**Farmer adoption-based rapid networking for targeting optimal agro-conservation practices**

**Abstract**

The ever-increasing pollution of rivers worldwide must be immediately addressed before it becomes irreversible. The non-point source pollution from agricultural fields is gradually being identified as one of the most prominent sources of river water pollution. The present study proposes a rapid and cost-effective amelioration of agricultural non-point source pollution by integrating a novel graph network-based optimization technique and farmers' conservation identity measure with systematic watershed hydrological modeling using the Soil and Water Assessment Tool (SWAT). Four conservation practices: riparian buffers, conservation tillage, cover crops, and nutrient management have been selected for demonstrating the proposed model applicable to the agriculture-intensive land areas in three districts within northern India, draining to the Hindon River (a tributary of the Yamuna). A field-scale survey for the four major subdistricts of the study watershed was conducted to decipher the local farmers' conservation identity, age, and education through one-to-one interviews. After successfully calibrating and validating the SWAT model using monthly discharge and nitrate for the study watershed for 2010-2020, the selected BMPs were simulated using SWAT Calibration and Uncertainty Programs (SWAT CUP). Next, the optimized BMP combination obtained through graph network optimization was targeted to subbasins using farmer conservation identities and critical source areas (CSA). Finally, the performance of targeted BMPs under different scenarios was assessed using the developed hydrological model, resulting in the study findings. The adoption of riparian buffer and conservation tillage was identified as the most optimal combination for the study watershed, delivering an efficiency of 0.28 (i.e., the ratio of nitrate reduction (kg) to the total BMP cost ($)). Moreover, the findings from this study pinpoint the selected subbasins from the Purkaji and Khatauli subdistricts as the targeted locations for venturing farmer training, education, and incentivization efforts, encouraging rapid field-scale conservation practices adoption. The study offers a valuable framework that underlines the importance of including farmer behavioral responses to effectively disseminate BMP implementation plans, excluding which the BMP performance studies could be significantly biased or misleading.

**1.Introduction**

Unsustainable agricultural practices are progressively being recognized as the leading source of non-point source (NPS) pollution, causing the deterioration of river waters worldwide (Duda, 1993; Lam et al., 2010; Scavia et al., 2016; Wang et al., 2019). For instance, the extent of the hypoxic zone in the Gulf of Mexico has sprawled more than twice in the last four decades, attributed primarily to the extensive nutrients drained from the agricultural fields in the Upper Mississippi basin (Aggarwal et al., 2022a; Rabalais and Turner, 2019). For the European Union, agriculture significantly contributes to diffuse pollution, impairing 22% of surface water bodies and 28% of the groundwater (EEA, 2020). Even after enforcing several laws (like the Water Pollution Control Law (WPCL) and Yangtze River Protection Law (YRPL)) for NPS pollution control, the longest river in China observes around 50% of nitrogen and phosphorus load from agriculture alone (Xie et al., 2022).

The Ganga River (River Ganges), sheltering about half of the Indian population (more than 600 million), supporting 40% of the country's GDP, and even being greatly revered for its spiritual heritage, is no exception to this universal plight (TWB, 2015). The Indian government has taken various initiatives for Ganga rejuvenation, including the Ganga Action Plan (GAP), the coalition with eminent educational institutions and industries, and the National Ganga River Basin Authority (NGRBA). However, these initiatives were limited, focusing primarily on the abatement of sewerage pollution (NMCG, 2021). The contemporary Namami Gange initiative by the government of India (GOI) is an integrated and comprehensive program targeting a holistic river water restoration scheme through the implementation of four fundamental pillars (i.e., Nirmal, Aviral, Jan, and Gyan Ganga; NMCG, 2021). The initiative also exclusively encourages private sector involvement by facilitating Clean Ganga Fund (CGF) and cooperation from the state-level authorities (Ahmed et al., 2022; Chaudhary and Walker, 2019). However, agricultural NPS pollution has still been given a little focus, with a primary focus on promoting organic farming, improving irrigation water efficiency, etc., which are long-term plans and are hardly sufficient for prompt redressal of the emergence.

India, like the US and China, reckons a leading position in food production and fertilizer consumption (Investopedia, 2023; Statista, 2020), which supports or underpins a belief that "the Indian water bodies must also have been similarly stressed, which presently getting overwhelmed by the high-intensity pollution caused by the sewerage and industries." In fact, the apparent sewage nutrient pollution resulting in major algal blooms in the tributaries of the Ganges (Bowes et al., 2020; Pandey and Yadav, 2017), could have a significant contribution from agricultural NPS pollution. Nevertheless, prompt and proactive implementation of preventative measures in response to the current scenario is prudent than deferring action until the situation turns irreversible. The watershed models have been regarded as effective tools for simulating watershed scale hydrologic processes like modeling nutrients, pesticides, surface runoff, etc. (Uniyal et al., 2020).

Several watershed-scale models are available that can simulate the physical landscape processes (Verma and Jha, 2015). SWAT (Soil and Water Analysis Tool), an open access, semi-distributed eco-hydrological model, has been used extensively for modeling agricultural non-point sources pollution impacts on the hydrological components in the USA and other nations across the globe (Angello et al., 2021; Ba et al., 2020; Jaiswal et al., 2020; Kast et al., 2021; López-Ballesteros et al., 2023; Wang et al., 2020). SWAT is also competent in handling the complex interferences of varying land uses and management practices computationally efficiently (Purnell et al., 2020). Numerous studies conducted in the past showcase the effectiveness of SWAT in modeling the impact of a wide variety of conservation practices (like strip cropping, riparian buffers, terrace, vegetative buffers, etc.) on water quality and quantity in the agriculture-dominating landscapes (Engebretsen et al., 2019; Himanshu et al., 2019; Kaini et al., 2012; Liu et al., 2019; Uniyal et al., 2020). The conservation practices, or the Best Management Practices (BMPs), are the most common, efficient, and acknowledged programs that help contain agricultural NPS pollution by regulating chemical, physical, and biological processes like filtration, adsorption, denitrification, and so on (Jain and Singh, 2019; Lam et al., 2010; Liu et al., 2019b; Sharma and Malaviya, 2021). The inconsiderate implementation of BMPs on all sites requiring pollution reduction is one of the simplest methods for targeting BMPs. However, such practice would certainly be uneconomical as not all spatial units contribute effectively to river water impairments.

Thus, the researchers have employed optimization algorithms for targeting the BMPs on the sites engendering maximum pollution load, also known as critical source areas (CSAs), to meet the desired load reduction economically. For instance, Ahmadi et al. (2013) integrated SWAT with a multi-objective genetic algorithm to determine the optimized BMP types and locations for regulating pesticides and nutrients in Eagle Creek, Indiana. A new framework integrating the Markov approach, SWAT, and NSGA-II was developed by Chen et al. (2016) for optimizing BMPs and quantifying the water quality responses in the Three Georges Reservoir Region, China. Naseri et al. (2021) presented an optimization model framework to find the most cost-effective controls of sediment yield and runoff in the Fariman Dam watershed, Northeast of Iran, by optimizing soil and water conservation practices using SWAT and the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II). Wu et al. (2022) used a hybrid of SWAT and entropy weight method to evaluate and screen six BMP types' efficacy and cost-effectiveness. In addition to the plethora of research for developing efficient BMP delineation frameworks that target CSAs, most of the proposed models lack comprehensive/integrated allocation of conservation techniques, i.e., the focus is only on optimizing single BMP allocation for a spatial unit. It has been ascertained by past investigators that every BMP has its inherent limitations (Xia et al., 2020). For example, vegetated filter strips require a large implementation area or treat small drainage areas (UCONN, 2018), and detention ponds offer low runoff volume reduction (Stanley, 1996). Thus, a combination of practices is recommended to offset the mutual limitations of BMPs toward the attainment of the target pollution reduction goals (Jain and Singh, 2019). Moreover, the efficacious decision-making for BMP recommendation is only valuable if the suggested practices find their adoption in the fields. Thus, the participation of the related stakeholders, including policymakers, farmers/land managers, and advisors, in decision-making is also paramount (EPA, 2014; Peltonen-Sainio et al., 2019).

