



Integrating human decision-making into a hydrological model to accurately estimate the impacts of agricultural policies



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Agriculture is a major contributor to nutrient pollution that drives eutrophication in aquatic ecosystems.

This study integrates hydrological modeling with farmer behavioral analysis to assess the effectiveness of two agricultural conservation practices—cover crops and reduced nitrogen fertilizer application—in reducing nitrate loss from fields in the Tar-Pamlico River Basin of North Carolina.

Survey responses from 279 farmers revealed widespread reluctance to adopt conservation practices, particularly strict fertilizer reductions. A hydrological model showed that applying each practice to 25 percent of agricultural land could substantially reduce nitrate export, with cover crops showing greater effectiveness than reduced fertilizer use. However, an integrated socio-hydrological model, which incorporated behavioral responses from farmers, predicted much smaller reductions in nitrate loss due to limited voluntary adoption. Specifically, nitrate reductions were overestimated by a factor of 8 for cover crops and by a factor of 25 for reduced fertilizer application when behavioral responses were excluded. This result highlights a critical limitation of traditional modeling approaches and underscores the importance of integrating human decision-making into environmental policy analysis.

By linking policy incentives with both biophysical and social responses, this study offers a more realistic framework for designing cost-effective and impactful agricultural conservation strategies.

Eutrophication has emerged as a global issue over the last century, primarily due to agriculture, a common major non-point source of nutrient pollution worldwide. Excessive fertilizer usage has exacerbated this problem, contributing significantly to nutrient runoff into water bodies¹. High nutrient loading can lead to harmful algal blooms², hypoxia³, and loss of biodiversity⁴, undermining the health of aquatic ecosystems and affecting water quality for recreation and wildlife^{5–7}.

Implementing agricultural Best Management Practices (BMPs), such as the strategic use of cover crops and the reduction of chemical nitrogen (N) fertilization rates, offers a targeted approach to mitigating the threat of excess nutrients in watersheds⁸. Cover crops, planted during times when the soil might otherwise be bare, play a crucial role in improving soil structure, enhancing water infiltration, and increasing soil organic matter content⁹. This leads to reduced runoff and erosion, thereby limiting the flow of nutrients into adjacent water bodies. Moreover, some cover crop species capture residual nitrogen from previous crop fertilization, effectively reducing nitrate leaching into groundwater and surface waters¹⁰. Reducing

the application rate of nitrogen fertilizers directly addresses a source of nutrient pollution¹¹. Together, these BMPs have the potential to contribute significantly to reducing excessive nutrients in agriculturally dominated watersheds, thus improving water quality and supporting the health of aquatic ecosystems as we adapt to the impacts of climate change^{9,11,12}.

Hydrological modeling using tools like the Soil and Water Assessment Tool Plus (SWAT+) allows researchers to evaluate the nutrient loading impacts of agricultural BMPs across various scales, aiding policymakers in mitigating nutrient pollution and potentially improving ecosystem health^{1,13–15}. However, traditional hydrological modeling studies often lack nuanced, data-driven methods for incorporating individual decision-making into policy analysis. Put simply, hydrological model simulations are sufficient for identifying the watershed impacts of specified land use changes but are ill-equipped to determine which specific land use changes will result from a given policy. This is especially relevant for agricultural BMPs, where both historical and current policies tend to encourage voluntary adoption rather than mandating specific practices. Integrating

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Table. 1 | Policy scenarios for hydrological and socio-hydrological modeling

Policy Scenario	Type of model	Description
Scenario 1	Hydrological Model	Baseline
Scenario 2	Hydrological Model	30% reduced N fertilizer application in 25% of the total agricultural area
Scenario 3	Hydrological Model	Cover crops implemented on 25% of the total agricultural land
Scenario 4	Socio-Hydrological Model	30% reduced N fertilizer application to areas based on the farmers' behavior model.
Scenario 5	Socio-Hydrological Model	Cover crops implemented in areas based on the farmers' behavior model.

people's perspectives—through behavioral modeling—into hydrological modeling is essential for aligning model outputs with real-world conditions. Such integration enhances the accuracy of simulations, effectively bridging the gap between biogeochemical process modeling and socio-economic dynamics^{16–22}.

