On Quantifying Water Quality Benefits of Healthy Soils

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Despite decades of research demonstrating links between many agricultural practices and water quality, the ability to predict water quality on the basis of changes in soil health remains severely limited. By better understanding how soil health affects downstream water quality, researchers and policymakers could prioritize different conservation practices while exploring more innovative soil health management strategies. Focusing on the Great Lakes region, we describe the value and challenges of different approaches to linking soil health and water quality, specifically applying nitrogen and phosphorus mass balances and adapting simulation models to better incorporate changing soil health conditions. We identify critical research needs, including paying greater attention to a broad suite of conservation practices and to biological indicators of soil health. We also discuss key barriers to farmer adoption of conservation practices from field to national scales, highlighting that improved scientific understanding alone is insufficient to drive widespread change.

Keywords: conservation policy, nutrient mass balance, nutrient management, environmental modeling, participatory solutions

Globally, widespread nutrient losses associated with more intensive and consolidated agriculture threaten environmental sustainability and farm viability (Carpenter et al. 1998, Basso et al. 2019). Excess applications of nitrogen (N) and phosphorus (P) through chemical fertilizers and animal manure exceed the proposed boundaries for resilient Earth systems (Steffen et al. 2015) and contribute to both soil and water quality problems (NRC 1993). Mounting frustration from the general public, who suffers the downstream externalities of modern agricultural production, has helped fuel the current interest in management practices that maintain productivity while improving environmental outcomes. A growing group of practitioners and researchers recognize that prioritizing practices that build soil health and retain N and P in agroecosystems offers a viable path to realizing water quality goals and improving long-term farm viability. Agricultural stakeholders would therefore benefit from coalescing around research and policy needs to advance soil health practices rather than maintaining the status quo, which will conceivably lead to regional water quality regulations. Incorporating soil health metrics into predictive water quality models is a critical need that would help translate decades of dialogue into action.

What, then, is soil health? (See box 1.) The term refers to the continued capacity of soil to function as a vital living ecosystem (NRCS 2018) and has become widely used over the past two decades. For the US Department of Agriculture's (USDA) Natural Resources Conservation Service, soil health represents a fundamental shift from striving to simply reduce soil erosion to building healthy agroecosystems and is helping to identify and address new knowledge gaps. The emphasis for building healthy soils is to promote biological activity. For instance, management practices that minimize disturbance (i.e., tillage) and provide diverse, continuous inputs of carbon (C) to soil can protect habitat by stabilizing soil structure and can also allow for reductions in external inputs. Healthy soils promote natural biogeochemical processes that enhance functions, such as nutrient cycling and availability to crops and water holding capacity, which help prevent erosion and runoff while boosting long-term productivity (Doran 2002, Karlen and Rice 2015).

Although *soil quality* typically describes underlying soil characteristics and processes (Wander et al. 2019), *soil health* emphasizes interactions among soil biological, chemical, and physical properties that indicate a soil's capacity to provide key functions. Importantly, soil health assessments are based on multiple ecological functions rather than being focused solely on crop productivity, which was the historical basis for evaluating soils. In 1993, the National Research Council (NRC) challenged the scientific community to jointly address soil and water quality goals (NRC 1993), recognizing that healthy soils are vital for sustaining environmental quality and food security. The NRC report also addressed the potential for using predictive models to identify strategies to improve soil health. Since the 1993 NRC report was published, public interest in and support for soil health

BioScience 70: 343–352.
doi:10.1093/biosci/biaa011 Advance Access publication 19 February 2020

Box 1. What is soil health?

Soil health builds on a solid foundation that reflects numerous complementary contributions, including soil conservation, soil carbon management, soil security, ecosystem services, and prevention of soil degradation (Karlen et al. 2019). Soil health is governed by interactions between ecosystem state factors and farm management decisions. With regard to farm management, soil health reflects a continuum of practices (figure 1). Soil health assessments integrate biological, chemical, and physical indicators of ecosystem properties and processes (figure 2), because they affect critical soil functions and influence ultimate management goals. The many functions of soil include biological activity; soil water infiltration, retention, and release; storing and cycling nutrients; and sequestering carbon.

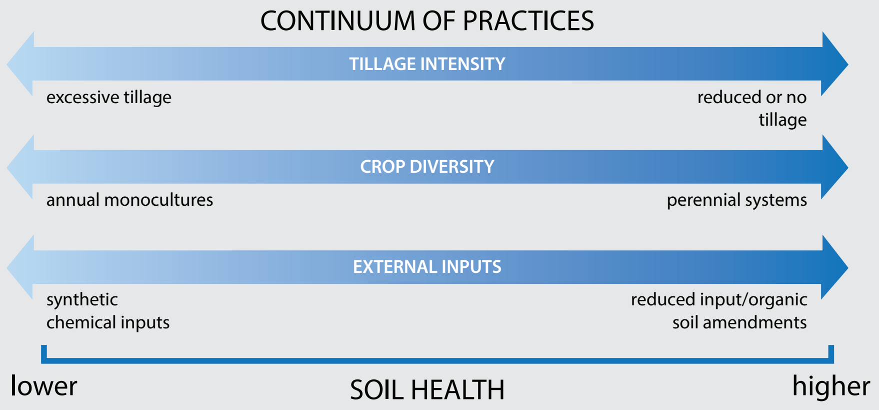

Figure 1. Conceptual diagram illustrating how agricultural management practices can influence soil health. Source: Adapted with permission from Karlen and colleagues (2019).

