Using an interdisciplinary approach to improve efficacy of agricultural conservation practices for protecting stream health

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ABSTRACT

Protecting water quality, biota, and ecosystem services of streams (cumulatively referred to as stream health) while increasing food production is a major global challenge. One way to balance these often-competing interests is through the installation of agricultural conservation practices, such as excluding livestock from streams via fencing and adjusting grazing patterns. However, conservation practices often do not improve stream health as expected. Failure to achieve stream health outcomes may be due to biophysical (e.g., conservation practices are not appropriate for the landscape) or social reasons (e.g., agricultural producers are not willing to use conservation practices). Therefore, the goal of my dissertation research was to understand factors influencing effectiveness of conservation practices using an interdisciplinary approach that integrates ecological engineering, ecology, and social science. My research focuses on southwest Virginia, a karst region where cattle grazing is common. In the introduction, I developed a social-ecological framework that outlines how the natural and social sciences can be used to guide effective placement and implementation of conservation practices and explain why interdisciplinary approaches are often necessary due to social-ecological connections that influence efficacy (i.e., feedbacks, heterogeneity, time lags, and thresholds). In Chapter 1, I modeled pollutant transport to characterize watershed features that contribute disproportionate amounts of pollutants to streams. I found that water, and associated nitrate, is primarily entering streams through subsurface pathways, whereas sediment is entering the stream through streambank erosion. Therefore, a combination of

conservation practices that stop nitrogen at its source (e.g., nutrient management plans) and stabilize streambanks (e.g., fenced riparian buffers) could be useful for protecting stream health. For Chapter 2, I sampled water quality, habitat, and macroinvertebrates from 31 streams within sub-watersheds that span a range of pollutant yields, conservation practice densities, and agricultural land use extent to understand the pathways through which conservation practices influence stream health. Agricultural land use increased total nitrogen and decreased macroinvertebrate diversity, but conservation practices stabilized nitrogen and improved bank stability. Despite such improvements, adverse effects on water quality and habitat still limited the biotic assemblage. Therefore, innovative conservation practices, higher densities of existing practices, or allowing more time for the effects of existing practices to improve water quality and habitat may be required to achieve stream health goals. For Chapter 3, I surveyed producers to understand if they continue to use their conservation practices after their cost-share contracts end (i.e., persistence) and factors that influence persistence. Persistence was most strongly related to producers' attitudes towards the conservation practice, producers' motivations, and practice durability. Therefore, persistence could be encouraged by using producers' motivations to focus messaging on ways conservation practices are achieving producers' goals and allocating more funding to practice maintenance. Overall, my interdisciplinary approach led to a greater understanding of pollutant dynamics, the pathways through which conservation practices influence stream health, and social constraints to persistence. This knowledge can inform what conservation practices may be most effective and strategies to keep appropriate practices on the landscape long enough to achieve stream health goals.

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GENERAL AUDIENCE ABSTRACT

As farmers work to feed a growing worldwide population, streams can inadvertently receive pollution, like excess sediment and nitrogen. Too much sediment can clog the gills of aquatic animals and reduce their habitat, and too much nitrogen can cause excessive plant growth and decrease the amount of oxygen in the water. The cumulative effects of pollution from farming can result in streams being unable to support human uses such as clean drinking water and fishing opportunities. To increase food production while protecting streams, government agencies help farmers pay for the costs of using conservation practices that can reduce pollution. Examples of conservation practices include keeping livestock out of streams with fences, ensuring the ground is covered with plants in between planting crops, and developing a plan for the maximum amount of fertilizer that can be used. Unfortunately, conservation practices are sometimes ineffective, and streams still become polluted despite their use. My goal was to understand why some conservation practices are ineffective and how conservation practices might be improved for southwest Virginia. In the introduction, I developed a framework that illustrates how connecting the natural and social sciences can improve conservation practice efficacy by guiding planning and placement of new practices. In Chapter 1, I used a computer program to simulate pollution within streams so that I could understand which locations have the greatest amount of pollution and why. I found that nitrogen typically enters streams through the water in the soil rather than water running

over the land surface and that sediment mostly enters the stream through erosion of the streambanks. These results suggest that conservation practices such as limiting the amount of nutrients placed on the landscape could be especially effective for reducing nitrogen pollution, whereas building fences to exclude cattle from streams and planting trees along streams can help reduce sediment pollution. For Chapter 2, I visited 31 streams in southwest Virginia that had varying amounts of pollution and conservation practices and collected water quality, habitat data, and aquatic insects. All these metrics are good indicators of pollution, but aquatic insects are particularly excellent indicators because their populations respond to cumulative changes in habitat and water quality. Streams with more conservation practices did not exhibit more diverse insect communities but did show stabilized water quality and habitat. These results indicate that the types of conservation practices currently used are not completely protecting streams and farmers may need to use more practices, new types of practices, or use their current practices for longer periods of time. For Chapter 3, I surveyed farmers to find out if they continue to use their conservation practices after funding from agencies ends, as well as their motivations for their actions. Farmers indicated that they were more likely to continue using conservation practices if their goals for using the practice were achieved and that they had difficulty keeping fences and trees from being destroyed by floods and wildlife. Government agencies could increase continued use of conservation practices by showing farmers how the practices are achieving their goals and by providing more funding to maintain practices. By combining research from several fields of study, I was able to better understand which conservation practices would be most effective in protecting streams and new ways to support farmers in using conservation practices.

To my Pop, Granny, Grandma, and Grandpa

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ATTRIBUTION

This dissertation is the culmination of four stand-alone manuscripts that have been, or are in the process of being, submitted to academic journals. Therefore, the various chapters are formatted differently, contain plural pronouns, may be repetitive, and do not flow perfectly.

- The Introduction is being prepared for submission to *Frontiers in Ecology and the Environment* under the title, "A social-ecological framework to improve outcomes of conservation practices for stream health". The introduction was coauthored with Serena Ciparis, Ashley A. Dayer, Jonathan A. Czuba, and Paul L. Angermeier.
- Chapter 1 is being prepared for submission to *Journal of Hydrology* under the title, "Development of a SWAT+ model to identify critical source areas in pastureland watersheds with karst topography". Chapter 1 was coauthored with Serena Ciparis, Paul L. Angermeier, and Jonathan A. Czuba.
- Chapter 2 is being prepared for submission to *Freshwater Ecology* under the title, "Stream health shows nonlinear, indirect responses to installation of agricultural conservation practices". Chapter 2 was coauthored with Serena Ciparis, Jonathan A. Czuba, Bryan L. Brown, and Paul L. Angermeier.
- Chapter 3 is currently under review for publication *in Journal of Soil and Water Conservation* under the title, "Landowners' cognitions and motivations coupled with practice durability influence persistence in agricultural best management practices". Chapter 3 was coauthored with Ashley A. Dayer, Serena Ciparis, Sara Bottenfield, and Paul L. Angermeier.

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INTRODUCTION

Abstract

Agricultural production can have unintended negative consequences for stream health. To protect stream health while continuing production, significant public investments have been made in agricultural incentive programs to install conservation practices. Unfortunately, due to a mix of biophysical and social factors, conservation practices do not always achieve stream health goals. Therefore, we outline a social-ecological framework that can guide interdisciplinary approaches that lead to implementation of conservation practices that effectively protects stream health. In particular, we describe how the natural sciences are used to select appropriate conservation practices based on locations on the landscape where they will be most effective. The social sciences can improve efficacy of conservation practices by increasing their adoption and by promoting agricultural producers' persistence in using practices after cost-share contracts end. Consideration of the various social-ecological connections that occur when conservation practices are placed on the landscape (e.g., heterogeneity, time lags, thresholds, and feedbacks) can improve management decisions regarding future implementation of conservation practices, ultimately striking a more socially acceptable balance between agricultural production and stream health outcomes.

Background

Management choices on agricultural lands commonly involve trade-offs between delivery of ecosystem services and maintenance of biological health of the streams and rivers draining those lands (Qiu *et al.* 2021), hereafter referred to as “streams” (*contra* Czuba and Allen 2023). Intensifying production of provisioning services (e.g., food and fiber) can alter the structure and function of streams (Allan 2004) by increasing pollutant concentrations (Carpenter *et al.* 1998), changing physical habitat (Newcombe and Macdonald 1991; Trimble and Mendel 1995), and altering flow and temperature regimes (Poff *et al.* 1997; Foufoula-Georgiou *et al.* 2015). Such changes to streams have contributed to the imperilment of many North American aquatic species, including fishes (Jelks *et al.* 2008), mussels (Strayer *et al.* 2004), gastropods (Johnson *et al.* 2013), and crayfishes (Taylor *et al.* 2007). Loss of aquatic species further alters the structure and function of streams and reduces their ability to provide crucial ecosystems services (Balvanera *et al.* 2006; Harrison *et al.* 2014), such as clean drinking water, climate regulation, and recreational opportunities (Millennium Ecosystem Assessment 2005; Villamagna *et al.* 2013). A decline in a stream’s capacity to provide these services is commonly considered a decline in stream health (Meyer 1997; Angermeier and Karr 2019).

In the United States, a healthy stream is broadly defined by the Clean Water Act as ‘fishable and swimmable’, reflecting the overarching importance of providing ecosystem services. Unhealthy streams are often placed on a state’s 303(d) list of impaired waters because they are not meeting water quality standards that support one or more specified uses (e.g., protection of aquatic life or recreation) designated by the Clean Water Act, 33 U.S.C. §1251 et seq (1972). This triggers a state to develop and submit a total maximum daily load (TMDL) to the U.S. Environmental Protection Agency (USEPA). A TMDL is the maximum amount of the pollutant causing the impairment that can enter the stream from the surrounding watershed and still allow the stream to meet water quality standards (USEPA 2024). Meeting TMDLs is often accomplished via regulatory actions imposed by the USEPA to reduce permitted point sources. Reduction of non-point sources of pollution is accomplished by many programs through various agencies and voluntary actions by agricultural producers, the latter of which is our focus.

Voluntary implementation of agricultural conservation practices (also known as best management practices), is used to not only meet TMDLs but is also used in non-TMDL situations to protect stream health and help producers improve agricultural production. Common examples of conservation practices include removing land from production, prescribed grazing, excluding livestock from streams, and planting cover crops (Natural Resources Conservation Service [NRCS] n.d.). Incentive programs are commonly used by state and federal conservation agencies to encourage voluntary implementation of conservation practices. The most common incentive programs on private lands within the United States include the Environmental Quality Incentives Program, Conservation Reserve Program, and Conservation Stewardship Program. The U.S. Department of Agriculture's (USDA) NRCS and states' soil and water conservation districts oversee these programs. These programs represent significant public investments in managing private lands to maintain the health of streams. For example, the Agriculture Improvement Act, Pub. L. No. 115-334 (2018) allocated $29 billion from fiscal years 2019 through 2023 to fund incentive programs.

Conservation incentive programs strive to use public funds effectively, but definitions of effectiveness — as well as preferences for measuring it — vary widely among interested parties (Rissman and Smail 2015; Perez and Cole 2020; NRCS 2024). Effectiveness could be measured as economic outcomes because producers are typically interested in maintaining profits (NRCS

2024). State and federal agencies often evaluate conservation programmatic effectiveness via output measures such as the amount of money spent, number of conservation practices installed, and number of producers enrolled (Hurlbert *et al.* 2023, USDA 2024). However, the goal of installing conservation practices is often to improve environmental outcomes (Northey 2020) such as addressing TMDLs and improving stream health. Outcome measurements related to protecting stream health could include measuring improvements in water quality, habitat, and biotic communities. To meet all these goals, agricultural incentive programs may need to balance social, ecological, and economic needs (Perez and Cole 2020).

Although certain conservation practices can benefit soil conditions (e.g., Amorim *et al.* 2020) and improve animal health (e.g., Malan *et al.* 2018) while simultaneously restoring and protecting water quality (Liu *et al.* 2017) and aquatic biota (e.g., Herman *et al.* 2015), they often do not contribute appreciably to overall stream health goals. A review of pollutant measurements at the field scale (Liu *et al.* 2017) showed that in some situations, conservation practices do not eliminate pollutants entering streams and may even increase certain pollutants in specific situations (e.g., Dinnes 2004; Dodd and Sharpley 2016). At the watershed scale, effectiveness can be even harder to gauge, as evidenced by widespread lack of long-term improvement in water quality and biotic conditions within the United States (Stets *et al.* 2020; USEPA 2023). From 1992–2012, at 633 sites across the United States, Stets *et al.* (2020) found that concentrations of total nitrogen were decreasing at only half of the sites and total phosphorus was increasing at more than half of the sites; however, total suspended solids were decreasing at most sites. Similarly, pollutants entering the Chesapeake Bay watershed have been reduced greatly but are still predicted to exceed the TMDL that was set by the USEPA to be reached by 2025 (Chesapeake Bay Foundation 2024) despite over $15 billion being spent on restoration from 2015–2023, much of which was directed towards incentive programs to deliver conservation practices (ChesapeakeProgress 2024).

Inability to improve stream health may stem from a failure to implement the right conservation practices for the landscape, in the right place, at the right time (Rittenburg *et al.* 2015), and in high enough densities (Sowa *et al.* 2016). In the Chesapeake Bay, for example, failure to achieve nutrient reduction goals may stem from not implementing enough of the right type of conservation practices and long lag times between conservation actions and nutrient responses (Chesapeake Bay Program's Scientific and Technical Advisory Committee 2023). There are many biophysical factors (e.g., soil type, landscape slope) that influence conservation practice efficacy and should be considered when making decisions regarding what practices to install and in what locations (Rittenburg *et al.* 2015; Capel *et al.* 2018). Even if conservation agencies develop plans for installing conservation practices that account for those ecological factors, producers may not be willing to install conservation practices, use them as suggested, or maintain them into the future (Nowak *et al.* 2006; Ribaudo 2015; Kalcic *et al.* 2015). Therefore, to efficiently use conservation incentive program funding by installing the most effective conservation practices — individually and collectively — it becomes crucial to couple and apply ecological and social knowledge.

Social-ecological systems (Dunham *et al.* 2018) and coupled human and natural systems (Quinn and Wood 2017) are both frameworks that join ecological and social concepts to facilitate studying and managing agricultural lands in ways that protect stream health and benefit producers (Bennett *et al.* 2015). Our goal is to design a social-ecological framework that can be applied to improve conservation practice efficacy for protecting stream health. We first broadly describe the components of our framework — acknowledging that we are only providing a few key examples of components that can be adapted to fit specific research needs. Then, we use the framework to described key components of conservation practice efficacy that can be improved using approaches from the natural sciences and the conservation social sciences. Finally, we demonstrate properties of conservation practice efficacy that connect social and ecological approaches. Our framework is one example of how social-ecological integration can lead to innovative solutions to complex environmental problems, such as balancing stream health and agricultural production.

Social-ecological framework

Our social-ecological framework is hierarchical and describes transcendent properties of social-ecological systems (Figure 1). The finest grain of the social-ecological system comprises attributes of the agricultural producer and stream. Attributes of streams include water quality, the biotic assemblage, associated habitat for biota, and stream connectivity. Producers' attributes include management choices (e.g., grazing density and location, fertilizer application regime), demographics, outlook for the future, values, and attitudes. The stream and producer are directly influenced by components of coarser grains (region, watershed), which include topography, soils, farm management history, hydrology, social networks, state agencies, and community organizations. Ultimately, finer-grain components of the social-ecological system are constrained by factors at coarser grains including the climate, geology, land-use patterns, national policies, federal agencies, market conditions and federal funding. Many of the components of the social-ecological system that influence conservation practice efficacy have been, and are appropriately, characterized through the lens of a single discipline and we outline these components in the sections, "Natural sciences" and "Social sciences", respectively. However, there are properties of social-ecological systems that transcend the natural or social sciences including thresholds, heterogeneity, time lags and feedbacks — terms that we fully explore in the section "Transcendent properties".

Natural sciences

Interactions among conservation practices, landscape features, and pollutants influence conservation practice effectiveness (Figure 2). The landscape controls how water moves pollutants and other materials through the environment (i.e., the hydrologic flow path), and conservation practices can influence the hydrologic flow path (Rittenburg *et al.* 2015; Capel *et al.* 2018). Thus, some conservation practices influence stream health via effects on water quality, instream habitat, and flow regime (i.e., temporal patterns of discharge), all of which can translate into biotic responses. When precipitation hits the landscape, it either accumulates (as snow or ice), flows along the surface as runoff, or infiltrates the soil — depending on water temperature, soil characteristics, and precipitation intensity. In situations where surface runoff occurs, sediment and chemicals that adhere to sediment particles (e.g., phosphorus) are the greatest threat to water quality (Capel *et al.* 2018). Excessive runoff can quickly (in minutes to hours) deliver pollutants to the stream (Meals *et al.* 2010; Hamilton 2012) and produce elevated flows that adversely reconfigure streambanks and streambeds. Practices that slow water flow and reduce the concentration of pollutants in the water (e.g., riparian buffers, conservation tillage, and nutrient management plans) are most effective when surface runoff the predominant hydrologic flow path (Rittenburg *et al.* 2015; Capel *et al.* 2018).

Water that infiltrates the soil has minimal direct influence on instream habitat but can affect instream water quality. Infiltrating water typically percolates to the groundwater unless it is intercepted by impenetrable clay soils, bedrock, soil macropores (often due to karst topography), engineering structures (e.g., agricultural drain tiles), which will cause water to move laterally through the soil. Lateral flow can transport pollutants to the stream in days (Rittenburg *et al.* 2015), but it can take centuries for pollutants to enter the stream through the groundwater; however, residence time varies greatly depending on the geology and amount of dissolved oxygen in the groundwater (Meals *et al.* 2010; Hamilton 2012). Chemicals that are typically dissolved in water (e.g., nitrate) move primarily along these two flow paths (Capel *et al.* 2018). In cases where nutrients move primarily through the groundwater and lateral flow, conservation practices such as removing land from production or controlled grazing are needed to stop pollutants at their source. In contrast, practices that trap pollutants (e.g., riparian buffers) can be counter-productive when pollutants are moving through lateral or groundwater flow paths because they increase infiltration, causing more nitrogen to be stored in the groundwater where it will slowly enter the stream over the long term (Capel *et al.* 2018).

Some common conservation practices, such as fencing livestock out of streams, may benefit stream health via pathways not described above. By excluding livestock from streams, riparian fencing can allow streambanks to re-stabilize (Grudzinski *et al.* 2020) in response to less trampling and subsequent regrowth of vegetation. As riparian woody vegetation matures, its roots further stabilize stream banks, it contributes woody debris (an important habitat component) to the stream channel, and it shades the stream, thereby improving the temperature regime (Ortiz-Gonzalez 2020). Excluding livestock from streams also eliminates their direct inputs of nutrients and bacteria, which degrade water quality and impacts human and livestock health.

Measuring a combination of water quality, habitat, and biotic responses can provide insight into the pathways through which conservation practices operate, and ultimately achieve (or fail to achieve) desired outcomes; however, few studies have investigated those pathways simultaneously. Efficacy of conservation practices is typically measured as improvements in water chemistry (e.g., Tuppad *et al.* 2010; Pearce and Yates 2017), reflecting legislative mandates to reduce pollutant loads (e.g., TMDLs) and the simplicity of measuring water quality compared to surveying the biotic community. Measuring water quality is appropriate for streams that are not supporting designated uses based on concentrations of a particular pollutant (e.g., impaired recreational use due to elevated concentrations of *Escherichia coli*) but for streams listed as impaired for other uses (e.g., impaired aquatic life use), measurement of water chemistry alone does not always allow for complete assessment of stream health (Karr 1993; Barbour *et al.* 1999). Ultimately, improvements to stream health also require the biota to recover, even though conservation practices are not designed to directly elicit biotic responses. Stream habitat must recover first because biota have specific requirements for habitat and flow regime. The timing, magnitude, and direction of biotic responses are influenced by an organism's lifespan, mobility, fecundity, and other biological traits (Poff 1997; Frimpong and Angermeier 2010). Thus, it may take many years for fishes to recover after restorative actions (Thomas *et al.* 2015) but only a few years for aquatic insects (Miller *et al.* 2010).

Interactions between conservation practices and the hydrologic flow path need to be understood in the context of the watershed for conservation practices to be most effective. The hydrologic flow path determines locations within the watershed that contribute disproportionate amounts of pollutants; these locations are where conservation practices will be most impactful (Gburek and Sharpley 1998; Heathwaite *et al.* 2005). These critical source areas can be identified via intensive field studies (Gburek and Sharpley 1998) or watershed models (e.g., Gitau *et al.* 2006; Giri *et al.* 2012). Efficacy of conservation practices is also influenced by their interaction on the landscape, which can be complementary (Tomer 2018), contradictory (Rittenburg *et al.*

2015), or provide critical redundancy in case of failure (Crow 2022). Two conservation practices could be contradictory if one conservation practice changes the hydrologic flow path (e.g., a terrace increases infiltration) and renders a downstream practice ineffective (e.g., a buffer designed to intercept surface runoff). In contrast, conservation practices could be complementary if they target different forms of a chemical or differentially account for hydrologic flow paths that change seasonally (Easton *et al.* 2008; Rittenburg *et al.* 2015). Lastly, conservation practices need to be implemented in high enough densities within the watershed to achieve stream health goals (Sowa *et al.* 2016).

Social sciences

Agricultural producers' behaviors ultimately determine the effectiveness of conservation incentive programs for restoring stream health because installing conservation practices is a voluntary behavior (Figure 3). Producers first must decide whether to implement a conservation practice (i.e., adoption) or not implement a conservation practice (i.e., non-adoption). Ideally, producers would adopt the right type and number of conservation practices and in the locations that would achieve greatest conservation practice efficacy based on the hydrologic flow path (Figure 2; see section Natural sciences). After a conservation practice is adopted and incentive program payments end, a producer must decide how long to continue or not continue to use a conservation practice — termed persistence and reversion, respectively (Dayer *et al.* 2018). The collective level of conservation practice persistence on the landscape (i.e., across many farms) ranges from 31% (Johnson *et al.* 1997) to 85% (Jackson-Smith *et al.* 2010) but is rarely quantified (Dayer *et al.* 2018). The choices made by a producer to adopt a conservation practice and persist in using that practice are influenced by factors that operate at multiple spatial grains (Dayer *et al.* 2018; Liu *et al.* 2018; Prokopy *et al.* 2019; Epanchin-Niell *et al.* 2022).

At a fine grain, producers' behaviors are influenced by their characteristics, the characteristics of their behavior, their past behavior, and the social structures in which producers are embedded. Some of the factors that have been used to predict adoption include producers' motivations (i.e., environmental or financial), attitudes towards the environment and conservation practices, previous adoption of other conservation practices, information use, awareness of programs or practices, amount of land owned that is vulnerable to pollution, farm size, income, and education (Prokopy *et al.* 2019). State and county conservation agencies and producers' relationships with family and neighbors are social structures that influence conservation behaviors (Liu *et al.* 2018; Epanchin-Niell *et al.* 2022). Less research has been conducted to understand factors that specifically influence persistence, but many of those factors overlap with those that influence adoption. Dayer *et al.* (2018) proposed that persistence is influenced by producers' cognitions (e.g., attitudes towards the environment and conservation practices), their motivations, the resources available to them, their social influences, and whether the conservation practice promotes behavioral inertia (e.g., formation of habits). This framework has been tested in the Great Plains, where persistence was related to both financial and environmental motivations, social influence, behavioral inertia, and resources but not cognitions (Barnes *et al.* 2023).

At the coarsest grain, national policies, economic conditions, federal agencies, and biophysical conditions all influence producers' decisions (Liu *et al.* 2018; Epanchin-Niell *et al.* 2022). National policies, such as the Farm Bill, allocate funding and set the directives for the state and federal agencies that interface with producers to deliver funds for implementation of conservation practices (Liu *et al.* 2018; Epanchin-Niell *et al.* 2022). Economic conditions (e.g., federal funding and market forces) influence the funding of agencies and the amount of money available to pay producers to use conservation practices (Liu *et al.* 2018; Epanchin-Niell *et al.* 2022). Biophysical conditions, such as the climate or soil conditions, can also influence behavior by making actions more or less feasible (e.g., built structures such as fencing can be destroyed by flooding; Liu *et al.* 2018; Epanchin-Niell *et al.* 2022). More research is needed to fully understand how these coarse-scale factors influence producer behavior (Prokopy *et al.* 2018).

The aforementioned factors, the potential consequences of behavior, and a decision-making process collectively result in producers' behaviors (Epanchin-Niell *et al.* 2022). Each decision made by a producer has assumed social, environmental, or economic consequences to individuals or society (Epanchin-Niell *et al.* 2022). However, the consequences of a behavior are not perfectly known by a producer and are subject to interpretation based on the assumed consequences and the many factors influencing behavior, leading to perceived consequences (Epanchin-Niell *et al.* 2022). In fact, Prokopy *et al.* (2018) found that a producer would be more likely to adopt a conservation practice if they expected it to increase production. The perceived consequences lead to the actual behaviors of adoption, non-adoption, persistence, or reversion, which influence future decisions (Epanchin-Niell *et al.* 2022).

Knowledge of the factors that influence producers' behaviors regarding conservation practices can be used to design behavior-change strategies that promote voluntary behavior and increase conservation practice efficacy (Dayer *et al.* 2018; Prokopy *et al.* 2019; Epanchin-Niell *et al.* 2022). Failure of conservation incentive programs to achieve widespread improvements in stream health is often attributed to weak participation in the locations that most need conservation practices (Ribaudo 2015; McLellan *et al.* 2018) — suggesting that incentives alone are not enough to facilitate widespread behavior change or that design and delivery of incentives requires adjustment. Although finances are often a barrier to pro-environmental behaviors, incentives may fail to achieve long-term behavior change because of other impediments to action such as lack of knowledge, inconvenience, confusing program rules, social norms, or government distrust. Other behavior-change strategies could be used to overcome these barriers and encourage conservation practice adoption and persistence. Targeting messaging and careful message framing can improve the effectiveness of education and outreach for encouraging adoption of conservation practices (e.g., Metcalf *et al.* 2019; Reddy *et al.* 2020). Encouraging social norms (i.e., standards shared by groups of people) by having producers display signs advertising their conservation actions could encourage greater use of conservation practices (Howley and Ocean 2021). Similarly, engaging respected producers in the dissemination of knowledge can lead to social learning and greater community buy-in (Rust *et al.* 2022). Although we focus on the ways that the social sciences can be used to encourage voluntary behavior, there are many other ways that the social sciences can benefit incentive programs, such as understanding producers' needs and goals and ensuring that conservation practices and incentives to install those practices are equitably distributed (Bennett *et al.* 2022).

Transcendent properties

A social-ecological framework leads to an interdisciplinary perspective that is useful for understanding the transcendent properties of social-ecological systems and improving conservation practice efficacy for protecting stream health (Figure 1). Integrating the various fields of social science (e.g., psychology, sociology, economics, education) into conservation programs can improve management practices, lead to better project designs, justify conservation actions, help achieve desired ecological outcomes, and reach socially equitable solutions (Bennett *et al.* 2017). Similarly, coupling the fields of engineering, ecology, economics, hydrology, and sociology can lead to improved stream restoration practices (e.g., Palmer *et al.*

2005; Palmer and Bernhardt 2006; Hawley 2018). Although interdisciplinary research can be challenging because funding opportunities are limited, rewards systems favor disciplinary research, and knowledge transfer among disciplines is difficult, the knowledge gained from interdisciplinary research can significantly improve conservation incentive programs. For example, there are properties of social-ecological systems (e.g., time lags, thresholds, social-ecological heterogeneity, and feedbacks) that transcend disciplinary science and application.

Time lags are a transcendent property of social-ecological systems because the timeframe for ecological recovery often does not match the timeframe of conservation programs. Some aspects of ecological recovery, such as geomorphic and biotic responses, can take decades or longer (Meals *et al.* 2010; Hamilton 2012), while typical cost-share contracts can be as short as one year for practices such as rotational grazing, but up to 20 years for some structural practices (NRCS n.d.). Therefore, it can be important to encourage persistence after cost-share contracts end so that practices remain in place long enough to achieve ecological recovery (Dayer *et al.* 2018). Additionally, maintained practices are more efficient at reducing nutrient input to streams than unmaintained practices (Bracmort *et al.* 2006; Liu *et al.* 2017). Interdisciplinary research can determine how long practices need to be installed and maintained for stream health to recover and how to encourage producers to use their practices long-term.

There are significant response thresholds along social and ecological gradients that must be exceeded before intended changes occur due to conservation practice implementation. For example, a threshold can occur when a certain number of producers must install conservation practices before practice density is great enough to achieve desired instream effects. These types of thresholds are common as illustrated by Figure 4, which shows total nitrogen increasing along a gradient of increasing conservation practice implementation until practice density reaches 0.30

conservation practices/ha (data derived from Chapter 2) at which point total nitrogen is stabilized. Unfortunately, it is often unknown what density of conservation practices is needed to achieve stream health goals and how to overcome social hurdles to reach those densities.

Heterogeneity is another common transcendent property of social-ecological systems. Critical source areas of pollutants are scattered across the landscape and may not correspond to the locations where producers are willing to adopt conservation practices (Nowak *et al.* 2006). Similarly, stream biota often require multiple habitats to complete their lifecycle (Schlosser and Angermeier 1995). These habitats may be spatially separated within watersheds, and thus affected by water draining from multiple farms. Interdisciplinary approaches can identify critical source areas and farms harboring habitat crucial for biota, then determine how to support or encourage producers to voluntarily implement appropriate conservation practices in those areas.

Feedbacks also occur within social-ecological systems due to many of the aforementioned transcendent properties (Epanchin-Niell *et al.* 2022). One example of a negative feedback that might occur is when producers' perceptions that conservation practices are ineffective dissuades them from implementing additional practices or promotes reversion to previous farming practices after contracts end. This could occur when stream health responses are delayed due to time lags or conservation practices do not meet producers' expectations for other reasons. In contrast, producers perceiving conservation practices as effective can lead to positive feedback and more conservation practices being implemented. Positive and negative feedback can either increase or inhibit progress by a conservation incentive program toward meeting stream health goals; therefore, management agencies can focus on encouraging positive feedback. For example, Chapter 3 shows that some producers expect conservation practices to have ecological benefits and other producers expected conservation practices to increase agricultural production; therefore, management agencies could promote positive feedback by focusing their messaging on how conservation practices are achieving each of those goals.

Conclusion

Conservation incentive programs have the potential to strike the desired societal balance between agricultural production and stream health. Therefore, billions of dollars have been spent to install conservation practices across the United States. Despite significant public investments in conservation incentive programs, widespread improvements in stream health have not materialized. Part of the failure to achieve stream health goals stems from lack of interdisciplinary approaches that account for the transcendent properties of social-ecological systems. Future studies could implement a social-ecological framework to understand how conservation practices influence stream health, determine the spatial arrangement and density that will achieve stream health goals, and how to interface with producers to achieve those goals. Our social-ecological framework provides an initial step toward the integrative approach needed to cost-effectively balance agricultural production and stream health and provides direction for future improvement of conservation practices.

References

Allan JD. 2004. Landscapes and riverscapes: The influence of land use on stream ecosystems. *Annu Rev Ecol Evol Syst* **35**: 257–84.

Amorim HCS, Ashworth AJ, Moore PA, *et al.* 2020. Soil quality indices following long-term conservation pasture management practices. *Agr Ecosyst Environ* **301**: 107060.

Angermeier PL and Karr JR. 2019. Ecological health indicators. In: Fath B (Ed). Encyclopedia of ecology (2nd edn). Cambridge, MA: Elsevier.

Balvanera P, Pfisterer AB, Buchmann N, *et al.* 2006. Quantifying the evidence for biodiversity effects on ecosystem functioning and services. *Ecol Lett* **9**: 1146–56.

Barbour MT, Gerritsen J, Snyder BD, and Stribling JB. 1999. Rapid bioassessment protocols for use in streams and wadeable rivers: Periphyton, benthic macroinvertebrates, and fish. Washington, DC: U.S. Environmental Protection Agency.

Barnes JC, Dayer AA, Gramza AR, *et al.* 2023. Pathways to conservation persistence: Psychosocial drivers of durable grasslands following the Conservation Reserve Program. *J Soil Water Conserv* **79**: 486–99.

Bennett EM, Cramer W, Begossi A, *et al.* 2015. Linking biodiversity, ecosystem services, and human well-being: Three challenges for designing research for sustainability. *Curr Opin Environ Sustain* **14**: 76–85.

Bennett NJ, Roth R, Klain SC, *et al.* 2017. Conservation social science: Understanding and integrating human dimensions to improve conservation. *Biol Conserv* **205**: 93–108.

Bennett NJ, Dodge M, Akre TS, *et al.* 2022. Social science for conservation in working landscapes and seascapes. *Frontiers in Conservation Science* **3**: 954930.

Bracmort KS, Arabi M, Frankenberger JR, Engel BA, and Arnold JG. 2006. Modeling long-term water quality impact of structural BMPs. *T ASABE* **49**: 367–74.

Capel PD, Wolock DM, Coupe RH, and Roth JL. 2018. A conceptual framework for effectively anticipating water-quality changes resulting from changes in agricultural activities. Reston, VA: U.S. Geological Survey.

Carpenter SR, Caraco NF, Correll DL, *et al.* 1998. Nonpoint pollution of surface waters with phosphorus and nitrogen. *Ecol Appl* **8**: 559–68.

Chesapeake Bay Foundation. 2024. 2022 state of the Blueprint. https://www.cbf.org/how-we-save-the-bay/chesapeake-clean-water-blueprint/state-of-the-blueprint/. Viewed 22 Jan 2024.

Chesapeake Bay Program's Scientific and Technical Advisory Committee. (2023). Achieving water quality goals in the Chesapeake Bay: A comprehensive evaluation of system response. Edgewater, MD: Chesapeake Bay Program

ChesapeakeProgress. 2024. Funding. https://www.chesapeakeprogress.com/funding

Crow RL. 2022. Evaluating the impacts of climate and stacked conservation practices on nutrient loss from legacy phosphorus agricultural fields (MS Thesis). Columbus, OH: The Ohio State University.

Czuba JA, and Allen GH. 2023. When does a stream become a river? *River Res Appl* **39**: 1925–29.

Dayer AA, Lutter SH, Sesser KA, *et al.* 2018. Private landowner conservation behavior following participation in voluntary incentive programs: Recommendations to facilitate behavioral persistence. *Conserv Lett* **11**: 1–11.

Dinnes DL. 2004. Assessments of practices to reduce nitrogen and phosphorus nonpoint source pollution of Iowa's surface waters. Des Moines, IA: Iowa Department of Natural Resources.

Dodd RJ and Sharpley AN. 2016. Conservation practice effectiveness and adoption: Unintended consequences and implications for sustainable phosphorus management. *Nutr Cycl Agroecosyst* **104**: 373–92.

Dunham JB, Angermeier PL, Crausbay SD, *et al.* 2018. Rivers are social–ecological systems: Time to integrate human dimensions into riverscape ecology and management. *WIREs Water* **5**: e1291.

Easton ZM, Walter MT, and Steenhuis TS. 2008. Combined monitoring and modeling indicate the most effective agricultural best management practices. *J Environ Qual* **37**: 1798–1809.

Epanchin-Niell RS, Jackson-Smith DB, Wilson RS, *et al.* 2022. Private land conservation decision-making: An integrative social science model. *J Environ Manage* **302**: 113961.

Foufoula-Georgiou E, Takbiri Z, Czuba JA, and Schwenk J. 2015. The change of nature and the nature of change in agricultural landscapes: Hydrologic regime shifts modulate ecological transitions. *Water Resour Res* **51**: 6649–71.

Frimpong EA and Angermeier PL. 2010. Trait-based approaches in the analysis of stream fish communities. *Am Fish S S* **73**: 109–36.

Gburek WJ and Sharpley AN. 1998. Hydrologic controls on phosphorus loss from upland agricultural watersheds. *J Environ Qual* **27**: 267–77.

Giri S, Nejadhashemi AP, and Woznicki SA. 2012. Evaluation of targeting methods for implementation of best management practices in the Saginaw River Watershed. *J Environ Manage* **103**: 24–40.

Gitau MW, Veith TL, Gburek WJ, and Jarrett AR. 2006. Watershed level best management practice selection and placement in the Town Brook Watershed, New York. *J Am Water Resour Assoc* **42**: 1565–81.

Grudzinski B, Fritz K, and Dodds W. 2020. Does riparian fencing protect stream water quality in cattle-grazed lands? *Environ Manage* **66**: 121–35.

Hamilton SK. 2012. Biogeochemical time lags may delay responses of streams to ecological restoration. *Freshw Biol* **57**: 43–57.

Harrison PA, Berry PM, Simpson G, *et al.* 2014. Linkages between biodiversity attributes and ecosystem services: A systematic review. *Ecosyst Serv* **9**: 191–203.

Hawley RJ. 2018. Making stream restoration more sustainable: A geomorphically, ecologically, and socioeconomically principled approach to bridge the practice with the science. *Bioscience* **68**: 517–28.

Heathwaite AL, Quinn PF, and Hewett CJM. 2005. Modelling and managing critical source areas of diffuse pollution from agricultural land using flow connectivity simulation. *J Hydrol* **304**: 446–61.

Herman MR, Nejadhashemi AP, Daneshvar F, *et al.* 2015. Optimization of conservation practice implementation strategies in the context of stream health. *Ecol Eng* **84**: 1–12.

Howley P and Ocean N. 2021. Doing more with less: Leveraging social norms and status concerns in encouraging conservation farm practices. *Land Econ* **97**: 372–87.

Hurlbert M, Bhardwaj A, and Akbari M. 2023. Best versus beneficial MP discourses: The significance of a change in discourse managing agricultural water quality in Canada. *J Environ Manage* **332**: 117289.

Jackson-Smith DB, Halling M, de la Hoz E, *et al.* 2010. Measuring conservation program best management practice implementation and maintenance at the watershed scale. *J Soil Water Conserv* **65**: 413–23.

Jelks HL, Walsh SJ, Burkhead NM, *et al.* 2008. Conservation status of imperiled North American freshwater and diadromous fishes. *Fisheries* **33**: 372–407.

Johnson PD, Bogan AE, Brown KM, *et al.* 2013. Conservation status of freshwater Gastropods of Canada and the United States. *Fisheries* **38**: 247–82.

Johnson PN, Misra SK, and Ervin RT. 1997. A qualitative choice analysis of factors influencing post-CRP land use decisions. *Journal of Agricultural and Applied Economics* **29**: 163–73.

Kalcic MM, Frankenberger J, Chaubey I, *et al.* 2015. Adaptive targeting: Engaging farmers to improve targeting and adoption of agricultural conservation practices. *J Am Water Resour As* **51**: 973–91.

Karr JR. 1993. Defining and assessing ecological integrity: Beyond water quality. *Environ Toxicol Chem* **12**: 1521–31.

Liu T, Bruins RJF, and Heberling MT. 2018. Factors influencing farmers' adoption of best management practices: A review and synthesis. *Sustainability* **10**: 432.

Liu Y, Engel BA, Flanagan DC, *et al.* 2017. A review on effectiveness of best management practices in improving hydrology and water quality: Needs and opportunities. *Sci Total Environ* **601–602**: 580–93.

Malan JC, Flint N, Jackson EL, *et al.* 2018. Offstream watering points for cattle: Protecting riparian ecosystems and improving water quality? *Agr Ecosyst Environ* **256**: 144–52.

McLellan EL, Schilling KE, Wolter CF, *et al.* 2018. Right practice, right place: A conservation planning toolbox for meeting water quality goals in the Corn Belt. *J Soil Water Conserv* **73**: 29A–34A.

Meals DW, Dressing SA, and Davenport TE. 2010. Lag time in water quality response to best management practices: A review. *J Environ Qual* **39**: 85–96.

Metcalf AL, Angle JW, Phelan CN, *et al.* 2019. More "bank" for the buck: Microtargeting and normative appeals to increase social marketing efficiency. *Soc Mar Q* **25**: 26–39.

Meyer JL. 1997. Stream health: Incorporating the human dimension to advance stream ecology. *J North Am Benthol Soc* **16**: 439–47.

Millennium Ecosystem Assessment. 2005. Ecosystems and human well-being: Synthesis. Washington, DC: Island Press.

Miller SW, Budy P, and Schmidt JC. 2010. Quantifying macroinvertebrate responses to in-stream habitat restoration: Applications of meta-analysis to river restoration. *Restor Ecol* **18**: 8–19.

Natural Resources Conservation Service. Conservation practice standards. https://www.nrcs.usda.gov/resources/guides-and-instructions/conservation-practice-standards. Viewed 24 Oct 2023.

Natural Resources Conservation Service (NRCS). 2024. Regional Conservation Partnership Program (RCPP) — Expectations of partners for project outcomes data and reporting. Washington, DC: NRCS.

Newcombe CP and MacDonald DD. 1991. Effects of suspended sediments on aquatic ecosystems. *N Am J Fish Manag* **11**: 72–82.

Northey B. 2020. Making conservation count: The importance of assessing resources and documenting outcomes to USDA. *J Soil Water Conserv* **75**: 49A.

Nowak P, Bowen S, and Cabot PE. 2006. Disproportionality as a framework for linking social and biophysical systems. *Soc Natur Resour* **19**: 153–73.

Ortiz-Gonzalez LI. 2020. Influences of vegetated buffers on fish habitat in agricultural streams in Michigan: Implications for conservation (MS Thesis). East Lansing, MI: Michigan State University.

Palmer MA and Bernhardt ES. 2006. Hydroecology and river restoration: Ripe for research and synthesis. *Water Resour Res* **42**: W03S07.

Palmer MA, Bernhardt ES, Allan JD, *et al.* 2005. Standards for ecologically successful river restoration. *Journal of Applied Ecology* **42**: 208–17.

Pearce NJT and Yates AG. 2017. Intra-annual variation of the association between agricultural best management practices and stream nutrient concentrations. *Sci Total Environ* **586**: 1124–34.

Perez M and Cole EJ. 2020. A guide to water quality, climate, social, and economic outcomes estimation tools: Quantifying outcomes to accelerate farm conservation practice adoption. Washington, DC: American Farmland Trust.

Poff NL. 1997. Landscape filters and species traits: Towards mechanistic understanding and prediction in stream ecology. *J N Am Benthol Soc* **16:** 391–409.

Poff NL, Allan JD, Bain MB, *et al.* 1997. The natural flow regime: A paradigm for river conservation and restoration. *Bioscience* **47**: 769–84.

Prokopy LS, Floress K, Arbuckle JG, *et al.* 2019. Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. *J Soil Water Conserv* **74**: 520–34.

Qiu J, Queiroz C, Bennett EM, *et al.* 2021. Land-use intensity mediates ecosystem service tradeoffs across regional social-ecological systems. *Ecosystems and People* **17**: 264–78.

Quinn JE and Wood JM. 2017. Application of a coupled human natural system framework to organize and frame challenges and opportunities for biodiversity conservation on private lands. *Ecol Soc* **22**: 39.

Reddy SMW, Wardropper C, Weigel C, *et al.* 2020. Conservation behavior and effects of economic and environmental message frames. *Conserv Lett* **13**: e12750.

Ribaudo M. 2015. The limits of voluntary conservation programs. *Choices* **30**: 1–5.

Rissman AR and Smail R. 2015. Accounting for results: How conservation organizations report performance information. *Environ Manage* **55**: 916–29.

Rittenburg RA, Squires AL, Boll J, *et al.* 2015. Agricultural BMP effectiveness and dominant hydrological flow paths: Concepts and a review. *J Am Water Resour As* **51**: 305–29.

Rust NA, Stankovics P, Jarvis RM, *et al.* 2022. Have farmers had enough of experts? *Environm Manage* **69**, 31–44.

Schlosser IJ and Angermeier PL. 1995. Spatial variation in demographic processes of lotic fishes: Conceptual models, empirical evidence, and implications for conservation. *Am Fish S S* **17**: 392-401.

Sowa SP, Herbert M, Mysorekar S, *et al.* 2016. How much conservation is enough? Defining implementation goals for healthy fish communities in agricultural rivers. *J Great Lakes Res* **42**, 1302–21.

Stets EG, Sprague LA, Oelsner GP, *et al.* 2020. Landscape drivers of dynamic change in water quality of U.S. rivers. *Environ Sci Technol* **54**: 4336–43.

Strayer DL, Downing JA, Haag WR, *et al.* 2004. Changing perspectives on pearly mussels, North America's most imperiled animals. *Bioscience* **54**: 429–39.