In a report by the EPA (2014), the importance and complexity of such "human dimensions" have been recognized, of which farmers or landowners are the chief players. Farmers decide which conservation practices to use, and there are many factors studied by the researchers like, community culture, education, age, and field size, which influence farmers' decisions and, ultimately, adoptions of conservation practices (Peltonen-Sainio et al., 2019; Wang et al., 2018). The farmer's experience of erosion, understanding of the effect of soil fertility declination, exposure to field-scale conservation solutions demonstrations (Ehiakpor et al., 2021), or the influence of community leaders are although valid measures of farmer conservation behavior cannot holistically determine the farmer conservation behavior. Thus, instead of relying on these factors or their particular combination and indirectly identifying farmers' BMP adoption likelihood, it is valuable if the farmers' willingness could be directly captured. "Conservation identity" or CI has been recognized as a profound criterion that can capture the farmers' BMP adoption consciousness and provide a sound measure of whether the farmer will adopt BMPs in his field or not (Burnett et al., 2018; Kast et al., 2021; Zhang et al., 2016). The basic principle underlying this measure is the identity theory, i.e., a person's traits, convictions, and beliefs reflect his/her identity (McGuire et al., 2015). The conservation identity measure in this study queries farmers through a field questionnaire survey on the traits of a good farmer (SQ1), imparting effectiveness in BMP targeting.

The present research extends a framework facilitating the prompt field-scale adoption of conservation practices by integrating robust hydrological modeling, graph network optimization, and farmer's conservation identities for attending to the ever-increasing non-point source pollution in the River Ganges. The novelty of the proposal is its recommendation of integrated BMPs using a novel graph network-based optimization technique and inclusion of the farmer actors that entrenches BMPs' field-scale application. One of India's most fertile and agricultural-intensive areas (the state of Uttar Pradesh), discharging its agriculture wastewater to the River Yamuna, has been selected to demonstrate the proposed model or framework. This study attempts to immediately and effectively address the agricultural non-point source pollution transport and prevent river water pollution. The objective of this study primarily includes 1.) simulation of the discharge, nutrient, and the BMPs applicable for the study watershed using the SWAT model, 2.) development of a novel integrated BMP optimization algorithm using graph theory, 3.) Incorporating farmers' conservation identities in watershed BMP delineation.

**2. Materials and Methods**

**2.1. Study area**

The land area encompassing the agricultural lands of Saharanpur, Muzaffarnagar, and Meerut districts has been selected as the study area for this research. These districts are the three leading agricultural regions of India’s largest food grain production state, Uttar Pradesh (IBEF, 2023). The land is situated amidst the fertile Indo-Gangetic plains and experiences a tropical climate with an annual average temperature of 23- 24 and precipitation of 800 to 1200 mm. The land is suitable for cultivating sugarcane, wheat, and rice crops besides maize, potato, and sorghum (Aggarwal et al., 2022b). However, the higher relative minimum support price (MSP) and increased per capita demand for sugarcane, wheat, and rice have led to their intensive cultivation causing excessive use of fertilizers and pesticides, impairing water quality and lowering water tables, and degrading the land fertility (DES, 2017; Kashyap and Agarwal, 2020; Kopittke et al., 2019; TD, 2017). Thus, this study proposes a framework for optimized targeting of integrated conservation practices incorporating farmers’ preferences for prompt amendment of these alarming issues.

**2.2. Framework for prompt targeting of CPs to field**

The framework proposed in this study (Fig. 1) uses hydrological modeling to evaluate the effect of BMP implementation on nutrient discharge at the watershed outlet. Consequently, the framework optimizes the BMP selection using a graph network optimization, considering maximization of nutrient reduction and minimization of cost as the two objectives, followed by targeting these BMPs to the subbasins. Firstly, a hydrological model is set up based on the various watershed datasets and observed discharge and nutrients at the watershed outlet. Next, the individual BMPs were simulated in the hydrological model, and their effect in terms of nitrate reduction is reported as the base scenario. Based on their reduction efficiency and costs, the optimized BMP combinations were retrieved through a graph network optimization method. Then, these BMP combinations are targeted to different subbasins in the hydrological model based on three scenarios considering farmers’ conservation identities and critical nitrate pollution. Finally, the impact of optimized BMPs under three scenarios on the selected subbasins was realized. The major analytical segments of the proposed framework are delineated in the following sections.

**2.2.1 Hydrological model setup**

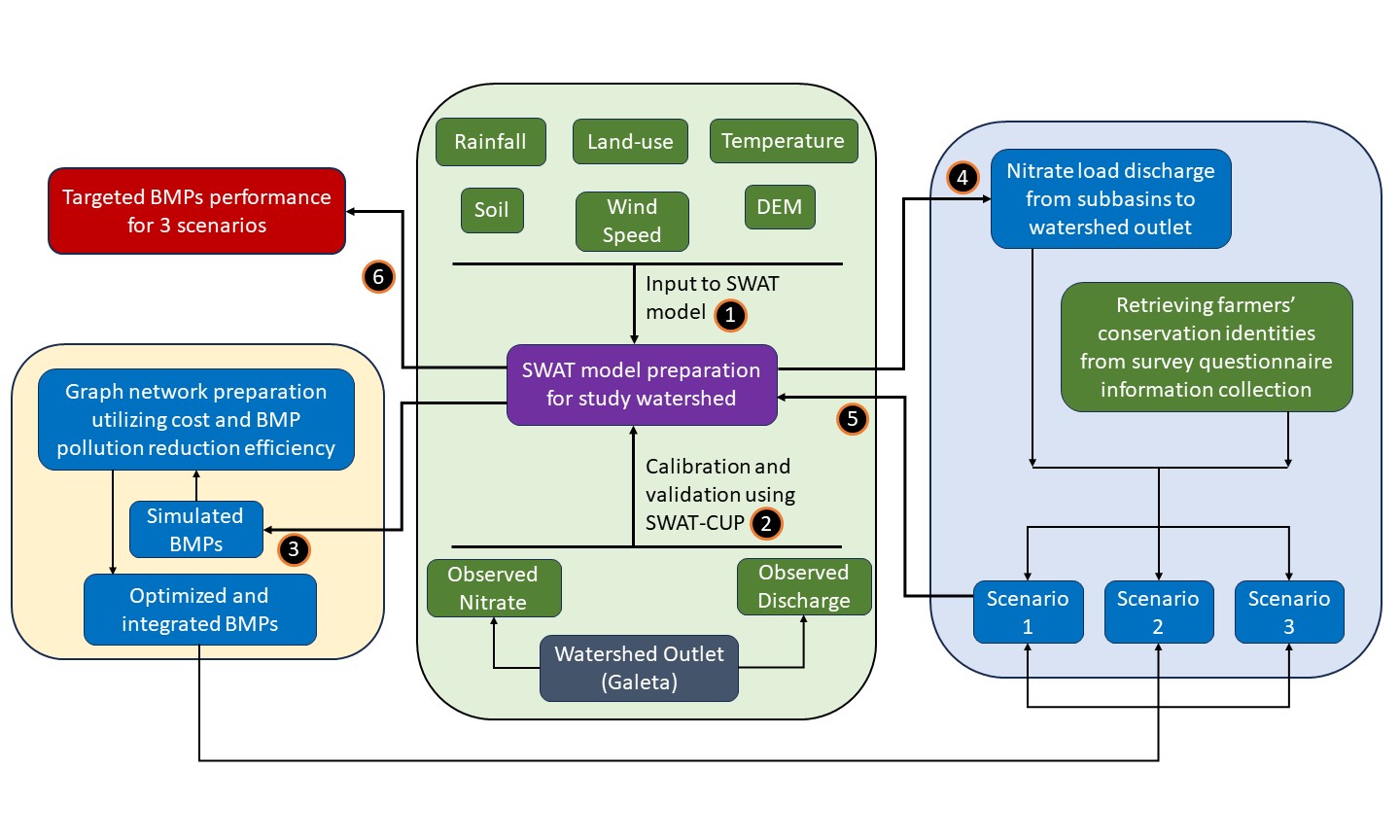
A recent release of ArcSWAT (2012.10.25 version) as an extension for ArcGIS 10.8 has been used to simulate the hydrological and nutrient runoff processes within the study watershed. The calibration and validation of the nitrate and river flow were executed for the period 2010-2020 (both inclusive) using the monthly flow and NO3 data obtained from the Central Water Commission, Ministry of Jal Shakti, Govt. of India, for the gauge station, Galeta, situated at the catchment outlet (Fig. 2). The datasets used for developing the SWAT model for the study watershed are provided in Table 1.

**Table 1. Datasets used in developing SWAT model.**

|  |  |  |  |
| --- | --- | --- | --- |
| **Category** | **Data** | **Source** | **Period** |
| Weather data | Rainfall | CWC Meteorological dataset | 2010-2020 |
|  | Temperature | CWC Meteorological dataset | 2010-2020 |
|  | Humidity | NASA POWER | 2010-2020 |
|  | Wind Speed | NASA POWER | 2010-2020 |
| Hydrological data | Runoff | CWC Guage | 2013-2020 |
|  | Nitrate | CWC Gauge | 2013-2020 |
| Topographic data | Land use | ESRI 2020 | 2021 |
|  | Soil | FAO-UNESCO | 2007 |
|  | DEM | USGS EarthExplorer | 2021 |

The spatial datasets, including the digital elevation model (DEM), land use, and soil, have been prepared using the ArcGIS, projected, and included in the ArcSWAT model. The various subdivisions of the land use, soil, and slope, along with their proportions respective to the entire watershed, are described in Table 2. Eventually, the study watershed was apportioned into 31 subbasins and/or 146 hydrological response units (HRUs).