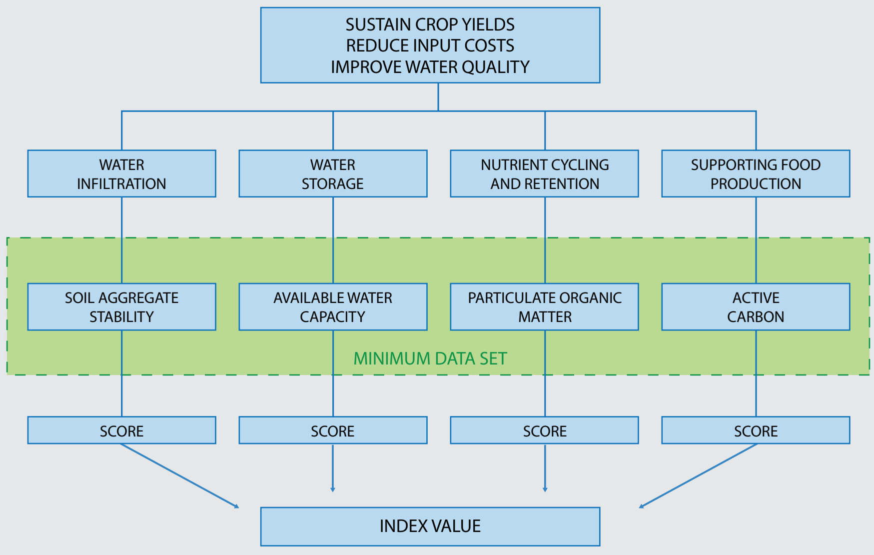

Figure 2. A soil health assessment framework based on integrated scoring functions has been used globally (Karlen et al. 2019) with a variety of indicators (e.g., aggregate stability, active carbon) that respond to changes in management relatively quickly and are cost effective to measure (Moebius-Clune et al. 2016). Soil health assessments are used to determine how various soil functions (e.g., water infiltration, nutrient retention) affect a specific management outcome (e.g., improved water quality, crop yields). The ultimate aim is to maintain well-functioning, living, and dynamic soil resources that sustainably meet food security goals. Source: Adapted with permission from Andrews and colleagues (2004).

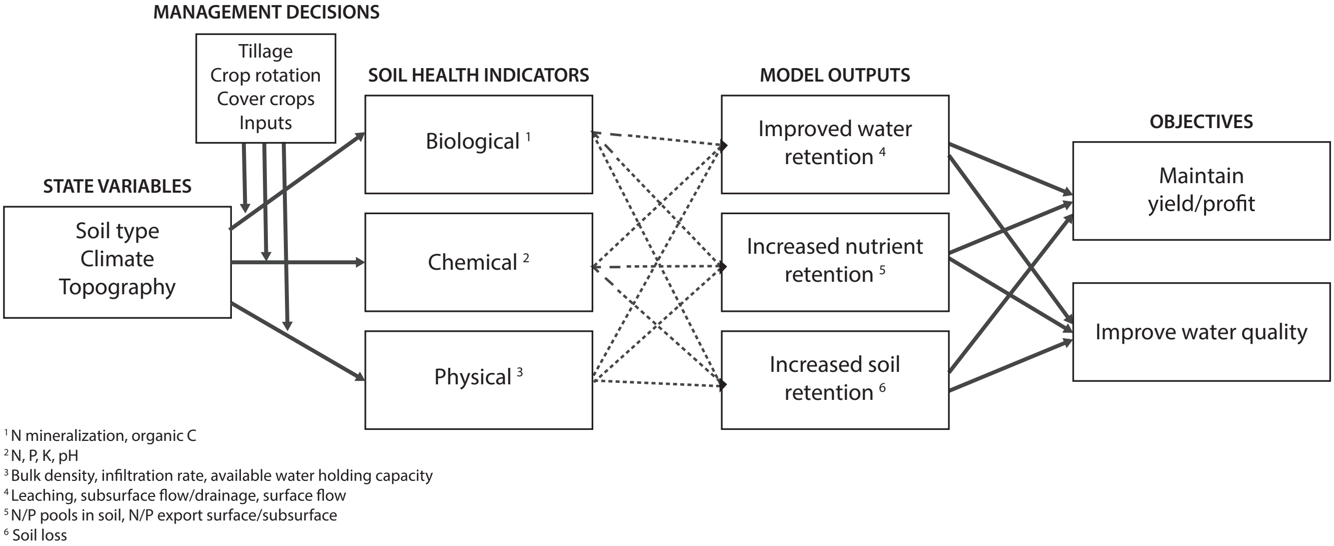

Figure 3. A conceptual diagram illustrating the complex links relating management, soil health, and water quality. The dashed lines represent the largest knowledge gaps.