Taylor CA, Schuster GA, Cooper JE, *et al.* 2007. A reassessment of the conservation status of crayfishes in the United States and Canada after 10+ years of increased awareness. *Fisheries* **32**: 372–89.

Thomas G, Lorenz AW, Sundermann A, *et al.* 2015. Fish community responses and the temporal dynamics of recovery following river habitat restorations in Europe. *Freshw Sci* **34**: 975–90.

Tomer MD. 2018. A twice-paired watershed experimental design to assess stacked practices through field-edge monitoring. *J Soil Water Conserv* **73**: 58–61.

Trimble SW and Mendel AC. 1995. The cow as a geomorphic agent — A critical review. *Geomorphology* **13**: 233–53.

Tuppad P, Kannan N, Srinivasan R, *et al.* 2010. Simulation of agricultural management alternatives for watershed protection. *Water Resour Manag* **24**: 3115–44.

U.S. Department of Agriculture (USDA). 2024. United States Department of Agriculture FY 2024 budget summary. Washington, DC: USDA.

U.S. Environmental Protection Agency (USEPA). 2023. National rivers and streams assessment: The third collaborative survey. Washington, DC: USEPA.

U.S. Environmental Protection Agency. 2024. Summary of the Clean Water Act. https://www.epa.gov/laws-regulations/summary-clean-water-act. Viewed 2 July 2024.

Villamagna AM, Angermeier PL, and Bennett EM. 2013. Capacity, pressure, demand, and flow: A conceptual framework for analyzing ecosystem service provision and delivery. *Ecol Complex* **15**: 114–21.

Figures

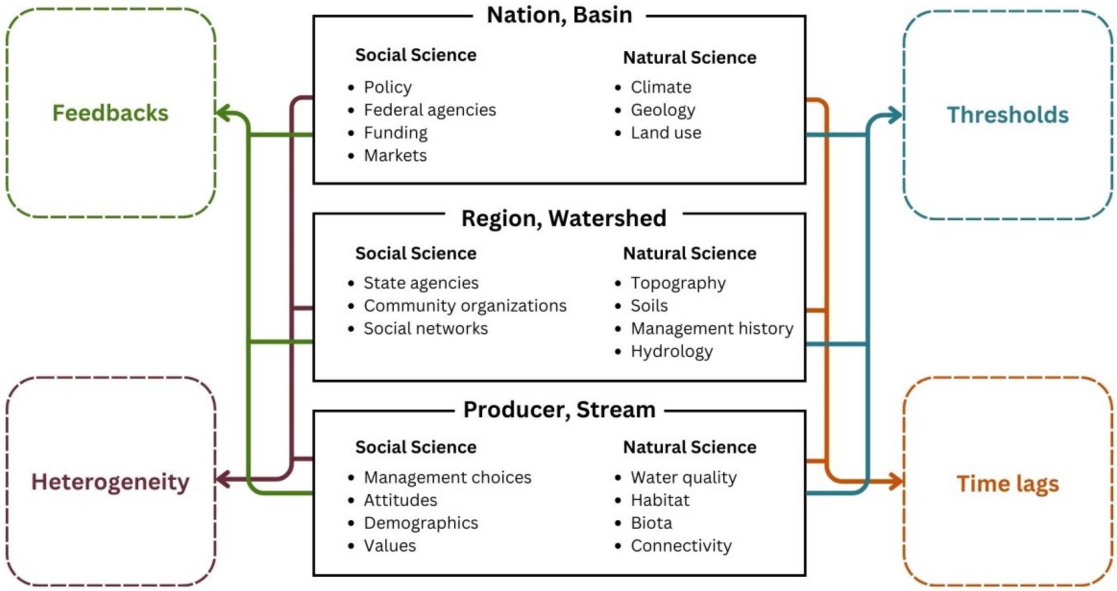

Figure 1. An example of a social-ecological framework that can be used to improve efficacy of agricultural conservation practices for protecting stream health. Three hierarchical subsystems (solid boxes) are shown for the social-ecological system. Each box includes examples of key factors or components that characterize a given subsystem, which are listed under the discipline typically used to understand those factors. Lastly, four transcendent properties (dashed boxes) are shown that emerge through integration of the social and natural sciences. Image Credit: Sami Thomas

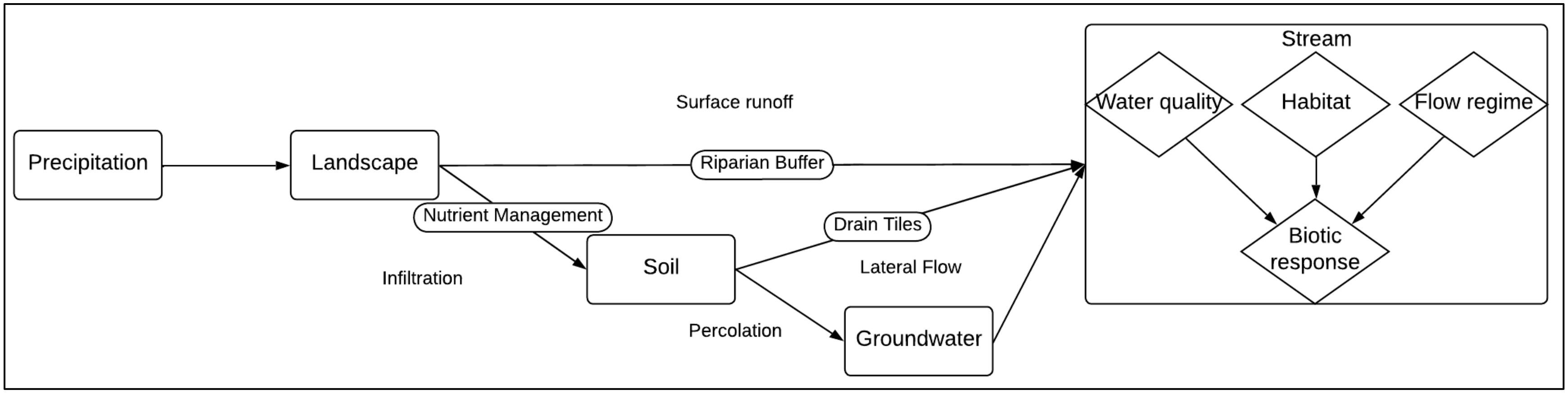

Figure 2. The most effective agricultural conservation practices (examples include nutrient management plans, riparian buffers, and drain tiles) consider the hydrologic flow path that is represented by the connections among the rectangles shown in the figure. There are two horizontal (surface runoff, subsurface lateral flow) and two vertical (infiltration, percolation) flow paths illustrated in the figure. Although the hydrologic flow path is shown moving in one direction, water also can move from the stream back to the groundwater and from the groundwater to the soil. Ultimately, conservation practice effectiveness can be measured by the instream responses indicated by diamonds.

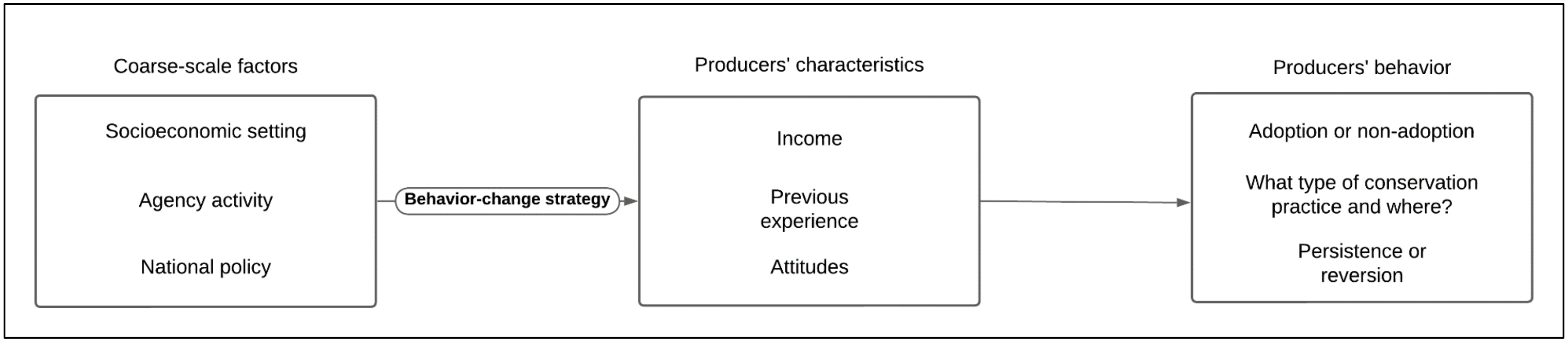

Figure 3. Factors at coarse scales influence agricultural producers' characteristics and their expectation for conservation practice outcomes, which ultimately leads to producer's behavior. Producers collaborate closely with management agencies to make decisions, so behavior-change strategies can be used by agencies to influence a producer's characteristics and ultimately their behavior, which can have implications for stream health.

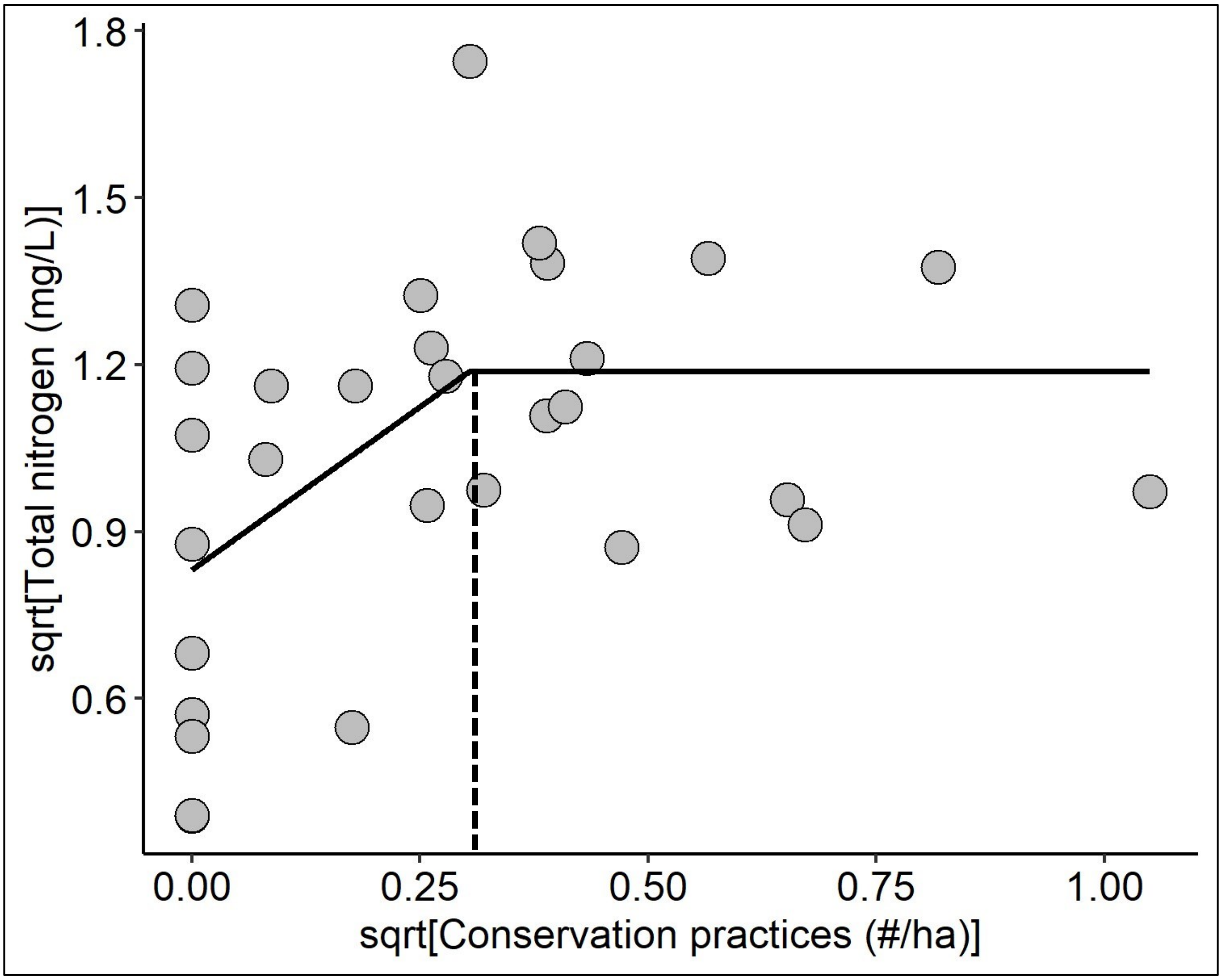

Figure 4. An example of a threshold (denoted by dashed vertical line) where conservation practice density needs to reach 0.30 practices/ha in a watershed before total nitrogen in the stream draining that watershed is stabilized. Data are derived from Chapter 2.

CHAPTER 1: DEVELOPMENT OF A SWAT+ MODEL TO IDENTIFY CRITICAL SOURCE AREAS IN PASTURELAND WATERSHEDS WITH KARST TOPOGRAPHY

Abstract

The goal of this research was to identify critical source areas (CSAs) of agricultural pollutants, so that efficacy of conservation practices might be improved. To our knowledge, no studies have applied Soil and Water Assessment Tool+ (SWAT+) to identify CSAs in pasturelands within karst regions. A SWAT+ model was built for a 27-year timeframe in southwest Virginia of the southern Appalachians — an area with extensive pasturelands and karst topography. The model satisfactorily predicted monthly streamflow at eight of twelve U.S. Geological Survey stream gages, and streamflow was most affected by the available water capacity and hydraulic conductivity of the soil, revealing that water, and associated pollutants, are moving primarily through subsurface pathways due to the karst topography of the region. Although indices of model fit indicated unsatisfactory sediment estimates at all gages, model-estimated monthly sediment loads were within an order of magnitude of measured values at nine of eleven gages — indicating that the model was still useful for identifying CSAs of sediment. We identified two watersheds that had particularly high predicted sediment yields where additional conservation practices would likely be beneficial. Predicted sediment yield was negatively associated with the extent of agricultural land cover but positively associated with urban land cover. The model unsatisfactorily predicted total nitrogen and total phosphorus. The results of this study provide practical recommendations for on-the-ground management of grazing lands to protect water quality in karst regions. Specifically, conservation practices that stabilize stream banks (e.g., fencing cattle out of streams) would be most effective at reducing sediment loads because streambanks are the primary sources of instream sediment. Similarly, conservation practices that

stop pollutants at their upland sources (e.g., nutrient management plans) would be most effective at reducing instream nitrogen in locations with karst topography. These findings also serve to advance the application of SWAT+ by providing recommendations for building a SWAT+ model to predict pollutant loads in a karst region with extensive pasturelands. For example, increasing the amount of water movement through the soil improved model estimates of streamflow. Also, the SWAT+ model appeared to have difficulty predicting sediment sources from pasturelands in our study area because the predominant source of sediment may be from the streambank (a process not captured in SWAT+) rather than upland fields.

Introduction

Protecting stream health from adverse instream effects of agricultural land use is a major challenge across the United States. Indicators of water quality, instream habitat, and aquatic biota show that most stream miles (including both larger rivers and smaller streams *contra* Czuba and Allen, 2023) across the United States are in fair or poor condition (U.S. Environmental Protection Agency [USEPA], 2023). One of the biggest contributors to poor biophysical conditions in streams is agricultural land use (Stets et al., 2020; Schürings et al., 2022), which can increase nutrients (Carpenter et al., 1998), change physical habitat (Newcombe & MacDonald, 1991; Trimble & Mendel, 1995), and alter the flow regime (Poff et al., 1997; Foufoula-Georgiou et al., 2015). Collectively, changes to streams caused by agricultural land use can reduce or disrupt the flow of ecosystem services provided by streams, such as clean drinking water, climate regulation, and recreation (Zhang et al., 2007; Bennett et al., 2022).

Agricultural conservation practices are the primary mechanism used in the United States to protect streams and associated ecosystem services while allowing food production to continue. There are many types of conservation practices, examples of which include livestock exclusion fencing, livestock watering facilities, and cover crops (Natural Resources Conservation Service [NRCS], n.d.). Although the exact number and costs of implemented conservation practices are unknown, the Farm Bill set aside $29 billion for agricultural incentive programs from fiscal years 2019 through 2023, which primarily funded the installation of conservation practices (Congressional Research Service, 2024). Further, Virginia alone has installed at least 400,000 conservation practices, totaling over half a billion dollars since 1998 (Virginia Department of Conservation and Recreation, 2024). Despite the extensive scope and costs of installing conservation practices, water quality and biota have not recovered to the expected extent in many locations (Liu et al., 2017; Stets et al., 2022). Often, conservation practices fail to be fully effective because they are not appropriate for the landscape conditions (Rittenburg et al., 2015; Capel et al., 2018), the density is too low to mitigate the impact of agricultural land use (Sowa et al., 2016), or they are not installed in the locations on the landscape that are contributing the greatest amounts of pollutants (Nowak et al., 2006; Ribaudo, 2015).

Areas on the landscape that contribute the most pollutants are often called critical source areas (CSAs; Pionke, 2000; Sharpley et al., 2002; Heathwaite, 2005). Interactions among land use, soil type, hydrologic condition, and topographic features create CSAs. For example, farms with steep slopes will contribute more nutrients to streams than farms with gentle slopes due to greater runoff from the steeply sloping landscape. Targeting conservation practice placement in CSAs can achieve greater reduction of nonpoint-source pollution than haphazard placement, which can increase conservation practice cost-effectiveness (Diebel et al., 2008; Cho et al., 2010a; Tuppad et al., 2010). For example, Diebel et al. (2008) found that targeting conservation practice placement in CSAs required implementation at half the number of fields compared to random placement of conservation practices to detect an effect on phosphorus reduction for most of the scenarios they evaluated. Field studies can be used to identify CSAs, but it is cost- and time-prohibitive to conduct field studies across large spatiotemporal extents. Instead, watershed models can be used to identify CSAs relatively quickly and easily for large areas.

The Soil and Water Assessment Tool (SWAT) is a watershed model that operates on a daily time step to estimate streamflow and pollutant transport and is useful for delineating CSAs (Arnold, 1998; Fu et al., 2019; Yuan et al., 2020). SWAT divides a watershed into subbasins, which comprise hydrologic response units (HRUs; Figure 1) that have similar slope, land cover, and soil characteristics. SWAT estimates pollutant yields for each HRU, and those yields can be summarized to identify CSAs at many spatial scales including HRUs (e.g., Cho et al., 2010b), fields (e.g., Daggupati et al., 2011), and subbasins (e.g., Tuppad et al., 2010). Before SWAT can be used to identify CSAs, it requires calibration and validation for the study area of interest (Abbaspour et al., 2018). Previous studies using SWAT differ markedly in their ability to accurately model pollutants due to available data for model building and calibration and landscape conditions (Gassman et al., 2007).

The Soil and Water Assessment Tool+ (SWAT+) was recently released to facilitate model maintenance, improve future code modifications, and foster collaborations among researchers (Bieger et al., 2017). The updated model allows greater flexibility in how water is routed through the environment by dividing subbasins into upland and floodplain landscape units (LSUs; Figure 1; Bieger et al., 2017), allowing for a more nuanced understanding of pollutant sources from the landscape and consequently CSAs. Because SWAT+ is relatively new, few studies have used a SWAT+ model for modeling pollutants (n = 23) compared to SWAT (n = 2,071; Gassman, 2023), fewer have used it for estimating CSAs (but see Tumsa, 2023 and Wu et al., 2023), and no studies have been done in karst watersheds (al Khoury et al., 2023).

Building a SWAT (or SWAT+) model to identify CSAs is especially important in karst environments. Approximately 20% of the United States displays karst topography and 33% of the karst area in the United States overlaps with pasturelands (Weary & Doctor, 2014; U.S. Geological Survey [USGS], 2019a). Karst environments are susceptible to pollution from agricultural land use because of extensive subsurface pathways through which water flows (Coxon, 2011; Erb & Maas, 2021). These subsurface pathways have significant implications for how pollutants move through the environment and which conservation practices will be most effective (Capel et al., 2018). Therefore, it is important to understand pollutant transport in karst environments with pastureland, so that appropriate conservation practices can be implemented. To that end, many studies have attempted to use SWAT to model pollutant transport in karst environments but with mixed success; however, to our knowledge no studies have applied SWAT+ to a karst region (al Khoury et al., 2023)

The goal of this research was to improve conservation practice efficacy through identification of CSAs in southwest Virginia, United States, a karst region where cattle grazing is a dominant land use. In southwest Virginia there has been extensive installation of conservation practices, the most common of which include prescribed grazing, livestock exclusion fencing, and livestock watering facilities (George Wallace, NRCS, 14 February 2022, written communication). Despite extensive conservation practice installation, 15% of streams are considered impaired in southwest Virginia (Virginia Department of Environmental Quality [VDEQ], 2022a) and there have been 27 Total Maximum Daily Loads developed as a result of water quality impairments (VDEQ, n.d.). To achieve our goal, our specific objectives were to 1) build, calibrate, and validate a SWAT+ model, 2) identify critical source areas in southwest Virginia and contrast those locations with conservation practice implementation, and 3) identify landscape factors that contribute to CSAs for southwest Virginia. This research serves as an advancement of SWAT+ application and can provide agencies with practical recommendations for conservation practice installation.

Material and methods

Study area

This study focused on the Clinch, Powell, North Fork Holston, and South Fork Holston HUC-8 watersheds of Virginia (CPH; Figures 1 and 2; USGS, 2024). The CPH are the headwaters of the Tennessee River and are within the Ridge and Valley ecoregion of the

Appalachian Mountains (USEPA, 2013). The Ridge and Valley ecoregion is characterized by long mountain ridges and valleys with an elevation that ranges from 300–1,740 m and averages 609 m (USGS, 2019b). The CPH has a humid subtropical climate (Beck et al., 2018) and has an average yearly rainfall of 1,241 mm and average low and high temperatures of 6.3 and 18.3 °C, respectively (data from 1995–2021; PRISM Climate Group, 2024). The CPH has a total area of 8,293 km^2 and is approximately 64% forest, 20% pastureland agriculture, and 9% urban area (USGS, 2019a). Silty-loam soils are the most common soil type in the CPH (NRCS, 2019). Lastly, a little over half of the CPH is karst topography (Weary & Doctor 2014).

Data sources

We compiled topography, stream network, land cover, soil, climate, streamflow, and water quality data to build a SWAT+ model (Table 1). Topographic data (30-m resolution) were obtained from the National Elevation Dataset (NED; USGS, 2019b). Stream network data were downloaded from the National Hydrography Dataset Plus Version 2 (USEPA & USGS, 2012) to assist with watershed delineation. We used the State Soil Geographic Database (STATSGO) as the soil layer in our model (NRCS, 2019) and obtained land-cover data from the 2016 National Land Cover Database (USGS, 2019a). Climate data were obtained from the PRISM Climate Group (2024) for the centroid of each HUC-12 watershed (n = 88 locations). Streamflow data were obtained from the USGS gages in the upper CPH (n = 11; USGS, 2020) and total nitrogen, total phosphorus, and total suspended solids data were downloaded from the VDEQ long-term water quality monitoring stations (VDEQ, 2022b) to calibrate and validate the SWAT+ model (Figure 1; Table 1). All geospatial layers were converted to the coordinate reference system NAD 83 UTM zone 17 in meters and clipped to the upper CPH.

Building the SWAT+ model

We used QSWAT+ interface (Dile et al., 2022; version 2.3.5) to delineate the watershed and create hydrologic response units (HRUs). First, channels were defined using the NED layer with a threshold of 2 km^2 (i.e., 2222 cells) needing to drain to a cell to create a channel. The stream network was burned into the NED layer to assist with channel creation. Channel geometry was calculated based on watershed drainage area using parameters from regional models (Bieger et al., 2015), where channel width (m) = 2.79 × drainage area$^{0.42}$ (km^2) and depth (m) = 0.23 × drainage area$^{0.29}$ (km^2). Further, we updated slope values for channels that had a slope of zero by averaging slope from the upstream and downstream channels (3% of channels). Subbasins were created around each channel and subbasins smaller than 25% of the mean subbasin area were merged. We then created LSUs by dividing the subbasins into upland and floodplain areas using digital elevation model inversion (Dile et al., 2022) with a ridge threshold of 2 km^2. Finally, the HRUs were defined by dividing the range of the watershed hillslopes into five equal classes; adding the soil, land-cover, and LSU maps; and retaining all HRUs. After delineating the watershed and defining the HRUs, the data were imported into the SWAT+ editor (Tech, 2023; version 2.2.2) where climate data were added, and model parameters were set using the default values. Solar radiation, wind speed, and humidity were simulated using the SWAT+ weather generator. We then calibrated the SWAT+ model (version 60.5.4) from 2004–2009 with a two-year warmup period for streamflow (m^3/sec), sediment loads (metric tons), nitrogen loads (kg), and phosphorus loads (kg) at daily (per day) and monthly (per month) time steps. After calibration was complete, the model was run from 1998–2021 with a three-year warmup period and validated from 2010–2021. We used Nash-Sutcliffe efficiency (NSE) to assess the SWAT+ model performance; values > 0.50 indicate satisfactory model performance for monthly time steps (Moriasi et al., 2007). Model fit was also evaluated by plotting measured pollutant and streamflow values against those estimated by the SWAT+ model and calculating correlation coefficients.

Calibration and validation

Streamflow — We first calibrated the model for streamflow. We selected 10 variables that we hypothesized would significantly influence streamflow predictions (Table 2). The most sensitive of those parameters was determined by repeatedly running the model under different parameter combinations using the SWAT+ Toolbox (James, 2022; version 1.0.2). The model results were assessed at one gage from each HUC-8 watershed within our study area (i.e., Powell, Clinch, North Fork Holston, South Fork Holston river watersheds; Table 3). Additionally, gages on Beaver Creek and Middle Fork Holston River were included (USGS gages 03478400 and 03474000; Table 3). Beaver Creek represents an urban drainage area, possibly sensitive to unique parameters, and Middle Fork Holston River is a major tributary not within a unique HUC-8 watershed. The SWAT+ model was most sensitive to adjusting soil available water capacity (awc) and soil hydraulic conductivity (k). Therefore, we calibrated the model against measured streamflow values using the dynamically dimensioned search algorithm in the SWAT+ Toolbox to determine the values for awc and k that resulted in the highest NSE value.

Sediment — Next, we calibrated the model for sediment loads. We first converted point measurements of total suspended solid concentrations (mg/L) collected by VDEQ (2022) to sediment loads (metric tons/day) by multiplying the concentration by the daily discharge and converting the units. Then, a linear relationship was developed between streamflow and sediment load at each VDEQ monitoring station. Streamflow explained at least 65% of the variation in the sediment loads for each relationship at each station. Therefore, we used the relationships to predict daily sediment loads from the daily streamflow data at each monitoring station.

We first turned off the effects of instream processes within the SWAT+ model by setting channel erosion and the channel cover factors to zero, which allowed for calibration of the SWAT+ model for landscape processes only. We then assessed the effect of changing the Universal Soil Loss Equation (USLE) cover factor and adding a grazing operation to the SWAT+ model. The USLE cover factor was changed from 0.005 to 0.5 and the USLE practice factor from 1 to 100 (i.e., unrealistically high numbers) to see if those changes influenced predicted daily sediment loads. We consulted a local Soil and Water Conservation District to determine the following parameters for the grazing operation: grazing occurring all year, default beef fertilizer, dry weight of biomass removed by grazing daily = 22.5 kg/ha, dry weight of biomass removed by trampling daily = 15 kg/ha, dry weight of manure deposited daily = 5.7 kg/ha, and minimum plant biomass for grazing to occur = 500 kg/ha. We expected 55% of the sediment loading to streams to be coming from the landscape (Noe et al., 2022); therefore, measured values were multiplied by 0.55 and compared to predicted values. With instream processes turned off, the SWAT+ model underpredicted monthly sediment loads and changing USLE cover and practice factors and adding a grazing operation had little effect on the predictions (Appendix Figure 1). We moved on to calibrating the SWAT+ model for instream sediment loads because changing additional parameters did not further improve sediment estimates from the landscape. Also, the estimate of 55% from Noe et al. (2022) is an approximation for a large region and for streams draining only the Chesapeake Bay (i.e., there may be differences among watersheds within the CPH) and we had observed that instream processes could compensate for the underprediction from the landscape based on predicted sediment loads for the SWAT+ model (Appendix Figure 1c).

To finish calibrating the SWAT+ model for sediment loads, we turned instream processes back on and determined which instream parameters (i.e., channel cover factor, channel erodibility factor, peak rate adjustment factor for sediment routing, and the exponent and linear parameters for calculating channel sediment routing) had the greatest influence on predicted sediment loads using the SWAT+ Toolbox (Table 2). Finally, the model was calibrated manually for the channel erodibility factor, which was the most sensitive parameter. Manual calibration consisted of adjusting channel erodibility incrementally until the value that most improved NSE values was achieved. We completed the calibration manually because the SWAT+ Toolbox was unable to display very small values for channel erodibility and small values were needed to improve sediment load estimates.

Nitrogen and phosphorus — We attempted to calibrate the SWAT+ model for daily (per day) and monthly (per month) nutrient loads. We first converted point measurements of total nitrogen (mg/L) and total phosphorus (mg/L) to loads (kg/day) following a similar process as for sediment. Then, we developed a linear relationship between streamflow and nitrogen and phosphorus loads at each VDEQ monitoring station. Streamflow explained 92% and 45% of the variation in nitrogen and phosphorus loads for each relationship at each station. Although some of the relationships for phosphorus explained < 50% of the variation, eight of ten relationships explained greater than 68%. Therefore, we used the relationships to predict daily nitrogen and phosphorus loads at each monitoring station. We assessed the influence of adjusting three parameters on the SWAT+ model's ability to predict daily nitrogen loads: 1) adding the cattle grazing operation described for sediment calibration, 2) increasing the initial concentration of nitrate in the aquifer (i.e., capturing effects of legacy nitrate stored in the aquifer), and 3) adjusting the ratio of nitrate in the surface runoff versus nitrate that percolates into the soil (nitrate percolation coefficient). These parameters were not supported by the SWAT+ Toolbox, so we changed the initial concentration in the aquifer to 1,000 mg/L and the nitrate percolation coefficient to 1 to assess how unreasonably high values of these parameters affected the model. Parameters were not changed for phosphorus because the initial predictions from the calibration period were on average close to observed values; the poor NSE values resulted from predictions that were inconsistently higher or lower than measured values (Table 3, Figure 8).

Identifying critical source areas

We used the results from the SWAT+ model to identify and map CSAs of predicted sediment yields (metric tons/ha/year) and then compared CSAs to current conservation practice installation. We did not map nitrogen or phosphorus predicted yields because we lacked confidence in those results (see results for sediment and nitrogen below). First, we totaled the annual predicted sediment yields from each LSU for each HUC-12 watershed. Then, we divided the HUC-12 watersheds into low, medium, and high yields with an equal number of watersheds in each bin. Finally, we summed the number of conservation practices within each HUC-12 watershed (database obtained from NRCS). and divided the watersheds into low, medium, and high conservation practice counts with an equal number of watersheds in each bin.

Landscape factors that contribute to critical source areas

We built a multiple linear regression model to assess the effects of landscape features on average annual predicted sediment yields (metric tons/ha/year) from LSUs, which can lead to a better understanding of factors influencing CSAs. The response variable was the log-transformed average annual sediment yield for each LSU created in SWAT+. We log transformed sediment yield to reduce the effect of outliers. We included landscape position (i.e., floodplain or upland) as a categorical predictor variable and suppressed the intercept. We also included proportion urban land cover, proportion forest land cover, proportion agricultural land cover, soil hydraulic conductivity, soil erodibility, and average LSU slope as continuous predictor variables. Continuous predictor variables were scaled and centered to have a mean of zero and standard deviation of one. Lastly, we explored all two-way interactions among the predictor variables. Interactions with $p > 0.10$ were considered non-significant and dropped from the final model. We used the *stats* package in the software R (R Core Team, 2023) to build the linear models.

Results

Calibration and validation

Streamflow — After calibration, the SWAT+ model generally predicted streamflow well and predictions were above or near the NSE cutoff of 0.50 at monthly timesteps at all gages except one (Table 3, Figures 3 and 4). Decreasing the soil's available water capacity by 0.26 mm and increasing the soil hydraulic conductivity by 24.5 mm/hr were most effective in improving SWAT+ model performance. The only location where NSE values were much below 0.50 was USGS gage 03529500, located in Big Stone Gap, Virginia (Figure 4). At most gages, SWAT+ overpredicted streamflow at low measured streamflow but underpredicted streamflow at high measured streamflow (Figures 3 and 4). Highly correlated ($r > 0.86$) log-transformed predicted and measured monthly streamflow at all gages also indicated good model fit.

Sediment — We modeled sediment loads within streams with mixed success, and no predictions were associated with NSE values above the 0.50 cutoff for monthly timesteps (Table 3, Figures 5 and 6). The SWAT+ model initially predicted sediment loads that were several orders of magnitude too high (Appendix Figure 1c). When we turned off the instream component of sediment processes, the SWAT+ model underpredicted sediment loads (multiplied by 0.55), especially at high-flow events (Appendix Figure 1a). The sensitivity analysis revealed that channel erodibility was the parameter that most influenced model output. Therefore, we focused on changing the channel erodibility factor and found that setting it to 0.00002 cm^3/N-s led to model predictions that were within an order of magnitude of the measured values at many gages except those in the Clinch River (Figures 5 and 6). Log-transformed predicted sediment load had a high correlation with log-transformed observed sediment load at all gages ($r > 0.81$), and the SWAT+ model tended to overestimate low observed values of sediment load and underestimate high observed values of sediment load (Figure 5). Although predicted sediment loads were much too low in the Clinch River, they were highly correlated with measured loads when values were log-transformed ($r = 0.85$ and 0.81; Figure 6). Overall, we felt the SWAT+ model did an adequate job of predicting sediment loads and the results could be used to identify watersheds that are CSAs of sediment, while acknowledging that predictions for the Clinch River are underestimated.

Nitrogen and phosphorus — The SWAT+ model did not predict total nitrogen or total phosphorus well (Table 3). None of the parameters that we evaluated (i.e., adding cattle grazing, increasing the initial concentration of nitrogen in the aquifer, and changing the nitrate percolation coefficient) influenced the model output for nitrogen loads. Only results for the validation period are shown because we observed only small differences between calibration and validation (Table 3, Appendix Figure 2). At all gages, the SWAT+ model greatly underpredicted total nitrogen loads (kg/month) compared to measured values (Figure 7). Despite the SWAT+ model greatly underpredicting nitrogen loads, high correlations among log-transformed predicted and measured values at all ($r = 0.71$) but one gage ($r = 0.53$) shows that the model has promise to accurately predict nitrogen loads if parameters can be adjusted to increase predicted loads. Although the SWAT+ model provided reasonable estimates of total phosphorus loads (kg/month) for the calibration period (Figure 8), phosphorus estimates were unacceptably low for the validation period (Figure 9). The SWAT+ model tended to underpredict phosphorus loads compared to measured values except at higher measured values where phosphorus load was overpredicted (Figures 8 and 9). Similar to total nitrogen, log-transformed predicted total phosphorus loads were highly correlated with log-transformed observed total phosphorus loads at most gages ($r > 0.76$) and moderately correlated at one gage ($r = 0.68$).

Identifying critical source areas

We identified CSAs within the upper CPH where installation of conservation practices could lead to the greatest reductions in sediment. Sediment yield (metric tons/ha/year) was particularly high in HUC-12 watersheds comprising the Clinch River watershed and a few other watersheds in the Powell, South Fork Holston, and North Fork Holston watersheds (Figure 10). Of these HUC-12 watersheds, Butcher Fork-South Fork Powell River, Toms Creek-Guest River, Big Spring Branch-Clinch River, Swords Creek-Clinch River, Middle Creek-Clinch River, Newland Hollow-North Fork Holston River, and Big Laurel Creek-Whitetop Laurel Creek have few conservation practices and high sediment yields.

Landscape factors that contribute to critical source areas

Our SWAT+ model contained 4,428 LSUs with varying landscape conditions and sediment yields. The upland land cover was 20% agriculture, 69% forested, and 6% urban, whereas the floodplain land cover was 27% agriculture, 47% forested, and 20% urban. The mean slope for upland and floodplain LSUs was 31% and 14%, respectively. Floodplain LSUs had a mean hydraulic conductivity of 80.7 ± 26.8 mm/hour, whereas upland LSUs had a mean hydraulic conductivity of 82.9 ± 22.1 mm/hr. The mean soil erodibility for upland and floodplain LSUs was 0.33 ± 0.04 metric tons·ha·hour/ha·MJ·mm and 0.32 ± 0.04 metric tons·ha·hour/ha·MJ·mm, respectively. The average predicted sediment yields for upland and floodplain LSUs were 1.82 metric tons/ha/year and 2.87 metric tons/ha/year, respectively.

Several landscape features were related to predicted sediment yields (Table 4). We dropped the predictor variables slope and proportion forest because they were highly correlated ($r > 0.6$) with several other predictor variables. Surprisingly, the proportion of agricultural land cover in a LSU was negatively associated with predicted sediment yield (Figure 11a). In contrast, predicted sediment yield was positively associated with increasing urban land cover, and urban land cover had a significant interaction with landscape position, with higher upland sediment yield for a given level of urban land cover (Figure 11b). As expected, increasing soil erodibility increased predicted sediment yields, and the effect of soil erodibility depended on landscape position, with lower upland sediment yield for a given value of soil erodibility. Hydraulic conductivity negatively affected predicted sediment yields, which may be because greater conductivity leads to more water moving through the soil (as opposed to over the soil surface), where sediment is captured or stored in the soil profile or groundwater.

Discussion

Our results provide novel insights into streamflow and pollutant dynamics for pasturelands with karst topography, so that conservation practices can be improved. We discuss how our results can be applied to installation of conservation practices specifically within the CPH and more broadly in pasturelands with karst topography. Unfortunately, the complexities of building watershed models like SWAT+ are rarely published (Fu et al., 2019), thereby limiting the capacity of new modelers to learn from previous experiences of others. Therefore, we also discuss challenges we encountered when building, calibrating, and validating our SWAT+ model to help advance SWAT+ application in karst regions with cattle grazing.

We found that several watersheds contributed disproportionate amounts of pollutants to streams but had few conservation practices installed, so these watersheds could be the focus of future conservation practice placement (Figure 10). In particular, Newland Hollow-North Fork Holston River and Big Spring Branch-Clinch River also had high agricultural land use, so these watersheds could particularly benefit from agricultural conservation practices. We define CSAs at the HUC-12 watershed scale but defining CSAs at finer scales (e.g., stream channels) would allow more specific targeting of conservation practice placement and potentially yield greater benefits for water quality. Unfortunately, issues building the SWAT+ model precluded us from taking this step. In particular, the width of headwater streams was too large, resulting in overestimation of sediment concentrations in the headwater streams despite replacing the default parameters with regional estimates (Bieger et al., 2015). We recommend that future studies identifying CSAs carefully check stream width and depth for streams of all sizes instead of only larger streams where gages are typically present and model checks occur.

Increased predicted sediment yields from SWAT+ were largely driven by increasing urban land cover and increased soil erodibility. Increasing urban land cover and soil erodibility would be expected to increase sediment yields, but we would also expect agricultural land cover to increase sediment yields. Instead, we observed a negative relationship between agricultural land cover that included a grazing operation and sediment yield from the landscape (Figure 11a). It is well known that sediment from agricultural land use is a pervasive problem in southwest Virginia (VDEQ, 2004; 2009; 2014); therefore, SWAT+ may not be accurately capturing the pathways through which cattle grazing influences sediment yields in southwest Virginia. For example, many pastures in southwest Virginia are mostly vegetated, so overland flow may not be the primary source of sediment as assumed by the USLE equation (Boomer et al., 2008). Instead, many streams in southwest Virginia have eroding banks, which may be the predominant sediment source in the region. If the effects of cattle grazing on streambanks were included in SWAT+, it may make for a more realistic model and allow for scenario analyses assessing the effects of altering grazing operations (e.g., rotational grazing and excluding cattle from riparian areas), which was initially a goal of this research.

Our results provide some insights into how water and pollutants move through karst environments when pasturelands are present, which can inform which conservation practices might most effectively mitigate CSAs. Increasing awc (i.e., how much water the soil can hold) and k (i.e., the rate of water movement through the soil) improved streamflow estimates at most gages, except USGS stream gage 03529500 where most of the upstream drainage is not karst topography (Figures 1 and 2). These parameters likely increase lateral flow through the soil, which could be an important contributor to high-flow events in our study because of the karst topography in the region (al Khoury et al., 2023). Nitrate is typically associated with water and may be moving along with water through lateral flow, so conservation practices that stop pollutants at their source are likely to be most effective for reducing nitrate (Rittenburg et al., 2015; Capel et al., 2018). Examples of conservation practices that stop pollutants at their source include removing agricultural land from production and nutrient management plans. In contrast, streambanks appear to be the predominant source of sediment, so conservation practices such as fencing can reduce streambank trampling by removing cattle from riparian areas (Trimble & Mendel, 1995; Grudzinski et al., 2020). Similarly, riparian buffers can stabilize streambanks and intercept sediment being lost from the landscape (Sweeney & Newbold, 2014).

We encountered challenges delineating the watershed and building HRUs within QSWAT+. There are many choices to make when building a watershed within QSWAT+, but the influence of these choices is not discussed within the user manuals (e.g., Dile et al., 2022) and rarely quantified in the literature. This lack of information is especially true for the SWAT+ model because it was developed in 2017 (Bieger et al., 2017) and has had relatively few publications compared to SWAT (Gassman, 2023). Streamflow and pollutant estimates within SWAT are affected by choices related to channel delineation (Arabi et al., 2006; Kumar & Merwade, 2009; Cho et al, 2010b), soil layer (Wang & Melesse, 2006; Bhandari et al., 2018), and HRU threshold (Her et al., 2015). We used a threshold of 2 km^2 to delineate channels because a larger threshold resulted in substantially fewer channels and a smaller threshold did not add any major channels. We used the STATSGO soil layer instead of the Soil Survey Geographic Database (SSURGO) because SSURGO frequently caused QGIS to crash and resulted in SWAT+ run times greater than two days. We decided not to remove HRUs from our final model because we felt that more HRUs would be more representative of the watershed and would allow for better modeling of conservation practices if desired (Her et al., 2015). However, after building our model, we learned that having too many HRUs significantly slows model runs and makes calibration more difficult (Jeffery Arnold, USDA Agricultural Research Station, 21 March 2024, written communication). SWAT+ application would benefit from future studies that explore the effect of choice regarding channel delineation, soil layer, HRU grouping, and other such decisions on model output. Further, it would be helpful to users if the impacts of these choices were discussed within the user guides.

We also had trouble calibrating the SWAT+ model for sediment. First, increasing the USLE cover and practice factors did not influence sediment loads, which suggests that changes made in the SWAT+ editor were not appropriately influencing the model. SWAT+ application would benefit from improvements in the SWAT+ editor so that changes to model parameters have the desired effect on model estimates. We also had difficulties adjusting channel erodibility, so that the value was appropriate for all HUC-8 watersheds within our study area (Figures 5 and 6), which suggests that sediment estimates could be improved if the SWAT+ model was divided into separate models for each of the HUC-8 watersheds in our study area. Future research should carefully weigh the pros (e.g., decreased calibration time) and cons (e.g., a single parameter may not represent the entire watershed) of modeling large watersheds using a single SWAT+ model.

The SWAT+ model unsatisfactorily predicted nitrogen in our study area. Our SWAT+ model greatly underpredicted total nitrogen loads, which was likely due to the underprediction of nitrate. The output from our SWAT+ model was about 60% nitrate and 40% organic nitrogen, but values observed in the field are typically closer to 80% nitrate and 20% organic nitrogen (VDEQ, 2022). Therefore, we focused on increasing the initial concentration of nitrate in the aquifer, changing the nitrate percolation coefficient, and adding a cattle grazing operation — none of which improved nitrogen estimates. However, when we increased the amount of manure deposited within the grazing operation to completely unrealistic levels, (i.e. 4,000 kg/cow/ha/day), predictions were closer to measured values. Similarly, Singh et al. (2023) and Buhr et al. (2022) found that nitrogen estimates were not sensitive to the nitrate percolation coefficient. Factors that nitrogen estimates were sensitive to include the humus mineralization of active organic nutrients (Singh et al., 2023) and denitrification exponential rate coefficient (Buhr et al., 2022; Singh et al., 2023). The SWAT+ model may not be accurately representing nitrogen movement within the karst system, the cattle grazing operation was not accurately simulating nitrogen deposition on the landscape, or the SWAT+ model was unable to account for legacy nitrogen, which can be stored in the groundwater for decades (Hamilton, 2012). Extensions added to SWAT, such as SWAT-MODFLOW-RT3D (Wei et al., 2019), may help improve nitrogen estimates for SWAT+.

