural metagenome assembled genomes (MAGs) to allow us to profile the functionalities of some key taxa. We did this by (1) identifying $\geq 97\%$ sequence identity across 253 base pair 16S rRNA

gene from the ASV to the MAG, and (2) by matching ASV and MAG taxonomy at the genus and species level using GTDB-Tk classification. MAGs with close representatives near relevant 16S rRNA genes were functionally annotated with DRAM v1.4.4 (Schaffer and Borton et al., 2020) to identify possible biogeochemical roles. Fungal ASVs were assigned to ecological guilds using FUNGuild90 (v1.2) (Nguyen et al., 2016). ANOVA was used to analyze fungal guild differences by management. 2,383 fungal ASVs were identified in FUNGuild as belonging to the 'probable' or 'highly probable' trophic modes of Symbiotroph, Pathotroph, or Saprotroph.

Network analyses tested for non-random co-variation patterns in microbial community composition (Shi et al, 2016). Co-occurrence networks were created using Spearman's correlation to test differences in occurrence and connectivity within the REGEN and CONV treatments (n = 4, Figure 3.9, SI Figure 3.8), as well as within-farm for bacterial and archaeal and fungal communities separately to calculate metrics (n = 16, SI Table 3.4). Data were rarefied to 10,000 reads per sample and collapsed into genera in Qiime2 prior to network construction in R via the *iGraph* (Csárdi et al., 2024), *Gephi* (Bastian et al., 2009), *Hmsic* (Harrel, 2024) packages. Genera were included in the networks if they occurred more than 10 times throughout the dataset, with a threshold of correlation greater than or equal to 0.75 and p-value ≤0.05 (Yang et al., 2023). Network parameters were extracted from these undirected, weighted networks, including nodes, edges, average weighted degree, average path length, clustering coefficient and modularity. These node attributes were calculated in the *iGraph* package, and Gephi (v0.10.0) was to designate a node as a network hub if it had a Kleinberg hub score > 0.8 (ACM-SIAM Symposium on Discrete Algorithms 1998; Röttjers and Faust, 2018). Included metrics and their definitions are listed in Table 3.

Table 3.2 Network metrics and definitions.

Metric	Definition	Citation
Nodes	The total membership in the network. Here, we use microbial genera.	Tonin et al., 2019

Edges	The total number of connections between nodes in the network. Here, edges are drawn when there is a significant correlation (Spearman's rho ≥ 0.75, $p \leq 0.05$) in co-occurrence between two or more genera in the network.	Tonin et al., 2019
Average weighted degree	The average weighted degree of a network is a measure of the number and strength of connections between nodes. The weight of the graph is the sum of the weights (here, Spearman correlations) given to all edges, divided by the total number of nodes.	Tonin et al., 2019
Network diameter	The shortest distance between the most disparate nodes. A larger network diameter may be an indication of decreased overall integration of the system	Shi et al., 2016
Modularity	A measure of the density or sparsity of connections within the network, where certain nodes are more highly connected to each other than to outside nodes. Increased modularity suggests the presence of sub-communities within the network	Shi et al., 2016
Average clustering coefficient	A measure of how tightly connected nodes are. A higher clustering coefficient indicates more interactions in the ecosystem.	Cornell et al., 2023
Average path length	The length of a path is the number of edges that a path uses to reach node to node. The average path length is the number of steps along with the shortest paths for all possible pairs of nodes in the network.	Tonin et al., 2019
Degree centrality	A measure of the number of direct connections a node has. In the context of centralization, it refers to the extent to which a single node (or a few nodes) dominate the network in terms of direct connections. High degree centrality indicates that a few nodes or a single node has a higher number of edges compared with other nodes in the network. High degree centrality may indicate genera with a high ecological importance in the network.	https://hub.graphistry.com/docs/graph-algorithms/centrality/y
Betweenness centrality	A measure of the extent to which a node lies on the shortest paths between other nodes in the network. Nodes with high betweenness centrality are likely to be critical connectors. High betweenness indicates that a few nodes may play a crucial node as intermediaries and may lie on the shortest path between other pairs of nodes.	https://hub.graphistry.com/docs/graph-algorithms/centrality/y
Kleinberg's hub centrality score	This measures the degree to which a node is connected to other nodes that are highly connected. It assigns higher scores to nodes that are linked to other hubs or nodes with high degrees. Here, we use a score of above 0.8 to indicate a "hub" organism.	Kleinburg, J.M. ACM-SIAM Symposium on Discrete Algorithms, 1998

3. Results

3.3 Differences in SOC and N stocks between adoption groups and variability with site characteristics

Average whole profile (0-100 cm) SOC stocks ranged from 91 to 184 Mg C ha^{-1}. On average, REGEN fields (including REGEN-recent and REGEN-long) had 6.8% higher SOC than their CONV neighbors (differences not statistically significant), with whole profile SOC differences between the

paired fields ranging from -46% to 31% (Figure 3.2). Small differences in SOC stock were observed at all depth increments (Figure 3.3a), although none were significant between adoption groups (except between pairs with minor differences in slope, see Figure 3.4). REGEN-long fields had on average 15.0% higher whole-profile SOC stocks than their CONV neighbors, while REGEN-recent fields had 5.2% lower SOC stocks than their CONV neighbors. Overall, these results suggest that regenerative practices can increase SOC stocks, but time since adoption matters. Different trends were observed in N stocks, however, where average N stocks tended to be higher in CONV fields across the 0-100 cm profile and at all depths (Figure 3.3b). It is possible that differences in total N stocks can be attributed to higher rates of synthetic N fertilizer application on CONV fields. On average, CONV fields received 72 kg N ha^{-1} yr^{-1}, while REGEN-recent and REGEN-long fields received 65 and 62 kg N ha^{-1} yr^{-1}, respectively. It should be noted that we were unable to collect fertilization records from all farmer participants, so this dataset is incomplete, and differences are not statistically significant.

To evaluate the impact of other agroecosystem drivers on SOC and N stocks, we used a linear mixed effects model to investigate the combined effect of adoption group, depth, sand%, slope and MAP on SOC and N stocks and related variables. The combined effect of adoption group and soil depth increment explained most of the variance in SOC stock (R^2 = 0.54). Additionally, SOC stocks (Mg C ha^{-1})

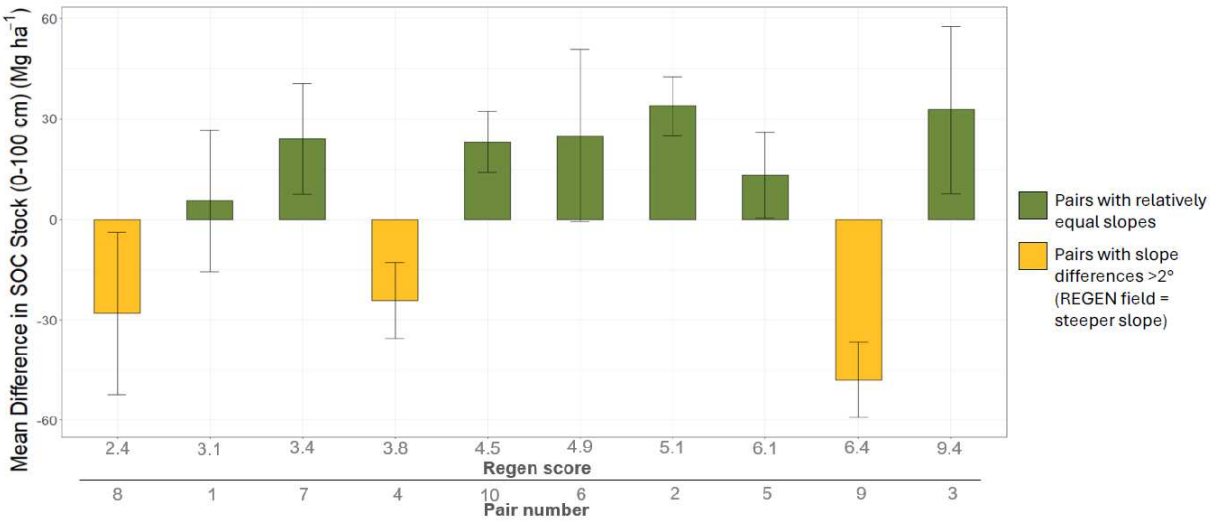


Figure 3.2 Mean difference in whole profile (0-100 cm) SOC stock (Mg ha^{-1}) between regenerative and conventional paired farms. Bars represent the mean difference in SOC, with error bars indicating the

standard error of the mean. Yellow bars indicate pairs with differences (~2°) in average slope between the fields. Green bars indicate pairs that have nearly equal slopes. The pairs are ordered by increasing Regen Index score, a composite index indicating the number of years no-till and cover crops have been used.

varied significantly with sand % (*est. = -0.014 Mg C ha^{-1} per 1% increase in sand, SE = 0.001, p < 0.001*), field slope (*est. = -0.167 Mg C ha^{-1} per degree increase in slope, SE = 0.055, p < 0.001*), and MAP (*est. = -0.003 Mg C ha^{-1} per additional mm of precipitation, SE = 0.002, p < 0.1*), but not significantly with adoption group. Similarly, whole profile N stocks (Mg N ha^{-1}) varied significantly with sand % (*est. = -0.012 Mg N ha^{-1} per % increase in sand, SE = 0.001, p < 0.001*), and slope (*est. = -0.081 Mg N ha^{-1} per degree increase in slope, SE = 0.047, p < 0.1*), but not significantly with adoption group. There were three pairs of farms where the CONV field had significantly higher whole profile SOC and N stocks than their REGEN neighbors, specifically pairs 4, 8, and 9 (Figure 3.5). We hypothesize that seemingly minor differences in slope (where the REGEN fields were ~2° steeper than the CONV field) resulted in decades of differential soil erosion and SOC displacement prior to the adoption of regenerative practices. Amongst all sampled fields, there was a significant difference *(p < 0.001)* in slope between REGEN and CONV. Average slopes were 2.25 and 1.57 for regenerative and conventional fields, respectively. RUSLE2 modeling results of select farm pairs indicate that a ~2° difference in slope can lead to 3x higher erosion rates, with erosion intensified on sloping fields managed with intensive tillage practices (Table 3). For example, the REGEN field of pair 9 has an average slope of 3.7° while the CONV field has a slope of 1.4°, where the modeled soil loss rates under chisel plow management are 7.8 and 2.7 Mg ha^{-1} yr^{-1}, respectively. Erosion of this magnitude is estimated to result in SOC displacement of 0.20 and 0.07 Mg C ha^{-1} yr^{-1}, respectively. On the other hand, modeling results confirm that conservation practices such as terracing (Table 3, field R4 simulation) may help prevent topsoil loss.

3.4 Differences in SOM-C fractions, roots, and litter between adoption groups and variability with site characteristics

Significant differences were observed between REGEN (REGEN-long and REGEN-recent are included in one group in these analyses due to the small sample size) and CONV treatments in select

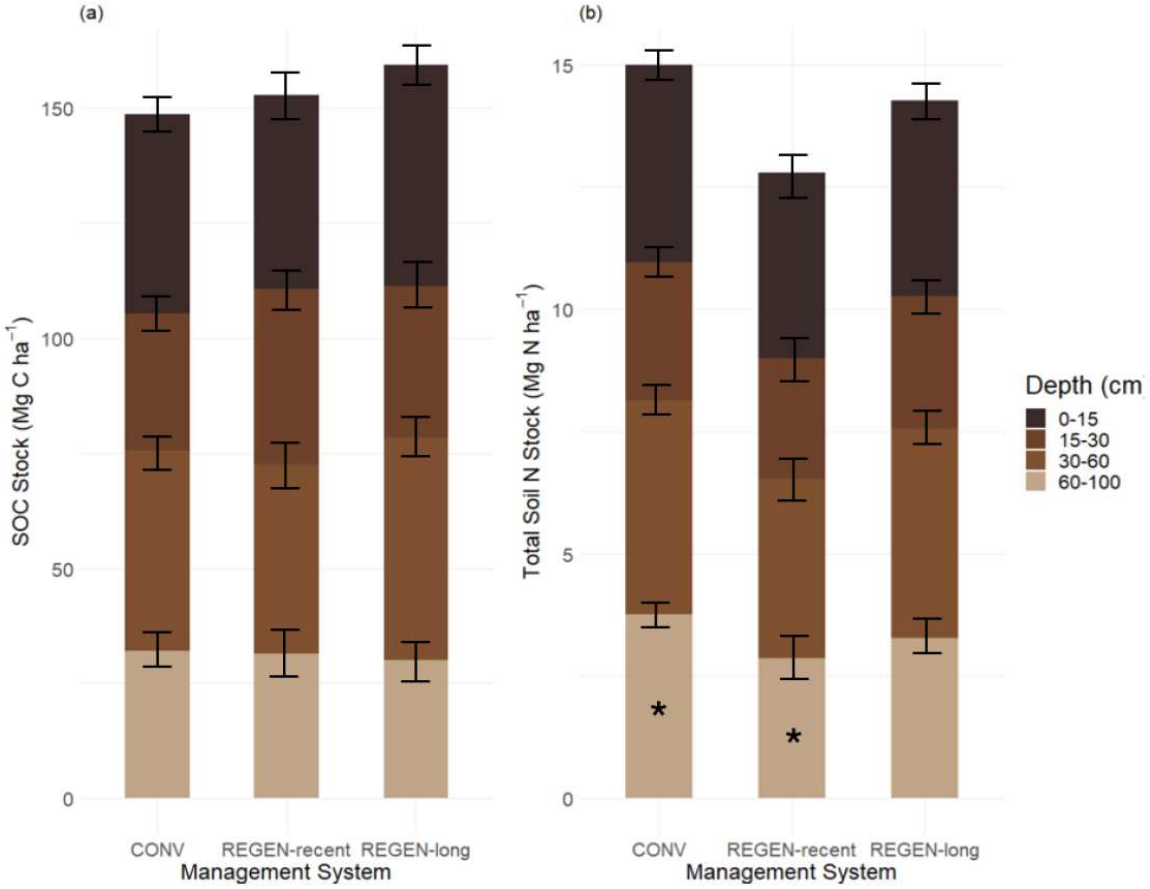


Figure 3. Few differences in SOC and N stocks were observed when slope differences between fields is minimal. Estimated marginal means (derived from the linear mixed-effect model) of whole profile (0-100 cm) SOC stocks (a) and total N (b) stocks, separated by depth layer and management system (CONV, REGEN-recent, REGEN-long). The average slope of the sampled points (n = 544) did not differ. Error bars represent standard errors for each depth layer. Significant differences are indicated with asterisks (** = p value < 0.05).

SOM-C fractions, where the REGEN fields contained an estimated 5.8 Mg ha^{-1} (*SE = 3.46, p < 0.1*) more MAOM-C in the 15-30 cm depth layer and 0.11 Mg ha^{-1} (*SE = 0.14, p < 0.1*) more CHAOM-C in the 0-15 cm depth layer than CONV fields (Figure 3.5). Differences in LPOM C stocks were not significantly different between adoption groups, although the C:N ratio of the LPOM tended to be higher in the 0-15 cm depth layer of REGEN fields (*est. = 1.98, SE = 1.38, p <0.1*).

Differences in crop surface litter C were significant (*p < 0.05*), with REGEN-recent fields containing more litter C (Mg ha^{-1}) than CONV fields or REGEN-long term fields (*REGEN-recent = 2.1*

Mg C ha^{-1}, REGEN-long= 0.61 Mg C ha^{-}, CONV = 0.69 Mg C ha^{-1}). It is possible that long-term REGEN practice use, where no-till management is combined with cover crops for consecutive years, alleviates potential challenges associated with excessive crop litter accumulation under no-till. Litter C also varied significantly with MAP, where pairs with higher MAP tended to have less litter C *(est. = -0.024, SE = 0.007, p < 0.05)*. Whole profile root C stocks (Mg ha^{-1}) did not vary significantly with adoption group but tended to be lower in locations with higher MAP *(est. = -0.013, SE = 0.006, p < 0.05).*

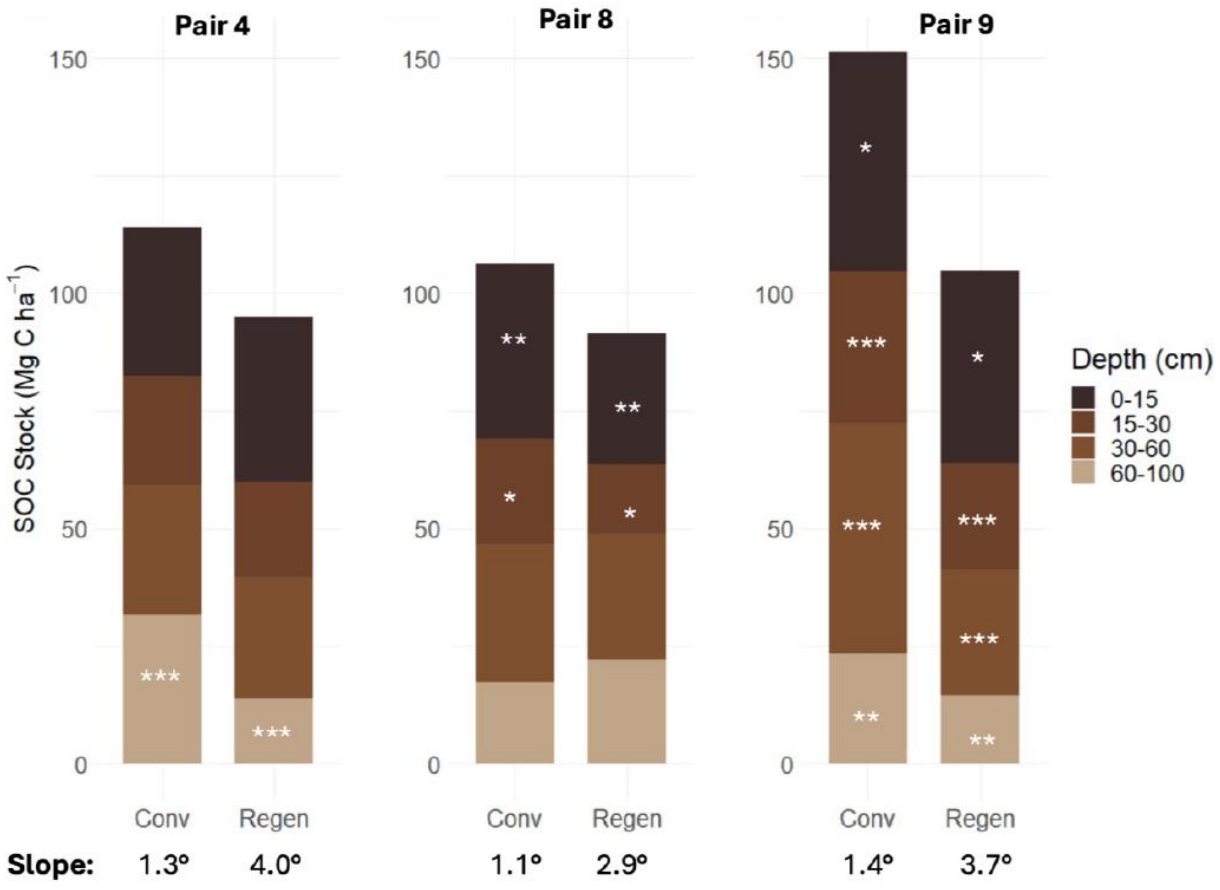


Figure 3.4 SOC stocks differ significantly with depth for the three pairs with greater differences in slope. Slope differences between the REGEN and CONV fields was ~2°. Average slope of the sampled points (n = 209) is indicated for each sample type. Significant differences are indicated with asterisks (* = p value < 0.1, ** = p value < 0.05, *** = p value < 0.001).

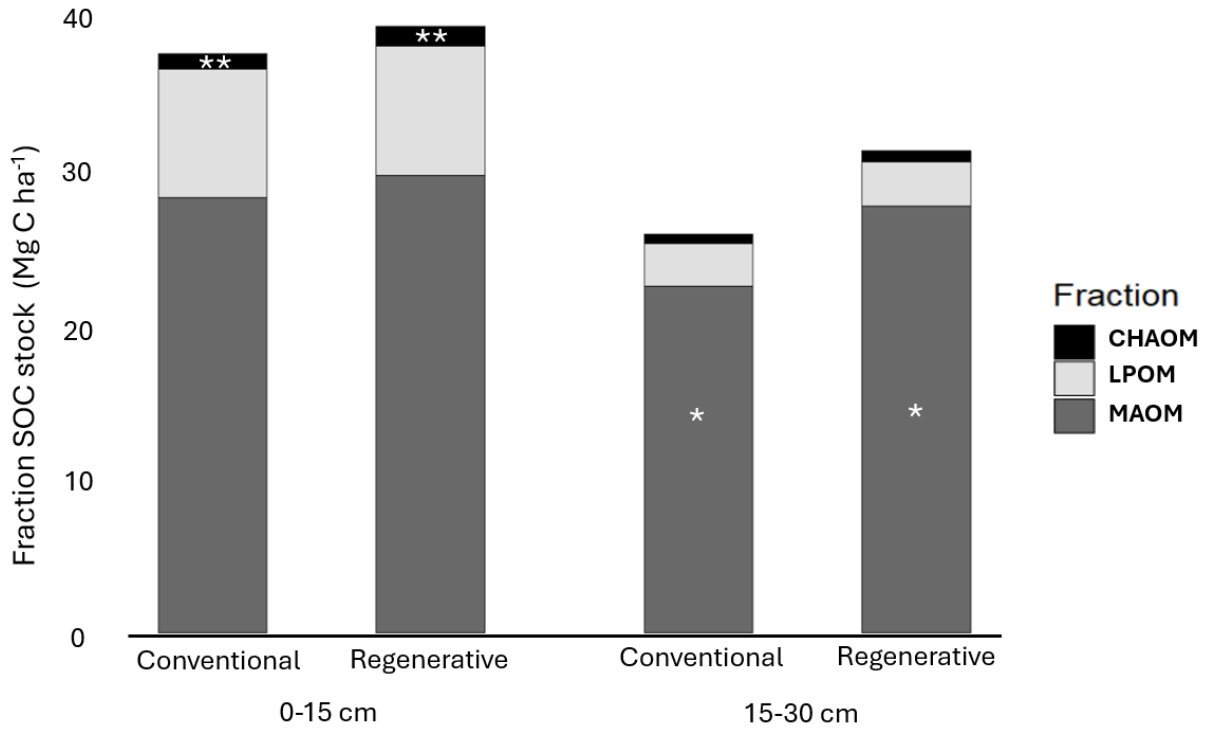


Figure 3.5 SOC fractions differ with depth and management. Here, we show the SOM-C stocks content by fraction and depth. SOC fractions were separated by size and density for the 0-15 and 15-30 cm depth layers. In surface soils (0 - 15 cm) CHAOM-C (coarse heavy associated organic matter C) was significantly increased under REGEN management, while in deeper soils (15-30 cm) MAOM C (mineral associated organic matter C) was significantly increased under REGEN management. No differences in LPOM (light particulate organic matter C) were detected at either depth. Asterisks indicate significant differences (* = p value < 0.1, ** = p value < 0.05).

Table 3.3 RUSLE2 predicted soil erosion rates and estimated C loss rates for farm pairs with slope differences ~2°. Predicted soil loss is calculated using the mean C stock and BD for the 0-15 cm depth increment of the CONV field.

Farm Pair	Field ID	Management practice	Predicted soil loss rate (Mg ha^{-1} yr^{-1})	Predicted C loss (Mg C ha^{-1} yr^{-1})
9	**R9** *slope = 3.7* *texture = silty clay loam*	Moldboard plow	19.1	0.48
		Chisel plow	7.8	0.20
		No-till	1.9	0.05
		No-till + Cover Crops	1.1	0.03
	C9 *slope = 1.4* *texture = silty clay loam*	Moldboard plow	6.5	0.16
		Chisel plow	2.7	0.07
		No-till	0.7	0.02
		No-till + Cover Crops	0.2	0.00
8	**R8**	Moldboard plow	21.5	0.54

	slope = 2.9 *texture = silt loam*	Chisel plow No-till No-till + Cover Crops	9.6 2.2 1.5	0.24 0.06 0.04
	C8 *slope = 1.1* *texture = silt loam*	Moldboard plow Chisel plow No-till No-till + Cover Crops	6.5 3.4 1.0 0.4	0.16 0.08 0.03 0.01
4	**R4** *slope = 4.0, terraced* *texture = silty clay loam*	Moldboard, no terracing Moldboard plow (w/ terraces) Chisel plow (w/ terraces) No-till (w/ terraces) No-till + Cover Crops (w/ terraces)	9.7 2.4 1.0 0.1 0.0	0.24 0.06 0.02 0.00 0.00
	C4 *slope = 1.3* *texture = silty clay loam*	Moldboard plow Chisel plow No-till No-till + Cover Crops	2.1 0.8 0.1 0.0	0.05 0.02 0.00 0.00

3.3 Soil microbial community results: Structure, diversity, and function

3.3.1 Microbial biomass and alpha diversity across treatments

Bacterial and archaeal community sequencing resulted in 4,613,422 bacterial reads which were clustered in DADA2 at 100% identity into 33,122 ASVs, with 3,742,734 reads and 29,929 ASVs remaining after quality control (SI Figure 3.2). ITS gene sequencing resulted in 4,210,490 fungal reads which were clustered at 100% identity into 12,035 ASVs, with 2,931,224 reads and 11,488 ASVs remaining after filtering and quality control (SI Figure 3.3). Total microbial biomass did not change with management practice but was greatest in surface soils (0-15 cm, 1858 ng DNA/ g soil) compared to deeper soils (15-30 cm, 832 ng DNA/ g soil) ($p < 0.05$).

On average, REGEN farms had greater bacterial evenness and fungal richness and diversity (Shannon's H) ($p < 0.1$) (SI Figure 3.4). There were also significant differences in bacterial and archaeal diversity, evenness, and richness by pair, with the REGEN site in pair 3 having the highest richness and diversity and lowest evenness and the CONV site in pair 7 having the lowest diversity and richness and highest evenness. For both bacterial/archaeal and fungal communities, depth significantly affected all alpha diversity metrics, with surface soils having greater diversity, richness, and evenness than deeper

soils ($p < 0.1$). Spearman's correlations were then used to identify significant relationships between diversity metrics and environmental parameters. Bacterial/ archaeal diversity had moderate positive correlations with CHAOM-C (*rho = 0.57*), LPOM-C *(rho = 0.45*), and total N Stock (*rho = 0.48*); fungal richness had a moderate positive correlation with CHAOM-C (*rho = 0.44*, *p < 0.1*) (Figure 3.6). Overall, these results indicate that although management had some effect on aspects of alpha diversity metrics, there were consistent correlations between increased microbial alpha diversity and SOC fractions and soil N.

3.3.2 Microbial beta-diversity is impacted by physical, chemical, and biological determinants

Both bacterial/archaeal and fungal communities were structured by pair, depth, pair*depth interaction, and management system, with these four factors explaining 32.6% of the total variance in the bacterial and archaeal community and 18.2% in the fungal community (*p < 0.1*) (SI Figure 3.5 & 3.6). The Mantel test showed that N fertilizer application rate (*mantel R = 0.16, p = 0.009*), pH (*mantel R = 0.15, p = 0.015*), and field slope (*mantel R = 0.11, p = 0.03*) correlated most strongly with bacterial/ archaeal community. The fungal community was significantly correlated with MAOM-C stock (*mantel R = 0.26, p = 0.003*), N fertilizer application rate (*mantel R = 0.17, p = 0.009*), and field slope (*mantel R = 0.13, p = 0.012*) (Figure 3.6, SI Figure 3.7). Taken together, these results show that significant relationships exist between microbial community compositions and biological, chemical, and physical determinants, despite beta diversity metrics failing to adequately explain these relationships.

3.3.3 Enriched and core taxa associated with management systems

At the broad taxonomic levels, we noticed some small differences in bacterial and fungal membership across management. The relative abundance of Chloroflexota was significantly higher under CONV management, comprising 32.2% of the total phyla compared with 23.6% of the REGEN community. Under REGEN management the phylum Verrucomicrobiota had greater relative abundance, comprising 28.8% of the REGEN community and 23.0% of the CONV community (SI Figure 3.8). Although there were no differences in the fungal community by management in phyla or trophic mode

abundances, Glomeromycota were significantly more abundant under REGEN management in all pairs except pair 7 ($p < 0.05$) (SI Figure 3.8). Overall, at broad taxonomic levels, little variation with management is observed, particularly in the fungal community, although the observed difference in Glomeromycota may be of interest for future management directives given this group's symbiotic association with crops.

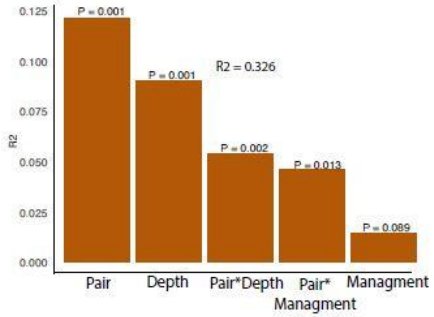
However, at finer taxonomic levels we identified 12 core bacterial/ archaeal ASVs unique to CONV and 30 core ASVs unique to REGEN, along with 26 core ASVs that were conserved across all samples regardless of treatment. Core taxa present across all samples, regardless of management practice, included genera from Burkholderiales and Chthoniobacterales, as well as *Nitrospira C japonica,* the latter of which was ubiquitous across the farm pairs. REGEN core taxa included strains from the genera *Nitrosocosmicus* and *Rubrivax*, as well as seven novel families within the order Chthoniobacterales. We also found one ASV, genus *UBA11361 sp*. from Ktedonobacteraceae, that was enriched under REGEN management across all samples and depths (Figure 3.7). In contrast, taxa associated with CONV management comprised novel members from the families Gemmatimonadaceae and Ktedonobacteraceae, as well as the order Chthoniobacterales.

Additionally, we identified six core ASVs in the fungal community: one unique to REGEN and five unique to CONV. The core ASV under REGEN management was identified as *Ceratobasidium sp.*, while ASVs belonging to *Udeniozyma ferulica*, *Cheilymenia sp.*, and *Mortierella sp.* were associated with CONV (SI Figure 3.9c). Shared ASVs included *Exophiala pisciphila*, *Heydenia sp.*, *Ganoderma applanatum*, and another *Mortierella sp.* These results show that while specific ASVs respond to differences in management, most genera or families are shared across management systems and soil environments, particularly in the bacterial/ archaeal community.