assessments have grown significantly. Because of advances in computing, monitoring, and research, our understanding of soil health processes (Veum et al. 2014, Moebius-Clune et al. 2016, Fine et al. 2017) and the predictive capabilities of models have also both increased significantly. We also have more advanced knowledge of the complex links between management decisions and soil health (Hurisso et al. 2016, Moebius-Clune et al. 2016). However, our ability to predict water quality improvements because of specific changes in soil health remains a critical research gap for integrating soil health into state and regional nutrient management plans (figure 3), despite decades of research efforts and awareness of the need to address eutrophication and hypoxia. By better understanding how in-field soil health affects downstream water quality, researchers and policymakers could prioritize best management practices while exploring more innovative soil health strategies for mitigation of harmful algal blooms (Karlen and Rice 2015).

In the present article, we identify pressing research needs to advance understanding of links between soil health and water quality. To narrow the challenge, we focus on the Lake Erie watershed. Located in the US Great Lakes Region, Lake Erie has approximately 25,740 square kilometers of freshwater that is experiencing intense eutrophication, increasingly variable weather patterns, and harmful algal blooms (Michalak et al. 2013, Brooks et al. 2016). The EPA's domestic action plan (EPA 2018) for the Lake Erie watershed specifically identifies the need to prioritize soil health in future conservation efforts. We connect soil health and water quality modeling perspectives to summarize current knowledge and highlight critical gaps in our ability to link soil health management practices to watershed-scale N and P reductions.

Understanding soil health: Advances and research gaps

As was shown in box 1, soil health assessments use chemical, physical, and biological indicators to assess soil functional status (Veum et al. 2014, Fine et al. 2017). This more comprehensive evaluation distinguishes soil health assessments from traditional soil tests (primarily used to determine lime and fertilizer inputs) that focus on physiochemical metrics such as pH and soil nutrient concentrations (figure 3; e.g., Doran and Zeiss 2000, NRCS 2018). Soil organic matter is the source of C in soil, which fuels the soil food web and is therefore tightly coupled to biological and physical properties. For instance, physical indicators of soil health, such as aggregate stability and soil structure, are influenced by plants and microorganisms (Lehmann et al. 2017). Building on an extensive body of research on soil biology in agroecosystems (e.g., Uphoff 2005), many of the new soil health indicators assess biological processes. These include C and N mineralization rates, active C, extracellular enzyme activities, phospholipid fatty acids, and particulate organic matter. Mineralization rates, particulate organic matter, and other indicators of relatively rapidly cycling fractions of soil organic matter (SOM) are critical for understanding N and P cycling (Marriott and Wander 2006, Hurisso et al. 2016). This is because total SOM is not an ideal indicator of soil nutrient availability, given that the largest fractions of SOM turn over slowly (Marriott and Wander 2006). Soil health assessments, then, are important for realizing water quality goals because a broad suite of soil properties and processes, including SOM and microbial activity, influence water infiltration and N and P availability, thus contributing to overall soil function. Numerous agricultural management practices can either improve or impair these soil indicators and, consequently, soil health (box 1; Moebius-Clune et al. 2016). In watersheds such as Lake Erie, soil degradation (i.e., decreased soil health) due to intensive management practices (e.g., excessive tillage, fertilization, irrigation) increases the potential for water pollution and ultimately decreases long-term farm productivity.

Two dominant global drivers of soil health decline, soil erosion and the loss of SOM, are largely the result of intensive management practices focused on short-term yield goals that lead to insufficient C input, excessive crop residue removal and tillage, limited crop rotation diversity, and poor drainage control. In fact, several decades of research have assessed how agricultural management affects soil processes at various scales (i.e., plot, field, farm, catchment, watershed). For instance, 18 long-term (i.e., from decades to more than a century) cropping systems experiments in the United States have been incorporated into the USDA Agricultural Research Service's (USDA-ARS) Long-Term Agroecosystem Research network, which is now coordinating experimental efforts across sites to determine general characteristics of sustainable agroecosystem management (Spiegal et al. 2018). Individually, these experimental sites have identified organic nutrient sources; reduced or no-tillage practices; reduced chemical inputs, seasonal, and overwintering cover crops; and integrated perennial species into more diverse and extended crop rotations as effective strategies for improving soil functions and reducing potential for nutrient losses (e.g., Drinkwater et al. 1998, Liebman et al. 2013, Robertson et al. 2014). However, ongoing research is essential for refining the development and interpretation of soil health indicators on the basis of reproducible methods that are tailored to regional conditions (Wander et al. 2019). More research is also needed to fully understand the effects of soil health practices on P export and the partitioning of losses as soluble or particulate P (International Joint Commission 2018). Furthermore, although it is well documented that particular combinations of these practices can maintain or increase crop yields and provide water quality benefits at specific locations, because of variation in soil types, climate, specific management practices, and other variables across sites, there is a lack of generalizable knowledge to predict how management drives short- and long-term changes in soil health and water quality outcomes at scale. Such predictive knowledge should play a stronger role in policy development, including for improved state and regional nutrient management plans.