The SWAT+ model also unsatisfactorily predicted phosphorus. It was unexpected that the SWAT+ model reasonably predicted phosphorus for the calibration period but not the validation period — especially considering that there were not major differences in sediment estimates between the two periods and phosphorus is typically associated with sediment. Legacy phosphorus could be accumulating in the streambed and resuspended during high-flow events (Wallington et al., 2024). We did not spend much time attempting to improve phosphorus estimates because excessive sediment loads are generally more of a concern in our study area, but future studies could improve phosphorus estimates by adjusting some of the following parameters: phosphorus enrichment ratio for loading with sediment, the phosphorus availability index, or the parameters affecting instream phosphorus (e.g., local settling rate for organic phosphorus). Alternatively, recent modifications to SWAT+ aim to more accurately capture the role of instream processes on phosphorus transport within a watershed (Wallington & Cai, 2023).

Despite the difficulties we encountered in building a SWAT+ model for predicting sediment and nutrient loads, the model showed great potential for understanding transport and delivery of pollutants. We were able to identify CSAs of sediment where implementation of conservation practices could achieve greater pollutant reduction (Figure 10). Additionally, the SWAT+ model revealed that pollutants are delivered to streams in our study area through streambank erosion and subsurface pathways. Future studies would benefit from improving how SWAT+ models pollutant transport in karst systems (i.e., 20% of the United States), and identifying the influence of different parameter choices in building the model.

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References

Abbaspour, K. C., Vaghefi, S. A., & Srinivasan, R. (2018). A guideline for successful calibration and uncertainty analysis for soil and water assessment: A review of papers from the 2016 international SWAT conference. *Water*, *10*(1), 6. https://doi.org/10.3390/w10010006

Arabi, M., Govindaraju, R. S., Hantush, M. M., & Engel, B. A. (2006). Role of watershed subdivision on modeling the effectiveness of best management practices with SWAT. *Journal of the American Water Resources Association*, *42*(2), 513–528. https://doi.org/10.1111/j.1752-1688.2006.tb03854.x

al Khoury, I., Boithias, L., & Labat, D. (2023). A review of the application of the Soil and Water Assessment Tool (SWAT) in karst watersheds. *Water*, *15*(5), 954. https://doi.org/10.3390/w15050954

Arnold, J. G., Srinivasan, R., Muttiah, R. S., & Williams, J. R. (1998). Large area hydrologic modeling and assessment part I: Model development. *American Water Resources Association*, *34*(1), 73–89. https://doi.org/10.1111/j.1752-1688.1998.tb05961.x

Beck, H. E., Zimmermann, N. E., McVicar, T. R., Vergopolan, N., Berg, A., & Wood, E. F. (2018). Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific Data*, *5*, 180214. https://doi.org/10.1038/sdata.2018.214

Bennett, E. M., Baird, J., Baulch, H., Chaplin-Kramer, R., Fraser, E., Loring, P., Morrison, P., Parrott, L., Sherren, K., Winkler, K. J., Cimon-Morin, J., Fortin, M. J., Kurylyk, B. L., Lundholm, J., Poulin, M., Rieb, J. T., Gonzalez, A., Hickey, G. M., Humphries, M., …

Lapen, D. (2021). Ecosystem services and the resilience of agricultural landscapes. In D. A. Bohan, A. J. Vanbergen (Eds.), *Advances in Ecological Research* (Vol. 64, pp. 1–43). Academic Press. https://doi.org/10.1016/bs.aecr.2021.01.001

Bhandari, R., Thakali, R., Kandissounon, G.A. A.D., Kalra, A., & Ahmad, S. (2018). Effects of soil data resolution on the simulated stream flow and water quality: Application of watershed-based SWAT model. In S. Kamojjala (Ed.), *World Environmental and Water Resources Congress 2018: Watershed Management, Irrigation and Drainage, and Water Resources Planning and Management* (pp. 376–386). American Society of Civil Engineers.

Bieger, K., Rathjens, H., Allen, P. M., & Arnold, J. G. (2015). Development and evaluation of bankfull hydraulic geometry relationships for the physiographic regions of the United States. *Journal of the American Water Resources Association*, *51*(3), 842–858. https://doi.org/10.1111/jawr.12282

Bieger, K., Arnold, J. G., Rathjens, H., White, M. J., Bosch, D. D., Allen, P. M., Volk, M., & Srinivasan, R. (2017). Introduction to SWAT+, a completely restructured version of the Soil and Water Assessment Tool. *Journal of the American Water Resources Association*, *53*(1), 115–130. https://doi.org/10.1111/1752-1688.12482

Boomer, K. B., Weller, D. E., & Jordan, T. E. (2008). Empirical models based on the Universal Soil Loss Equation fail to predict sediment discharges from Chesapeake Bay catchments. *Journal of Environmental Quality*, *37*(1), 79–89. https://doi.org/10.2134/jeq2007.0094

Buhr, D. X., Lammers, R. W., & Bledsoe, B. P. (2022). Global sensitivity analyses of key riparian nitrogen models. *Environmental Modelling and Software*, *158*, 105542. https://doi.org/10.1016/j.envsoft.2022.105542

Capel, P. D., Wolock, D. M., Coupe, R. H., & Roth, J. L. (2018). *A conceptual framework for effectively anticipating water-quality changes resulting from changes in agricultural activities*. https://doi.org/10.3133/sir20175095

Carpenter, S. R., Caraco, N. F., Correll, D. L., Howarth, R. W., Sharpley, A. N., & Smith, V. H. (1998). Nonpoint pollution of surface waters with phosphorus and nitrogen. *Ecological Applications*, *8*(3), 559–568. https://doi.org/10.1890/1051-0761(1998)008[0559:NPOSWW]2.0.CO;2

Cho, J., Vellidis, G., Bosch, D. D., Lowrance, R., & Strickland, T. (2010a). Water quality effects of simulated conservation practice scenarios in the Little River Experimental watershed. *Journal of Soil and Water Conservation*, *65*(6), 463–473. https://doi.org/10.2489/jswc.65.6.463

Cho, J., Lowrance, R. R., Bosch, D. D., Strickland, T. C., Her, Y., & Vellidis, G. (2010b). Effect of watershed subdivision and filter width on SWAT simulation of a coastal plain watershed. *Journal of the American Water Resources Association*, *46*(3), 586–602. https://doi.org/10.1111/j.1752-1688.2010.00436.x

Congressional Research Service. (2024). *The 2018 Farm Bill (P.L. 115-334): Summary and side-by-side comparison*. https://crsreports.congress.gov/product/pdf/R/R45525

Coxon, C. (2011). Agriculture and karst. In P. E. van Beynen (Ed.), *Karst Management* (pp. 103–138). Springer. https://doi.org/10.1007/978-94-007-1207-2_5

Czuba, J. A., & Allen, G. H. (2023). When does a stream become a river? *River Research and Applications*, *39*(9), 1925–1929. https://doi.org/10.1002/rra.4185

Daggupati, P., Douglas-Mankin, K. R., Sheshukov, A. Y., Barnes, P. L., & Devlin, D. L. (2011). Field-level targeting using SWAT: Mapping output from HRUs to fields and assessing limitations of GIS input data. *Transactions of the ASABE*, *54*(2), 501–514.

Diebel, M. W., Maxted, J. T., Nowak, P. J., & vander Zanden, M. J. (2008). Landscape planning for agricultural nonpoint source pollution reduction I: A geographical allocation framework. *Environmental Management*, *42*, 789–802. https://doi.org/10.1007/s00267-008-9186-3

Dile, Y., Srinivasan, R., & George, C. (2022). *QGIS Interface for SWAT+, version 2.3*.

Erb, K., & Maas, B. J. (2021). Intersection of agriculture and karst terrains, risks, and solutions. In G. A. Brick & E. C. Alexander Jr. (Eds.), *Cave and karst of the upper Midwest, USA* (pp. 283–296). Springer. https://doi.org/10.1007/978-3-030-54633-5_10

Foufoula-Georgiou, E., Takbiri, Z., Czuba, J. A., & Schwenk, J. (2015). The change of nature and the nature of change in agricultural landscapes: Hydrologic regime shifts modulate ecological transitions. *Water Resources Research*, *51*(8), 6649–6671. https://doi.org/10.1002/2015WR017637

Fu, B., Merritt, W. S., Croke, B. F. W., Weber, T. R., & Jakeman, A. J. (2019). A review of catchment-scale water quality and erosion models and a synthesis of future prospects. *Environmental Modelling and Software*, *114*, 75–97. https://doi.org/10.1016/j.envsoft.2018.12.008

Gassman, P. W., Reyes, M. R., Green, C. H., & Arnold, J. G. (2007). The Soil and Water Assessment Tool: Historical development, applications, and future research directions. *Transactions of the ASABE*, *50*(4), 1211–1250. https://doi.org/10.13031/2013.23637

Gassman, P. (2023). *SWAT literature database for peer-reviewed journal articles*. https://www.card.iastate.edu/swat_articles/

Grudzinski, B., Fritz, K., & Dodds, W. (2020). Does riparian fencing protect stream water quality in cattle-grazed lands? *Environmental Management*, *66*, 121–135. https://doi.org/10.1007/s00267-020-01297-2

Hamilton, S. K. (2012). Biogeochemical time lags may delay responses of streams to ecological restoration. *Freshwater Biology*, *57*(s1), 43–57. https://doi.org/10.1111/j.1365-2427.2011.02685.x

Heathwaite, A. L., Quinn, P. F., & Hewett, C. J. M. (2005). Modelling and managing critical source areas of diffuse pollution from agricultural land using flow connectivity simulation. *Journal of Hydrology*, *304*(1–4), 446–461. https://doi.org/10.1016/j.jhydrol.2004.07.043

Her, Y., Frankenberger, J., Chaubey, I., & Srinivasan, R. (2015). Threshold effects in HRU definition of the Soil and Water Assessment Tool. *Transactions of the ASABE*, *58*(2), 367–378. https://doi.org/10.13031/trans.58.10805

James, C. (2022). *SWAT+ Toolbox v1.0 documentation*. https://celray.github.io/docs/swatplus-toolbox/v1.0/index.html

Kumar, S., & Merwade, V. (2009). Impact of watershed subdivision and soil data resolution on SWAT model calibration and parameter uncertainty. *Journal of the American Water*

Resources Association, *45*(5), 1179–1196. https://doi.org/10.1111/j.1752-1688.2009.00353.x

Liu, Y., Engel, B. A., Flanagan, D. C., Gitau, M. W., McMillan, S. K., & Chaubey, I. (2017). A review on effectiveness of best management practices in improving hydrology and water quality: Needs and opportunities. *Science of the Total Environment*, 601–602, 580–593. https://doi.org/10.1016/j.scitotenv.2017.05.212

Moriasi, D. N., Arnold, J. G., van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE*, *50*(3), 885–900. https://doi.org/10.13031/2013.23153

Natural Resources Conservation Service. (n.d.). *Conservation Practice Standards*. Retrieved October 24, 2023, from https://www.nrcs.usda.gov/resources/guides-and-instructions/conservation-practice-standards

Natural Resources Conservation Service. (2019). *Web soil survey*. https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx

Newcombe, C. P., & MacDonald, D. D. (1991). Effects of suspended sediments on aquatic ecosystems. *North American Journal of Fisheries Management*, *11*(1), 72–82. https://doi.org/10.1577/1548-8675(1991)011<0072:eossoa>2.3.co;2

Noe, G. B., Hopkins, K. G., Claggett, P. R., Schenk, E. R., Metes, M. J., Ahmed, L., Doody, T. R., & Hupp, C. R. (2022). Streambank and floodplain geomorphic change and contribution to watershed material budgets. *Environmental Research Letters*, *17*(6), 064015. https://doi.org/10.1088/1748-9326/ac6e47

Nowak, P., Bowen, S., & Cabot, P. E. (2006). Disproportionality as a framework for linking social and biophysical systems. *Society and Natural Resources*, *19*(2), 153–173. https://doi.org/10.1080/08941920500394816

Pionke, H. B., Schnabel, R. R., Gburek, W. J., Sharpley, A. N., & Elwinger, G. F. (2002). Seasonal flow, nutrient concentrations and loading patterns in stream flow draining an agricultural hill-land watershed. *Journal of Hydrology*, *220*(1–2), 62–73. https://doi.org/10.1016/s0022-1694(99)00064-5

Poff, N. L., Allan, J. D., Bain, M. B., Karr, J. R., Prestegaard, K. L., Richter, B. D., Sparks, R. E., & Stromberg, J. C. (1997). The natural flow regime: A paradigm for river conservation and restoration. *BioScience*, *47*(11), 769–784. https://doi.org/10.2307/1313099

PRISM Climate Group. (2024). *PRISM climate data*. https://prism.oregonstate.edu/

R Core Team. (2023). *A language and environment for statistical computing*. https://www.R-project.org/

Ribaudo, M. (2015). The limits of voluntary conservation programs. *Choices*, *30*(2), 1–5.

Rittenburg, R. A., Squires, A. L., Boll, J., Brooks, E. S., Easton, Z. M., & Steenhuis, T. S. (2015). Agricultural BMP effectiveness and dominant hydrological flow paths: Concepts and a review. *Journal of the American Water Resources Association*, *51*(2), 305–329. https://doi.org/10.1111/1752-1688.12293

Schürings, C., Feld, C. K., Kail, J., & Hering, D. (2022). Effects of agricultural land use on river biota: A meta-analysis. *Environmental Sciences Europe 34*, 124. https://doi.org/10.1186/s12302-022-00706-z

Sharpley, A. N., Kleinman, P. J. A., McDowell, R. W., Gitau, M., & Bryant, R. B. (2002). Modeling phosphorus transport in agricultural watersheds: Processes and possibilities. *Journal of Soil and Water Conservation*, *57*(6), 425–439.

Singh, S., Hwang, S., Arnold, J. G., & Bhattarai, R. (2023). Evaluation of agricultural BMPs' impact on water quality and crop production using SWAT+ model. *Agriculture*, *13*(8), 1484. https://doi.org/10.3390/agriculture13081484

Sowa, S. P., Herbert, M., Mysorekar, S., Annis, G. M., Hall, K., Nejadhashemi, A. P., Woznicki, S. A., Wang, L., & Doran, P. J. (2016). How much conservation is enough? Defining implementation goals for healthy fish communities in agricultural rivers. *Journal of Great Lakes Research*, *42*(6), 1302–1321. https://doi.org/10.1016/j.jglr.2016.09.011

Stets, E. G., Sprague, L. A., Oelsner, G. P., Johnson, H. M., Murphy, J. C., Ryberg, K., Vecchia, A. V., Zuellig, R. E., Falcone, J. A., & Riskin, M. L. (2020). Landscape drivers of dynamic change in water quality of U.S. rivers. *Environmental Science and Technology*, *54*(7), 4336–4343. https://doi.org/10.1021/acs.est.9b05344

Sweeney, B. W., & Newbold, J. D. (2014). Streamside forest buffer width needed to protect stream water quality, habitat, and organisms: A literature review. *Journal of the American Water Resources Association*, *50*(3), 560–584. https://doi.org/10.1111/jawr.12203

Tech, J. (2023). *SWAT+ installation and help*. https://swatplus.gitbook.io/docs

Trimble, S. W., & Mendel, A. C. (1995). The cow as a geomorphic agent — A critical review. *Geomorphology*, *13*, 233–253. https://doi.org/10.1016/0169-555X(95)00028-4

Tuppad, P., Douglas-Mankin, K. R., & Mcvay, K. A. (2010). Strategic targeting of cropland management using watershed modeling. *Agricultural Engineering International: CIGR Journal*, *12*(3), 1–19.

Tumsa, B. C. (2023). The response of sensitive LULC changes to runoff and sediment yield in a semihumid urban watershed of the upper Awash subbasin using the SWAT+ model, Oromia, Ethiopia. *Applied and Environmental Soil Science*, *2023*, 6856144. https://doi.org/10.1155/2023/6856144

U.S. Environmental Protection Agency and U.S. Geological Survey. (2012). *National hydrography dataset plus – NHDPlus*. https://nhdplus.com/NHDPlus/NHDPlusV2_data.php

U.S. Environmental Protection Agency. (2023). *National rivers and streams assessment: The third collaborative survey.* https://riverstreamassessment.epa.gov/webreport/

U.S. Environmental Protection Agency. (2024). *Ecoregions*. https://www.epa.gov/eco-research/ecoregions

U.S. Geological Survey. (2019a). *NLCD 2016 land cover (CONUS)*. https://www.mrlc.gov/data/nlcd-2016-land-cover-conus

U.S. Geological Survey. (2019b). *1 Arc-second Digital Elevation Models (DEMs) – USGS National Map 3DEP downloadable data collection*. https://apps.nationalmap.gov/viewer/

U.S. Geological Survey. (2020). *USGS current water data for Virginia*. https://waterdata.usgs.gov/va/nwis/rt

U.S. Geological Survey. (2024). *Hydrologic unit maps*. https://water.usgs.gov/GIS/huc.html

Virginia Department of Conservation and Recreation. (2024). *Virginia agricultural BMP and CREP database query form*. https://casdsis.dcr.virginia.gov/htdocs/progs/BMP_query.aspx

Virginia Department of Environmental Quality. (n.d.). *Approved TMDLs*. https://www.deq.virginia.gov/our-programs/water/water-quality/tmdl-development/approved-tmdls

Virginia Department of Environmental Quality. (2004). *Total Maximum Daily Load (TMDL) development for the Upper Clinch River Watershed*.

Virginia Department of Environmental Quality. (2009). *Bacteria and benthic Total Maximum Daily Load development for Middle Fork Holston River*.

Virginia Department of Environmental Quality. (2014). *Bacteria and sediment TMDL development Lower Clinch River Watershed, VA*.

Virginia Department of Environmental Quality. (2022a). *Virginia's 2022 305(b)/303(d) water quality assessment integrated report*. https://www.deq.virginia.gov/our-programs/water/water-quality/assessments/integrated-report

Virginia Department of Environmental Quality. (2022b). *DEQ environmental data mapper*. https://apps.deq.virginia.gov/EDM/

Wallington, K., & Cai, X. (2023). Updating SWAT+ to clarify understanding of in-stream phosphorus retention and remobilization: SWAT+P.R&R. *Water Resources Research*, *59*, e2022WR033283. https://doi.org/10.1029/2022WR033283

Wallington, K., Cai, X., & Kalcic, M. (2024). Evaluating the longevity of in-stream phosphorus legacies: A downstream cascade of recovery following point source remediation. *Science of the Total Environment*, *912*, 168711. https://doi.org/10.1016/j.scitotenv.2023.168711

Wang, X., & Melesse, A. M. (2006). Effects of STATSGO and SSURGO as inputs on SWAT model's snowmelt simulation. *Journal of the American Water Resources Association*, *42*(5), 1217–1236. https://doi.org/10.1111/j.1752-1688.2006.tb05296.x

Weary, D. J., & Doctor, D. H. (2014). *Karst in the United States: A digital map compilation and database*. https://doi.org/10.3133/ofr20141156

Wu, T., Zhu, L., Shen, S., Zhu, A. X., Shi, M., & Qin, C. Z. (2023). Identification of watershed priority management areas based on landscape positions: An implementation using SWAT+. *Journal of Hydrology*, *619*, 129281. https://doi.org/10.1016/j.jhydrol.2023.129281

Yuan, L., Sinshaw, T., & Forshay, K. J. (2020). Review of watershed-scale water quality and nonpoint source pollution models. *Geosciences, 10*(1), 25. https://doi.org/10.3390/geosciences10010025

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

Tables and figures

Table 1. Data sources compiled to run and calibrate the Soil and Water Assessment Tool+.

Data	Source	Website	Accessed
Topography	National Elevation Dataset	https://apps.nationalmap.gov/viewer/	June 2020
Stream network	National Hydrography Dataset Plus Version 2	https://tinyurl.com/y4st74vh	January 2020
Land cover	National Land Cover Database	https://www.mrlc.gov/data	April 2019
Soil	State Soil Geographic Database	https://tinyurl.com/yc4r4zdh	July 2020
Climate	Parameter-elevation regressions on independent slopes model	https://prism.oregonstate.edu/	August 2020
Streamflow	U.S. Geological Survey current water data for Virginia	https://tinyurl.com/yyew8asr	June 2022
Water quality	Virginia Department of Environmental Quality	https://tinyurl.com/2p86s7v2	June 2022

Table 2. Parameters evaluated for influence on streamflow and sediment load estimates from the Soil and Water Assessment Tool+. All parameters were changed relative to values within the provided range. The values for the most influential parameters that resulted in the best model performance are also given. "-" indicates that streamflow and sediment loads were not sensitive to the parameter; therefore, there was not a value that gave the best model performance.

Response variable	**Parameter**	**Description**	**Range**	**Unit**	**Value**
	epco	plant uptake compensation factor	-1 to 1	none	-
	esco	soil evaporation compensation factor	-1 to 1	none	-
	n	Manning's roughness coefficient	-0.35 to 0.1	none	-
	k	soil saturated hydraulic conductivity	-50 to 50	mm/hr	-
Streamflow	awc	soil available water capacity	-0.3 to 0.3	mm H_20/mm	-0.26
	cn2	curve number	-10 to 10	none	24.48
	alpha	baseflow alpha factor	-0.05 to 0.15	days	-
	flo_min	minimum aquifer storage to allow return flow	-2 to 2	m	-
	revap_co	groundwater "revap" coefficient	0 to 0.4	none	-

	revap_min	threshold depth of water in the shallow aquifer for “revap or percolation to the deep aquifer to occur	0 to 50	m	-
Sediment load	cherod	channel erodibility	0 to 0.1*	cm^3/N-s	0.0002
	cov	channel cover	0 to 0.1	none	-
	adj_pkr_sed	peak rate adjustment factor for sediment routing in the main channel	0 to 1	none	-
	lin_sed	linear parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing	0.0001 to 0.01	none	-
	spexp	exponent parameter for calculating sediment re-entrained in channel sediment routing	1 to 1.5	none	-

*Calibration values were changed from 0 to 0.000001

Table 3. Nashe-Sutcliffe efficiency values from Soil and Water Assessment Tool+ (SWAT+) model calibration (Cal) and validation (Val) for streamflow (m^3/sec), sediment loads (metric tons), nitrogen loads (kg), and phosphorus loads (kg) for daily (D; per/day) and monthly (M; per/month) timesteps. Streamflow predictions from the SWAT+ model were compared to values measured at 11 U.S. Geological Survey gages in the upper Clinch, Powell, North Fork Holston, and South Fork Holston HUC-8 watersheds. Water quality predictions from the SWAT+ model were compared to values measured at 10 Virginia Department of Environmental Quality long-term monitoring stations that were near the gages. There were negligible differences between calibration and validation for nitrogen; therefore, results are shown only for calibration.

		Streamflow				Sediment				Nitrogen		Phosphorus			
		D		M		D		M		D	M	D		M	
Gage	**Station**	**Cal**	**Val**	**Cal**	**Val**	**Cal**	**Val**	**Cal**	**Val**	**Val**	**Val**	**Cal**	**Val**	**Cal**	**Val**
03531500	6BPOW138.91	0.52	0.57	0.50	0.49	0.26	0.13	0.10	-0.03	-0.24	-0.91	-31.34	-199.44	-6.78	-63.57
03529500	6BPOW179.20	0.41	0.45	0.40	0.34	0.23	0.27	-0.53	0.27	-0.33	-1.21	-7.04	-103.25	-0.44	-33.12
03527220*	-	0.49	0.50	0.64	0.45	-	-	-	-	-	-	-	-	-	-
03524000	6BCLN271.50	0.43	0.59	0.46	0.53	-0.02	-0.03	-0.46	-0.51	-0.26	-1.25	-4.14	-194.57	-0.36	-39.98
03527000	6BCLN206.70	0.41	0.54	0.48	0.54	-0.07	-0.04	-0.47	-0.31	-0.18	-0.76	-0.07	-102.57	-1.30	-39.54
03488000	6CNFH085.20	0.48	0.55	0.57	0.58	0.36	0.28	0.41	0.25	-0.28	-1.06	-134.20	-1138.90	-30.32	-399.90

03475000	6CMFH013.21	0.39	0.38	0.66	0.76	0.28	0.21	0.37	0.27	-0.50	-1.58	-161.22	-548.15	-15.59	-135.52
03474000	6CMFH033.40	0.50	0.63	0.63	0.73	0.29	0.32	0.21	0.46	-0.81	-2.40	-182.56	-2355.79	-18.93	-525.72
03473000	6CSFH075.61	0.55	0.59	0.66	0.63	0.30	0.24	0.39	0.27	-0.25	-1.18	-100.68	-577.05	-22.61	-264.46
03478400	6CBEV020.86	-2.25	-0.63	0.40	0.80	-0.75	0.21	0.16	0.40	-0.63	-1.30	-260.18	-139.44	-23.37	-27.42
03471500	6CSFH097.42	0.29	0.48	0.56	0.65	-6.84	-1.22	-16.80	-5.02	-0.34	-1.37	-957.27	-2813.24	-204.11	-1095.52

*Gage 03527220 lacked an associated Virginia Department of Environmental Quality long-term monitoring station, and any data on sediment, nitrogen, or phosphorus.

Table 4. Results of a multiple linear regression model used to determine factors that influence sediment yield (metric tons/ha/year) for 4,428 landscape units within the Clinch, Powell, North Fork Holston, and South Fork Holston HUC-8 watersheds in Virginia, United States. The Soil and Water Assessment Tool+ was used to estimate sediment yield. The intercept was suppressed so the results for both floodplain and upland landscape units can be easily interpreted. Coefficients are scaled and centered to have a mean of zero and standard deviation (SD) of one.

Coefficient	**Estimate ± SD**	***p*-value**
Hydraulic conductivity (mm/hr)	-0.04 ± 0.01	< 0.01
Agriculture (unitless)	-0.01 ± 0.01	0.06
Floodplain (unitless)	0.81 ± 0.01	< 0.01
Upland (unitless)	1.11 ± 0.01	< 0.01
Urban (unitless)	0.51 ± 0.01	< 0.01
Soil erodibility (metric tons·ha·hour/ha·MJ·mm)	0.15 ± 0.01	< 0.01
Upland X urban	0.25 ± 0.02	< 0.01
Upland X soil erodibility	-0.04 ± 0.01	< 0.01

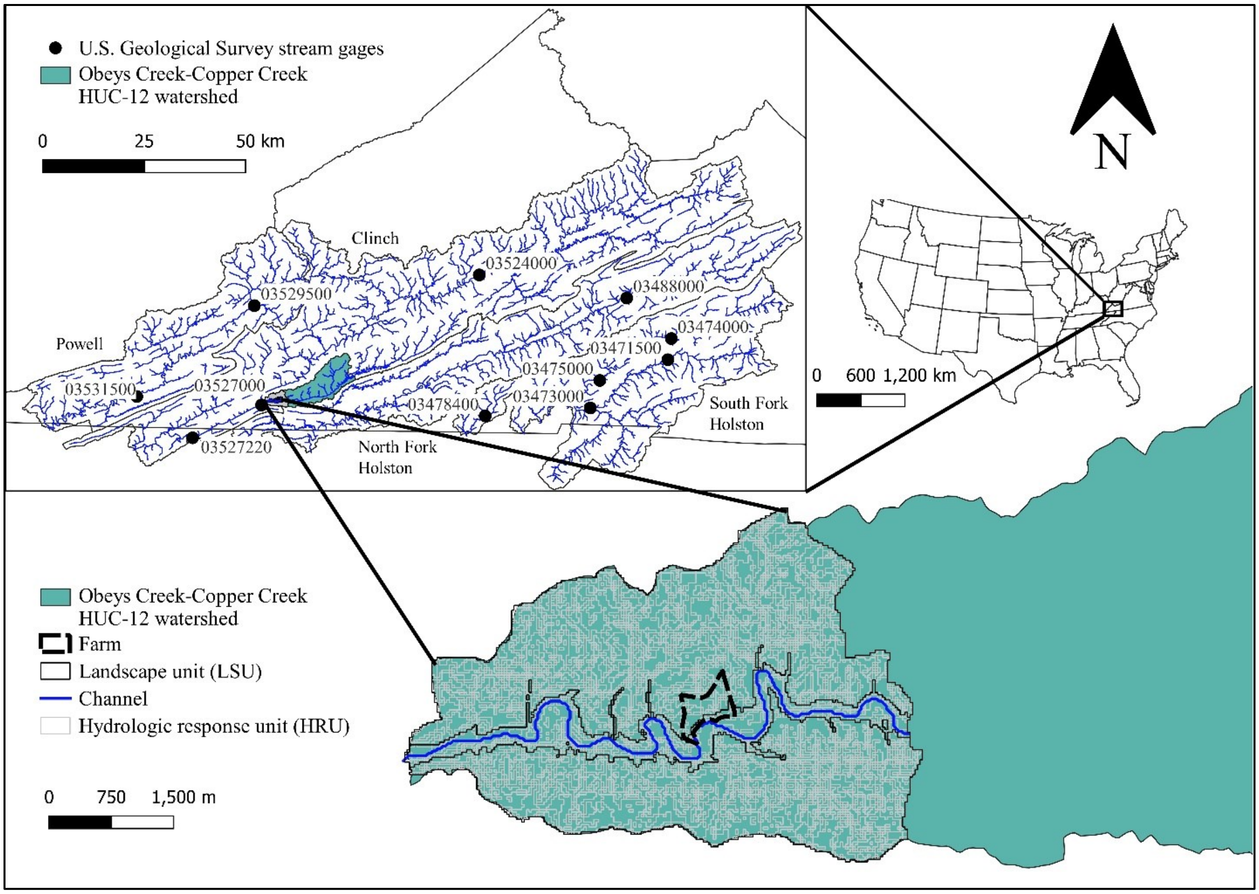

Figure 1. Illustration of the various spatial scales at which output from the Soil and Water Assessement Tool+ (SWAT+) can be summarized to understand critical source areas of pollutants. SWAT+ estimates sediment (metric tons/ha), nitrogen (kg/ha), and phosphorus (kg/ha) yields from hydrologic response units, which can be summarized at a variety of spatial scales including farms and landscape units. Pollutant yields are routed to channels which become instream loads. Landscapes units are divided into upland and floodplain units in SWAT+, which is an improvement upon SWAT that lumped upland and floodplain units into a single subbasin. Data from the U.S. Geological Survey stream gages and Virginia Department of Environmental Quality long-term water quality stations (locations coincide with the gages) were used to calibrate and validate the SWAT+ model.

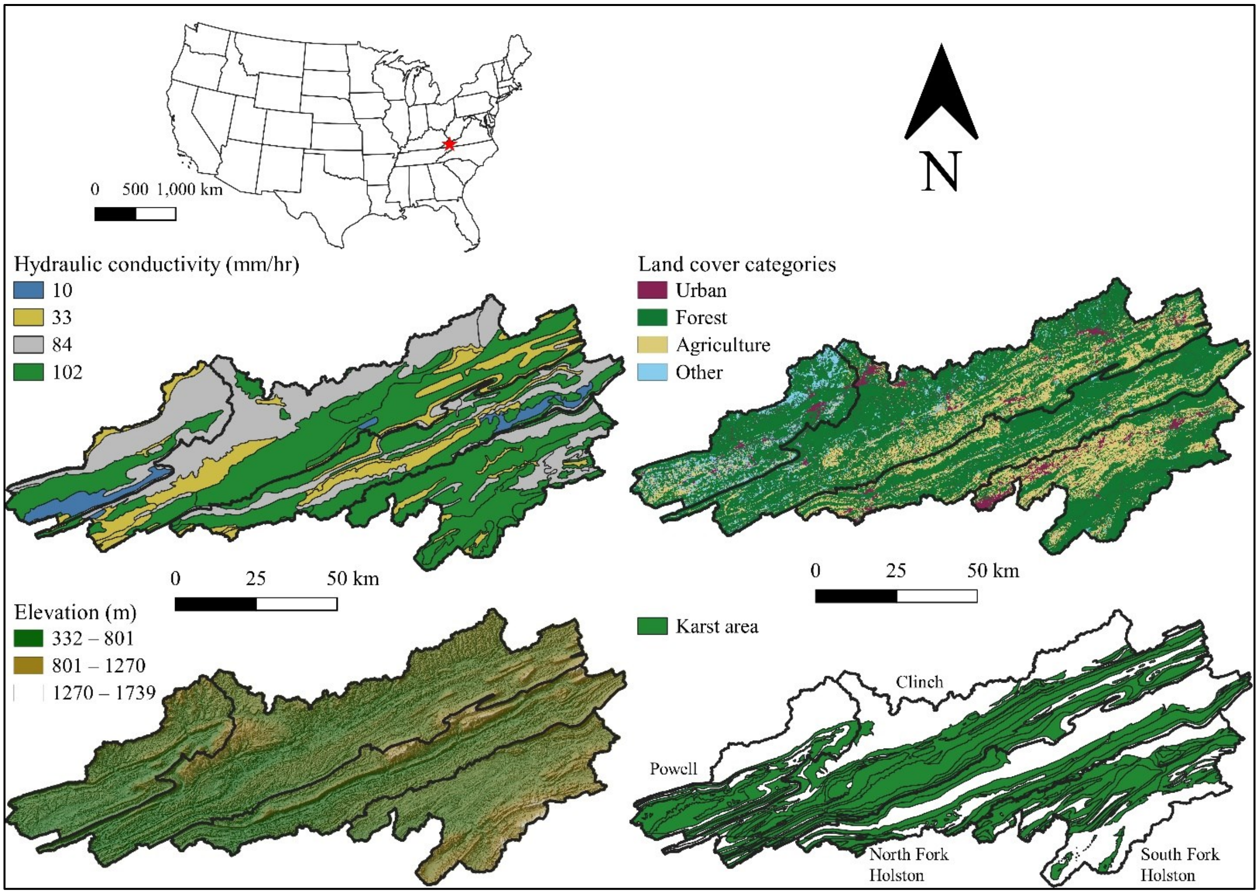

Figure 2. The Soil and Water Assessment Tool+ (SWAT+) was used to model streamflow, sediment, total nitrogen, and total phosphorus within the Clinch, Powell, North Fork Holston, and South Fork Holston HUC-8 watersheds in Virginia, United States. In addition to rainfall (not shown), soil characteristics (e.g., hydraulic conductivity), land cover, and elevation are important inputs to SWAT+ that are used to model streamflow and pollutant transport. The karst topography of our study area has a major influence on streamflow, pollutant transport, and ultimately, SWAT+ model performance.

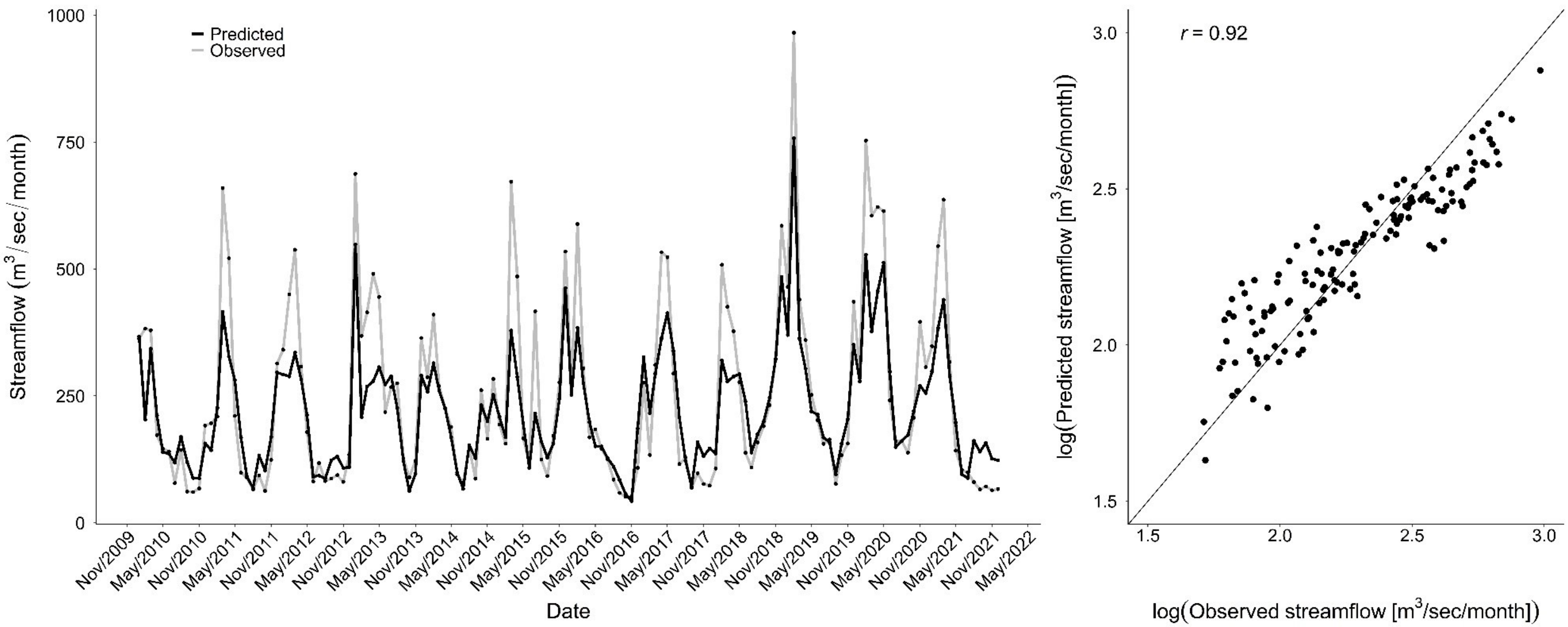

Figure 3. Streamflow (m^3/sec/month) observed at U.S. Geological Survey gage 03475000 (Middle Fork Holston River near Meadowview, Virginia, United States) compared to streamflow predicted by the Soil and Water Assessment Tool+. The Nash-Sutcliffe efficiency (NSE) for streamflow predictions at this gage was the second best of all gages and indicated good fit (0.76). Streamflow predictions were similar for most other gages except for 03529500 (Table 3, Figure 4).

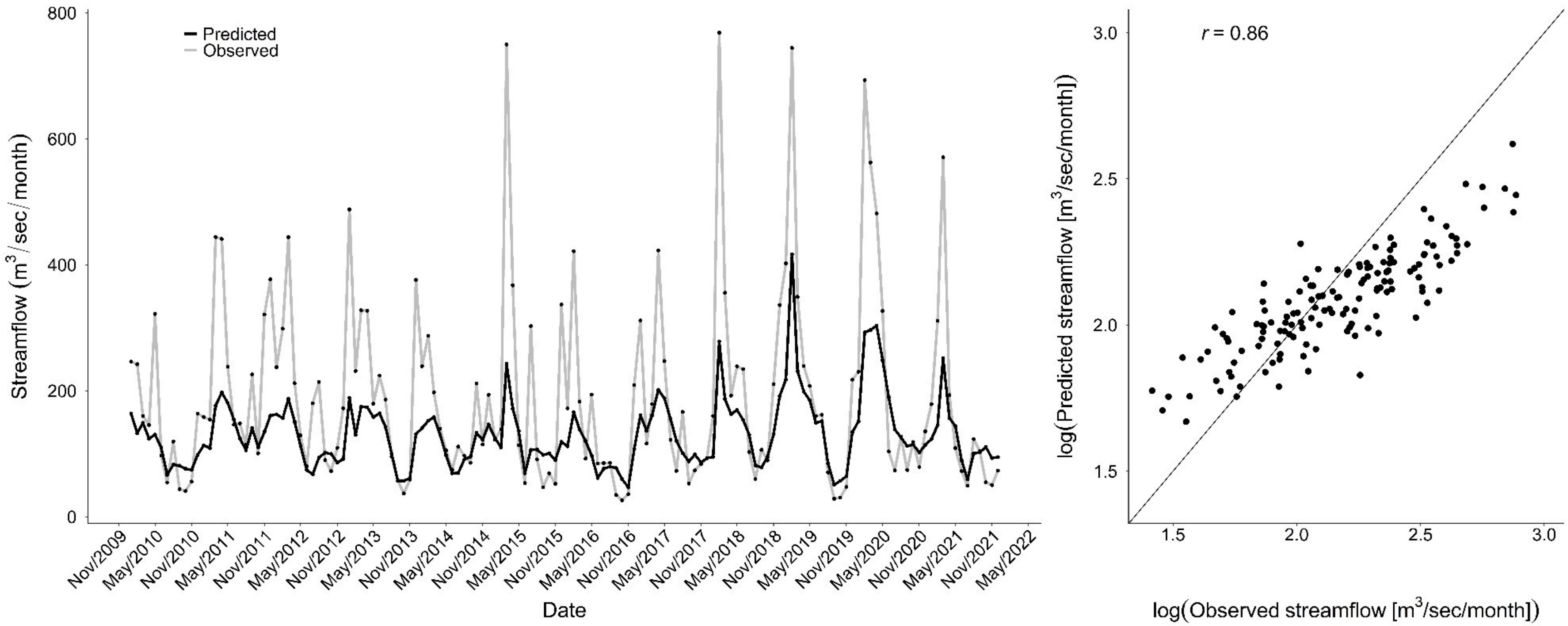

Figure 4. Streamflow (m^3/sec/month) observed at U.S. Geological Survey gage 03529500 (Powell River at Big Stone Gap, Virginia, United States) compared to streamflow predicted by the Soil and Water Assessment Tool+. The Nash-Sutcliffe efficiency (NSE) for streamflow predictions at this gage was worse than all other gages and indicated unsatisfactory fit (0.34). Streamflow predictions at all other gages had NSE values near or above 0.5, indicating good fit (Table 3, Figure 3).

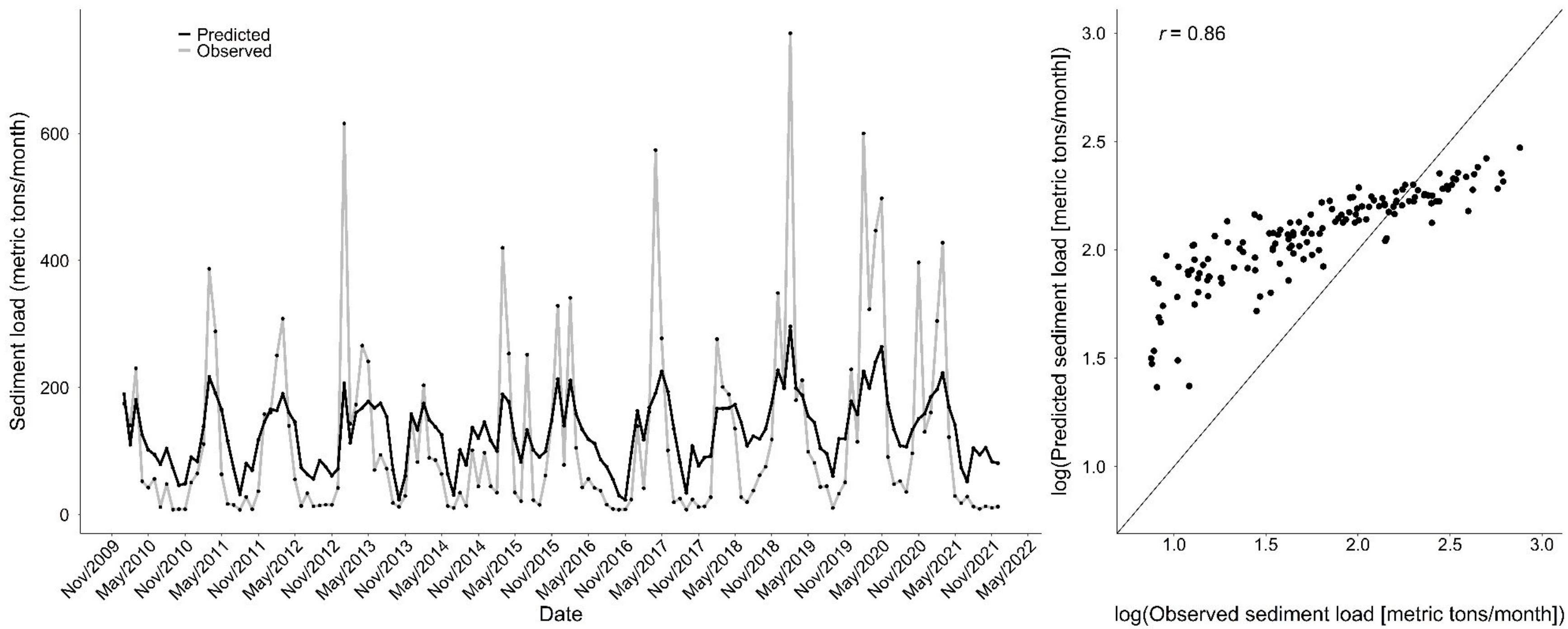

Figure 5. The sediment load (metric tons/month) observed at Virginia Department of Environmental Quality water quality monitoring station 6CMFH033.40 located near U.S. Geological Survey gage 03474000 (Middle Fork Holston River at Seven Mile Ford, Virginia, United States) compared to the sediment load predicted by the Soil and Water Assessment Tool+. The Nash-Sutcliffe efficiency for sediment load predictions at this gage was better than all other gages but indicated unsatisfactory fit (0.46). Sediment load predictions were similar at all other gages except those in the Clinch River (Table 3, Figure 6).