In response to the outlined challenges, this study will undertake a multifaceted approach that combines nitrate modeling with an evaluation of the effectiveness of cover crops and reduced nitrogen application rates in mitigating field-edge nitrate export. Recognizing the importance of socio-economic factors in the adoption and success of BMPs, this research will also integrate the human dimension through a farmer behavioral model. Finally, by comparing the outcomes of traditional hydrological modeling with those informed by a farmer behavioral model, this study aims to highlight the added value of embedding social dynamics into hydrological models. We contribute to an increasing literature that highlights the bias of performing policy analyses that fail to account for changes in human action^{23,24}, but this work is novel in several ways. It is the first of its kind to integrate farmer behavioral modeling to a SWAT+ hydrological model, but more broadly it also differs in the depth of integration between hydrological and behavioral models. Similar integrative approaches should enhance the accuracy of model predictions and provide actionable insights for policymakers, ultimately contributing to more effective and sustainable watershed management strategies.

The objectives of this study are to: (1) simulate BMPs, specifically cover crops and reduced fertilizer application, using the SWAT+ model for the Tar-Pamlico watershed in coastal North Carolina, and (2) compare the impacts of different policies on the reduction of nitrate leaving agricultural fields, which is a large driver of ecosystem health, using the SWAT+ hydrological model and a socio-hydrological model that combines SWAT+ with a farmer behavioral model. We compared the outcomes of a baseline model with two different policies related to cover crops and reduced fertilizer application using both hydrological and socio-hydrological modeling approaches (Table 1).

Results and discussion

To build a farmer behavioral model, we estimated a mixed logit model on a data set of farmer survey responses to a discrete choice experiment (more details in Materials and Methods and Supplementary Information). Mixed logit models allow for preference heterogeneity on unobservable factors, allowing for a rich diversity of preferences for conservation contracts in a farmer population²⁵. The model highlighted significant factors influencing farmers' choices regarding conservation contracts (Fig. 1C and Table S1). The payment variable indicated that higher payments on average significantly increase the likelihood of farmers accepting conservation contracts ($P < 0.001$), underscoring the importance of financial incentives. Figure 1C presents standardized coefficient estimates, which are derived by multiplying the model coefficient by the standard deviation of the variable in question. A full set of coefficient estimates is presented in Supplementary Information.

We also observed a general hesitancy of farmers to agree to conservation contracts through a positive value in the alternative-specific constant (ASC) for the status-quo of no conservation contract ($P = 0.003$). As expected, the inclusion of each agricultural BMP had a negative impact on farmer desire for the contract, though only strict nitrogen application limits were statistically significant ($P = 0.014$). Model results revealed

significant preference heterogeneity among farmers represented by large and significant standard deviation estimates of preference parameters for the ASC ($P = 0.005$) and for cover crops ($P = 0.028$). Results showed that the source of funding (state/federal agencies vs. private conservation groups) did not affect farmer willingness to agree to the contract.

Policy Simulations

To estimate the impact of conservation policies in our study area, we ran several SWAT+ simulations (Table 1 and Fig. 2). Our first, denoted Scenario 1, represents a baseline simulation for the current land use in the watershed. To establish this baseline, we used the annual average total nitrate loss from Hydrological Response Units (HRUs)-scale for the period of January 2003 to December 2019. Scenarios 2 and 3 represent the use of our hydrological model to simulate the effects of a 30% reduction in N-application and the use of winter wheat cover crop, respectively. Agricultural land represents 212 HRUs or 5,050 km² in our model. For Scenarios 2 and 3 the 25% of agricultural land in the watershed that would yield the greatest NO₃-N reductions from implementing the simulated BMP were identified (Supplementary Information). The scenarios then assumed that the specific BMP is applied to all land in these targeted HRUs. When performing a benefit-cost analysis of this policy action, we assumed that farmers are compensated for the BMP adoption at current cost share rates from the USDA's Environmental Quality Incentives Program (EQIP).