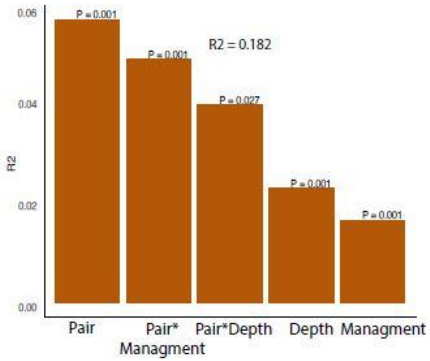
3.3.4 Bacterial community network complexity responses to management system

REGEN and CONV networks differed greatly in both the bacterial and archaeal communities, with some network metrics being statically different across communities (Figure 3.7a). REGEN networks

a. Bactieral/ archaeal community PERMANOVA results



b. Fungal Communitiy PERMANOVA results



Mantel test ($p < 0.05$) r2 0.1 - 0.25

SPLS r2 0.71<

SPLS r2 0.51 - 0.70

SPLS r2 0.30 - 0.50

c. Relationships between environmental parameters, diversity metrics,network metrics, and microbial communities

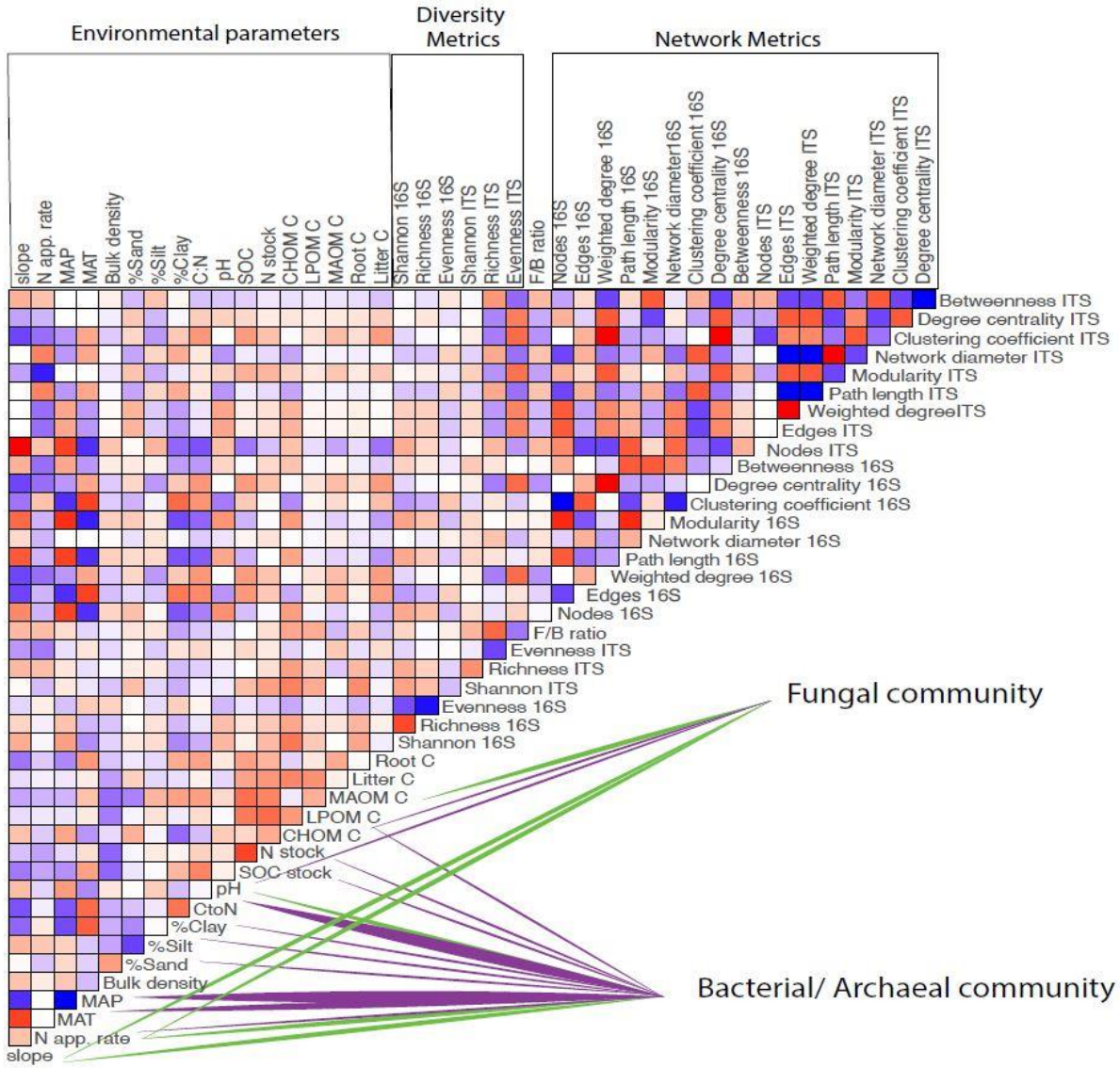
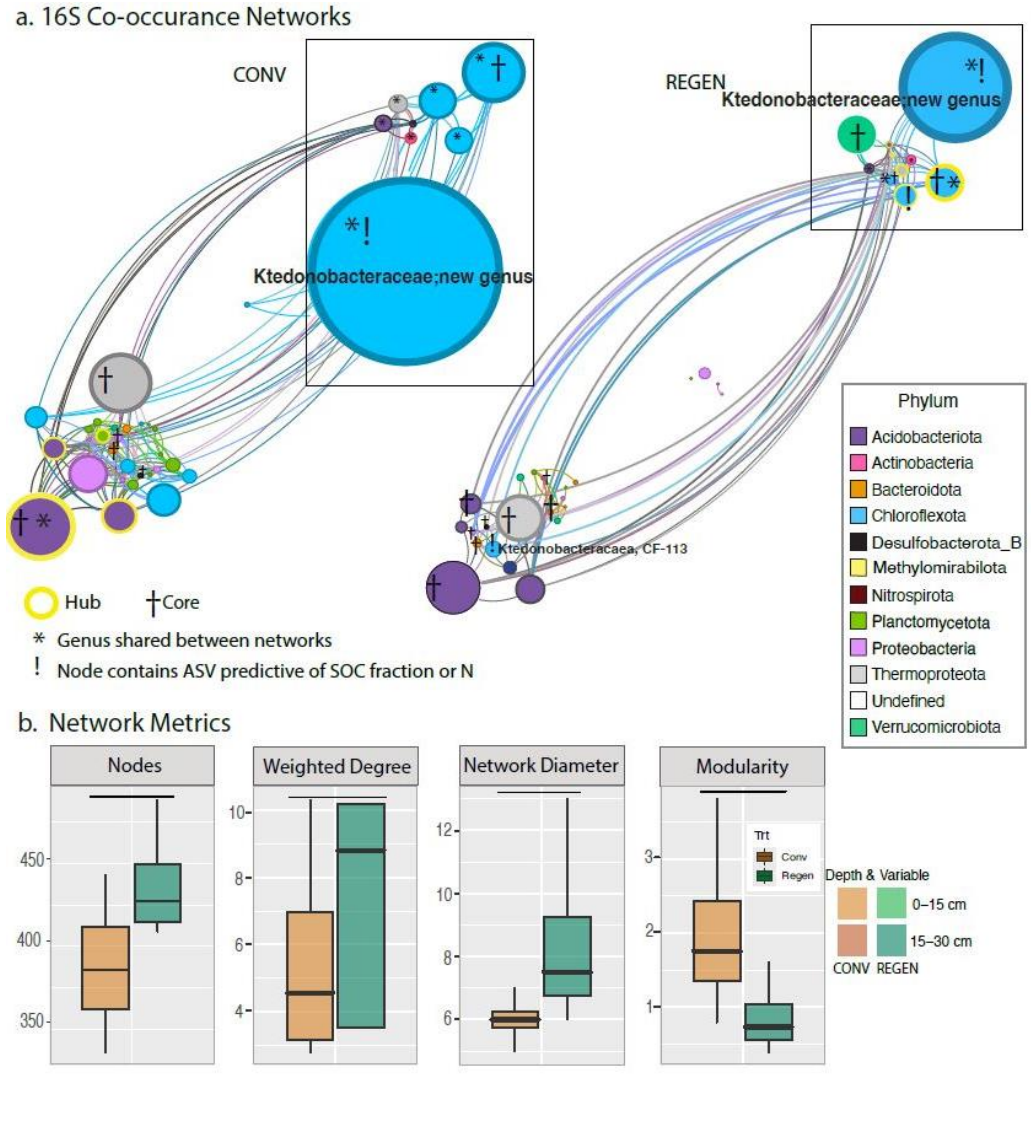


Figure 3.6 Total community variance is best explained by farm pair, sampling depth and management strategy, while other analyses reveal connections between factions of the soil microbial community metrics and environment. A) Bacterial and archaeal community composition is most impacted by farm pair ($R^2 = 0.12$, $p = 0.001$), depth ($R^2 = 0.09$, $p = 0.001$), the interaction of pair & depth ($R^2 = 0.05$, $p = 0.080$), the interaction of pair & management ($R^2 = 0.05$, $p = 0.013$), and management ($R^2 = 0.014$, $p = 0.089$). Overall, these factors account for 32.6% of community variation. B) Fungal community composition is most impacted by farm pair ($R^2 = 0.056$, $p = 0.001$), the interaction of pair & management ($R^2 = 0.048$, $p = 0.001$), the interaction of pair & depth ($R^2 = 0.039$, $p = 0.027$), depth ($R^2 = 0.023$, $p = 0.001$), and management ($R^2 = 0.016$, $p = 0.001$). Overall, these factors account for 18.2% of community variation. NMDS visualizations can be found in SI Figures 3.5 & 3.6c) Moderately strong relationships exist between environmental parameters, diversity metrics, network metrics and the microbial community. First, the heatmap shows relationships between numerous parameters ($-0.35 \leq$ spearman's rho ≤ 0.35; $p \leq 0.1$). Second, bacterial and archaeal and fungal community compositions correlate with slope, N application rate, pH and MAOM-C stock (green lines, $0.1 \leq$ Mantel $r \leq 0.25$; $p \leq 0.05$). Finally, members of each community were found to be significantly predictive of SOC stocks and environmental parameters (SPLS $r2 \geq 0.3$). Members of the bacterial and archaeal community were predictive of MAP, % Clay, pH, SOC stock, N stock, CHAOM-C stock, and members of the fungal community were predictive of pH and CHAOM-C stock.

(n = 8) contained an average of 438 nodes (interconnected members), 5156 edges (connections between members), and were overall larger with an average diameter of 8.5, while CONV networks (n = 8) were significantly less complex with an average of 388 nodes, 4633 edges, and an average network diameter of 6.0. REGEN networks were also significantly more connected ($p < 0.1$) than CONV networks as measured by average weighted degree, or the average number of links per node in a network (Shi et al., 2016; Xue et al., 2022). Lastly, CONV networks had greater modularity than REGEN, indicating that CONV had more connections between nodes within the modules but more sparse connections between nodes in different modules ($p < 0.1$; Zhu et al., 2022). Similarly, in the fungal community, REGEN networks (n = 8) had significantly more connections between members (614 edges REGEN vs 359 CONV) and shorter path length (3.70 in REGEN vs 4.30 in CONV) compared to CONV networks, although the size (number of nodes) and connectedness (weighed degree) were not significantly different, most likely due to low richness and diversity and limiting the interpretation of these networks (SI Figure 3.9). However, bacterial/archaeal network results indicate that management impacted network interconnectedness, with potential consequences for ecosystem-level function as determined by relationships between genera.


a. 16S Co-occurance Networks
CONV
REGEN
Ktedonobacteraceae;new genus
Ktedonobacteraceae;new genus
Ktedonobacteraceae; CF-113
Hub
Core
* Genus shared between networks
! Node contains ASV predictive of SOC fraction or N
Phylum
Acidobacteriota
Actinobacteria
Bacteroidota
Chloroflexota
Desulfobacterota_B
Methylomirabilota
Nitrospirota
Planctomycetota
Proteobacteria
Thermoproteota
Undefined
Verrucomicrobiota
b. Network Metrics
Nodes
Weighted Degree
Network Diameter
Modularity
Trt
Conv
Regen
Depth & Variable
0–15 cm
15–30 cm
CONV REGEN

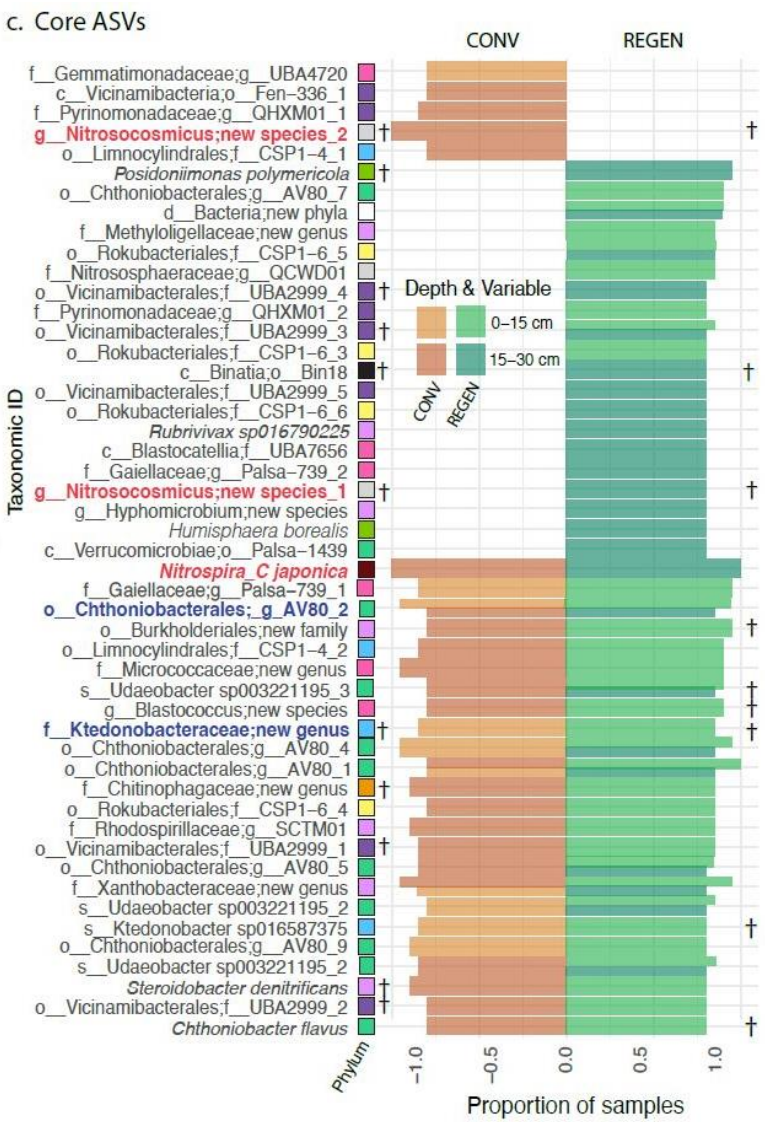

c. Core ASVs
CONV
REGEN
Taxonomic ID
f__Gemmatimonadaceae;g__UBA4720
c__Vicinamibacteria;o__Fen−336_1
f__Pyrinomonadaceae;g__QHXM01_1
g__Nitrosocosmicus;new species_2
o__Limnocylindrales;f__CSP1−4_1
Posidoniimonas polymericola
o__Chthoniobacterales;g__AV80_7
d__Bacteria;new phyla
f__Methyloligellaceae;new genus
o__Rokubacteriales;f__CSP1−6_5
f__Nitrososphaeraceae;g__QCWD01
o__Vicinamibacterales;f__UBA2999_4
f__Pyrinomonadaceae;g__QHXM01_2
o__Vicinamibacterales;f__UBA2999_3
o__Rokubacteriales;f__CSP1−6_3
c__Binatia;o__Bin18
o__Vicinamibacterales;f__UBA2999_5
o__Rokubacteriales;f__CSP1−6_6
Rubrivivax sp016790225
c__Blastocatellia;f__UBA7656
f__Gaiellaceae;g__Palsa−739_2
g__Nitrosocosmicus;new species_1
g__Hyphomicrobium;new species
Humisphaera borealis
c__Verrucomicrobiae;o__Palsa−1439
Nitrospira_C japonica
f__Gaiellaceae;g__Palsa−739_1
o__Chthoniobacterales;_g_AV80_2
o__Burkholderiales;new family
o__Limnocylindrales;f__CSP1−4_2
f__Micrococcaceae;new genus
s__Udaeobacter sp003221195_3
g__Blastococcus;new species
f__Ktedonobacteraceae;new genus
o__Chthoniobacterales;g__AV80_4
o__Chthoniobacterales;g__AV80_1
f__Chitinophagaceae;new genus
o__Rokubacteriales;f__CSP1−6_4
f__Rhodospirillaceae;g__SCTM01
o__Vicinamibacterales;f__UBA2999_1
o__Chthoniobacterales;g__AV80_5
f__Xanthobacteraceae;new genus
s__Udaeobacter sp003221195_2
s__Ktedonobacter sp016587375
o__Chthoniobacterales;g__AV80_9
s__Udaeobacter sp003221195_2
Steroidobacter denitrificans
o__Vicinamibacterales;f__UBA2999_2
Chthoniobacter flavus
Depth & Variable
0–15 cm
15–30 cm
CONV
REGEN
Phylum
−1.0
−0.5
0.0
0.5
1.0
Proportion of samples

Figure 3.7. Bacterial/ archaeal network analyses reveal connections between management and community interconnectedness and incorporate hub and core taxa. a) Network analysis of 16S community reveals increased network complexity under regenerative management as well as modules containing key ASVs – those that are hubs nodes, core taxa, and/or predictive of SOM fraction (SOC or CHAOM-C). Nodes with less than four edges were removed for ease of visualization. Node size is reflective of abundance, and nodes are colored by phyla. Hub nodes (nodes with a Kleinburg hub centrality score < 0.80 (Röttjers & Faust, 2018)) are outlined in yellow, nodes containing core ASVs are indicated by †, genera shared between networks are indicated by *. Nodes that contain an ASV predictive of an SOC fraction are indicated by **!** and taxa name. Correlative relationships between these taxa and the predicted environmental parameter can be found in SI Figure 3.11 Boxes are placed around the module shared by CONV and REGEN. B) Increases in Nodes, weighted degree and network diameter, and a decrease in modularity is observed in the REGEN networks, compared to CONV. C) Numerous core taxa, ASVs found in 70% or more of samples (Neu et al., 2021), were observed under both CONV and REGEN management at both depths, as indicated by color. Taxa in red text indicates that the ASV matched to a MAG, and the organism in blue text indicates that the ASV is predictive of an SOC fraction. † indicates a core ASV that is also part of a node genus in either CONV (left) or REGEN (right). Phyla are indicated by color.

3.3.5 Correlations of microbial community attributes with soil biological or chemical attributes

We next evaluated if the network topologies were correlated with soil properties. We found that both bacterial/archaeal and fungal network metrics were significantly correlated ($p < 0.05$) with CHAOM-C. This fraction was moderately correlated with bacterial (*rho = 0.52*) and fungal nodes (*rho = 0.55*) and average path length (*rho = 0.42*), suggesting that differences in SOC stabilization pathways may shape microbial co-associations and interactions. Further, the number of nodes in bacterial/archaeal and fungal networks correlate with % sand ($p < 0.001$, *rho = 0.39* and *0.70*, respectively), indicating that soil texture and organic matter coatings on larger mineral particles (CHAOM) may be a determining factor of microbial community structure (Figure 3.6).

We also used sparse Partial Least Squares (sPLS) regression to explore how individual microbial taxa (ASVs) predict SOC and soil N. Fungal ASVs were strong predictors of the CHAOM-C fraction and pH, while bacterial/ archaeal ASVs better predicted total SOC, soil N, field slope, and mean annual precipitation (MAP). Variable Importance in Projection (VIP) scores helped identify which ASVs were most influential (VIP > 1; Borton et al., 2018). All ASVs had VIP scores higher than 1, with those associated with SOC, CHAOM-C, and nitrogen stocks having scores far higher. The highest VIP members included ASVs from Ktedonobacteraceae, Nitrososphaeraceae, Nitrosopumilaceae, and

Chthoniobacterales and, these ASVs are therefore considered highly predictive of SOC dynamics. Notably, these taxa were also central "hubs" in both REGEN and CONV soil networks or core taxa in these communities, indicating strong influence, and the relative abundance of these genera correlated positively with SOC fractions (SI Figure 3.10). For example, one bacterial ASV from order Chthoniobacterales was found in 85% of REGEN samples (a “core” organism) and had exceptionally high VIP scores (>65) for predicting SOC and the CHAOM-C fraction. Another ASV, from the family Nitrosophaeraceae, was predictive with SOC, despite being primarily known for nitrification. These ASVs could be linked to previously published genomes (Yerlan et al., 2022), and all possessed genes for xylose, hemicellulose, and sucrose transformations, as well as several undefined CAZymes (SI Figure 3.11). Likewise, some fungal ASVs were highly predictive of CHAOM-C, including *Heydenia*, *Podila*, and Cheilymenia, and their relative abundances correlated with CHAOM-C (SI Figure 3.12). Given these are all saprotrophs, the association with these taxa and organic C processing is clearer than some of the bacterial lineages, suggesting a more complex role of fungi in the turnover and stabilization of organic matter at these sites. Collectively, this regression-based modeling reveals strong relationships between members of the microbial community and SOC turnover, particularly in the CHAOM-C fraction.

4. Discussion

4.1 Regenerative practices appear to increase SOC stocks, but land use history matters

Through analysis of paired farms using contrasting management systems, we demonstrated that long-term REGEN management has the potential to increase SOC stocks relative to CONV management. For fields where a positive difference between the CONV/REGEN neighboring pairs was observed (excluding pairs with average slope differences >1.5°), we found potential SOC sequestration rates between 0.15-0.69 Mg ha^{-1} yr^{-1}, with a mean rate of 0.32 Mg ha^{-1} yr^{-1}. This rate agrees with those from long-term experiments that evaluate the potential for no-till and cover crops to increase SOC stocks in the Upper Corn Belt region (Al-Kaisi & Kwaw-Mensah, 2020; Jordahl et al., 2023; Poffenbarger et al., 2020; Qin et al., 2023). However, it is important to note that claims of net C sequestration cannot be made with

comparisons between a treatment (i.e., REGEN) and a control (i.e., CONV) if the initial C stock is not known (Don et al., 2024). In the absence of baseline SOC measurements, the neighboring CONV field is assumed to reflect the management practices and SOC stocks of the REGEN field prior to the adoption of regenerative practices (i.e., no-till and cover crops). Although efforts were taken to reduce variability between paired farms, it is likely that small differences in soil texture, topography, and management history resulted in different baseline SOC stocks, complicating the across-the-fence comparison. Further, our results demonstrate that seemingly small differences in topography between paired fields likely influenced erosive history and SOC change trajectories. We observed that among fields with relatively minor (~2-4°) slopes, the sloped fields had significantly lower whole profile SOC stocks than neighboring fields on flatter ground (Figure 3.4). Across the sample, REGEN fields were often located on steeper fields than their conventional neighbors. It is likely that producers adopt REGEN practices such as no-till on more degraded parcels of land first, especially if managing soil erosion is a primary concern (Pittelkow et al., 2015). This study highlights the importance of considering slope and erosive history in MRV protocols and study designs, as these factors significantly influence SOC accrual and displacement (Senthilkumar et al., 2009; Van Oost & Six, 2023). Additionally, slope and landscape position should be included in spatially explicit process-based models and remotely-sensed estimations of SOC stocks (Odebiri et al., 2024; Pierson et al., 2022; Thaler et al., 2021). In summary, REGEN management has the potential to increase SOC relative to CONV, but variability in baseline SOC stocks resulting from differences in topography or land use history must be considered in estimating the management effect sizes, especially when conducting across-the-fence comparisons.

4.2 Density-separated SOM-C fractions offer insights into dynamics of SOC change

Separating SOM-C into fractions with differing formation pathways, function, and persistence can provide insights into the dynamics of SOC accrual or depletion under different management systems (Lavallee et al., 2020). As expected, differences in the mineral-associated fractions (MAOM-C and CHAOM-C) were most prominent, as this is where most SOC resides in agricultural systems. Notably, differences in the CHAOM-C and MAOM-C, but not LPOM-C, were associated with microbial

community structure and diversity. This contrasts with previous studies that found POM-C formation is promoted in systems with higher microbial diversity (Cotrufo et al., 2022). On the other hand, we did not find differences in LPOM-C with management, as other studies of regenerative cropping systems have. For example, a global meta-analysis of regenerative cropping practices found that no-till and cropping intensification (i.e., elimination of summer fallow, cover cropping, perennial plantings, etc.) can increase POM-C (19.7% and 33.3%, respectively) and MAOM-C (8.5% and 7.1% respectively), with even greater gains in integrated crop-livestock systems (38.1% increase in POM-C)(Prairie et al., 2023). It is possible that a corn-soybean rotation with cereal rye cover crops does not provide sufficient biomass or biochemical diversity to increase the LPOM-C fraction. Additionally, it is possible that the combined size-density fractionation scheme that we employed, where the sized based POM fraction is separated into LPOM and CHAOM, offers a more nuanced view of changes in SOC fractions. The CHAOM-C fraction, composed of mineral particles > 53 μm with an organic matter coating or organic molecules bound to metal oxide coatings does not contain significant C, but it does contribute substantial mass. Additionally, the CHAOM-C fraction is shown to have unique properties and mechanisms of formation, such as a lower C:N ratio than silt- or clay-sized MAOM and faster incorporation of complex organic OM (Samson et al., 2020; Sokol et al., 2022). If we had used a simple size fractionation scheme (where CHAOM-C and LPOM-C are lumped together as particulate organic matter C, or POM-C), we may have incorrectly concluded there was a change in the labile, quick cycling POM fraction. Density fractionation allowed us to properly distinguish between LPOM and CHAOM fractions, as the formation pathways and stability of these two fractions differ significantly (Leuthold et al., 2024). On the other hand, possible methodological issues with density fractionation should not be overlooked. While our soil mass recovery was always within ±5%, SOC recovery (based on the total C stock in the bulk soil) was somewhat low (mean of 77%). Low SOC recoveries are typical of density fractionation methods, as every step of the fractionation and elemental analysis process introduces additional opportunities for mass loss and/or instrument error (Leuthold et al., 2024). Overall, separating SOM into fractions with differing formation pathways,

function, and persistence offered significant insights into SOC stabilization processes and potential relationships with microbial community structure.

4.3 Microbial community structure is predictive of SOC and related properties

4.3.1 Microbial networks and taxa are predictive of SOC

Key microbial modulators of SOC change were identified through our analyses of microbial community structure and diversity, including the analysis of co-occurrence networks using Spearman correlation and graph theory (Liang et al., 2017; Shi et al, 2016; Trivedi et al., 2018). Although alpha and beta diversity metrics did not adequately describe the connections between community composition and environmental parameters, other analyses revealed core microbial members for each management system and/or key players predictive of carbon cycling. We also linked several of these organisms to agriculturally relevant MAGs via 16S rRNA gene and taxonomy, providing deeper insight into the functioning of this complex community. Finally, multiple network topological metrics consistently showed that microbial co-occurrence patterns in the CONV and REGEN management types were markedly different. Network analysis has emerged as a promising analytical approach to studying multispecies co-occurrence and, hence, to evaluating assembly rules, niche differentiation, and expected functionality of integrated species assemblages (Sun et al., 2017; Prieto-Rubio et al., 2024; National Academies of Sciences, Engineering, and Medicine, 2024).

4.3.2 Microbial communities relate directly to SOC stocks, while alpha and beta diversity are less responsive to management

PERMANOVA analyses revealed that the strongest driver of composition in both communities was depth, followed by management system (Figure 3.6). Adding soil chemical parameters to the PERMANOVA model did not improve fit; therefore, alternative methods were employed to explore the relationships between microbial communities and SOC, as well as other environmental and management factors. The Mantel test revealed significant relationships between environmental/management factors and bacterial and fungal community composition. Specifically, N fertilization rate, pH, and field slope were associated with bacterial and archaeal community composition, while MAOM-C stock, N

fertilization rate, and field slope influenced fungal community composition (Figure 3.6). pH and N fertilization are recognized as key environmental features structuring microbiomes (e.g., Rousk et al., 2010; Naz et al., 2022; Wang et al., 2018; Zhou et al., 2017; Ouyang & Norton, 2020; Dincă et al., 2022), however, less is known about the impact of field slope on microbial communities. It is likely that historical erosion and SOC displacement on steeper fields exerts influence on microbial community composition and structure. Previous research indicates that eroded sites have lower microbial network complexity (Qiu et al., 2021), homogenized bacterial communities (Xiao et al., 2017), and decreased fungal richness (Du et al., 2021; Jamshidi et al., 2023). Understanding these dynamics is crucial for developing effective soil management practices to prevent soil erosion, protect SOC stocks, and enhance microbial diversity.

The correlation between the fungal community and the mineral-associated SOM fractions (MAOM-C and CHAOM-C) stocks is particularly interesting, as research suggests that the role of mineral-associated fractions in short-term carbon cycling may be underestimated (Xue et al., 2022; Yu et al., 2022). Mineral-associated OM fractions have a lower C:N ratio than POM and provide a source of plant and microbe assimilable organic compounds, particularly when organic molecules are loosely bound to mineral surfaces (Sokol et al., 2022). We found a correlation between MAOM-C/CHAOM-C and the fungal community, including specific ASVs that predict CHAOM-C stocks (Figure 3.7). Fungi often have higher carbon use efficiency than bacteria, along with the ability to colonize mineral surfaces with expansive hyphal structures (Sokol et al., 2022; Hannula & Morriën, 2022); thus, fungal necromass is often more closely linked to MAOM formation than POM (Wang et al., 2021; Li et al., 2015). Whalen et al., 2024 found that fungal contributions to the formation of MAOM and POM are related to distinct fungal traits, with ‘multifunctional’ fungal species contributing most to stable SOM formation.

In our study, we noted an increase in the phylum Glomeromycota, a phylum that contains many arbuscular mycorrhizal fungi (AMF), though not in the trophic mode Symbiotroph, at three out of four REGEN farms. Enhanced AMF necromass may bind to or coat mineral surfaces to form CHAOM and MAOM, increasing SOC storage in the mineral fractions (Hannula & Morriën, 2022), as well as nutrient

availability to crops (Li et al., 2024b). Therefore, understanding the role of fungal communities in SOM formation, along with their sensitivity to management, could significantly advance our knowledge of C storage in agricultural systems.

4.4.3 Analyses reveal taxa central to C and N processing

Our SPLS regression analysis with VIP identified ASVs that predict C and N stocks, with some also showing beneficial properties for plant health. A key predictor of C storage was a core lineage from the genus AV80 within the order Chthonobacteriales, phylum Verrucomicrobia, which is nearly ubiquitous across the paired farms and predictive of CHAOM-C, total SOC, and N stocks (Figure 3.8, SI Figure 3.10). This recently described endophytic lineage (Bünger et al., 2020) is only minimally known, but the Chthonobacteriales order is common in agricultural soils, and has been reported to possess plant growth-promoting properties (Aguirre-von-Wobeser et al., 2018; Li et al., 2021; Souza et al., 2015). Other members of the phylum Verrucomicrobia are also recognized as agriculturally and environmentally significant, capable of utilizing various C sources. These organisms are rapid rhizosphere colonizers and may help alleviate biotic and abiotic stress by freeing nutrients contained in OM (Baliyarsingh et al., 2022). Additionally, fungal ASVs from the genera *Podila* and *Cheilymenia* also have plant protective properties (SI Figure 3.9). For example, *Podila*, common in agricultural soils, may help protect crops against nematode infections (Telagathoti et al., 2022), although on-farm research on either of these lineages remains limited. The presence of growth promoting and plant-protective microbial genera may serve to stabilize yields and increase plant biomass, thereby increasing SOC inputs to the soil (Sarfraz et al., 2019).

4.3.4 Network analyses reveal connections between community interactions and carbon fractions

To further investigate microbial community interactions, we employed network analyses to identify non-random co-variation patterns, indicative of shared interactions or ecological niches among community members (Shi et al., 2016). We hypothesized that management system would significantly impact network architecture, anticipating that the more frequent soil disturbances and periods of bare fallow under CONV management would lead to reduced network complexity (Xue et al., 2022). Aligned

with this prediction, our results demonstrated that REGEN management is associated with bacterial and archaeal community networks that were both larger and more complex than CONV, reflected through increased average weighted degree and network diameter (Shi et al 2016), despite having no significant differences in species richness or diversity between treatments. This complexity implies that members of REGEN communities are more likely to engage in direct interactions, enhancing metabolic exchanges and facilitating horizontal gene transfer (Li et al., 2020). Bacterial and archaeal taxa under REGEN management may exhibit increased potential for direct interactions, as indicated by a higher number of connections per node.

The lower modularity observed in REGEN networks compared to CONV networks indicates a decrease in distinct communities within the network and reinforces the notion of heightened interconnectedness among organisms in REGEN systems. For example, we also observed one module in a bacterial and archaeal network that appears to have gained taxa under REGEN compared with CONV management, which may be attributed to increased C availability and decreased disturbance in the REGEN systems. Shi et al (2016) also found larger and more connected networks in higher-nutrient rhizosphere soils compared to surrounding bulk soils, indicating that higher SOC observed in REGEN soils is driving more microbial interactions and larger, more complex networks. Additionally, complex and well-connected networks associated with regenerative management tend to have greater resistance to abiotic and biotic stressers, contributing to overall resilience (Xue et al., 2022; National Academies of Sciences, Engineering, and Medicine, 2024).

Surprisingly, fungal networks exhibited contrasting trends, showing greater complexity and larger sizes under conventional (CONV) management. Additionally, CONV management led to an increased average weighted degree, suggesting more connections per node, which contradicts findings from other researchers (Xue et al., 2022). It is important to note that the structure and functioning of fungal co-occurrence networks are known to be highly context-dependent, influenced by factors such as niche partitioning, varying responses to soil texture, and crop specificity (Xue et al., 2022; Prieto-Rubio et al., 2024; Liao et al., 2020; Sun et al., 2017). Given the higher level of site variability in this study compared

to controlled field experiments, site variation may have contributed to the observed fungal associations in the current study. Overall, the results underscore the complexity of fungal dynamics in different management contexts.

However, in both communities, we identified a significant correlation between network membership (increased nodes) and CHAOM-C stock (rho: 0.36 & 0.32, bacteria/archaea & fungi, respectively, $p < 0.005$ for both) and a moderate negative correlation between MAOM-C stock and fungal nodes (rho = -0.36, $p < 0.005$). These relationships suggest that a metabolically complex microbial community may enhance functional complexity within the soil ecosystem, where diverse spatial and temporal carbon inputs, and diverse microbial drivers, can promote the formation of chemically or physically stable SOC (Lehmann et al., 2020). However, the inverse relationship between fungal nodes and MAOM may indicate that increased fungal interactions may not always support MAOM formation. The relationship between fungal connectedness and MAOM-C may have implications for future management strategies, as it has been shown that fungal communities contribute more to MAOM than plants or bacteria (Klink et al., 2022; Cotrufo et al., 2019; Sokol et al., 2022).

Altogether, the results of this study highlight the complex role of the microbiome in which many players contribute to C storage, as well as the usefulness of network analyses in taxonomy- or gene-based agricultural microbiome studies (National Academies of Sciences, Engineering, and Medicine, 2024). Given the high degree of between-site variability in this on-farm study compared to controlled experiments, differences between treatments were often masked. However, this study contributes significantly to the limited body of research on regenerative management systems and soil microbial communities conducted in commercial agricultural settings (Bradford et al., 2023; Hermans, et al., 2023). On-farm studies, though they may lack the statistical power of experimental plots, may help identify key variables driving SOC or microbial community structure, while allowing for easier translation of scientific results to land managers (Ellis & Paustian, 2024; Hartmann & Six, 2023).

4.4 Observational experiments shine light on potentially overlooked variables

This study demonstrates both the benefits and challenges of on-farm experimentation in comparison to controlled field experiments. Ideally, we would have numerous randomized block experiments established across the range of U.S. agricultural regions to represent the diverse conditions encountered on commercial farms, while maintaining experimental control. In the absence of such experiments, carefully designed observational studies such as the one presented here can shine light on variables influencing SOC accrual and stability that may otherwise be overlooked in more simplified controlled experiments. As previous literature has emphasized, it takes approximately 10 years of consistent practice use for differences in SOC to be detected through sampling (Necpalova et al., 2014). Our results supported this principle, as the most notable differences in SOC stock were observed on the REGEN-long fields that used no-till for 12-40 years and cover crops for 7-20. On average, REGEN-recent fields did not contain more SOC than their CONV neighbors, while REGEN-long sites contained 15% more SOC on average. Our results demonstrate that practice duration and topographical setting, as it relates to soil degradation and historical erosion, highly influence baseline SOC stocks and the potential for REGEN practices to significantly bolster SOC storage. Furthermore, our results demonstrate that management-induced changes in microbial community networks were statistically significant, despite the high level of variability across and between sites.

However, the challenges of designing observational, on-farm studies should not be understated. First, identifying neighboring farms with equal topography and historical management was not possible in all cases due to the challenge of contacting farmers amenable to sampling. More extensive preliminary interviews, remote sensing analyses, and preliminary sampling could be used to identify pairs with more similar baseline conditions. Second, it is possible that our sampling numbers were too low to detect changes in SOC variables in some cases, given the low signal-to-noise ratio present on commercial fields with high spatial heterogeneity. Texture, slope, drainage, and management history can vary significantly across a given field, impacting the accrual and loss of SOC over time. Bradford et al., 2023 found sampling densities and field numbers on the order of 1.2 samples ha^{-1} and 30+ fields is sufficient to detect SOC change at the project level, while detecting differences at the field-level remains difficult (Bradford

et al., 2023). Our average sampling density was below this recommendation at 3 samples ha^{-1} for 22 fields. There is significant feasibility tradeoffs associated with increasing sample size, both in the number of fields sampled and the quantity/depth of cores collected (Stanley et al., 2023).