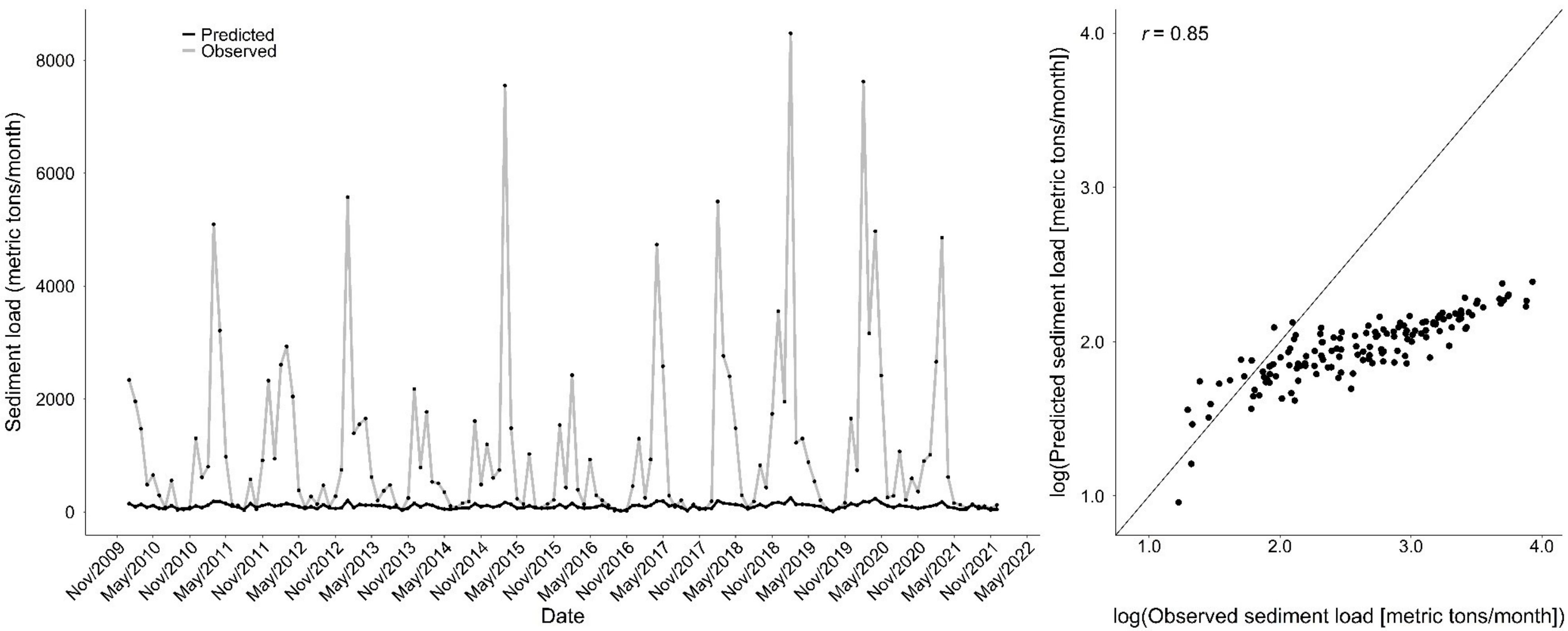

Figure 6. The sediment load (metric tons/month) observed at Virginia Department of Environmental Quality water quality monitoring station 6BCLN271.50 located near U.S. Geological Survey gage 03524000 (Clinch River at Cleveland, Virginia, United States) compared to the sediment load predicted by the Soil and Water Assessment Tool+. The Nash-Sutcliffe efficiency for sediment load predictions were worse at this gage than all other gages and indicated unsatisfactory fit (-0.51). Sediment predictions extremely underestimated measured values at both gages in the Clinch River (Table 3).

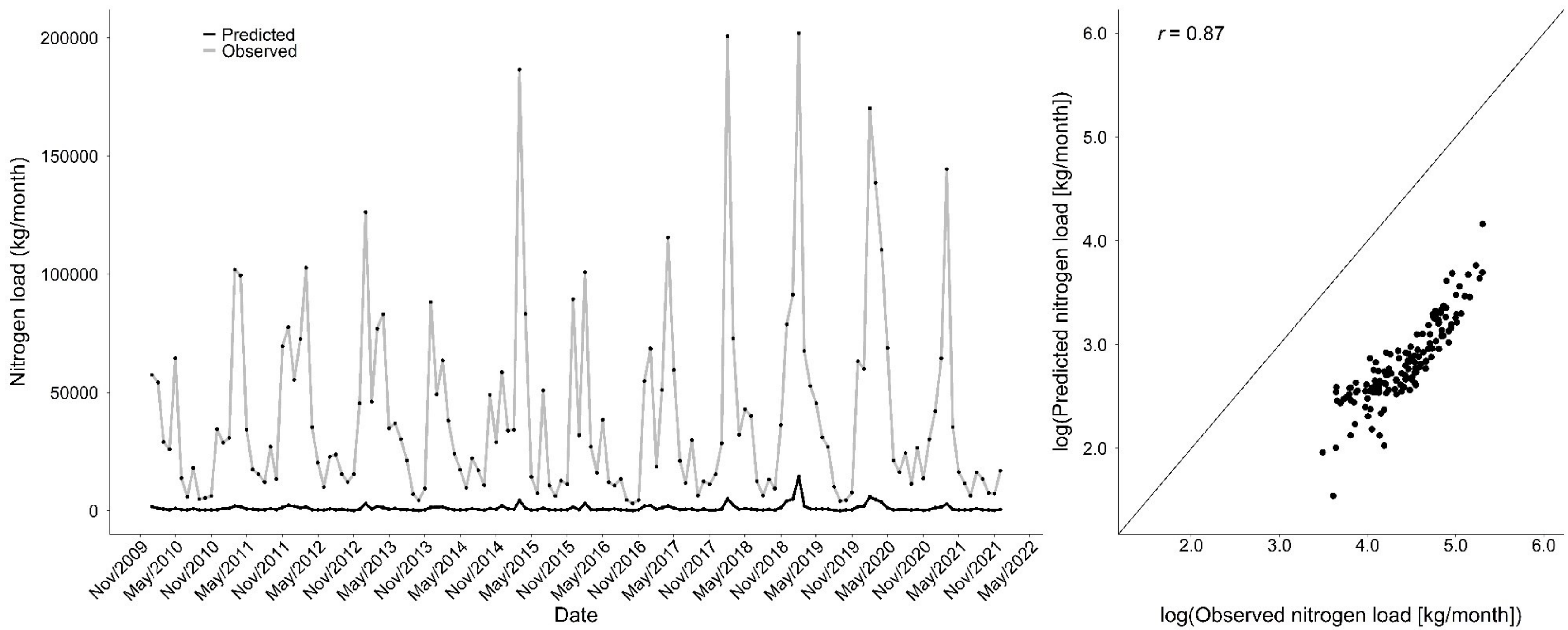

Figure 7. The total nitrogen load (kg/month) observed at Virginia Department of Environmental Quality water quality monitoring station 6BPOW138.91 located near U.S. Geological Survey gage 03531500 (Powell River near Jonesville, Virginia, United States) compared to the nitrogen load predicted by the Soil and Water Assessment Tool+. Because measured nitrogen loads were greatly underpredicted by the SWAT+ model, the Nash-Sutcliffe efficiency (NSE) indicated unsatisfactory fit for this gage (-0.91) and all other gages (Table 3).

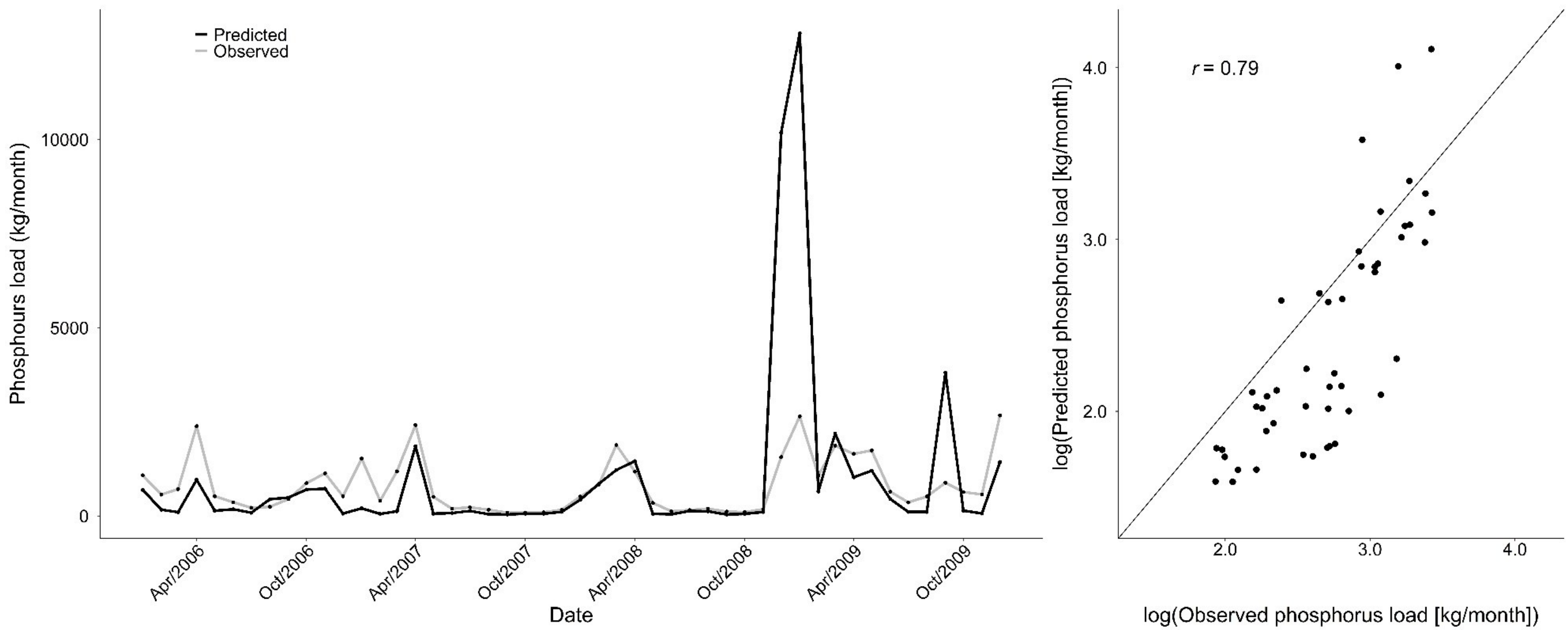

Figure 8. The total phosphorus load (kg/month) observed at Virginia Department of Environmental Quality water quality monitoring station 6BPOW138.91 located near U.S. Geological Survey gage 03531500 (Powell River near Jonesville, Virginia, United States) compared to the phosphorus load predicted by the Soil and Water Assessment Tool+ for the calibration period. This Nash-Sutcliffe efficiency (NSE) for phosphorus load predictions was the fourth best for this gage and indicated unsatisfactory fit (-6.78). Poor NSE values were largely driven by greatly overpredicting phosphorus during a few months and most locations with measured values showed similar results to those shown in Figure 8, so we did not change parameters within the model for phosphorus.

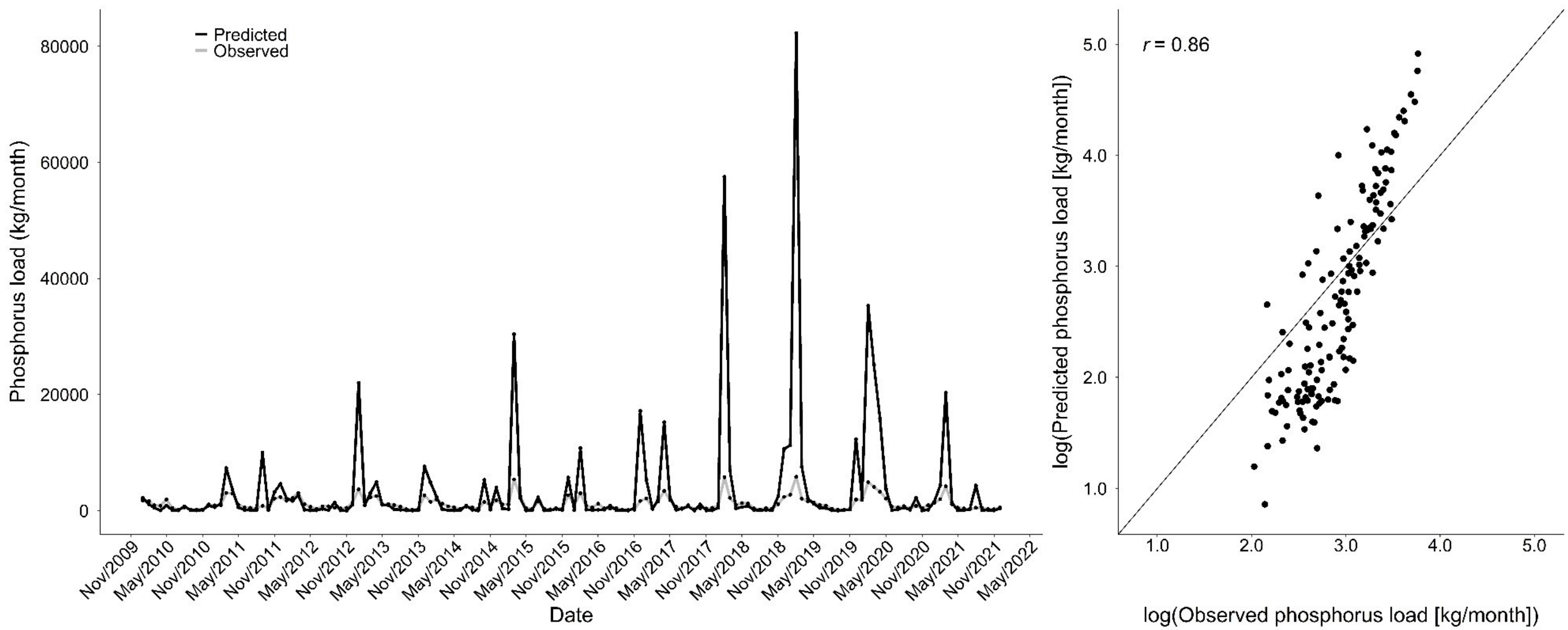

Figure 9. The total phosphorus load (kg/month) observed at Virginia Department of Environmental Quality water quality monitoring station 6BPOW138.91 located near U.S. Geological Survey gage 03531500 (Powell River near Jonesville, Virginia, United States) compared to the phosphorus load predicted by the Soil and Water Assessment Tool (SWAT+) for the validation period. Because the SWAT+ model greatly overpredicted phosphorus loads at high measured levels of phosphorus, but underpredicted phosphorus at low measured levels, the Nash-Sutcliffe efficiency indicated unsatisfactory fit at this gage (-63.57) and all other gages (Table 3).

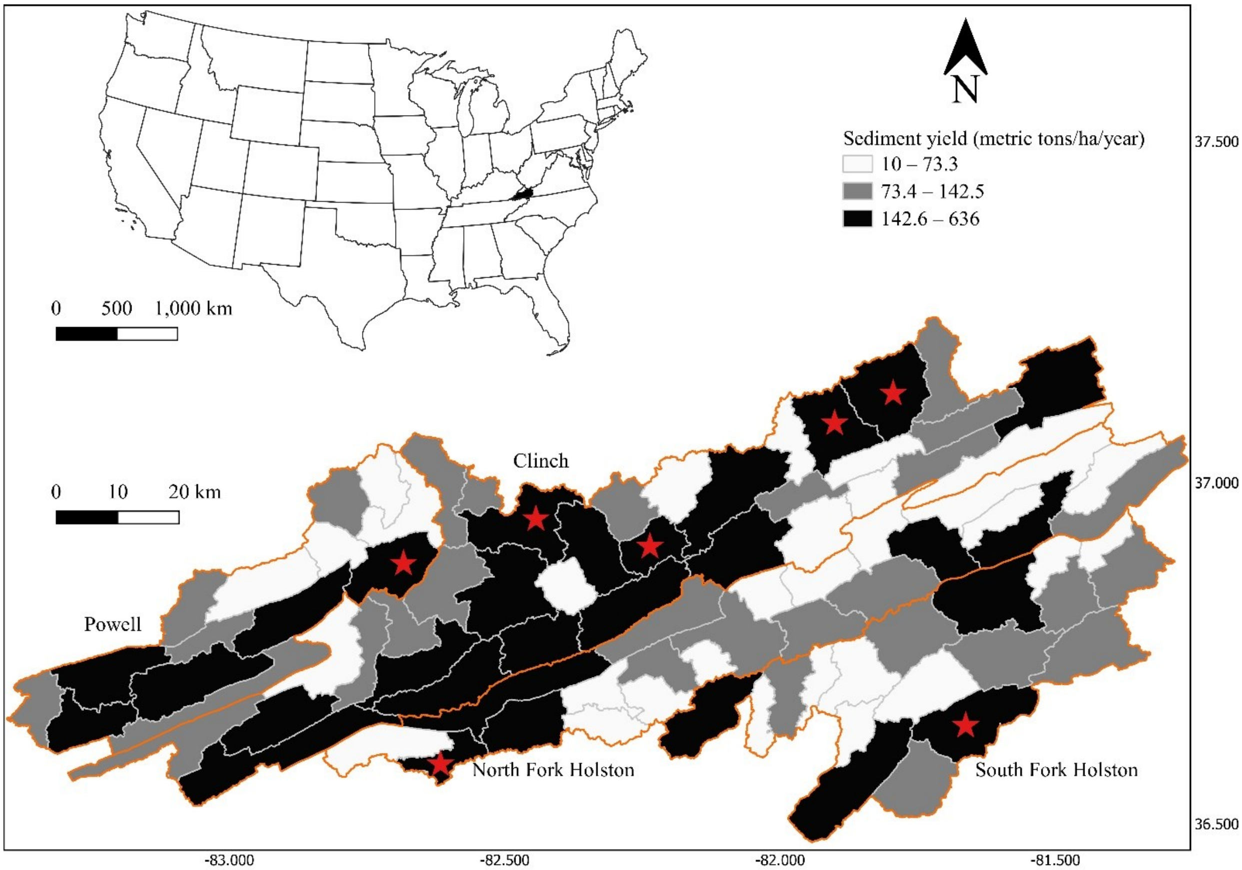

Figure 10. The mean predicted annual sediment yield (metric tons/ha/year) delivered to the streams in each HUC-12 watershed in the Clinch, Powell, North Fork Holston, and South Fork Holston HUC-8 watersheds of Virginia, United States. Stars within a watershed indicate that the watershed has a high sediment yield but few conservation practices installed. Sediment yields were derived from the Soil and Water Assessment Tool+. We categorized HUC-12 watersheds as low, medium, or high sediment yield, with an equal number of watersheds in each bin.

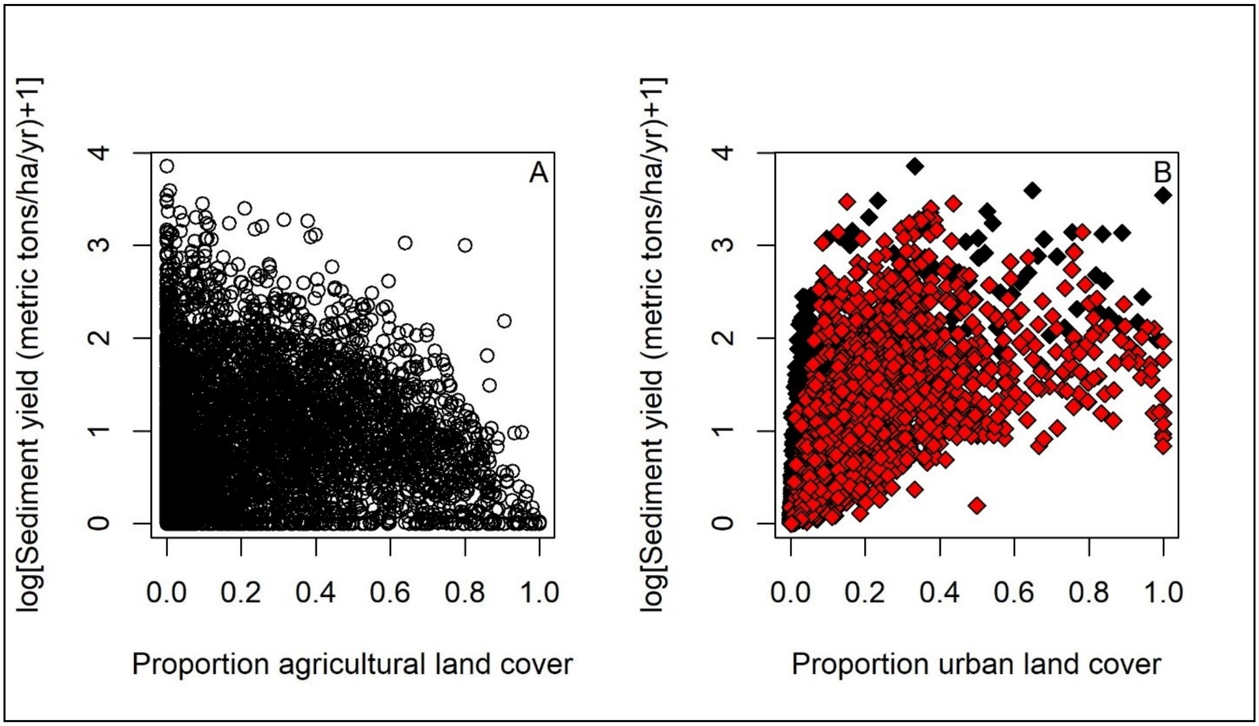

Figure 11. Relationships between agricultural ($p < 0.01$) and urban land cover ($p < 0.01$) and sediment yield (metric tons/ha/year) predicted by the Soil and Water Assessment Tool+. There was a significant interaction between urban land cover and landscape position (upland = black points, floodplain = red points), with higher upland sediment yield for a given level of urban land cover. This figure was derived from a multiple linear regression model that developed a relationship between sediment yield from 4,428 landscape units (LSUs) and the predictor variables soil erodibility, proportion agricultural land cover, proportion urban land cover, hydraulic conductivity, and landscape position (Table 4).

Appendix

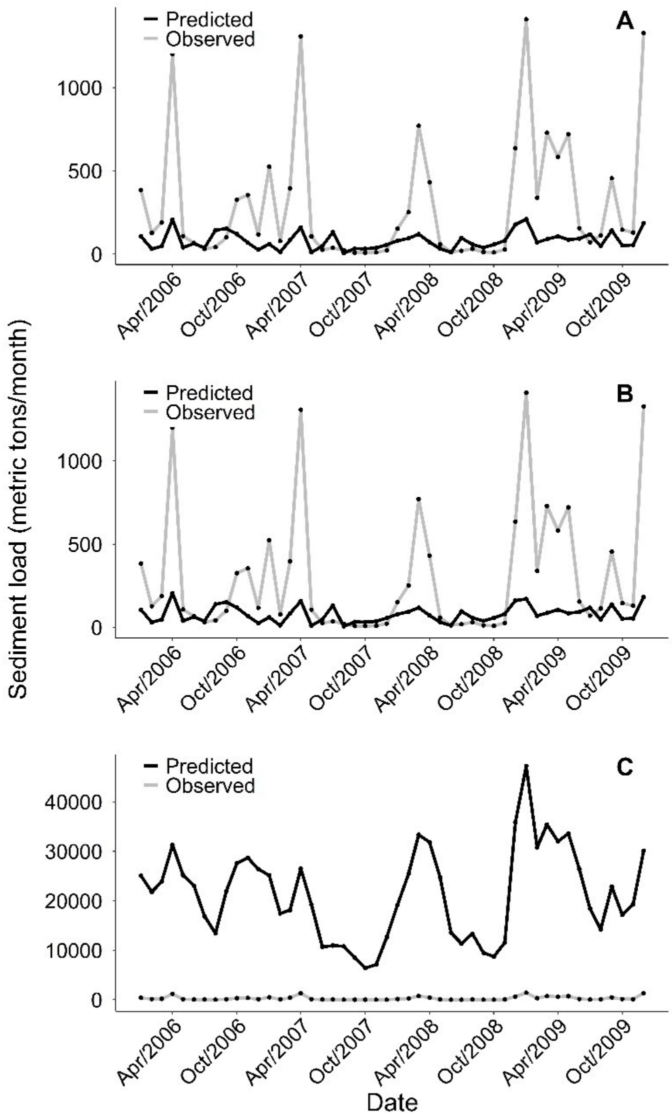

Figure 1. The sediment load (metric tons/month) observed at Virginia Department of Environmental Quality water quality monitoring station 6BPOW138.91 located near U.S. Geological Survey gage 03531500 (Powell River near Jonesville, Virginia, United States) compared to the sediment load predicted by the Soil and Water Assessment Tool+. Panels A and B show the predicted sediment loads before and after adding a cattle grazing operation with instream processes turned off. Panel C shows the predicted sediment loads with instream processes turned on.

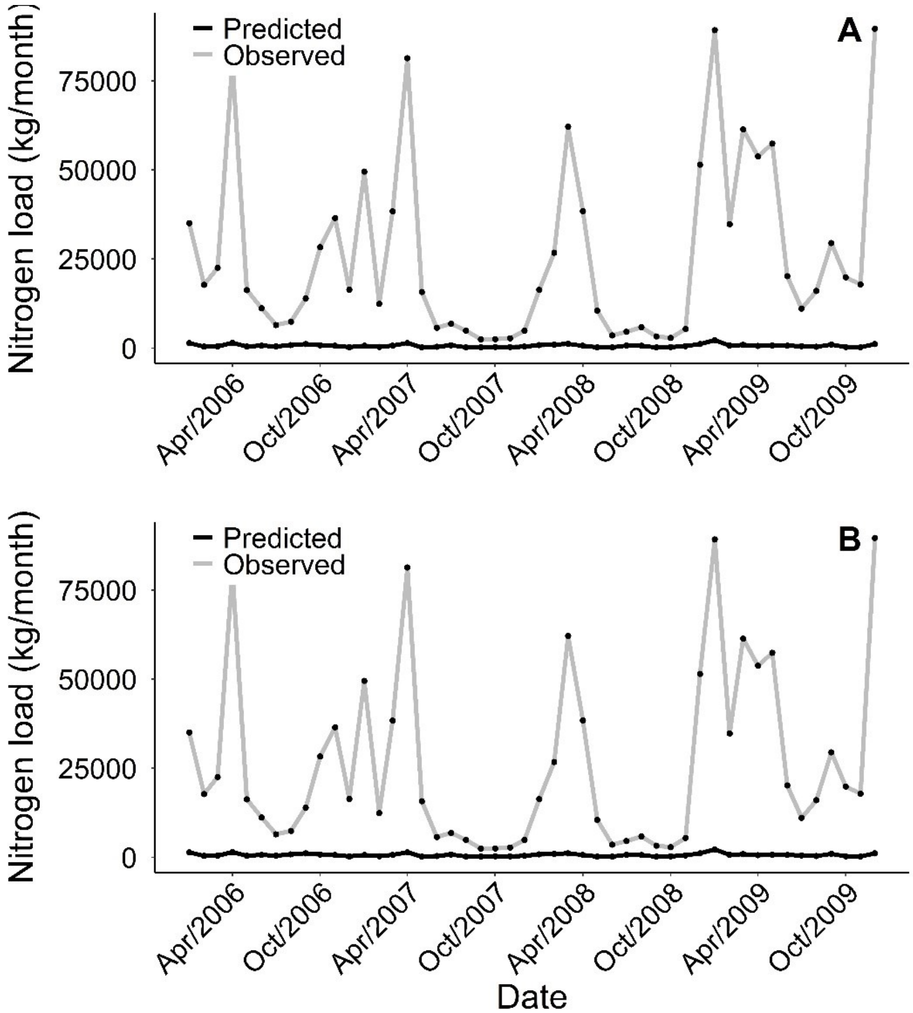

Figure 2. The total nitrogen load (kg/month) observed at Virginia Department of Environmental Quality water quality monitoring station 6BPOW138.91 located near U.S. Geological Survey gage 03531500 (Powell River near Jonesville, Virginia, United States) compared to the nitrogen load predicted by the Soil and Water Assessment Tool+ for the calibration period. Panel A shows the nitrogen load before the initial concentration of nitrate in the aquifer was changed to 1,000 mg/L (an unrealistically high concentration) and panel B shows the nitrogen load after the change. The unrealistic increase of nitrate in the aquifer had little effect on nitrogen estimates. Adding a cattle grazing operation and changing the ratio of nitrate in the surface runoff versus nitrate that percolates into the soil had similar negligible effects on total nitrogen estimates.

CHAPTER 2: STREAM HEALTH SHOWS NONLINEAR, INDIRECT RESPONSES TO INSTALLATION OF AGRICULTURAL CONSERVATION PRACTICES

Abstract

Use of agricultural conservation practices can allow food production to continue while protecting stream health. Biotic assemblages are the most comprehensive indicator of stream health, but biotic responses do not commonly indicate that agricultural conservation practices improve stream health as intended. Our objective was to understand the pathways through which installation of conservation practices influences biotic responses in watersheds where pastureland is a predominant land use. We collected water quality, instream habitat, and macroinvertebrate assemblage data from 31 sites in the upper Tennessee River watershed of southwest Virginia, United States. Several statistical methods were used to examine linear and nonlinear relationships among water quality, instream habitat, macroinvertebrate assemblage composition, land cover, and conservation practice implementation. Our results showed that conservation practices increase bank stability. In contrast, conservation practices do not reduce total nitrogen or substrate embeddedness but do stabilize total nitrogen around 1.4 mg/L. In turn, the macroinvertebrate assemblage displays positive and negative threshold responses to changes in water quality and habitat. Therefore, conservation practices have an indirect effect on biotic assemblages through changes in water quality and habitat. Overall, current implementation of conservation practices in our study area appears unable to improve instream conditions to levels that support healthy biotic assemblages. Improving instream conditions further may require innovative conservation practices, more targeted placement of practices in critical source areas of pollutants, or higher densities of practice implementation.

Introduction

In ecosystems dominated by agricultural land use, food production is often valued more than the services provided by streams draining those farms (e.g., water purification), which can lead to declines in stream health (Baron et al. 2002, Bennett et al. 2021). Intensifying agricultural production can reduce water quality (Carpenter et al. 1998), degrade instream habitat (Newcombe and MacDonald 1991, Trimble and Mendel 1995), and harm biota (Schürings et al. 2022). Collectively, these changes to stream ecosystems have the potential to diminish ecosystem services such as clean drinking water, recreational opportunities, and even food production — resulting in a decline in human wellbeing (Millennium Ecosystem Assessment 2005). Streams that lose capacity to support ecosystem services are often considered unhealthy (Meyer 1997, Karr 1999).

Appropriate management choices on agricultural lands can protect stream health (Power 2010, Kremen and Merelender 2018) but stream health responses to agricultural conservation practice installation vary greatly. Agricultural conservation practices (e.g., prescribed grazing, riparian fencing) are often installed to increase production while protecting other ecosystem services (Natural Resources Conservation Service [NRCS] 2022). Typically, landowners volunteer to install conservation practices and state and federal agencies cover part of the installation cost through incentive programs. Conservation practices often reduce sediment, nitrogen, phosphorus, and bacteria in streams, but efficiencies of practices vary widely due to many factors such as practice type and location of installation (Liu et al. 2017, Grudzinski et al. 2020). Improvements in water quality are important indicators of attaining stream health; however, biotic assemblages provide a more integrated assessment of overall stream health (Karr 1981, Karr 1999, Angermeier and Karr 2019). Biotic metrics sometimes respond positively to conservation practice installation (Wang et al. 2002, Herman et al. 2015, Miltner 2015, Holmes et al. 2016, Sowa et al. 2016), but a lack of biotic response is also common (Sovell et al. 2000, Nerbonne and Vondracek 2001, Yates et al. 2007, Gabel et al. 2012, Holmes et al. 2016).

The complex pathways that influence biotic responses in streams may contribute to variable effects of conservation practice installation on stream health. At the coarsest scale, geology, climate, and land use constrain instream conditions (Poff 1997, Stevenson et al. 1997, Yates and Bailey 2006), with land use having the greatest potential influence within a watershed (Fig. 1). Instream conditions, such as temperature, streamflow, habitat, and water quality interact to directly influence biotic responses (Poff et al. 1997, Stevenson et al. 1997, Maloney and Weller 2011). Ultimately, conservation practice installation is expected to reduce or alter the impacts of agriculture on instream conditions, and as a result, improve biotic conditions (Fig. 1).

Determining the pathways that influence biotic responses is complicated by thresholds that are common in ecological relationships. Thresholds are points at which small changes in one variable are associated with large changes in another variable (Suding and Hobbs 2009). For example, Yates et al. (2007) found a wide range of habitat quality and biotic responses when conservation practice participation was low but a narrow range when participation was high. Nonlinear statistical methods such as logistic regression and boosted regression trees can account for thresholds (Elith et al. 2008, Ficetola and Denoël 2009) but threshold regression models (e.g., piecewise regression; Fong et al. 2017) and threshold indicator analysis (TITAN; Baker and King 2010) can identify specific points along gradients at which thresholds occur.

It is estimated that 49% of the streams in southern Appalachia are in poor condition with agricultural land use as a primary cause (U.S. Environmental Protection Agency [USEPA] 2023). Streams in this region contain a high diversity of aquatic organisms — many of which are of conservation concern (Elkins et al. 2019), which creates a need to understand and improve conservation practice effectiveness for protecting stream health. Therefore, in southern Appalachia, we investigated 1) specific relationships among conservation practices, landscape conditions, water quality, instream habitat, and stream biota and 2) points at which thresholds occur in those relationships to better understand the pathways through which conservation practices influence stream health. Ultimately, understanding these complex pathways will help agencies and producers make decisions (e.g., what conservation practices to use, where, and what density) that will lead to improved efficacy of conservation programs in the region.

Methods

Study area

We focused our research within the Upper Clinch, Powell, North Fork Holston, and South Fork Holston HUC-8 watersheds (U.S. Geological Survey 2024) in southwest Virginia, United States, which are representative of the Southern Appalachian region (Fig. 2). Streams and rivers in these watersheds support several federally listed threatened and endangered freshwater mussels and fishes (Virginia Department of Game and Inland Fisheries 2015). In southwest Virginia specifically, only 16% of the streams are impaired, with unrestricted cattle access being the leading cause of impairment, but many streams have not been assessed (Virginia Department of Environmental Quality 2022). Our study area comprises watersheds that represent strong gradients of agricultural land use (Appendix Fig. 1), sediment yield (Appendix Fig. 2), and conservation practice placement (Appendix Fig. 3) — allowing for a strong statistical design for detecting biophysical responses to conservation practices.

Site selection

We selected subbasins within our study area that represented a range of predicted sediment yields (tons/ha/year), agricultural land use extent, and conservation practice implementation intensity (Fig. 2, Table 1). The Soil and Water Assessment Tool+ (SWAT+) was used to define subbasins (n = 1,736) and estimate sediment yields (Mouser et al. 2020). Each subbasin was ranked as high, medium, or low for conservation practice count (see *Conservation practice data* below), percentage riparian agricultural land use (i.e., within a buffer that extends 15 m on each side of the stream), and estimated sediment yield, with an equal number of observations in each category for land use and estimated sediment yield. For number of conservation practices, all subbasins with no conservation practices were ranked low (n = 719) and remaining subbasins were split between medium (n = 507) and high (n = 510). We removed subbasins with any the following features: a) low riparian agricultural land use, b) > 2% urban land use, c) pour-point segment > 3rd order (Strahler, as defined in SWAT+), d) medium conservation practice count or predicted sediment yield, and e) received drainage from the Appalachian Plateau (coalfield) ecoregion. Removing these subbasins allowed us to focus on subbasins (n = 248) with substantial agricultural land, minimize confounding influences of urban land use, coal mining, and stream size, and have large gradients in estimated sediment yield and conservation practice implementation.

From the remaining subbasins, we sampled 31 (1 site near the pour-point in each) that represented a gradient of agricultural land use and conservation practice density (Table 1). Sites were approximately 100 m in length and representative of the characteristics of the stream (Barbour et al. 1999). We focus on subbasin agricultural land use hereafter because it provided more interpretable categories for the analysis of variance (ANOVA) described below (Table 1).

As part of a pilot study, 15 subbasins within Copper Creek watershed were sampled in autumn 2019 and spring 2020, for a total of 30 sampling events. Sites at all 31 subbasins were sampled in autumn 2020 and 2021 and spring 2021 and 2022, resulting in 124 sampling events at all sites and a total of 154 sampling events.

Conservation practice data

We obtained a conservation practice database for our study area from NRCS. We determined the goal of each practice from the NRCS conservation practice standards (NRCS n.d.) and removed practices from the database that were either not focused on agricultural management (e.g., wildlife habitat development, NRCS practice code 644) or not aimed at sediment or nutrient reduction (e.g., spring development, NRCS practice code 574), and screened the database for our focal subbasins, resulting in a total of 48 unique conservation practices that have been implemented 1,869 times. The 7 most common practices were prescribed grazing (n = 528), brush management (n = 314), fencing (n = 224), watering facilities (n = 185), livestock pipelines (n = 123), access control (n = 122), and nutrient management (n = 121). Finally, we divided the number of conservation practices in each subbasin by the area of the subbasin to create the variable conservation practice density (Table 2).

Landscape variables

We collated landscape variables (i.e., hillslope and agricultural extent) that might influence stream health (Table 2). We extracted the slope of each subbasin (%) from the SWAT+ model. We also calculated the percent agricultural land use within the subbasin containing our site by calculating the number of pixels for each NLCD land use category within the subbasin (U.S. Geological Survey 2019), summing the number of pixels for hay/pasture and row crop land use, dividing this sum by the total number of pixels, and multiplying by 100. We hypothesized that slope and agriculture might account for variation in the aquatic assemblage not explained by our other variables.

Instream data

We collected water quality data from the 31 sites. During each sampling event, we collected 1,000 ml of water for total suspended solid samples (TSS), 250 ml for total nitrogen (TN) and total phosphorus (TP) samples, and 100 ml for *E. coli* bacteria samples. Samples were stored on ice and returned to the Water Quality Laboratory at Virginia Tech within 24 hours for analysis following the laboratory's standard protocols. Water quality sampling was not conducted in spring 2020 because of laboratory closures due to COVID-19. Values below the limit of detection (n = 1 for TSS, n = 2 for TN, n = 25 for TP) were assigned the value for the limit of detection. Missing water quality data (n = 15 for each water quality parameter) were assigned the mean of all the samples collected. Total phosphorus was highly correlated with TSS (r = 0.71); therefore, we focus on TSS hereafter.

We also collected indicators of instream habitat quality from the 31 sites. Starting spring 2020, during each sampling event, we selected 100 substrate particles from a riffle and measured the entire height of the particle perpendicular to the stream bed and the depth of the embedded plane. The depth of the embedded plane was then divided by the entire height to calculate proportion embeddedness of each particle. Then we calculated the mean embeddedness of all 100 particles measured at a site during a collection event to obtain the variable "measured embeddedness". In spring 2022 only, habitat indices were assessed over an entire site, following the U.S. Environmental Protection Agency rapid habitat assessment protocol for high-gradient streams (Appendix A-1 from Barbour et al. 1999). Bank stability was visually estimated by assigning an integer from 0–10 for each bank and then summing the score, where 0 means 100%

of the bank has erosional scars and 10 means 0% of the bank has erosional scars. Similarly, embeddedness was visually estimated by assigning an integer of 0–20, where 0 means gravel, cobble, and boulder particles are 100% surrounded by fine sediment (i.e., silt and sand) and 20 means gravel, cobble, and boulder particles are 0% surrounded by fine sediment. Initial analyses revealed no significant relationships between measured embeddedness and other variables, so we focused our analyses on visual embeddedness because the 2 variables are characterizing similar stream conditions.

Biotic indices

Lastly, we collected benthic macroinvertebrates during each sampling event. We kicked substrate from a total of 3 m^2 of riffle habitat into a D-frame net that were visually selected to represent the best available riffle habitat within our 100-m site (Barbour et al. 1999). Macroinvertebrate samples were preserved and stored in 100% ethanol. Individuals were subsampled to 200 organisms and identified to genus by an independent contractor that maintains Society for Freshwater Science genus-level certification. We summarized macroinvertebrate collections in several ways. First, we derived the Virginia Stream Condition Index (VSCI), which is a multimetric index that includes the total number taxa; the number of Ephemeroptera, Plecoptera, and Trichoptera (EPT) taxa, percent Ephemeroptera individuals, percent Plecoptera plus Trichoptera minus Hydropsychidae individuals, percent Chironomidae individuals, and percent individuals in the 2 most dominant taxa (Burton and Gerritsen 2003). We also calculated the proportion of individuals collected at each site that were classified as EPT taxa, minus the pollution-tolerant family Hydropsychidae (proportion EPT) and we counted the number of EPT taxa (EPT taxa) to avoid the potential influence of abundant taxa. We also assigned each taxon to a functional-feeding group (i.e., collector-filterer, collector-gather, generalist, macrophyte-piercer, predator, scraper, or shredder) and habit group (i.e., burrower, climber, clinger, crawler, diver, generalist, skater, sprawler, or swimmer) based on published literature (e.g., Brigham et al. 1982, Barbour et al. 1999) and the professional judgment of experienced biologists.

Statistical analyses

We used several statistical analyses to understand the effects of conservation practices on stream health. First, a combination of linear and non-linear models was used to explore the indirect effects of conservation practices on stream health while accounting for threshold responses. A path analysis would have been ideal for exploring these relationships (Fan et al. 2016), but we were unable to build informative models — likely due to non-linear relationships among the variables. We further explored the connections between water quality and biota and habitat and biota using TITAN (Baker and King 2010), which can account for assemblage-level threshold responses. Boosted regression trees were used to explore the relative effects of water quality, instream habitat, landscape factors, and conservation practices on aquatic biota while accounting for nonlinear relationships. Boosted regression trees are useful for this type of investigation because they can handle outliers and account for nonlinear effects (Elith et al. 2008). Finally, many of the relationships between conservation practice density and water quality, habitat, and biota depended on agricultural land use; therefore, sites were grouped into agricultural extent and conservation practice density categories and relationships were explored using analysis of variance (ANOVA). All analyses were conducted using the statistical software R (R Core Team 2023) with a significance level of $\alpha = 0.10$, when applicable.