While both scenarios led to land management changes on 1,260 km² of agricultural land, annual average nitrate loss from all agricultural HRUs in Scenarios 2 and 3 were 1.03×10^7 and 9.74×10^6 kg NO₃⁻-N, respectively (Table 2). Compared with annual average nitrate loss of 1.13×10^7 kg NO₃⁻-N in the Baseline scenario, these represent significant decreases of 1.05×10^6 and 1.60×10^6 kg NO₃⁻-N, using the Wilcoxon signed-rank test (Wilcoxon statistic = 0.0, p-value = 2.40e-09 for Scenario 2-Baseline comparison and Wilcoxon statistic = 0.0, p = 3.57e-08 for Scenario 3-Baseline comparison)²⁶. The superior performance of the winter wheat cover crop in reducing nitrate loss is likely due to its ability to capture residual nitrogen²⁷, which SWAT+ simulates through plant uptake and other nitrogen cycle processes. In comparison, reducing fertilizer application (Scenario 2), while effective overall, might not be as effective as the use of winter wheat cover crops in preventing nitrate leaching.

In contrast to the hydrological model simulations, Scenarios 4 and 5 used a socio-hydrological model. As in Scenarios 2 and 3, the socio-hydrological models identified the same 25% of agricultural land that resulted in the greatest nitrate export reductions from the target BMP. Rather than assuming growers will apply BMPs to all agricultural lands, the socio-hydrological model uses simulations based on our farmer behavioral model to predict the proportion of farmers who would agree to conservation contracts at the given compensation rate provided by EQIP in the targeted HRUs (Materials and Methods and Supplementary Information). These simulations revealed low enrollment (3.75% of farmers) for strict nitrogen restrictions, indicating reluctance towards committing to reducing fertilizer application. In contrast, cover crop adoption showed higher willingness (26.2% of farmers in our simulation), though the actual new acreage increase was more modest (14.5% of acreage), since about half of these farmers had already used cover crops on the same fields in the previous year, as indicated by their prior survey responses. Understanding these behavioral insights is crucial for designing effective environmental policies and simulating realistic agricultural management scenarios.