Many soil health functions may link agricultural production and N and P loading. We focus on hydrologic capacity, N and P retention and cycling through SOM and associated biological activity, and sustaining crop productivity as the most immediate and relevant functions within the agricultural sector (figure 3). Hydrologic capacity increases water infiltration and storage, which, in turn, reduces surface runoff and leaching from agricultural fields. Greater retention in SOM and more efficient cycling are especially important for N and P because of their importance to crop productivity and their roles in the eutrophication of aquatic ecosystems. Finally, increased stability and resilience of crop yields is essential not only to meet food, feed, fiber, and fuel demands under more variable climate conditions but also to ensure that farmers have sufficient income to implement new practices and long-term management changes.

Several critical research gaps should be addressed to enable current models to connect soil health indicators to outcomes including sustained or increased crop yields and improvements in water quality. Despite a general understanding of the links between agroecosystem management practices and soil health indicators and those between management and water quality (e.g., the integration of best management practices into water quality models), we lack comprehensive data sets specifically linking soil health measurements to water quantity and quality. One example of a relevant effort is the Agricultural Collaborative Research Outcomes System being developed by the USDA-ARS (Delgado et al. 2018) to link data from several projects including the Greenhouse Gas Reduction through Agricultural Carbon Enhancement Network, Resilient Economic Agricultural Practices, and the Nutrient Use and Outcome Network. Such comprehensive data sets will ultimately enhance our ability to quantify and predict water quality outcomes at watershed scales associated with different soil management practices that directly influence soil health (figure 4).

Understanding and modeling links among management, soil health, and nutrient pollution

Along with an improved scientific understanding of soil health dynamics, the application of ecosystem assessments in agricultural landscapes has also increased. This is a vital first step, because it is at field and landscape scales that links among agricultural management decisions, soil health response, and water quality outcomes must be quantified. Ecosystem-based approaches are therefore necessary to account for links between soil health status and water quality outcomes if appropriate, high-quality data can be compiled. We discuss two key approaches, mechanistic models and N and P mass balances, which can be adapted and integrated in novel ways to make these links and address this complex problem.

Mechanistic models. A number of mechanistic models are available to predict the impacts of best management practices on N and P losses from agricultural fields or their effects on downstream water quality. Our article is not intended to be exhaustive but is, instead, limited to a subset of models that are commonly applied to evaluate agricultural management practices: the soil and water assessment tool (SWAT) model (Arnold et al. 2012), the century/daycent model (Parton et al. 1998), and the agricultural policy/environmental extender (APEX) model (Williams et al. 1998). The latter is the model underlying the Nutrient Tracking Tool, a decision support tool being promoted in the Great Lakes Region for water quality tracking and trading programs. Each of these models has been applied to simulate

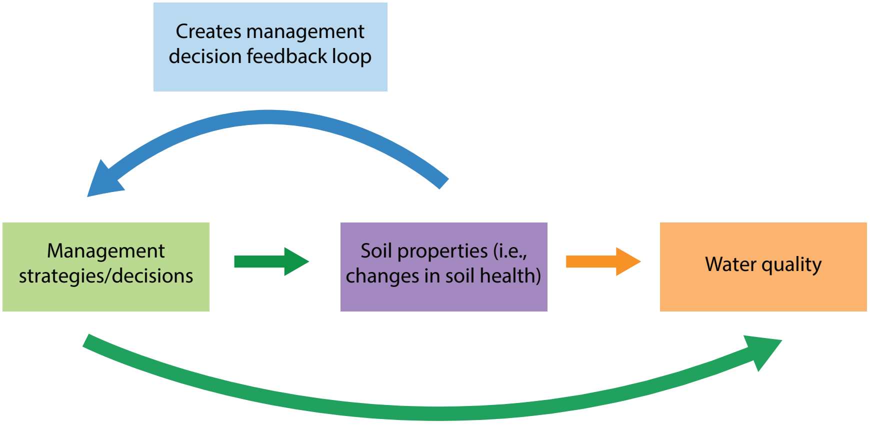

Figure 4. Links between farm management practices and soil properties and between management and water quality (the green arrows), have been fairly well characterized, particularly at plot and field scales. However, the ability to quantify and predict water quality outcomes at watershed scales associated with different soil health indicators (the orange arrow) is lacking.

soil health practices (e.g., Wang et al. 2008, Campbell et al. 2014, Scavia et al. 2017).