We modeled relationships among water quality, habitat, conservation practice density, landscape variables, and biota using simple linear, exponential decay, and quadratic plateau models. We used the latter 2 models to assess potential threshold responses. Because sampling multiple times at the same site resulted in non-independence and a random effect could not be added to these types of models, we calculated the mean of each variable for each site across sampling events (i.e., reducing the data matrix to 31 rows). We calculated the arithmetic mean for all variables except *E. coli* and instead calculated the geometric mean, which is more appropriate for left-skewed data due to many values that were at the maximum limit of detection. Most variables were either square-root or log10 transformed to approximate a normal distribution (Table 2). We visually assessed for outliers using boxplots and by plotting Cook's distance values. The plots revealed potential outliers for TN, TSS and *E. coli* bacteria but we chose not to remove the outliers for TN and TSS because they followed the general pattern and removal did not significantly change the model outputs described below. However, the outlier for *E. coli* bacteria did not follow the general pattern and occurred at a site that had consistently higher values than other sites (presumably because of constant cattle access), so it was removed. Simple linear regression models were built using the *lm* function from the stats package in R (R Core Team 2023). We used the functions *asymptotic_ineg* and *linear.plateau* from the AgroReg package (Shimizu and Goncalves 2024) to build the exponential decay and quadratic plateau models. We used visual inspections of relationships, model coefficient *p*-values, and indices of the proportion variation explained (i.e., R^2 and pseudo R^2) to determine which model best explained the influence of conservation practice density on each variable. None of those models adequately explained the relationship between conservation practice density and both embeddedness and bank stability, so we used the function *chgptm* from the package chngpt to model a breakpoint regression with two disjunct flat lines to further assess those two relationships (Fong et al. 2017).

We continued to explore nonlinear relationships between macroinvertebrate assemblage composition and each water quality and habitat variable using TITAN (Baker and King 2010). We first removed taxa that occurred at < 6 sites. Then we ran TITAN using 500 bootstrapped runs. We used TITAN to determine 2 macroinvertebrate assemblage thresholds: a) where individual taxa have the largest cumulative negative response to environmental gradients and b) where individual taxa have the largest cumulative positive response. The assemblage thresholds were based only on "high purity" taxa (i.e., taxa that are consistently assigned the same response direction) and "high reliability" taxa (i.e., taxa that are consistently assigned the same threshold value).

We developed boosted regression trees to understand the relative influence of several variables on stream health. Our response variables for the models were VSCI, proportion EPT, and EPT taxa. Our predictor variables included conservation practice density, the 2 landscape variables, the 2 habitat variables, and the 3 water quality variables (Table 2). We checked for correlations between pairs of variables, and most were < 0.39. Agriculture was highly correlated with TN (r = 0.71) and slope (r = -0.75), so we dropped slope from the models but retained agriculture because of its known effect on stream health. The models were being used to explore relationships among the variables and not make predictions, so we were not concerned about high correlations among variables in the model. We included watershed and season as additional predictor variables in the boosted regression trees to account for spatial and temporal non-independence among sampling events. We set the tree complexity to 2 because we thought that 2-way interactions would be sufficient to explain our response variables (Elith et al. 2008). We also set learning rate to 0.05 and bag fraction to 0.5 because these settings achieved the minimum number of 1,000 trees (Elith et al. 2008).

Because many of the relationships between conservation practice density and water quality, habitat, and biota were not significant and depended on agricultural land use, we further explored these relationships using ANOVA. First, we assigned each site to 1 of 5 bins (Table 1): high subbasin agricultural land use, low conservation practice density ($n = 4$); high agriculture, high conservation ($n = 9$); medium agriculture, high conservation ($n = 9$); medium agriculture, low conservation ($n = 3$); or low agriculture, low conservation ($n = 6$). We then built ANOVA models with the response variables TN, TSS, *E. coli*, bank stability, embeddedness, VSCI, proportion EPT, and EPT taxa and site classification as the treatment. Finally, we tested for differences between categories using Tukey's test.

Results

Conservation practice data and landscape variables

Conservation practice density and landscape conditions were quite variable across sites (Table 2). Subbasins within Copper Creek and Laurel Creek tended to have high density of conservation practices, whereas subbasins within Tumbling Creek, Big Moccasin, and Cedar Creek tended to have low conservation practice density. Six sites were categorized as low agriculture within the subbasin (all in Tumbling Creek), 12 sites as medium, and 13 as high. Most sites were within subbasins with an average slope < 25% ($n = 16$) and 1 site was within a subbasin with an average slope > 40%.

Instream data

Water quality for collection events often exceeded thresholds for biotic impairment. Measurements for TN were typically above the USEPA (2000) ambient water quality criteria recommendations to protect aquatic life in the Ridge and Valley Ecoregion (0.30 mg/L; $n = 123$). Although standards for *E. coli* are typically based on a geometric mean for several collections in a 30-day period, 93 single-day collections for *E. coli* were greater than the USEPA (2021) recommended value of 126 colony forming units/100mL (note that the units are slightly different). There are not federal recommendations for TSS, but collections were typically < 5 mg/L (*n* = 107); 12 collections were > 10 mg/L. Visual estimates of embeddedness indicated that most sites (*n* = 17) were slightly embedded (i.e., score between 11 and 15), but some sites had very little (*n* = 7) or moderate (*n* = 7) embeddedness (Barbour et al. 1999). We observed stable banks at most sites (*n* = 20), 7 sites with unstable banks, and 4 sites with stable banks (Barbour et al. 1999).

Biotic indices

Benthic macroinvertebrate diversity and calculated biotic indices generally indicated healthy streams (Table 2). We removed 102 taxa from the TITAN analysis because they occurred at < 6 sites — resulting in 31,790 individuals from 102 taxa in the final database. The most common taxa were *Optioservus* (*n* = 5,698), Chironomidae (*n* = 3,543), and Baetidae (*n* = 2,049). Clingers (*n* = 72) were the most common habit group followed by crawlers (*n* = 71) and burrowers (*n* = 8), whereas the most common functional-feeding groups were collector-gatherers (*n* = 31), predators (*n* =24), and scrapers (*n* = 23). The Virginia Stream Condition Index indicated that for most sampling events (*n* = 112) sites were not impaired (i.e., VSCI > 61), but when sampling events were averaged, sites in Big Cedar Creek and Tumbling Creek watersheds were impaired (Burton and Gerritsen 2003). At sites identified as impaired, VSCI scores were driven by slightly lower than average taxa counts, slightly greater than average percentage of Chironomidae and the top 2 dominant taxa, and much lower than average percentages of pollutant-tolerant taxa (i.e., those classified as EPT). The variables proportion EPT and EPT taxa followed patterns similar to VSCI and were lower on average in Big Cedar Creek and Tumbling Creek watersheds.

Statistical analyses

Agricultural land use negatively affected water quality, habitat, and the macroinvertebrate assemblage. The simple linear regression models indicated that agricultural land use was positively related to TN ($p < 0.01$, Fig. 3a) and *E. coli* ($p < 0.01$) but not TSS ($p = 0.41$), embeddedness ($p = 0.74$), or bank stability ($p = 0.38$). Slope was negatively related to agriculture ($p < 0.01$), and conservation practice density was positively related with agriculture ($p = 0.08$). Finally, agriculture was negatively related to proportion EPT ($p < 0.01$, Fig. 3b), VSCI ($p = 0.09$), and number of EPT taxa ($p < 0.01$).

Conservation practice density appeared to improve or stabilize several measures of water quality and physical habitat above certain density thresholds (Fig. 3). The linear plateau model explained the greatest amount of variation (pseudo-$R^2 = 0.25$) in the response of TN to conservation practice density, where TN increased until a density of 0.30 conservation practices/ha was reached, after which TN was stable around 1.4 mg/L ($p = 0.03$; Fig. 3c). Exponential decay models explained more variation in the relationships between conservation practice density and TSS (pseudo-$R^2 = 0.02$; Fig. 3d) and *E. coli* (pseudo-$R^2 = 0.07$; Fig. 3e) than other models, but coefficients for the exponents were not statistically significant ($p > 0.10$). Although we could not calculate R^2 for a breakpoint regression, it best explained the relationship between conservation practices and bank stability (Fig. 3f). When conservation practice density was greater than 0.41 conservation practices/ha, bank stability received an average score of 16.4, while lower conservation practice densities were associated with average bank stability scores of

12.4 ($p < 0.01$). None of the models explained the relationship between conservation practices and embeddedness.

The macroinvertebrate assemblage exhibited strong negative and positive threshold responses along gradients in water quality and habitat. Importantly, thresholds where the most taxa begin to decline or increase (as indicated by TITAN) were typically lower than the thresholds at which conservation practices stabilized water quality (Table 3; Figs. 3 and 4–8). For example, our regression models indicated that TN was stabilized by conservation practice installation at 1.4 mg/L, but TITAN indicated the majority of negative indicator taxa began to decline at 0.65 mg/L, whereas the majority of positive indicator taxa increased at 1.07 mg/L. Similarly, *E. coli* and TSS were stabilized around 625 most probable number (MPN)/100ml and 5 mg/L, respectively, but taxa began to decline at 246 MPN/100ml and 1.07 mg/L, respectively, and increase at 245.57 MPN/100ml and 4.72 mg/L, respectively. Because less embeddedness and more bank stability are preferred, biotic responses should be interpreted inversely to those presented for water quality. Our analysis indicated that conservation practices would stabilize banks around a score of 16, but taxa did not begin to increase until bank stability reached 17.5. We did not find a threshold for how embeddedness would respond to conservation practice installation, but negative indicator taxa began to decline at 13, whereas positive indicator taxa began to increase at 12.50. Positive responses to *E. coli* and embeddedness and negative responses to bank stability are difficult to interpret because there were several distinct thresholds where multiple taxa displayed the same response, resulting in wide confidence intervals.

The suite of taxa exhibiting threshold responses varied widely among gradients. More taxa exhibited threshold responses to TN and *E. coli* than to other environmental variables (Table 3). Even though TSS, embeddedness, and bank stability are all closely linked to fine sediment dynamics, only 2 (*Stenelmis*, Pleuroceridae) of the 14 taxa negatively affected by fine sediment (as represented by these measures) exhibited threshold responses in the same direction to more than 1 measure of fine sediment (Figures 5, 7–8). In fact, *Seratella* and Asellidae showed opposite response to bank stability and embeddedness. There were no obvious patterns in assemblage response by taxa, functional feeding group, or habit group (Figures 4–8). For example, similar numbers of taxa classified as EPT (indicated by E, P, and T, respectively, after taxon names in Figures 4–8) responded positively and negatively along water quality gradients. It is interesting that genera within the family Elmidae (*Microcylloepus*, *Optioservus*, *Oulimnius, Promoresia*, *Stenelmis*) often showed opposite responses to the same water quality variable despite being assigned to the same feeding and habit groups.

Boosted regression trees revealed that agricultural land use, season, and watershed had the greatest influence on the macroinvertebrate assemblage, but conservation practices and TN also had strong effects on the macroinvertebrate assemblage (Fig. 9). All three response variables (i.e., proportion EPT, EPT taxa, and VSCI) responded similarly to the predictor variables, but proportion EPT had stronger relationships, so we only discuss the proportion EPT results. The regression tree explained 44.7% of the variation in proportion EPT. The boosted regression trees found that agriculture explained the greatest variation in proportion EPT (18.9%) followed by season (17.6%), watershed (16.7%), conservation practice density (12.1%), TN (9.0%), *E. coli* (7.9%), TSS (7.6%), bank stability (5.3%), and embeddedness (4.9%). Interestingly, conservation practice density had a quadratic relationship with proportion EPT, wherein conservation practice density was positively correlated with biotic condition at very low levels of conservation practice implementation but negatively correlated at higher levels of implementation (Fig. 9).

Comparing categories of conservation practice density and agricultural land use confirmed that increased conservation practice density improves some metrics of water quality and habitat, but those improvements did not translate into changes in the macroinvertebrate assemblage (Table 4, Fig. 10). There were significant differences between sites with low agriculture and low conservation practice density and sites with high agriculture and low conservation practice density for TN (p = 0.02), bank stability (p = 0.08), proportion EPT (p = 0.01), and EPT taxa (p = 0.02), confirming that agriculture can adversely affect water quality and habitat. In many cases, conservation practices seemed to improve instream conditions but often not by statistically significant amounts. For example, bank stability was significantly (p = 0.05) better at sites with high agriculture and high conservation practice density than at sites with high agriculture and no practices. Further, *E. coli* and TSS tended to be lower at high agriculture sites with conservation practices compared to those without, but those relationships were not significant. Interestingly, proportion EPT appeared to improve in sites with medium agriculture and high conservation practice density compared to those with medium agriculture and low conservation practice density (p = 0.03).

Discussion

Overall, our results suggest that conservation practice installation has the potential to protect some aspects of stream health. The direct relationship between conservation practice density and macroinvertebrate assemblage response suggested that higher densities of conservation practices were not beneficial for biota (Figs. 9b and 10). However, higher conservation practice densities improved, or at least stabilized, some metrics of water quality and habitat (Figs. 3 and 10), but not to levels that were below thresholds that caused abrupt shifts in the macroinvertebrate assemblage (Figs. 4–8). These results demonstrate the importance of accounting for the complex pathways (including indirect and nonlinear effects) through which conservation practices influence stream health to understand and improve conservation practice efficacy.

Pathways through which conservation practices influence stream health

It is encouraging that conservation practices were associated with greater bank stability, as we would expect stable banks to reduce fine sediment loads and substrate embeddedness, which would benefit the aquatic assemblage (Newcombe and MacDonald 1991, Kemp et al. 2011, Hirschler et al. 2024). In fact, we observed that increased numbers of conservation practices appeared to reduce variability in TSS; however, TSS stabilized around 5 mg/L (Fig. 3d), which exceeds the threshold of 1 mg/L where the macroinvertebrate assemblage begins to shift in response to increasing TSS (Fig. 5). We also did not observe any relationships between conservation practices and embeddedness — increased embeddedness can reduce habitat and oxygen, leading to decline in biota (Kemp et al. 2011). Sediment stored in the floodplain or stream channel from past streambank degradation that is remobilized during storms (Hamilton 2012) or sediment loads from upstream land uses may be contributing to TSS levels that limit the macroinvertebrate assemblage.

We also observed that current implementation of conservation practices has not improved TN, which may be altering aquatic communities. Our results demonstrate that macroinvertebrates begin to respond negatively to TN at 0.65 mg/L (Fig. 4), but all sites (except 1) with medium or high agricultural land use exceeded that value on average. Further, current conservation practice density stabilizes TN around 1.4 mg/L (Fig. 3c). These levels exceed regulatory recommendations to protect aquatic life in the Ridge and Valley Ecoregion (0.30 mg/L; USEPA 2000), values recommended for preventing eutrophication (0.90 mg/L; Dodds and

Welch 2000), and the ability of biota to remove nitrate (0.15 mg/L; Mulholland et al. 2008). Avoiding eutrophication is especially important because it can impact human health, harm biota, reduce recreation opportunities, and ultimately impact downstream water sources (Dodds and Welch 2000). It is crucial that conservation practices are effective at reducing TN to avoid adverse effects on human and stream health.

Thresholds

Our results reveal that stream health often shows a nonlinear response to conservation practices — indicating potential statistical considerations and opportunities for future research. We observed nonlinear responses for almost all the relationships (Figs. 3–9), which is typical for studies evaluating stream health responses to water quality (Kaller and Hartman 2004, Yates et al. 2007, Keitzer et al. 2016, Sowa et al. 2016). Therefore, future research would benefit from analytical designs and statistical models that account for these nonlinear effects. We were able to account for nonlinear effects using boosted regression trees, exponential decay, quadratic plateau, breakpoint, and TITAN models, so these are options for future studies. One major shortfall of these models was our inability to include random effects, which could account for spatial and temporal autocorrelation of sampling locations. Additionally, our research questions fit the framework of a path analysis (Fan et al. 2016), but we were unable to build an informative model, which may have been due to nonlinear effects. Lastly, controlled field and laboratory studies can aid in determining exact thresholds at which biota decline.

Conservation implications

We may not have observed a response of TN to conservation practice implementation because the response can display a long lag time. The primary component of TN in our study area is nitrate, which primarily moves dissolved in water and can remain in the groundwater for centuries (Hamilton 2012). Therefore, we may not have observed a response of TN to conservation practice adoption because it may take more time for TN levels in the stream to respond and for that response to translate to aquatic biota (Meals et al. 2010). Groundwater tracing studies could determine if elevated TN is due to current or past land use (e.g., Moore et al. 2006, Clune and Denver 2012). Knowing the source of elevated TN could help agencies weigh options for future conservation practices. For example, if elevated TN is from past land use, managers may simply need more time to observe effects of conservation practices.

If elevated TN is from current land use, then innovative conservation practices or greater densities of current practices may be required to reduce TN to levels that no longer limit biota. Conservation practices that stop pollutants at their source are typically most effective for reducing nitrate concentrations (Rittenburg et al. 2015; Capel et al. 2018). One such option could be removing agricultural land from production via programs to aid in land retirement (e.g., Conservation Reserve Program, Farm Service Agency 2024). Nutrient management plans are an alternative option for reducing pollutants at their source locations, but these plans are already quite common in southwest Virginia. Although riparian buffers do not capture nitrate in deep groundwater, buffers are useful for reducing nitrogen in shallow groundwater (Sweeney and Newbold 2014; Rosa et al. 2017). Riparian buffers are used in southwest Virginia but are less common than other practices and many landowners have difficulty maintaining buffers (see Chapter 3), so there is capacity to increase use of buffers, especially if greater attention is paid to designing and maintaining them.

Conservation social science studies may be useful for encouraging adoption and continued use of conservation practices, especially in critical source areas (CSAs) of pollutants. Targeting conservation practice placement in CSAs can improve efficacy of conservation practices for reducing pollutant loads (Heathwaite 2005, Nowak et al. 2006). Adoption of conservation practices is voluntary; therefore, in situations where CSAs overlap with landowners that are resistant to adoption, conservation social science studies can be used to understand how adoption might be encouraged (Prokopy et al. 2019). Similarly, continued use of conservation practices after cost-share contracts end (i.e., persistence) can be encouraged so that conservation practices are in place long enough to achieve biotic responses (Dayer et al. 2018). Encouraging persistence can be especially important for practices such as riparian buffers that are often destroyed by wildlife and floods (see Chapter 3) and to reduce pollutants such as nitrate that may have long lag times in the groundwater.

Our results also indicate that current metrics for assessing stream health might not be sufficient to understand the impact of agriculture in headwater streams. In Virginia, VSCI scores are used to indicate stream health and identify impaired locations that may require restoration efforts (Burton and Gerritsen 2003). Even though our results showed that water quality was at levels that could harm the macroinvertebrate assemblage, VSCI indicated that many streams were healthy (i.e., scores > 61). These multimetric indices of stream health that are used by many states can be biased towards larger streams and aim to identify many different stressors (e.g., Burton and Gerritsen 2003). Therefore, to evaluate the efficacy of conservation practice programs, it could be beneficial to develop indices that are sensitive to changes in land use. Although our methods were not designed to help create indices, our results do indicate some potential avenues that can be explored. We did not observe clear responses based on taxonomic, functional feeding, or habit groups across varying water quality and habitat metrics (Figs. 4–8), so metrics might need to be specific to water quality parameters of interest. Interestingly, our study and others found that beetles in the family Elmidae often respond to changes in water quality due to agriculture (Braccia and Voshell 2006, 2007); therefore, incorporating taxa such as elmids could aid in identifying sites that are impaired by agricultural land use.

Conclusion

Our study reveals some of the pathways through which conservation practices influence stream health, which can provide insight for conservation programs. For example, future research could develop innovative conservation practices so that conservation programs improve instream conditions for biota. These studies should carefully choose response metrics that are sensitive to changes in land use and incorporate nonlinear effects into their design. Further, social science should be incorporated into practice design and implementation to ensure that practices are socially acceptable and equitable (Bennett et al. 2017, Bennett et al. 2022). Therefore, interdisciplinary collaborations involving social scientists, ecologists, and engineers will be crucial for improving efficacy of conservation programs for protecting stream health.

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Literature cited

Angermeier, P. L., and J. R. Karr. 2019. Ecological health indicators. Pages 391–401 *in* B. Fath (editor). Encyclopedia of ecology. 2nd Edition. Elsevier, Amsterdam, Netherlands.

Baker, M. E., and R. S. King. 2010. A new method for detecting and interpreting biodiversity and ecological community thresholds. Methods in Ecology and Evolution 1:25–37.

Barbour, M. T., J. Gerritsen, B. D. Snyder, and J. B. Stribling. 1999. Rapid bioassessment protocols for use in streams and wadeable rivers: Periphyton, benthic macroinvertebrates, and fish. U.S. Environmental Protection Agency, Washingtion, DC.

Baron, J. S., N. L. Poff, P. L. Angermeier, C. N. Dahm, P. H. Gleick, N. G. Hairston, R. B. Jackson, C. A. Johnston, B. D. Richter, and A. D. Steinman. 2002. Meeting ecological and societal needs for freshwater. Ecological Applications 12:1247–1260.

Bennett, E. M., J. Baird, H. Baulch, R. Chaplin-Kramer, E. Fraser, P. Loring, P. Morrison, L. Parrott, K. Sherren, K. J. Winkler, J. Cimon-Morin, M. Fortin, B. L. Kurylyk, J. Lundholm, M. Poulin, J. T. Rieb, A. Gonzalez, G. M. Hickey, M. Humphries, K. Bahadur KC, and D. Lapen. 2021. Ecosystem services and the resilience of agricultural landscapes. Pages 1–43 *in* D. A. Bohan, and A. J. Vanbergen (editors). Advances in Ecological Research. Academic Press, London, United Kingdom.

Bennett, N. J., M. Dodge, T. S. Akre, S. W. J. Canty, R. Chiaravalloti, A. A. Dayer, J. L. Deichmann, D. Gill, M. McField, J. McNamara, S. E. Murphy, A. J. Nowakowski, and M. Songer. 2022. Social science for conservation in working landscapes and seascapes. Frontiers in Conservation Science 3:954930.

Bennett, N. J., R. Roth, S. C. Klain, K. Chan, P. Christie, D. A. Clark, G. Cullman, D. Curran, T. J. Durbin, G. Epstein, A. Greenberg, M. P. Nelson, J. Sandlos, R. Stedman, T. L. Teel, R. Thomas, D. Veríssimo, and C. Wyborn. 2017. Conservation social science: Understanding and integrating human dimensions to improve conservation. Biological Conservation 205:93–108.

Braccia, A., and J. R. Voshell. 2006. Environmental factors accounting for benthic macroinvertebrate assemblage structure at the sample scale in streams subjected to a gradient of cattle grazing. Hydrobiologia 573:55–73.

Braccia, A., and J. R. Voshell. 2007. Benthic macroinvertebrate responses to increasing levels of cattle grazing in blue ridge mountain streams, Virginia, USA. Environmental Monitoring and Assessment 131:185–200.

Brigham, A. R., W. U. Brigham, and A. Gnilka. 1982. Aquatic insects and Oligochaetes of North and South Carolina. Midwest Aquatic Enterprises, Mahomet, Illinois.

Burton, J., and J. Gerritsen. 2003. A stream condition index for Virginia non-coastal streams. U.S. Environmental Protection Agency, Washington, DC.

Capel, P. D., D. M. Wolock, R. H. Coupe, and J. L. Roth. 2018. A conceptual framework for effectively anticipating water-quality changes resulting from changes in agricultural activities. U.S. Geological Survey, Reston, Virginia.

Carpenter, S. R., N. F. Caraco, D. L. Correll, R. W. Howarth, A. N. Sharpley, and V. H. Smith. 1998. Nonpoint pollution of surface waters with phosphorus and nitrogen. Ecological Applications 8:559–568.

Clune, J. W., and J. M. Denver. 2012. Residence time, chemical and isotopic analysis of nitrate in the groundwater and surface water of a small agricultural watershed in the Coastal Plain, Bucks Branch, Sussex County, Delaware. U.S. Geological Survey, Reston, Virginia.

Dayer, A. A., S. H. Lutter, K. A. Sesser, C. M. Hickey, and T. Gardali. 2018. Private landowner conservation behavior following participation in voluntary incentive programs: Recommendations to facilitate behavioral persistence. Conservation Letters 11:1–11.

Dodds, W. K., and E. B. Welch. 2000. Establishing nutrient criteria in streams. Journal of the North American Benthological Society 19:186–196.

Einheuser, M. D., A. P. Nejadhashemi, S. P. Sowa, L. Wang, Y. A. Hamaamin, and S. A. Woznicki. 2012. Modeling the effects of conservation practices on stream health. Science of the Total Environment 435–436:380–391.

Elith, J., J. R. Leathwick, and T. Hastie. 2008. A working guide to boosted regression trees. Journal of Animal Ecology 77:802–813.

Elkins, D., S. C. Sweat, B. R. Kuhajda, A. L. George, K. S. Hill, and S. J. Wenger. 2019. Illuminating hotspots of imperiled aquatic biodiversity in the southeastern US. Global Ecology and Conservation 19:e00654.

Fan, Y., J. Chen, G. Shirkey, R. John, S. R. Wu, H. Park, and C. Shao. 2016. Applications of structural equation modeling (SEM) in ecological studies: An updated review. Ecological Processes: 5:19.

Ficetola, G. F., and M. Denoël. 2009. Ecological thresholds: An assessment of methods to identify abrupt changes in species-habitat relationships. Ecography 32:1075–1084.

Fong, Y., Y. Huang, P. B. Gilbert, and S. R. Permar. 2017. chngpt: Threshold regression model estimation and inference. BMC Bioinformatics 18:454.

Farm Service Agency. 2024. Conservation Reserve Program (CRP). Farm Service Agency, Washington, DC.

Gabel, K. W., J. D. Wehr, and K. M. Truhn. 2012. Assessment of the effectiveness of best management practices for streams draining agricultural landscapes using diatoms and macroinvertebrates. Hydrobiologia 680:247–264.

Grudzinski, B., K. Fritz, and W. Dodds. 2020. Does riparian fencing protect stream water quality in cattle-grazed lands? Environmental Management 66:121–135.

Hamilton, S. K. 2012. Biogeochemical time lags may delay responses of streams to ecological restoration. Freshwater Biology 57:43–57.

Heathwaite, A. L., P. F. Quinn, and C. J. M. Hewett. 2005. Modelling and managing critical source areas of diffuse pollution from agricultural land using flow connectivity simulation. Journal of Hydrology 304:446–461.

Herman, M. R., A. P. Nejadhashemi, F. Daneshvar, D. M. Ross, S. A. Woznicki, Z. Zhang, and A. H. Esfahanian. 2015. Optimization of conservation practice implementation strategies in the context of stream health. Ecological Engineering 84:1–12.

Hirschler, M., A. Villamagna, P. L. Angermeier, and E. Laflamme. 2024. Deposited sediment influences occurrence of functional traits of stream fishes. Ecology of Freshwater Fish 33:e12768.

Holmes, R., D. G. Armanini, and A. G. Yates. 2016. Effects of best management practice on ecological condition: Does location matter? Environmental Management 57:1062–1076.

Kaller, M. D., and K. J. Hartman. 2004. Evidence of a threshold level of fine sediment accumulation for altering benthic macroinvertebrate communities. Hydrobiologia 518: 95–104.

Karr, J. R. 1981. Assessment of biotic integrity using fish communities. Fisheries 6:21–27.

Karr, J. R. 1999. Defining and measuring river health. Freshwater Biology 41:221–234.

Keitzer, S. C., S. A. Ludsin, S. P. Sowa, G. M. Annis, J. G. Arnold, P. Daggupati, A. M. Froelich, M. E. Herbert, M. V. Johnson, A. M. Sasson, Anthony, H. Yen, M. J. White, and C. A. Rewa. 2016. Thinking outside of the lake: Can controls on nutrient inputs into Lake Erie benefit stream conservation in its watershed? Journal of Great Lakes Research 42:1322–1331.

Kemp, P., D. Sear, A. Collins, P. Naden, and I. Jones. 2011. The impacts of fine sediment on riverine fish. Hydrological Processes 25:1800–1821.

Kremen, C., and A. M. Merenlender. 2018. Landscapes that work for biodiversity and people. Science. 362:eaau6020.

Liu, Y., B. A. Engel, D. C. Flanagan, M. W. Gitau, S. K. McMillan, and I. Chaubey. 2017. A review on effectiveness of best management practices in improving hydrology and water quality: Needs and opportunities. Science of the Total Environment 601–602:580–593.

Maloney, K. O., and D. E. Weller. 2011. Anthropogenic disturbance and streams: Land use and land-use change affect stream ecosystems via multiple pathways. Freshwater Biology 56:611–626.

Meals, D. W., S. A. Dressing, and T. E. Davenport. 2010. Lag time in water quality response to best management practices: A review. Journal of Environmental Quality 39:85–96.

Meyer, J. L. 1997. Stream health: Incorporating the human dimension to advance stream ecology. Journal of the North American Benthological Society 16:439–447.

Millennium Ecosystem Assessment. 2005. Ecosystems and human well-being: Synthesis. Island Press, Washington, D.C.

Miltner, R. J. 2015. Measuring the contribution of agricultural conservation practices to observed trends and recent condition in water quality indicators in Ohio, USA. Journal of Environment Quality 44:1821–1831.

Moore, K. B., B. Ekwurzel, B. K. Esser, G. B. Hudson, and J. E. Moran. 2006. Sources of groundwater nitrate revealed using residence time and isotope methods. Applied Geochemistry 21:1016–1029.

Mouser, J., P. Angermeier, and S. Ciparis. 2020. Evaluating efficacy of agricultural BMPs. Natural Resources Conservation Service, Washington, D.C.

Mulholland, P. J., A. M. Helton, G. C. Poole, R. O. Hall, S. K. Hamilton, B. J. Peterson, J. L. Tank, L. R. Ashkenas, L. W. Cooper, C. N. Dahm, W. K. Dodds, S. E. G. Findlay, S. V. Gregory, N. B. Grimm, S. L. Johnson, W. H. McDowell, J. L. Meyer, H. M. Valett, J. R. Webster, C. P. Arango, J. J. Beaulieu, M. J. Bernot, A. J. Burgin, C. L. Crenshaw, L. T. Johnson, B. R. Niederlehner, J. M. O'Brien, J. D. Potter, R. W. Sheibley, D. J. Sobota, and S. M. Thomas. 2008. Stream denitrification across biomes and its response to anthropogenic nitrate loading. Nature 452:202–205.

Natural Resources Conservation Service. (n.d.). Conservation practice standards. (Available from: https://www.nrcs.usda.gov/resources/guides-and-instructions/conservation-practice-standards)

Natural Resources Conservation Service. 2022. Supporting America's working lands. Natural Resources Conservation Service, Washington, DC. (Available from: https://www.nrcs.usda.gov/sites/default/files/2022-09/Supporting%20Americas%20Working%20Lands.pdf

Nerbonne, B. A., and B. Vondracek. 2001. Effects of local land use on physical habitat, benthic macroinvertebrates, and fish in the Whitewater River, Minnesota, USA. Environmental Management 28:87–99.

Newcombe, C. P., and D. D. MacDonald. 1991. Effects of suspended sediments on aquatic ecosystems. North American Journal of Fisheries Management 11:72–82.

Nowak, P., S. Bowen, and P. E. Cabot. 2006. Disproportionality as a framework for linking social and biophysical systems. Society and Natural Resources 19:153–173.

Poff, N. L. 1997. Landscape filters and species traits: Towards mechanistic understanding and prediction in stream ecology. Journal of the North American Benthological Society 16:391–409.

Poff, N. L., J. D. Allan, M. B. Bain, J. R. Karr, K. L. Prestegaard, B. D. Richter, R. E. Sparks, and J. C. Stromberg. 1997. The natural flow regime: A paradigm for river conservation and restoration. BioScience 47:769–784.

Power, A. G. 2010. Ecosystem services and agriculture: Tradeoffs and synergies. Philosophical Transactions of the Royal Society B: Biological Sciences 365:2959–2971.

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

R Core Team. 2023. A language and environment for statistical computing. https://www.R-project.org/.

Rittenburg, R. A., A. L. Squires, J. Boll, E. S. Brooks, Z. M. Easton, and T. S. Steenhuis. 2015. Agricultural BMP effectiveness and dominant hydrological flow paths: Concepts and a review. Journal of the American Water Resources Association 51:305–329.

Rosa, D. J., J. C. Clausen, and Y. Kuzovkina. 2017. Water quality changes in a short-rotation woody crop riparian buffer. Biomass and Bioenergy 107:370–375.

Shimizu, G. D., and L. S. Goncalves. 2024. Package ‘AgroReg’. (Available from: https://cran.r-project.org/web/packages/AgroReg/index.html)

Schürings, C., C. K. Feld, J. Kail, and D. Hering. 2022. Effects of agricultural land use on river biota: A meta-analysis. Environmental Sciences Europe 34:124.

Sovell, L. A., B. Vondracek, J. A. Frost, and K. G. Mumford. 2000. Impacts of rotational grazing and riparian buffers on physicochemical and biological characteristics of southeastern Minnesota, USA, streams. Environmental Management 26:629–641.

Sowa, S. P., M. Herbert, S. Mysorekar, G. M. Annis, K. Hall, A. P. Nejadhashemi, S. A. Woznicki, L. Wang, and P. J. Doran. 2016. How much conservation is enough? Defining implementation goals for healthy fish communities in agricultural rivers. Journal of Great Lakes Research 42:1302–1321.

Stevenson, R. J. 1997. Scale-dependent determinants and consequences of benthic algal heterogeneity. Journal of the North American Benthological Society 16:248–262.

Suding, K. N., and R. J. Hobbs. 2009. Threshold models in restoration and conservation: A developing framework. Trends in Ecology and Evolution 24:271–279.

Sweeney, B. W., and J. D. Newbold. 2014. Streamside forest buffer width needed to protect stream water quality, habitat, and organisms: A literature review. Journal of the American Water Resources Association 50:560–584.

Trimble, S. W., and A. C. Mendel. 1995. The cow as a geomorphic agent — A critical review. Geomorphology 13:233–253.

U.S. Environmental Protection Agency. 2000. Ambient water quality criteria recommendations: Information supporting the development of state and tribal nutrient criteria for rivers and streams in nutrient ecoregion XI. U.S. Environmental Protection

Agency, Washington, DC. (Available from: https://www.epa.gov/nutrientpollution/ecoregional-nutrient-criteria-rivers-and-streams)

U.S. Environmental Protection Agency. 2021. Factsheet on water quality parameters: *E. coli (Escherichia coli)*. U.S. Environmental Protection Agency, Washington, DC. (Available from: https://www.epa.gov/awma/e-coli-parameter-factsheet)

U.S. Environmental Protection Agency. 2023. National rivers and streams assessment: The third collaborative survey. U.S. Environmental Protection Agency, Washington, DC. (Available from: https://riverstreamassessment.epa.gov/webreport/)

U.S. Geological Survey. 2019. NLCD 2016 land cover (CONUS). (Available from: https://www.mrlc.gov/data/nlcd-2016-land-cover-conus)

U.S. Geological Survey. 2024. Hydrologic unit maps. (Available from: https://water.usgs.gov/GIS/huc.html)

Virginia Department of Environmental Quality. 2022. Virginia's 2022 305(b)/303(d) water quality assessment integrated report. Virginia Department of Environmental Quality, Richmond, Virginia. (Available from: https://www.deq.virginia.gov/our-programs/water/water-quality/assessments/integrated-report)

Virginia Department of Game and Inland Fisheries. 2015. Virginia's 2015 wildlife action plan. Virginia Department of Game and Inland Fisheries, Henrico, Virginia. (Available from: https://dwr.virginia.gov/wildlife/wildlife-action-plan/wildlife-action-plan-2015/)

Wang, L., J. Lyons, and P. Kanehl. 2002. Effects of watershed best management practices on habitat and fish in Wisconsin streams. Journal of the American Water Resources Association 38:663–680.

Yates, A. G., and R. C. Bailey. 2006. The stream and its altered valley: Integrating landscape ecology into environmental assessments of agro-ecosystems. Environmental Monitoring and Assessment 114:257–271.

Yates, A. G., R. C. Bailey, and J. A. Schwindt. 2007. Effectiveness of best management practices in improving stream ecosystem quality. Hydrobiologia 583:331–344.

Figures

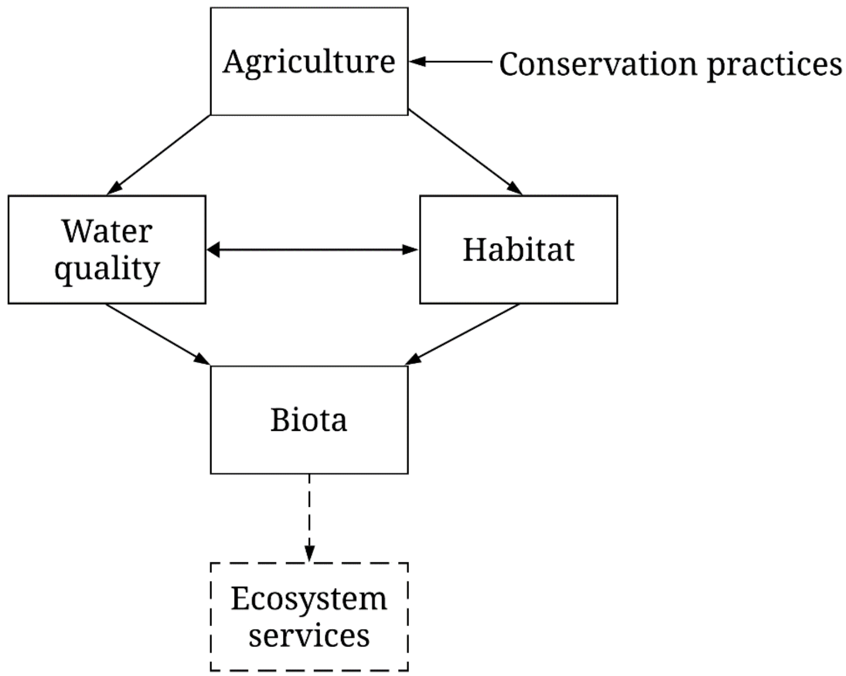

Fig. 1. Hypothesized pathways through which agricultural conservation practices influence stream health. Agricultural land use influences instream water quality and habitat, both of which influence biotic responses. Therefore, agriculture has an indirect effect on biotic responses that is mediated by conservation practices. Collectively, water quality, habitat, and biotic responses provide a picture of stream health (i.e., a stream's ability to provide ecosystem services). Ecosystem services are indicated with a dashed border, as they were not measured in this study. Notably, streamflow constrains biotic responses (Poff 1997), and is influenced by some conservation practices (Einheuser et al. 2012); however, we excluded streamflow from our framework because the types of conservation practices used in southwest Virginia (e.g., livestock exclusion fencing) are not aimed at influencing streamflow.

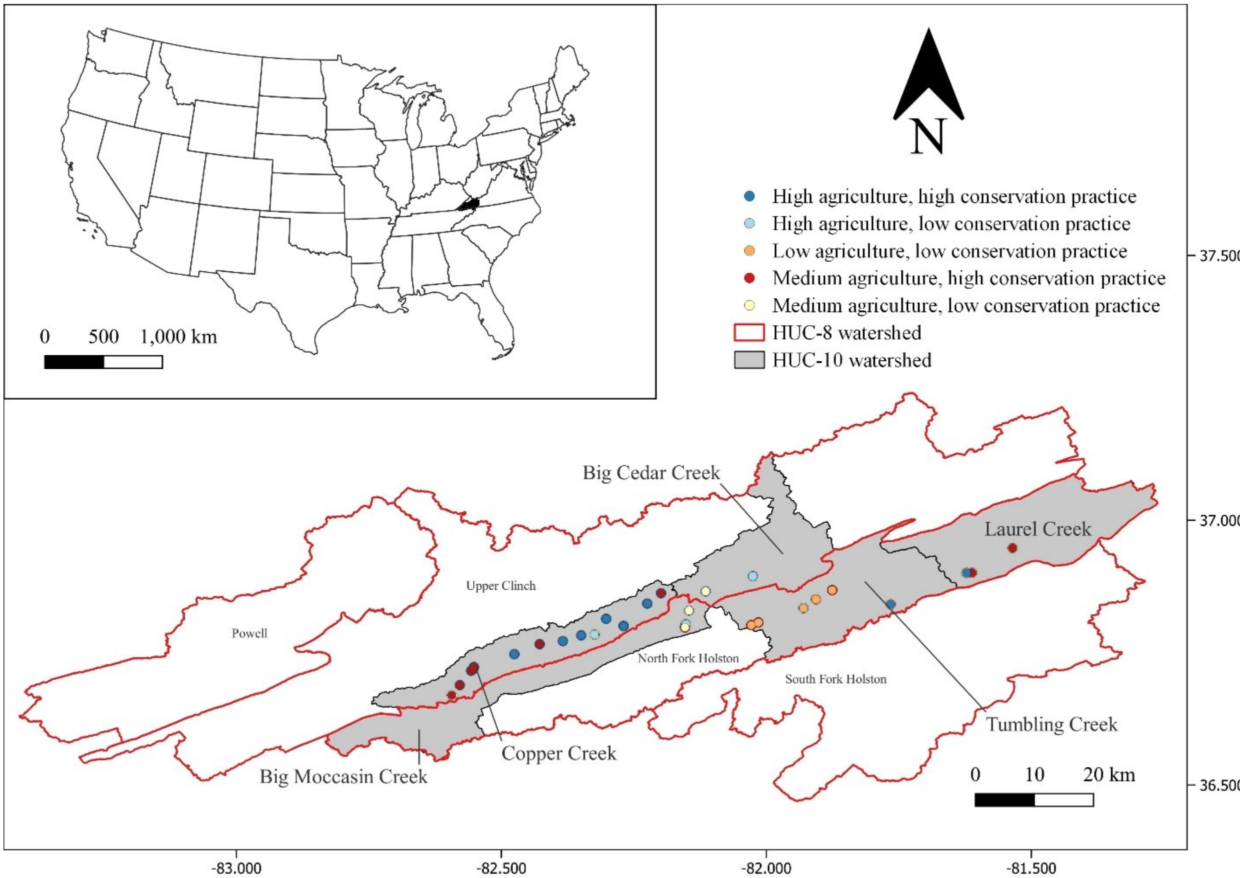

Fig. 2. Map of the Upper Clinch, Powell, North Fork Holston, and South Fork Holston HUC-8 watersheds in southwest Virginia, United States. Within those watersheds, we sampled sites within 31 subbasins that represent a range of agricultural land use extent (%) and conservation practice density (#/ha).

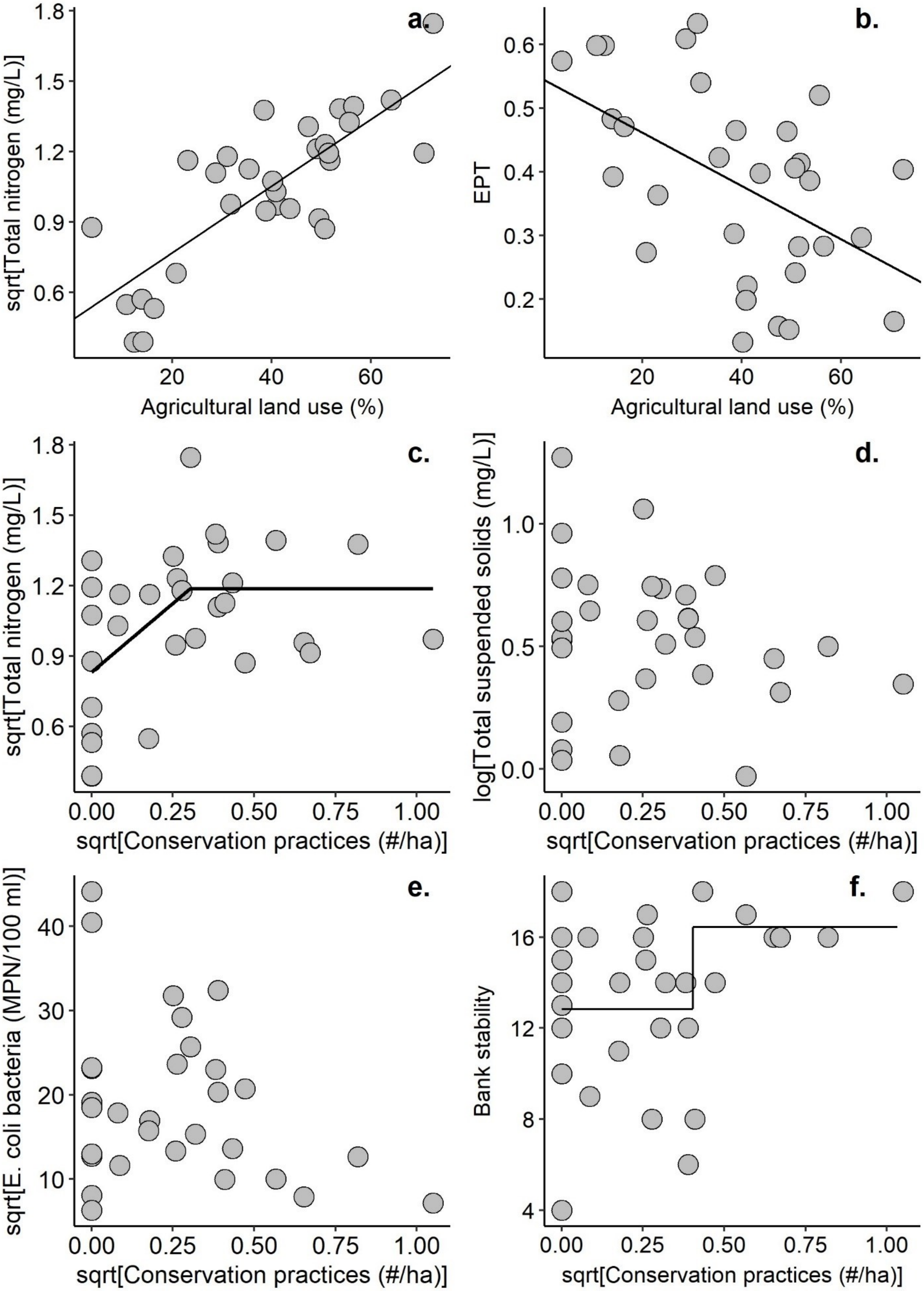
a.
b.
c.
d.
e.
f.
sqrt[Total nitrogen (mg/L)]
EPT
log[Total suspended solids (mg/L)]
sqrt[E. coli bacteria (MPN/100 ml)]
Bank stability
Agricultural land use (%)
sqrt[Conservation practices (#/ha)]
0.00
0.25
0.50
0.75
1.00
20
40
60

Fig. 3. Agricultural land use negatively affects water quality and biota but conservation practices appear to improve or stabilize water quality and habitat. A simple linear regression model showed that agricultural land use increased (a.; $p < 0.01$) total nitrogen and decreased (b.; $p < 0.01$) the proportion of macroinvertebrate individuals collected at a site that were classified as Ephemeroptera, Plecoptera, or Trichoptera minus individuals in the family Hydropsychidae (EPT). The relationship between conservation practice density and total nitrogen (c.) was best explained by a linear plateau model ($p = 0.03$). The relationships between conservation practice density and total suspended solids (d.) and *E. coli* bacteria (e.) were best explained by exponential decay models but those relationships were not significant ($p > 0.10$). Lastly, the relationship between conservation practices and bank stability (f.) was best explained by a stepwise breakpoint regression model ($p < 0.01$). See Table 2 for descriptions of each variable.