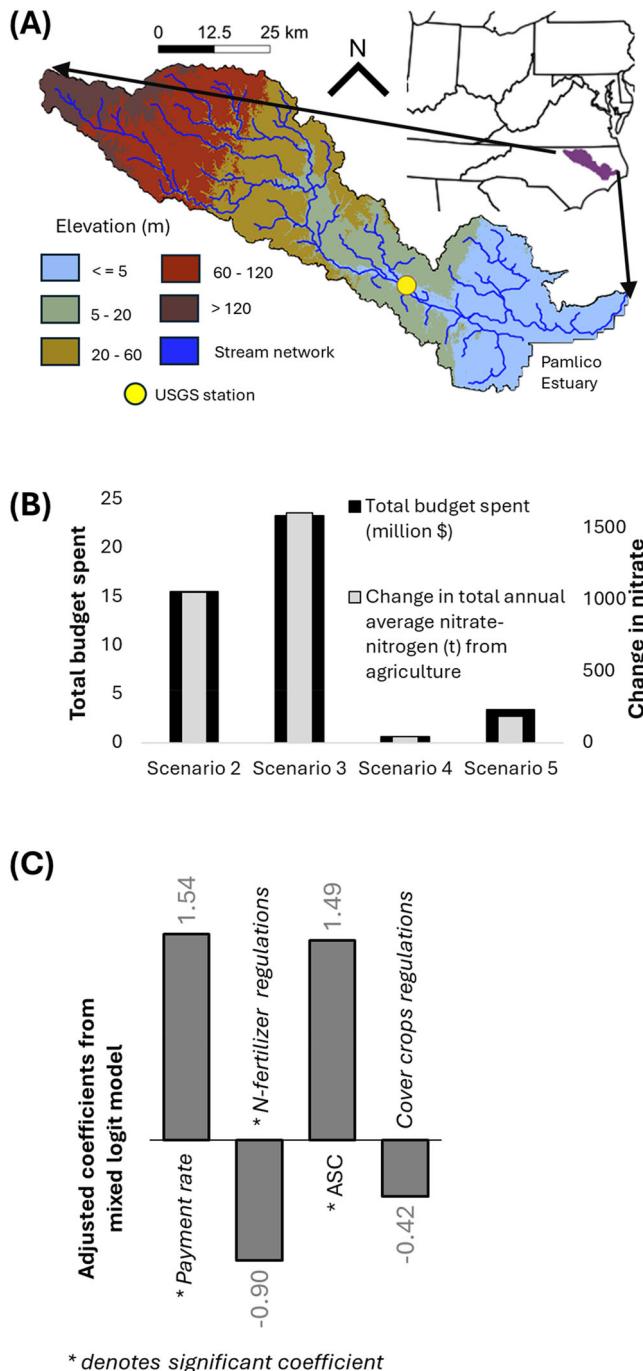


Fig. 1 | Socio-hydrological modeling and key results. A Elevation map of the Tar-Pamlico watershed used in the hydrological model, B budget and nitrate reduction comparison from the hydrological and socio-hydrological model, C adjusted coefficients from the mixed logit model (ASC Alternative Specific Constant).

Scenario 4 (reduced N fertilization) led to management changes on only 50 km² of agricultural land and resulted in an annual average reduction of 42,000 kg NO₃-N relative to the Baseline scenario. While Scenarios 2 and 4 evaluated the same basic policy, the hydrological model predicts that the policy will reduce agricultural nitrate export by 9.27% while the socio-hydrological model finds only a 0.37% reduction. While less extreme, model results revealed a similar trend with cover crops. Scenario 5 results in the conversion of 180 km² and a nitrate reduction of 187,000 kg NO₃⁻-N. As with reduced N application, the socio-hydrological model predicts a much smaller cover crop impact of 1.65% nitrate reduction compared to the 14.1% reduction in the hydrological model.

We summarize the effectiveness and financial implications of each policy in Fig. 1B, which illustrates the impact of various policy scenarios on the total budget spent and the change in annual average nitrate export per area across all HRUs where the BMPs were implemented. Scenario 2 resulted in a cost of \$15.5 million and total benefits equal to \$21.9 million using an estimated benefit of \$20.90 per kg of nitrate from Ribaudo et al.²⁸, which translates to a predicted benefit-cost ratio of 1.41. Scenario 3 was estimated to cost \$23.3 million, which was a higher price driven by the higher EQIP compensation rate for adopting cover crops. Coincidentally, the higher per-acre nitrate reduction from this policy resulted in a nearly identical benefit-cost ratio, of 1.44. Likewise, the socio-hydrological model did not substantially alter the benefit-cost ratios (ranging from 1.12 to 1.57), suggesting that failing to account for farmer preferences is less likely to lead to misperceptions in the efficiency of a policy and more likely to produce erroneous expectations in the scale of the change. This is in part, however, due to our similar targeting approach across models. Since all scenarios target only the top 25% of agricultural HRUs based on BMP effectiveness, they are in effect holding the efficiency of the policies relatively constant across hydrological and socio-hydrological models. By contrast, a model that held the scope of adoption constant would yield a reduced estimate of the policy's effectiveness in the socio-hydrological model. In contrast to the \$50 compensation per acre for reduced N application and \$75 compensation per acre for cover crops, our farmer behavioral model indicates that achieving adoption rates in Scenarios 4 and 5 that match the hydrological model adoption rates would require per acre payments of \$339 and \$264, respectively. Such payments would reduce the benefit-cost ratios to 0.32 and 0.27 for reduced N application and cover crop policies, respectively (see SI Section 8 for a discussion of survey and policy scenario limitations).