5. Conclusion

In summary, on-farm studies are imperfect, but useful, as they can reflect the diverse soil types and topographical settings where commercial farms are situated, along with the systems-level outcomes of different management systems (Ellis & Paustian, 2024). This observational study highlights the intricate interactions between regenerative management practices, SOC stocks, and microbial community interactions across a landscape level study in the Midwestern region of the United States. We see that regenerative practices appear to increase SOC stocks, although this effect may be masked by the condition of the land prior to implementing these practices. We also provide evidence for the usefulness of density-based fractionation methods for understanding where and how SOC is stored, and potential interrelationship with the soil microbial community. We highlight the significance of understanding the roles of various microbial taxa in carbon (C) and nitrogen (N) dynamics, particularly under different management systems. The identification of specific taxa that may influence these cycles suggests potential pathways for enhancing soil health and SOC storage. By employing network metrics, we shed light on the complex interplay between microbial dynamics and C cycling, emphasizing this as a promising area for future research. Finally, our findings strongly advocate for the integration of on-farm, system-level studies with microbiome analyses, which can yield invaluable insights for bolstering soil health, SOC storage, and microbial diversity. We show that on-farm studies that work collaboratively with producers to understand the impacts of their management choices and field conditions can help bridge the gap between academic research and on-farm realities. Overall, this study contributed to a deeper understanding of regenerative agricultural practices and their potential to enhance SOC storage and ecosystem resilience.

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SIMULATING HISTORIC EROSION IMPROVES SOIL ORGANIC CARBON STOCK ESTIMATION USING THE DAYCENT MODEL[4]

1. Introduction

Agricultural soils in intensive crop production regions have experienced significant reductions in soil organic carbon (SOC) compared to their native ecosystem counterparts. Soils of the US Corn Belt, and other major agricultural regions across the globe, have lost up to 70% of their original SOC following conversion to agriculture (Crews & Rumsey, 2017; McLauchlan, 2006). Accelerated decomposition of SOC following land use conversion or with conventional tillage practices comprises a significant historical and ongoing source of CO_2 emissions to the atmosphere (Houghton et al., 2012; Reicosky, 1997). Additionally, historic and modern intensive tillage practices used in the US Corn Belt have resulted in the erosion of 1.4 ± 0.5 Pg of C from hillslopes, displacing essential topsoil resources (Thaler et al., 2021). It is possible to mitigate the impacts of historic agricultural mismanagement and rebuild SOC stocks by adopting practices that reduce erosion, increase C inputs, and decrease C outputs. In fact, agricultural practices such as no-till planting and cover crops have the potential to increase SOC stocks in row cropping systems, while delivering a suite of environmental and agronomic co-benefits (Bai et al., 2019; Blanco-Canqui et al., 2011; Paustian et al., 2019), including erosion prevention (Chen et al., 2022). If shifts towards agricultural best management are to contribute to climate adaptation and mitigation, robust tools for quantifying the impact of practice changes on SOC stocks and other soil properties are needed. Indeed, there is significant interest in improving quantification methods of SOC stock change, with implications for agricultural incentive programs, regulatory frameworks, and voluntary carbon markets (Berardi et al., 2020; Bradford et al., 2023; Oldfield, Lavallee, et al., 2022).

[4] Ellis, E., Alvaro Fuente, J., Paustian, K., Simulating historic erosion improves soil organic carbon stock estimation using the DayCent model. [In prep].

SOC stock change can be measured through direct soil sampling, estimated through remote sensing of SOC-related ecosystem proxies, and/or simulated through process-based models of agroecosystem processes (Angelopoulou et al., 2019; Oldfield, et al., 2022; Pierson et al., 2022). Both remote sensing models and process-based models require parameterization, calibration, and validation using direct measurements of soil and biomass properties. For example, the DayCent process-based model has been iteratively parameterized, calibrated, and validated with data from a variety of ecosystems and agricultural settings (Gurung et al., 2020; Mathers et al., 2023; Necpálová et al., 2015), mostly using measurements derived from long term experiments (Bista et al., 2024; S. J. Del Grosso et al., 2006; Dold et al., 2021a; Mathers et al., 2023; Ogle et al., 2010). Thus, the DayCent model is well suited for modeling experimental scenarios where management is consistent from year to year, topography and soil types are controlled, and a time series of direct measurements are available. Applying the DayCent model to simulate a wide range of on-farm settings could be improved using measured data from a range of climates, soil types, topographies, and management systems. Increasingly, DayCent is used to simulate activities and outcomes on commercial farms with more complex management scenarios and land use histories, presenting a suite of challenges unique to on-farm research (Ellis & Paustian, 2024). These challenges include a lack of reliable and complete management activity records from commercial producers, unknown land use history, and the presence of variable soil types and topographies across agricultural regions. As DayCent and similar process-based models are increasingly applied to complex on-farm scenarios, additional considerations must be taken to accurately simulate the complexity and variability of real-world agroecological settings (Pierson et al., 2022). One such consideration is modeling commercial farmland with variable topography and a history of soil erosion, as defines many parcels of land in U.S. Midwest and other agricultural regions.

‘Space-for-time’ or chronosequence field studies have been used across subfields of ecology, particularly where long-term experiments don’t exist or real-world management conditions are of interest (de Oliveira Ferreira et al., 2021; Dupla et al., 2022; Machmuller et al., 2015; Mosier et al., 2021;

Rosenzweig et al., 2018). In a space-for-time approach, neighboring parcels of land that have been managed under contrasting management systems for a significant period are sampled as a natural experiment (Pickett, 1989; Walker et al., 2010). A necessary element of this approach is identifying fields with similar soil types, topography, drainage, and common land use history, the last of which can be difficult to determine. Remote sensing tools to reconstruct land use history are under development, but these tools are largely limited to the period for which high frequency/high-quality satellite imagery is available (after ~1980) and rely on local knowledge of actual land use practices (Bégué et al., 2018; Copenhaver & Mueller, 2024). Further, space-for-time substitution assumes that the processes influencing soil properties are the same on the neighboring parcels of land, and thus, initial' SOC stocks should be similar prior to the adoption of the management changes of interest. If these assumptions hold true and care is taken to minimize across and between field variability, on-farm measurements generated through space-for-time substitution experiments may contribute to model improvements for real-world scenarios (Ellis & Paustian, 2024).

In this study, we used a dataset of 'across-the-fence' soil measurements, yearly field activity data, and yield records from paired regenerative and conventional farms (Ellis et al. [*In prep*]) to evaluate DayCent model performance in simulating outcomes in commercial farm settings. The regenerative farms in this dataset were under no-till management for at least seven years and cover cropped for at least five years, while the conventional farms were tilled annually or biannually and bare fallowed over the winter. The objectives of this study were to evaluate the potential impact of soil erosion on measured and simulated SOC stocks on slightly sloping fields, to test assumptions inherent to across-the-fence experiments, and identify additional considerations that should be taken when assessing the long-term dynamics of SOC stocks on commercial farms. First, we evaluated the impact of modeling historical and contemporary erosion and deposition processes on simulations of SOC stocks. Next, we evaluated the ability of the model to simulate measured or reported data from a total of ten farms (five neighboring pairs), for 1) ten years of corn and soybean yields and 2) field-scale SOC stocks (0-20 cm). Additionally, we evaluated a

key assumption implicit in across-the-fence farm comparisons: namely, that SOC stocks of the paired CONV and REGEN fields were relatively equal prior to adoption of REGEN practices, under the assumption that soil types, topography, and land use history were well controlled between the pairs. Our efforts should contribute to process-based model improvements for simulating SOC accrual and other soil processes in complex on-farm settings.

2. Methods

2.1 Site selection and description

In the fall of 2022, soil and biomass samples and farm-level management activity data were collected from ten pairs of neighboring farms using contrasting management systems, (as described in Ellis, et al. [*In prep*]). The ten farm pairs were located across Iowa and Southern Minnesota and were identified through interpersonal networking and "snowball" sampling techniques (Naderifar et al., 2017). Farm pairs were selected based on adherence to one of two management systems: 1) Regenerative (REGEN), defined here as fields managed with at least seven years continuous no-till and at least five years continuous cover cropping, versus 2) conventional (CONV), defined as fields managed with annual or biannual tillage and no cover crops (i.e., bare winter fallow). We assumed that prior to adoption of REGEN practices, those farms were managed similarly to the CONV farm in each pair. All farms were planted to a predominately corn/soybean rotation (with occasional periods of continuous corn or soybeans on some farms). All fields were planted to soybeans in the 2022 crop year when soil samples were collected. SSURGO soil maps were used to identify areas of matching or very similar soil types between the paired farms. We also took care to ensure the topography of all fields and sampled areas was mostly flat, avoiding fields with any sloping areas at or above 5 degrees. A Giddings truck mounted soil sampling probe (Giddings Inc., Windsor, CO, USA) was used to collect samples at nine randomized, georeferenced sampling sites per field. At each sampling site, cores were collected at the corners of a north-oriented isosceles triangle, with 100 cm side lengths and a 60 cm base. One core was taken to 100 cm depth (or as

deep as possible) and two cores to 30 cm depth. The cores were composited by depth increment (0-15, 15-30, 30-60, and 60-100 cm) at each of the nine sampling sites (SI Figure 4.1). Crop residues were collected by clipping the crop material present in a 15 cm diameter circle at the north apex of each sampling triangle. Geolocator balls were buried at the north apex of each sampling triangle to enable precise resampling in the future.

While efforts were made to collect comprehensive management activity records for all fields sampled, farmers records were incomplete in most cases. A discussion of the challenges of collecting management records from commercial producers is presented in Ellis & Paustian, 2024. Given the lack of complete records, five farm pairs (ten individual fields) with semi-complete management data from both the REGEN and CONV neighbor were selected for model simulations. The selected fields range in size from 13 to 61 ha (average size = 32 ha) and were located across the study region. Selected soil/field properties and management info for the ten fields are provided in Table 1 and complete management records are provided in SI Table 1.

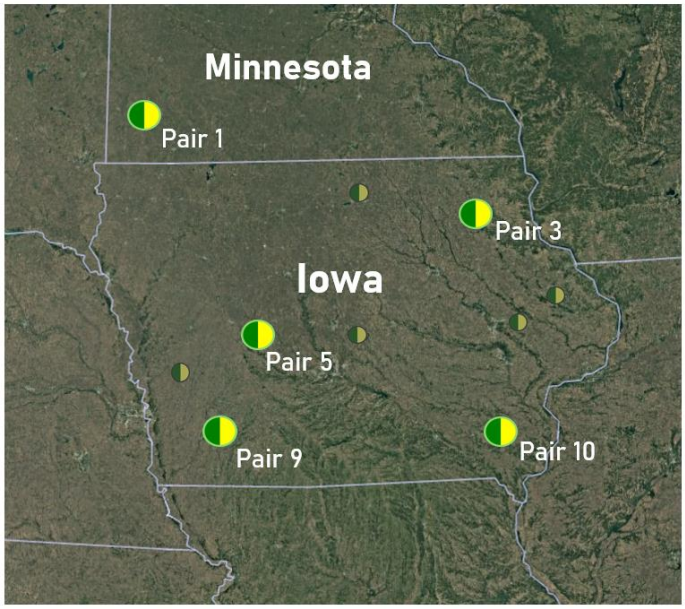

Figure 4.1 Locations of the 10 sampled REGEN/CONV farm pairs. Larger green/yellow dots indicate the locations of the farm pairs modeled in RUSLE2 and DayCent, while the smaller, grayed-out dots indicate the location of the farm pairs that did not provide sufficient data for model simulations.

2.2 Soil/biomass processing and analysis

Soil processing and laboratory analyses, including gravimetric water content, bulk density, soil texture, inorganic C, and total C and N, were conducted in the EcoCore Facilities and Soil Innovation Laboratory at Colorado State University. Soil processing and analyses are briefly described here and described in more detail in Ellis et al., [*In prep*].

After weighing each field-moist soil sample, a representative sub-sample was collected to determine gravimetric water content. The remainder of the sample was first sieved (at field moisture) to 8mm and a subsample (~180 g) was sieved to 2mm, removing crop residues, roots and rocks at each sieving. Roots and rocks > 2mm were dried at 60°C for 24 hours. Soil texture (sand, silt, and clay weight percent) was determined by wet sieving (53 μm sieve) for sand content, while clay content was determined using the hydrometer method (Gee & Bauder, 1986). Soil pH was determined using a pH probe in a 1:2 soil to deionized water slurry. Bulk density of the fine soil fraction (particles <2mm) was determined using oven-dry sample mass and volume, subtracting the weight and volume of rocks. A subsample of 2 mm sieved soil was ground to a fine powder and analyzed for total C and N through dry combustion on an elemental analyzer (Elementar vario ISOTOPE CUBE - Langenselbold, Germany). All samples were tested for presence of carbonates using an HCl acid fizz test procedure. In samples with a positive fizz test, carbonates were quantified using the pressure transducer method (Sherrod et al., 2002). Where inorganic C was present, the concentration of inorganic C was subtracted from total C to find SOC concentration.

We used two methods to calculate SOC stocks: 1) fixed-depth (FD), and 2) equivalent soil mass (ESM). The ESM method, where SOC stocks are compared across treatments using a common mineral soil mass rather than a common depth, is recommended to account for changes in soil volume due to management. The fixed-depth method, where SOC stocks are calculated for a known depth interval using bulk density and SOC concentration, is still commonly used to calculate SOC stocks. Historically, most model validation studies and parameterization were conducted using the FD method. Thus, we evaluate

the ability of the model to simulate stocks calculated using both methods, to potentially identify biases in the model when simulating practices that lead to a change in bulk density (i.e., tillage). SOC stocks were calculated using the equivalent soil mass method (Ellert et al., 2002; Wendt & Hauser, 2013) with an R script provided by von Haden et al. (2020). We used the R for ESM script to extrapolate the SOC concentration measurement for 0-15 cm to the 0-20 cm depth increment used in the DayCent model. For the FD method we estimated SOC stocks to the 0-20 cm depth increment by multiplying the 0-15 cm stock measurement by 0.33, assuming the bulk density and SOC stock does not differ significantly in the 15-20 cm layer.

Table 4.1 Average soil properties (pH, clay %, and sand %) for top 20 cm, field slope (degrees), along with select management data (years no-till, years cover crops, mean N fertilization rate (mean of N applied over two-year corn-soybean rotation, kg ha^{-1} y^{-1}), and manure application type, if applicable. NR = data not reported by producer.

Pair ID	Field ID	Management	pH	Clay %	Sand %	Soil moisture class	Mean field slope (°)	Years No-till	Years Cover Crops	N fert. rate (kg ha^{-1})	Manure application
1	C1	CONV	6.40	28.0	33.7	Udic to Aquic	1.9	0	0	NR	N/A
	R1	REGEN	6.54	26.0	34.5	Udic to Aquic	1.5	8	6	68	N/A
3	C3	CONV	6.17	18.0	31.6	Udic	2.7	1	1	73	N/A
	R3	REGEN	6.46	18.3	42.6	Udic to Aquic	2.3	30	20	54	N/A
5	C5	CONV	5.33	27.4	29.9	Udic to Aquic	1.5	0	0	69	N/A
	R5	REGEN	5.33	26.9	33.0	Udic to Aquic	1.2	14	14	69	N/A
9	C9	CONV	5.74	33.5	2.8	Udic	1.4	3	2	77	Chicken litter
	R9	REGEN	6.05	33.8	3.0	Udic	3.7	30	12	83	Chicken litter
10	C10	CONV	6.07	28.0	3.5	Udic	2.0	2	0	22	Swine slurry
	R10	REGEN	5.70	29.9	3.0	Udic	0.6	30	7	27	N/A

Table 4.2 Measured SOC stocks and bulk densities (0-20 cm) for the paired farms, calculated using two different methods: 1) fixed depth (FD), and 2) equivalent soil mass (ESM) methods. Stocks are reported as means, and standard error of the mean (±SE) for each SOC stock is also presented.

Pair ID	Field ID	Management	Bulk density (g cm^{-3})	SOC stock (FD method) (Mg ha^{-1})	±SE SOC stock (FD method) (Mg ha^{-1})	SOC stock (ESM method) (Mg ha^{-1})	±SE SOC stock (ESM method) (Mg ha^{-1})
1	C1	CONV	1.17	68.3	5.8	68.3	4.3
	R1	REGEN	1.29	82.2	5.4	69.9	5.5
3	C3	CONV	1.37	44.3	2.4	44.3	2.6
	R3	REGEN	1.32	66.3	6.9	70.6	6.6
5	C5	CONV	1.29	72.8	4.8	75.6	5.2
	R5	REGEN	1.28	75.8	2.7	75.8	4.6
9	C9	CONV	1.22	64.2	1.4	64.2	1.5
	R9	REGEN	1.24	56.8	1.3	55.9	1.4
10	C10	CONV	1.23	61.3	1.4	61.3	1.5
	R10	REGEN	1.22	68.1	3.1	69.1	3.9

2.3 DayCent model description

DayCent is the daily time-step version of the Century model, a process-based ecosystem model designed to simulate biomass accumulation, nutrient cycling, SOC stocks, and GHG emissions in a variety of managed and unmanaged ecosystems (Parton et al., 1998). The model consists of several sub-models, including crop growth, SOM decomposition/stabilization, soil water processes, and N mineralization/immobilization. The model contains three conceptual SOC pools parameterized with different turnover times: active (annual), slow (decadal), and passive (centurial). SOC turnover and stabilization are modified by daily precipitation and temperature data, along with soil texture variables. We used the DD17centEVI version of the model that outputs SOC stock simulations to 20 cm (Bista et al., 2024; dos Reis Martins et al., 2022). We maintained model defaults for most parameters, except those indicated in the model input description below.

2.4 Model inputs

Weather data from 1982 to 2022, including maximum and minimum temperature (°C) and precipitation (cm), were obtained for each field, based on the nearest 4x4 km grid cell from the PRISM weather dataset (PRISM Climate Group, 2023). The same 40 years of daily climate data were circularly iterated into the equilibrium and base history simulation periods. Laboratory measurement of soil texture (clay and sand percent) and pH were used to build site and soil files for each field. Since there were small variations in soil properties between the paired farms, we used separate soil and site files for each field, but one weather file was used for each pair. Drainage parameters (DRAIN) were adjusted based on the drainage class of each soil, where DRAIN was reduced for aquic soils and manually calibrated to measured SOC data after calibration of crop growth parameters (see below).

Soil organic matter pools were initialized under native grassland conditions for 7000 years, or until equilibrium conditions were reached. The grassland simulation consisted of a mixed grassland prairie (50% cold, 50% warm), with low to high intensity grazing throughout the year, and an 8- or 10-year fire return interval. We adjusted the fire interval and grassland productivity patterns for the southern sites, assuming a more frequent fire interval (8-year) and higher grass productivity (Zouhar, 2021). From 1841 to 2012 (base history), we simulated a series of historical management practices common to the study region by referencing USDA National Agricultural Survey (NAS) records and previous DayCent modeling efforts in the US Corn Belt region (Zhang et al., 2020). Table 3 summarizes the crop rotations, tillage, grazing, and fertilizer application simulated in each base history block. Given the significant increase in productivity potential of field crops from the beginning of the simulation period to today (due to genetic improvement and crop protection inputs), we simulated unique crop types for corn, oats, soybeans, and temperate grass clover pasture as productivity increased over time by modifying the PRDX parameter, which specifies the maximum potential production.

Table 4.3 Crop rotations and management practices simulated for the base history period (1841 to 1982). Since precise management history was not available for the individual farms or farm pairs for this period, we assumed the same historical management practices for all farms. Crop codes: C = corn, O = oats, P = pasture, S = soybeans.

Years simulated in block	Rotation	Crop productivity	Grazing	Tillage	Fertilizer application
1841 to 1860	C-C-C-O-P	Low	1 out of 5 years	MP (spring and fall)	None
1861 to 1929	C-C-O-P	Low	2 out of 5 years	MP (spring and fall)	None
1930 to 1950	C-O-P	Low to moderate	1 out of 3 years	DR (spring and fall)	Syn. N in corn years
1951 to 1982	C-S	High	None	DR (corn year fall only)	Syn. N in corn years

Ten years of management data (including detailed yearly planting/harvest activities, synthetic fertilizer application, tillage practices, cover crop planting, and manure application) were used to schedule model events for the modern history period (summarized in SI Table 1). For the CONV fields, we assumed the same management practices reported for the 2013-2022 were used from 1983-2013. If no-till or cover crops were adopted on the CONV field in the last year or two of the modern period, we assume those practices were not used before the year they were first reported. For the REGEN fields, we assume practices used on the neighboring CONV field reflect standard management prior to regenerative practice adoption. For REGEN fields that have used regenerative practices for more than ten years, we assume the same management practices reported in 2013-2022 were used in previous years for which we do not have precise management records. In cases where the management information obtained from the producer was incomplete (i.e., missing fertilization rates, tillage dates, etc.), we used records obtained from the neighboring field (where appropriate) and/or county averages. Since DayCent does not allow two crops to be simultaneously, less common regenerative practices such as relay cropping were not simulated, although techniques to so have been proposed (Della Chiesa et al., 2022). When management records indicate the farmer “planted green” into an existing cover crop or seeded cover crops before cash crop harvest, we scheduled the planting event for the day after cover crop termination or harvest.

Default values for model version DD17centEVI were retained for most parameters. The plant growth model was calibrated for the modern period using ten years of field-level yields obtained from each producer using methods described in Del Grosso et al., 2011. Corn and soybean yields were used separately for model calibration and validation, and model performance was evaluated using the entire dataset. We assumed crop moisture contents of 15.5% and 13.0% for corn and soybeans (Karlen et al., 2015), respectively, and converted grain yields to grain C by assuming grain C concentrations of 44.7% and 54% for corn and soybeans (Dold et al., 2021b), respectively. From 1983 onwards the same high productivity corn and soybean crop types were simulated on all fields (except pair 1) by calibrating the PRDX and HIMAX parameters to reflect reported yields. Pair 1 is located in southern Minnesota where temperatures are lower, growing seasons are shorter, and cold tolerant varieties are likely planted. Thus, we adjusted parameters impacting crop sensitivity to cold conditions (PPDF (1), PPDF(2)) to reach similar levels of yield productivity to the Iowa sites.

We used the Revised Universal Soil Loss Equation, Version 2 (RUSLE2) (USDA-ARS, 2013) model to estimate yearly erosive soil loss given the unique soil types, climates, slopes, management practices, and typical yields of each field. The model was parameterized using county-level climate data, soil textural class, relative organic matter content, estimated soil permeability, and average corn/soybean yields for each field. The average field slope for the sampled area was calculated using the *raster* R package. We assumed a horizonal slope length of 1000 ft for each field (maximum slope length option in RUSLE2 model). We simulated the tillage practices used in the base and modern history periods for each field, including moldboard plow, chisel plow, and no-till, as well as the combination of cover crops and no-till. After obtaining a yearly erosion mass loss rate, we scheduled annual or biannual erosion events in DayCent according to the tillage practices in use at the time. Previous sensitivity analyses indicate that scheduling multiple erosion events per year to reflect frequent soil loss does not affect model outcomes (Lugato et al., 2016). Additionally, depositional processes were simulated on all fields with a slope less than 2°, by estimating that 30% of the eroded soil mass in each erosion event is deposited back onto the field. We accounted for the impact of topsoil loss on subsequent exposure of the subsoil by adjusting the

SOC pool composition of the subsoil layers, following methods used by Lugato et al., 2015. The subsoil SOC pools at time t = 0 are calculated as a fraction of topsoil pools according to the following equation:

$$SSL(t0) = (0.2 \times Active\ pool\ (surface)) + (0.4 \times Slow\ pools\ (surface)) + (0.8 * Passive\ pool\ (surface)) \quad \textbf{(Eq2)}$$

Field-level evaluation and modeling of erosional and depositional processes, such as the grid-scale methods used in Lugato et al., 2015, is beyond the scope of this analysis as our goal was to develop a relatively simple technique to simulate the impact of erosion on SOC stock change trajectories. To estimate the SOC loss from the RUSLE2 estimated erosion rate, we used the following equation:

$$Est.C\ loss\ (Mg\ C\ ha^{-1}\ yr^{-1}) = Est.erosion\ rate\ (Mg\ C\ ha^{-1}\ yr^{-1}) * \frac{SOC\ stock\ (Mg\ ha^{-1})}{BD\ (cm^{-3}) * 15\ cm * 100} \quad \textbf{(Eq 1)}$$

Assuming the CONV field can be used as a proxy for the baseline SOC stocks of the REGEN field, we used the average SOC stock and BD measurements from the CONV field to estimate annual SOC loss from both the REGEN and CONV fields.

2.5 Model evaluation and statistics

A linear regression model was used to evaluate the relationship between simulated and reported yields, with separate lines fitted for REGEN and CONV fields. Model performance was assessed using the coefficient of determination (R^2) to quantify goodness-of-fit and the root mean square error (RMSE) to evaluate variability. The coefficient of variation (CV) was calculated by field for farmer-reported yields to investigate whether variability in model fit was driven by actual yield variability. We calculated the mean and standard deviation of the CV for each management system and crop.

Linear regression models were employed to assess the fit of simulated to measured soil organic carbon (SOC) stocks. To evaluate the impact of simulating erosion in DayCent, we compared the fit of modeled data to SOC measurements both before and after incorporating erosion events. Statistical significance was considered at $p < 0.1$, reflecting the inherent variability of the study sites.

3. Results

3.1 SOC stocks: Fixed depth vs. equivalent soil mass

Measured SOC stocks in the 0-20 cm depth increment varied slightly depending on the calculation method used (FD vs. ESM method). Stocks ranged from 44.3 to 82.2 Mg C ha^{-1} (FD method) or from 44.3 to 75.8 Mg C ha^{-1} (ESM method). Differences in SOC stock varied significantly with management system, but the level of significance changes with the SOC stock calculation method used (*FD method: REGEN minus CONV SOC stock estimate = 6.0 Mg C ha^{-1}, SE = 2.5 Mg C ha^{-1}, p = 0.02; ESM method: REGEN minus CONV SOC stock estimate = 5.28 Mg C ha^{-1}, SE = 2.8 Mg C ha^{-1}, p = 0.06*). Differences in calculated stocks between the two methods were driven by small differences in bulk density between the pairs, which may be a consequence of management differences or variations in texture. Differences between the paired REGEN and CONV farms ranged from 22 Mg C ha^{-1} to -8.3 Mg C ha^{-1}, with the REGEN field containing more SOC than the CONV on average, except for pair 9. It is likely that differences in slope between field C9 (*slope = 1.4*) and R9 (*slope = 3.7*) lead to differential rates of soil erosion and baseline SOC stocks. We attempted to account for historical erosion processes on all of the farms by adding estimated erosion events to DayCent simulations.

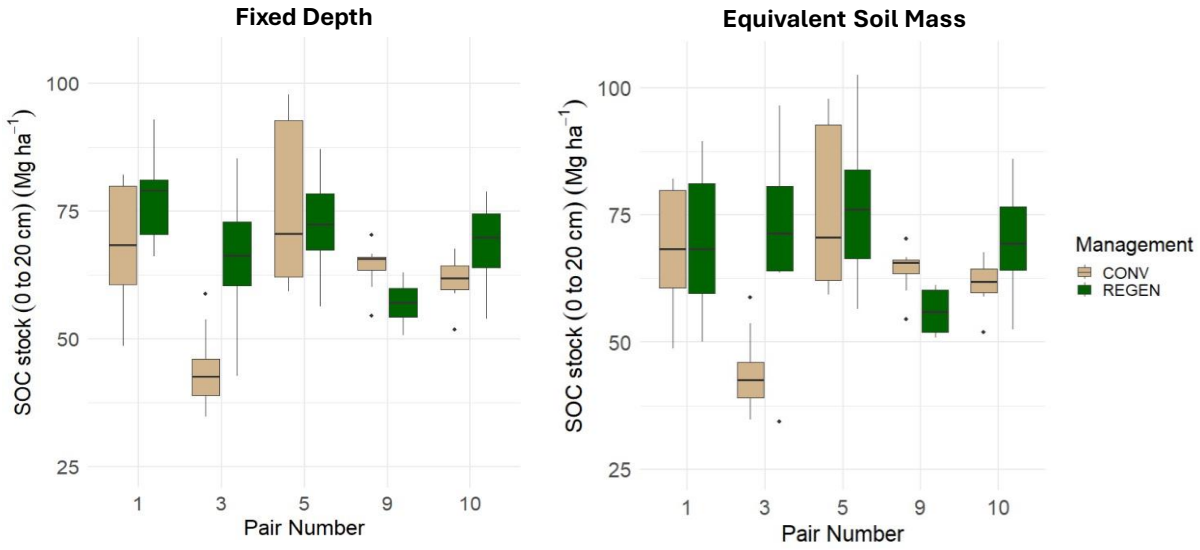

Figure 4.2 Boxplots displaying soil organic carbon (SOC) stocks in Mg ha^{-1} for the 0–20 cm depth increment under conventional (CONV; tan) and regenerative management (REGEN; green) across paired

fields. The left panel shows SOC stocks calculated using the fixed depth (FD) method, while the right panel shows SOC stocks calculated to an equivalent soil mass (ESM) to account for management induced bulk density differences.

3.2 DayCent simulation of corn and soybean grain C

Grain C simulated in DayCent and farmer reported grain C were similar in trend and magnitude, with slight variations in fit between management system. For the CONV fields, the simulated vs. reported grain C yields had a RMSE of 0.66 Mg C ha^{-1} and $R^2 = 0.82$, while REGEN simulated vs. reported grain C had a RMSE of 0.68 Mg C ha^{-1} and $R^2 = 0.78$ (Figure 4.3). It is possible that the lower R^2 and higher RMSE for the REGEN grain C is driven by higher variability in the farmer-reported yields, but yield stability (evaluated using coefficient of variation (CV)) was not notably different between management systems for corn or soybeans, although REGEN yields tended to be slightly higher than CONV yields. Mean corn yields were 11.9 and 11.5 Mg ha^{-1} for the REGEN and CONV fields, respectively. The mean CV of the REGEN corn yields was 0.14 ± 0.04 Mg ha^{-1}, and 0.13 ± 0.07 Mg C ha^{-1} for the CONV fields. Mean soybean yields were 3.8 and 3.6 Mg ha-1 for the REGEN and CONV fields, respectively, with mean CVs of 0.10 ± 0.05 and 0.10 ± 0.09, respectively. Differences in mean yields and yield variability were not statistically significant between management systems for either crop. Since variability in the reported yields is not significant, it is possible that the DayCent model tends to underpredict grain C where regenerative practices such as no-till or cover crops are simulated.

Additionally, it appears drought years are outliers in simulations of grain C, where grain C is either under or overestimated by the model compared to farmer-reported values. The discrepancy between the simulated and reported values may be attributed to how available water or drought stress affect plant growth in the DayCent model. Two yield years (2013 and 2020) had a relatively high concentration of outlier values, where the simulated yields were either under or over the farmer-reported values compared to yield simulations in an average precipitation year (2015) (Figure 4.4). In 2013, seven out of nine values were over-predicted (modeled value is greater than measured value) by the simulation. According to the precipitation data and historical reports, 2013 was a significant drought year across much of the study

region, with an extreme lack of precipitation in the late summer and early fall months (Figure 4.4). It is possible that the yield impacts of low water availability late in the growing season are not well simulated by the model. 2020 was also a significant drought year and the simulated yields also deviate from the reported values. 2020 was characterized by early and late season drought conditions, along with a powerful derecho that caused extensive damage to crops and infrastructure. Interestingly, soybean yields tend to be under-predicted (modeled value is less than the measured value) in 2020. It is possible that the timing of water scarcity has differential impacts on crop biomass and grain accumulation in the DayCent model. Overall, the modeled values for grain C align closely with the farmer-reported values, indicating the plant growth sub model was adequately calibrated to reported values.

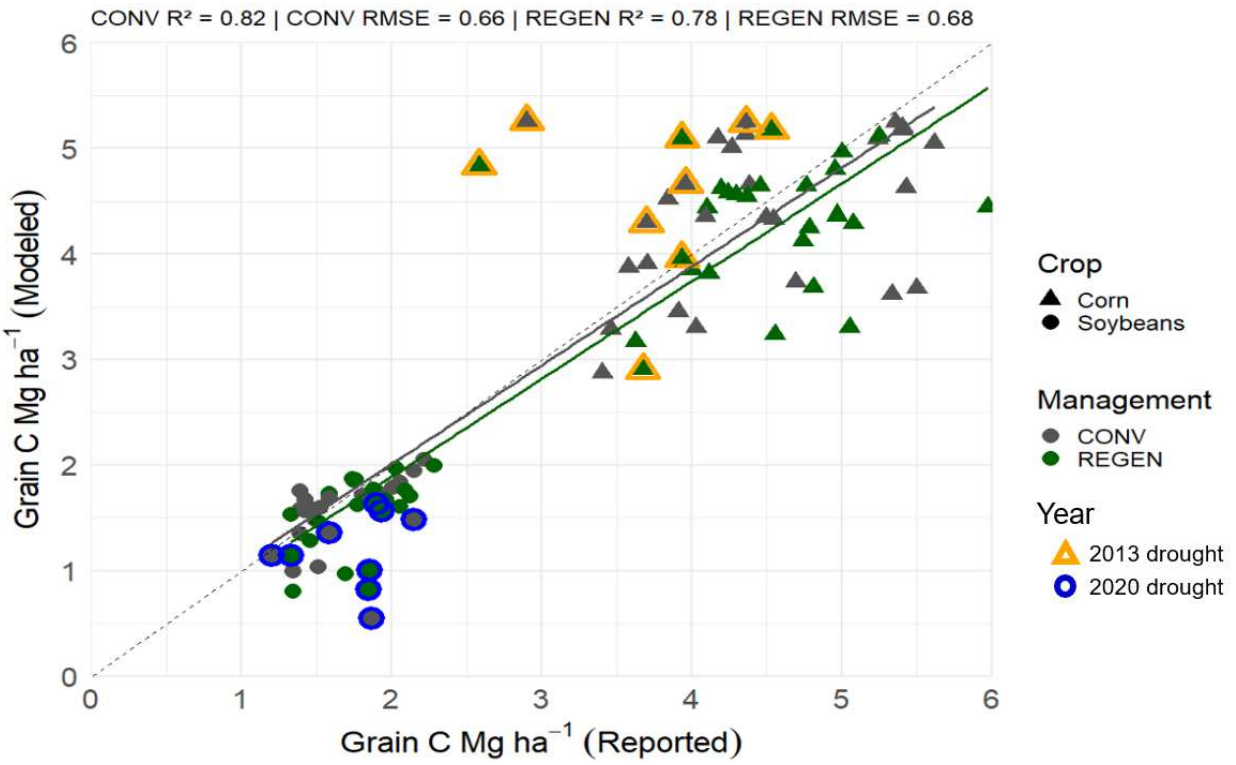

Figure 4.3 Modeled versus reported grain C yields (Mg ha^{-1}) for corn and soybeans under conventional (CONV) and regenerative (REGEN) management. The solid line represents the 1:1 line, while the dashed lines represent the linear regression fits for each management system. Drought years are identified by colored outlines: 2013 (orange triangles) and 2020 (blue circles), where modeled results deviate from reported yields. Regression results show agreement between modeled and reported grain C for conventional (R^2 = 0.82, RMSE = 0.66) and regenerative (R^2 = 0.78, RMSE = 0.68) systems, with outliers mostly concentrated in drought years.