Further, the calibration and validation of the developed model included parameter sensitivity analysis using the SUFI-2 algorithm (Abbaspour et al., 2007). The calibration and validation of the simulated river flow and the nitrate loads were conducted for monthly time steps for 2013-2017 and 2018-2020 using 12 and 18 parameters (Table S1) sensitive to flow and nitrate loads. Various statistical parameters, including the percentage of observed data enveloped by the modeling result (the 95PPU) - P-factor, thickness of the 95PPU envelope - R-factor, coefficient of determination - R2 (Eq. 2), Nash-Sutcliffe - NS (Eq. 1), and ratio of the root mean square error to the standard deviation of the measured data – RSR (Eq. 3) have been used to evaluate the model performance.



**Fig. 1. A systematic framework for the proposed approach for prompt adoption of the conservation practices.**

**Table 2. Areas apportioned for different land uses, soils, and slopes in the study watershed.**

|  |  |  |  |
| --- | --- | --- | --- |
| **Land use, Soil, and Slope allocation** | | **Area (ha)** | **% Watershed Area** |
| Land use | Agricultural Land – Generic (AGRL):  Sugarcane (SUGC)  Winter Wheat (WWHT)  Rice (RICE) | 133757.66  69139.33  49945.11  14673.22 | **85.56**  44.22  31.94  9.39 |
|  | Forest-deciduous (FRSD) | 5402.59 | **3.46** |
|  | Perennial Indiangrass (INDN) | 48.58 | **0.03** |
|  | Residential (URBN) | 17017.95 | **10.89** |
|  | Water (WATR) | 103.43 | **0.07** |
| Soil | FAO Soil Classification:  Jc45-2a-3739  Lo5-2a-3810 | 28707.75  127622.46 | **18.36**  **81.64** |
| Slope | 0 – 0.75 | 65866.86 | **42.13** |
|  | 0.75 – 1.5 | 63709.76 | **40.75** |
|  | 1.5 – 2.25 | 20013.46 | **12.8** |
|  | > 2.25 | 6740.11 | **4.31** |

A map of a state

Description automatically generated

**Fig. 2. Study area location in the Uttar Pradesh (India) and its various land use classes.**

(1)

(2)

(3)

Where X is the variable (i.e., discharge or nitrate), the subscripts o and s refer to observed and simulated variables, and i is the ith data in the complete dataset range. The model results for the calibration and validation periods of the simulated river flow and nitrate load are presented in Table 3. The detailed definitions of these statistical measures can be found in (Jhs et al., 2019; Karim C. Abbaspour, 2015).

**2.2.2 Selection and simulation of conservation practices for nitrate load management**

Four conservation practices, viz., riparian buffers, conservation tillage, cover crops, and nutrient management, were chosen based on the study area slope, existing agricultural practices and environment, and discussion with the landowners (SQ1) and many agricultural experts. The riparian buffers absorb pollutants from agricultural runoff and are effective when situated along the edge of the surface waterbodies, draining agricultural runoff (Luo et al., 2017). On the other hand, conservation tillage is an in-field practice that reduces soil disturbance, thereby minimizing erosion and improving organic matter concentration by limiting the plowing process in conventional agricultural systems (Lv et al., 2023; Xia et al., 2020). Nutrient management is pivoted at the considerate application of the fertilizers, i.e., the correct quantity, right time, and suitable location for attaining optimal growth of the plants, curtailing fertilizer overdoses, and minimizing nutrient runoff (Tomer, 2014). The cover crops differ from the cash crops cultivated for sale and harvesting (Merfield, 2019). These are primarily used for covering the soil, which helps improve soil fertility, control soil erosion, build organic matter, increase infiltration, and improve soil structure.

The parameters related to the BMP processes, as mentioned above, were identified (Zhang et al., 2023), and quantitative adjustments to these parameters were made to replicate their field-scale performance as reported by past studies (MDA, 2012; Nouri et al., 2022; Udias et al., 2016). The reduction efficiencies of the simulated BMPs in the watershed subbasins were evaluated using Equation 4.

(4)

Here the discussion on BMP Simulation in SWAT CUP can come followed by the table (<https://doi.org/10.1016/j.scitotenv.2023.164428>)

**2.2.3 Optimal BMP combination identification using graph theory**

The graph theory, in conjunction with the bellman-ford algorithm, is employed in this study to identify the shortest path or the combination of BMPs resulting in maximum efficiency, i.e., maximization of the ratio of nitrate load reduction and minimization of the cost incurred by a BMP. A graph (G) is denoted as the collection of edges (E) and nodes (N), i.e., G = (N, E). Fig. 3a and 3b represent two graph networks (simplified tree network and complex-strict network, respectively) used in this study. The 1, 2, 3, and 4 *Circles* indicate nodes with BMPs. *Diamond* nodes are the starting and the ending nodes. *Triangles* are the dummy nodes facilitating the unbiased selection of any permutation of the selected BMPs and their combinations, i.e., any single BMP or any set of multiple BMPs.

A diagram of a diagram

Description automatically generated

**Fig. 3a. BMPs streamlined graph network**

**A diagram of a diagram

Description automatically generated**

**Fig. 3b. BMPs complex graph network**

The two graphs represent the same BMP network; however, graph 3a is valuable for its organized and systematic tree-like structure that simplifies the graph network construction for any given number of BMPs. On the other hand, graph 3b is significant as it overcomes the complexity associated with graph 3b and simplifies the network presentation.

For instance, a graph network optimizing n number of BMPs would result in 2n paths, allowing all possible combinations of the selected BMPs. The graph edges in the present study represent the negative efficiencies (i.e., efficiencies of BMPs multiplied with -1 to retrieve maximum efficiency combination through shortest path) of the BMPs, i.e., if an edge is directed from node a to node b; it carries the efficiency of the BMP in node b, in case the targeted node is dummy the edge carries zero efficiency. However, graph network optimization can be used to optimize BMP selection considering other parameters such as cost minimization or nutrient reduction maximization. The graph (Fig. 3) also includes dummy vertices, facilitating the unbiased selection and combination of 2, 3, or 4 BMPs. The following is the pseudo-code for the Bellman-Ford algorithm:

|  |  |
| --- | --- |
| **Line No.** | **Pseudo code for Bellman ford** |
| 1  2  3  4  5  6  7  8  9  10  11  12  13  14  15 | **function** bellford (G,E)  for each node N in G  distance[n] 🡨 infinity  prevnode[n] 🡨 0  distance[ns] 🡨 0 #where ns is the source node  for each node N in G  for each edge (m, n) in G  store 🡨 distance [m] + length (m, n)  if store < distance [n]  distance [n] 🡨 store  prevnode [n] 🡨 m  for each edge (m, n) in G  if distance [m] + length (m, n) < distance (n)  print (“Negative cycle exists”)  **return** distance [], prevnode[]  ` |

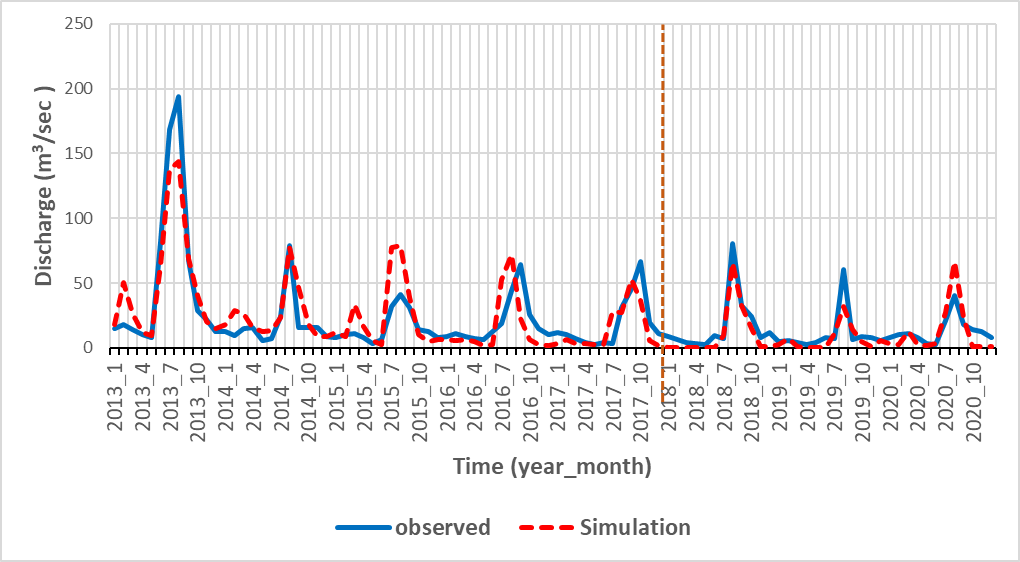
**2.2.4 Conservation identities assignment and optimized BMPs targeting**

We conducted a farmer survey within the study watershed to capture farmer conservation identity in the region. We queried five representative farmers from each district within the watershed through seven distinct conservation traits to capture the overall conservation consciousness of the farmers (Burnett et al., 2018; Zhang et al., 2016). Each conservation trait was measured on a 5-point Likert scale, and farmers were requested to rate seven traits based on their understanding of a good farmer from 0 (not at all) to 4 (absolutely yes; supplementary material). The average of survey scores for each trait represents the farmer CI. The farmer conservation identities were aggregated and normalized over the districts to underscore district-wise variation in farmer CI. The CI obtained from this process was finally assigned to subdistricts influenced by Morna, Purkaji, Shahpur, and Khatauli. Under three scenarios, the optimized BMPs were targeted to subdistricts based on their nitrate load discharge and farmer CI. The targeted BMPs' performance under three scenarios was finally assessed by modifying the SWAT model parameter files for the subdistricts.