Conclusion

This study develops a socio-hydrological model by integrating hydrological modeling (engineering framework) with farmers' behavioral responses (econometric framework) to manage nutrient loading in coastal watersheds, offering important policy insights. In the Tar-Pamlico watershed, the SWAT+ model effectively simulated nitrate loss from agricultural fields, demonstrating that a 30% reduction in fertilizer application and the use of a winter wheat cover crop significantly reduced nitrate export. The study developed a farmer behavioral model, revealing a general reluctance to adopt BMPs, with financial incentives as a crucial determinant. The socio-hydrological models, which account for farmer preferences, highlighted the overestimation of nitrate reductions (by factors of 8 for cover crops and 25 for reduced fertilizer applications, respectively) with the traditional hydrological modeling approach. Through this novel engineering-economics integrated framework, we underscore the importance of flexible, targeted policies for optimizing BMP adoption and cost efficiency. This study emphasizes the need for socio-economic integration in environmental modeling to develop more effective and sustainable watershed management strategies in the face of ongoing climate change.

The Tar-Pamlico basin, characterized by extensive agricultural activity and diverse land uses, provides a complex environment for implementing nitrate reduction policies. The varying results observed across scenarios can be attributed to the inherent differences in traditional hydrological and socio-hydrological models. It is noteworthy that the conclusions of this integrative work amount to a retelling of an old story in a novel way. This result shares the same theme of many other integrative research, specifically that models built on only natural or human dimensions will be biased. However, previous work often highlights how policy simulations erroneously assume status-quo behavior and ignore dynamic and nonlinear changes in behavior in response to policy changes. This current work highlights how standard policy simulations in hydrological modeling unrealistically ignore status quo behavior by presuming that a policy can achieve large land use changes when, under current conditions, farmers are not making those changes.