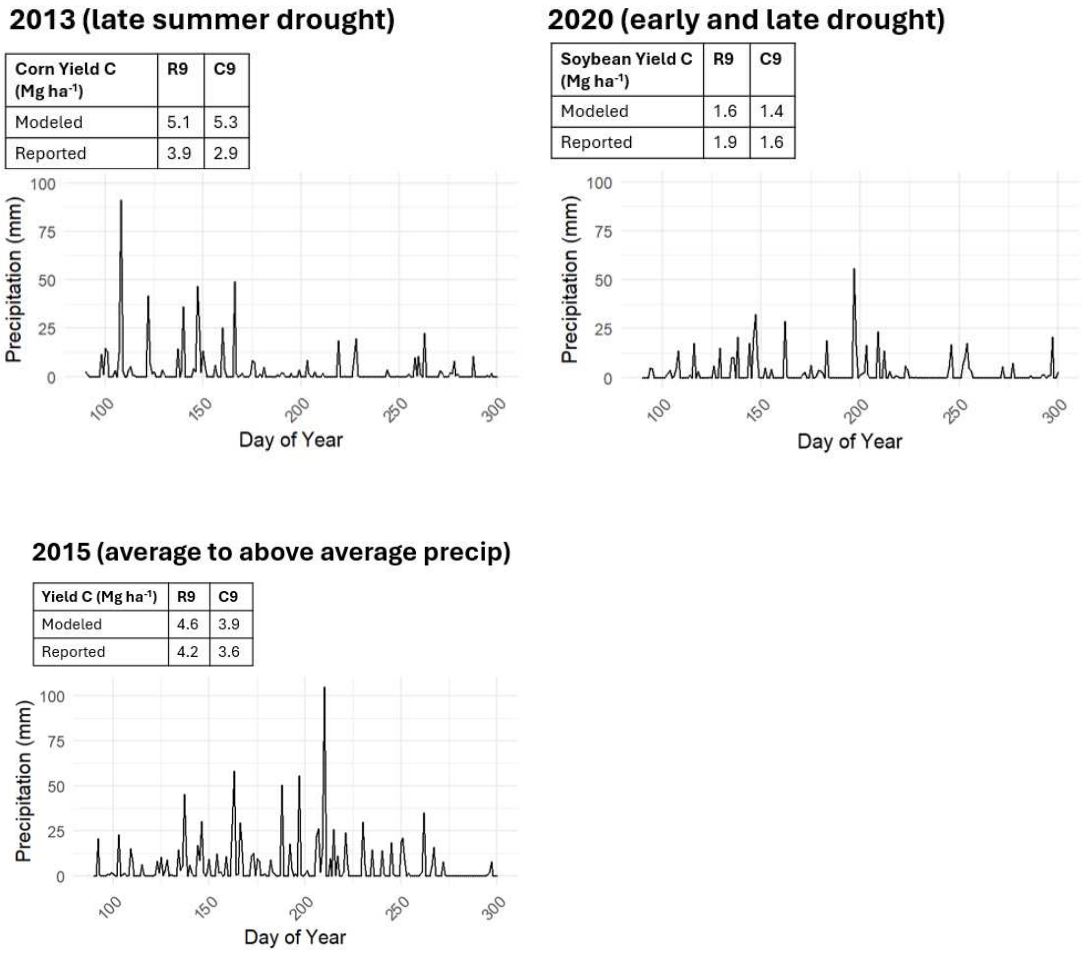

Figure 4.4 Growing season precipitation (mm) for 2013 and 2020, years where yields were under and over predicted in DayCent simulations. 2013 was a late season drought, while 2020 had longer dry periods in the spring and fall. Yields are over predicted by the model in 2013, and underpredicted in 2020. 2015 records show an average to slightly above average precipitation year, and modeled yields show closer agreement to reported values.

3.3 RUSLE2 erosion estimations

RUSLE2 model results highlight the combined impact of field slope and management practices on soil erosion and SOC displacement. Among the evaluated practices, moldboard plow fields exhibited the highest predicted soil loss (19.05 Mg ha^{-1} yr^{-1}) and carbon loss rate (0.66 Mg C ha^{-1} yr^{-1}) on the steepest field (slope = 3.7°), reflecting the risk of erosive loss when intensive tillage is used on even moderately sloping land. In contrast, the rate of soil loss is predicted to decrease significantly when reduced till (chisel plow) or no-till practices are adopted on moderately sloping fields. The combined impact of no-till

and cover crops is predicted to reduce soil erosion rates to to 0.65 Mg ha^{-1} yr^{-1} on the steepest slope sampled, and to nearly zero on flater slopes. The predicted SOC loss rates, which range from 0.02 to 0.66 Mg C ha^{-1} yr^{-1} depending on field slope and texture, highlight the potential significance of erosion processes on SOC stock change trajectories. The erosion and deposition rates listed below were added as events in the DayCent model simulations according to what tillage practices are used during different simulation periods (example schedule file is shown in SI Figure 4.2).

Table 4.4 RUSLE2 predicted soil erosion, deposition, and C loss rates for farm pairs simulated under different tillage and cover cropping practices. The erosion and deposition rates listed below were added as events in the DayCent model simulations according to what tillage practices are used during different simulation periods. Predicted soil loss is calculated using the mean C stock and BD for the 0-15 cm depth increment of the CONV field (Eq 2).

Farm Pair	Field ID, slope, & textural class	Management practice(s) evaluated	Predicted soil loss rate (Mg ha^{-1} yr^{-1})	Deposition rate (Mg ha^{-1} yr^{-1}) (only applied to fields < 2° slope)	Predicted C loss (Mg C ha^{-1} yr^{-1})
1	R1	Moldboard plow	2.70	0.81	0.08
	(slope = 1.5)	Chisel plow	0.91	0.27	0.03
	clay loam	No-till	0.16	0.05	0.00
		No-till + Cover Crops	0.06	0.02	0.00
	C1	Moldboard plow	3.00	0.90	0.09
	(slope = 1.9)	Chisel plow	1.30	0.39	0.04
	clay loam	No-till	0.20	0.06	0.01
		No-till + Cover Crops	0.00	0.00	0.00
3	R3	Moldboard plow	9.60		0.16
	(slope = 2.3)	Chisel plow	3.00		0.05
	loam	No-till	0.32		0.01
		No-till + Cover Crops	0.15		0.00
	C3	Moldboard plow	11.00		0.18
	(slope = 2.7)	Chisel plow	4.20		0.07
	loam	No-till	0.56		0.01
		No-till + Cover Crops	0.20		0.00
5	R5	Moldboard plow	3.70	1.11	0.10
	(slope = 1.2)	Chisel plow	1.70	0.51	0.05
	clay loam	No-till	0.28	0.08	0.01
		No-till + Cover Crops	0.06	0.02	0.00
	C5	Moldboard plow	5.10	1.53	0.14
	(slope = 1.5)	Chisel plow	2.10	0.63	0.06
	clay loam	No-till	0.32	0.10	0.01

		No-till + Cover Crops	0.08	0.02	0.00
9	R9 (slope = 3.7) *silty clay loam*	Moldboard plow	19.05		0.66
		Chisel plow	7.85		0.27
		No-till	1.88		0.07
		No-till + Cover Crops	0.65		0.04
	C9 (slope = 1.4) *silty clay loam*	Moldboard plow	6.50	1.95	0.16
		Chisel plow	2.69	0.81	0.07
		No-till	0.69	0.21	0.02
		No-till + Cover Crops	0.16	0.05	0.00
10	R10 (slope = 0.6) *silty clay loam*	Moldboard plow	1.00	0.30	0.02
		Chisel plow	0.55	0.17	0.01
		No-till	0.10	0.03	0.00
		No-till + Cover Crops	0.00	0.00	0.00
	C10 (slope = 2.0) *silty clay loam*	Moldboard plow	3.80	1.14	0.09
		Chisel plow	1.70	0.51	0.04
		No-till	0.20	0.06	0.00
		No-till + Cover Crops	0.00	0.00	0.00

3.4 DayCent simulations of SOC stocks

Modeled SOC stocks were compared to measured stocks calculated using the ESM method, since this method accounts for management-induced differences in bulk density (von Haden et al., 2020; Wendt & Hauser, 2013). SOC stocks calculated using the FD method are also plotted in Figure 4.5 for comparison. For four farm pairs ESM SOC stocks did not differ much from FD SOC stocks, but the values did differ substantially for pair 1. Field C1 and R1 had significantly different bulk densities (C1 = 1.17 g m^{-3} and R1 = 1.29 g m^{-3}), which is likely driving the different results based on SOC calculation method. Regenerative practices were adopted on field R1 relatively recently (8 years no-till, 6 years cover crops), so it is possible bulk density has increased slightly in the absence of tillage that would otherwise break up soil layers.

SOC stock change trajectories simulated in the DayCent model showed distinct trends across REGEN and CONV management systems. For the modern simulation period (1983 to 2023), simulations of REGEN fields showed C accruing at a faster rate than their CONV neighbors, although both management systems were accruing carbon (Figure 4.5). As expected, the point where no-till and cover cropping practices are added to the REGEN fields initiaties an increase in SOC accrual rate. Notably, several of the

paired field simulations start at significantly different baseline SOC stocks in 1983, despite management practices being the same up to that point. For example, the REGEN and CONV fields of pair 1 had simulated baseline SOC stocks of 51.5 and 62.4 Mg C ha^{-1}, respectively. Since weather was held constant between the paired fields, divergent baseline stocks are attributed to differences in soil properties and slope between the paired fields. To test the impact of soil properteis on SOC stock baselines, we reran the REGEN field simulations using the soils parameterization file (which contained measured soil textures and pH values and empirically derived bulk density, wilting point, field capacity, organic matter, root fraction, and saturated hydraulic conductivity (Ksat)) from the CONV neighbor. For pair 1, holding soil properties constant between the paired fields led to significantly different simulation outcomes, despite only minor differences in texture (R1: clay% = 28.61, sand% = 32.27; C1: clay% = 29.13, sand% = 32.70). When field R1 was simulated with the soil properties from field C1, the baseline and modern SOC stock values were shifted to 51.5 to 62.7 and 68.0 to 78.9 Mg C ha^{-1}, respectively. Similarly, when field R3 was simulated with the soil properties from field C3, the simulated baseline and modern SOC values increased by 7.68 and 9.45 Mg C ha^{-1}, respectively. The soils of field C3 and R3 also had more notable differences in texture, particularly in sand content (R3: clay% = 18.14 , sand% = 45.89; C3: clay% = 21.87, sand% = 34.6). The results of this analysis confirm the sensitivity of the DayCent model to soil properties (namely soil texture), which influence water and nutrient flows, SOC decompostion, and plant growth (Bonan et al., 2013; Parton et al., 1987).

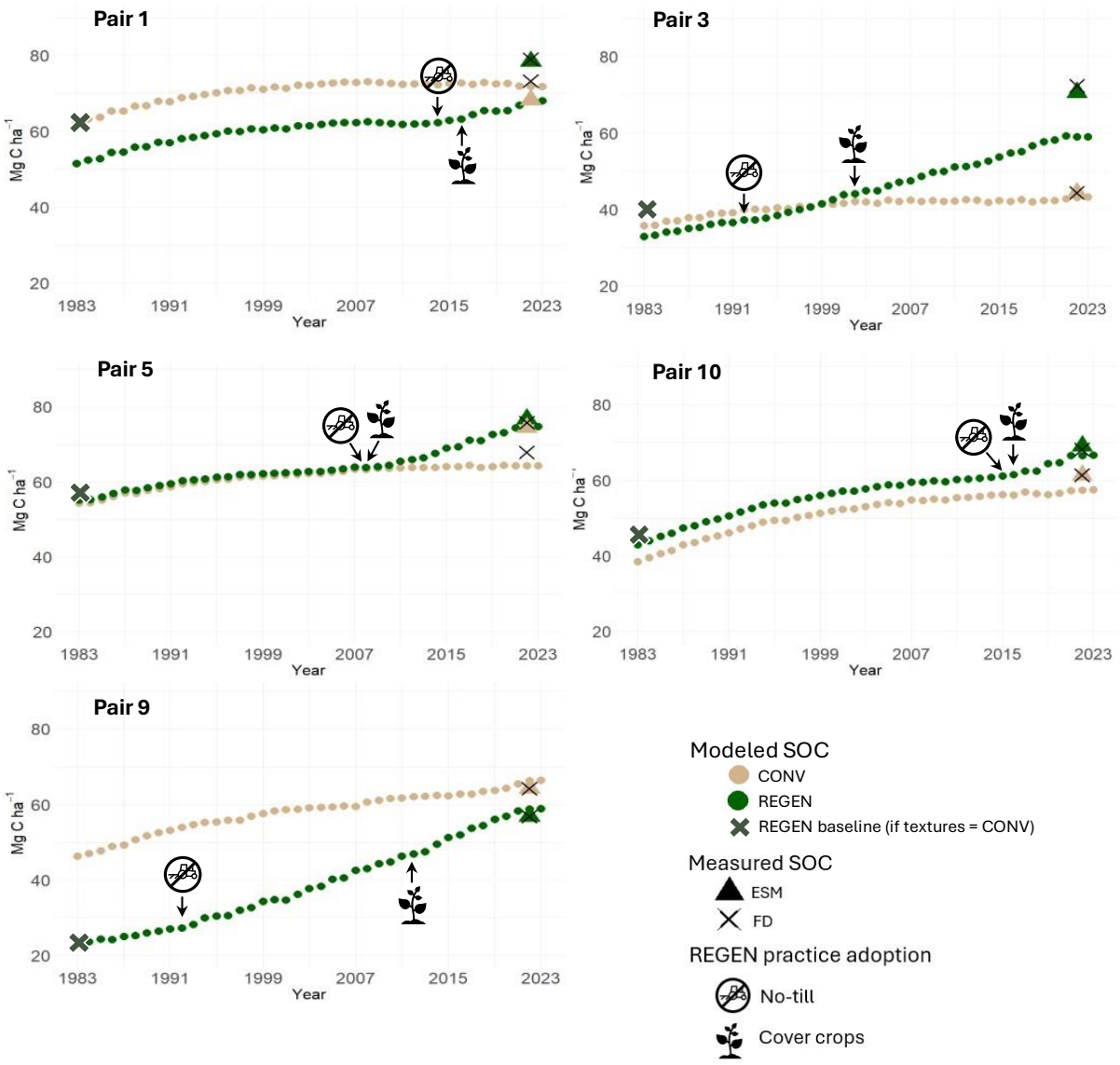

Figure 4.5 Modeled SOC stocks (Mg C ha^{-1}) from 1983 to 2022 across five neighboring farm pairs under conventional (CONV; tan) and regenerative (REGEN; green) management. Modeled timeseries values are represented as dots, while the 2022 measured SOC values are indicated as symbols based on SOC calculation method: triangles for equivalent soil mass (ESM) and crosses for fixed depth (FD) SOC stock. Icons indicate when no-till and cover crops were adopted on the REGEN fields. The grayish-green "X" at the 1983 time point indicates the simulated hypothetical SOC stock baseline value if soil textures were equivalent between the REGEN and CONV members of each pair (REGEN field is simulated with the soil inputs from the CONV field.

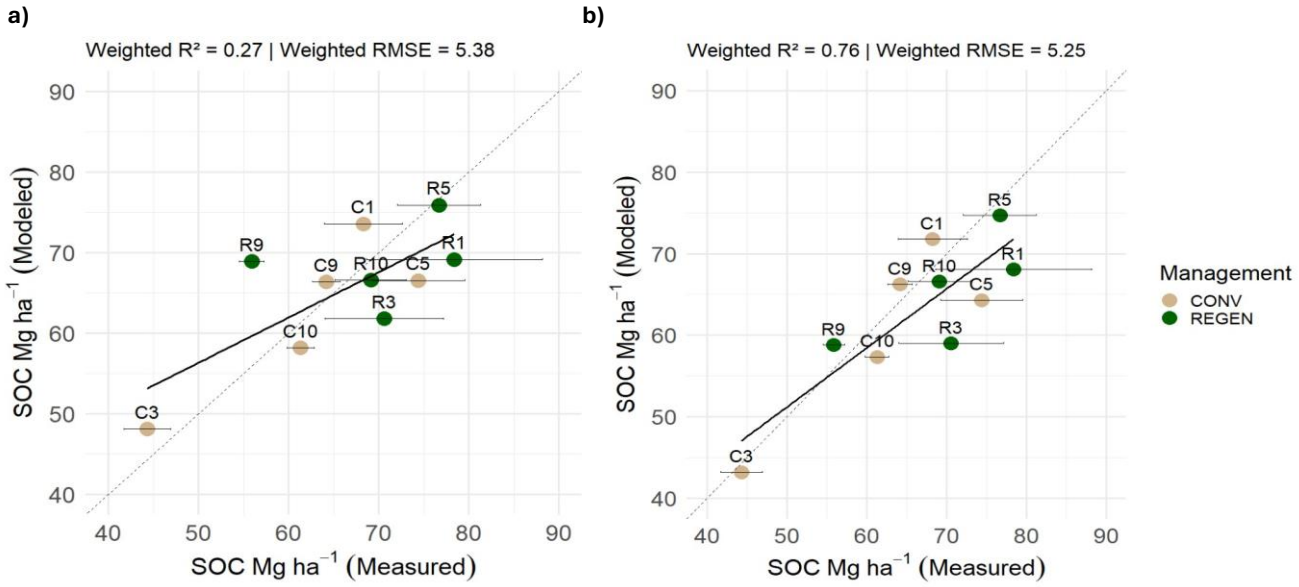

Figure 4.6 Modeled versus measured soil organic carbon (SOC) stocks (Mg ha^{-1}) for conventional (CONV; tan) and regenerative (REGEN; green) management. Panel (a) shows model fit prior to the addition of erosion processes, with a weighted R^2 of 0.27 and a weighted RMSE of 5.38. Panel (b) shows improved model performance after simulating erosion and deposition processes, with a weighted R^2 of 0.76 and a weighted RMSE of 5.25. The solid black line represents the regression fit, while the dashed 1:1 line indicates perfect agreement between modeled and measured values.

Comparing Figure 4.6a (measured vs. modeled SOC without simulating erosion/deposition) to Figure 4.6b (measured vs. modeled SOC with estimated erosion/deposition added to simulation) demonstrates a significant improvement in weighted R^2 (from 0.27 to 0.76), indicating that the updated model explains a greater proportion of the variance in the measured SOC values. However, this improvement only shifts the RMSE (from 5.38 to 5.25), which suggests the model may be overfit to outlier values. These results indicate that adding erosion to the model better captures the variability in SOC stock simulations, including those of eroded fields which were previously overpredicted by the model. However, the overall prediction accuracy has decreased for non-outlier values, leading to a higher RMSE. This tradeoff suggests that while the updated simulations better capture erosion-induced variability, they introduce greater deviations in other parts of the dataset. This highlights the ever-present challenge of balancing simulation complexity with prediction accuracy in process-based modeling.

4. Discussion

4.1 Simulating SOC stocks in DayCent: FD vs. ESM method

We evaluated the ability of the DayCent model to simulate measured SOC stocks calculated using two different methods: 1) FD method, where SOC stocks comparisons are made across equivalent soil depths and known soil volumes; and 2) ESM method, where SOC stock comparisons are made across consistent mineral soil masses to account for the impact of BD or SOM change that may occur under practice change. Most DayCent parameterization, calibration, and validation studies use the FD method (or the method is not stated) to calculate SOC stocks (Bista et al., 2024; Mathers et al., 2023), but more recent studies employ the ESM method (Chang et al., 2013; Dold et al., 2021b; Zani et al., 2023). As the soil science community moves towards the ESM method as the gold standard for comparing SOC stock differences between management systems or points in time, potential biases in the DayCent model to the FD method should be systematically evaluated.

4.2 Unique challenges of process-based modeling on commercial farms

Process-based modeling of commercial farm landscapes and management scenarios presents unique challenges that differ from modeling controlled experimental settings (Ellis & Paustian, 2024). A major obstacle is the need to obtain robust management records from farmers, including detailed information about field activities, including planting, harvesting, tillage, fertilization, and yields. In our experience, farmers' records are often incomplete, and lack of data can hinder the accurate simulation of agricultural processes. This challenge highlights the need for innovative solutions to generate field level management data that takes the onus off the producer, such as integrating modeling efforts with precision agriculture technologies or remote sensing techniques. Further, historical land management records (going back 20 years or more) are often completely unavailable, requiring modelers to make assumptions that can greatly affect model outcomes (Hartman et al., 2011). This challenge presents an opportunity for use of historical satellite imagery to reconstruct historical land use or gap fill existing records (Bégué et al., 2018; Deines et al., 2019; Souza et al., 2020).

Our results underscore a key limitation of on-farm field studies: the assumption that soil properties are similar between paired fields based on existing soil maps, despite the lack of preliminary sampling to confirm this. While we attempted to select areas of matching or similar soil types between the paired farms using SSURGO soil maps, several pairs had greater differences in measured soil properties (including texture and bulk density) than expected. Preliminary soil sampling could have refined site selection and better control for variability between paired fields. However, this also reflects the inherent complexity of commercial farmland, where soil textures, topography, and land use history can vary significantly within a single field. While researchers can strive to account for this variability through thoughtful study design, it is equally important to acknowledge the value of on-farm observational studies to highlight overlooked drivers of SOC change, such as field slope and historical erosion (Pennock & Frick, 2001). Our on-farm studies highlighted the differential influence of erosion processes on fields with seemingly minor differences in slope (~2-3°). Our results highlight the trade-offs between the experimental control afforded by controlled long-term research sites and the benefits of system-level studies of real-world farm settings.

4.3 Simulating erosion processes in DayCent: Application of RUSLE2

The displacement of SOC through erosion is recognized as a major driver of SOC redistribution in agricultural landscapes, with severe environmental and economic consequences (Chappell et al., 2014; Lugato et al., 2016; Thaler et al., 2022, 2022). As highlighted by Thaler et al. (2021), the loss of topsoil in the U.S. Midwest decreases crop yields by an estimated 6 ± 2% annually, translating to $2.8 ± $0.9 billion in economic losses across the Corn Belt. Remote sensing methods have emerged as valuable tools for identifying erosion hotspots and estimating their environmental economic consequences. However, their applicability is limited to areas with exposed soil, leaving significant gaps in residue-covered or no-till agricultural systems (Angelopoulou et al., 2019). While DayCent has been applied at fine spatial resolutions to estimate the SOC impacts of soil erosion at the regional scale (Lugato et al., 2016), our method of coupling RUSLE2 and DayCent can be applied without detailed spatial analysis. By pairing the DayCent model with empirical erosion models, we can extend the capability of process-based models

to estimate erosive soil loss, SOC displacement, and SOC change trajectories in a range of agricultural settings. The resulting estimates are a significant step forward in addressing the limitations of existing models and improving our understanding of erosion's role in shaping SOC stocks.

Degraded and eroded lands also represent areas of high potential for carbon sequestration, given their high SOC debts (Amelung et al., 2020; Bossio et al., 2020; Sanderman et al., 2017). Identifying erosion hotspots and assessing their potential as CO_2 sinks through process-based modeling can highlight priority areas for management intervention. Such targeted efforts not only improve the accuracy of SOC stock accounting but also guide regenerative practice adoption to enhance SOC storage in degraded areas.

In summary, integrating erosion dynamics into process-based SOC models addresses a critical gap in our understanding of agricultural soil systems. This approach enables a more accurate quantification of SOC change trajectories and provides insights into the ongoing impacts of historic and ongoing erosion. By identifying high-priority areas for regenerative practice intervention, we can progress towards more sustainable land management and enhanced carbon sequestration in agricultural systems.

5. Conclusion

This study demonstrates the importance of including erosion processes in SOC simulations for process-based models like DayCent. Particularly when simulating SOC processes on commercial fields with slight slopes (between 2° and 5°), erosion processes should be estimated and added to model events. By integrating empirical erosion data with model simulations, we improved SOC stock estimations, particularly in erosion-affected landscapes. When historical erosion processes were accounted for, the DayCent model accurately simulated the SOC changes associated with the adoption of regenerative practices, compared to conventionally managed neighboring fields. Future research could expand on-farm sampling and erosion estimation to a regional-scale to further test the DayCent model improvements with erosion simulation.

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AGRICULTURAL CONSERVATION NETWORKS IN IOWA[5]

1. Introduction

Iowa farmlands are renowned for their agricultural and economic productivity on an industrial scale. However, these rural lands face various environmental challenges, including soil erosion, waterway nitrogen pollution, and vulnerability to flooding and droughts that threaten their long-term sustainability and economic viability. Fortunately, many agricultural conservation practices (e.g., no-till, cover crops, wildlife habitat management) can reduce the environmental impacts of agriculture while continuing to reach yield goals. Despite considerable investments in incentive programs and technical support by the U.S. Department of Agriculture (USDA), Iowa Department of Agriculture and Land Stewardship (IDALS), and various non-governmental organizations, the overall adoption of conservation practices remains low. Research on conservation adoption has consistently focused on individual and farm-level factors to understand adoption behavior. Demographics such as farm size and land ownership have been positively associated with adoption (Zhang et al., 2018). Additionally, attitudinal factors such as risk tolerance and stewardship motivations have been associated with greater use of conservation practices (Bitterman et al., 2019; Popovici et al., 2023; Upadhaya & Arbuckle, 2021). However, meta-analyses of conservation adoption research indicate no consistent predictors of farmers' adoption behavior (Knowler & Bradshaw, 2007; Prokopy et al., 2019). For example, Prokopy et al. (2019) meta-analysis found that predictive factors, like land tenure, behave differently across studies. Overall, these meta-analyses call for a focus on structural factors that examine the socio-ecological context, including the social context in which farmers are situated.

[5] Ellis, E., Luxton, I., Arnold, P., Shakya, P., Lee, J., Ravetta, E., Toombs, T., Mook, A., Cross, J. (2023). *Agricultural conservation networks in Iowa.* Environmental Defense Fund & Institute for Research in the Social Sciences (CSU).

One method for examining the social context and the influence of social connections is called Social Network Analysis (SNA). This approach uses interviews and surveys to learn about the social connections (called "ties") between farmers and their friends, family**,** neighbors, and other professionals. It can also be used to identify sources of trusted information. SNA is useful for visualizing and exploring the impact of social connections on values, behaviors, and practices.

This study investigates the role of Iowa farmers' social networks in influencing the adoption behavior of conservation practices. We explore how farmers' social networks influence their behaviors by communicating and enforcing social norms. Networks serve as the channels through which knowledge and experiences are shared. Through surveying and interviewing Iowa farm operators, we examine how farmers' social networks influence behavior across multiple social scales. While previous studies utilizing SNA have primarily sought to identify community stakeholders, this study identifies the variety of sources farmers learn from, share information with, and view as trusted sources. We include a discussion of strategic implications to identify how the findings of this report may be translated into action to promote conservation adoption and inform future research efforts.

1.2 History of Iowa agriculture and conservation efforts

The current agricultural system in Iowa emerged from the volatile economic period of the 1980s farm crisis, along with the integration of technological and mechanical innovations allowing farmers to work on larger land areas. Iowa farmers face significant economic risks and uncertainty due to surging farmland values and increasing production costs. To overcome risk and remain competitive, the average farm size in Iowa has increased over the past several decades while the overall number of farm operations has declined. The most recent 2017 Census of Agriculture shows that Iowa lost 2,533 farm operations (about 3% of all operations) between 2012 and 2017, likely due to farmland consolidation (Edwards, 2019).

Iowa is among the most agriculturally productive states in the nation, with agriculture as the economic anchor for most counties. As with all agricultural production, the natural resources that make such economic prosperity possible are also at risk of degradation due to the prioritization of yield over environmental health (Leitschuh et al., 2022). Conservation efforts in the state are vital to ensuring continued economic prosperity and ecosystem health. Additionally, conservation efforts within Iowa can have impacts that ripple beyond the state's borders, particularly at the watershed scale. Given the documented link between Midwest agricultural activities and hypoxia in the Gulf of Mexico (Burkhart & James, 1999), efforts to reduce nutrient pollution can improve water quality locally and nationally. Iowa farmers have made significant progress incorporating conservation into agricultural production, partially thanks to financial and technical assistance programs. For instance, in 2022, the USDA's Natural Resources Conservation Service (NRCS) supplied Iowa farms with $70 million in funding for conservation and easement programming (NRCS, 2022). Additionally, efforts to increase adoption are also occurring among non-governmental organizations in Iowa. An analysis of survey data from Practical Farmers of Iowa (PFI) found that 71% of farmers adopted conservation practices thanks to their membership in the PFI (Asprooth et al., 2023). While conservation is important to Iowa farmers, there is a need to identify what factors influence practice adoption to encourage more widespread management change.

2. Study methods and systems framework

2.1 Sample

We surveyed 38 farmers from 10 counties in Iowa to compare the adoption of conservation practices in neighboring counties and across the state. We initially recruited farmers from neighboring Henry and Washington counties (southeast Iowa) because of documented disparities in adopting conservation practices. Despite their geographical and agronomic similarities, Washington County farmers have embraced cover crops at a rate twice that of Henry County farmers (20% vs. 10%). The adoption of cover crops was chosen as an indicator since it often reflects the broader use of conservation practices

(Wallander et al., 2021). Initial recruitment was carried out in Washington and Henry counties using a list provided by the NRCS and expanded through participant referrals. Participants from additional counties (Fayette, O'Brien, Wapello, Adams, Jasper, Jefferson, Johnson, Story) were also included to increase the sample size and assess the generalizability of findings. Cover crop adoption rates in the surveyed counties ranged from 5.0% to 20.4%, averaging 12.4%, slightly higher than the statewide average of 10.1% (USDA NASS, 2017).

2.2 Data collection

We used Network Canvas to collect data on social network characteristics and farm operations, including size, land tenure, commodities, and conservation practices. These practices were sourced from the NRCS list, with additional innovative practices added by the research team's soil scientist. The social network portion of the survey asked participants to name individuals within their social network to whom they go for conservation practice information or advice. The participants were free to identify members of their network anonymously (using initials or nicknames) if desired. We gathered information about each network member, including their relationship to the participant, what conservation practices they discuss, and their level of trustworthiness, innovativeness, and expertise. Participants also selected conservation-related organizations from which they received information and answered open-ended questions about adoption influences, barriers, and environmental challenges. Likert-scale questions assessed community perceptions of conservation practice use and practice impacts.

2.3 Analysis

Data collection was completed between December 2022 and March 2023. All surveys were exported from Network Canvas, cleaned, and imported into R for analysis and visualization. The initial data analysis phase included descriptive statistics for demographic and Likert-scale variables. We then analyzed different trends by groups, such as age, county adoption rate (high vs. low), types of

relationships, and crops and/or livestock produced. We used the Pearson correlation to assess the significance for correlations and determined significance based on p-values lower than 0.05.

We also included two types of social network analysis: 1) personal network analysis, in which we assess the networks of each individual farmer, and 2) two-mode network, where we connect farmers with the organizations, they reference for conservation information. Personal network analysis was carried out using the Igraph and Egor packages in R, which facilitate the assessment of the size and structure of each farmer's network and the characteristics of individuals within the network.

Open-ended responses were exported and coded thematically using NVivo, a software used for qualitative data analysis. In addition to coding open-ended responses, two research team members coded the conservation practices using a modified version of Peterson St-Laurent's (2021) "Resistance, Resilience, and Transformation" typology of conservation practices. Practices were categorized as 1) *fundamental* practices in the current system, 2) *improved* to enhance the current system function, or 3) *transforming* how the current agricultural system functions. The research team reached a consensus for coding discrepancies by considering how each practice is applied to the landscape and referencing the team members' professional, academic, and practical experiences with the practices in question.

2.4 Systems framework

We analyzed our data from a systems perspective, which outlines varying levels of social influence on individual actions. In this analysis, we focused on five distinct layers, including:

1) *Individual Level:* Individual farmers and their characteristics, practices, and attitudes around agricultural conservation.

2) *Interpersonal Network:* The people within each individual network to whom they go for information about conservation practices, including what conservation practices they discuss, as well as their network connections' knowledge, leadership, and innovative experience in conservation, according to the participant.

3) *Perceptions of Community:* The perceived social norms and local community attitudes toward conservation, according to the participant.

4) *Local and Regional data:* Local and regional policies, programs, and incentives and their impact on adoption rates of conservation practices.

5) *Societal Influences:* conservation information is accessed through social media, agricultural news media, government programs, and other agricultural organizations with a broader reach than the local community.

This framework offers a nuanced perspective on the drivers and barriers shaping conservation practices by examining individual behaviors within the context of interpersonal networks, community norms, local/regional policies, and overarching societal influences. Mapping relationships and connections between individual networks can reveal patterns of influence, knowledge sharing, and innovation diffusion within a community. Furthermore, data analyzed within a systems framework can be better contextualized within the community's social norms and regional policies, helping to identify how these factors affect conservation practices. Understanding local, regional, and societal network influences can inform the development of more effective policies, incentives, and interventions to promote agricultural conservation.

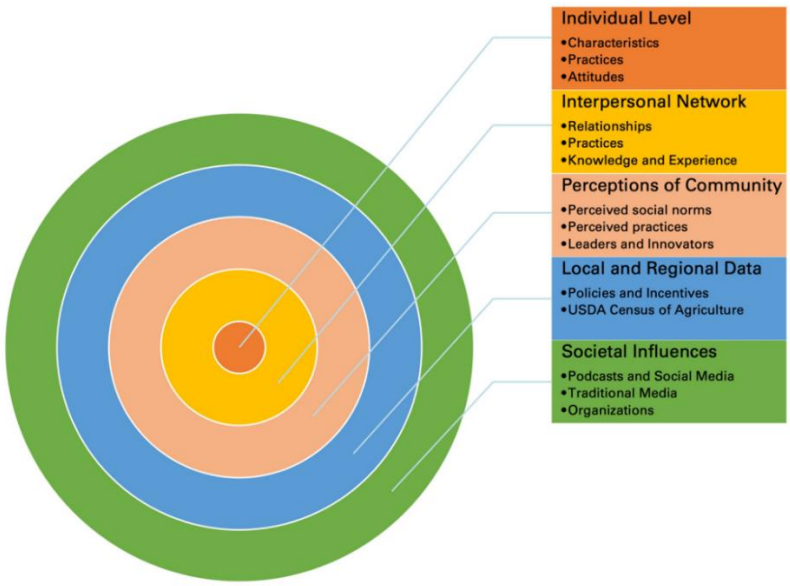

Figure 5.1 Systems framework for analyzing how social networks and broader societal factors influence conservation practice use on Iowa farmland.