These models have relatively robust links among soil physical properties, management practices (i.e., reduced tillage), and water quality. To some extent, these models also link soil chemical properties and water quality, but that is still only a partial understanding of soil health, which integrates physical, chemical, and biological properties and processes. Therefore, despite decades of model development and in-field research trials, the ability to model the impacts of a broad suite of conservation practices on soil health and water quality outcomes is limited. This is particularly the case for less common conservation practices, such diversified crop rotations and the use of legume N sources, which are also the practices that long-term experiments suggest have the greatest promise for mitigating water pollution. Several factors contribute to this limitation, including a smaller body of literature on diversified management when compared with low-diversity row crop systems; limited data linking practices to water quality at larger spatial scales such as watersheds (cf. Randall et al. 1997); and a limited capacity to model mechanistic links among management, soil health properties, and water quality. Furthermore, many complex plant–microbe–soil interactions that drive N and P cycling in farm fields and at larger scales are not fully understood. Biological indicators of soil health provide a wealth of knowledge about soil function; however, the ability to directly link these indicators to management recommendations for improved water quality is a complex and important research need. Consequently, new bridges are needed among scientists quantifying biological, chemical, and physical aspects of soil health and field and watershed modelers.

In general, each of these models can simulate ecosystem properties and processes that are closely aligned with the concept of soil health, including rainfall infiltration or runoff, soil water content, evapotranspiration, crop growth as a function of water and nutrient uptake, litter decomposition, SOM cycling, mineralization of nutrients, and nutrient export. The models are distinguishable by their intended scale of application (i.e., SWAT is generally applied at the watershed scale, APEX at field or small-watershed scales, and century/daycent at the field scale), and by specific submodules that constitute different relative strengths. For example, century/daycent offers a relatively advanced simulation of C and N gas fluxes and SOM dynamics. As a result, SWAT and APEX modelers have incorporated century/daycent submodels to simulate changes in SOM and N gas (Izaurralde et al. 2006, Zhang et al. 2013, Yang et al. 2017).

Although the transformations of N and P are complex and different (e.g., adsorption of mineral P to soil particles, whereas mineral N is more soluble), each model simulates these chemical and physical processes and can provide reasonable projections of system outcomes as a consequence of individual components, processes, and their interactions. For example, measured and modeled outcomes of cover crops or buffer strips on runoff or leaching—and, therefore, the transport of contaminants to surface- or groundwater bodies—are often in good agreement (e.g., Singer et al. 2011). Many modeling studies conducted in the Lake Erie watershed have predicted improvements in water quality with practices such as no-tillage, filter strips, and use of cover crops (e.g., up to 18% reductions in total N and P loads), but their results suggest that combinations of best management practices are needed to achieve more substantial reductions in N and P loading (Bosch et al. 2013, Smith et al. 2015). Consequently, mechanistic models are important tools to clarify how conservation practices affect N and P losses. However, most modeling studies in the Lake Erie region were validated with limited field observations, consider a limited range of best management practices, and lack data linking different management strategies to changes in soil health.

To help advance the science of soil health and water quality modeling, we note common limitations within the three models in their representation of response to known soil health practices (e.g., cover crops, reduced tillage, crop rotation, perennial crops), changes in soil health indicators, and nutrient loss. Specifically, the models currently lack detailed simulation of biological processes such as microbial community composition and diversity, extracellular enzyme activities, or measurable SOM pools, which are important indicators of soil health. In addition, biological processes are restricted to the topsoil (i.e., up to 30 centimeters) in most models, whereas field studies have shown that management can substantially alter subsoil SOM and affect nutrient cycling (e.g., Bell et al. 2012). Another concern is that many models include simplistic representations of macropore flow, which is known to be influenced by management practices and can significantly affect N and P losses, especially in fine-textured, artificially drained soils within the Western Lake Erie Basin. To keep the models manageable, operational, and therefore somewhat simplistic, many also exclude representation of some important links and interactions between system components or processes. For example, although these models can predict N and P loss as a consequence of multiple soil physical properties (i.e., bulk density, available water capacity, and hydraulic conductivity), they generally do not simulate dynamic changes and temporal fluctuations that are known to occur in response to various soil health practices, although the APEX model offers an option to dynamically simulate available water capacity because of changes in SOM. Overall, these models do not simulate some very important soil health indicators and likely ignore important mechanisms by which soil health practices influence N and P losses from agricultural fields and landscapes. This is not an insurmountable barrier, given that simulation model development is an ongoing process.