**3. Results**

**3.1. SWAT model evaluation and farmers’ conservation identities inclusion**

The SWAT model developed for the study area was calibrated and validated for discharge (m3/sec.) using 12 groundwater, reach, runoff, and soil-cropping process parameters (Table S1). Six additional parameters were used to model nitrate (kg.) at the Galeta (study watershed outlet) located in the Hindon River basin (a tributary of Yamuna River). We used observed monthly data for 2013-2017 and 2018-2020 years to calibrate and validate our SWAT model, where the initial years from 2010-2012 were apportioned for stabilizing and balancing the hydrological stocks in the model (Ayana and Srinivasan, 2019) (Figs. 4 and 5).



**Fig. 4. Calibration and Validation of simulated discharge at the watershed outlet.**

The cross-validation resulted in corresponding P-factor, R-factor, R2, NS, and RSR performance statistical metrics (Table 3, Figs. 6 and 7). The calibration and validation P-factor (0.77 and 0.6), R2 (0.64 and 0.73), and NS (0.6 and 0.62) for discharge and P-factor (0.88 and 0.89), R2 (0.76 and 0.75), and NS (0.76 and 0.68) for nitrate were considered satisfactory to represent the intra-agricultural watershed processes, although, other statistical parameters did not show very accurate model predictions for all calibration and validation stages. Both statistical and visual comparisons were made to ensure the simulation's accuracy.

**Fig. 5. Calibration and Validation of simulated nitrate at the watershed outlet.**

Overall, the monthly streamflow and nitrate variations were reproduced at the watershed outlet, and the majority of the trends are rightly described. However, it could be observed that some of the peaks show up in advance while some low peaks are overestimated. These slight deviations in estimation could be due to the inaccuracy of the land use data and/or the soil patterns/soil type classification data tending to the inaccurate judgment of the antecedent soil moisture, thus conveying faster runoff response. Further, the responses collected from the twenty representative farmers, five from each subdistrict, were used to estimate the farmers’ conservation identities for the study area.

**Table 3. Uncertainty prediction and model performance evaluation for steam discharge and nitrate.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Parameter | Monthly stream flow | | Nitrate load | |
| Cal. | Val. | Cal. | Val. |
| P-factor | 0.77 | 0.6 | 0.88 | 0.89 |
| R-factor | 14.29 | 2.12 | 1.35 | 2.44 |
| R2 | 0.64 | 0.73 | 0.76 | 0.75 |
| NS | 0.6 | 0.62 | 0.76 | 0.68 |
| RSR | 0.63 | 0.62 | 0.49 | 0.56 |

A graph with a red line and a red line

Description automatically generated

**Fig. 6. Coefficient of determination scatter plot for the simulated discharge.**

A graph with a red line and a line

Description automatically generated

**Fig. 7. Coefficient of determination scatter plot for the simulated nitrate.**

The farmers in Shahpur had the highest CI of 90%, remarked as resilient. Purkaji had the lowest CI of 10%, minimal. While the farmers in Morna and Khatauli exhibited moderate minus (61.54%) and moderate plus (67.69%) CI respectively. Note that the farmer CI for a subbasin was assigned an average representative farmer CI value from the subdistrict with closer proximity. This was materialized by generating a buffer around each subdistrict, and the subdistrict partaking maximum subbasin area was selected as the influencer subdistrict for that subbasin.

A map of the state of sweden

Description automatically generated

**Fig. 8. Farmers’ conservation identities bifurcation for the study watershed.**

Twelve subbasins were found to be influenced by the Shahpur subdistrict and were assigned with resilient CI. Purkaji, Morna, and Khatauli influenced ten, four, and five subbasins, respectively (Fig 8).

**3.2. Assigning BMPs to the subbasins incorporating graph theory optimization approach**

The nitrate load from the subbasins showed substantial variations across the watershed (Fig. 9). The 50%, 75%, and 100% subbasins influenced by Purkaji, Khatauli, and Shahpur showed low (<2.5 kg/acre) to weak (2.5 to 5 kg/acre) nitrate load contribution to the watershed outlet whereas all the subbasins related to Morna demonstrated high to severe (>5 kg/acre) nitrate delivery. We conceived three different scenarios to realize the effect of farmer CI in effective BMP planning and targeting in addition to targeting based on CSA(s). These scenarios entail BMP targeting considering the CSAs or subbasins with critical nitrate load production (Scenario 1); BMP targeting based on the farmer conservation identities (Scenario 2); and BMP targeting bearing the combined consideration of farmers’ CI and critical nitrate subbasins (Scenario 3). The subbasins with moderate to severe nitrate impact were chosen for assigning BMPs under the critical nutrient loading scenario. The adoption of the BMPs under farmers’ conservation identity scenario considers only subbasins with moderate and resilient farmer CI.

All four simulated BMPs, as discussed in section 2.2.2, when applied on watershed subbasins, resulted in the nutrient reduction at the watershed outlet, and consequently, their individual reduction capacities using equation 4 were gauged. The cover crops showed maximum nitrate load reduction (84%) and consumed maximum costs ($105 /acre). On the other hand, the conservation tillage practice offered a good nitrate reduction (68%) and at a minimum cost of $10 /acre. The expenditure or cost required for implementing selected BMPs, and their various nutrient reduction potentials have been provided in Table 4.

A map of the state of maharashtra

Description automatically generated

**Fig. 9. Nitrate load intensity in the different subbasin reaches and their source sub-districts.**

**Table 4. Cost and nitrate reduction potential of BMPs.**

|  |  |  |
| --- | --- | --- |
| **Best management practices** | **Cost ($/acre)** | **Nitrate load reduction (%)** |
| Nutrient Management | 11.6 | 13 |
| Conservation Tillage | 10 | 68 |
| Cover Crops | 105.1 | 84 |
| Riparian Buffer | 23.4 | 80 |

Different combinations of these four BMPs, ranging from integrated applications of all four BMPs to individual BMP application and their different permutations, were considered, and the most efficient BMP combination was determined using graph theory and the Bellman-ford algorithm. The two criteria (cost and reduction efficiency for each BMP) considered during optimization resulted in riparian buffers and conservation tillage combination being the most efficient (0.1882) followed by the nutrient management and conservation tillage (0.1592) and then nutrient management and riparian buffers (0.1128) among all possible combinations.

**3.3. Targeting BMP adoption to subbasins based on nitrate load generation and farmer’s CI**

The previous section deliberated nitrate reduction and efficiency (a tradeoff between cost and nutrient reduction potential) of individual BMP adoption in all watershed subbasins. The discussion in the present section is pivoted to utilizing identified optimal practice combinations and evaluating their impact under three scenarios. The efficiencies, cost, and nitrate reduction for the selected BMPs under three different scenarios have been summarized in Table 5. In addition to the three scenarios, the Base scenario includes BMPs in all watershed subbasins. The Real values presented in the base scenario highlight the Base scenario values with consideration of farmer behavioral response and actual BMP adoption in the watershed subbasins. In the first scenario, the BMP allocation corresponding to CSAs was materialized by restricting the adoption of BMPs to 11 subbasins with critical nitrate delivery (Fig. 10a), i.e., the subbasins belonging to the Purkaji, Morna, and Khatauli subdistricts. Considering only subbasins with critical nitrate concentration, i.e., in the first scenario, a 50% (12.2 Gg for RB+CT) nitrate reduction in the base scenario can be achieved at 30% (21.7 million $ for RB+CT) of the total cost demanded in the base scenario. Thus, the efficiencies in the first scenario are substantially elevated by 47% to 50% over the base scenario (Table 5). Also, the results under the first scenario indicated riparian buffer and conservation tillage BMP combination to be the most cost-efficient (0.279) for the selected subbasins. In the second scenario, a set of fifteen different subbasins with moderate plus and resilient farmer CI were selected for BMP implementing BMPs (Fig. 10b). The efficiencies in the second scenario resulted in efficiencies lower than the first scenario for all 3 BMP combinations. Scenario 3, encompassing BMPs as an intersection of the sets of BMPs in the first and second scenarios, showed (Fig. 10c) a significant increment of efficiencies compared to the second scenario. However, the total nitrate reduction in the third scenario has been significantly lowered compared to the first scenario. Note the consistent efficiencies trend for three different subbasin selections or scenarios, i.e., riparian buffer’s combination with conservation tillage always occupies the first strand and its combination with nutrient management the least. The perceived pattern is primarily due to the similar land use, slope, weather, and agricultural practices in the watershed subbasins. However, the SWAT model BMP suggestions are expected to diverge for the heterogeneous landscapes considerably.