3. Results

3.1 Farmer characteristics and conservation practices adopted

We surveyed 16 farmers in Washington County, 9 in Henry County, and 12 from other counties in the state. Figure 5.2 illustrates the location of participants and whether they are in a high-adoption or low-adoption county. High-adoption counties are those with cover crop adoption rates above the statewide average. 95% of participants were male, 100% were white, and ages ranged from 28 to 82, with an average age of 55. Farm size ranged from 40 to 5200 acres. 58% of farmland acres are owned by the primary operator. Farmers age 60+ own 33% more acres than younger farmers, on average. 97% of participants produced corn and soybeans. Participants also produced livestock, forage crops, small grains, and specialty crops. In the following section, we discuss the major findings of this research, including:

1. The most frequently applied fundamental, improved, and transformational conservation practices and adoption practices by type of farm production.
2. Farmer attitudes toward agricultural conservation practices.
3. The role of social networks and community perspectives, including how friends, neighbors, and local agricultural leaders influence conservation practice adoption.
4. The role of local incentives and government programs in encouraging farmers to adopt conservation practices.
5. The role of broader societal influences, such as media and regulations, in shaping farmer attitudes and adoption practices.

3.2 Types of conservation practices and levels of adoption

Analyzing farmers' adoption of conservation practices and their motivations is crucial for promoting agricultural sustainability and assessing the influence of social networks in disseminating innovation. Some conservation practices are more difficult to adopt than others. Some fit easily into the existing production system (i.e., crop rotation), while others require a transformation of the current mode of production on a portion of acres (i.e., upland wildlife habitat establishment). Figure 5.3 illustrates several

conservation practices commonly used by participants. We organize these practices according to the following typology:

- *Fundamental:* commonly used conservation practices, often prescribed or mandated in some production systems or ecologically sensitive areas.
- *Improved:* practices that reduce the environmental impacts of existing production systems, often requiring a financial or technical investment from the producer.
- *Transformational:* practices that transition to fundamentally different ways of farming or land uses (e.g., away from annual row crops toward perennial vegetation, pasture, or restoration of native ecosystems).

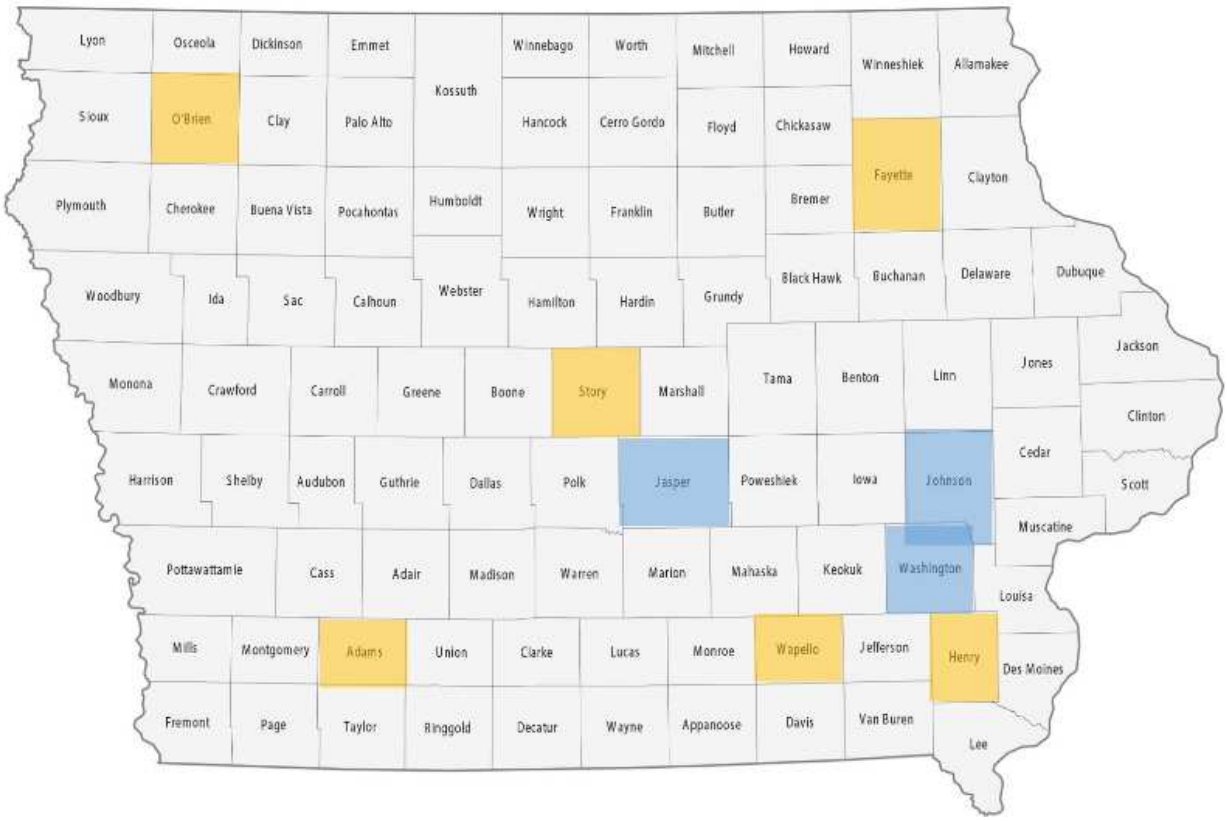

Figure 5.2 We surveyed 38 farmers from nine different counties across Iowa. Counties with cover crop use above the statewide average (10.1%) are classified as "high-adoption" (shown in blue), while counties with below-average cover crop use are classified as "low-adoption" (shown in yellow).

While research suggests that improved and transformational practices are superior, effective use can be a learning curve. In our sample, *fundamental practices*, particularly crop rotation and grassed waterways, are the most reported practices, especially in high conservation areas. Nearly all farmers in our sample use a variation of a corn-soybean rotation to reduce pest pressure and nutrient input requirements. The most common *improved practices* are no-till and cover crops in high-adoption areas. Interestingly, multispecies cover crops are more commonly practiced among respondents in low-adoption areas. These farmers could be local innovators less connected to neighbors doing similar things. Among the *transformational practices*, conservation cover, which means planting a permanent cover crop specifically to restore soil health, is used by farmers in both high- and low-adoption counties in our sample. Other transformational practices remain uncommon, even in our sample of conservation-minded farmers. However, upland wildlife habitat management, where a portion of the farm provides habitat for wildlife during their lifecycle, was more common in counties with low adoption of other conservation practices.

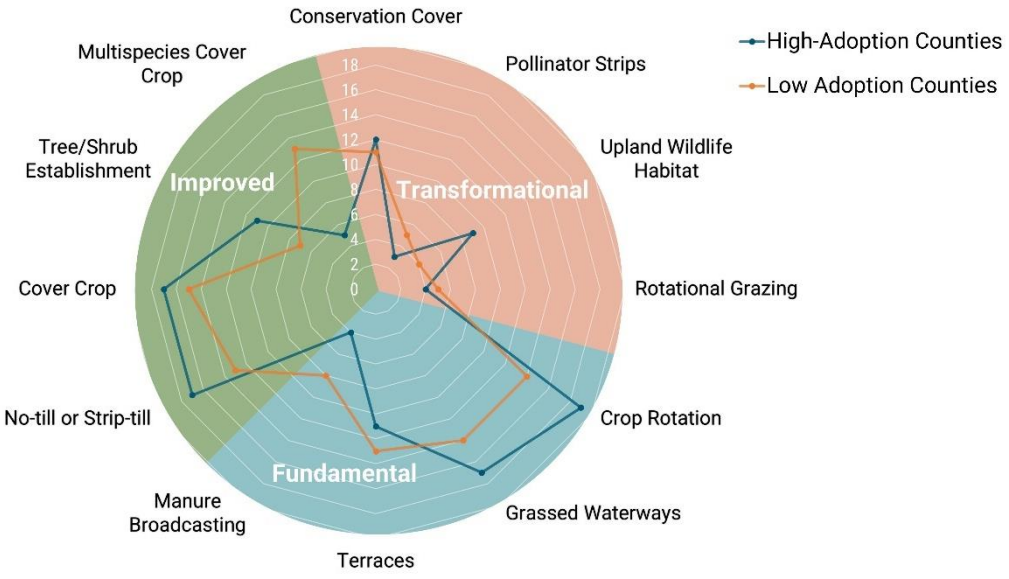

Figure 5.3 The number of farmers using select conservation practices, separated by counties with high-adoption of conservation practices (blue line) and low-adoption (orange-line). The practices are organized into three categories: 1) "fundamental", basic conservation efforts; "improved", practices that require a

greater financial or technical investment; and “transformational”, practices that transition to fundamentally different ways of farming.

Some conservation practices are more likely to be adopted in specific production systems. In Figure 5.4, we see that farmers who plant a combination of corn, soybeans, alfalfa, and livestock are more likely to adopt agricultural conservation practices. Multi-crop farmers are more likely to adopt transformational conservation practices, such as rotational grazing and upland wildlife habitat. The results suggest that farmers deviating from strict corn-soybean rotations to create a greater diversity of crops and livestock are more likely to adopt conservation practices incorporating alternative land uses.

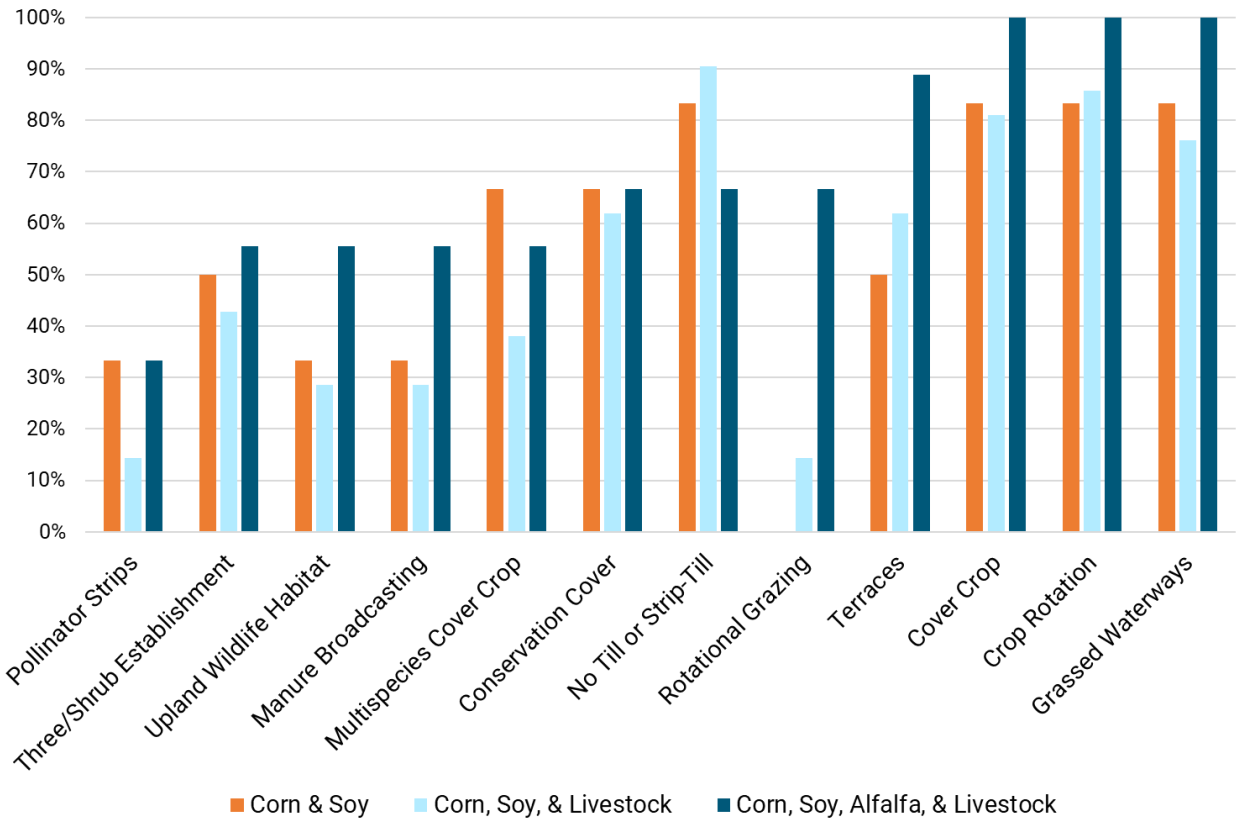

Figure 5.4 The rate of conservation practice used by types of crops produced. Farmers who plant a combination of corn, soybeans, alfalfa, and livestock are usually most likely to adopt agricultural conservation practices and multi-crop farmers are more likely to adoption transformational conservation practices.

3.3 Values, beliefs, and barriers to adoption of conservation practices

Figure 5.5 illustrates farmers' attitudes toward conservation practices and how their community responds to management choices. All participants in low-adoption counties “strongly agree” that they are “looking to increase conservation on their farms.” In contrast, half of the participants in the high-adoption counties “agree.” However, farmers in high-adoption counties are more likely to agree that the “community benefits from their conservation efforts,” that “conservation changes their farm operations positively,” that they are “known for experimenting with conservation,” and that they “feel their conservation efforts are appreciated” by their community. Although the high-adoption county respondents were more likely to view agricultural conservation practices positively, the differences between the two groups are minimal.

Responses to open-ended survey questions illustrate that farmers are motivated by various factors when adopting new conservation practices. These include a desire to protect the soil for future generations, to respond to land and operation needs (e.g., erosion, soil water capacity, labor, cost-sharing benefits), and to increase the resilience of their operation through expanded economic opportunities offered by conservation practice adoption.

Many farmers in our sample highlighted the importance of protecting soil for future generations as a driving force for conservation practices. Many respondents had a family legacy of farming the land. These family farms viewed maintaining or improving soil health as essential to sustain the land for future generations. One farmer stated, *“We want to hand this down to our kids and make it better for them. Why wouldn't we want to improve it for kids and the community?”*

Many participants spoke of the difficulty of restoring soil health once it has been depleted, emphasizing the need to prevent soil degradation proactively. As the cost of land increases, farmers also noted that expanding operations has become increasingly complex, thus further highlighting the need to “*protect what we have for the next generation.”*

Farmers also identified challenges and barriers to adopting conservation practices, including cost, the size of their operation, and their unique land and operation needs:

"*When deciding against adoption, cost is a huge factor. We are limited because of the size of our farm. Take cover crops, for example. If you have a massive operation, you can make a good return on your investment even when buying new equipment. It is more complex with smaller-scale operations. The second thing is the availability of labor to implement new practices because we raise hogs full-time, and there is a limit to how much we can get done. On the positive side, no-till saves us money and time and requires less equipment. When we look at something, what will it cost us? Getting that return is more difficult if it takes a long time.*"

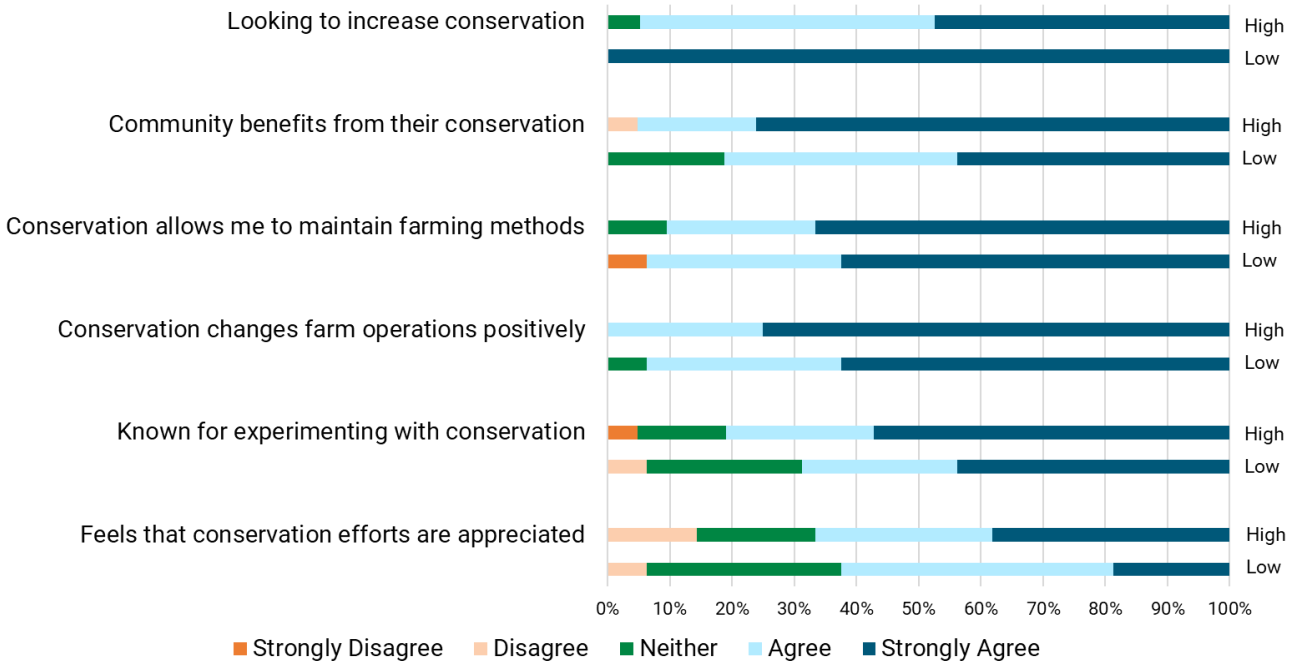

Figure 5.5 Farmer attitudes toward agricultural conservation practices, organized by high- and low-county adoption counties. Although the high-adoption county respondents were more likely to view agricultural conservation practices positively, the differences between the two groups are minimal.

Farmers often highlighted the practical advantages of conservation practices. Conservation practices were used to navigate land and operational needs, such as reducing labor demands through no-till or using cover crops to reduce soil erosion and nitrogen loss. Participants recognized that adopting conservation practices might require initial investment and effort, but they believed the long-term benefits

were worth it. Conservation practices with observed benefits and low adoption costs were more likely to be sustained through land operation changes and spread throughout the community.

In the context of social networks, when farmers experience tangible benefits from conservation practices with relatively low adoption costs, they are more likely to continue using these practices and share their success stories with their peers. This can trigger a ripple effect within their agricultural community, as word-of-mouth and shared experiences within social networks can lead to broader adoption and sustained use of these practices. We discuss the positive impact of peer modeling in more detail in the following sections.

3.4 The role of information, innovation, and trust in the adoption of conservation practices

1) *Social networks influence access to conservation information.*

Farmers are most likely to report discussing agricultural conservation practices with local friends, neighbors, and family. They also seek advice from USDA employees, agronomists, and university extension agents. They trust the views of transactional relations such as seed or chemical salespersons to a much smaller extent.

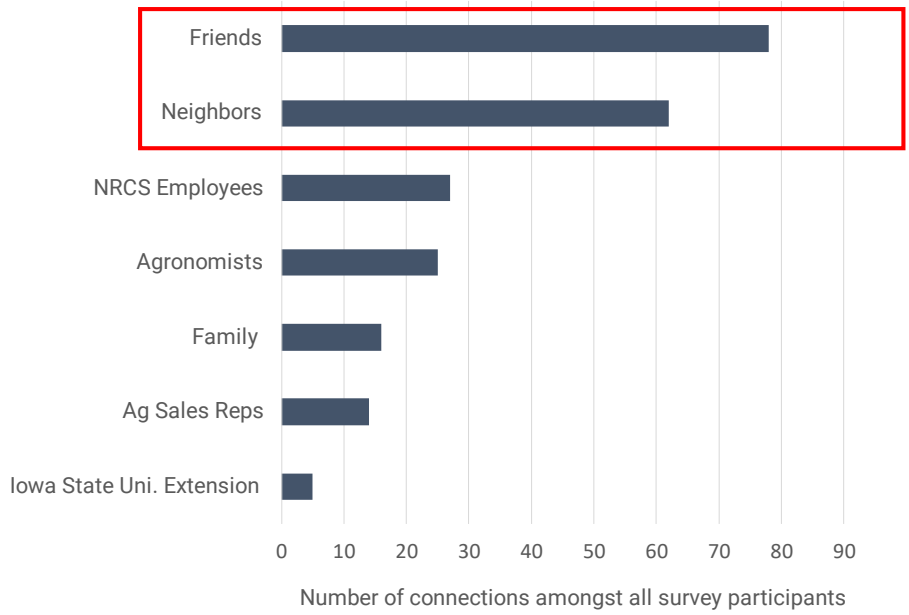

Figure 5.6 Number of connections mentioned by all farmers surveyed, organized by relationship type. Friends and neighbors were the most common type of personal connection from which survey participants received conservation information.

2) *Degree of knowledge, trust, and innovation impact how network connections influence conservation adoption.*

Respondents were asked three Likert scale questions regarding the level of trust they have with individuals in their social network, as well as the individuals' level of knowledge and innovation around conservation practice use. For each question, we separated responses into three groups of connections: 1) Personal relationships (e.g., family, friends, neighbors), 2) Professional relationships (e.g., USDA employee, Extension agent, landlord), and 3) Other (e.g., acquaintance, equipment dealer, sales representative).

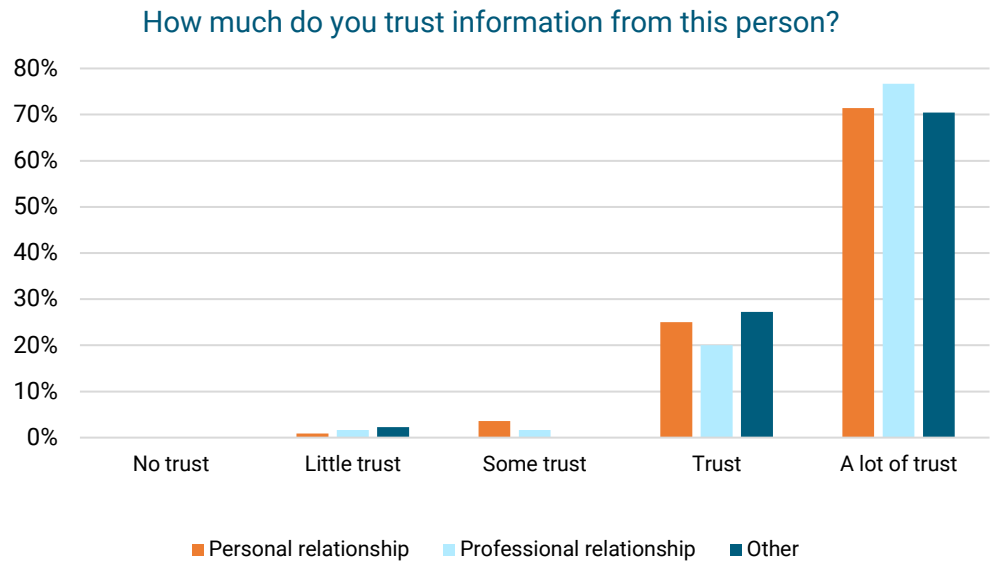

Figure 5.7 Percent of farmers' ratings of the trust they have in information from members of their social network organized by relationship type. Farmers had "trust" or "a lot of trust" from members of their network, with more farmers having "a lot of trust" in their professional relationships.

For the first question (*How much do you trust information from this person*?), most farmers said they have "trust" or "a lot of trusts." While all three relational groups are similar, more farmers had a "a lot of trust" in the knowledge of their professional relationships.

Responses to the second question (*How knowledgeable is this person regarding land stewardship needs in your area?*) were slightly more varied. Most were "moderately knowledgeable" or higher across

all relationships. Farmers found most personal and professional relationships to be "very knowledgeable" or "extremely knowledgeable."

Those in the "Other" category had the widest variation of responses, with slightly less than 10% saying "not very knowledgeable" and nearly 50% saying "extremely knowledgeable." This is unsurprising as the "other" category holds a wider variety of relationships, and individuals were frequently located outside the local community, making knowledge about local needs more variable.

The last question (*To what extent do you consider this person an innovator of land stewardship?*) showed the greatest response variation. Farmers found their personal relationships to be "somewhat innovative" or "very innovative," although responses were recorded across the spectrum. However, 60% of those in the "Other" category were classified as "very innovative." Individuals in the "Other" category included agricultural experts, consultants, and farming and environmental conservation professionals. These individuals represent a diverse network of people with varying agricultural roles and expertise, including seed production, conservation, agronomy, and business. Additionally, this list includes mentors, colleagues, and acquaintances who provide support and guidance in farming and related endeavors while not necessarily being farmers themselves.

Thus, the variation in perceived innovation may result from the individual's occupation – many were not farmers and, while they were sources of knowledge, were not considered conservation innovators. Across all questions, farmers seem to have a high level of trust in members of their social networks, seeing them as being somewhat or highly knowledgeable and many as innovative.

These findings illustrate that farmers in the study demonstrated high trust in individuals within their social networks, regardless of the type of relationship. This trust is crucial for information sharing and decision-making within farming communities. Trust, knowledge exchange, and innovation diffusion within these networks are key drivers of adopting conservation practices. The strong trust in professional relationships, such as USDA employees and Extension agents, indicates the importance of these experts in providing valuable guidance and information related to conservation practice use.

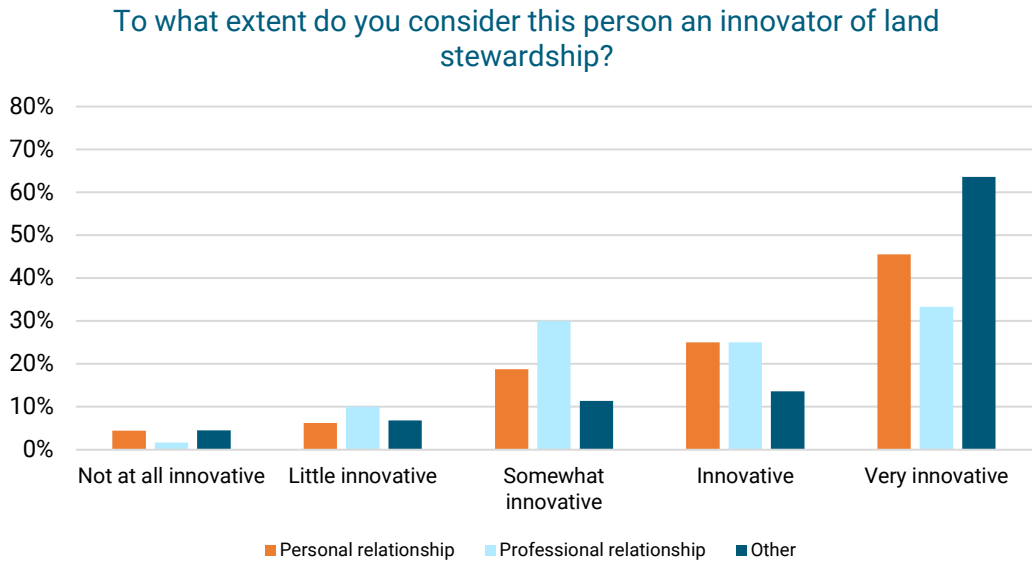

Figure 5.9 Percent of farmers' ratings of how they perceive other individuals' land stewardship innovation, grouped by the type of relationship. Most farmers viewed their networks members as "somewhat innovative", "innovative", or "very innovative". Interestingly, "other" members were perceived to be the most innovative.

Farmers perceive individuals in their personal and professional networks as highly knowledgeable, illustrating the role of social networks in disseminating valuable knowledge and best practices among farmers. Personal relationships, like family and friends, also play a significant role in knowledge exchange. The perception of innovativeness varied widely among different relationship categories. While personal relationships were generally seen as somewhat or very innovative, the "Other" category, consisting of agricultural experts, consultants, and business partners, had a higher proportion classified as "very innovative." This suggests that individuals with diverse agricultural roles and expertise contribute significantly to innovation within the farming community. Expanding connections to diverse individuals is key to encouraging practice adoption.

3.5 Community characteristics and conservation practice adoption

The social network data revealed differences in relationships and conservation practices discussed between counties with high conservation practice adoption versus low-adoption counties. For example, improved (i.e., cover crops and no-till) and transformational practices (i.e., pollinator strips and rotational

grazing) are discussed more often among individuals in high-adoption counties (Table 1). Interestingly, the types of connections varied substantially between high- and low-adoption counties. Farmers in high-adoption counties often turn to agricultural professionals for conservation practice information, while farmers in low-adoption counties are likelier to consult friends and neighbors.

Differences in the types of relationships in high- and low-adoption counties may be explained by variability in access to agricultural professionals, local referrals to agricultural professionals by friends and neighbors, and trust in the knowledge and experience of agricultural professionals. Further, farmers in high-adoption counties tend to have slightly longer relationships, with higher levels of trust and perceived knowledgeability. However, farmers from high-adoption counties perceive their connections as less innovative on average, perhaps because the standard for innovative agriculture has been raised in those communities.

Finally, farmers in high-adoption areas have, on average, more connections (3.7) from whom they seek advice regarding conservation practices than farmers in low-adoption areas (3.0). Farmers in low-adoption counties have more densely connected networks, where about half of all individuals know each other, versus only about a third in high-adoption networks. Furthermore, high-adoption areas report more connections with individuals not connected with others in their networks (0.52 vs. 0.31 in low-adoption networks). To see a representation of all farmer networks in this study, see SI Figure 5.1.

The network statistics above suggest that farmers in high-adoption networks, on average, tend to be connected to a more diverse range of individuals with distinct knowledge and experiences. In contrast, those in low-adoption areas are more likely to be exposed to knowledge and experiences that other members of their networks reinforce. These findings affect how information and innovation flow through farmer networks and how these connections may be strengthened to encourage conservation adoption. For example, high-adoption counties may benefit from diversifying their connections, potentially leading to greater exposure to innovative ideas and practices. In contrast, low-adoption areas may benefit from strengthening existing connections and building new ones to encourage knowledge sharing and adopting innovative practices.

Understanding these network dynamics can inform strategies for promoting conservation practices, emphasizing the importance of leveraging diverse networks, building trust in professional expertise, and fostering connections that encourage the exchange of innovative ideas within agricultural communities.

Table 5.1 Practices of farmer connections and network characteristics. Farmers in high-adoption counties often turn to agricultural professionals for conservation practice information, while farmers in low-adoption counties are more likely to consult friends and neighbors. [1]*Average degree* refers to the mean number of relationships from whom the respondent seeks advice regarding agricultural conservation practices. *Density* refers to the percentage of connected individuals among all possible connections in a network. *Average isolates* refer to the number of individuals not connected to anyone else other than the respondent in the network.

Conservation practices discussed with alters	**High adoption**	**Low adoption**
Tree/shrub establishment	5.97%	6.08%
No-till or strip-till	38.8%	48.7%
Cover crop	62.7%	55.7%
Multispecies cover crop	29.9%	14.8%
Conservation cover	8.96%	6.09%
Pollinator strips	7.46%	0%
Upland wildlife habitat	1.49%	3.48%
Rotational grazing	10.4%	7.83%
Types of relationships		
Friends	41.8%	43.5%
Neighbors	28.4%	37.4%
Family	5.97%	10.4%
Agricultural professionals	40.3%	25.2%
Relationships		
Length	23.6 years	21.21 years
Trust	4.75	4.64
Innovative	3.74	4.17
Knowledgeable	4.26	4.11
Network statistics[6]		
Average degree	3.7	3.0
Density	0.36	0.49
Average isolates	0.52	0.31

1) *Learning from the challenges and successes of peers is a driving force of conservation practice adoption.*

Farmers often turn to those in their community who have successfully adopted conservation practices for advice, sharing of best practices, and troubleshooting. Survey responses from farmers in high and low- and high-adoption counties highlighted the importance of peers to motivate change in their communities and beyond. Learning from other farmers' lived experiences, challenges, and successes was critical in influencing adoption. Peers provide experiential knowledge and practical insights that address local challenges and conditions, making the adoption process less daunting:

> *"Watching what other people are doing in the community and seeing what worked for them and why it did not work has been helpful for me. We had some things that did not work through the years, and I was able to network with other people and learn about their successes and challenges."*
>
> *"I think what has motivated me most has been the results. They work. Some guys say if Roger can make it work, and he has not gone broke, then it works. I watched Sean some and saw the successes; I had to figure out how to implement it onto corn. I did that, and it worked."*

When farmers see their neighbors succeeding with these techniques, it shows that these practices work and can be successful in the local context. The presence of positive peer role models and the opportunity to learn from others in the community was a driving force in adoption for many farmers. In addition to sharing information, some farmers also shared equipment to reduce the cost of adoption. For farmers lacking connections to other adopters, the internet became a place of farmer-to-farmer connection and knowledge sharing.

Importantly, while most farmers in our sample highlighted the positive impact of peers, peers can also have negative influences on behavior change. For example, when peers predominantly model existing or traditional practices (i.e., the status quo), it can create a sense of normalcy and inertia within the community. This normalization or "lock-in" makes it challenging for individuals to deviate from

established norms and embrace new, innovative approaches. If most peers resist change, this can create a culture of resistance within the community. New ideas or alternative practices may be met with skepticism or resistance, making it difficult for innovators to gain support. To combat the negative influences of peers modeling the status quo, efforts should be made to promote a culture of innovation, knowledge sharing, and openness to change within farmer networks. Sharing success stories, educating peers about the benefits of conservation, and creating support networks beyond local community boundaries can encourage positive change.

2) *Farmers in high-adoption counties are more likely to perceive their community as enthusiastic about conservation than farmers in low-adoption counties.*

Figure 5.10 shows responses to Likert scale questions regarding how farmer participants perceive their community's attitudes toward conservation practices. Farmers in high-adoption counties report higher levels of agreement with all statements, including strongly agreeing that their community is: "enthusiastic about incorporating conservation," "willing to try new conservation practices," "open to sharing conservation information," and "concerned with soil health and water quality." Further, most farmers in high-adoption counties agree or strongly agree that they have access to various options for marketing crops and livestock. Responses from farmers in low-adoption counties indicate their community is less concerned with environmental health and less enthusiastic about adopting conservation practices.