To advance simulation-modeling science and better predict soil health status and potential effects on water quality, we suggest two broad strategies for model improvement. First, given that mechanistic models currently input soil health indicators (e.g., bulk density and available water capacity) as static values prior to model execution, those parameters could be amended prior to model execution to improve predictions of how soil health practices may influence the overall system. This approach could reduce the overall simulation bias, but seasonal or daily changes would not be correctly represented. Furthermore, this would require users to estimate the changes in parameters prior to setting up the simulation, which is time consuming and reduces the ease of using a model. A second approach would be to modify the mechanistic models (i.e., source code change) to force inclusion of soil health indicators using either empirical or mechanistic equations. This is a model improvement task that will require intensive measurement data, understanding of the processes to derive equations, and consensus among researchers and practitioners regarding which practices and soil health parameters are most important and influential on the desired outcome (i.e., improved water quality). As a result, we do not recommend the explicit simulation of all processes germane to soil health. For example, forcing the simulation of detailed soil microbial processes in the SWAT model is highly unlikely to have a meaningful impact. However, new generations of SOM models include microbial biomass or activity and other measurable SOM pools with differing turnover times and also consider greater soil profile depths (e.g., the MEMS model; Robertson et al. 2019). Other cropland models better capture spatial and temporal dynamics of soil hydraulic properties and their effects on multiple soil N and P pools in response to management practices (e.g., the SALUS model; Basso et al. 2006). Furthermore, integrating these models into watershed models would better represent N and P cycling dynamics that link soil health with water quality outcomes. Model evaluation and comparison exercises need to be performed to balance the number of processes represented in each model and to improve accuracy by including the most important processes. In addition to determining how to link biological indicators of soil health to watershed models, our suggested top three processes to be included and tested are the direct effects of tillage and soil compaction on soil bulk density and soil hydraulic parameters (e.g., available water capacity, macropore fraction, and hydraulic conductivity), the impacts of SOM on soil bulk density and soil hydraulic parameters, and SOM dynamics in deep soil (current models only simulate SOM in topsoil). Taken together, these suggested amendments to mechanistic models would provide a better understanding of how soil health practices affect nutrient losses and water quality. There are other model improvements, not directly related to soil health indicators, which would improve simulated water and nutrient flows. For example, the models may be improved by replacing their one-dimensional hydrology submodel with a three-dimensional one. Together with our suggested improvements for soil health indicators, such adaptions to these models would provide more accurate predictions to inform management and policy decisions.

Nutrient mass balance: An ecological concept and indicator of farm nutrient losses. Along with improved mechanistic models, applying nutrient mass balances at multiple spatial scales can provide data that connects management decisions (i.e., a transition toward soil health) and potential outcomes for water quality. Mass balances are simple quantifications of complex nutrient cycling processes, calculated as the sum of nutrient inputs minus harvested outputs for a bounded system. They have been widely applied to identify N and P surpluses across fields, farms, watersheds, and other scales since their development in ecosystem ecology (Bormann and Likens 1967). Mass balance is a robust, ecosystem-based indicator of potential N and P losses where inputs of either nutrient have exceeded removal in crop harvests over time (Drinkwater and Snapp 2007, Robertson and Vitousek 2009, McLellan et al. 2018).

At watershed and regional scales, mass balance models have shown that net anthropogenic N and P inputs closely predict loads of those nutrients in rivers that cause freshwater or coastal marine eutrophication (Caraco and Cole 1999, Howarth et al. 2012, Goyette et al. 2016). Application of synthetic fertilizers and manure for crop production is a primary source of these nutrient inputs. For specific lakes, the relationship between external P inputs and water quality is also well documented (e.g., Smith et al. 2006) and shows the need to reduce P fertilizer inputs to reduce losses (Han et al. 2012, Kara et al. 2012). However, many watersheds in the Great Lakes region have stored soil P (i.e., legacy P) resulting from decades of P inputs that exceeded P removal in crop harvest (International Joint Commission 2018). For