**Table 5. Model analysis results for the optimized set of BMPs under three scenarios.**

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **BMP combination**  **Scenario** | **Nitrate Reduction (Gg)** | | | | **Costs (million $)** | | | | **Efficiencies** | | | |
| **Base *(Real)*** | **1st** | **2nd** | **3rd** | **Base *(Real)*** | **1st** | **2nd** | **3rd** | **Base *(Real)*** | **1st** | **2nd** | **3rd** |
| Riparian Buffer + Conservation Tillage | 12.2  *(6.8)* | 6.05 | 2.5 | 1.55 | 70.2  *(44.1)* | 21.7 | 20.8 | 5.59 | 0.19  *(0.15)* | 0.28 | 0.12 | 0.28 |
| Conservation Tillage + Nutrient Management | 6.66  *(3.71)* | 3.31 | 1.38 | 0.84 | 45.4  *(28.5)* | 14 | 13.4 | 3.58 | 0.16  *(0.13)* | 0.24 | 0.10 | 0.23 |
| Riparian Buffer + Nutrient Management | 7.65  *(4.26)* | 3.8 | 1.58 | 0.97 | 73.6  *(46.2)* | 22.7 | 21.8 | 5.86 | 0.11  *(0.09)* | 0.17 | 0.07 | 0.17 |

**4. Discussion**

**4.1. Efficacy of the developed hydrological model for targeting BMPs**

The performance of the developed SWAT model was evaluated using two sets of parameters, i.e., uncertainty in the model prediction and the evaluation of the model performance. The general measure of good uncertainty modeling suggests that high p-factor (towards 1) and low r-factor value (towards zero) (Mengistu et al., 2019). Also, Karim C. Abbaspour (2015) suggests that a p-factor of more than 0.7 and an r-factor near 1 for the calibration and validation of flow from a watershed are acceptable. Thus, the p-factor of 0.77 and 0.88 for calibration of the discharge and nitrate showed that the simulated model explained about 77% and 88% of the observed flow and observed nitrate. The R-factor (2.12 and 2.44) obtained corresponding to the validation of flow and nitrate is also within the acceptable ranges. Its low value highlights the lower model uncertainty or low 95PPU thickness.

A group of maps with different colored areas

Description automatically generated

**Fig. 10. Watershed subbasin selection corresponding to a.) critical nitrate load, b.) high farmer conservation identities and, c.) their combination scenarios.**

Besides these, the performance evaluation parameters for the calibration and validation processes, i.e., (0.76 > R2 & NS > 0.6, RSR < 0.63), also delivered satisfactory results, indicating a decent explanation of the observed variables by the simulated modeling results.

Moreover, the underestimation and overestimation peaks in the simulated results could be explained by the unavailability or lack of the observed dataset at the study location (Poméon et al., 2018), unaccountability of the anthropogenic influences on land-surface-air nexus by the model, or inaccuracy in the metrological, land use, soil information datasets (Bennour et al., 2022). Further, using the empirical soil conservation service (SCS) curve number for runoff simulation in SWAT could also explain the perceived inaccuracy, as the SCS curve number forsakes the length and intensity of the storm.

**4.2. Farmer conservation identities, critical nitrate, and graph theory**

The resilient or high conservation identity of the farmers in the subbasins corresponding to the Shahpur sub-district could be true because of the interplay of multiple factors such as age, education, experience, field size, and exposure to conservation communities (Peltonen-Sainio et al., 2019; Wang et al., 2018). According to the survey conducted (Supplementary material) among the farmers from 4 sub-districts, we found the average age of the farmers in Shahpur was least (around 32) compared to other sub-districts, and their education level is university graduate and post-graduate. The age factor features receptivity, while the education level features comprehensibility (Damianos and Giannakopoulos, 2002). The young and educated farmers are considerably more adaptive to new technologies and more prepared to take risks because they have/can afford extended planning horizons; the researchers in the past have also pointed to young farmers as “gamblers,” which justifies relatively higher environmentally stewardship among the farmers in Shahpur subdistrict compared to others (Damianos and Giannakopoulos, 2002; EC, 2023; Tina Casey, 2018). Similarly, the farmers’ CIs in other sub-districts could be explained.

On the other hand, the high nitrate pollution in the selected subbasins within the watershed could be explained based on their trend, i.e., the higher concentration of the nitrate load is noticed in the subbasins situated alongside the river channel. This could be true because the regions near the river channels/waterbodies have always been more agriculture-intensive and majorly sight of industrial/commercial activities as they have easy access to water and drainage (Khan et al., 2021). Further, the graph theory optimization approach suggested three options for controlling nitrate pollution. These options include the combined use of riparian buffers and conservation tillage, conservation tillage and nutrient management, and nutrient management and riparian buffers. The highest efficiency of riparian buffers and conservation tillage combination could be explained based on their physical characteristics. Conservation tillage is a source control practice that minimizes the pollution generation at its onset, preventing the dispersal of pollution into the atmosphere. Conservation tillage minimizes rainfall and tillage effects by protecting the soil surface using crop residues (Awad et al., 2012; Meier et al., 2017). Riparian buffers (an end treatment technique) would help control the pollution left over post-conservation tillage treatment. Recognizing the high efficiency of the riparian buffers featured by retention, absorption, and denitrification has also been reported by researchers in the past (Luo et al., 2017; Mander, 2008); the combination of two these two techniques as the most efficient could be justified. The higher efficiency of the conservation tillage and nutrient management compared to nutrient management and riparian buffers could be true because of the minimal cost requirements of nutrient management. As mentioned by the previous researchers (Clausen et al., 1996; Nouri et al., 2022; Xia et al., 2020), the conservation tillage has high pollution reduction capacity. Though nutrient management is not that potent at nitrate pollution prevention (only 10-15% reduction) (Udias et al., 2016), its little support at minimal cost leverages the source control potential of the conservation tillage surpassing the combined efficiency of the riparian buffers and nutrient management (Singh et al., 2021; Yadav et al., 2019). The combination of riparian buffer with nutrient management is weaker than riparian buffer and conservation tillage because nutrient management is a weaker source control practice than conservation tillage.

**4.3. Role and importance of farmer conservation consciousness inclusion in effective BMP targeting**

The present section discusses the results of constraining the BMP adoption to the selected subbasin based on the three scenarios. Scenario 1 follows an inherent assumption that the BMPs in all subbasins function homogeneously or have equivalent or consistent performance throughout the watershed. However, the participation of farmers is an essential prerequisite for the successful implementation, execution, and performance of BMPs (Ma et al., 2012). Farmer participation is an outcome of a multitude of factors such as farmers' education level, age, financial status, farm size, community factors like the influence of neighbours, and connection with the environmentally oriented professionals at the local, district, or state level (Adam Reimer, 2012). Thus, the second scenario included farmers' conservation identity for selecting subbasins for BMP adoption. The involvement of the farmers' factors imposed significant changes (lowered) to the nitrate reduction, costs, and efficiencies of the base scenario pointed as 'Real' results in the base scenario (Table 5). Consequently, the assumption of homogeneity in farmer participation throughout the watershed or adoption of BMPs solely based on critically polluted subbasins could be deemed ineffectual.