3) *In high-adoption counties, farmers who report that their community is concerned about soil and water health also fell that their conservation efforts are appreciated.*

Figure 5.11 shows correlations between Likert scale survey questions regarding community perceptions and individual attitudes towards conservation practices. If a farmer responds "strongly agree" to one question, they are likely to respond similarly to a question that is shown to be correlated. For example, the correlation indicates that the perceived community "concerned about soil and water health" significantly correlates to the community being "enthusiastic about conservation" and "willing to try conservation practices."

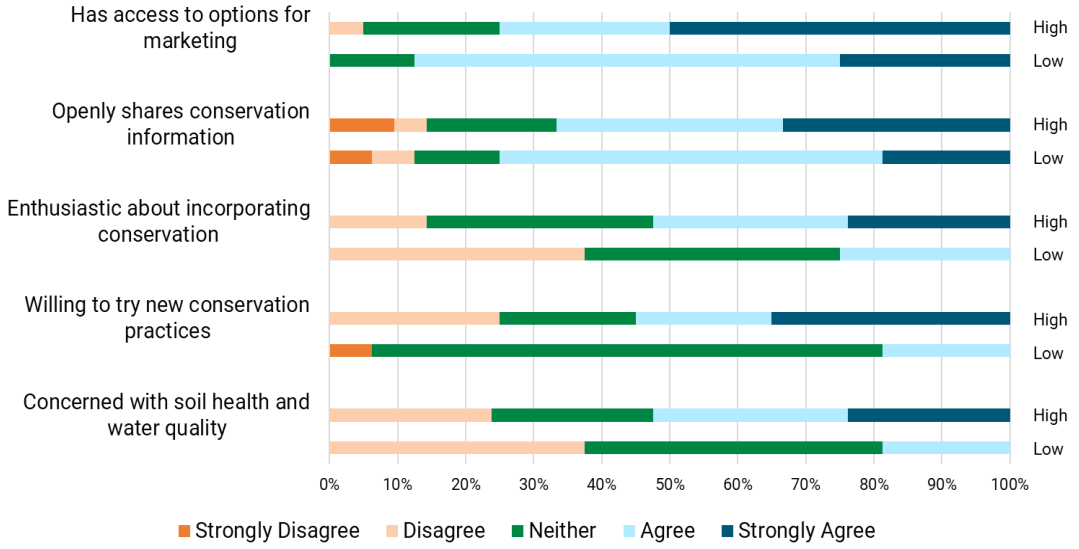

Figure 5.10 This chart illustrates differences in community attitudes and perceptions in high-adoption and low-adoption counties regarding conservation practices. These values are based on the farmer's perspective of their community. Farmers in high-adoption counties reported higher levels of agreements across statements. Farmers in low-adoption counties indicated that their community is less concerned with soil health and water quality and less enthusiastic about conservation.

We also see that the community's "willingness to share conservation information" strongly correlates to "enthusiasm for conservation" and "willingness to try conservation." Having access to various "options for marketing grains/livestock" also correlates strongly with perceived community "enthusiasm for conservation" and willingness to "share conservation information" (Figure 5.11). "Looking to increase conservation" on their farm was strongly correlated with "experimenting with new practices." Further, farmers who felt their "conservation efforts are appreciated" by other farmers and their community also felt that their community "benefited from their conservation efforts," which "positively changed how their

farm operates." In summary, we found moderate to strong correlations between people who 1) feel the community appreciated conservation efforts, 2) that their community benefits from their conservation efforts, and 3) that the community is enthusiastic about conservation. Similarly, we also find correlations between 1) believing that the community benefits from conservation and 2) community enthusiasm for conservation with 3) community willingness to try conservation and 4) community willingness to share conservation information. These findings suggest that farmers are more likely to feel appreciated in relatively conservation-oriented communities.

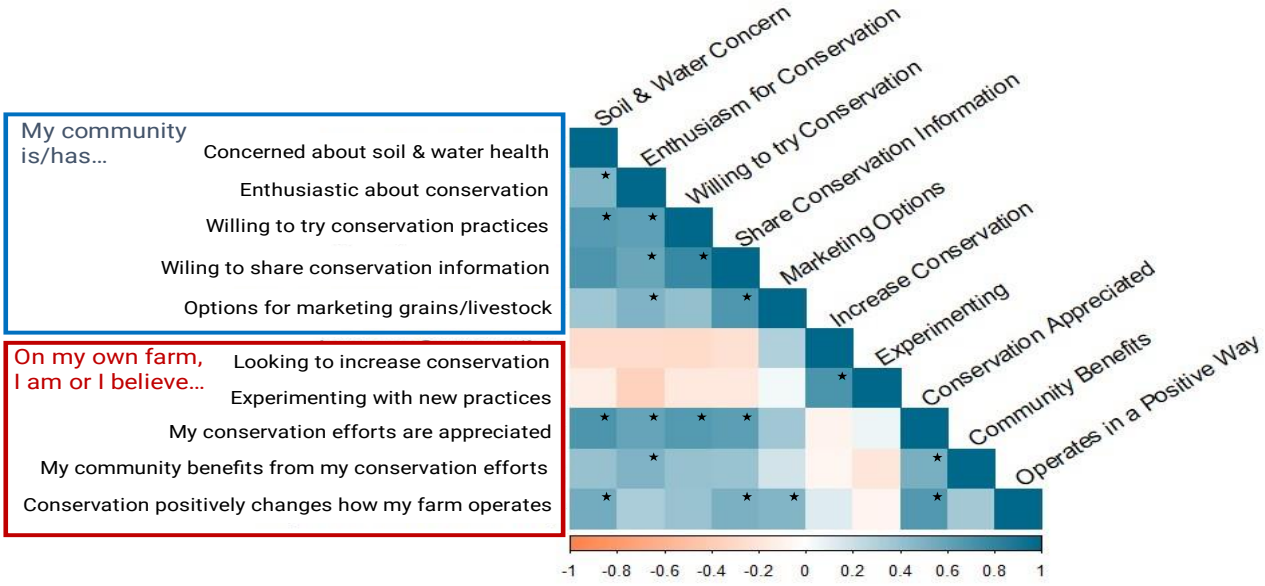

Figure 5.11 Correlation of high-adoption farmers' community perspectives and farming operations in their county. Red indicates a negative correlation, while blue indicates a positive correlation. The strength of the correlation is illustrated by the color shade. A * indicates the correlation has a significance at p-value of < 0.05.

4) *In low-adoption counties, farmers who report experimenting with agricultural conservation practices also feel that their conservation efforts are appreciated.*

Figure 5.12 shows similar correlations to those reported in the high-adoption county figure (Figure 5.11). However, farmers in the low-adoption subsample, in contrast to those in high-adoption counties, have a weak negative correlation between "options for marketing grains and livestock" and variables describing the community's interest in conservation. This suggests that lacking marketing options for

marketing unique products derived from conservation-oriented production (i.e., cover crop seed, organic products, grass-fed livestock) might lower community interest in conservation.

Furthermore, there are considerably weaker correlations between variables concerning community appreciation for conservation, willingness to share information, and concern for soil and water health. This suggests that individual adopters of conservation practices in low-adoption counties may benefit from programming that supports adoption and informs communities of the broader impact of conservation beyond the farm level.

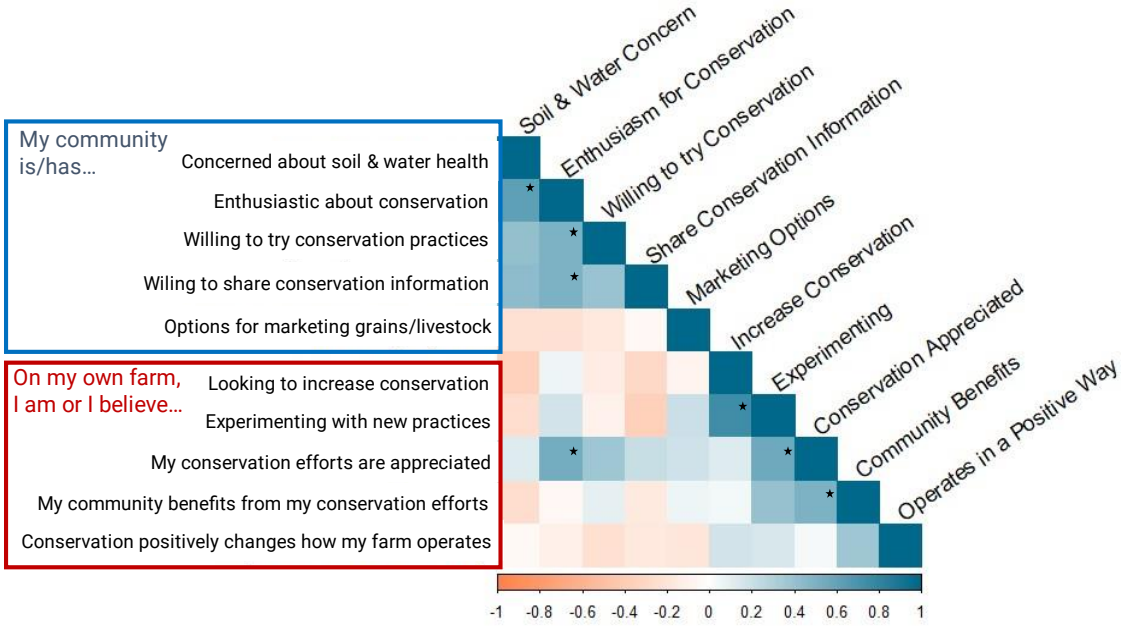

Figure 5.12 Correlation of high-adoption farmers' community perspectives and farming operations in their county. Red indicates a negative correlation, while blue indicates a positive correlation. The strength of the correlation is illustrated by the color shade. A * indicates the correlation has a significance at p-value of < 0.05.

There are weak negative correlations regarding community benefits and conservation, where respondents believe the community benefits (see Figure 5.5 under Attitudes and Motivations) but rate the community low for interest in conservation. Social networks in these areas may not provide the same level of communal support and recognition for conservation efforts. Consistent with high-adoption counties, there is a strong significant correlation between wanting to increase conservation and experimenting with conservation, experimenting with conservation, believing that conservation is appreciated, and believing that conservation is appreciated and benefiting the community. Social

recognition is likely an important aspect in adopting conservation practices, illustrating the influence of social networks and perceptions of community values on farmer attitudes and behaviors. Communities with higher perceived enthusiasm, information sharing, and recognition for conservation efforts are more likely to see increased adoption, while low-adoption areas may require more targeted interventions, such as expanding connections to other networks, to promote conservation.

5) Community perspectives of conservation may lead to differences in practice adoption.

Table 2 shows correlations between farmer perspectives and the use of twelve common conservation practices, organized into "fundamental," "improved," and "transformational practices." Manure broadcasting negatively correlates with community concern for soil and water health, meaning farmers are less likely to use this practice if concern for soil and water health is high. This is likely because manure is an excellent fertilizer that can help build soil organic matter, but it also has the potential for runoff that compromises water quality. Terrace farming, a method of cropping that can prevent erosion, is significantly correlated with community willingness to share conservation information. Maintaining grassed waterways, a practice used to improve runoff quality significantly correlates with the belief that conservation benefits the farm.

	Community Perspective					Farm Operations				
	Soil & Water Concern	Enthusiasm for Conservation Practices	Willing to try Conservation Practices	Share Conservation Information	Marketing Options	Increase Conservation	Experimenting	Conservation Appreciated	Community Benefits	Operates in a Positive Way
Transformational practices										
Conservation Cover	-0.05	0.01	-0.23	-0.31	-0.01	0.21	0.20	0.04	-0.24	0.16
Pollinator Strips	-0.11	-0.29	-0.08	-0.40	-0.15	0.13	0.10	-0.18	-0.08	0.05
Upland Wildlife Habitat	0.07	0.12	-0.09	-0.04	0.18	0.33	0.42	0.24	-0.10	-0.06
Rotational Grazing	-0.18	-0.24	-0.20	-0.15	-0.03	0.05	0.02	-0.49	-0.61	-0.13
Improved practices										
Crop Rotation	0.25	0.11	0.09	-0.07	-0.07	-0.01	-0.11	0.21	-0.12	0.02
Grassed Waterway	0.17	-0.10	-0.14	-0.22	-0.19	-0.08	-0.21	0.00	-0.20	0.34
Terraces	0.05	0.17	-0.06	0.28	0.15	-0.24	-0.14	0.17	-0.05	-0.18
Manure Broadcasting	-0.43	-0.21	-0.18	-0.21	-0.04	0.12	0.21	-0.12	-0.06	-0.03
Fundamental practices										
Cover Crop	-0.15	-0.20	-0.10	-0.15	-0.21	-0.18	0.07	0.10	-0.27	-0.11
No-till or Strip-till	0.24	0.22	0.24	0.08	0.16	0.01	0.09	0.49	0.13	-0.09
Multi-species Cover Crop	-0.47	-0.52	-0.30	-0.31	-0.31	0.08	0.19	-0.06	0.02	0.02
Tree Shrub	0.17	0.04	-0.11	0.02	0.00	0.08	-0.08	0.11	0.16	0.37

Significance	0.1	0.05	0.01

Table 5.2 Correlation table of community perspectives and fundamental, improved, and transformational conservation practices. Perception of community attitudes as well as individual farmers' attitudes toward conservation shape where and when various conservation practices are implemented.

There is a positive correlation between no-till/strip-till use and community appreciation for conservation practices. A positive correlation exists between establishing trees or shrubs, a practice that benefits the farm and surrounding ecosystem, and the belief that their farm operates positively. Multispecies cover cropping negatively correlates with several variables describing community interest in conservation. Most farmers using multi-species cover crops reside in low-adoption counties with less community investment and interest in adopting conservation practices. Farmers use multi-species cover crops to grow crops organically or to raise livestock, often deviating from the status quo production systems used by their neighbors. There is also a moderately significant correlation between no-till or strip-till, a method to retain soil health, and conservation being appreciated in the community.

Finally, in transformational practices, establishment of upland wildlife habitat correlates with increased conservation and experimentation. This suggests that farmers who utilize upland wildlife habitats actively seek ways to increase conservation on their farms and are known for experimenting with new practices. Rotational grazing is negatively correlated with community appreciation of one's conservation practices and broader community and farm benefits of conservation practices. Farmers who use rotational grazing also feel their conservation efforts do not benefit or are not appreciated by their community. We suspect this is the case because raising cattle on pasture is no longer a common practice in Iowa, where most acres are dominated by row crop production. Some participants who utilized rotational grazing were reincorporating livestock into their operations to diversify production, which can improve overall farm resiliency. Community members may not fully comprehend the ecological and economic benefits of these resource management practices. They may associate them with more traditional continuous grazing practices, leading to soil degradation. Additionally, the benefits of rotational grazing, such as improved climate resilience, soil health, and forage quality, may take time to manifest fully, leading some farmers to feel that the broader community and their farm do not have

immediate advantages. Finally, there is a negative correlation between pollinator strips, enthusiasm for conservation practices, and willingness to share conservation information in the community, perhaps due to respondents' beliefs that they are more committed to conservation than others.

6) Community values and norms influence conservation practice adoption.

As illustrated above, self-reported perceptions of community norms influence how farmers approach agricultural conservation practices. Perceived community values and norms motivate farmers to adopt practices prioritizing environmental stewardship and sustainable land management:

> "*What most influenced me to adopt these practices was trying to leave the farm in better shape than when I started. Part of it was to show the neighbors that I was using these practices. I was trying to keep up with what other neighbors were doing and be a positive influence."*

Learning from neighbors, participating in local agricultural networks, and attending community events expose farmers to successful examples and encourage the exchange of knowledge about conservation practice adoption. Additionally, the desire to maintain a positive reputation within the community and leave a legacy for future generations often drives farmers to embrace practices that enhance soil health, reduce erosion, and protect natural resources.

However, negative pressures, such as the fear of failure and community attitudes not supporting conservation practices, can pose significant challenges for farmers considering adoption. The concern of failing while attempting new methods can be daunting, especially in communities where success is closely observed. The fear of being perceived as unsuccessful due to not conforming to conventional practices can discourage farmers from taking risks with innovative conservation practices. Additionally, being part of a community that is not pro-conservation can create a sense of isolation, making it difficult for farmers to find local support, resources, or role models for guidance.

3.6 The role of federal, state and regional programs

Participants spoke of the importance of federal, state, and regional conservation programs that provide cost-share opportunities and technical assistance for adopting conservation practices. At the federal level, USDA NRCS programs such as the Environmental Quality Incentives Program, Conservation Stewardship Program, and the Agricultural Conservation Easement Program provide financial and technical assistance for practices such as cover cropping, no-till, and conservation cover. State and regional programs administered by local soil and water conservation districts, watershed groups, and nonprofit organizations such as Practical Farmers of Iowa also administer conservation support programs. The goals of these programs vary based on local resources and environmental concerns. Additionally, farmers may receive federal crop insurance discounts through the USDA's Risk Management Agency. Research indicates the use of cover crops significantly reduces crop insurance claims in the face of extreme weather events, suggesting cover crops are a beneficial practice for farm-level resilience and reducing the cost of federal crop insurance administered through the Farm Bill.

Table 5.3 Average farm characteristics for high- and low-adoption counties. In our sample, there were no differences in farm operation characteristics between high- and low-adoption counties. Statistics from USDA 2017 Census of Agriculture.

	median	**mean**	**max**	**min**	**SD**
Total number of farm operations					
high adoption	1058	1002	1257	636	268
low adoption	892	871	1265	509	253
Average operation size, in acres					
high adoption	300	306	384	242	61.8
low adoption	311	331	439	279	59.8
Number of operations larger than 1000 acres					
high adoption	58	64	99	40	26
low adoption	59	68	103	49	22
Average land asset value, in dollars per acre					
high adoption	6700	6744	8037	5538	1033
low adoption	6722	7083	9727	4876	2127
Average annual crop sales per acre					
high adoption	457	429	473	330	67.6
low adoption	423	421	566	285	121

Although research suggests larger farmers are more likely to adopt conservation practices, comparing the eight counties in Iowa in our sample, we found no differences in farm operation characteristics, including operation size, number of large operations, or average land asset value, between high- and low-adoption counties (Table 3).

While county-level data on the use of assistance structures is not widely available, we evaluated several variables that may indicate general participation in financial and technical assistance programs (Table 4). On average, in high-adoption counties, more acres are enrolled in conservation easement programs where farmland is permanently or temporarily set aside. This may reflect awareness of opportunities to receive payments or the amount of marginal farmland in the county. Further, funding received for federal government programs and state revolving funds was more significant in the high-adoption counties. The number of certified crop advisors and educational field days offered was somewhat similar in the high- and low-adoption counties, suggesting these variables may not be strong determinants of adoption differences within the sample.

Table 5.4 2017 County-level participation in conservation programs and access to conservation advising/education. Farmers in high-adoption counties receive more funding from federal governmental programs and state revolving funds and have more acres enrolled in conservation easement programs. Statistics from USDA 2017 Census of Agriculture.

	median	**mean**	**max**	**min**	**SD**
Percent of county acres enrolled in conservation easement programs					
high adoption	0.7	0.9	1.79	0.37	0.64
low adoption	0.4	0.4	0.52	0.31	0.08
Government program support received per acre, in dollars *(where receipts are available)*					
high adoption	29.8	36.2	36.1	9.41	11.8
low adoption	23.7	24.8	37.9	16.2	7.66
State Revolving Fund program support received per acre, in dollars					
high adoption	2.19	30.9	11.8	0.73	58.4
low adoption	1.92	3.68	13.9	0.46	5.12
Number of certified crop advisors in the county					
high adoption	14.5	13.5	24	1	9.47
low adoption	11.5	14.5	37	2	13.6
Number of field days offered within a 25-mile radius					
high adoption	7	15.8	45	4	19.6
low adoption	5	12.8	48	2	17.6

3.7 Governmental policies, regulations, and available financial support

Farmers in our sample indicated that government initiatives, such as incentive programs and subsidies for sustainable practices, have provided key financial support and resources to implement conservation methods. Cost-effectiveness and potential profitability were crucial factors in adopting conservation practices. Farmers identified how conservation practices increased the resilience of their operations by providing economic benefits and new opportunities. This was often related to cost-sharing incentives but also linked to expanded market opportunities. Farmers were also more frequently adopting practices with cost-share benefits, such as cover crops. Many farmers spoke about government incentive programs as influential in adopting conservation practices:

"The cost-share to start motivated me to adopt cover crops, and then I saw the benefits. Specifically, grazing cattle on them is where I see the most benefit. It saves on extra feed."

These programs have helped alleviate the initial costs associated with transitioning to more environmentally friendly approaches, making it more feasible for farmers to adopt practices like cover cropping, reduced tillage, and nutrient management. Notably, farmers must be aware of incentive programs to utilize them. Farmers frequently learned about these programs through conversations with others in the area, as well as through their local NRCS agents. NRCS agents who were aware of new incentive programs and communicated them to farmers were crucial for encouraging adoption and subsequent sharing of enrollment information amongst farmer networks.

Moreover, regulations aimed at reducing soil erosion, protecting water quality, and promoting sustainable land use have prompted farmers to adopt practices that align with these goals. In some cases, farmers expressed wanting to opt into conservation versus being mandated through regulations:

"If we want to keep farming like we do, we will have to implement these things [conservation practices]. I feel like, at some point, we might be forced to do it. I do not want to be told to do things, so I would rather be innovative."

Maintaining autonomy over their operation was a driving force for farmers to adopt conservation practices to stay ahead of potential regulatory mandates.

Regarding network implications, these findings highlight the importance of effective communication and knowledge-sharing mechanisms within farming communities. Peer-to-peer discussions and discussions with NRCS representatives are instrumental in spreading awareness about government programs and encouraging adoption. Additionally, the network effect of shared experiences and the benefits of conservation practices can motivate more farmers to participate in these initiatives. Overall, policies and regulations, when combined with effective information dissemination within farming networks, can accelerate the adoption of conservation practices, promote sustainability, and enhance the resilience of farming communities.

3.8 Access to Information Related to Conservation Practices

When asked about what kinds of organizations, media, or social media the farmers in our sample consult to learn about agricultural conservation practices, federal government organizations, including the Farm Service Agency and the NRCS, were the most consulted resources. Iowa State University mainly offers university Extension services in this region. Some individuals specifically mentioned the Leopold Center for Sustainable Agriculture. State government organizations such as the Iowa Department of Agriculture and Land Stewardship, the Iowa Department of Natural Resources, and the Soil and Water Conservation District were frequently mentioned. Unlike other states, Iowa farmers, including those in our sample, maintain close contact with local nonprofit farming-related organizations such as Practical Farmers of Iowa, Iowa Farm Bureau, Iowa Farmers Union, and commodity-specific organizations, including the Iowa Corn Growing Association and Iowa Soybean Association. Regarding media, several farmers in our sample report read Farm Progress/Wallaces Farmer and Acres. Furthermore, many consult social media sources such as Facebook and TikTok, podcasts, and YouTube videos. Finally, a small group of farmers consult agronomic consulting companies and agricultural retailers.

When comparing societal resources consulted by age group, older farmers tend to rely slightly more on traditional sources such as federal and state government organizations and university extension services. Older generation farmers disproportionately consult print, such as agricultural magazines. In contrast, the younger generation likes to use online sources such as podcasts, YouTube videos, and social media. While this is a more common source among younger farmers, the older generation of farmers over 60 are also relatively active in following online media related to agricultural conservation practices (Figure 5.13).

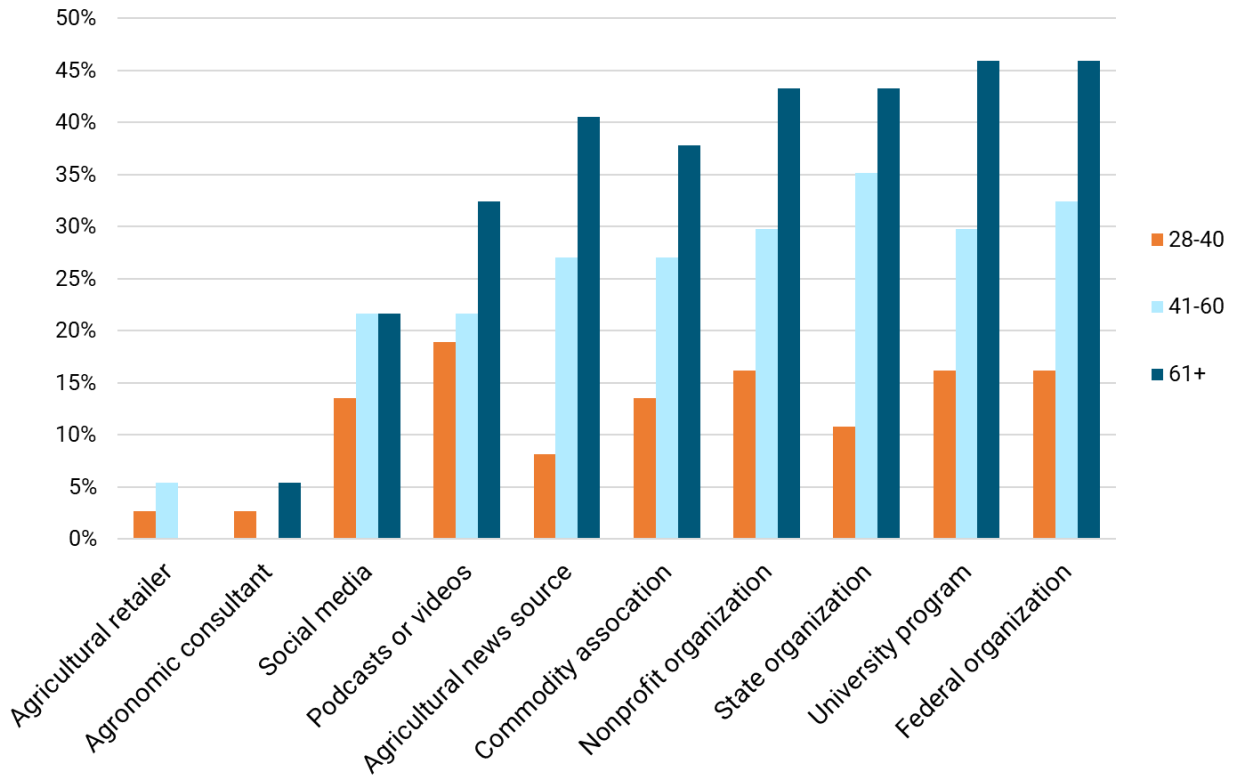

Figure 5.13 Top societal influences by age group. The youngest subset of farmers uses modern information sources like social media and podcasts at rates that are similar to or greater than traditional information sources such as the state and federal organizations.

When comparing societal influences, farmers in high-adoption countries are more likely to report taking advantage of any information source except agricultural retailers. This suggests that the diversity of information and exposure to different perspectives within their social networks may contribute to the greater adoption of conservation practices. Access and community recommendations for specific sources of land stewardship information may also drive this discrepancy between sources.

In summary, social networks play a significant role in how farmers access information about agricultural conservation practices. Different generations within the farming community may have varying preferences for information sources, but the influence of peer recommendations and community connections remains strong. The use of newer online and social media sources among younger farmers reflects the evolving landscape of information sharing within agricultural networks. These insights

underscore the importance of considering generational differences and social networks when designing strategies for disseminating knowledge and encouraging the adoption of conservation practices.

1) *Similar to social networks, farmers consult networks of print and digital information sources aligned with their agricultural interests and goals.*

To learn what sources of information farmers consult regarding agricultural conservation practices, respondents were asked to select their preferred sources from a predetermined list of information sources. Farmers could also add information sources that were not provided on the list. Figure 5.14 represents the network of sources most frequently mentioned together.

Sources in the center of the network tend to be consulted often by most farmers in our sample, while a smaller number of farmers consulted sources on the periphery. The colors represent an algorithm of sources that tend to cluster, meaning that multiple farmers in our sample tend to mention a similar combination of sources. Federal and state government organizations and university Extension services are in the center. This illustrates that most farmers in the sample frequently consulted these sources and that these organizations can amplify each other's messages. Online sources outside the local community, such as YouTube, podcasts, and social media, are often mentioned together.

In green, we see the mainstream farming organizations that may include some conservation organizations. In peach color, we see organizations that tend to be the most innovative and have a mission to advance sustainable agriculture. Finally, in blue, we see conservation-oriented organizations, sometimes incorporating agriculture in their agenda, and other times, agricultural organizations strongly emphasizing conservation. This means that while some mainstream and centrally positioned sources such as YouTube, podcasts, and social media may be consulted by a substantial proportion of the farmer population, there is a tendency to frequently consult a combination of like-minded organizations regarding agricultural conservation practices. This implies they are drawn to sources that align with their interests and goals.

While farmers tend to consult like-minded organizations, there is also the potential for bridging and cross-pollinating ideas and practices across information sources. For instance, the overlap between mainstream farming organizations and conservation-oriented organizations suggests an opportunity for knowledge exchange and the adoption of sustainable practices within more conventional farming communities. Organizations are numbered in Figure 5.14; see SI Figure 5.2 for a legend.

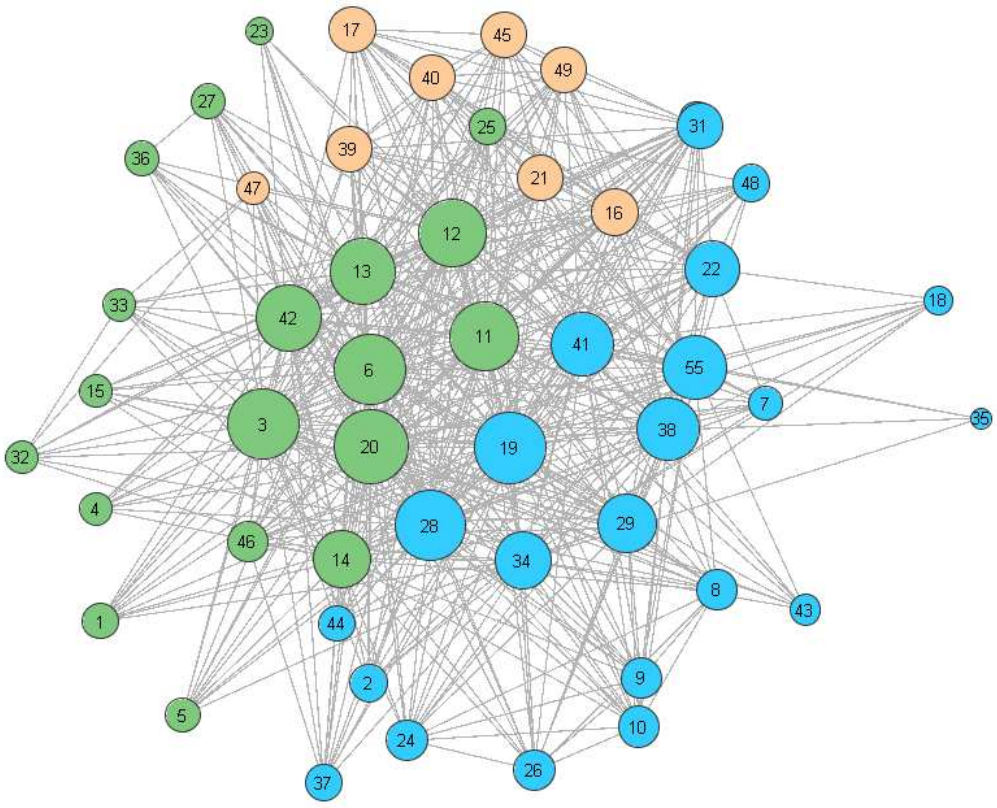

Figure 5.14 Farmers sought out conservation information from a variety of traditional, conservation-minded, and conservation-oriented sources. The network shows the information sources farmers mentioned and the ties indicate when they were mentioned together in an interview. Organizations that are closer to the center of the network indicate the most used sources and less commonly used sources are positioned toward the edge. The colors indicate which organizations were most often used together and reveal underlying patterns. The blue group is characterized by traditional agricultural information sources. The green group represents conservation focused information sources. The orange group represents local and grassroots conservation organizations.

2) *Farmers use social media to learn from the challenges and successes of other conservation-minded farmers.*

Social media platforms like X (formerly Twitter), Instagram, Facebook, and podcasts play a crucial role in shaping the adoption of agricultural conservation practices. Social media enables farmers to share their experiences, learn from each other's successes and challenges, and access insights outside of their community. Participants identified social media as a critical source of information, particularly when learning about the successes and challenges of farmers who had adopted a practice of interest:

> "*In 1994, I stumbled upon online forums, so I no longer relied on what local people focused on... The more I shared, the more other people shared. And then, we got invited to speak to places, tell our story, and learn more from others. I put much research into what we do before we take the first step. I learn from other people's mistakes, which helps me be more successful. We have had failures, but we turn those into learning and success moves forward."*

One participant in our sample had their own YouTube series where they shared more about their farm operation and conservation-related information with other farmers. Another participant hosts a podcast inviting farmers to share the successes and challenges they experience as they adopt new practices. Social media and podcasts contribute to breaking down geographic and informational barriers, creating a community where farmers can share information across contexts and more localized networks.

For farmers using social media to share about practice adoption, organizations can play a key role in further amplifying their message and expanding their reach. Supporting farmers who create online content through funding and resources can amplify their reach and impact. Financial support can help cover the costs of creating and sharing informative content, such as videos, podcasts, or blog posts. Organizations interested in promoting conservation practices can consider offering grants specifically to facilitate content creation related to agricultural conservation. This financial support not only aids individual farmers but also contributes to the broader dissemination of valuable knowledge. Organizations can consider creating online knowledge exchange platforms to facilitate further knowledge sharing among

farmers. These platforms can cultivate a network where farmers can share insights, ask questions, and learn from each other's experiences. Allocating funding for developing and maintaining such platforms can foster community, expand farmers' networks across geographic boundaries, and provide a centralized hub for farmers interested in conservation practices to connect and collaborate.

4. Conclusions

This report shows the importance of collecting data about multiple levels of social scale and social networks to examine the variety of societal influences on farmers' adoption of agricultural conservation practices in Iowa. Understanding how these levels interact is essential for promoting the adoption of agricultural practices that support sustainability in farming, benefit soil health, wildlife, pollution, climate mitigation, and improve both the quality and quantity of production yields.

1) Individual level

At the individual level, farmers are likely to use fundamental practices such as crop rotation and grassed waterways, which are considered mainstream agricultural practices. Improved practices that enhance sustainability and yield or quality, such as cover crops and no-till, are standard in our sample. A smaller proportion of farmers in our sample use transformational practices designed to improve soil, water, and the environment, often forgoing agricultural yields. Most agrarian conservation practices are more common in areas with high adoption rates.