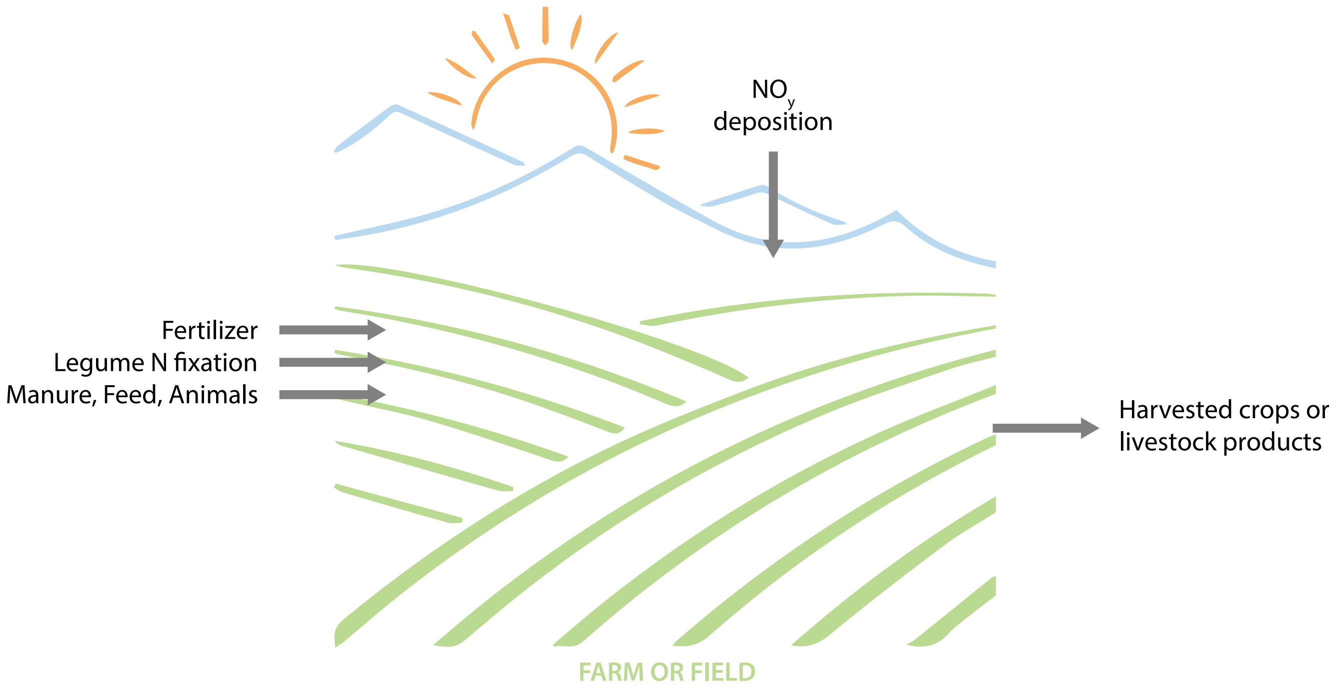

Figure 5. Farm- or field-scale N and P mass balances are calculated as the sum of N or P inputs to a farm or field, minus the N or P removed from the farm or field with harvested crops for a complete crop rotation or longer. N and P surpluses are indicators of N and P losses.

such nutrient saturated agroecosystems, it may take years for P loads to decrease to desired levels, even if inputs are curtailed (Meunich et al. 2016). Similarly, we acknowledge that even if soil health practices are widely adopted in the near term, there will likely be a delay for realizing water quality improvements in the Lake Erie watershed.

Mass balances can also serve as indicators of N and P pollution from cropping systems at smaller spatial scales (Zhang et al. 2015, McLellan et al. 2018). Although researchers in agronomy and ecology have quantified N and P balances of varying complexity for decades, partial field- and farm-scale N and P balances are an underused tool for linking management to both soil health and water quality outcomes. Partial field- and farm-scale balances focus on the largest nutrient flows managed by farmers (figure 5) and do not include specific nutrient loss pathways or complex internal cycling processes (Robertson and Vitousek 2009). Although they are relatively simple, N and P balances are useful for comparing management systems across working farms in a region and for linking management strategies to environmental performance (e.g., Basso et al. 2019); however, few studies have applied balances to assess a wide range of conservation strategies, such as diversified crop rotations. One study on 95 farms in the Corn Belt showed that rotations with legume N sources and perennial forages had the most efficient N balances (Blesh and Drinkwater 2013).

To use N and P mass balance as proxies for N and P losses from fields, it is necessary to assume a steady state for the SOM pool. Not accounting for internal nutrient cycling dynamics assumes that changes in total soil C, N, and P stocks are minor relative to the large nutrient flows managed by farmers (e.g., fertilizer or manure inputs and removal with harvested crops) and the corresponding N and P surpluses. This assumption may not hold if SOM is changing relatively quickly in a field. For instance, accumulation of particulate organic matter pools and increases in microbial respiration in response to adoption of certain soil health practices would mean that SOM is a source of N and P in a partial balance that is unaccounted for. However, the steady state assumption is typically valid for farms with relatively stable management histories (e.g., 5 or more years), particularly if the balances are tracked over complete crop rotation cycles or longer (McLellan et al. 2018). In addition, changes in soil health, such as the accumulation of SOM pools, should ultimately allow for reductions in external N and P inputs to soil, because of greater microbial activity and internal nutrient cycling capacity (Drinkwater and Snapp 2007, Hurisso et al. 2016), eventually balancing nutrient budgets and improving water quality outcomes (Blesh and Drinkwater 2013).

Partial N and P balances could be readily applied to estimate the expected water quality outcomes of different soil health practices by collecting data on N and P inputs and harvested exports from groups of farmers that have adopted these practices. This is important because soil health practices may be insufficient for mitigating N and P losses if they are not accompanied by reductions in external N and P inputs. Mass balances are a useful tool for assessing potential for N and P losses on the basis of data that are relatively easy to access (McLellan et al. 2018). Indeed, farm-scale nutrient balances have been applied to environmental monitoring of agriculture in Europe (Oenema et al. 2003) and have also been integrated into policies to decrease N balances at regional and national scales (OECD 2013, EEA 2017). However, they have not been applied as a policy tool in the United States, in part because of agrienvironmental policies that prioritize economic incentives over regulation (Potter and Wolf 2014). Despite this, there is recent interest in their application to voluntary conservation or certification schemes in the United States (McClellan et al. 2018). Finally, a critical research gap is the need to integrate on-farm soil health assessments with ecosystem approaches such as field- and watershed-scale nutrient balances to better understand relationships between management practices focused on building soil health and the potential for N and P losses across scales. These relationships can be further refined through collaborations with scientists applying the predictive models described above.