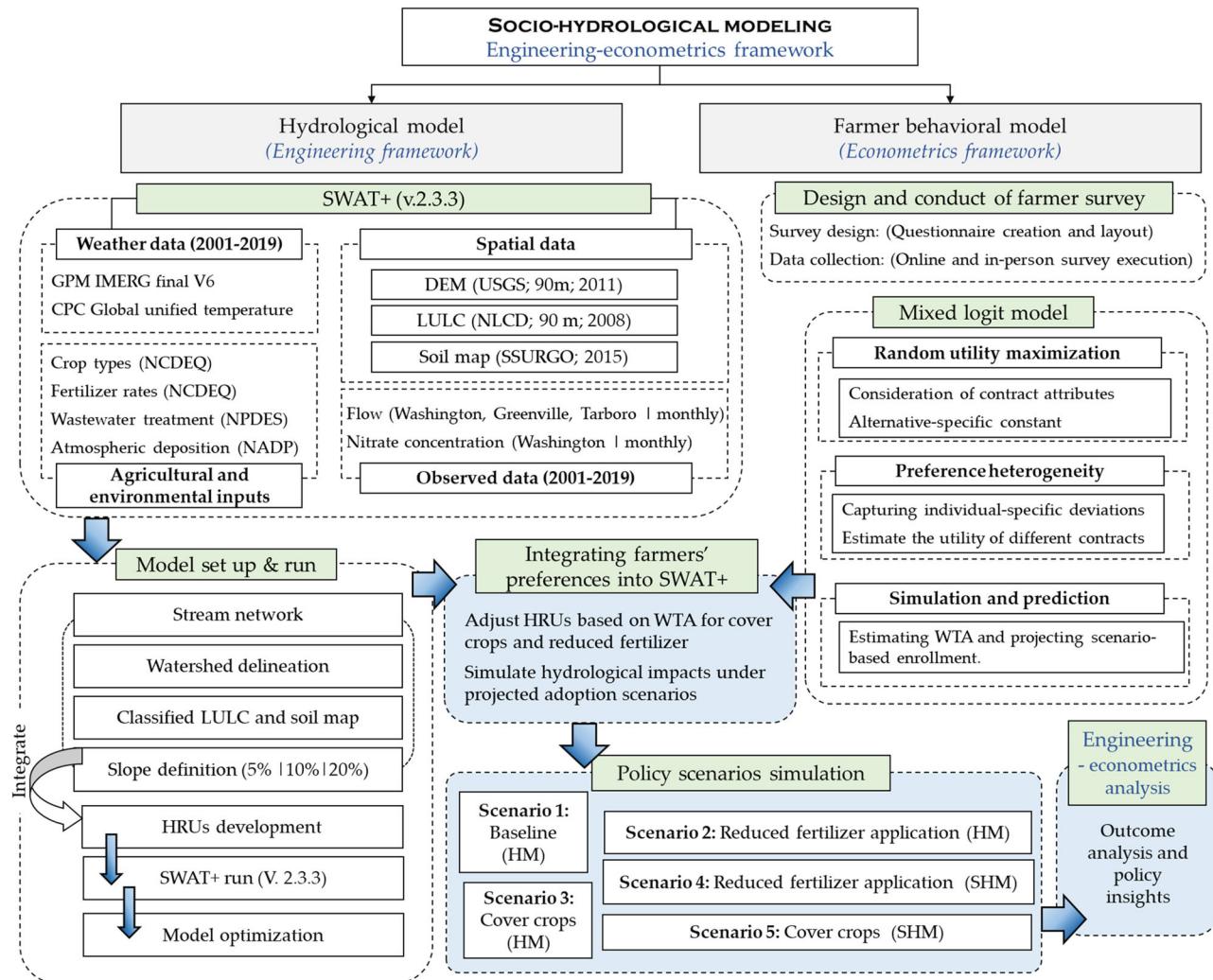


Fig. 2 | Methodological framework for incorporating the SWAT+ model and econometric model (farmer behavioral model) in assessing agricultural nitrate loss.

Overall, these findings underscore the importance of integrating socio-hydrological models into policy design, as they offer a more nuanced understanding of the interactions between human and natural systems. This approach is especially valuable in agri-environmental policy, where historical strategies have tended to avoid mandates and regulations in favor of voluntary incentive programs—programs that farmers can choose to adopt or reject at their own discretion. Understanding the preferences, constraints, and incentives that influence farmers' decisions to adopt conservation practices is vital for designing effective environmental policies. These behavioral insights serve as foundational components for simulating policies within hydrological models, ensuring that such models reflect realistic agricultural management scenarios.

Materials and methods

Study Area

We applied the socio-hydrological modeling framework to the Tar-Pamlico watershed (Fig. 1A and Supplementary Information), a coastal watershed in eastern North Carolina covering 16,576 km² and with a population of 470,000. This watershed, characterized by its diverse land use, including agriculture (27.9%), forests (33.9%), and wetlands (31.9%), supports a variety of crops with soybeans (40%), corn (19%), and cotton (19%) the predominate agricultural crops. The Tar-Pamlico watershed plays a significant role in nutrient discharges to the Pamlico estuary, an area currently facing challenges with algae blooms attributed to excessive nitrate levels^{29–34}.

Hydrological model (engineering framework)

SWAT+ provides comprehensive modeling of watershed and sub-watershed dynamics, serving as a critical tool for decision-making in water resource management, agricultural planning, and environmental conservation. It offers insights into the effects of land management practices on water quality and agricultural productivity by simulating complex environmental processes. SWAT+ uses a semi-distributed hydrological framework and enhanced spatial flexibility, allowing detailed analyses of plant yield, denitrification rates, and nitrate loss in groundwater, surface water, and lateral flows. This capability supports policy development and planning, enabling evaluations of the impacts of land use changes on ecosystem health³⁵.