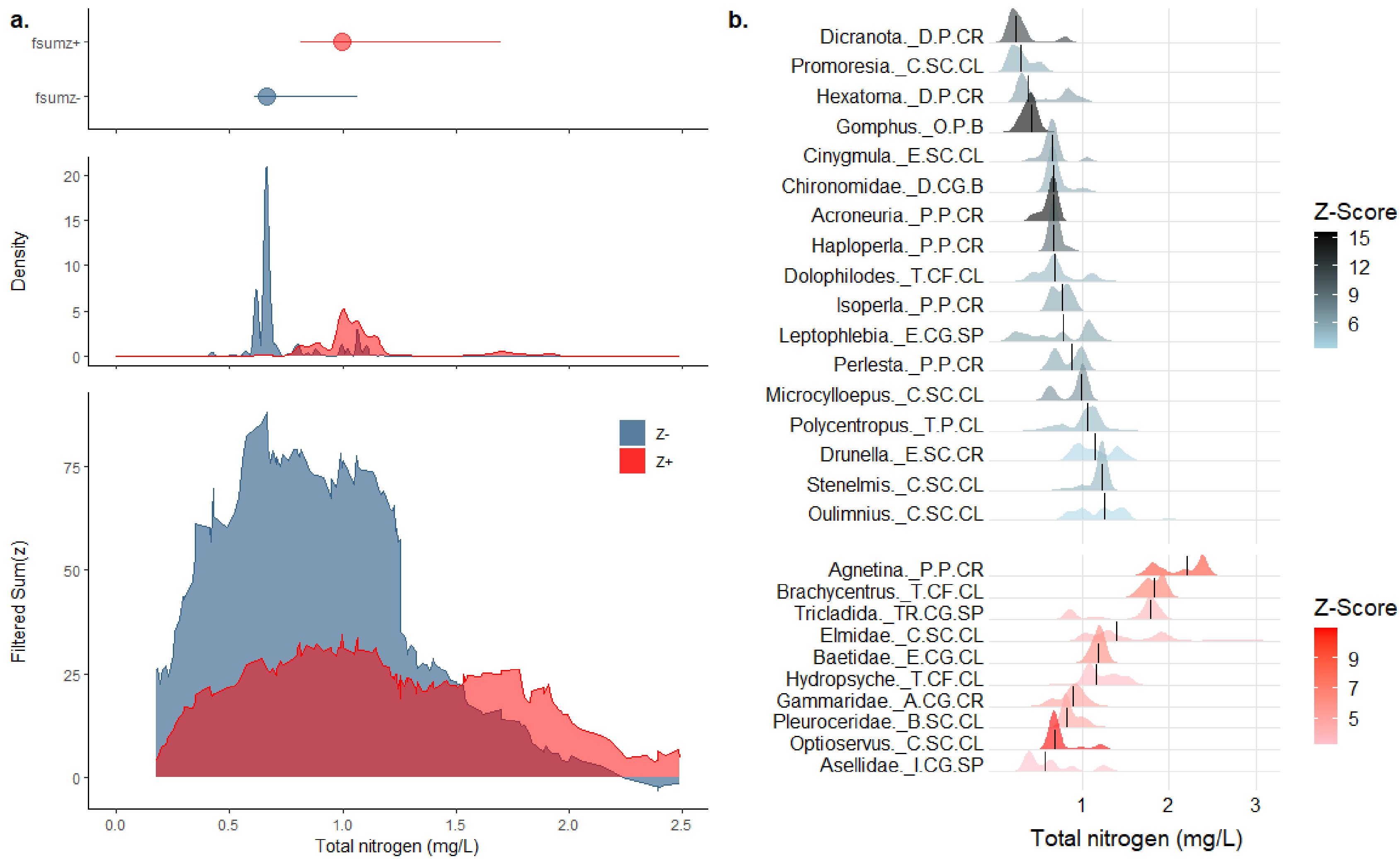

Fig. 4. Threshold responses by the benthic macroinvertebrate assemblage (a.) and individual taxa (b.) to variation in total nitrogen (mg/L) as indicated by Threshold Indicator Analysis (see Table 3). Red represents positive responses; blue represents negative

responses. For 4a., the top panel shows the estimated changepoints (integrated across all taxa) with 95% confidence intervals, the middle panel displays the probability density of changepoints accumulated across 500 bootstrap replicates, and the bottom panel displays the magnitude of change across taxa along the nitrogen gradient, where peaks in y-values indicate points along the gradient that produce large amounts of change in community structure and correspond with change points in the top panel. For 4b., listed taxa are annotated (in order) by their membership in taxonomic, functional feeding, and habit groups. Each taxon-specific plot represents the probability density of changepoints accumulated across 500 bootstrap replicates. B = Basommatophora, D = Diptera, DE = Decapoda, C = Coleoptera, O = Odonata, E = Ephemeroptera, M = Megaloptera, P = Plecoptera, T = Trichoptera, TR = Tricladida, A = Amphipoda, I = Isopoda; CG = Collector-Gatherer, CF = Collector-filterer, G = Generalist, P = Predator, SC = Scraper, SH = Shredder; CR = Crawler, CL = Clinger, B = Burrower, G = Generalist, SP = Sprawler

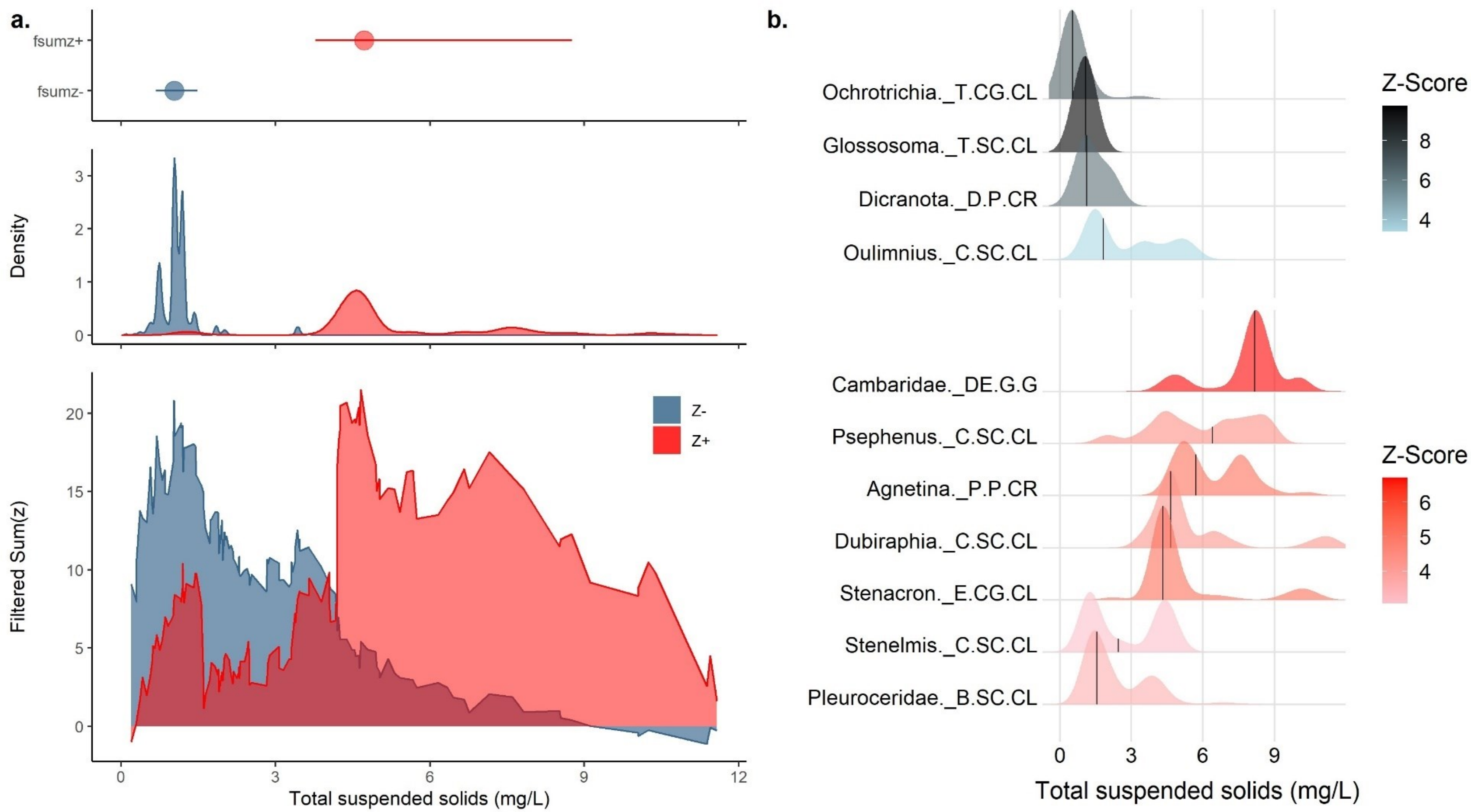

Fig. 5. Threshold responses by the benthic macroinvertebrate assemblage (a.) and individual taxa (b.) to variation in total suspended solids (mg/L) as indicated by Threshold Indicator Analysis (see Table 3). Red represents positive responses; blue represents negative responses. For 5a., the top panel shows the estimated changepoints (integrated across all taxa) with 95% confidence intervals, the middle panel displays the probability density of changepoints accumulated across 500 bootstrap replicates, and the bottom panel

displays the magnitude of change across taxa along the nitrogen gradient, where peaks in y-values indicate points along the gradient that produce large amounts of change in community structure and correspond with change points in the top panel. For 5b., listed taxa are annotated (in order) by their membership in taxonomic, functional feeding, and habit groups. Each taxon-specific plot represents the probability density of changepoints accumulated across 500 bootstrap replicates. B = Basommatophora, D = Diptera, DE = Decapoda, C = Coleoptera, O = Odonata, E = Ephemeroptera, M = Megaloptera, P = Plecoptera, T = Trichoptera, TR = Tricladida, A = Amphipoda, I = Isopoda; CG = Collector-Gatherer, CF = Collector-filterer, G = Generalist, P = Predator, SC = Scraper, SH = Shredder; CR = Crawler, CL = Clinger, B = Burrower, G = Generalist, SP = Sprawler

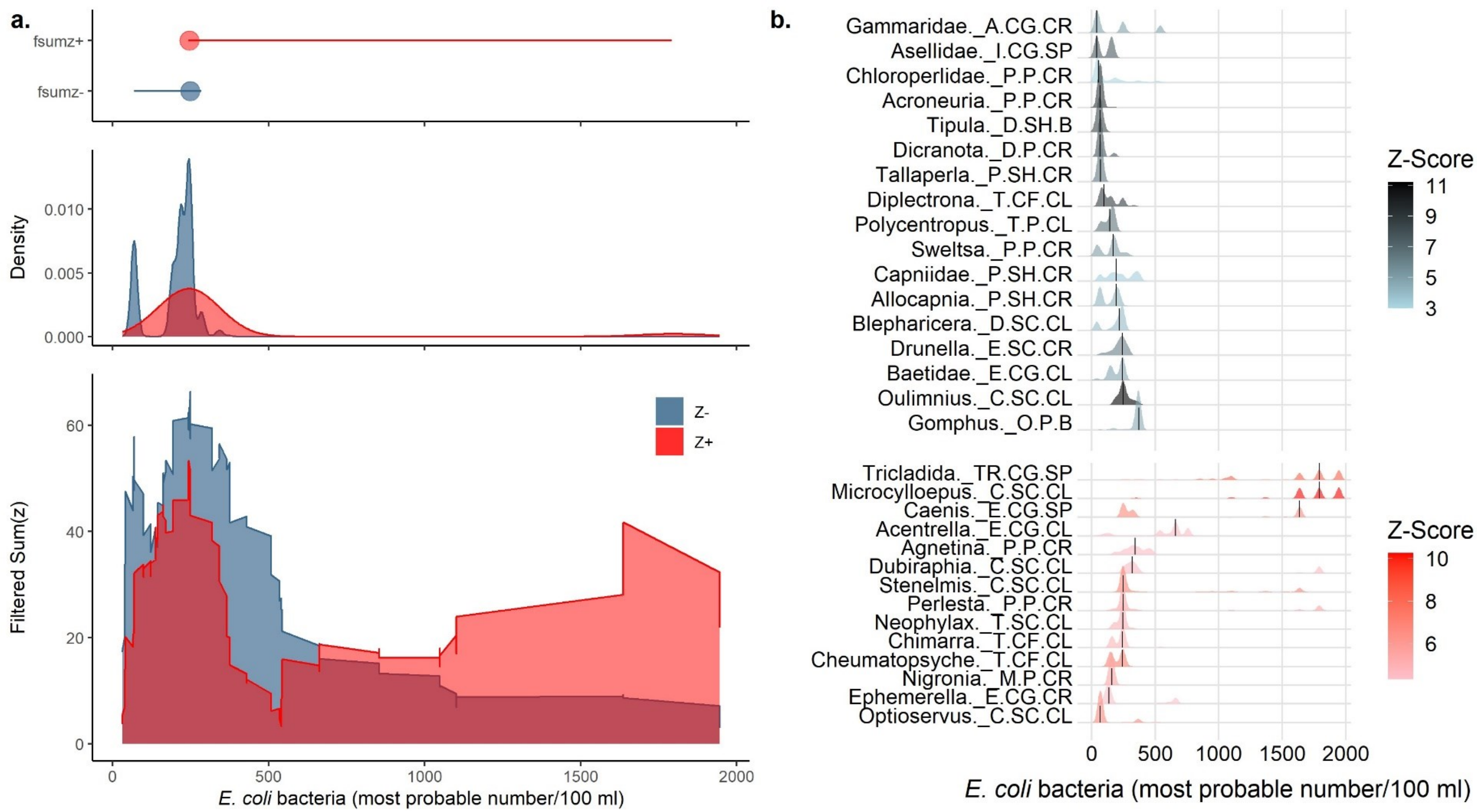

Fig. 6. Threshold responses by the benthic macroinvertebrate assemblage (a.) and individual taxa (b.) to variation in *E. coli* bacteria (most probable number/100ml) as indicated by Threshold Indicator Analysis (see Table 3). Red represents positive responses; blue represents negative responses. For 6a., the top panel shows the estimated changepoints (integrated across all taxa) with 95% confidence intervals, the middle panel displays the probability density of changepoints accumulated across 500 bootstrap replicates,

and the bottom panel displays the magnitude of change across taxa along the nitrogen gradient, where peaks in y-values indicate points along the gradient that produce large amounts of change in community structure and correspond with change points in the top panel. For 6b., listed taxa are annotated (in order) by their membership in taxonomic, functional feeding, and habit groups. Each taxon-specific plot represents the probability density of changepoints accumulated across 500 bootstrap replicates. B = Basommatophora, D = Diptera, DE = Decapoda, C = Coleoptera, O = Odonata, E = Ephemeroptera, M = Megaloptera, P = Plecoptera, T = Trichoptera, TR = Tricladida, A = Amphipoda, I = Isopoda; CG = Collector-Gatherer, CF = Collector-filterer, G = Generalist, P = Predator, SC = Scraper, SH = Shredder; CR = Crawler, CL = Clinger, B = Burrower, G = Generalist, SP = Sprawler

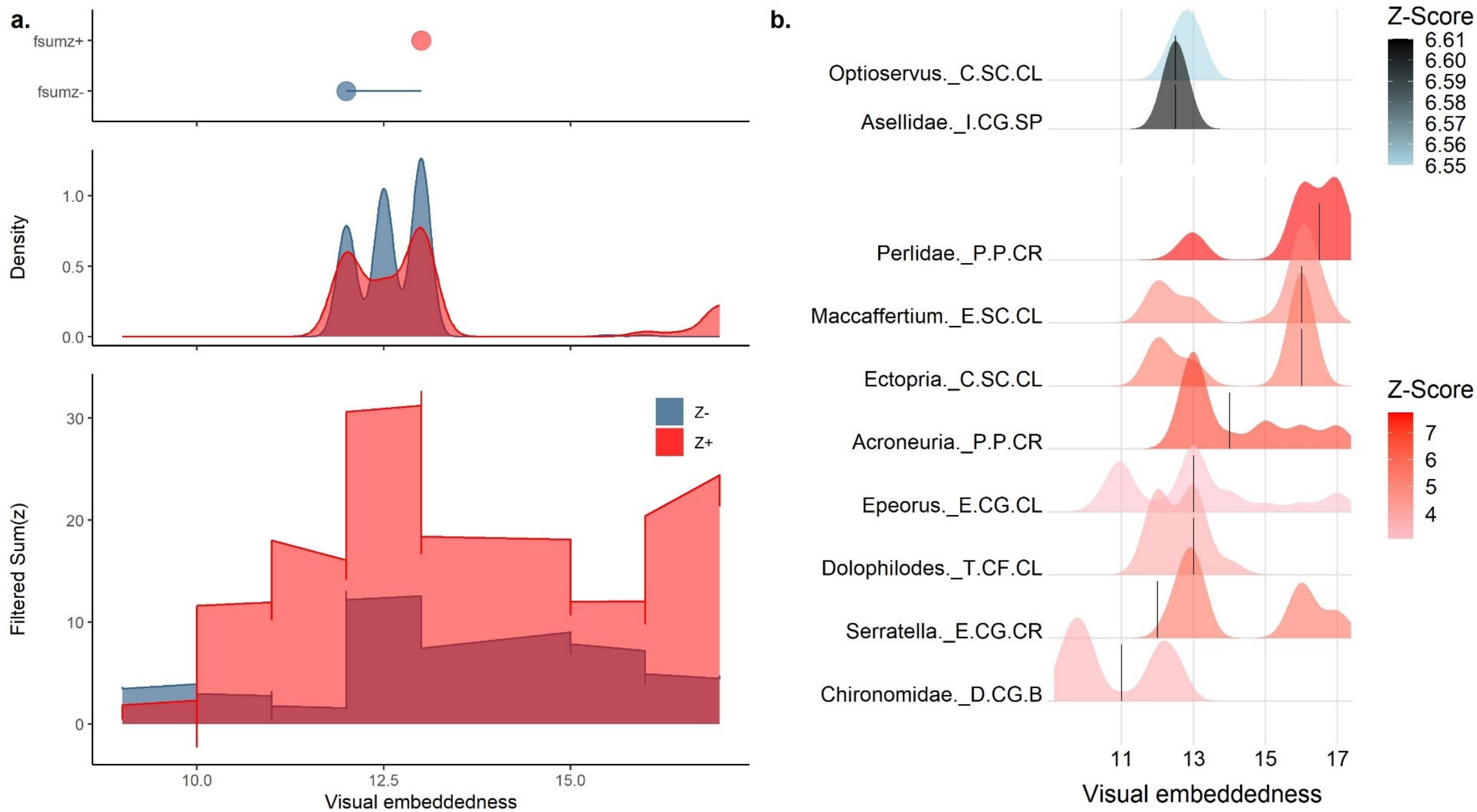

Fig. 7. Threshold responses by the benthic macroinvertebrate assemblage (a.) and individual taxa (b.) to variation in visually estimated embeddedness as indicated by Threshold Indicator Analysis (see Table 3). Red represents positive responses; blue represents negative responses. For 7a., the top panel shows the estimated changepoints (integrated across all taxa) with 95% confidence intervals, the middle panel displays the probability density of changepoints accumulated across 500 bootstrap replicates, and the bottom panel

displays the magnitude of change across taxa along the nitrogen gradient, where peaks in y-values indicate points along the gradient that produce large amounts of change in community structure and correspond with change points in the top panel. For 7b., listed taxa are annotated (in order) by their membership in taxonomic, functional feeding, and habit groups. Each taxon-specific plot represents the probability density of changepoints accumulated across 500 bootstrap replicates. B = Basommatophora, D = Diptera, DE = Decapoda, C = Coleoptera, O = Odonata, E = Ephemeroptera, M = Megaloptera, P = Plecoptera, T = Trichoptera, TR = Tricladida, A = Amphipoda, I = Isopoda; CG = Collector-Gatherer, CF = Collector-filterer, G = Generalist, P = Predator, SC = Scraper, SH = Shredder; CR = Crawler, CL = Clinger, B = Burrower, G = Generalist, SP = Sprawler

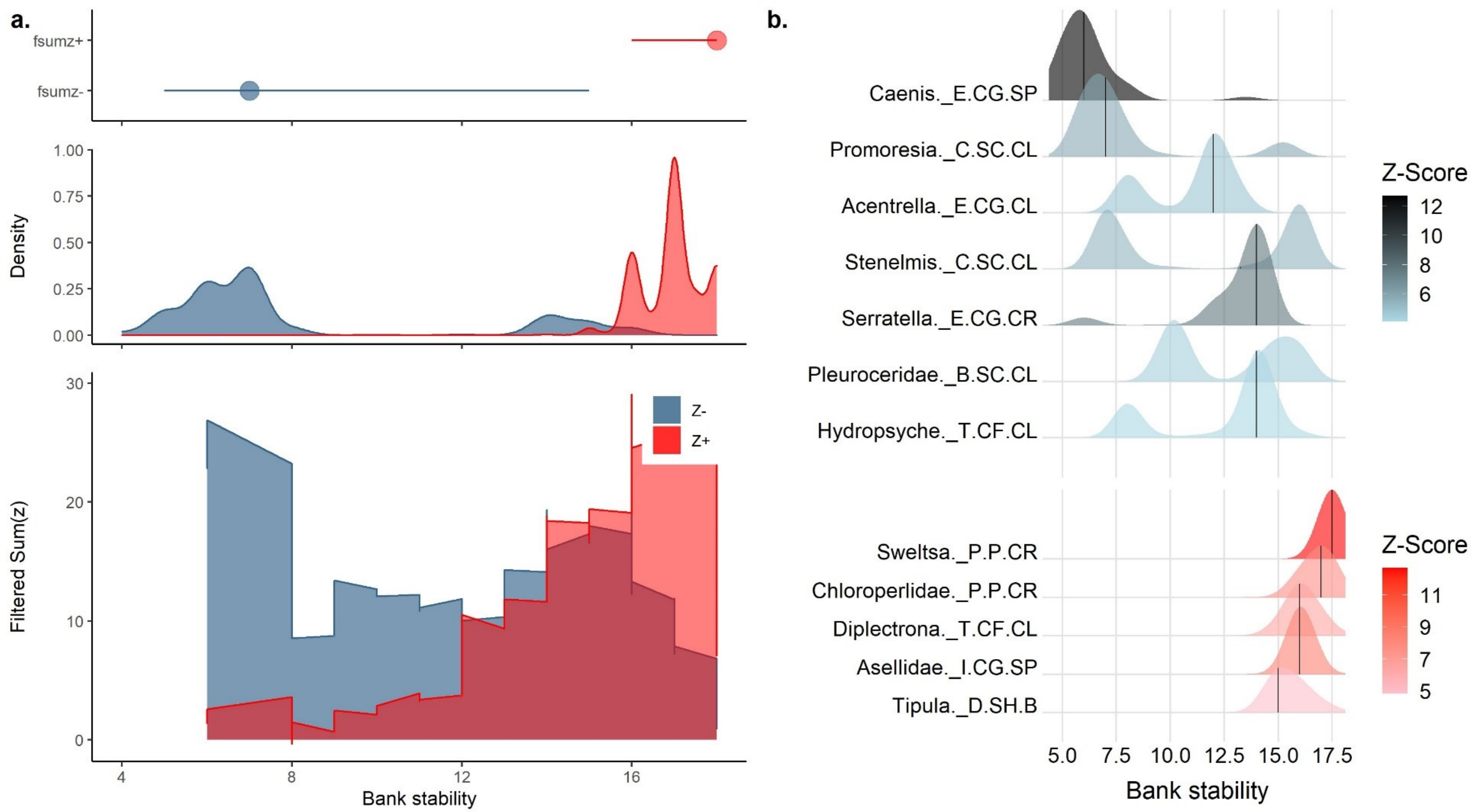

Fig. 8. Threshold responses by the benthic macroinvertebrate assemblage (a.) and individual taxa (b.) to variation in bank stability as indicated by Threshold Indicator Analysis (see Table 3). Red represents positive responses; blue represents negative responses. For 8a., the top panel shows the estimated changepoints (integrated across all taxa) with 95% confidence intervals, the middle panel displays the probability density of changepoints accumulated across 500 bootstrap replicates, and the bottom panel displays the

magnitude of change across taxa along the nitrogen gradient, where peaks in y-values indicate points along the gradient that produce large amounts of change in community structure and correspond with change points in the top panel. For 8b., listed taxa are annotated (in order) by their membership in taxonomic, functional feeding, and habit groups. Each taxon-specific plot represents the probability density of changepoints accumulated across 500 bootstrap replicates. B = Basommatophora, D = Diptera, DE = Decapoda, C = Coleoptera, O = Odonata, E = Ephemeroptera, M = Megaloptera, P = Plecoptera, T = Trichoptera, TR = Tricladida, A = Amphipoda, I = Isopoda; CG = Collector-Gatherer, CF = Collector-filterer, G = Generalist, P = Predator, SC = Scraper, SH = Shredder; CR = Crawler, CL = Clinger, B = Burrower, G = Generalist, SP = Sprawler

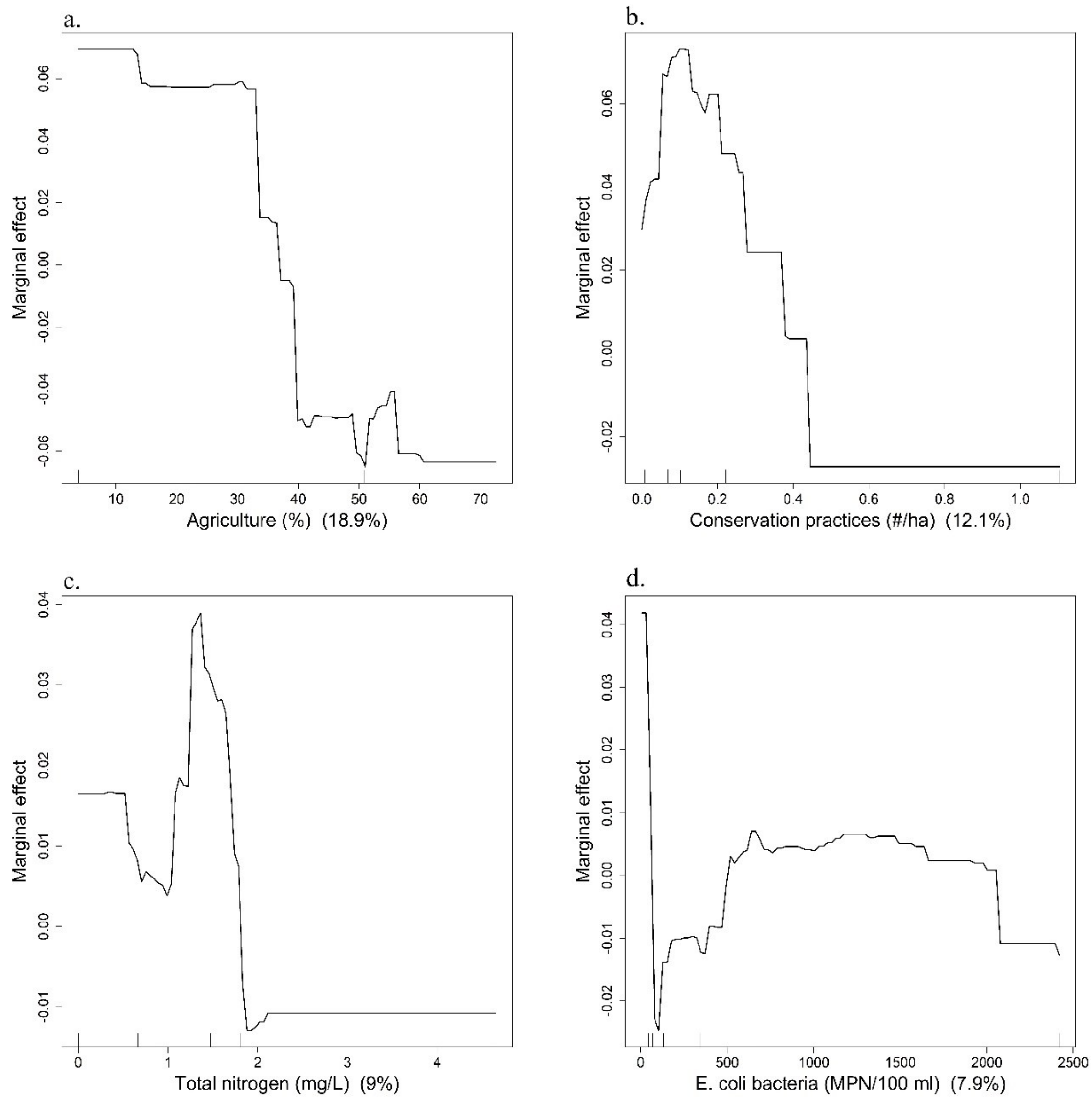

Fig. 9. The top 4 predictors of the proportion of macroinvertebrate individuals collected at a site that were classified as Ephemeroptera, Plecoptera, or Trichoptera minus individuals in the family Hydropsychidae, as indicated by boosted regression trees. Each y-axis shows the effect of the predictor variable on the response after accounting for other variables. Readers should focus on the shape of the plotted relationship and each predictor's relative influence (shown in parentheses on the x-axis legend) rather than the numerical scale of the y-axis. A higher relative influence indicates a stronger relationship between the predictor and response variables. The

predictor variables' season and watershed also had strong relative influence (17.6% and 16.7%, respectively) but are not shown because they were included in the model to account for non-independence of sampling events. MPN = most probable number

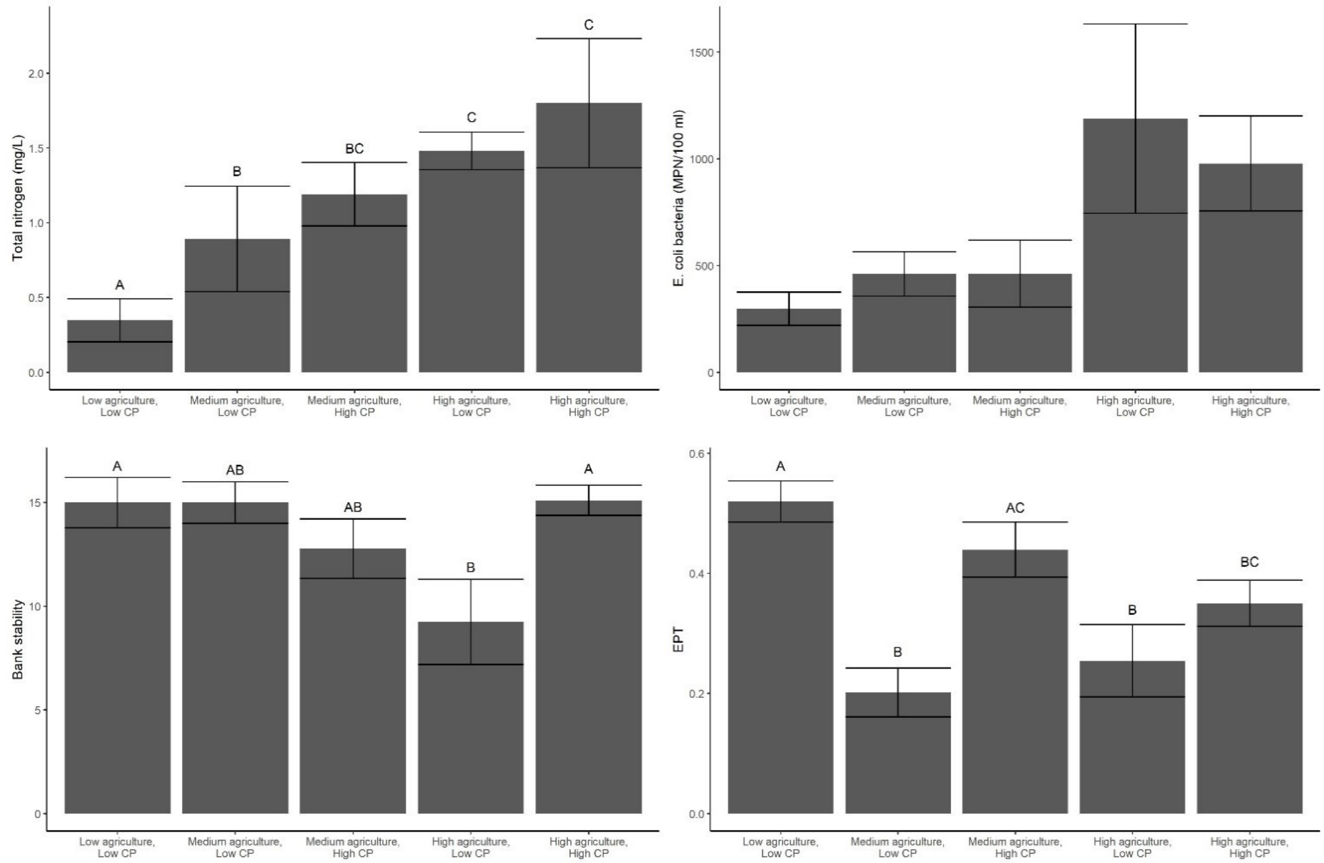

Fig. 10. Results of analysis of variance on categories representing gradients in agricultural land use and conservation practice density. Bars represent the mean water quality and habitat for each category with 90% confidence intervals. Bars with different letters above them indicate statistically significant ($p < 0.1$) differences in means. No differences were statistically significant for *E. coli* bacteria. EPT = Proportion of individuals collected at each site classified as EPT, minus the pollution-tolerant family Hydropsychidae

Tables

Table 1. We chose 31 sites distributed across the Copper Creek, Laurel Creek, Tumbling Creek, Big Moccasin Creek, and Big Cedar Creek HUC-10 watersheds in southwest Virginia, United States. These sites represent a range of agricultural land use (Ag, %), conservation practice density (CP, #/ha), and estimated sediment yields (Sed, tons/ha/year) within the subbasin around the site. Subbasins were defined and sediment yields were estimated by the Soil Water Assessment Tool+ model described in Mouser et al. (2020). Sites were ranked as low, medium, or high amounts of agricultural land and high or low sediment yield and conservation practice density within the subbasin surrounding the site. ID = site identification code, Lat = latitude, Lon = longitude

ID	HUC10	Lat	Lon	Ag	Rank	CP	Rank	Sed	Rank
TC-UC792	Tumbling Creek	36.802	-82.028	3.8	Low	0.00	Low	0.62	Low
TC-EF639	Tumbling Creek	36.851	-81.906	10.8	Low	0.03	Low	1.44	Low
TC-BC868	Tumbling Creek	36.807	-82.015	12.4	Low	0.00	Low	0.01	Low
TC-RM582	Tumbling Creek	36.868	-81.876	13.9	Low	0.00	Low	0.26	Low
TC-SH803	Tumbling Creek	36.807	-82.015	14.1	Low	0.00	Low	1.8	Low
TC-WF1719	Tumbling Creek	36.834	-81.930	16.3	Low	0.00	Low	17.41	High
BM-SF836	Big Moccasin	36.798	-82.154	20.8	Med	0.00	Low	1.31	Low
BC-WB666	Big Cedar Creek	36.866	-82.115	40.2	Med	0.03	Low	23.76	High
BM-NF734	Big Moccasin	36.829	-82.146	40.9	Med	0.15	Low	16.65	High
CC-AB29	Copper Creek	36.766	-82.428	23.1	Med	0.07	High	21.12	High
LC-CB576	Laurel Creek	36.901	-81.612	28.7	Med	0.08	High	0.21	Low
LC-W0422	Laurel Creek	36.948	-81.535	31.1	Med	0.16	High	0.63	Low

CC-OC56	Copper Creek	36.723	-82.552	31.8	Med	0.66	High	28.01	High
CC-PB64	Copper Creek	36.716	-82.557	35.4	Med	0.06	High	31.82	High
CC-UC03	Copper Creek	36.862	-82.199	38.4	Med	0.00	High	19.89	High
CC-PC67	Copper Creek	36.689	-82.578	38.8	Med	0.01	High	34.14	High
CC-FB75	Copper Creek	36.670	-82.594	41.1	Med	1.07	High	3.25	Med
CC-SB58	Copper Creek	36.719	-82.553	43.7	Med	0.42	High	30.98	High
BC-MB584	Big Cedar Creek	36.895	-82.025	47.4	High	0.00	Low	23.48	High
BC-LC678	Big Cedar Creek	36.866	-82.115	51.4	Med	0.18	Low	17.86	High
CC-MC22	Copper Creek	36.784	-82.324	51.7	High	0.44	Low	18.08	High
BM-NF832	Big Moccasin	36.804	-82.152	70.6	High	0.21	Low	23.44	High
CC-CC44	Copper Creek	36.747	-82.476	49.1	High	0.07	High	26.4	High
LC-UC559	Laurel Creek	36.901	-81.622	49.5	High	0.00	High	0	Low
LC-UC756	Laurel Creek	36.841	-81.765	50.7	High	0.01	High	0.7	Low
CC-GC24	Copper Creek	36.783	-82.349	50.8	High	0.15	High	21.07	High
CC-CC05	Copper Creek	36.843	-82.225	53.7	High	0.06	High	26.75	High
CC-MC14	Copper Creek	36.814	-82.302	55.6	High	0.31	High	39.33	High
CC-JB25	Copper Creek	36.772	-82.384	56.5	High	0.14	High	27.97	High
CC-LC16	Copper Creek	36.800	-82.269	64	High	0.00	High	18.95	High
CC-UC15	Copper Creek	36.800	-82.269	72.5	High	0.09	High	14.48	High

Table 2. Description, range, and mean ± standard deviation (SD) of each variable used in the statistical analyses. Some variables were collected once for each site and others were collected for each sampling event, which is reflected in the sample size (n). We transformed some variables to approximate a normal distribution for all models except the boosted regression trees and threshold indicator analysis. E = Ephemeroptera, P = Plecoptera, T = Trichoptera

Variable	Description	Range	Mean ± SD	n	Transformation
Conservation practice density (#/ha)	Number of conservation practices within the subbasin containing the site divided by the area of the subbasin	0–1.10	0.15 ± 0.24	31	Square root
Slope (%)	Average hillslope of the subbasin containing the site	15.92–46.53	25.77 ± 6.48	31	Square root
Agriculture	Percent agricultural land use within the subbasin containing the site	3.8–72.5	38.99 ± 18.05	31	None
TSS (mg/L)[a]	Concentration of total suspended solids in the water at each site	0.02–44.8	4.20 ± 5.31	139	Log
TN (mg/L)[a]	Concentration of total nitrogen in the water at each site	0–4.65	1.25 ± 0.77	139	Square Root
E. coli (most probable number/100 ml)[a]	Concentration of *E. coli* bacteria in the water at each site	6.30–2419.20	653.08 ± 799.65	139	Square root
Embeddedness (unitless)	Visual estimate from 0–20, where 0 indicates coarse substrate particles (i.e. gravel, cobble boulder) are 100% surrounded by fine sediment and 20 indicates 0% surrounded by fine sediment	9–18	12.60 ± 2.41	31	None

Bank stability (unitless)	Visual estimate from 0–10 for each streambank (summed), where 0 indicates 100% of the bank has erosional scars and 10 indicates 0% of the bank has erosional scars	4–18	13.79 ± 3.53	31	None
VSCI (unitless)	Virginia stream condition index. Multimetric index comprising number of EPT taxa, % E individuals, % P plus T minus Hydropsychidae individuals, % Chironomidae individuals, and % individuals in the 2 most dominant taxa	34.05–83.63	65.08 ± 9.16	154	None
Proportion EPT (unitless)	Proportion of individuals collected at each site classified as EPT, minus the pollution-tolerant family Hydropsychidae	0–0.87	0.38 ± 0.20	154	None
EPT taxa (#)	Number of EPT taxa	0–25	12.99 ± 3.79	154	None

[a] Water quality data were not collected spring 2020 because of laboratory closures due to COVID-19.

Table 3. The threshold indicator analysis revealed changepoints (cp), or thresholds, at which the majority of the macroinvertebrate taxa responded negatively (-) or positively (+) to selected water quality and habitat variables. Each threshold is the value of the variable that had the greatest total change in indicator values across individual taxa. Also shown are 95% confidence intervals (ci) based on 5th and 95th percentiles from 500 bootstrap replicates and the number of pure and reliable taxa (*n*), out of 102 taxa tested, that responded positively or negatively. See Table 2 for descriptions of each variable.

Variable	cp	ci	*n*
TN -	0.65 mg/L	0.57–1.08	17
TN +	1.07 mg/L	0.81–1.81	11
TSS -	1.04 mg/L	0.78–3.45	4
TSS +	4.72 mg/L	4.2–8.93	7
E. coli -	242.88 mg/L	67.92–283.66	17
E. coli +	245.57 mg/L	242.88–1790.69	13
Embeddedness -	13.00	12.00–13.00	2
Embeddedness +	12.50	12.00–17.50	9
Bank stability -	6.00	5.00–15.00	5
Bank stability +	17.50	16.00–18.00	6

Table 4. Mean ± standard deviation for water quality, habitat, and biotic variables that were compared among the following categories of sites (Table 1): high subbasin agricultural land use, high conservation practice density (HH); high agriculture, low conservation (HL); medium agriculture, high conservation (MH); medium agriculture, low conservation (ML); or low agriculture, low conservation (LL). See Table 2 for descriptions of each variable.