Though the inclusion of CIs considers the subjectivity of BMP performance/acceptance in the subbasins, the efficiencies of the BMPs were considerably lowered (Table 5), even more than the base scenario. This highlighted that the subbasins with critical nitrate concentrations are incongruous with those with moderate or resilient CIs. Hence, the third scenario was conceived that counteracts the limitations of the first two. An intersection of the BMPs from the first two scenarios was exercised. 3rd scenario considerably lowered the subbasins that necessitate BMP adoption. This notably lowers the cost of BMP installation compared to the first scenario, which does not consider the farmer conservation identity while suggesting target subbasins. It could be noted that with the lower selection of subbasins, the cumulative nitrate reduction at the watershed outlet was also plunged. This low cumulative nitrate reduction suggests the profound need for cultivating farmers' conservation consciousness in the critical nitrate subbasins, except for four subbasins corresponding to Morna. (Fig. 10c). A variety of interventions and programs, such as incentivization, policies, outreach, and environmental education programs, are different ways to encourage farmer participation (Chapman et al., 2019; Vaske et al., 2020). Thus, the novel SWAT-Graph framework, in addition to underscoring the role of farmer conservation identity in BMP delegation and deterring homogenous educational programs, incentivization policies, and learning opportunities for the farmers, guides the governmental and non-governmental agencies in systematic and effective farmer training, education, and incentivization outreach.

**5. Conclusions**

The pollution in the river Ganges is ever-increasing, and many action plans and pledges promising to bring Ganges water to the pure state have failed, like a cascade, one after another (Stuart Butler, 2022). With about 50% of the Indian population dependent on the water of the Ganges (WWF, 2023), the effective/promising cleansing techniques implementations cannot wait any further. Thus, the present research proposes an immediate remedial action technique for controlling the agricultural non-point source pollution (one of the significant pollution source, Shah and Parveen, 2021; Singh and Singh, 2020) transfer to the river Ganges. The present study integrates the concept of farmer conservation identity and a novel graph network-based optimization with the vitality of a robust hydrological and BMP simulation model, SWAT, for the prompt adoption of effective BMPs along with their on-ground placement propositions along with the suggested locations to target farmers’ conservation consciousness cultivation efforts. The graph network approach enables the selection of integrated BMPs that can aid in mutually offsetting or settling the limitations of each selected practice.

Further, considering the farmer’s conservation identity enables capturing the farmers’ willingness towards BMP adoption, who are the sole ultimate BMP adoption decision makers and maintainers, directing the effective placement of the proposed BMPs. The proposed approach demonstrated for 8510 km2 agriculture-intensive watershed draining in Hindon River (a tributary of Yamuna) recommends the implementation of the (BMPs applicable for the study region) riparian buffers in conjunction with conservation tillage to the subbasins influenced by the Morna subdistrict in the study area to retrieve the maximum nitrate reduction efficiency of 0.28) followed by the application of conservation tillage and nutrient management (0.23); and riparian buffer and nutrient management (0.17). The lack of data availability in this study limited the use of daily/hourly discharge and nutrient data; however, the accuracy of the research outcomes could be enhanced by using more robust datasets. Future research could also consider nitrate load contributions from the sub-surface groundwater flow. The analytical study of the four scenarios, including the base scenario, also revealed that consideration of critical nitrate subbasins alone for BMP targeting is insufficient. Further, studying the effects of BMP performance on nutrient or pollution reduction could be highly misleading (depicted by the real values under a Base scenario in Table 5) if the farmers’ behavioral response factor is not included in the analysis. Thus, the proposed framework for BMP planning and targeting could be a valuable guide for researchers, watershed planners, and government policymakers for delivering effective and prompt conservation practices implementation suggestions.

**References**

Abbaspour, K.C., 2015. SWAT‐CUP: SWAT Calibration and Uncertainty Programs ‐ A User Manual. Swiss Federal Institute of Aquatic Science and Technology, Eawag, Duebendorf, 1-100.

Abbaspour, K.C., Vejdani, M. and Haghighat, S., 2007. SWAT-CUP calibration and uncertainty programs for SWAT. Modsim 2007: International Congress on Modelling and Simulation: Land. Water and Environmental Management: Integrated Systems for Sustainability, Christchurch, New Zealand.

Adam Reimer, 2012. U.S. Agricultural Conservation Programs Trends and Effects on Farmer Participation. United States: National Agricultural and Rural Development Policy Center.

Aggarwal, S., Magner, J., Srinivas, R., Sajith, G., 2022a. Managing nitrate-nitrogen in the intensively drained upper Mississippi River Basin, USA under uncertainty: a perennial path forward. Environmental Monitoring and Assessment 194, 704. https://doi.org/10.1007/s10661-022-10401-4

Aggarwal, S., Srinivas, R., Puppala, H., Magner, J., 2022b. Integrated decision support for promoting crop rotation based sustainable agricultural management using geoinformatics and stochastic optimization. Computers and Electronics in Agriculture 200, 107213. <https://doi.org/10.1016/j.compag.2022.107213>

MDA, 2012. The Agricultural BMP Handbook for Minnesota. <https://wrl.mnpals.net/islandora/object/WRLrepository%3A2749/> (accessed 09.11.2023).

Ahmadi, M., Arabi, M., Hoag, D.L., Engel, B.A., 2013. A mixed discrete-continuous variable multiobjective genetic algorithm for targeted implementation of nonpoint source pollution control practices: A MIXED-VARIABLE MOGA FOR OPTIMAL ALLOCATION OF BMPS. Water Resour. Res. 49, 8344–8356. https://doi.org/10.1002/2013WR013656

Ahmed, N., Yashfeen, A., Brijesh, K., Yadav, 2022. Emerging Trends in Technology & its Impact on Law.

Angello, Z., Behailu, B., Tränckner, J., 2021. Selection of Optimum Pollution Load Reduction and Water Quality Improvement Approaches Using Scenario Based Water Quality Modeling in Little Akaki River, Ethiopia. Water 13, 584. https://doi.org/10.3390/w13050584

Awad, Y.M., Blagodatskaya, E., Ok, Y.S., Kuzyakov, Y., 2012. Effects of polyacrylamide, biopolymer, and biochar on decomposition of soil organic matter and plant residues as determined by 14C and enzyme activities. European Journal of Soil Biology 48, 1–10. https://doi.org/10.1016/j.ejsobi.2011.09.005

Ayana, E.K., Srinivasan, R., 2019. Chapter 12 - Impact of the Grand Ethiopian Renaissance Dam (GERD) and climate change on water availability in Sudan, in: Melesse, A.M., Abtew, W., Senay, G. (Eds.), Extreme Hydrology and Climate Variability. Elsevier, pp. 137–149. https://doi.org/10.1016/B978-0-12-815998-9.00012-9

Ba, W., Du, P., Liu, T., Bao, A., Chen, X., Liu, J., Qin, C., 2020. Impacts of climate change and agricultural activities on water quality in the Lower Kaidu River Basin, China. J. Geogr. Sci. 30, 164–176. https://doi.org/10.1007/s11442-020-1721-z

Bennour, A., Jia, L., Menenti, M., Zheng, C., Zeng, Y., Asenso Barnieh, B., Jiang, M., 2022. Calibration and Validation of SWAT Model by Using Hydrological Remote Sensing Observables in the Lake Chad Basin. Remote Sensing 14, 1511. https://doi.org/10.3390/rs14061511

Bowes, M.J., Read, D.S., Joshi, H., Sinha, R., Ansari, A., Hazra, M., Simon, M., Vishwakarma, R., Armstrong, L.K., Nicholls, D.J.E., Wickham, H.D., Ward, J., Carvalho, L.R., Rees, H.G., 2020. Nutrient and microbial water quality of the upper Ganga River, India: identification of pollution sources. Environ Monit Assess 192, 533. https://doi.org/10.1007/s10661-020-08456-2

Burnett, E., Wilson, R.S., Heeren, A., Martin, J., 2018. Farmer adoption of cover crops in the western Lake Erie basin. Journal of Soil and Water Conservation 73, 143–155. <https://doi.org/10.2489/jswc.73.2.143>

Chapman, M., Satterfield, T., Chan, K.M.A., 2019. When value conflicts are barriers: Can relational values help explain farmer participation in conservation incentive programs? Land Use Policy 82, 464–475. https://doi.org/10.1016/j.landusepol.2018.11.017

Chaudhary, M., Walker, T.R., 2019. River Ganga pollution: Causes and failed management plans (correspondence on Dwivedi et al. 2018. Ganga water pollution: A potential health threat to inhabitants of Ganga basin. Environment International 117, 327-338). Environ Int 126, 202–206. https://doi.org/10.1016/j.envint.2019.02.033

Chen, L., Wei, G., Shen, Z., 2016. Incorporating water quality responses into the framework of best management practices optimization. Journal of Hydrology 541, 1363–1374. https://doi.org/10.1016/j.jhydrol.2016.08.038

Clausen, J.C., Jokela, W.E., Potter III, F.I., Williams, J.W., 1996. Paired Watershed Comparison of Tillage Effects on Runoff, Sediment, and Pesticide Losses. Journal of Environmental Quality 25, 1000–1007. https://doi.org/10.2134/jeq1996.00472425002500050011x

Damianos, D., Giannakopoulos, N., 2002. Farmers’ participation inagri‐environmental schemes in Greece. British Food Journal 104, 261–273. https://doi.org/10.1108/00070700210425705

DES, 2017. Pocket Book of Agricultural Statistics 2017. <https://agricoop.nic.in/sites/default/files/pocketbook_0.pdf> (accessed 09.11.23).