In addition, farmers who produce multiple crops are more likely to adopt conservation practices. This is likely due to broader networks increasing the likelihood of discussing conservation practices, farm size, and opportunities to incorporate, for example, livestock in their corn, soy, and alfalfa growing practices. Farmers in low-adoption areas are more likely to report wanting to increase conservation, suggesting a possible insufficiency in opportunities, incentives, and access to networks with expertise in agricultural conservation practices. Farmers in high-adoption areas more often report experimenting with conservation practices, benefiting from conservation practices, and being appreciated by their community for their use

of conservation practices. In qualitative findings, we learned that the main barriers to adoption are new conservation practices' cost and time investment.

2) Interpersonal level

At the interpersonal level, our network analysis shows that farmers most frequently report discussing agricultural practices with friends and neighbors. Respondents see their farmer-peers and local professionals, such as friends and neighbors, as knowledgeable, trustworthy, and innovative network members. Comparing the low- and high-adoption counties, the embeddedness of local agricultural experts, Extension agents, or agronomists in guiding farmers through the process of adopting agricultural conservation practices aligns with substantially higher adoption rates for most practices. Furthermore, on average, connections in high-adoption counties receive slightly more trust, are considered slightly more knowledgeable, and are rated less innovative. Regarding network structure, we found high-adoption farmers have a more extensive network of individuals from whom they seek advice regarding agricultural conservation practices. These networks are also more diverse, with fewer relationships between the reported individuals than low-adoption counties.

Qualitative findings indicated that learning groups and peer models had been an encouraging factor in trying out new evidence-based practices because farmers could observe what worked for friends and neighbors who practice agriculture on similar soils and climatic conditions. Participants emphasized their reliance on fellow farmers' knowledge, recognizing the importance of lived experiences when venturing into new agricultural practices. They view peer models as trustworthy information sources to mitigate experimentation risks. Finally, having peers nearby to share equipment is an effective cost-management strategy. To encourage practice adoption, peer-to-peer learning networks and community engagement initiatives, including organizing community meetings, workshops, events, and field days where farmers can share their conservation efforts and success stories and provide hands-on demonstrations, are important interpersonal strategies to leverage.

3) Community Level

At the community level, social network dynamics are pivotal in understanding the differences between low-adoption and high-adoption counties. Farmers in low-adoption counties perceive lower community support and environmental sustainability concerns. When examining individual farmers' conservation efforts within their community context, respondents expressed a greater personal interest in advancing conservation and a willingness to experiment compared to their perspective of their broader community. We found substantial differences in marketing options and perceived community support and interest in conservation, with strong positive correlations in high-adoption counties and weak negative correlations in low-adoption counties. In high-adoption countries, there were strong correlations between perceived community interest in conservation and feeling appreciated. In contrast, in low-adoption countries, there were significant correlations between willingness to experiment with conservation and conservation being appreciated.

These findings suggest that social recognition is associated with a willingness to adopt agricultural conservation practices. However, there were primarily negative associations when comparing the adoption of practices with perceived community attitudes. This suggests that farmers invested in conservation may feel their community is not as supportive and concerned as they would like. Therefore, many farmers in this sample may be ahead of their community and influence others as much as their community affects them. These findings demonstrate the critical influence of social networks and community perspectives on farmers' conservation behaviors. They also highlight the need to harness these dynamics to bridge the gap between individual commitment and community-level support for agricultural conservation practices.

4) Local-Regional Level

At the local-regional level, high-adoption counties have, on average, more acres enrolled in conservation easements, receive more dollars in government and State Revolving Fund support per acre, and have more certified advisors and crop field days. In high-adoption areas, there is a higher concentration of farms. However, the number of large farms, the average size of farms, and land asset

value tend to be similar. These findings suggest that adopting conservation practices highly depends on available resources, such as agricultural professionals, learning events, and financial support. Investment in resources to increase adoption of conservation practices makes sense not only from a sustainability perspective but also from an economic perspective, as high-adoption counties receive substantially more in crop sales per acre.

5) Societal Level

At the societal level, some sources of information, such as agricultural organizations and various forms of media, operate on a larger scale, such as the state, national, or international level. Government-funded organizations are frequently consulted by farmers of all ages and low- and high-adoption counties. Most farmers consult multiple sources of information regarding agricultural conservation practices. Analysis by age group, low- and high-adoption counties, and social network analysis revealed that certain types of information are more likely to reach specific demographics. For example, younger farmers are more likely to use social media, while older farmers are more likely to consult magazines. Notably, farmers in high-adoption counties consume more types of information overall. Finally, farmers will likely obtain information from sources with similar objectives and messages. For example, farmers who primarily seek out mainstream agricultural resources are likely to report seeking information from multiple similar-minded organizations. At the same time, those who are explicitly conservation-minded tend to follow organizations with deep roots in land stewardship and conservation. Therefore, an effective network of collaboration between organizations would amplify and reinforce the message about more sustainable and higher yield practices.

5. Implications

1) *System-Based Data Collection:* System-based data is essential to understand better how different layers of society influence the adoption of agricultural conservation practices. By understanding how information flows and decisions are made within social networks, interventions can be

designed to align with existing communication channels and community dynamics. Farmers seek advice, guidance, and information from their social networks. Recognizing the impact of peer influence and community norms within these networks can inform strategies to promote conservation practices. For example, leveraging influential individuals within social networks can help disseminate knowledge and encourage adoption at a grassroots level.

2) *Individual-Level Implications:* At the individual level, the findings emphasize the importance of farmer-peers, friends, and neighbors as influential sources of information. Farmer attitudes toward conservation practices are not only shaped by personal beliefs but also influenced by social networks. Farmers in a close-knit community where conservation practices are widely embraced may have more positive attitudes toward adoption. Friends, neighbors, and local agricultural leaders can play a pivotal role in shaping these attitudes through peer modeling, shared values, and community norms. In this context, social networks act as conduits for transmitting attitudes and beliefs related to conservation practices. Promoting networking events and farmer meetups can facilitate peer interactions for sharing experiences and advice on agricultural conservation practices.
3) *Interpersonal-Level Implications:* It is essential to identify influential farmers, local agricultural leaders, Extension agents, and organizations within the community who are willing to experiment with conservation practices and can then serve as champions for those practices. Ideal candidates are local farmers who have already adopted these practices because personal experiences are more convincing than scientifically found benefits in building awareness and encouraging others to adopt practices. These influential conservation-minded members of the local agricultural community should be encouraged to share their experiences at public events such as workshops, field days, webinars, and seminars to educate other farmers about the benefits of conservation practices, such as improved soil health, reduced erosion, and increased yield potential. Agricultural experts, Extension agents, and agronomists should be trained to reinforce the examples of innovative farmers. These professionals can offer personalized and transparent

recommendations based on specific farm conditions, soil types, and cropping systems to increase the chances of successfully adopting conservation practices and provide information related to cost, time investment, and impacts on yield.

4) *Community-Level Implications:* Farmers care about meeting social norms and being valued by their local community. Given these findings, increasing awareness of agricultural conservation practices within the local community can be facilitated through networking events, social gatherings, or farmer meetups that both acknowledge the efforts of farmers who have successfully incorporated innovative practices and encourage others to follow their lead and spread use of the practice until it becomes a community norm. Community-level interventions leveraging social networks and community norms can be powerful drivers of change in agricultural conservation practices. By creating an environment where innovation is celebrated, knowledge is freely shared, and positive peer influence is harnessed, the adoption of conservation practices can become a community norm.
5) *Local-Regional Implications:* High-adoption areas benefit from more resources such as conservation easements, government funding, certified advisors, and educational events. The availability of these resources strongly correlates with adoption rates, highlighting the importance of resource accessibility. Local incentives and government programs, often disseminated through local agricultural organizations and government agencies, can be key to encouraging farmers to adopt conservation practices. These programs provide financial and technical support, making it more financially feasible for farmers to implement these practices. Farmers share information about these incentives and programs within social networks, influencing others to participate. Peers who have benefited from such programs may act as advocates and encourage their network connections to enroll.
6) *Societal-Level Implications:* Collaboration between government-funded organizations, agricultural groups, and media outlets is critical to amplifying and reinforcing messages about conservation practices. Tailoring information dissemination to reach specific demographics, such as younger

farmers through social media and older farmers through magazines, is essential for effective outreach. Collaboration among these entities can also facilitate peer-to-peer influence within social networks. When farmers receive information from trusted sources like government organizations, agricultural groups, or respected media outlets, they are more likely to share it within their social networks. This peer-to-peer dissemination can lead to discussions, knowledge exchange, and norm-setting within the farming community, ultimately driving adoption. In this way, messages from trusted sources contribute to the establishment of community norms and trust within networks. When conservation practices are consistently promoted and supported by trusted sources at the societal level, they are more likely to become part of the accepted wisdom within farming communities. This, in turn, influences community values, attitudes, and the adoption of conservation practices. Financial support to start, maintain, and promote trusted sources and create opportunities for collaborative efforts can be an effective strategy to encourage the adoption of conservation practices.

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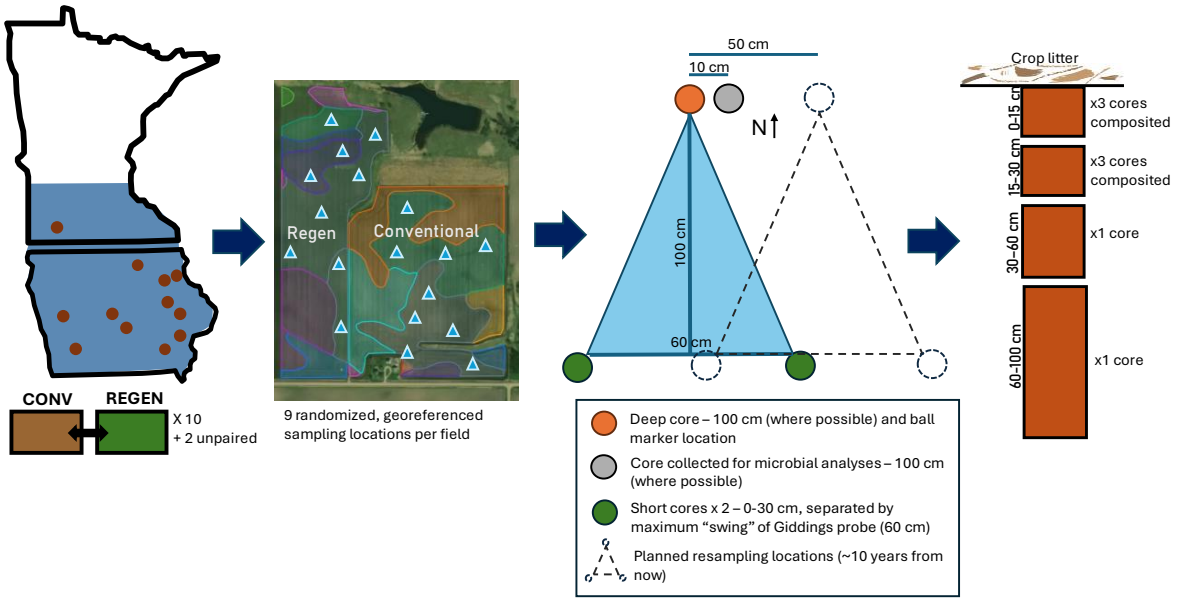
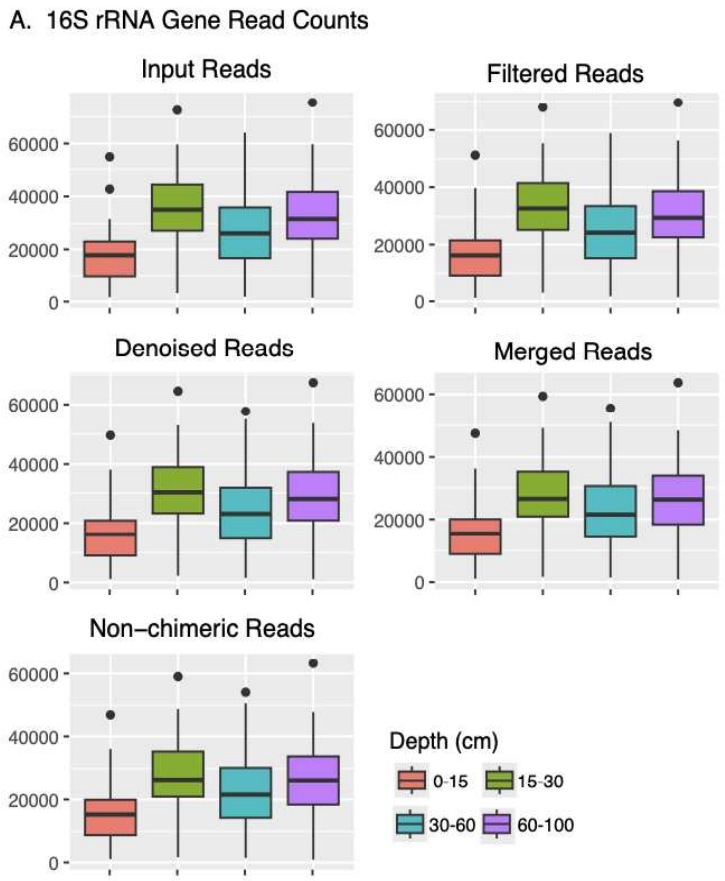
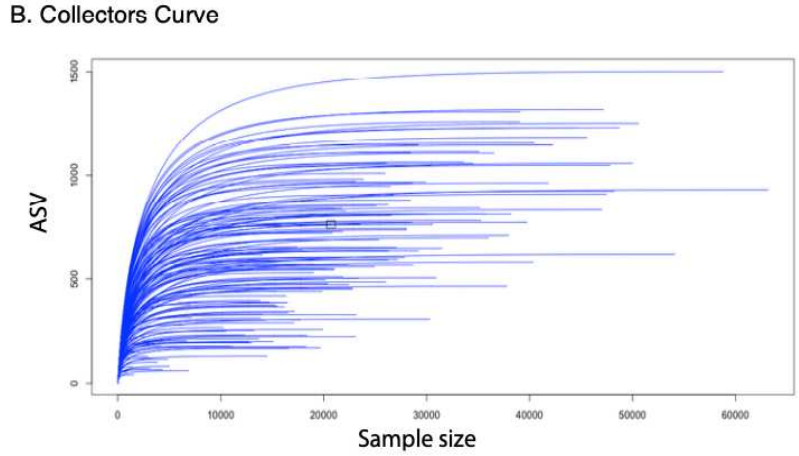
Appendix 1: Supplemental Figures for Chapter 3

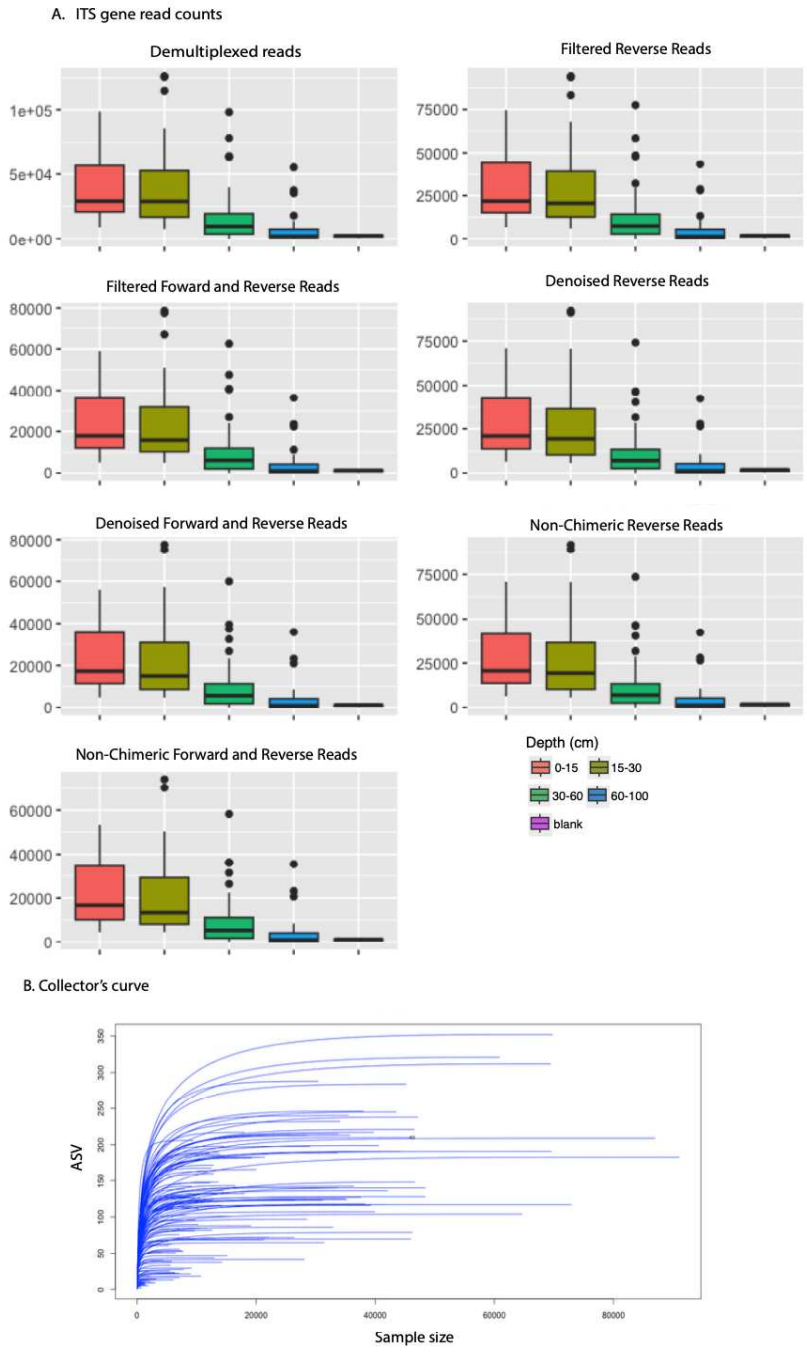


SI Figure 3.1 Sampling design for paired REGEN/CONV fields. Fields were located across Iowa and Southern Minnesota. Nine randomized sampling sites on matching or similar soil types were identified. Samples were collected at the corners of a north-oriented isosceles triangle with a base of 60 cm and a height of 100 cm. One deep core and two short cores were collected at each triangle and were cut along four depth increments (0-15, 15-30, 30-60, 60-100). Samples from the top two depth increments were homogenized across the three cores. An additional core was collected for microbial analyses ~ 10 cm from the deep core location and cut along the same depth increments, using sterilized implements.

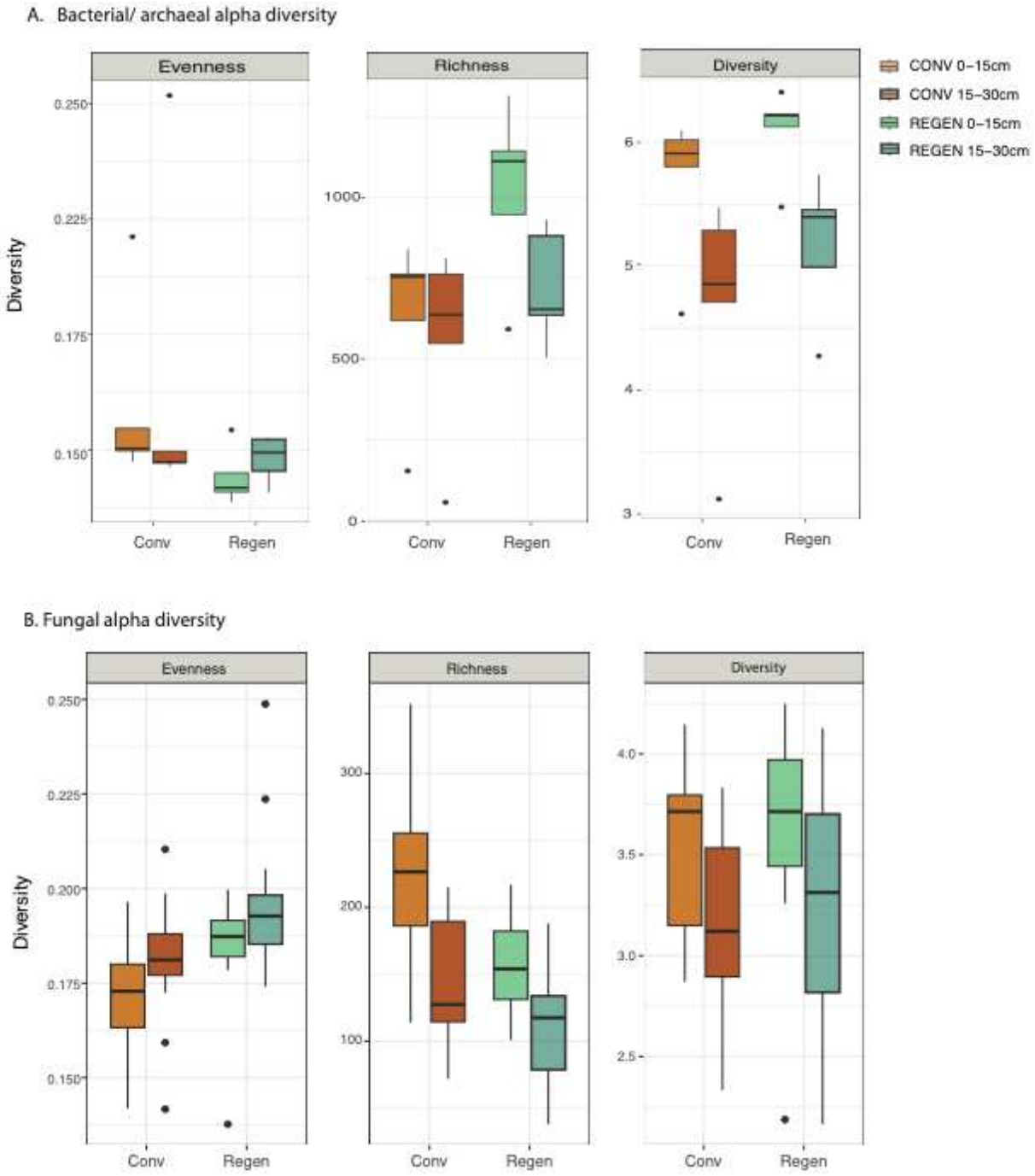




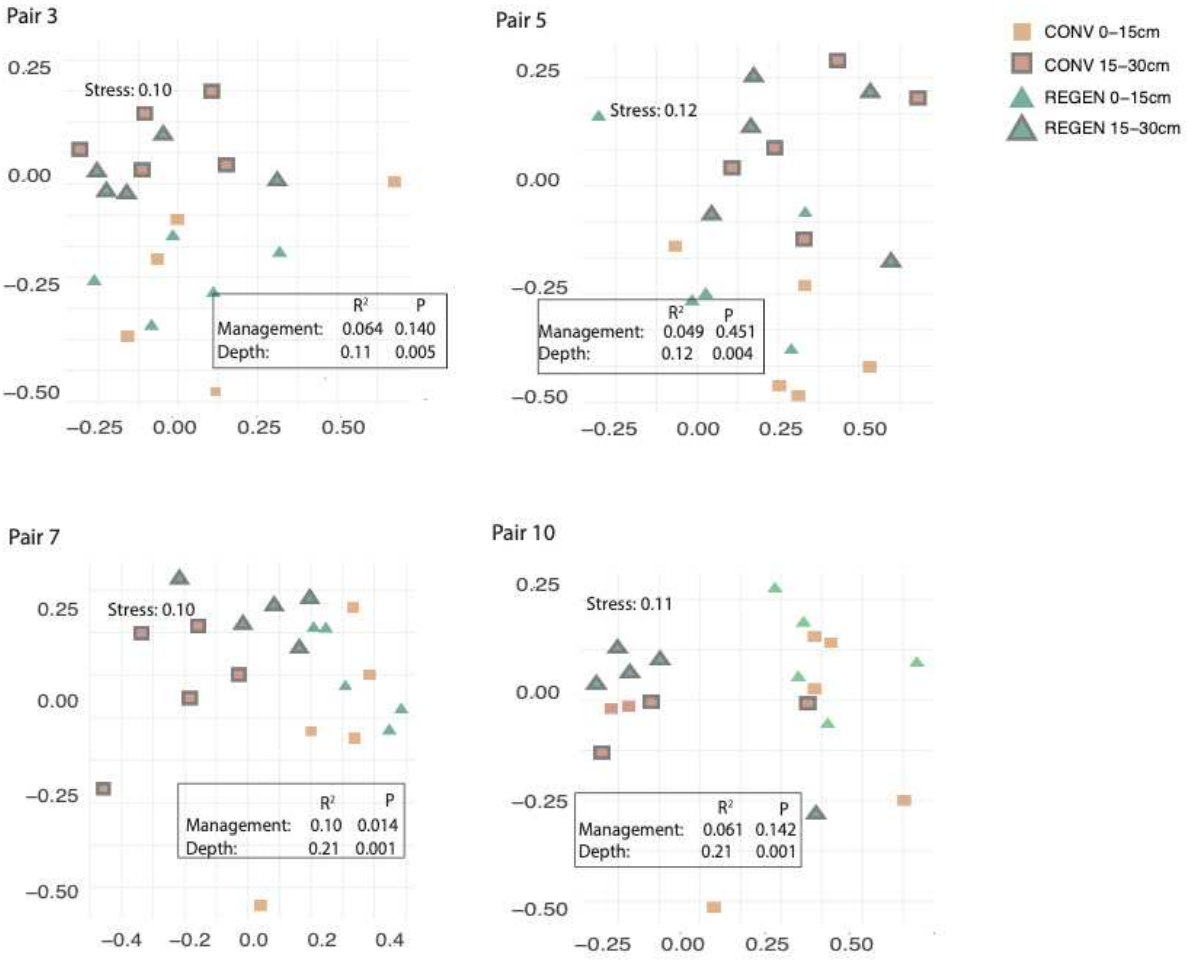
SI Figure 3.2 16S rRNA gene read counts and rarefaction curve. A) Gene counts at all stages of denoising and quality control filtering at all four depths. B) Collector's Curve of number of ASVs acquired with sequencing depth per sample.



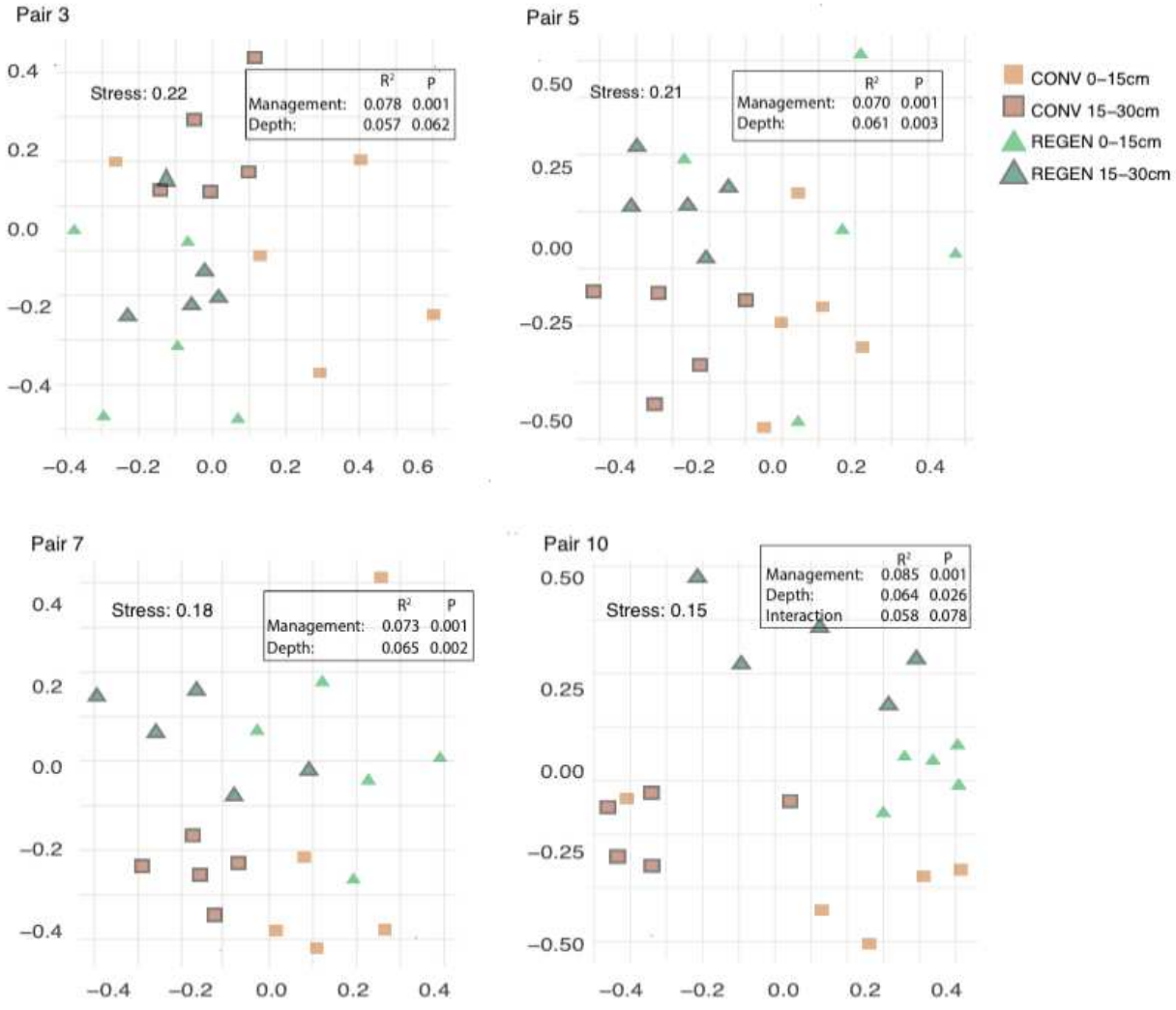
SI Figure 3.3 ITS gene read counts and rarefaction curve. A) Read counts at all stages of denoising and quality control filtering at all four depths with two methods of denoising: 1) both forward and reverse reads and 2) forward reads only. A greater number of reads remained after denoising with forward reads only, due to low reverse read quality. We also observed a precipitous drop in read counts for the deepest depths (30-60cm and 60-100 cm) compared with the shallower depths. As such, only the forward reads from the top two layers were used for downstream analyses. B) Collector's curve for ITS ASVs from all depths acquired with sequencing depth per sample.



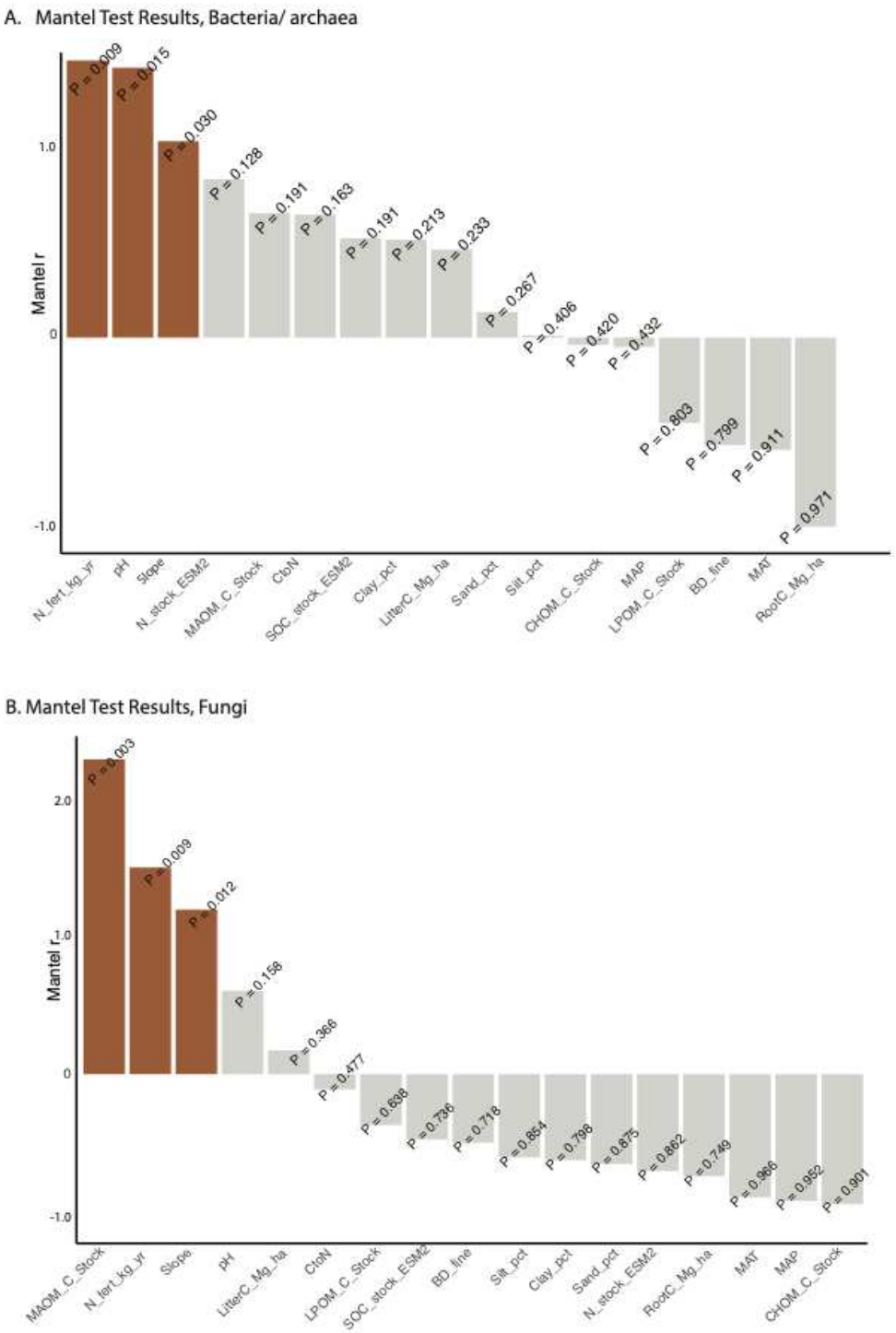
SI Figure 3.4 Alpha diversity metrics (Shannon's H diversity, richness (counts), and Pielou's J evenness) for A) bacterial/archaeal and B) fungal communities. * indicates significant difference by treatment at p< 0.1 (Kruskal Wallis test). Outliers, designated as 2.5 times the standard deviation above and below the mean were removed prior to statistical analyses.