Category	TN	TSS	*E. coli*	Bank stability	Embeddedness	VSCI	Proportion EPT	EPT taxa
HH	1.80 ± 0.79	4.75 ± 3.62	978.58 ± 667.18	15.11 ± 2.20	12.22 ± 2.81	63.89 ± 7.13	0.35 ± 0.11	11.86 ± 3.54
HL	1.48 ± 0.15	7.4 ± 7.51	1188.86 ± 886.47	9.25 ± 4.11	13.00 ± 1.41	63.71 ± 7.06	0.25 ± 0.12	11.95 ± 1.00
MH	1.19 ± 0.38	2.87 ± 1.43	462.01 ± 471.47	12.77 ± 4.29	12.88 ± 2.36	65.75 ± 6.62	0.43 ± 0.13	13.12 ± 2.16
ML	0.89 ± 0.37	4.35 ± 1.14	460.50 ± 179.04	15.00 ± 1.73	11.00 ± 1.00	57.37 ± 4.81	0.20 ± 0.07	9.75 ± 2.38
LL	0.34 ± 0.21	3.49 ± 3.34	297.85 ± 191.09	15.00 ± 2.96	13.66 ± 3.26	70.70 ± 3.39	0.51 ± 0.08	17.37 ± 1.79

Appendix

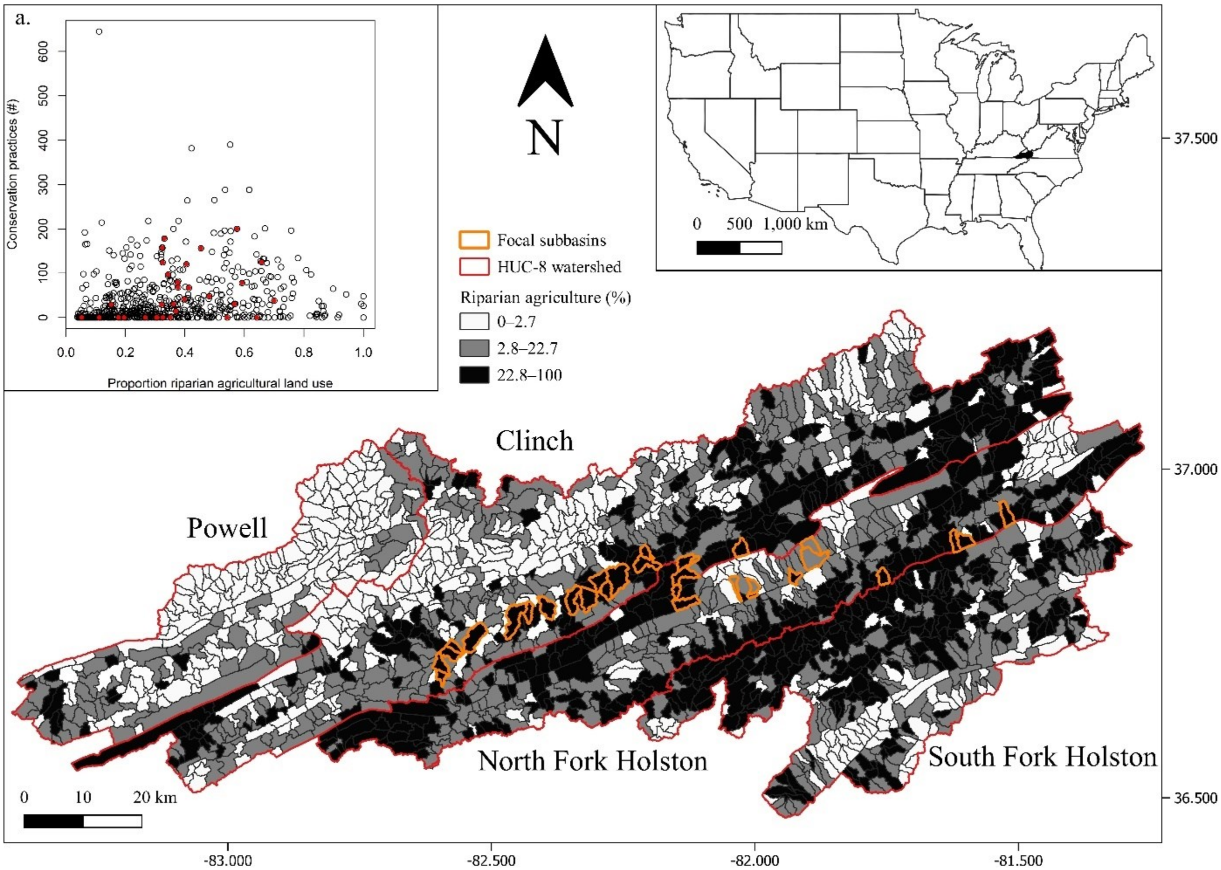

Fig. 1. Our focal subbasins showed a broad range of riparian agricultural land use. After removing subbasins that were influenced by urban land use or mining, drained to streams > 3rd order, or did not have agricultural land use within the riparian area, we selected focal subbasins (red dots, inset a.) that displayed a range of conservation practice installation intensity for more intensive study, which led to a gradient of agricultural land use (Table 1). Subbasins were defined by the Soil Water Assessment Tool+ model described in Mouser et al. (2020).

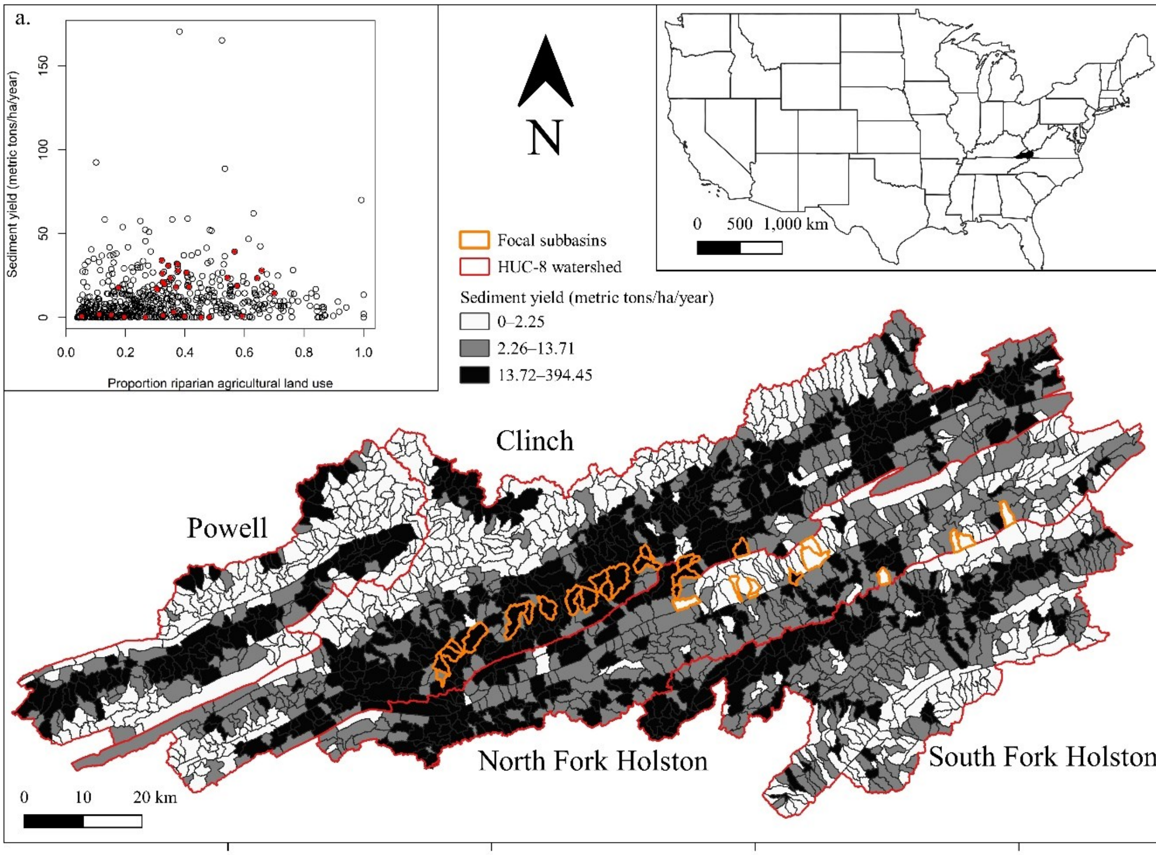

Fig. 2. Our focal subbasins show a broad range of sediment yields (metric tons/ha/year). After removing subbasins that were influenced by urban land use or mining, drained to streams > 3rd order, or did not have agricultural land use within the riparian area, we selected focal subbasins (red dots, inset a.) that displayed a range of sediment yields for more intensive study (Table 1). Subbasins were defined and sediment yields were estimated by the Soil Water Assessment Tool+ model described in Mouser et al. (2020).

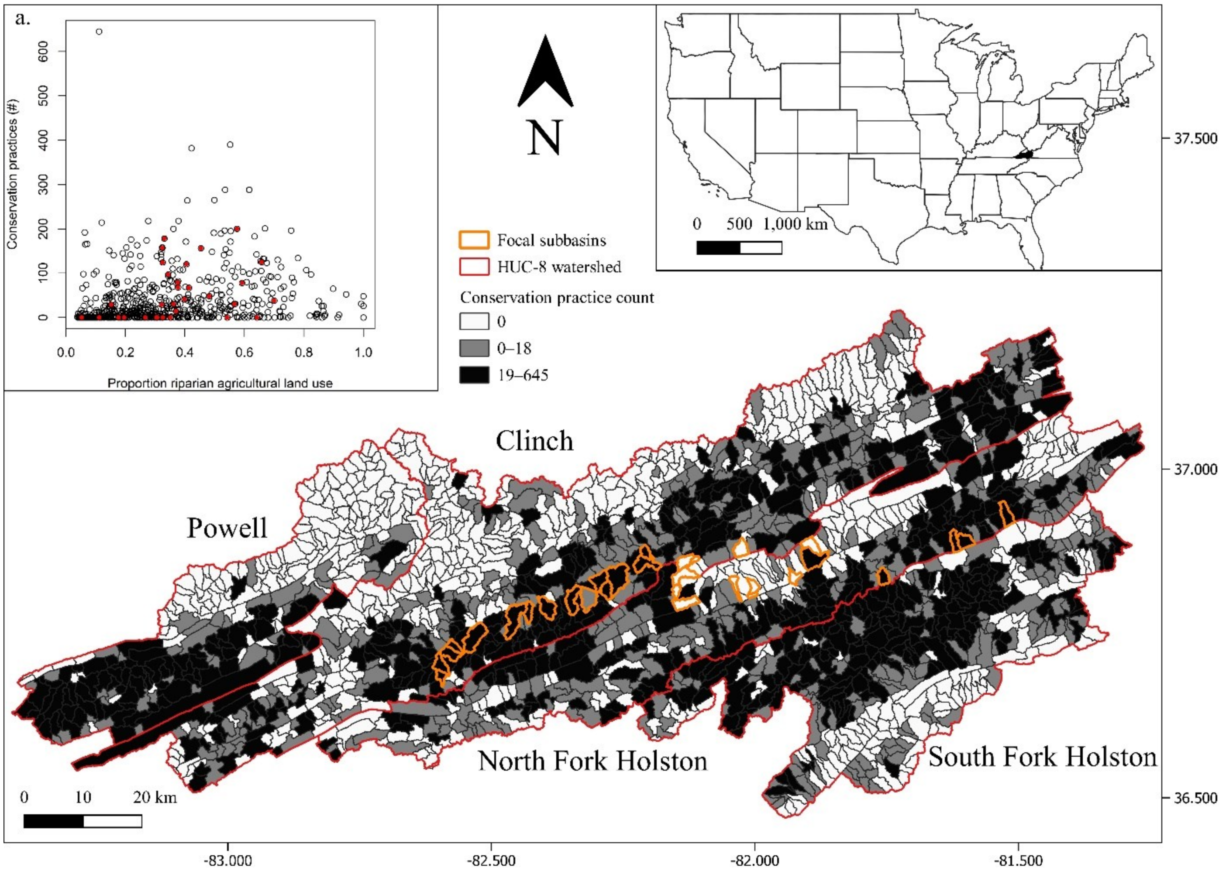

Fig. 3. Our focal subbasins show a broad range of conservation practice installation intensity. After removing subbasins that were influenced by urban land use or mining, drained to streams > 3rd order, or did not have agricultural land use within the riparian area, we selected focal subbasins (red dots, inset a.) that displayed a range of conservation practice installation intensity for more intensive study (Table 1). Subbasins were defined by the Soil Water Assessment Tool+ model described in Mouser et al. (2020).

CHAPTER 3: LANDOWNERS' COGNITIONS AND MOTIVATIONS COUPLED WITH PRACTICE DURABILITY INFLUENCE PERSISTENCE IN AGRICULTURAL BEST MANAGEMENT PRACTICES

Abstract

Agricultural best management practices (BMPs) are installed voluntarily by landowners to protect stream health while continuing food production. Cost-share contracts through state and federal agencies support BMP installation. Although BMPs show potential to recover stream health, recovery has not been as extensive or as quick as expected. One potential way to improve efficacy of BMPs is through promoting persistence, or the continued use of BMPs after cost-share contracts end. The rate of persistence and the factors (e.g., landowner environmental attitudes and resources) that influence persistence are often unknown. Therefore, our objective was to survey landowners to better understand BMP persistence in southwest Virginia. We mailed surveys to 889 landowners. Their responses were analyzed quantitatively using logistic regression and qualitatively via coding. We found that the rates of persistence for vegetative practices, cattle-exclusion fencing, off-stream watering structures, and pasture management were 74%, 84%, 94%, and 94%, respectively. Results from both the quantitative and qualitative analyses indicated that landowner cognitions (i.e., attitudes towards BMPs, the environment, and agencies), environmental motivations, and practice durability influence persistence. Our results highlight ways that persistence could be encouraged if that is the policy or programmatic goal of agencies by: 1) providing targeted messaging focused on landowners' motivations that demonstrates the benefits of persistence, 2) ensuring that responsibility to maintain BMPs is transferred during changes in land tenure, and 3) allocating more funding to BMP maintenance.

Introduction

Protecting stream health while increasing agricultural production to feed a growing human population is a major global challenge. Stream health is the ability of streams to meet social and ecological needs (Meyer 1997). Healthy streams are critical for human well-being (Millennium Ecosystem Assessment 2005), especially via links to human health, safety, security, and living standards (Angermeier et al. 2021). Agricultural land use threatens stream health through nonpoint-source pollution that decreases water quality, degrades instream habitat, and harms biota (Allan 2004; USEPA 2023). Agricultural production also fulfills a critical human need and production will need to increase by 1.1% per year until 2032 to feed the growing global population (OECD/FAO 2023). To protect stream health and continue food production, state (e.g., VDCR 2023) and federal agencies (NRCS n.d.) encourage landowners to participate in agricultural conservation programs, which are entirely voluntary.

Agricultural conservation programs typically comprise cost-share agreements between agencies and landowners to implement agricultural best management practices (BMPs). Agricultural BMPs include management practices (e.g., prescribed grazing and cover crops) and structural practices (e.g., cattle-exclusion fencing, riparian buffers, and off-stream watering structures). Often, the agency pays most of the BMP cost with the expectation that farmers will maintain the BMP for its lifetime, which can range from one year for some management practices to upwards of 15 years for some structural practices (NRCS n.d.; VDCR 2023). Billions of dollars have been spent on implementing BMPs across the United States — the 2018 Farm Bill allocated $29 billion from fiscal years 2019 through 2023 for conservation program (Congressional Research Service 2019) and nearly $808 million has been spent in Virginia alone since 1998 (VDCR 2024). To ensure that money and time are spent wisely and effectively when addressing stream health declines, it is crucial that BMPs achieve stream health goals now and into the future.

Despite increasing participation in agricultural conservation programs and more BMPs on the landscape, stream health has not recovered as quickly or extensively as expected (Liu et al. 2017). For example, nutrient reduction goals set by United States Environmental Protection Agency to be reached in 2025 will not be met if nutrient reductions for the Chesapeake Bay continue at the current rate (Chesapeake Bay Foundation 2023). Failure to achieve stream health goals may reflect insufficient participation in cost-share programs, especially in locations that contribute excessive amounts of pollutants (Sowa et al. 2016). Despite not fully achieving conservation goals in some contexts, participation in conservation programs is often beneficial when BMPs are implemented correctly and can lead to improved water quality (Byers et al. 2005, Bracmort et al. 2006), instream habitat (Wang et al. 2002), and biotic indices (Herman et al. 2015). Therefore, increasing participation could enhance stream health outcomes. Landowner participation in cost-share programs includes initial adoption of BMPs, re-enrollment in BMP programs (if available), or persistence in using BMPs after the cost-share agreement ends (Dayer et al. 2018).

Although BMP persistence is less studied than adoption, persistence can be equally important for improving and maintaining stream health (Jackson-Smith et al. 2010, Dayer et al. 2018). Persistence is defined as continued participation in conservation behavior after short-term financial incentive payments end. Persistence is the opposite of reversion, which is when a landowner returns to pre-contract management behavior or fails to maintain a structural practice (Dayer et al. 2018). Persistence is crucial because it can take many years for stream health to respond as intended to BMP implementation and associated stream restoration efforts (Meals et al. 2010; Reid 2018). Long-term maintenance of BMPs also promotes their effectiveness. For example, structural BMPs (e.g., terraces) maintained in good condition doubled the amount of sediment removed compared to unmaintained practices (Bracmort et al. 2004, 2006). Lastly, persistence is especially important when there are no new landowners who are willing or able to install BMPs, so the only option for managers would be to encourage persistence (Dayer et al. 2018).

In some cases, promoting persistence can cost less than targeting new landowners, especially if persistence does not involve new contracts (Dayer et al. 2018). For example, maintained BMPs may have higher benefit-to-cost ratios than unmaintained BMPs (Bracmort et al. 2004, 2006). Landowners might be encouraged to continue to apply management BMPs or maintain structural BMPs without agency funding, or at least for less funding than needed for new practices or infrastructure. Yet, maintenance costs could be a challenge for some landowners. Some conservation incentive programs have funds for maintenance, but the presumed greater conservation benefits associated with new practices are often prioritized over funding maintenance of existing BMPs, especially in locations with lower funding allocations. Despite the potential importance of persistence in achieving stream health goals and cost-effective BMP programs, the rate of persistence is unknown in most locations (Dayer et al. 2018), making it difficult to weigh relative advantages of promoting increased adoption versus persistence.

Many social, ecological, and institutional factors influence a landowner’s decision to choose persistence at the conclusion of cost-share funding (Figure 1). Dayer et al. (2018) identified five pathways through which we can understand landowner persistence. The first pathway, landowner cognitions, includes their attitudes and perceptions towards BMPs, management agencies, and the environment. The second pathway is landowners' motivations, which can be extrinsic (e.g., financial incentives) or intrinsic (e.g., environmental concerns). The third pathway involves landowner habits (e.g., grazing cattle in a particular rotation), which can become established via implementation of BMPs. Barnes et al. (2023) expanded the terminology to behavioral inertia, which includes maintaining the status quo as well as establishing habits. The fourth pathway reflects the resources available to landowners such as their finances, the information available to them, and the quality of their farmland. Finally, the fifth pathway is a landowner's social influences (e.g., their neighbors' and community's attitudes). Although not described in Dayer et al. (2018), landowner demographics (e.g., age and level of formal education) can predict adoption (Prokopy et al. 2019) and we suspect they may be another important predictor of persistence.

It is also important to recognize the spatial and temporal scales at which factors operate to influence conservation behavior (Liu et al. 2018; Epanchin-Niell et al. 2022; Figure 1). Many factors that influence behavior — the biophysical setting, the economy, government policies, conservation organizations, and social structure (Liu et al. 2018; Epanchin-Niell et al. 2022) — operate at coarse scales (i.e., the watershed, state, or country where a landowner resides). For example, a watershed that experiences high flooding frequency (i.e., a biophysical factor) may have lower landowner persistence for livestock-exclusion fencing practices than a watershed with a low flooding frequency due to the risk of fences being destroyed by floods. Factors at the watershed scale shape characteristics of the farm (e.g., quality of the land, farm size, and farm income) and constrain characteristics of the landowner (e.g., cognitions and resources). The characteristics of the landowner will ultimately lead to their decision to persist or revert at the conclusion of their cost-share contract, which will feed into future decisions based on their experience (Epanchin-Niell et al. 2022), or by creating behavioral inertia.

Understanding the factors that influence behavior is important for developing behavior-change strategies (McKenzie-Mohr 2011). If encouraging persistence is important to achieve stream health, then strategies to increase persistence can be developed. For example, Lutter et al. (2019) suggested that appealing to a broad array of motivations through advertisement and fostering trust could improve long-term management because cognitions (e.g., agency trust) and environmental motivations were important predictors of persistence in forest conservation practices. Barnes et al. (2020) found that landowners often could not re-enroll in the USDA Conservation Reserve Program after their contracts ended and made future land management decisions based on the best financial choice; therefore, managers might work with landowners to find other conservation programs that meet their financial needs.

To promote the long-term efficacy of BMP programs, it is important to understand the influence of persistence on stream health and how managers might best promote persistence if it is beneficial for achieving healthy streams. Therefore, our overall objective was to survey landowners to better understand BMP persistence. Specifically, we surveyed landowners to determine if they persisted in using BMPs in watersheds of southwest Virginia. Additionally, we determined factors that lead landowners to persist in using BMPs. Management agencies can leverage factors that influence persistence to effectively engage with landowners and promote persistence if warranted.

Materials and methods

Study area

We surveyed farmers in Bland, Russell, Scott, Smyth, Tazewell, and Washington counties, Virginia, United States (Figure 2) — an area representative of the Appalachian Region in terms of land use and demographics, and other small-scale cattle-grazing operations in terms of types of BMPs implemented. We focused our surveys on landowners within the Big Moccasin Creek (BMC), Big Cedar Creek (BCC), Copper Creek (CC), Laurel Creek (LC), and Tumbling Creek (TC) 10-digit hydrologic units (USGS 2024). Several of these watersheds are used intensively for hay or pastureland (BMC = 33%, BCC = 36%, and CC = 39%); however, LC and TC are only 21% and 18% agricultural use, respectively (USGS 2019). On average, 29% of our study area is used for agriculture, which is similar to the average of 28% across the entire Appalachian Region (Kerrick et al. 2022). The average farm size for counties in our study area is 161 acres (USDA 2024), while the average farm size in the Appalachian Region as a whole is 147 acres (Kerrick et al. 2022). Demographics in our focal counties are similar to rural Appalachia as a whole (Pollard and Jacobsen 2020) and show an aging population (i.e., almost half are > 50 years old) that is mostly high school-educated or less (> 50% of the population) and primarily white (> 91%; USCB 2023). Lastly, each focal watershed has had thousands of BMPs implemented from 2005–2021: BCC = 1,406, BMC = 2,425, TC = 2,585, LC = 2,978, and CC = 5,673 (George Wallace, USDA Natural Resources Conservation Service [NRCS], 14 February 2022, written communication), providing a useful location to understand persistence in BMP programs.

Mail surveys

Our sampling frame comprised landowners in the focal watersheds who have expired agricultural BMPs. Contact information for landowners was obtained from tax parcel data and Virginia Soil and Water Conservation Districts. To collect data from the tax parcels, BMP data were obtained from Virginia Department of Conservation and Recreation (VDCR) and NRCS. The BMP data were then restricted to practices that have met their lifespan according to the Conservation Practice Data Entry System (NRCS n.d.) and Virginia Agricultural Cost Share Manual (VDCR 2023). Next, the BMP data were overlaid on a Virginia tax parcels shapefile using QGIS (QGIS Development Team 2023). Because the QGIS shapefile did not contain contact data, the interactive Geographic Information System webpage for each county containing the focal watersheds was used to pull landowner contact information for each tax parcel. The contact information from the tax parcels was supplemented with VDCR contact information for all landowners who have agricultural conservation practices in our focal watersheds. The dataset from VDCR could not be truncated to contain only landowners with expired contracts because it was not georeferenced or related to BMP data. We combined the datasets and removed any contacts that had the same first name, middle initial, and last name and were located in the same town, resulting in a final mailing list of 889 landowners.

We mailed surveys to landowners using standard practices (Dillman et al. 2014). Survey implementation began with an initial survey invitation sent in May 2022 (Supplementary Files 1 and 2), a reminder postcard two weeks later (Supplementary File 3), and a final survey to non-respondents after two more weeks (Supplementary File 4). In March 2023, we mailed a one-page follow-up survey to gauge non-response bias (Supplementary Files 5 and 6). The survey contained three sections: the first section determined the extent of landowner persistence in using

BMPs after cost-share contracts end, the second section determined landowner characteristics that may relate to persistence, and the third section asked about landowner demographics.

Questions for the first section determined if the landowner qualified for the survey and asked questions specific to BMPs. The first two questions in the survey were used to filter out landowners who did not have BMPs or whose BMPs were still under contract. The initial filter questions were followed by questions specific to four categories of BMPs: cattle-exclusion fencing, off-stream watering structures, permanent vegetation, and pasture-management practices. Questions about each BMP category were preceded by a filter question (hereafter, the BMP filter question) to help the landowner decide if they should answer the questions related to that category. For all practices except cattle-exclusion fencing, we asked landowners to write in the type of BMP that was installed because there are multiple types of off-stream watering structure, permanent vegetation, and pasture-management practices. We then asked landowners to estimate the year the BMP was installed so we could check if it might still be under contract (see *Quantitative analysis* section below) and to understand the influence of coarse-scale variables on BMPs (e.g., differences in funding availability and changes in precipitation among years). To understand landowner attitudes towards BMPs, we asked if the practice accomplished what they wanted. Persistence in a BMP was determined by asking if landowners used their BMP after their government contract ended, where "yes" indicates persistence and "no" indicates reversion in a BMP. Lastly, to understand behavioral inertia regarding each BMP type, we asked landowners if using their BMP was easier than not using it.

The second section of the survey determined landowners' environmental attitudes, attitudes towards agencies that engage in BMP programs, motivations, environmental awareness, and social influences that may relate to BMP persistence and determined landowners' preferred mode of communication. To capture landowner environmental attitudes, we asked the extent to which they agreed or disagreed with eight statements about their attitudes towards the environment using a 5-point Likert scale (modified from Genskow and Prokopy 2011). To understand landowner attitudes toward agencies that engage in BMP programs, we then asked the extent to which landowners agreed or disagreed with three statements regarding their trust in those agencies (modified from Lutter et al. 2019). To understand landowner motivations, we asked respondents to indicate the importance (from not at all important to extremely important) of three statements each about landowners' financial and environmental concerns and (modified from Lutter et al. 2019). We also asked the extent to which they agreed or disagreed with a statement each about injunctive and descriptive norms that gauge the social influences acting on a landowner (Fishbein and Ajzen 2010). Lastly, we asked landowners to select their top three sources from a predefined list for how they preferred to receive information about soil and water conservation issues.

The third section of the survey asked about landowner demographics. We asked each landowner to estimate their farm size and income to understand how the resources available to them might influence persistence. We also provided a series of items to determine landowner age, education, gender, and race. Finally, we asked for a response to the open-ended question, "What would encourage you to use your conservation practices after state or federal contracts end?"

Quantitative analysis

We used the following criteria to determine if responses would be included in the quantitative analysis and determine the response rate. The first two filter questions appeared to confuse many landowners because 26 respondents either did not answer those questions or provided a subsequent answer that contradicted the answer they provided. For example, eight landowners indicated their BMPs were still under contract, but answered “yes” to the BMP filter question (i.e., Did you implement any [insert BMP name] as part of your state or federal contract that you are no longer legally required to use?) and provided data about BMPs. Because of these discrepancies, we assessed the eligibility of a given survey response using a combination of the BMP filter question and the responses to when the BMP was installed. If a landowner answered “yes” to the BMP filter question and indicated their structural practices (i.e., cattle-exclusion fencing, off-stream watering structures, permanent vegetation) were installed prior to 2018 or their pasture management practices were installed prior to 2021, then the respondent’s survey responses were included in the quantitative analysis. If both the BMP filter question and the date were not answered, then we used the first two filter questions to decide if the survey was eligible. Lastly, to reduce pseudoreplication, we removed any responses that came from the same landowner, had the same BMP description, and had the same answer to the questions about persistence, behavioral inertia, and BMP attitudes.

We developed indices for the responses to questions that explained a single underlying concept. All analyses were completed using the statistical software R (R Core Team 2023). We first conducted an exploratory factor analysis (EFA) using the psych package (Revell 2022) to determine the validity of averaging the environmental attitudes and motivations survey question responses. To conduct the EFA, we visually determined the number of factors to retain in the analysis using scree plots and then ran a principal components analysis with a varimax rotation. Responses to the environmental attitude survey items were best explained by one factor and responses to all but one statement loaded strongly onto that factor. Therefore, an index of environmental attitudes was created by averaging the score of the seven statements that loaded strongly. Landowners' motivations were best explained by two factors; responses to statements related to environmental motivations loaded onto the first factor, while responses to financial motivations statements loaded onto the second factor. Therefore, an index of environmental motivations and an index of financial motivations were created by averaging the responses to the statements within each group. Indices of agency attitudes and social influences were created by averaging the responses to survey questions related to each concept. We then calculated Cronbach's alpha to gauge internal consistency of the items in the indices related to environmental attitudes, environmental motivations, financial motivations, social influences, and agency attitudes (Cronbach 1951). Environmental attitudes, environmental motivations, financial motivations, social influences, and agency attitudes had alpha values of 0.88, 0.81, 0.64, 0.74, 0.70, respectively. Because the alpha value for financial motivation was below the recommended cutoff of 0.70 (Vaske 2019), we included responses to all three questions as separate variables in the analysis described below.

To determine factors that influence persistence in BMP programs, we developed a logistic regression model using the lme4 package (Bates et al. 2015). Our response variable was persistence (1) or reversion (0) in using a BMP. If any open-ended responses contradicted the indicated BMP status, then we changed the response as indicated ($n = 4$). For example, one respondent marked that an off-stream watering structure was no longer in use but said they replaced the original structure, which would actually be a case of persistence. Year since installation, BMP attitudes, behavioral inertia, financial motivations (i.e., the variables property value, income, and cost share), environmental motivations, environmental attitudes, social influences, agency attitudes, farm size (acres), income (dollars), age (years), education, gender, and race were selected as predictor variables for our model. All variables that were not highly correlated were included and assessed simultaneously in a single model. Because every respondent identified as white (two also identified as Native American), race was not included in the analysis due to low variance. The social influences scale was highly correlated with the environmental attitudes scale ($r = 0.65$), so we did not include the social influences scale in the final model because we felt that attitudes would be a stronger predictor of behavior. Similarly, behavioral inertia was highly correlated with attitudes towards each BMP ($r = 0.51$), so behavioral inertia was excluded from the final model. All continuous variables were scaled and centered to improve interpretability of the results. Also, farm size was natural log-transformed to approximate a normal distribution. Gender was treated as a categorical variable with the levels, "male", "female", and "other." The category "other" was treated as the reference and contained responses of "prefer not to say" and non-responses. Lastly, we included landowner as a random effect to account for the nested structure of the data (i.e., landowners often install more than one BMP). We used $\alpha < 0.1$ as our cutoff for statistical significance because we were more concerned about missing potential predictors of persistence (i.e., Type II error) than incorrectly interpreting a variable as significant (i.e., Type I error). Binned residual plots and confusion matrices were constructed to assess model performance.

Qualitative analysis

We coded the responses to open-ended questions, notes written in the survey margins, and data provided via phone conversations to provide greater context for interpreting the quantitative results (Table 1). We followed a modified version of the grounded-theory approach developed by Glaser and Strauss (1967) and summarized in Williams and Moser (2019). We began by creating codes as we read through the data and continued until no new codes emerged. We then assigned each code to emergent categories.

Results and discussion

We found that reported persistence of BMPs designed to protect stream health was high in southwest Virginia ($\bar{x}$ = 86% for all practices). Persistence was strongly predicted by attitudes towards BMPs and year since implementation, whereas environmental attitudes and environmental motivations weakly predicted persistence. Because of high correlation with other factors, we were unable to distinguish the roles of social influences and behavioral inertia in persistence. Future studies could focus on using different questions or social network analysis (Wood et al. 2014) to better understand the role social influences play in persistence. Similarly, different wording or placement within the survey may help determine the role of behavioral inertia in persistence. We used a relatively simple question (i.e., Is using the practice easier than not using it?) immediately after the question about attitudes, which may have influenced the responses. Our qualitative results supported the quantitative findings and also revealed that durability of BMPs and agency interactions with landowners may influence persistence.

Our results were based on 84 surveys that were considered eligible for the quantitative analysis and 96 responses for the qualitative analysis. Sample sizes for the qualitative and quantitative results differed because the quantitative results only contained data that could be used to quantify persistence, whereas the qualitative results contained any written or verbal responses. Based on the CASRO estimator, our final response rate for the quantitative analysis was 23%. Four surveys were removed because they were sent to the same landowner. Of the remaining surveys, we considered 678 to be of unknown eligibility because they were not returned. We considered 123 surveys ineligible because they either did not have BMPs, the BMPs were still under contract, or insufficient data were provided to determine BMP status. The response rate for the non-response survey was only 6% — 631 surveys were not returned, 31 were ineligible, and only 13 were eligible. We felt the results of our analyses were valid because there were no major differences between the initial survey responses and responses to the non-response survey (Appendix 1, Table 1). Additionally, we felt our model was adequate based on our assessments of fit (Appendix 1, Figure 1, Table 2).

Our logistic regression model revealed that landowners who felt BMPs accomplished what they wanted (i.e., had a positive attitude toward the BMP) were more likely to persist in using BMPs after their cost-share contracts ended ($p < 0.01$, Table 2, Figure 3). Attitudes are among the strongest predictors of behavior in general (Ajzen 1991; Stern 2000) and participation in agricultural conservation programs specifically (Dayer et al. 2018; Prokopy et al. 2019). Surprisingly, we also found a negative relationship between more general environmental attitudes and persistence ($p = 0.06$, Table 2). There could be many explanations for this counterintuitive relationship. Perhaps, landowners with strong positive environmental attitudes had higher initial expectations of their BMPs and reverted when expectations were not met, or those with weaker environmental attitudes persisted because the BMPs were beneficial for their farming operation. A simpler explanation may be that we found a spurious relationship based on the high p-value ($p = 0.06$). Similarly, Barnes et al. (2023) found that only a couple measures of landowner attitudes were related to persistence in the Conservation Reserve Program. The relationship between environmental attitudes and persistence may warrant further exploration in future research.

Landowners' positive attitudes towards BMPs may be linked to having positive experiences with BMP programs; therefore, creating positive experiences may increase persistence (Dayer et al. 2018). Landowner motivations for installing BMPs need to be aligned with the observed outcomes of the program if landowners are to feel that the program is successful and have a positive experience (Dayer et al. 2018). Environmental motivations were a marginally significant predictor of persistence in our logistic regression model (*p* = 0.09, Table 2), and more landowners judged BMP success based on observed environmental benefits (*n* = 19) than financial benefits (*n* = 14; Table 1). The following quote exemplifies a landowner who is primarily motivated by environmental concerns: "Programs that are very beneficial are self-perpetuating. Clean water is essential to life in all forms." In contrast, a landowner who may be more driven by financial concerns is illustrated by this quote: "We will maintain what we have because it improves the quality of life for our livestock & improves our farm greatly." Similar to environmental attitudes, this relationship could be spurious, suggesting that future studies could further investigate the relationship between environmental motivations and persistence. Lutter et al. (2019) studied intentions to persist in forest conservation programs and found that environmental motivations were also predictors of persistence. In contrast to our results, Lutter et al. (2019) also found that financial motivations were significant predictors of persistence.

Persistence varied by BMP type, which may reflect the durability or quality of the different practices. Eleven landowners remarked about the poor quality of some BMPs. Vegetative practices, which were typically riparian buffers, had the lowest level of persistence at 73.6%, and five landowners mentioned that the trees they planted died or were destroyed by wildlife. Cattle-exclusion fencing had the next lowest level of persistence (84.2%), followed by off-stream watering structures (93.9%) and pasture management (93.9%). Cases of reversion for fencing and watering structures were often due to poor construction, as demonstrated by the following quote, "The contractor that installed my water system apparently failed to install piping correctly. I had many leaks due to joint leaks. At times my water bill/usage was outragess [sic]. I was forced to go back to stream watering." In some instances, BMP failure did not lead to reversion when landowners had the resources to continue using the practice and felt it was important enough. For example, one landowner remarked, “When they [referring to a water structure] work there is no reason not to use them. I only replaced my ball tank because it became too much trouble to keep them working and they froze sold in the winter. Maybe insist on using approved tanks of higher quality. I am still using the tire tank located in the same place the ball tanks were.” However, not all landowners have the means to replace BMPs that no longer work, as revealed by one landowner: “We would have continued to use the well, but it no longer works, and we couldn't afford to have it replaced.”

The way state and federal agencies interface with landowners can also play a role in landowners’ decisions to persist. We hypothesized that agency trust would be a significant predictor of persistence because developing trust among stakeholders is an important component in achieving environmental sustainability in general (Stern and Coleman 2015) and BMP programs specifically (Dayer et al. 2018). Trust was not a significant predictor of persistence ($p > 0.10$); however, our qualitative results support our hypothesis. Landowners discussed the role of honesty ($n = 2$), distrust of government/agencies ($n = 8$), and the service that they received from specific agency personnel ($n = 8$) in decisions regarding persistence. For example, one landowner wrote, “I do not have much confidence in government programs, BUT without this program I would not be able to produce 10,000–15,000 lb of beef for consumers. The USDA office in Abingdon VA with Bill Moss and Jason Haynes was very helpful and professional.” The non-significant quantitative results may simply reflect our low sample size or our question wording. For example, instead of focusing our questions on landowner perceptions of specific agency personnel, we might have asked landowners how they perceive entire agencies.

Lastly, we found that persistence may be influenced by coarse-scale factors. Unsurprisingly, persistence was negatively associated with year since installation (Table 2, Figure 4), which may reflect that landowners are more likely to revert as practices age. However, the relationship between year and persistence may also reflect differences in environmental conditions among years (e.g., a large flood), political changes (Liu et al. 2018), or changes in agency personnel that landowners trusted (see quote in previous paragraph). Unfortunately, our data were too sparse (i.e., not enough responses during each year) to treat year as a categorical variable, which would allow us to explore these concepts in more detail. We also found that persistence was high compared to reversion for Copper Creek but lower for other watersheds (Figure 2). Landowners' perceptions of environmental issues, agency presence, and/or the biophysical setting could differ among the watersheds and influence persistence (Liu et al. 2018). Integration of ecological data (e.g., soil type) could help understand the role of those factors in persistence, but we were unable to relate landowner contact information to where the BMP was installed (i.e., landowner home addresses may be in different locations than their farms). If geographic coordinates of each farm were available, we could have assessed how soil type, flood frequency, or land susceptibility to erosion influenced persistence.

Summary and conclusions

Our results add to the growing academic literature about rates of BMP persistence in agricultural conservation programs and its contribution to stream health goals. Other studies estimated persistence to range from 31% to 85%, but all except one focused on behavioral intentions rather than actual persistence, which may not align perfectly (Dayer et al. 2018). Jackson-Smith et al. (2010) found persistence to be 83% in the Little Bear River watershed of northern Utah, United States. Our estimate of 86%, and the BMPs assessed, are quite similar to those of Jackson-Smith et al. (2010) whose data contained similar numbers of fencing and prescribed grazing but fewer instances of off-stream watering structures. Our estimate may be slightly higher because Jackson-Smith et al. (2010) verified persistence in the field but we did not. Barnes et al. (2020, 2023) found 67% of landowners persisted in cropland retirement after enrollment in the Conservation Reserve Program. However, cropland retirement is quite different than the practices we studied, which may explain the lower rates of persistence. Our results represent an initial assessment of BMP persistence in southwest Virginia, which can feed into ecological models that distinguish the relative importance of promoting persistence versus initial adoption of BMPs in achieving stream health goals.

We found that using mixed methods (i.e., combining qualitative and quantitative approaches) is crucial for understanding landowners' behaviors. Mixed methods allow researchers to use narrative to add meaning to numbers, use numbers to add precision to narrative, and allow results to be corroborated (Johnson and Onwuegbuzie 2004). We initially intended to focus only on a quantitative analysis but phone calls and notes left by the landowners revealed a much more nuanced picture of persistence that would not have been revealed by a quantitative analysis alone. For example, one landowner marked in the survey that they no longer used a practice (i.e., reversion) but then wrote a note indicating that they had built new wells, which would actually be a case of persistence. We encourage future studies to explore mixed-methods approaches that allow for landowners to detail their thoughts and opinions. For instance, future studies could include both open- and closed-ended questions in a survey or complement survey work with interviews. Our survey did include an open-ended question but would have benefited from additional questions that were practice-specific and explored why landowners chose to revert.

Our results have practical implications for state and federal agencies that work directly with landowners. If encouraging persistence is identified as a policy or programmatic goal, then our results reveal some areas that could be explored for creating behavior-change strategies. Allocating more funding for continuing BMPs already initiated (as opposed to building new practices) could be an effective first step in increasing persistence, especially for landowners who have limited resources. However, our results reveal that in many cases persistence could be encouraged without financial incentives because many landowners (n = 20) were interested in non-financial forms of support from agencies, such as additional information. Targeted messaging (e.g., Metcalf et al. 2019; Reddy et al. 2020) could be used to encourage persistence in those cases where landowner finances are not limiting. Based on our results, targeted messaging could focus on the benefits that persistence accrues for either the farm itself or the greater environment, depending on specific landowner motivations. If targeted messaging is used, our survey revealed that the preferred means of communication were printed materials and direct conversations with professionals (Table 3).

Persistence could be encouraged by developing a method to track when farm tenure changes and ensuring that responsibility for BMP maintenance is transferred. Technically, the original applicant to the BMP program is liable for maintaining practices when farm tenure changes (unless the Agricultural Best Management Practice Maintenance Agreement Transferring Responsibility for Best Management Practice form is completed), but realistically the BMPs are often no longer used. Our qualitative analysis revealed 20 cases (21%) where the landowner either no longer farmed or the farm was sold. For example, one landowner stated, “The previous owner of the property had waterers installed”, but then indicated they did not have BMPs and were not required to maintain them. In many cases we could not verify that these lands truly had BMPs installed, or the land was still being farmed, but it is highly likely that these were instances of reversion. If so, then persistence could be increased by facilitating the appropriate transfer of the BMP liability, possibly starting with ensuring that new landowners are aware of their obligations.

In summary, our paper adds to the growing literature about persistence in BMPs after cost-share contracts end and provides some practical ways that agencies could promote persistence. Our results indicated that persistence is high for the practices we investigated, which evidences the commitment of farmers to the environment and the quality of work done by state and federal agencies to interface with landowners and install BMPs. Although stream health goals have not been met in many locations, widespread participation in BMP programs has the potential to balance agricultural production with stream health.

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References

Ajzen, I. 1991. The theory of planned behavior. Organizational Behavior and Human Decision Processes 50(20):179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Allan, J.D. 2004. Landscapes and riverscapes: The influence of land use on stream ecosystems. Annual Review of Ecology, Evolution, and Systematics 35:257–284. https://doi.org/10.1146/annurev.ecolsys.35.120202.110122

Angermeier, P.L., L.A. Krometis, M.J. Stern, and T.L. Hemby. 2021. Exploring relationships among stream health, human well-being, and demographics in Virginia, USA. Ecological Indicators 121:107194. https://doi.org/10.1016/j.ecolind.2020.107194

Barnes, J. C., M. Sketch, A.R. Gramza, M.G. Sorice, R. Iovanna, and A.A. Dayer. 2020. Land use decisions after the Conservation Reserve Program: Re-enrollment, reversion, and persistence in the southern Great Plains. Conservation Science and Practice 2(9):1–15. https://doi.org/10.1111/csp2.254

Barnes, J. C., A.A. Dayer, A. R. Gramza, M. Sketch, A.M. Dwyer, and R. Iovanna. 2023. Pathways to conservation persistence: Psychosocial drivers of durable grasslands following the Conservation Reserve Program. 78(6):486–499. https://doi.org/10.2489/jswc.2023.00215

Douglas B., M. Maechler, B. Bolker, and S. Walker. 2015. Fitting linear mixed-effects models using lme4. Journal of Statistical Software 67(1):1–48. doi:10.18637/jss.v067.i01.

Bracmort, K.S., M. Arabi, J.R. Frankenberger, B.A. Engel, and J.G. Arnold. 2006. Modeling long-term water quality impact of structural BMPs. Transactions of the ASABE 49(2):367–374. https://doi.org/10.13031/2013.20411

Bracmort, K.S., B.A. Engel, and J.R. Frankenberger. 2004. Evaluation of structural best management practices 20 years after installation: Black Creek Watershed, Indiana. Journal of Soil and Water Conservation 59(5):191–196.