Duda, A.M., 1993. Addressing Nonpoint Sources of Water Pollution Must Become an International Priority. Water Science and Technology 28, 1–11. https://doi.org/10.2166/wst.1993.0398

EC, 2023. Young farmers. https://agriculture.ec.europa.eu/common-agricultural-policy/income-support/young-farmers\_en (accessed 7.18.23).

EEA, 2020. Water use and environmental pressures — European Environment Agency [WWW Document]. URL https://www.eea.europa.eu/themes/water/european-waters/water-use-and-environmental-pressures (accessed 5.25.21).

Ehiakpor, D.S., Danso-Abbeam, G., Mubashiru, Y., 2021. Adoption of interrelated sustainable agricultural practices among smallholder farmers in Ghana. Land Use Policy 101, 105142. https://doi.org/10.1016/j.landusepol.2020.105142

Engebretsen, A., Vogt, R.D., Bechmann, M., 2019. SWAT model uncertainties and cumulative probability for decreased phosphorus loading by agricultural Best Management Practices. CATENA 175, 154–166. https://doi.org/10.1016/j.catena.2018.12.004

EPA, 2014. EPA-USDA-USGS Working Meeting on Management Strategies for Reactive Nitrogen and Co-Pollutants. (accessed 7.18.23).

Himanshu, S.K., Pandey, A., Yadav, B., Gupta, A., 2019. Evaluation of best management practices for sediment and nutrient loss control using SWAT model. Soil and Tillage Research 192, 42–58. https://doi.org/10.1016/j.still.2019.04.016

IBEF, 2023. About Uttar Pradesh: Tourism, Agriculture, Industries, Economy & Geography. India Brand Equity Foundation. https://www.ibef.org/states/uttar-pradesh (accessed 7.18.23).

Investopedia, 2023. 4 Countries That Produce the Most Food. Investopedia. https://www.investopedia.com/articles/investing/100615/4-countries-produce-most-food.asp (accessed 5.3.23).

Jain, C.K., Singh, S., 2019. Best management practices for agricultural nonpoint source pollution: Policy interventions and way forward. World Water Policy 5, 207–228. https://doi.org/10.1002/wwp2.12015

Jaiswal, R.K., Yadav, R.N., Lohani, A.K., Tiwari, H.L., Yadav, S., 2020. Water balance modeling of Tandula (India) reservoir catchment using SWAT. Arab J Geosci 13, 148. https://doi.org/10.1007/s12517-020-5092-7

Jhs, B., Alt, F., Ad, L., Lc, A., 2019. The influence of spatial discretization on HEC-HMS modelling: a case study. IJH 3, 442–449. https://doi.org/10.15406/ijh.2019.03.00209

Kaini, P., Artita, K., Nicklow, J.W., 2012. Optimizing Structural Best Management Practices Using SWAT and Genetic Algorithm to Improve Water Quality Goals. Water Resour Manage 26, 1827–1845. https://doi.org/10.1007/s11269-012-9989-0

Karim C. Abbaspour, 2015. SWAT‐CUP: SWAT Calibration and Uncertainty Programs ‐ A User Manual.

Kashyap, D., Agarwal, T., 2020. Food loss in India: water footprint, land footprint and GHG emissions. Environ Dev Sustain 22, 2905–2918. https://doi.org/10.1007/s10668-019-00325-4

Kast, J.B., Kalcic, M., Wilson, R., Jackson-Smith, D., Breyfogle, N., Martin, J., 2021. Evaluating the efficacy of targeting options for conservation practice adoption on watershed-scale phosphorus reductions. Water Research 201, 117375. https://doi.org/10.1016/j.watres.2021.117375

Khan, A.S., Anavkar, A., Ali, A., Patel, N., Alim, H., 2021. A Review on Current Status of Riverine Pollution in India. Biosci., Biotech. Res. Asia 18, 9–22. https://doi.org/10.13005/bbra/2893

Kopittke, P.M., Menzies, N.W., Wang, P., McKenna, B.A., Lombi, E., 2019. Soil and the intensification of agriculture for global food security. Environment International 132, 105078. https://doi.org/10.1016/j.envint.2019.105078

Lam, Q.D., Schmalz, B., Fohrer, N., 2010. Modelling point and diffuse source pollution of nitrate in a rural lowland catchment using the SWAT model. Agricultural Water Management 97, 317–325. <https://doi.org/10.1016/j.agwat.2009.10.004>

Liu, Y., Guo, T., Wang, R., Engel, B.A., Flanagan, D.C., Li, S., Pijanowski, B.C., Collingsworth, P.D., Lee, J.G., Wallace, C.W., 2019a. A SWAT-based optimization tool for obtaining cost-effective strategies for agricultural conservation practice implementation at watershed scales. Science of The Total Environment 691, 685–696. https://doi.org/10.1016/j.scitotenv.2019.07.175

Liu, Y., Wang, R., Guo, T., Engel, B.A., Flanagan, D.C., Lee, J.G., Li, S., Pijanowski, B.C., Collingsworth, P.D., Wallace, C.W., 2019b. Evaluating efficiencies and cost-effectiveness of best management practices in improving agricultural water quality using integrated SWAT and cost evaluation tool. Journal of Hydrology 577, 123965. https://doi.org/10.1016/j.jhydrol.2019.123965

López-Ballesteros, A., Trolle, D., Srinivasan, R., Senent-Aparicio, J., 2023. Assessing the effectiveness of potential best management practices for science-informed decision support at the watershed scale: The case of the Mar Menor coastal lagoon, Spain. Science of The Total Environment 859, 160144. https://doi.org/10.1016/j.scitotenv.2022.160144

Luo, C., Li, Z., Wu, M., Jiang, K., Chen, X., Li, H., 2017. Comprehensive study on parameter sensitivity for flow and nutrient modeling in the Hydrological Simulation Program Fortran model. Environ Sci Pollut Res 24, 20982–20994. <https://doi.org/10.1007/s11356-017-9741-7>

Lv, L., Gao, Z., Liao, K., Zhu, Q. and Zhu, J., 2023. Impact of conservation tillage on the distribution of soil nutrients with depth. Soil and Tillage Research, 225, p.105527.

Ma, S., Swinton, S.M., Lupi, F., Jolejole-Foreman, C., 2012. Farmers’ Willingness to Participate in Payment-for-Environmental-Services Programmes. Journal of Agricultural Economics 63, 604–626. https://doi.org/10.1111/j.1477-9552.2012.00358.x

Mander, Ü., 2008. Riparian Zone Management and Restoration, in: Encyclopedia of Ecology. Elsevier, pp. 3044–3061. https://doi.org/10.1016/B978-008045405-4.00076-8

McGuire, J.M., Morton, L.W., Arbuckle, J.G., Cast, A.D., 2015. Farmer identities and responses to the social–biophysical environment. Journal of Rural Studies 39, 145–155. https://doi.org/10.1016/j.jrurstud.2015.03.011

Meier, S., Curaqueo, G., Khan, N., Bolan, N., Cea, M., Eugenia, G.M., Cornejo, P., Ok, Y.S., Borie, F., 2017. Chicken-manure-derived biochar reduced bioavailability of copper in a contaminated soil. J Soils Sediments 17, 741–750. https://doi.org/10.1007/s11368-015-1256-6

Mengistu, A.G., van Rensburg, L.D., Woyessa, Y.E., 2019. Techniques for calibration and validation of SWAT model in data scarce arid and semi-arid catchments in South Africa. Journal of Hydrology: Regional Studies 25, 100621. https://doi.org/10.1016/j.ejrh.2019.100621

Merfield, C.N., 2019. Integrated Weed Management in Organic Farming, in: Organic Farming. Elsevier, pp. 117–180. https://doi.org/10.1016/B978-0-12-813272-2.00005-7

Naseri, F., Azari, M., Dastorani, M.T., 2021. Spatial optimization of soil and water conservation practices using coupled SWAT model and evolutionary algorithm. International Soil and Water Conservation Research 9, 566–577. https://doi.org/10.1016/j.iswcr.2021.04.002

NMCG, 2021. Namami Gange Annual Report 2020-2021. <https://nmcg.nic.in/writereaddata/fileupload/19_NMCG%20Annual%20Report%202020-21English.pdf> (accessed 09.11.23).