Farmer adoption

Academic efforts to draw stronger connections among soil health, N and P mass balances, and water quality models may prove useful for policy developers and land use planners, but they will not directly translate into on the ground decision changes by farmers. Simply providing more accurate information and better predictive models will have a minimal impact for on-farm decisions because of a suite of social–ecological factors that constrain farmer adoption of conservation practices at larger scales (Stuart and Gillon 2013). This is especially true for the diversified practices that cropping systems experiments suggest hold the most promise for mitigating N and P losses, which would represent transformative changes for many grain and livestock farms. Indeed, despite decades of promoting fairly common conservation practices, overall farmer adoption remains low throughout the Corn Belt. For example, cover crops are currently being used on less than 3% of planted acres and less than 20% is being managed using no-till practices (USDA 2017).

At the farm level, some farmers dispute the potential impacts of different management practices on water quality, whereas others accept responsibility but are not acting. For instance, Floress and colleagues (2017) noted that half of their study participants in Indiana did not believe that fertilizer was a significant contributor to water quality impairments, and farmers in Saginaw Bay, Michigan, attributed urban sources of water pollutants as more responsible for poor water quality than agricultural sources (Eanes et al. 2017). Similarly, even though a study in Iowa (Karlen et al. 2005) confirmed that using a late-spring soil nitrate test for corn N fertilizer recommendations could significantly reduce N losses in drainage water, concerns about the increased risk caused farmers to revert to prestudy fertilization practices and therefore negate documentable water quality improvements realized during the project. The fear of increased production risk may also explain why 55% of the farmers in the western Lake Erie basin reported a willingness to use cover crops, but the current adoption rate is only 30% (Wilson et al. 2019).

Research on cover crop adoption has identified numerous barriers, which are relevant to adoption of soil health practices generally, at scales ranging from individual farms to national policies. These constraints include difficulties of establishing cover crops into highly productive corn–soybean rotations (e.g., a short period for cover crop growth between main crops), the cost of obtaining seed, and economic incentives in national farm policy, including crop insurance schemes that maintain high-input cropping systems (Blesh and Wolf 2014, Roesch-McNally et al. 2017). For farmers who are willing but not yet using cover crops and other recommended conservation practices, the biggest barrier is often perceived efficacy. Efficacy reflects both a farmer's confidence in their ability to implement the practices successfully and their belief in the effectiveness of the recommended practices (Gardezi and Arbuckle 2019, Wilson et al. 2018, 2019). The reasons efficacy is low differ for each particular practice but generally have to do with a range of challenges including short-term costs, weather-related implementation problems, and perceived complexity of the practice. Moving forward, there is a need to build farmer efficacy more broadly.

One option to address this challenge at the farm scale would be through interactive decision support tools that capitalize on N and P mass balances and improved mechanistic models. Such tools could allow individual farmers to assess the effectiveness of particular practices on a field by field basis, so that the recommendations are personalized as opposed to randomly allocated at a watershed scale. For an individual farmer, these tailored management plans may improve adoption of the soil health practices rooted in a particular support tool. However, models need to accurately capture the dynamics of soil health to build confidence in the proposed solutions. Finally, supporting widespread transitions to soil health practices on farms will also require reassessing current farm bill and state-led conservation incentive programs for their utility in driving long-term management change within agriculture.

Conclusions

Soil health is increasing in importance across the agricultural sector because of narrowing profit margins and a desire among producers and consumers to sustain soil and water resources for future generations. To make meaningful change in conservation we must couple scientific efforts to assess soil health with mechanistic modeling of soil processes and water quality. Specifically, we identify several immediate research needs. First, models may be modified to include processes important to soil health using either empirical or mechanistic equations. Such improvements will require robust investments in data collection and synthesis for model validation, particularly for the newer indicators of soil health that reflect complex biological and physical processes in agroecosystems. Second, future research should integrate on-farm soil health assessments with field- and watershed-scale N and P balances. This research will prove critical for understanding the relationship between building soil health through conservation practices and N and P losses, with potential for direct application as policy tools. Finally, despite decades of awareness among stakeholders that eutrophication presents a global sustainability challenge, minimal progress has been made, in large part because of social and economic barriers within the agricultural sector. Therefore, in addition to advancing the scientific goals outlined in the present article, there is an urgent need to develop improved decision support tools for farmers alongside rethinking our current approach to conservation incentive programs, to increase the likelihood of management practice adoption. Researchers and practitioners should outline a clear and concise set of conservation practices that achieve joint soil health and water quality goals and develop innovative policies and approaches to overcome the large socioeconomic barriers to widespread farmer adoption.

Acknowledgments

We thank all participants of the 2018 workshop “Improving Models of Nutrient Loading and Harmful Algal Blooms through a Watershed-Scale Approach that Emphasizes Soil Health and Upland Farming Practices,” whose contributions helped us develop the ideas in this article. The workshop was coordinated by the Michigan Environmental Council and by the Cooperative Institute for Great Lakes Research (CIGLR), which represents a cooperative agreement between NOAA and the University of Michigan (no. NA17OAR4320152), with funding provided by CIGLR. We thank the workshop steering committee, Craig Stowe, Robyn Wilson, and Mark Rowe, and four anonymous reviewers whose comments improved the manuscript.

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