Byers, H.L., M.L. Cabrera, M.K. Matthews, D.H. Franklin, J.G. Andrae, D.E. Radcliffe, M.A. McCann, H.A. Kuykendall, C.S. Hoveland, and V.H. Calvert. 2005. Phosphorus, sediment, and *Escherichia coli* loads in unfenced streams of the Georgia Piedmont, USA. Journal of Environmental Quality 34(6):2293–2300. https://doi.org/10.2134/jeq2004.0335

Chesapeake Bay Foundation. 2023. 2022 State of the Blueprint. https://www.cbf.org/how-we-save-the-bay/chesapeake-clean-water-blueprint/state-of-the-blueprint/.

Congressional Research Service. 2019. The 2018 Farm Bill (P.L. 115-334): Summary and Side-by-Side Comparison. https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://crsreports.congress.gov/product/pdf/R/R45525&ved=2ahUKEwip37iy07eFAxUPGtAFHXjXDpQQFnoECBcQAQ&usg=AOvVaw2tIOyiFxTd2G1L-Y0-2zas

Cronbach, L.J. 1951. Coefficient alpha and the internal structure of tests. Psycometrika 16:297–334.

Dayer, A.A., S.H. Lutter, K.A. Sesser, C.M. Hickey, and T. Gardali. 2018. Private landowner conservation behavior following participation in voluntary incentive programs: Recommendations to facilitate behavioral persistence. Conservation Letters 11(2):1–11. https://doi.org/10.1111/conl.12394

Dillman, D.A., J.D. Smyth, and L.M. Christian. 2014. Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method, 4th ed. Hoboken, NJ: John Wiley & Sons, Inc.

Epanchin-Niell, R.S., D.B. Jackson-Smith, R.S. Wilson, M. Ashenfarb, A.A. Dayer, V. Hillis, G.D. Iacona, E.M. Markowitz, S.T. Marquart-Pyatt, and T. Treakle. 2022. Private land conservation decision-making: An integrative social science model. Journal of Environmental Management 302:113961. https://doi.org/10.1016/j.jenvman.2021.113961

Fishbein, M. and I. Ajzen. 2010. Predicting and Changing Behaviour: The Reasoned Action Approach. New York, NY: Psychology Press. https://doi.org/10.4324/9780203838020

Genskow, K. and L. Prokopy. 2011. The Social Indicator Planning and Evaluation System (SIPES) For Nonpoint Source Management: A Handbook for Watershed Projects, 3rd ed. Great Lakes Regional Water Program.

Glaser, B.G. and A. Strauss. 1967. The Discovery of Grounded Theory: Strategies for Qualitative Research. Chicago: Aldine.

Herman, M.R., A.P. Nejadhashemi, F. Daneshvar, D.M. Ross, S.A. Woznicki, Z. Zhang, and A. Esfahanian. 2015. Optimization of conservation practice implementation strategies in the context of stream health. Ecological Engineering 84:1–12. https://doi.org/10.1016/j.ecoleng.2015.07.011

Jackson-Smith, D.B., M. Halling, E. de la Hoz, J.P. McEvoy, and J.S. Horsburgh. 2010. Measuring conservation program best management practice implementation and maintenance at the watershed scale. Journal of Soil and Water Conservation 65(6):413–423. https://doi.org/10.2489/jswc.65.6.413

Johnson, B.R., and A.J. Onwuegbuzie. 2004. Mixed methods research: A research paradigm whose time has come. Educational Researcher 33(7):14–26. https://doi.org/10.3102/0013189X033007014

Kerrick, B., E. Sandusky, B. De Corte, and E. Hostetler. 2022. Agriculture and Local Food Economies in the Appalachian Region. Washington, DC: Appalachian Regional Commission.

Knowles, J.E., and C. Frederick. 2023. merTools: Tools for Analyzing Mixed Effect Regression Models. R package version 0.6.1. https://CRAN.R-project.org/package=merTools

Liu, T., R.J.F. Bruins, and M.T. Heberling. 2018. Factors influencing farmers' adoption of best management practices: A review and synthesis. Sustainability 10(2):1–26. https://doi.org/10.3390/su10020432

Liu, Y., B.A. Engel, D.C. Flanagan, M.W. Gitau, S.K. McMillan, and I. Chaubey. 2017. A review on effectiveness of best management practices in improving hydrology and water quality: Needs and opportunities. Science of the Total Environment 601–602:580–593. https://doi.org/10.1016/j.scitotenv.2017.05.212

Lutter, S.H., A.A. Dayer, and J.L. Larkin. 2019. Young forest conservation incentive programs: Explaining re-enrollment and post-program persistence. Environmental Management 63(2):270–281. https://doi.org/10.1007/s00267-018-1127-1

McKenzie-Mohr, D. 2011. Fostering Sustainable Behavior: An Introduction to Community-Based Social Marketing, 3rd ed. Gabriola Island: New Society Publishers.

Meals, D.W., S.A. Dressing, and T.E. Davenport. 2010. Lag time in water quality response to best management practices: A review. Journal of Environmental Quality 39:85–96. https://doi.org/10.2134/jeq2009.0108

Metcalf, A.L., J.W. Angle, C.N. Phelan, B.A. Muth, and J.C. Finley. 2019. More "bank" for the buck: Microtargeting and normative appeals to increase social marketing efficiency. Social Marketing Quarterly 25(1):26–39. https://doi.org/10.1177/1524500418818063

Meyer, J.L. 1997. Stream health: Incorporating the human dimension to advance stream ecology. Journal of the North American Benthological Society 16(2):439–447. https://doi.org/10.2307/1468029

NRCS (Natural Resources Conservation Service). n.d. Conservation Practice Standards. https://www.nrcs.usda.gov/resources/guides-and-instructions/conservation-practice-standards.

NRCS. n.d. Conservation Practice Data Entry System. https://cpdes.sc.egov.usda.gov/publicView.

OECD/FAO (Organisation for Economic Co-operation and Development and Food and Agriculture Organization). 2023. OECD-FAO Agricultural Outlook 2023-2032. Paris: OECD Publishing. https://doi.org/10.1787/08801ab7-en

Pollard, K., and L.A. Jacobsen. 2020. The Appalachian Region: A Data Overview from the 2014–2018 American Community Survey. Washington, DC: Appalachian Regional Commission.

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

QGIS Development Team. 2023. QGIS Geographic Information System. QGIS Association. http://www.qgis.org

R Core Team. 2023. R: A Language and Environment for Statistical Computing. Vienna, Austria.

Reddy, S.M.W., C. Wardropper, C. Weigel, Y.J. Masuda, S. Harden, P. Ranjan, J.M. Getson, L.A. Esman, P. Ferraro, and L. Prokopy. 2020. Conservation behavior and effects of economic and environmental message frames. Conservation Letters 3:e12750 https://doi.org/10.1111/conl.12750

Reid, J. L. 2018. *Restoration Ecology's* silver jubilee: Big time questions for restoration ecology. Restoration Ecology 26(6):1029–1031. https://doi.org/10.1111/rec.12883

Revell, W. 2022. Procedures for Psychological, Psychometric, and Personality Research. R package version 2.2.9. https://CRAN.R-project.org/package=psych

Sowa, S.P., M. Herbert, S. Mysorekar, G.M. Annis, K. Hall, A.P. Nejadhashemi, S.A. Woznicki, L. Wang, and P.J. Doran. 2016. How much conservation is enough? Defining implementation goals for healthy fish communities in agricultural rivers. Journal of Great Lakes Research 42(6):1302–1321. https://doi.org/10.1016/j.jglr.2016.09.011

Stern, M.J., and K.J. Coleman. 2015. The multidimensionality of trust: Applications in collaborative natural resource management. Society & Natural Resources 28(2):117–132. https://doi.org/10.1080/08941920.2014.945062

Stern, P.C. 2000. Toward a coherent theory of environmentally significant behavior. Journal of Social Issues 56(3):407–424.

USDA. 2024. Census of Agriculture: Virginia State and County Data. Washington, DC: USDA.

USCB (United States Census Bureau). 2023. Census Bureau Tables. https://data.census.gov/table

USEPA (United States Environmental Protection Agency). 2023. National Rivers and Streams Assessment: The Third Collaborative Survey. EPA 841-R-22-004. Washington, DC: USEPA, Office of Water and Office of Research and Development. https://riverstreamassessment.epa.gov/webreport

USGS (United States Geological Survey). 2019. NLCD 2016 Land Cover (CONUS). https://www.mrlc.gov/data/nlcd-2016-land-cover-conus

USGS. 2024. Hydrologic Unit Maps. https://water.usgs.gov/GIS/huc.html

Vaske, J.J. 2019. Survey Research and Analysis, 2nd ed. Champaign, IL: Sagamore-Venture Publishing.

VDCR (Virginia Department of Conservation and Recreation). 2023. Virginia Agricultural Cost Share Manual. https://consapps.dcr.virginia.gov/htdocs/agbmpman/agbmptoc.htm.

VDCR. 2024. Virginia Agricultural BMP and CREP Database Query Form. https://casdsis.dcr.virginia.gov/htdocs/progs/BMP_query.aspx.

Wang, L., J. Lyons, and P. Kanehl. 2002. Effects of watershed best management practices on habitat and fish in Wisconsin streams. Journal of the American Water Resources Association 38(3):663–680. https://doi.org/10.1111/j.1752-1688.2002.tb00988.x

Williams, M., and T. Moser. 2019. The art of coding and thematic exploration in qualitative research. International Management Review 15(1):45–55.

Wood, B.A., H.T. Blair, D.I. Gray, P.D. Kemp, P.R. Kenyon, S.T. Morris, and A.M. Sewell. 2014. Agricultural science in the wild: A social network analysis of farmer knowledge exchange. PLoS ONE 9(8):e105203. https://doi.org/10.1371/journal.pone.0105203

Tables

Table 1. We coded open-ended questions in the survey, notes written in the survey margins, and phone conversations, then identified six emergent categories using a modified grounded-theory approach. Descriptions of the criteria used to assign the codes and examples of quotes that were given the code are provided. BMP = best management practice

Category	Code	Description	Example
Success (n = 23)	Improve (n = 14)	The BMP improved the operation.	"…without this program I would not be able to produce 10,000–15,000 lb of beef for consumers."
	Environment (n = 19)	The BMP improved environmental quality.	"Very exciting to witness the wildlife and bird benefitting from both programs on approx. 28 acres here."
	Success (n = 2)	The reason for BMP success was not specified.	"Practice was successful and you can see the results."
Values (n = 14)	Distrust (n = 5)	Government or agency distrust was mentioned.	"Our concern is government confiscation of waterways by the Federal Government (as attempted by President Obama). Those who own the land are the best stewards of the land, not a bureaucrat of Washington, DC sitting at a desk."
	Future Generations (n = 2)	Choices were influenced by future generations.	"Yes, practices are put in place to help ensure future generations can have & enjoy the resource that so many currently abuse."
	Equity (n = 3)	Funds should be more equitably distributed.	"The contracts should be spread out among all farms not just a few that seem to set the bulk of state or federal funds!!"

	Common Sense (n = 3)	A common-sense approach to management should be used.	"Common sense approach to reinstall fence practices upon flood or wildlife damage during time of contract."
	Honest (n = 2)	Honesty, or dishonesty, of the agency personnel was mentioned.	"I was told upfront what the practices would provide for my property and me personally. In turn I was told what I was expect to provide from my end of the agreement."
Support (n = 39)	Service (n = 8)	The landowner received quality service from agency personnel.	"The USDA office in Abingdon VA with Bill Moss and Jason Haynes was very helpful and professional."
	Money (n = 23)	Additional funding was desired.	"More payments to farmer."
	Reinstall (n = 6)	Practices should be reinstalled or fixed if damage occurs during contract.	"Common sense approach to reinstall fence practices upon flood or wildlife damage during time of contract."
	Information (n = 7)	More information from agencies was desired.	"To meet with local agency to see other opportunity."
	Time (n = 2)	Time was mentioned as a limiting resource.	"Finding labor, time, & money to continue."
	Labor (n = 2)	Labor was mentioned as a limiting resource.	"Finding labor, time, & money to continue."
	Assistance (n = 14)	The landowner desired additional assistance from agency personnel but was not specific.	"Continued consultation with NRCS."
Turnover (n = 20)	Death (n = 6)	The landowner had died.	"[name redacted] passed away in 2019 and I sold the farm."
	Sold (n = 10)	The land had been sold.	"I sold the farm and retired in 2014."
	Retired (n = 6)	The landowner retired from farming.	"[name redacted] is 92 years old, so she no longer farms."

	Old (n = 6)	Age played a role in their decisions.	"I am old and no longer able to chase our hills and valleys."
	Inherit (n = 2)	The farm was inherited.	"[name redacted] is deceased. I'm his son, and now manage the farm."
Practice (n = 11)	Died (n = 5)	Trees died due to flooding, beaver damage, etc.	"The tree planting in fenced off areas failed miserably. High mortality rate and area overtaken with invasive species."
	Quality (n = 5)	The quality, or lack thereof, of practices was mentioned.	"I think the fences that is put around the streams should be construcked [sic] for years to come."
	Broke (n = 5)	The BMP broke during the contract.	"When they work there is no reason not to use them. I only replaced my ball tank because it became too much trouble to keep them working and they froze sold in the winter."
	Ease (n = 2)	The ease of practice use was a factor in decision making.	"Ease of management."
Programmatic (n = 7)	Penalty/Reward (n = 1)	Responsible management choices should be rewarded and irresponsible farming choices should be met with penalties.	"Irresponsible farming should have negative financial consequences/penalties, not promoting the idea that you have the run the livestock in the streams before you qualify for cost share."
	Flexibility (n = 5)	More flexibility or options regarding conservation practices was desired.	"Fewer restrictions on what the projects provide."
	Ambiguous (n =1)	Program rules were ambiguous.	"I didn't reinroll because the new CREP rules were too ambiguous."
	Wait (n = 1)	Long wait time for payments or installation.	"Long wait times and delayed payment on programs offered should be adjusted to help farmers implement programs."

Table 2. Results from a logistic regression model predicting landowner persistence (1) or reversion (0) for 285 responses from 84 landowners. Estimates for each coefficient (± standard deviation) are reported on the logit scale. Coefficients are defined in the *Quantitative Analysis* section of Materials and Methods. Estimates for non-significant results (NS) are not shown (p > 0.1).

Coefficient	Estimate	p
Intercept	3.62 ± 1.62	0.03
Year	-1.15 ± 0.40	< 0.01
BMP attitude	1.65 ± 0.37	< 0.01
Property value	NS	0.18
Income	NS	0.19
Cost-share	NS	0.32
Environmental motivation	0.94 ± 0.55	0.09
Environmental attitude	-1.31 ± 0.70	0.06
Trust	NS	0.36
Acre	NS	0.50
Age	NS	0.56
Education	NS	0.24
Male	NS	0.85
Female	NS	0.91

Table 3. Landowners preferred ways to receive information about soil and water conservation issues. Each of 84 landowners selected their top three sources. Entries under "Number" reflect the total number of selections across landowners. Respondents that selected "Other" suggested they preferred to receive information through email and experienced farmers.

Source	**Number**
Printed materials	73
Conversation with conservation professionals	44
Workshop	31
Other internet sources	20
Conversation with neighbors or friends	20
Social media	11
Conversation with family members	6
Television	2
Other	2

Figures

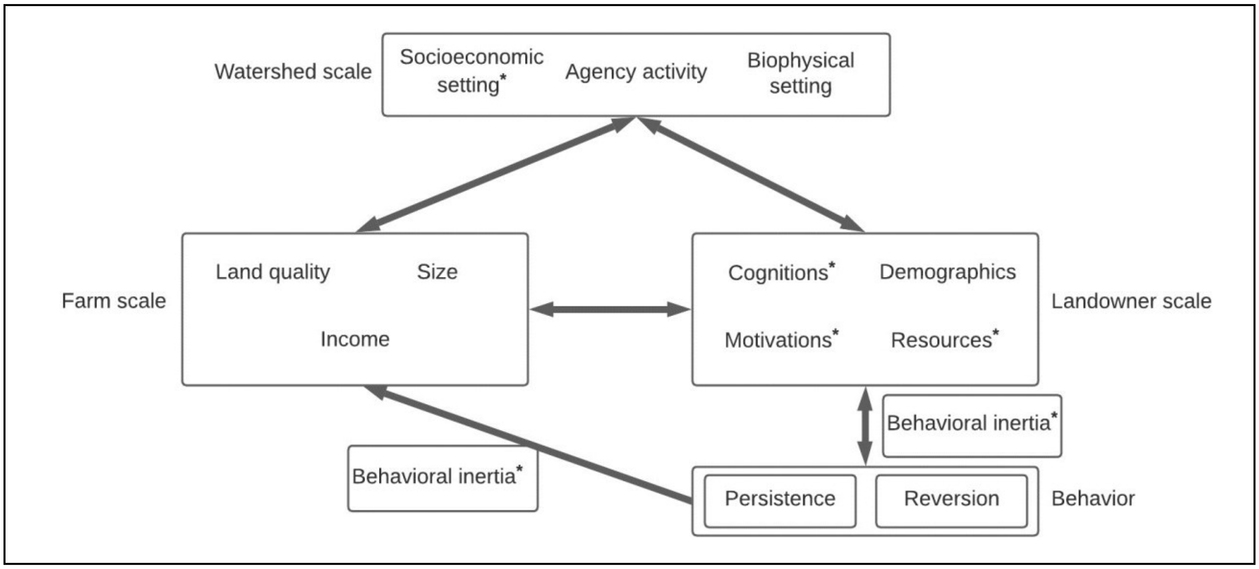

Figure 1. A complex set of hierarchical factors influence a landowner's decision to persist or revert in implementing best management practices at the conclusion of cost-share funding. Factors at the watershed scale influence factors at both the farm and landowner scales, and factors at the landowner scale ultimately influence a landowner's decision to persist or revert, which can affect the farm or the landowner (direction of influence is denoted by arrows). The asterisks denote the pathways from Dayer et al. (2018) through which persistence can be influenced. For our purposes, the social influences pathway from Dayer et al. (2018) is a part of the socioeconomic setting.

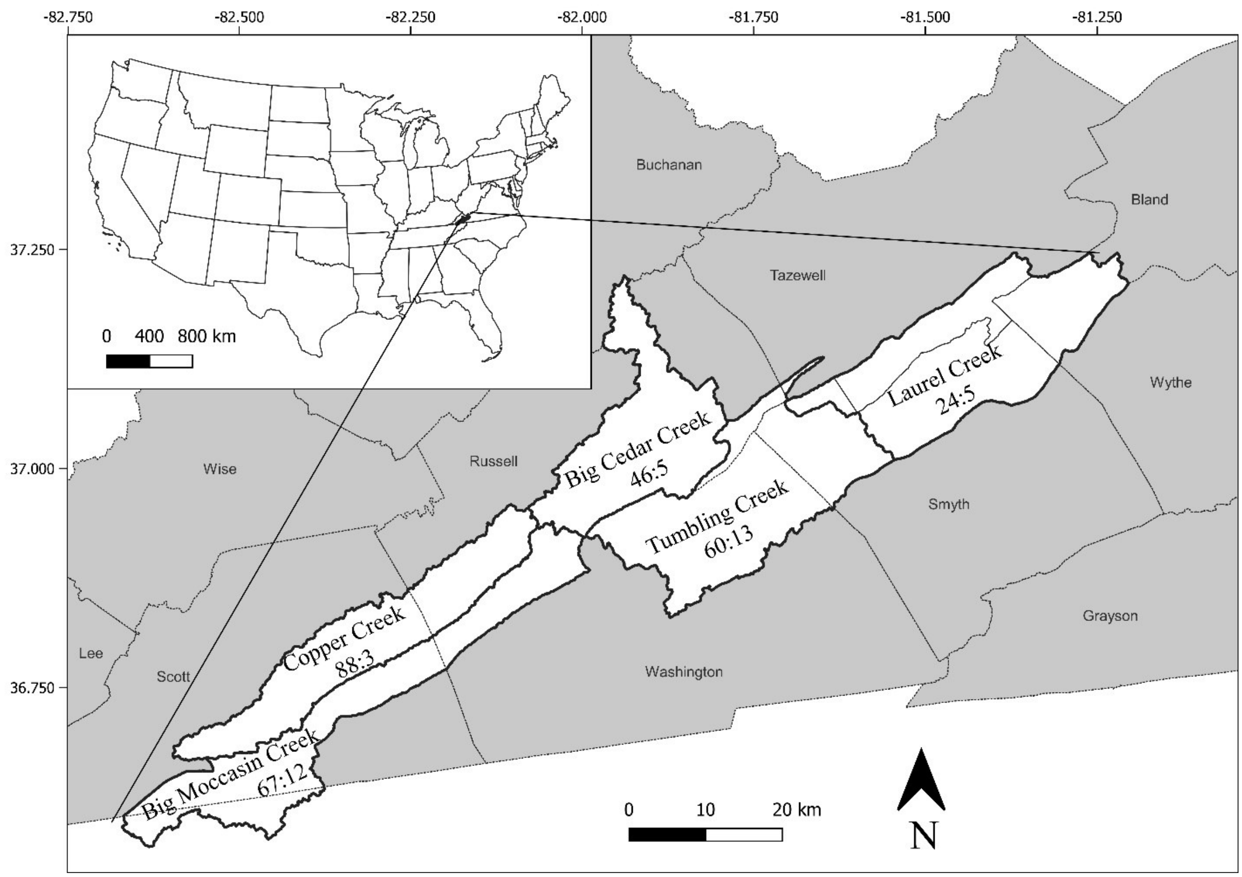

Figure 2. The watersheds (white shapes with darker outline) and counties (grey shapes with lighter outline) in southwest Virginia, United States, where we conducted mail surveys to understand landowner persistence in using agricultural best management practices (BMPs) after cost-share contracts ended. The border of Russel and Washington counties overlaps the southern borders of Big Cedar Creek and Big Moccasin Creek watersheds. The ratios represent the number of BMPs for which landowners persisted in using after their cost-share contracts ended compared to the number of BMPs for which landowners reverted to previous farming practices.

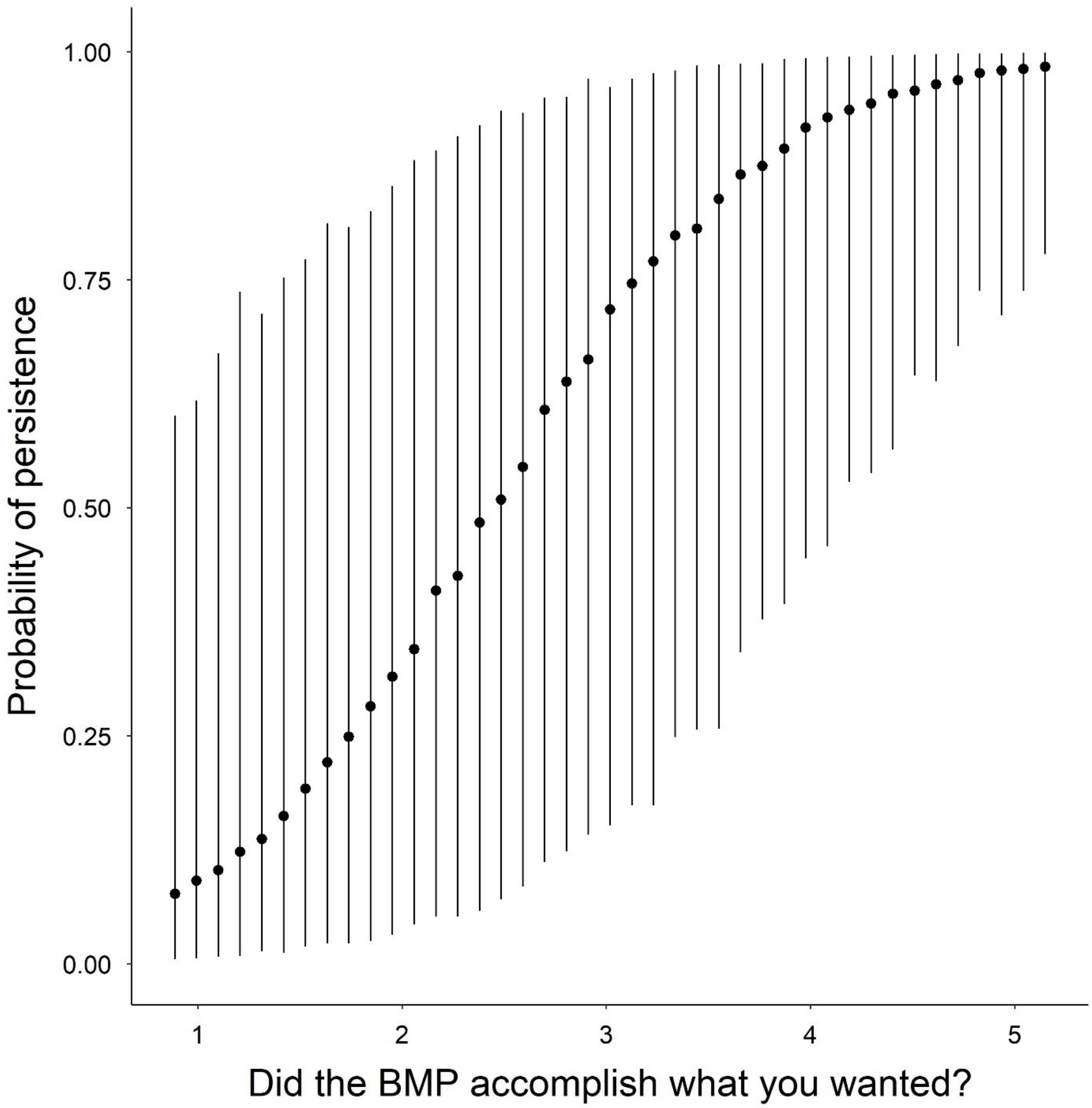

Figure 3. Modeled relationship between response to the question "Did the BMP accomplish what you wanted?" and probability of persistence (1) or reversion (0) for 285 responses from 84 landowners ($p < 0.01$). The response was recorded on a Likert scale from 1 to 5, where 1 = strongly disagree and 5 = strongly agree. Dots indicate the predicted value and lines indicate 90% prediction intervals. The predictInterval function from the library merTools (Knowles and Frederick 2023) was used to predict persistence from a simulated dataset where all other

continuous variables were held at mean levels, the variable gender was set to “male”, and the random effect was set to the landowner with the most responses. BMP = best management practice

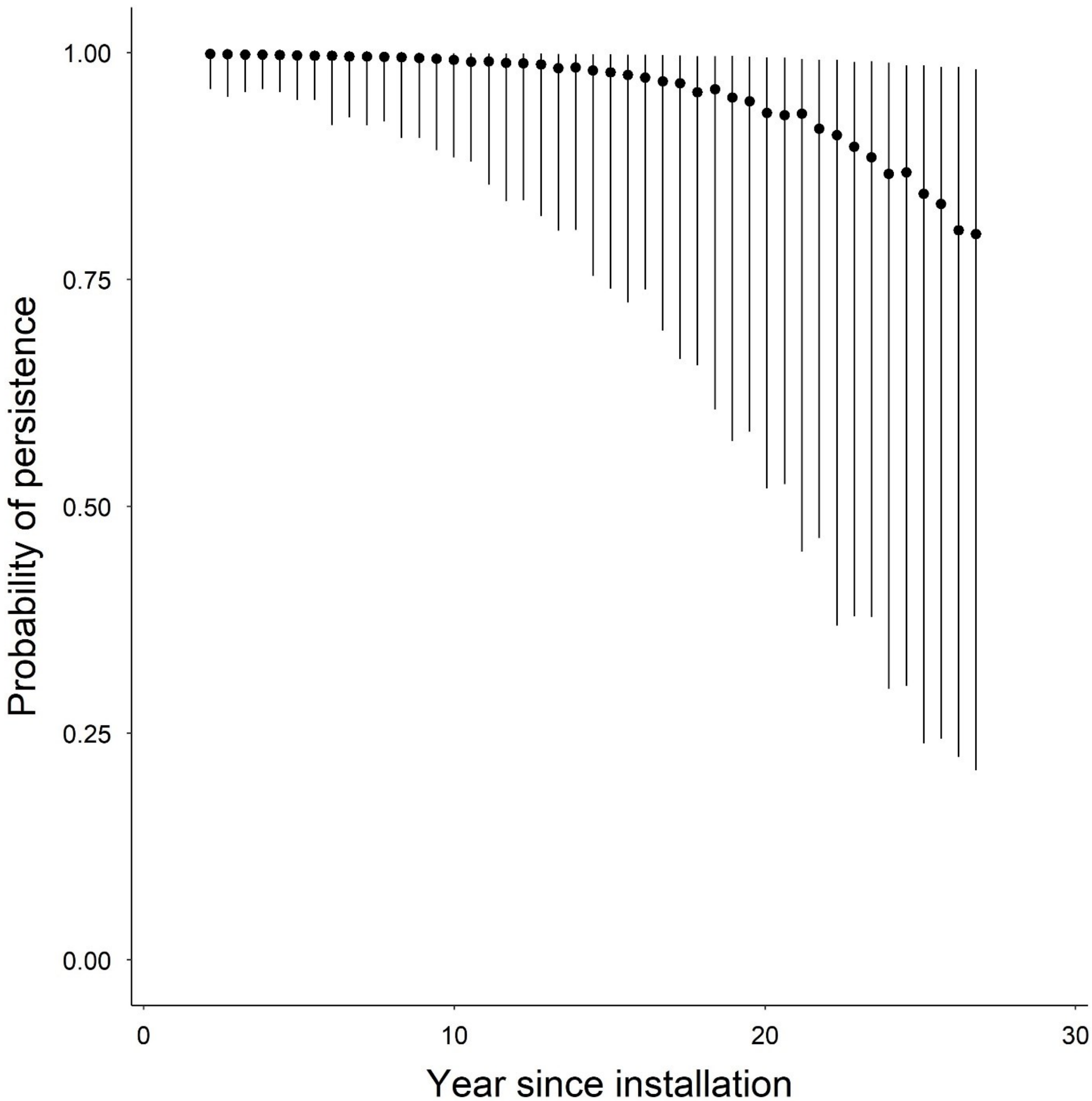

Figure 4. Modeled relationship between year since installation and probability of persistence (1) or reversion (0) for 285 responses from 84 landowners ($p < 0.01$). Dots indicate the predicted value and lines indicate 90% prediction intervals. The predictInterval function from the library merTools (Knowles and Frederick 2023) was used to predict persistence from a simulated dataset where all other continuous variables were held at mean levels, the variable gender was set to "male", and the random effect was set to the landowner with the most responses.

Appendix

Table 1. Demographic comparison between respondents to the initial survey and respondents to the non-response survey.

Category	Response	Survey	Non-response
Sex	Male	69	10
	Female	10	3
	Prefer not to say/no response	5	None
Education	< High school	1	None
	High school diploma	29	5
	Associate's degree	15	4
	Undergraduate degree	19	1
	Graduate or professional degree	13	2
	Prefer not to answer/no response	7	None
Farm size	Open-ended	173.1 ± 192.7 acres	114.7 ± 170.5 acres
Age	Open-ended	66.1 ± 10.6 years	60.9 ± 12.6 years

Table 2. The confusion matrix revealed that the logistic regression model predicted persistence correctly 89% of the time. This table shows the number of times that persistence and reversion in the actual data were predicted correctly by the model. For example, 12 times the data showed that a landowner reverted, and the model predicted reversion would occur, but 6 times the data showed that a landowner reverted, and the model predicted they would persist.

		Actual values	
		Reversion	Persistence
Predicted values	Reversion	12	26
	Persistence	6	241

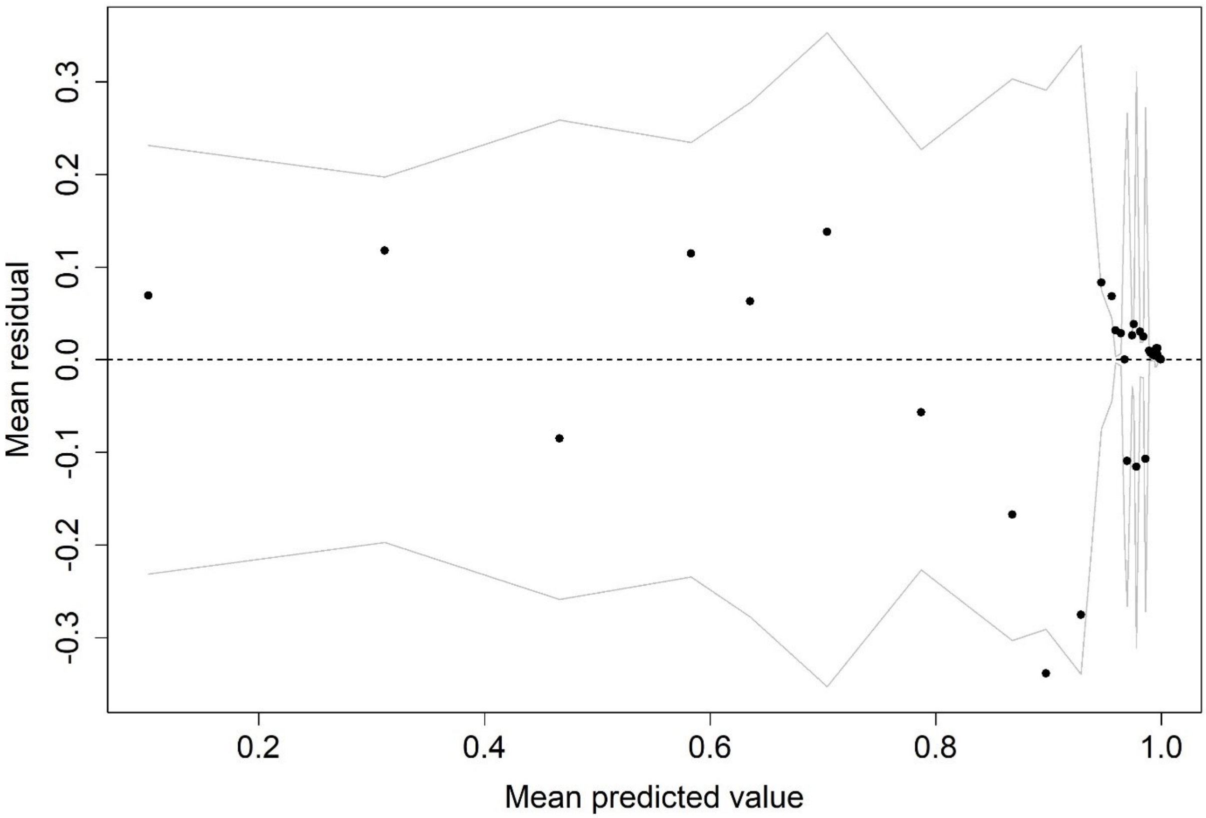

Figure 1. Binned residual plot used for assessing the performance of the logistic regression model. The data have been divided into 40 bins and the mean residual value versus the mean predicted value have been plotted for each bin. If the model were actually true, 95% of the binned residuals should fall within the gray lines, which represent ±2 standard-error bounds. The plot revealed that much of the data were clustered around 1.0, which was expected because most survey responses indicated persistence. Further, >95% of the binned residuals fall outside of the gray lines. These trends are slightly concerning; therefore, caution is urged when interpreting the model output because predictions may be unreliable. Despite the concerning trends, we felt the model was acceptable for interpreting the broad patterns, especially when supported by the qualitative results.

CONCLUSION

My research aimed to understand how conservation practices influence stream health with the ultimate goal of providing insight into how conservation practice efficacy can be improved. Improving efficacy of conservation practices is necessary for protecting stream health while producing food. Often, studies of conservation practice efficacy are disciplinary in nature and focus on either the social or natural sciences, but conservation practice efficacy is simultaneously influenced by social and ecological factors. Therefore, a social-ecological framework was used to combine approaches from ecological engineering, conservation social science, and stream ecology. Integrating these disciplines led to a more robust understanding of conservation practice efficacy. For example, the SWAT+ model revealed that nitrogen is likely moving through subsurface pathways, which may explain why greater conservation practice density did not decrease nitrogen to levels that were not limiting for biota (as indicated by the models described in Chapter 2). Therefore, based on the results from Chapter 3, agricultural producers could be encouraged to continue using conservation practices after their contracts end by focusing messaging from agencies on how the practice accomplishes the producer's goals. Future research that aims to improve agricultural conservation programs would benefit from research that integrates both social and natural sciences to understand what conservation practices are needed, where they are needed, and ways facilitate voluntary use of practices.

Key findings

Chapter 1 identified landscape factors that influence pollutant dynamics, which is an initial step to understanding where conservation practices are most needed and what practices will be most effective. The SWAT+ model revealed that increasing water movement through the soil led to improved estimates of streamflow — likely mimicking the karst topography of southwest Virginia. Because nitrate is dissolved in water and most of the nitrogen in southwest Virginia is nitrate, nitrogen is also moving through subsurface pathways. However, the SWAT+ model unsatisfactorily predicted nitrogen loads in streams. The SWAT+ model also unsatisfactorily predicted sediment loads in streams, which may indicate that sediment loads are being derived from the streambank rather than field runoff as assumed by sediment models within SWAT+ (Boomer et al., 2008). These results serve to advance SWAT+ application by demonstrating the need to develop more accurate models of nitrogen movement through subsurface pathways and sediment erosion from streambanks. Further, these results in conjunction with Chapter 2, reveal which conservation practices could be beneficial for improving stream health in karst environments with cattle grazing (discussed in the section Synthesis).

Building on Chapter 1, my second chapter investigated stream health responses to conservation practice installation. Ultimately, biotic responses provide the best indicator of stream health, but many studies only focus on water quality responses to conservation practice installation and those that do focus on biotic responses provide ambiguous results (e.g., Holmes et al., 2016; Sowa et al., 2016). Ambiguous results may stem from failure to account for the complex pathways through which biota are influenced by conservation practice installation. I found that current conservation practice densities can stabilize streambanks and total suspended solids (Chapter 2, Figure 3), but those changes were not translated to decreased embeddedness or improved biotic indices (Chapter 2, Figures 9 and 10). Biotic indices may not have responded to changes in water quality and habitat because conditions did not meet thresholds where the biotic assemblage changes (Chapter 2, Figures 4–8).

My final chapter used methods from the social sciences to learn more about a key social component of conservation practice efficacy — persistence. Persistence occurs when producers continue to use their practices after cost-share contracts end (Dayer et al., 2018) and is often an unspoken goal of conservation incentive programs. Considering the potential long lag times for nitrate movement through the groundwater (Meals et al., 2010), persistence could be critically important for keeping practices in place long enough to achieve stream health goals. I found that persistence was high in southwest Virginia, but opportunities exist to encourage greater persistence. For example, producers indicated that many riparian buffers were destroyed by wildlife or floods. There were also many cases where producers had retired and these may be cases of reversion, which could mean that my research underestimated persistence. If desired by management agencies, persistence could be encouraged by allocating more funding to maintenance, focusing messaging on how the conservation practice accomplished a producer's goals, or better tracking of land tenure changes.

Synthesis

The combined results from Chapters 1 and 2 provide insight into what conservation practices would be most effective in karst environments with cattle grazing. Nitrogen pollution is a persistent problem in southwest Virginia and innovative conservation practices may be required to reduce nitrogen loads within streams. Current conservation practices are unable to reduce total nitrogen below 1.4 mg/L (Chapter 2, Figure 3) but the biotic community begins to change at 0.6 mg/L (Chapter 2, Figure 4). The SWAT+ model showed that much of the water, and consequently nitrogen, is moving through the soil; therefore, conservation practices that stop nitrogen at its source may be most effective for reducing nitrogen loads in streams (Capel et al., 2018). Conservation practices that stop pollutants at their source, specifically nutrient management plans, are already quite common in southwest Virginia; therefore, innovative and novel conservation practices may need to be developed to remediate nitrogen. Results from Chapters 1 and 2 suggest that streambank erosion is a large source of sediment loads in streams and current conservation practices can improve bank stability (Chapter 2, Figure 10) but not to levels that protect biota (Chapter 2, Figures 9 and 10). Greater densities of current practices may be needed to mitigate negative effects of eroding streambanks.

Achieving greater conservation practice densities and creating new types of practices may require interdisciplinary solutions. For example, integrating conservation social science into ecological research can lead to improved and more equitable management outcomes (Bennet et al., 2017). Results from Chapter 3 showed that producers' attitudes towards conservation practices and motivations for using those practices were important reasons they chose to continue using practices after their cost-share contracts ended. Therefore, targeting messaging based on producers' motivations to encourage positive attitudes towards conservation practices may help to keep conservation practices on the ground long enough to observe improvements in stream health. Conservation social science could also be used to develop innovative conservation practices and test their acceptance by producers (Bennet et al., 2022).

Future research

The hard work, time, and money invested by producers, the Soil and Water Conservation Districts, Natural Resources Conservation Service, and other stakeholders is yielding benefits for some aspects of stream health in southwest Virginia. However, much work is still needed to improve other components of stream health and to ensure healthy streams into the future. Interdisciplinary research can provide novel insights into how both the landscape and people function, so that conservation programs are able to achieve ecologically and socially beneficial results. For example, my results revealed that innovative practices might be necessary to reduce nitrogen to levels that are no longer limiting for biota, which would require interdisciplinary research. Designing a study that could reduce nitrate levels in streams would require integration of hydrology, conservation social science, ecology, and engineering. Concepts from hydrology could lead to a better understanding of the source of nitrogen in streams (i.e., legacy nitrate in the groundwater or nitrogen constantly being leached from manure on the landscape). After understanding the source of nitrogen, engineers can work to design strategies to mitigate the pollution source. In concert with the design of the practice, social scientists could determine if the practice would be equitable and socially acceptable and develop strategies to encourage voluntary uptake of the new practices. Finally, ecologists would determine if stream health goals will be met by the newly designed conservation practice. Interdisciplinary studies as described here will lead to agricultural conservation practices that are socially acceptable and are able to achieve desired stream health outcomes.

References

Bennett, N. J., Roth, R., Klain, S. C., Chan, K., Christie, P., Clark, D. A., Cullman, G., Curran, D., Durbin, T. J., Epstein, G., Greenberg, A., Nelson, M. P., Sandlos, J., Stedman, R., Teel, T. L., Thomas, R., Veríssimo, D., & Wyborn, C. (2017). Conservation social science: Understanding and integrating human dimensions to improve conservation. *Biological Conservation*, *205*, 93–108. https://doi.org/10.1016/j.biocon.2016.10.006

Bennett, N. J., Dodge, M., Akre, T. S., Canty, S. W. J., Chiaravalloti, R., Dayer, A. A., Deichmann, J. L., Gill, D., McField, M., McNamara, J., Murphy, S. E., Nowakowski, A. J., & Songer, M. (2022). Social science for conservation in working landscapes and seascapes. *Frontiers in Conservation Science*, *3*, 954930. https://doi.org/10.3389/fcosc.2022.954930

Boomer, K. B., Weller, D. E., & Jordan, T. E. (2008). Empirical models based on the Universal Soil Loss Equation fail to predict sediment discharges from Chesapeake Bay catchments. *Journal of Environmental Quality*, *37*(1), 79–89. https://doi.org/10.2134/jeq2007.0094

Capel, P. D., Wolock, D. M., Coupe, R. H., & Roth, J. L. (2018). *A conceptual framework for effectively anticipating water-quality changes resulting from changes in agricultural activities*. https://doi.org/10.3133/sir20175095.

Dayer, A. A., Lutter, S. H., Sesser, K. A., Hickey, C. M., & Gardali, T. (2018). Private landowner conservation behavior following participation in voluntary incentive programs: Recommendations to facilitate behavioral persistence. *Conservation Letters*, *11*(2), 1–11. https://doi.org/10.1111/conl.12394

Holmes, R., Armanini, D. G., & Yates, A. G. (2016). Effects of best management practice on ecological condition: Does location matter? *Environmental Management*, *57*(5), 1062–1076. https://doi.org/10.1007/s00267-016-0662-x

Meals, D. W., Dressing, S. A., & Davenport, T. E. (2010). Lag time in water quality response to best management practices: A review. *Journal of Environmental Quality*, *39*, 85–96. https://doi.org/10.2134/jeq2009.0108

Sowa, S. P., Herbert, M., Mysorekar, S., Annis, G. M., Hall, K., Nejadhashemi, A. P., Woznicki, S. A., Wang, L., & Doran, P. J. (2016). How much conservation is enough? Defining implementation goals for healthy fish communities in agricultural rivers. *Journal of Great Lakes Research*, *42*(6), 1302–1321. https://doi.org/10.1016/j.jglr.2016.09.011