In this study, we employed the SWAT+ model developed by Tapas et al.¹, which was specifically optimized to simulate monthly flow and nitrate loads in the Tar-Pamlico River basin. The simulation period extended from January 2001 through December 2019, including a two-year warm-up. The model was then calibrated from January 2003 through December 2011 and validated from January 2012 through December 2019 for monthly flow and nitrate loads at Washington, NC. In addition, we cross-validated the model's performance for monthly flow at Greenville and Tarboro, NC (January 2003 through December 2019). Tapas et al.¹ employed a soft calibration procedure³⁶ for key variables—including plant yield, denitrification, and nitrate export—at the HRU scale, thereby establishing an ideal platform for implementing and assessing various agricultural BMPs and their impacts on

Table 2 | Cost-benefit analysis of different engineering and econometric scenarios [HM Hydrological Modeling, SHM Socio-Hydrological Modeling]

Policy Scenarios	Approach	Additional Area Converted (km ²)	Total Budget Spent in million dollars (\$)	Area Enrolled (km ²)	Total annual average NO ₃ -N (kg) from agriculture	Change in total annual average NO ₃ -N (kg) from agriculture	Change in nitrate per area (kg km ⁻²)	Benefit per enrolled area (\$ km ⁻²)	Total benefits in million dollars (\$)	Benefit-cost ratio
Scenario 1	-	0	0	0	11,339,000				0	
Scenario 2	HM	1260	15.5	1260	10,288,000	1,051,000	830	117400	21.9	1.41
Scenario 3	HM	1260	23.3	1260	9,737,000	1,602,000	1270	26600	33.5	1.44
Scenario 4	SHM	50	0.6	50	11,297,000	42,000	900	18800	0.94	1.57
Scenario 5	SHM	180	3.4	330	11,152,000	187,000	1000	21900	3.8	1.12

Notes: The benefit of one kg N reduction used in this analysis is \$20.90 from Ribaudo, et al. (2005).

nutrient loss from agricultural fields. Further details regarding the SWAT+ model¹ can be found in Supplementary Information.

BMP Simulation

We simulated two commonly used BMPs in watershed modeling (Fig. 2): cover crops and reduced fertilizer application rates^{37,38}. Winter wheat was the cover crop, which is commonly used in the Tar-Pamlico Basin³⁹. We simulated planting of the cover crop 14 days after harvesting the main summer cash crop. The cover crop was terminated prior to planting the summer crop the following spring. We applied a 30% reduction in nitrogen fertilizer use to simulate policies related to nitrogen application restrictions.

Farmers' behavioral model (econometrics framework)

We conducted a survey (Supplementary Information) among farmers in the Tar-Pamlico River basin and other coastal areas in eastern North Carolina to gauge farmers' interest in voluntary conservation programs. By incorporating scenarios that reflect aspects of existing and hypothetical agricultural working land support programs (i.e., Environmental Quality Incentives Program, or EQIP), the survey sought to capture farmers' perspectives on and likely response to potential policies and economic incentives. The survey asked farmers about their specific farming practices, environmental concerns, and the potential impact of policy changes on these practices (more details in Supplementary Information). The survey incorporated a choice experiment to gauge farmers' preferences for various hypothetical voluntary conservation contracts aimed at reducing nutrient export (Supplementary Information). The response rate was 16%, and we received in total 76 responses providing enough data to include them in the construction of the farmer behavioral model. Our farmer behavioral model is built on a Random Utility Maximization (RUM) framework and farmer preferences for conservation contracts were modeled using a mixed logit model (Supplementary Information). To counteract hypothetical bias in our survey responses, we used a certainty recoding approach⁴⁰⁻⁴².