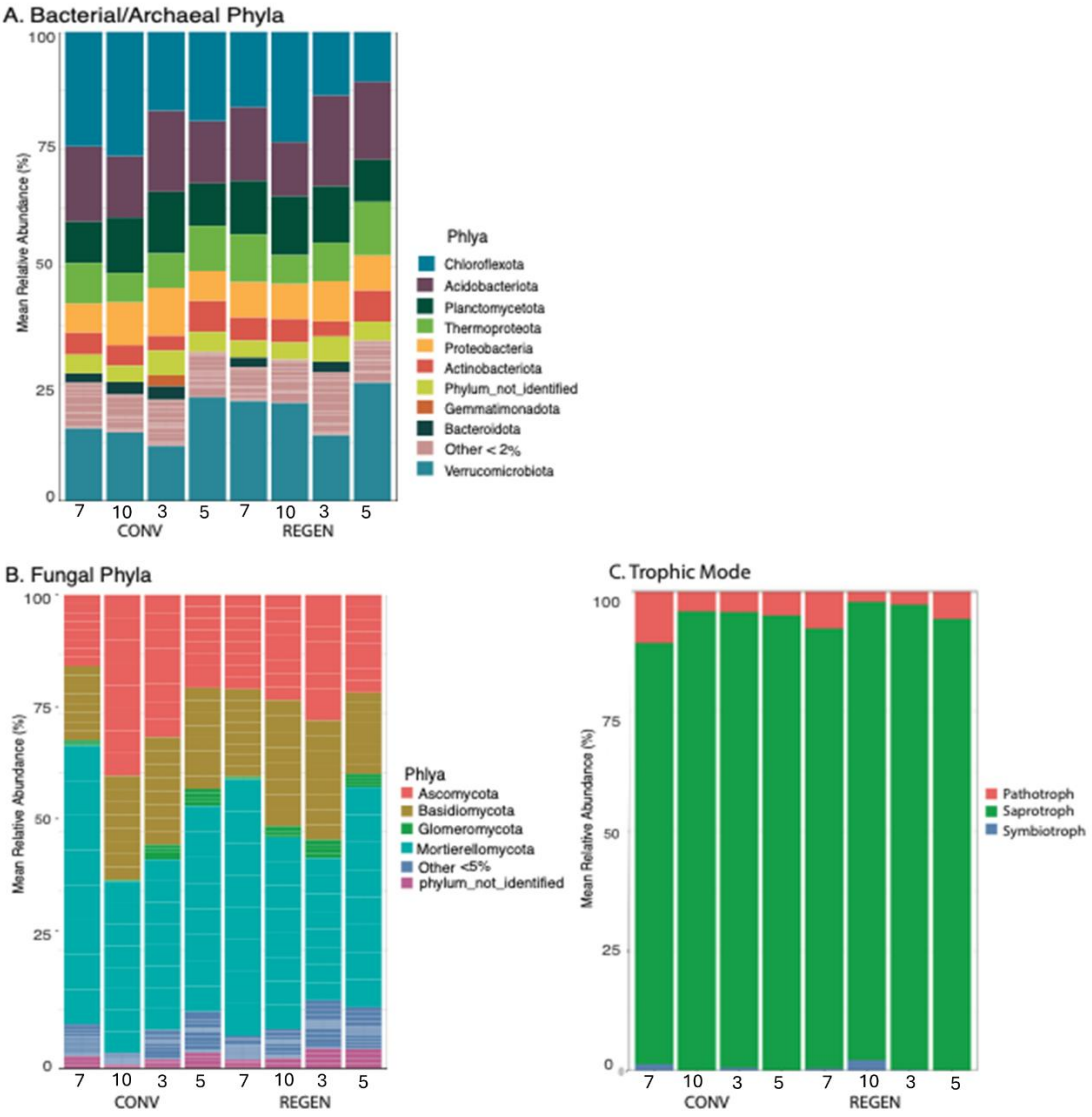
SI Figure 3.5 NMDS plots representing bacterial/ archaeal beta diversity by farm pair. Bray Curtis distances were calculated for the relative abundance transformed bacteria/ archaeal community by farm pair. Overall, depth was the biggest driver of community variation, followed by management. For all, the level of significance was set to $p < 0.1$.



SI Figure 3.6 NMDS plots representing fungal beta diversity by farm pair. Bray Curtis distances were calculated for the relative abundance transformed community by farm pair. Overall, management was the stronger driver of community variation within pairs, followed by depth. For all, level of significance was set to $p < 0.1$.

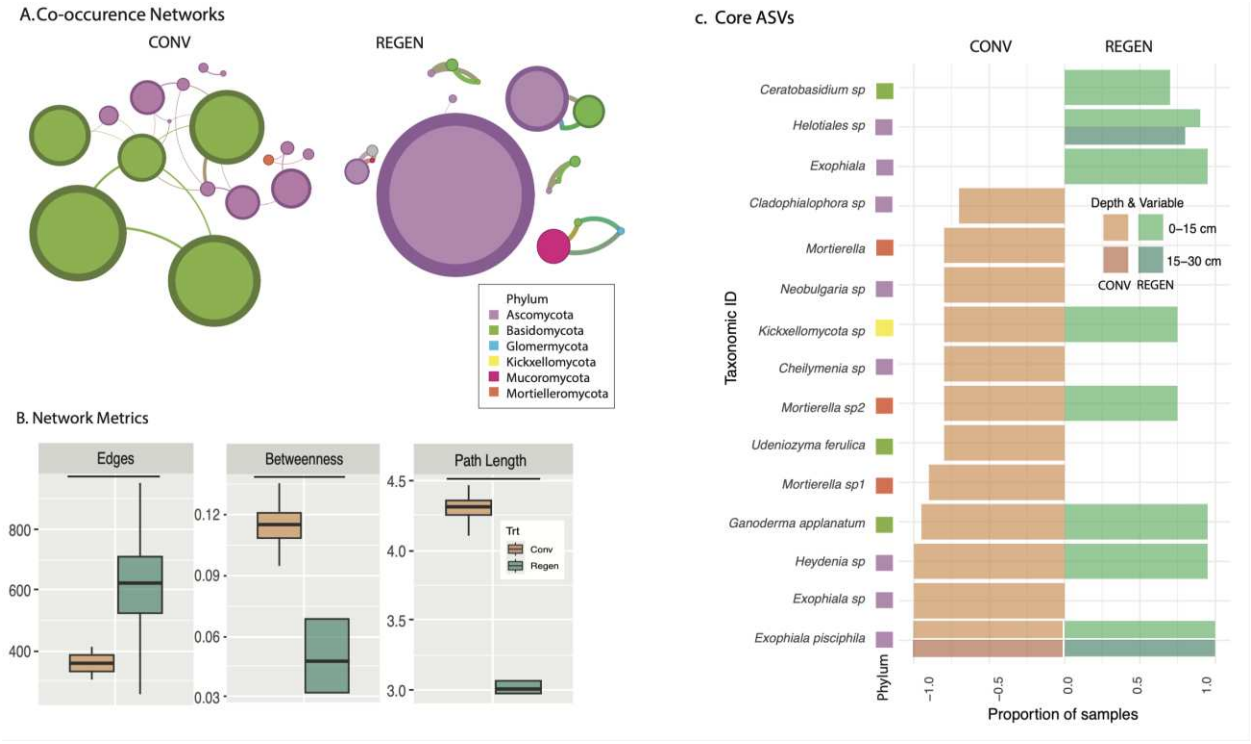


SI Figure 3.7 Mantel Test results for A) bacteria/archaea and B) fungi for relative abundance transformed communities across depths. For the bacterial/archaeal community (A) N fertilization rate, pH, and slope were most strongly correlated with community

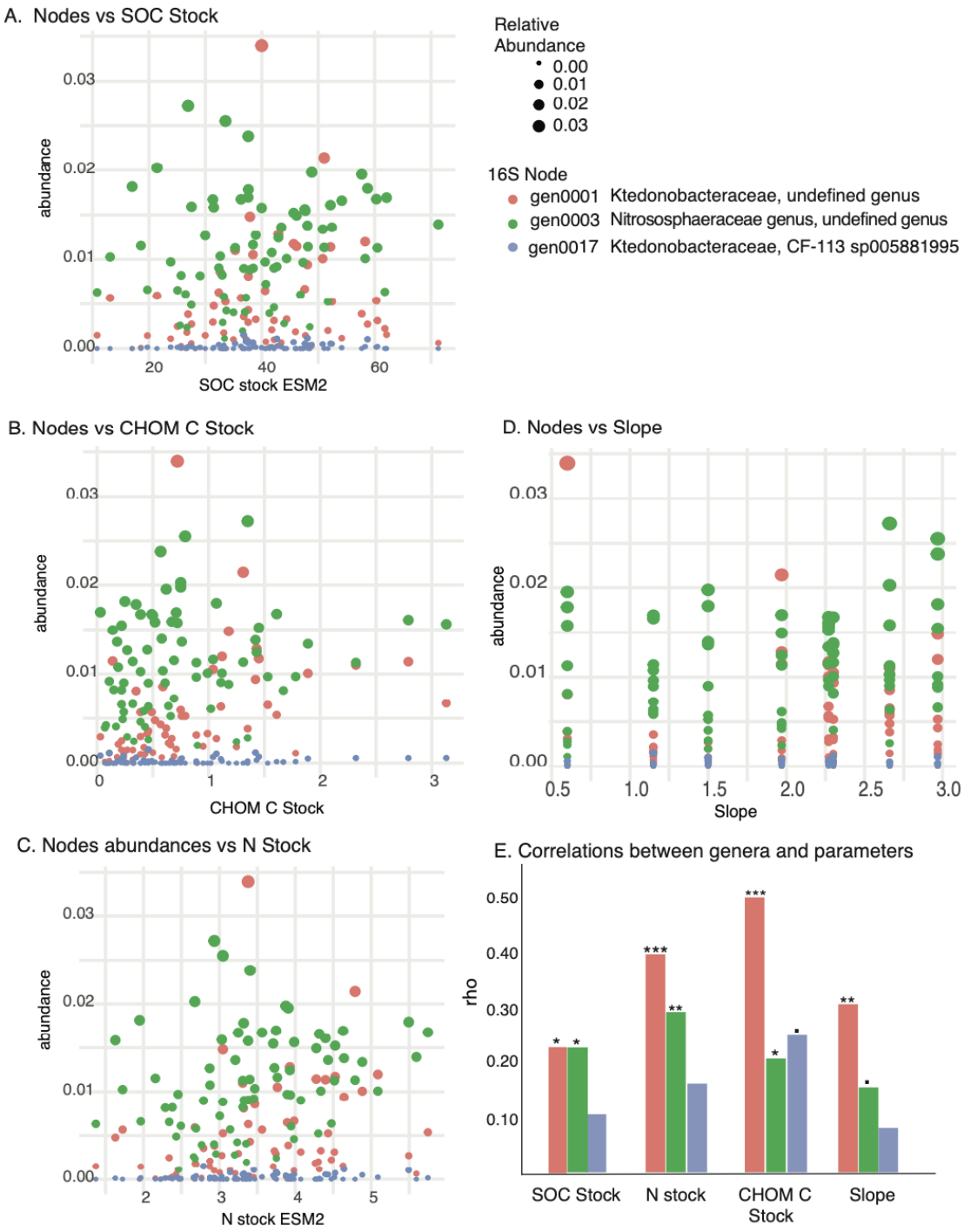


SI Figure 3.8 Taxonomic composition for Bacteria & Archaea and Fungal phyla and fungal trophic mode. Relative abundance is shown for most abundant phyla from the A) bacterial/ archaeal community. The phyla Chloroflexota and Verrucomicrobiota were the most abundant, comprising 22.3% and 20.7% of the total bacterial and archaeal community, respectively, followed by Acidobacteriota (17.2%) and Planctomycetota (12.2%) (SI Figure 3.3). Chloroflexota was significantly more abundant under CONV treatment, comprising 32.2% of the total phyla compared with 23.6% of the REGEN community. Verrucomicrobiota, on the other hand, was significantly more abundant under REGEN management, comprising 28.8% of the REGEN community and 23.0% of the CONV community. B) fungal community across eight sample types (four farm pairs and two management treatments). Phyla are distinguished by color. The phylum Mortierellomycota was the most abundant, comprising 41.8% of the total fungal community. This was followed by Ascomycota (25.3%), Basidiomycota (22.2%), and Glomeromycota (4.54%). C) Fungal trophic mode. 2,383 ASVs were assigned to ecological guilds using FUNGuild90 (v1.2) (Nguyen et al., 2016) with guilds included that were classified as 'highly probable' or 'probable' to

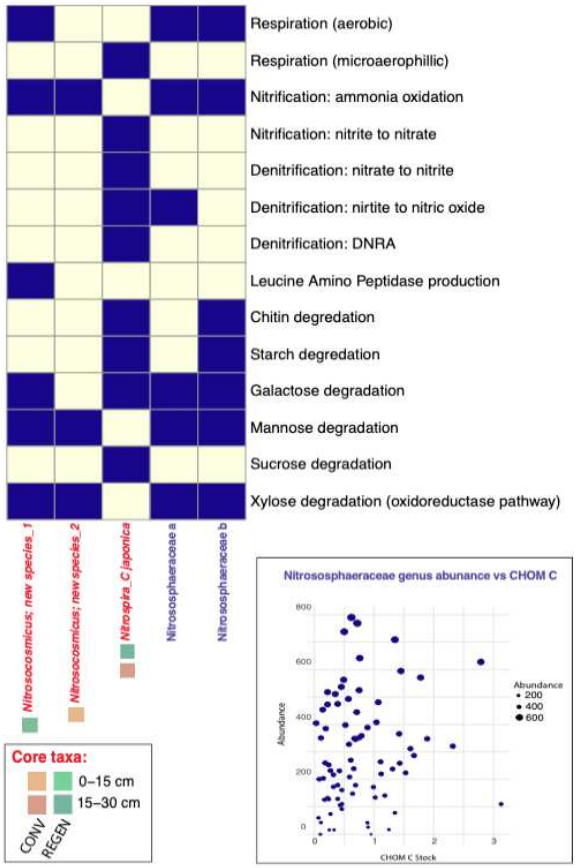
minimize overinterpretation and ASVs excluded if they were classified into more than one category with the exception of 'Saprotroph-Pathotroph,' which was reclassified as 'Saprotroph' per FunGuild author instructions. Trophic modes are differentiated by color. 94.6% of ASVs were identified as Saprotrophs, 6.0% were identified as putative Pathotrophs, and 0.83% were identified as Symbiotrophs



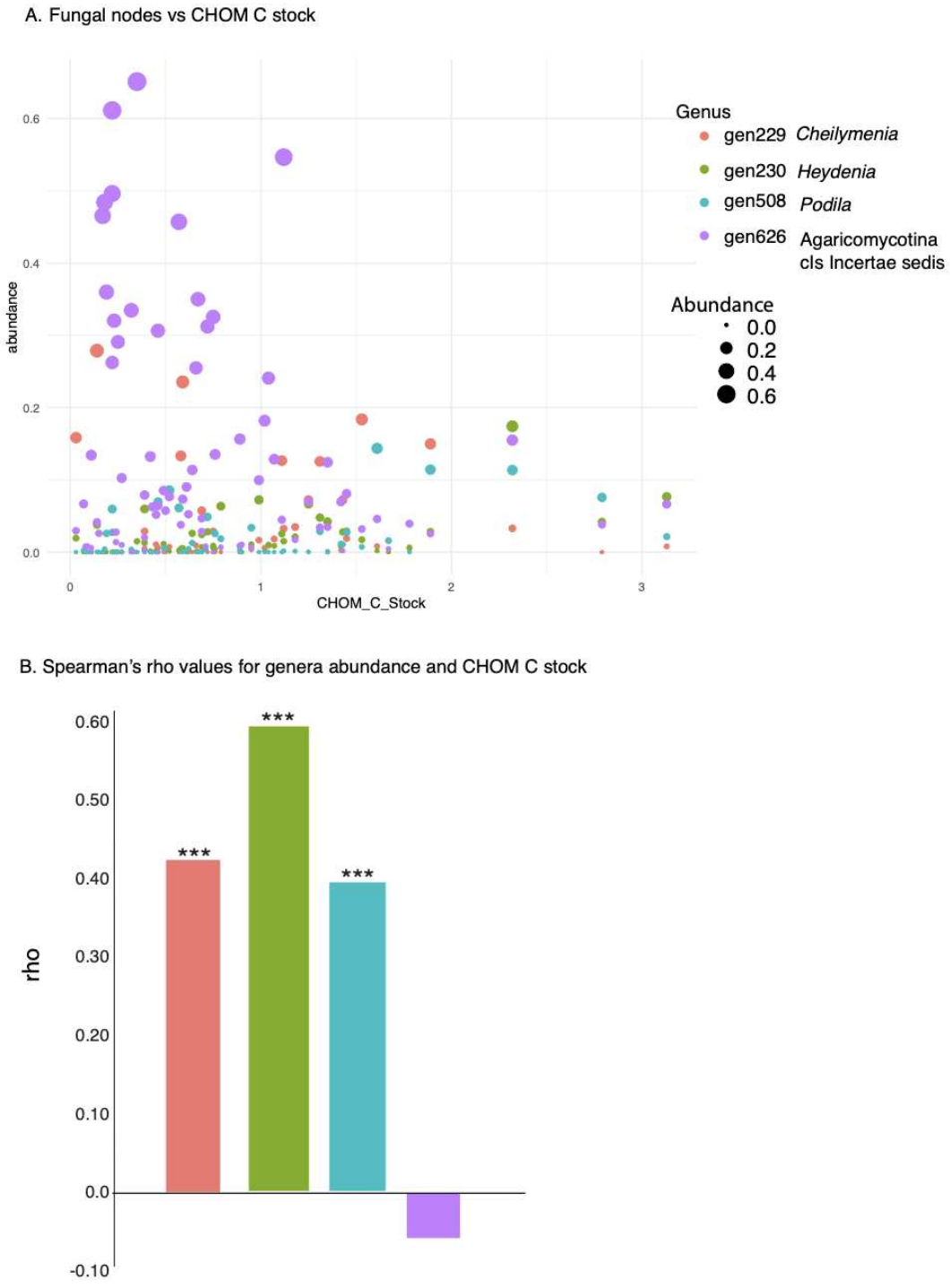
SI Figure 3.9 Fungal co-occurrence networks, network metrics, and core ASVs. a) Network analysis of fungal community reveals increased network complexity under CONV management. Nodes with less than two edges were remove for ease of visualization. Node size is reflective of abundance, and nodes are colored by phyla. No core or predictive ASVs are present in the network as visualized due to low connectivity. B) Significant increases in number of Edges were observed in the REGEN networks compared with CONV, and Significant increases in betweenness and path length were observed in the CONV networks compared with REGEN networks. C) ASVs found in 70% or more of samples under either management were determined to be "core" (Neu et al., 2021), were observed under both CONV and REGEN management at both depths, as indicated by color. Notably, an ASV identified as *Exophiala pisciphilia* is present in all samples.



SI Figure 3.10 Bacterial/archaeal genera with ASVs predictive of environmental parameters correlate positively with these parameters. These genera represent nodes with ASVs predictive of these metrics. Genera relative abundance correlates with A) SOC Stock, B) CHAOM C stock, C) N Stock, and D) Slope. For all, genera are differentiated by color and size of point reflects abundance. E) Spearman's rho values summarized: . = p value < 0.1, * = p value < 0.05, ** = p value < 0.01, *** = p value < 0.001

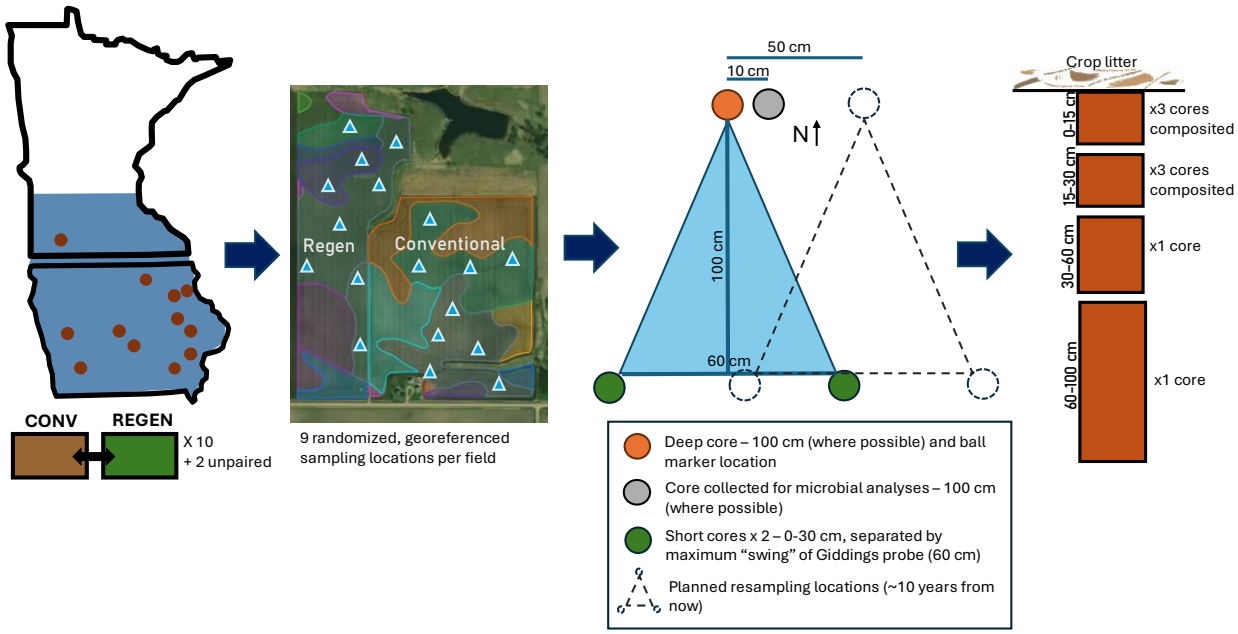


SI Figure 3.11 16S ASV Matches to MAGs. The heatmap show presence and absence of C and N cycling genes in the genomes associated with key ASVs. Out of the 685 ASVs that could be linked to agriculturally relevant MAGs, five are described in detail in text. Three are core ASVs (red text). These include 2 ASVs from genus *Nitrosocosmicus* (red text), one a core member of REGEN management and one a core member of CONV management, with slightly different functional profiles possibly reflective of differential nutrient and C availability under the two management types. Both ASVs' 16S rRNA gene sequences were matched to the 16S rRNA gene of a MAG at 97% identity across 253 base pairs. Another ASV, *Nitrospira C japonica*, is a core member of both REGEN and CONV farms at 15 – 30 cm deep, and its matched genome has the functional potential to perform many steps in the N cycle as well as degrade several sources of C. This ASV was a taxonomic match to a MAG at the genus level. Another ASV, identified as Nitrososphaeraceae, unidentified genus, (blue text) was predictive of CHAOM C stocks through Sparse Partial Least Squares regression and matched to two MAGs at 97% across 253 bp. One MAG (Nitrososphaeraceae b) possessed many genes related to C degradation. At the genus level, the relative abundance of Nitrososphaeraceae, unidentified genus, correlated positively with CHAOM C stocks.



SI Figure 3.12 Fungal nodes with ASVs predictive of CHAOM C stock correlate positively with this fraction. A) Four fungal genera contained ASVs predictive of CHAOM-C. Genera are differentiated by color and size of point reflects abundance. B) Spearman's rho values summarized. *** = $p < 0.001$.

Appendix 2: Supplemental Figures for Chapter 4



SI Figure 4.1 Sampling design for paired REGEN/CONV fields. Fields were located across Iowa and Southern Minnesota. Nine randomized sampling sites on matching or similar soil types were identified. Samples were collected at the corners of a north-oriented isosceles triangle with a base of 60 cm and a height of 100 cm. One deep core and two short cores were collected at each triangle and were cut along four depth increments (0-15, 15-30, 30-60, 60-100). Samples from the top two depth increments were homogenized across the three cores. An additional core was collected for microbial analyses ~ 10 cm from the deep core location and cut along the same depth increments, using sterilized implements.

SI Table 4.1 Typical field management data obtained from field managers/producers. Year-by-year management data was collected from 2013 to 2023, but average dates and rates are shown here.

Field ID	Mngmt. System	Years Cover Crops	Years No-Till	Rotation(s)	Planting date (Corn; Soybeans)	Harvest Date (Corn; Soybeans)	Average yield, Mg ha^{-1} (Corn; Soybeans)	Cover Crop Planting Date; Termination Date	Cover crop type(s)	CC terminati on	Tillage date(s)	Tillage implement (s)	N fert. dates (Corn; Soybeans)	N fert. rate, kg N ha^{-1}	Manure type	Manure application date	Manure app. rate, Mg ha^{-1}
C1	CONV	0	0	C-S	April 25th; May 5th	Sept. 25th; Oct 10th	11; 3				May 1st; Fall (after corn)	Field cultivator; disk ripper	Spring (corn years); Fall (before corn)	32; 120			
R1	REGEN	14	14	C-S	April 25th; May 5th	Sept. 25th; Oct 10th	11; 4			Chemical		No-till	Spring (corn years); Fall (before corn)				
C3	CONV	1	1	C-S; C-C	April 12th; May 11th	Oct. 25th; Oct 10th	12; 3				Spring; Fall (after corn)	Field cultivator; Disk ripper		179.336			
R3	REGEN	20	30	C-S; C-C	April 12th; May 11th	Oct. 1st; Sept. 29th	12; 3	Oct. 3rd and July 7th; May 2nd - June 13th	Cereal rye; 32 way mix	Roller-crimp; Chemical		No-till	May 16th (corn years only)	134.502			
C5	CONV	0	0	C-S	May 1st; May 9th	Oct 25th; Oct. 1st	12; 3				April 30th; Fall (after corn)	Field cultivator, disk ripper					
R5	REGEN	6	8	C-S	May 10th; May 27th	Oct 1st; Oct 20th	13; 3	Aug. to Oct.	Cereal rye, rapeseed, clover, oats, turnip, radish	Chemical	Nov. 1st	No-till; Strip till	Oct 20th (before corn)	134.502			
C9	CONV	2	2	C-S	April 26th; May 7th	Oct. 12th; Oct. 10th	14; 4	Oct. 8th; April 26th	Cereal Rye	Chemical	Fall	Disc Chisel	May 5th; Nov. 9th	55; 135	Chicken litter	Fall before corn (2020 only)	4
R9	REGEN	10	30	C-S	April 25th; May 6th	Sept. 30th; Oct. 12th	14; 4	Oct. 5th; April 23rd	Cereal Rye	Chemical		No-till	May 28th; Oct. 25th	69; 135	Chicken litter	Fall before corn	4
C10	CONV	0	3	C-S, C-C	April 25th; May 5th	Oct. 2nd; Oct. 22nd	16; 5				April 20th; Nov. 5th	Field cultivator; Chisel plow	June 5th; Nov. 10th	45; 135	Swine manure (liquid)	Fall before corn	39
R10	REGEN	6	7	C-S; C-C	April 26th; May 3rd	Sept. 25th; Oct. 10th	15; 3	Oct. 20th; May 5th	Cereal Rye, Hairy Vetch	Chemical		No-till	March 15th; Nov. 16th	29; 135			

0

```
Year Month Option
1            Block #1
1860         Last year
5            Repeats # years
1841         Output starting year
10           Output month
1.000        Output interval
F            Weather choice
Pair18.wth
  1 90  EROD 0.15
  1 105 CULT K
  1 136 CROP C1
  1 136 PLTM
  1 136 CULT I
  1 258 LAST
  1 258 HARV G
  1 287 CULT K
  1 300 EROD 0.15
  1 340 EROD -0.09
  2 90  EROD 0.15
  2 105 CULT K
  2 136 CROP C1
  2 136 PLTM
  2 136 CULT I
  2 258 LAST
  2 258 HARV G
  2 287 CULT K
  2 300 EROD 0.15
  2 340 EROD -0.09
  3 90  EROD 0.15
  3 105 CULT K
  3 136 CROP C1
  3 136 PLTM
  3 136 CULT I
  3 258 LAST
  3 258 HARV G
  3 287 CULT K
  3 300 EROD 0.15
  3 340 EROD -0.09
  4  75 CULT K
  4 90  EROD 0.15
  4 105 CROP OAT1
  4 105 PLTM
  4 105 CULT I
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  4 228 HARV G
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  4 258 PLTM
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  4 287 SENM
  4 300 EROD 0.15
  4 316 GRAZ W
  4 340 EROD -0.09
  5  75 FRST
  5 167 HARV H
  5 197 HARV H
  5 258 HARV H
  5 258 LAST
  5 258 SENM
  5 287 CULT K
  5 300 EROD 0.15
  5 340 EROD -0.09
-999 -999 X
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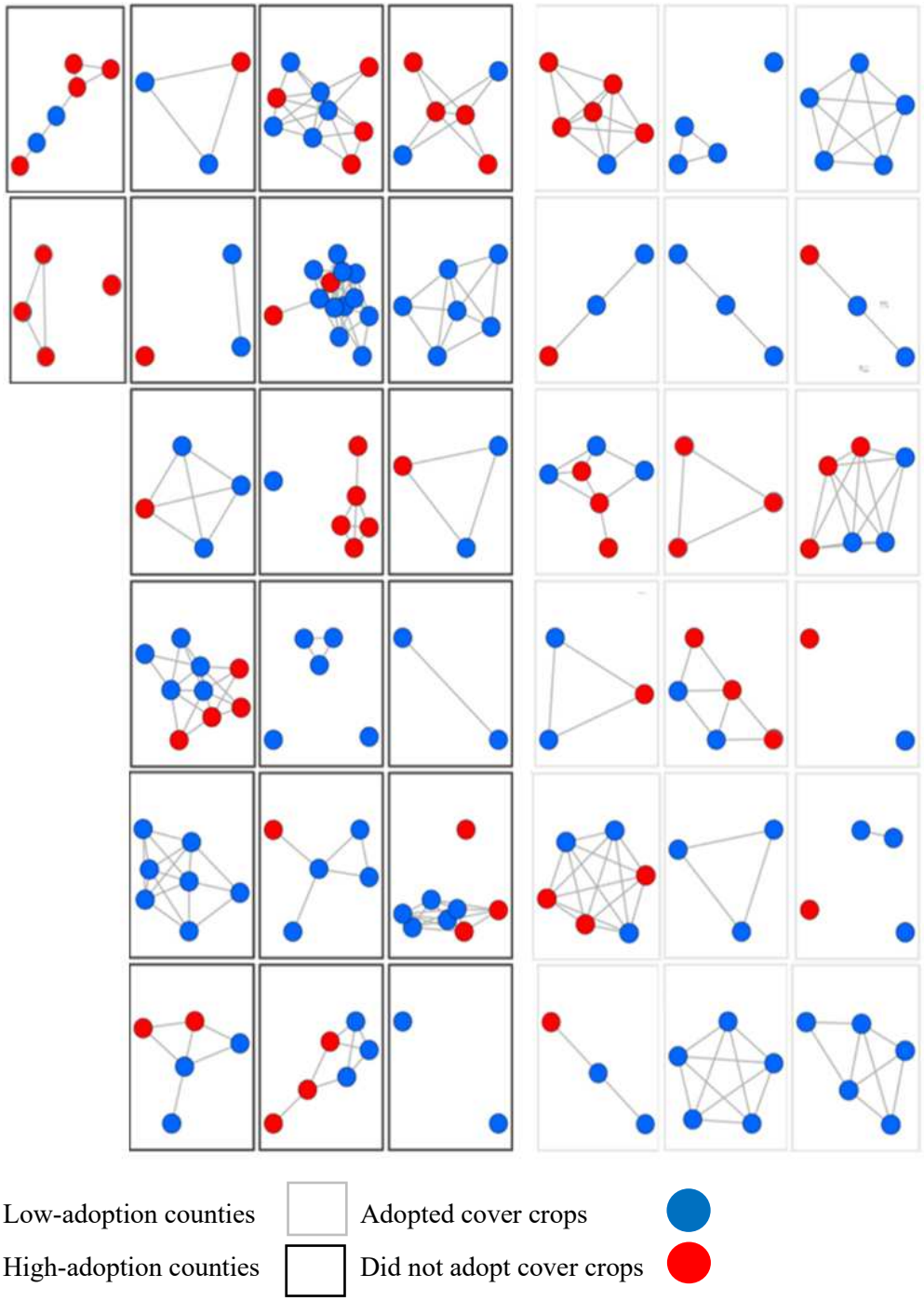
SI Figure 4.2 Example DayCent simulation block (Field C5) with estimated erosion and depositional events. Positive EROD events indicate soil loss, while negative EROD events indicate soil deposition.

Appendix 3: Supplementary Figures for Chapter 5



SI Figure 5.1 Farmers in high-adoption areas (left with black border) have larger networks and more diverse connections than farmers in low-adoption counties (right with grey border). Each box represents an Iowa farmer in the study. The red dots represent connections of the farmers that did not adopt cover crops, while the blue ones did adopt cover crops. A line between the dots means the connections know each other according to the interviewed farmer.

SI Table 5.1 Producer conservation information resource legend.

N	Organization
1	Continuum Ag
2	Facebook
3	AgriGrowth
4	Farm Progress / Wallaces Farmer
5	Cattleman's Association
6	Farm Service Agency
7	BECKs
8	Farmer Managers
9	Iowa Ag Water Alliance
10	Iowa Association of Farm Managers
11	Iowa Corn Growers Association
12	IA Department of Agriculture and Land Stewardship
13	Iowa Department of Natural Resources
14	Iowa Farm Bureau
15	Iowa Farmer Today
16	Iowa Farmers Union
17	Iowa Learning Farms
18	Acres USA
19	Iowa Soybean Association
20	Iowa State University Extension
21	Isaac Walton League
22	Leopold Center for Sustainable Agriculture
23	MOSA
24	National Association of Conservation Districts
25	National Corn Growers
26	National No Till
27	National pork board
28	Natural Resource Conservation Service
29	No-Till on the Plains
30	No-Till Farmer
31	Peasant Quail Turkey Federation
32	Peasants Forever
33	Podcast
34	No Till on the Plains
35	Pork check-off
36	Pork Producers Association
37	Practical Farmers of Iowa
38	Racoon River Watershed Association
39	RCND
40	Social media
41	Soil and Water Conservation District
42	Strip-Till Farmer Magazine
43	Tall Grass Prairie Grazing Conference
44	The Sparks
45	TikTok
46	Trees Forever
47	US Grains Council - international
48	Women in Food and Ag Network
49	YouTube