Nouri, A., Lukas, S., Singh, Shikha, Singh, Surendra, Machado, S., 2022. When do cover crops reduce nitrate leaching? A global meta‐analysis. Global Change Biology 28, 4736. https://doi.org/10.1111/gcb.16269

Pandey, J., Yadav, A., 2017. Alternative alert system for Ganga river eutrophication using alkaline phosphatase as a level determinant. Ecological Indicators 82, 327–343. https://doi.org/10.1016/j.ecolind.2017.06.061

Peltonen-Sainio, P., Jauhiainen, L., Laurila, H., Sorvali, J., Honkavaara, E., Wittke, S., Karjalainen, M., Puttonen, E., 2019. Land use optimization tool for sustainable intensification of high-latitude agricultural systems. Land Use Policy 88, 104104. https://doi.org/10.1016/j.landusepol.2019.104104

Poméon, T., Diekkrüger, B., Springer, A., Kusche, J., Eicker, A., 2018. Multi-Objective Validation of SWAT for Sparsely-Gauged West African River Basins—A Remote Sensing Approach. Water 10, 451. https://doi.org/10.3390/w10040451

Purnell, S., Kennedy, R., Williamson, E., Remesan, R., 2020. Metaldehyde prediction by integrating existing water industry datasets with the soil and water assessment tool. Water Research 183, 116053. https://doi.org/10.1016/j.watres.2020.116053

Rabalais, N.N., Turner, R.E., 2019. Gulf of Mexico Hypoxia: Past, Present, and Future. Limnology and Oceanography Bulletin 28, 117–124. https://doi.org/10.1002/lob.10351

Scavia, D., Kalcic, M., Muenich, R.L., Boles, C., Confesor, R., DePinto, J., Martin, J., Read, J., Redder, T., Robertson, D., Sowa, S., Wang, Y.-C., Yen, H., 2016. Informing Lake Erie Agriculture Nutrient Management via Scenario Evaluation.

Shah, Z.U., Parveen, S., 2021. Pesticides pollution and risk assessment of river Ganga: A review. Heliyon 7, e07726. https://doi.org/10.1016/j.heliyon.2021.e07726

Sharma, R., Malaviya, P., 2021. Management of stormwater pollution using green infrastructure: The role of rain gardens. WIREs Water 8. https://doi.org/10.1002/wat2.1507

Singh, R., Babu, S., Avasthe, R.K., Meena, R.S., Yadav, G.S., Das, A., Mohapatra, K.P., Rathore, S.S., Kumar, A., Singh, C., 2021. Conservation tillage and organic nutrients management improve soil properties, productivity, and economics of a maize-vegetable pea system in the Eastern Himalayas. Land Degradation & Development 32, 4637–4654. https://doi.org/10.1002/ldr.4066

Singh, R., Singh, G.S., 2020. Integrated management of the Ganga River: An ecohydrological approach. Ecohydrology & Hydrobiology 20, 153–174. https://doi.org/10.1016/j.ecohyd.2019.10.007

Stanley, D.W., 1996. Pollutant removal by a stormwater dry detention pond. Water Environment Research 68, 1076–1083. https://doi.org/10.2175/106143096X128072

Statista, 2020. Agricultural fertilizer consumption by country [WWW Document]. Statista. URL https://www.statista.com/statistics/1287852/global-consumption-fertilizer-by-country/ (accessed 7.18.23).

Stuart Butler, 2022. The Ganges: river of life, religion and pollution [WWW Document]. Geographical. URL https://geographical.co.uk/culture/the-ganges-river-of-life-religion-and-pollution (accessed 7.18.23).

TD, 2017. India’s Thirsty Crops Are Draining the Country Dry [WWW Document]. URL https://thediplomat.com/2017/04/indias-thirsty-crops-are-draining-the-country-dry/ (accessed 7.18.23).

Tina Casey, 2018. Sustainable Agriculture Means Sustaining More Young Farmers [WWW Document]. URL https://www.triplepundit.com/story/2018/sustainable-agriculture-means-sustaining-more-young-farmers/11341 (accessed 7.18.23).

Tomer, M.D., 2014. Watershed management. Book Chapter (Reference Module in Earth Systems and Environmental Sciences 2014).

TWB, 2015. The National Ganga River Basin Project [WWW Document]. World Bank. URL https://www.worldbank.org/en/news/feature/2015/03/23/india-the-national-ganga-river-basin-project (accessed 7.18.23).

UCONN, 2018. Vegetated Filter Strips/Level Spreaders | CT Stormwater Quality Manual. URL https://ctstormwatermanual.nemo.uconn.edu/11-design-guidance/vegetated-filter-strips-level-spreaders/ (accessed 7.18.23).

Udias, A., Malagò, A., Pastori, M., Vigiak, O., Reynaud, A., Elorza, F.J., Bouraoui, F., 2016. Identifying Efficient Nitrate Reduction Strategies in the Upper Danube. Water 8, 371. https://doi.org/10.3390/w8090371

Uniyal, B., Jha, M.K., Verma, A.K., Anebagilu, P.K., 2020. Identification of critical areas and evaluation of best management practices using SWAT for sustainable watershed management. Sci Total Environ 744, 140737. <https://doi.org/10.1016/j.scitotenv.2020.140737>

Vaske, J.J., Landon, A.C., Miller, C.A., 2020. Normative Influences on Farmers’ Intentions to Practice Conservation Without Compensation. Environmental Management 66, 191–201. https://doi.org/10.1007/s00267-020-01306-4

Verma, A.K., Jha, M.K., 2015. Evaluation of a GIS-Based Watershed Model for Streamflow and Sediment-Yield Simulation in the Upper Baitarani River Basin of Eastern India. J. Hydrol. Eng. 20, C5015001. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001134

Wang, Q., Qi, J., Li, J., Cole, J., Waldhoff, S.T., Zhang, X., 2020. Nitrate loading projection is sensitive to freeze-thaw cycle representation. Water Research 186, 116355. https://doi.org/10.1016/j.watres.2020.116355

Wang, Y., Bian, J., Lao, W., Zhao, Y., Hou, Z., Sun, X., 2019. Assessing the Impacts of Best Management Practices on Nonpoint Source Pollution Considering Cost-Effectiveness in the Source Area of the Liao River, China. Water 11, 1241. https://doi.org/10.3390/w11061241

Wang, Y., Yang, J., Liang, J., Qiang, Y., Fang, S., Gao, M., Fan, X., Yang, G., Zhang, B., Feng, Y., 2018. Analysis of the environmental behavior of farmers for non-point source pollution control and management in a water source protection area in China. Science of The Total Environment 633, 1126–1135. https://doi.org/10.1016/j.scitotenv.2018.03.273

Wu, L., Liu, X., Chen, J., Li, J., Yu, Y., Ma, X., 2022. Efficiency assessment of best management practices in sediment reduction by investigating cost-effective tradeoffs. Agricultural Water Management 265, 107546. https://doi.org/10.1016/j.agwat.2022.107546

WWF, 2023. The Ganges: India’s sacred river [WWW Document]. WWF. URL https://www.wwf.org.uk/where-we-work/ganges (accessed 7.18.23).

Xia, Y., Zhang, M., Tsang, D.C.W., Geng, N., Lu, D., Zhu, L., Igalavithana, A.D., Dissanayake, P.D., Rinklebe, J., Yang, X., Ok, Y.S., 2020. Recent advances in control technologies for non-point source pollution with nitrogen and phosphorous from agricultural runoff: current practices and future prospects. Applied Biological Chemistry 63, 8. https://doi.org/10.1186/s13765-020-0493-6

Xie, Z., Ye, C., Li, C., Shi, X., Shao, Y., Qi, W., 2022. The global progress on the non-point source pollution research from 2012 to 2021: a bibliometric analysis. Environmental Sciences Europe 34, 121. https://doi.org/10.1186/s12302-022-00699-9

Yadav, G.S., Lal, R., Meena, R.S., Babu, S., Das, A., Bhowmik, S.N., Datta, M., Layak, J., Saha, P., 2019. Conservation tillage and nutrient management effects on productivity and soil carbon sequestration under double cropping of rice in north eastern region of India. Ecological Indicators 105, 303–315. https://doi.org/10.1016/j.ecolind.2017.08.071

Zhang, W., Wilson, R.S., Burnett, E., Irwin, E.G., Martin, J.F., 2016. What motivates farmers to apply phosphorus at the “right” time? Survey evidence from the Western Lake Erie Basin. Journal of Great Lakes Research 42, 1343–1356. https://doi.org/10.1016/j.jglr.2016.08.007

Zhang, Z., Montas, H., Shirmohammadi, A., Leisnham, P., Negahban-Azar, M., 2023. Effectiveness of BMP plans in different land covers, with random, targeted, and optimized allocation. Science of The Total Environment 892, 164428. https://doi.org/10.1016/j.scitotenv.2023.164428