Estimation of farmer willingness to accept (WTA)

Using the results of our mixed logit model, we simulated farmer-specific preference parameters for the respondents (Supplementary Information). For each set of preference parameters, we used Hanemann's compensating variation formula⁴² to estimate WTA for a specific conservation contract. The WTA represents the minimum amount a farmer would accept to adopt the contract and is derived from estimated utility differences between the contract, status-quo of no contract, and the estimated marginal utility of income (Supplementary Information).

Simulation of Agri-environmental Policy (Socio-hydrological model integration)

Integrating the SWAT+ and farmer behavioral models is a crucial step toward achieving a comprehensive understanding of watershed dynamics and agricultural decision-making processes⁴³. By combining the insights gained from the farmer behavioral model (econometric framework) with the SWAT+ hydrological model (engineering framework), we developed an integrated framework (Fig. 2) that bridges the gap between policy interventions and on-the-ground agricultural practices⁴⁴. By analyzing farmers' willingness to adopt the target practices based on the incentives offered using current standard EQIP cost share rates, we estimated the extent of land conversion for cover crops and reduced fertilizer application. This integration allowed us to assess the effectiveness of incentive programs in promoting sustainable agricultural practices and inform policymaking for environmental conservation⁴⁵.

Table 1 outlines five distinct scenarios simulated in this study. Scenario 1 serves as the baseline, involving no implementation of additional BMPs. In addition to Scenario 1, we conducted a trial run by separately implementing the two BMPs on all HRUs to identify the top-performing HRUs, defined as an HRU that experienced the largest estimated difference in nitrate loss between Scenario 1 and our run with the target BMP applied to all HRUs. Using the findings from these trials, we identified the HRUs where the

practice was most effective, representing the top 25% of agricultural acreage in the watershed in terms of nitrate reduction, for each BMP. From an engineering perspective, these HRUs are considered the most ideal areas for BMP implementation to minimize the watershed's nitrate export⁴⁶. Scenarios 2 and 3 explored the impacts of a 30% reduction in N-fertilizer application rates and the use of cover crops, respectively, on the target 25% of agricultural land. These scenarios provided conservation contracts at current EQIP rates (\$50 per acre for nutrient application reduction, \$75 per acre for cover crops) and simulated perfect adoption and land use change within the targeted HRUs.

Scenarios 4 and 5 also examined the effects of reduced N-fertilizer application and cover crops, respectively, but these were based on a socio-hydrological model that incorporates the farmer behavior model. Parameter estimates from the farmer behavioral model generated farmer-specific WTA estimates for the target conservation contracts. In the simulation of farmer acceptance of these contracts, we assumed that any farmer whose estimated WTA is at or below the offered per-acre compensation of the contract will prefer the offered contract to the status quo and accept the new contract. Any farmer whose estimated WTA exceeds the offered payment in the contract prefers the status quo and will not accept the new contract. This approach allowed us to predict the proportion of farmers who will accept the conservation contracts offered and, consequently, what percentage of targeted HRUs will be converted. As with Scenarios 2 and 3, the policy is targeted at only the most productive quarter of HRUs, so all HRUs that are not targeted will not be converted to the BMP in question.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Data supporting the findings of this study are available in the Supplementary Information and through publicly accessible databases, with specific datasets accessible via the US Geological Survey (USGS), National Land Cover Database (NLCD), and Soil Survey Geographic Database (SSURGO). Links and details are provided in the Supplementary Information.

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Author contributions

M.R.T., G.H., R.E., and A.L.P. designed research; M.R.T., G.H., R.E., and M.M. performed research; M.R.T., G.H., and R.E. contributed new reagents/analytic tools; M.R.T. and G.H. analyzed data; and M.R.T. and G.H. wrote the paper with contributions from all authors.

Competing interests

The authors declare no competing interests.

Additional information

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