

Prioritization of the agricultural fields in the Little Arkansas river watershed, KS, with a SWAT+ model for Off-site BMP program

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Abstract

Soil erosion from agricultural land and transport of sediment into streams create serious water-quality problems, especially in watersheds that supply drinking water. The Little Arkansas River watershed (LTAK) in central Kansas supplies water to the City of Wichita and is subject to high sediment loads due to intensive farming, sloping land, and high hydrological connectivity between agricultural fields and stream networks. Addressing soil erosion and the associated transport of sediment into streams requires both clear identification of sediment sources and a reliable framework to prioritize agricultural fields for conservation intervention. The Off-site Best Management Practice (BMP) program, a state-sponsored initiative that incentivizes the implementation of BMPs on agricultural lands, provides the policy and operational context within which targeted conservation intervention can be implemented. The main goal of this study was to develop, calibrate, and apply a SWAT+ watershed model in the LTAK to (1) estimate sediment contributions from agricultural areas, (2) evaluate sediment reduction potential from selected BMPs, and (3) prioritize agricultural fields for BMP implementation to meet sediment reduction goals linked to urban water-quality protection.

The SWAT+ model was developed using spatial and environmental datasets, including a 10-m digital elevation model, land-use data from the NASS Cropland Data Layer, KARS sub-CLU agricultural field boundaries, STATSGO2 soils, HUC-12 sub-watershed boundaries, and observed hydro-meteorological data. Model calibration and validation followed a multi-site approach, incorporating observed streamflow from four locations: Alta, Halstead, Emma, and Sedgwick. Model performance was evaluated at both daily and monthly time steps using standard statistical measures, including Nash Sutcliffe Efficiency (NSE), percent bias (PBIAS), Kling Gupta Efficiency (KGE), and root mean square error (RMSE).

To evaluate the effectiveness of conservation practices, two management scenarios were developed and analyzed, comparing baseline agricultural conditions under which corn was uniformly applied across all croplands. The alternative conservation scenarios are no-till alone (BMP1) and a combination of no-till and cover crops (BMP2), with sediment reductions estimated at field and HUC-12 sub-watershed scales. Sediment outputs were converted from Hydrologic Response Units (HRUs) to field-based estimates and analyzed across multiple spatial scales to capture the spatial variability of erosion processes across the landscape. Additional analysis was conducted by selecting the 10 highest sediment-producing subbasins and further refining these areas using clustered hotspot identification. The results revealed strong spatial heterogeneity in sediment production, with a relatively small number of areas contributing a large share of total sediment yield within the watershed.

Building on these spatial findings, a Monte Carlo-based field selection framework was implemented to evaluate BMP implementation strategies. Field selection was performed across three spatial conditions: (1) all subbasins within the watershed, (2) selected high sediment-producing subbasins, and (3) clustered hotspot subbasins. For each condition, 1000 simulation runs were conducted, randomly selecting fields until a sediment reduction target of 160 tons per year, representing the estimated quantity of offsite sediment reduction credits needed each year for the City of Wichita's Offsite program, was achieved. The results consistently demonstrated that spatially informed selection strategies, particularly the clustered subbasins, reduced both the number of fields and the total treated area required to meet the target, indicating improved implementation efficiency.

This analysis considered exclusively cropland areas, with uniform corn cultivation applied across the entire land use to ensure consistent production conditions. Field prioritization was

assessed at watershed, HUC-12 subbasin, and individual field scales, with emphasis on higher sediment-producing areas based on landscape and spatial characteristics. This study offers a practical, model-based approach for identifying priority agricultural fields and guiding effective Off-site BMP implementation to protect water resources in the LTAK

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Dedication

This thesis is dedicated to my loving husband, my daughter Aahana, and my parents. Their unconditional support, encouragement, and belief in me have made this work possible.

Chapter 1 Introduction

1.1 Background

Soil erosion is a global environmental issue that affects both water quality and land productivity. It is estimated that approximately 75-100 billion tons of soil are lost annually worldwide due to water driven erosion processes, including surface rainfall, surface runoff (Montgomery, 2007; Pimentel et al., 1995a). These losses are further accelerated by land-use activities such as agriculture and urban development, leading to increased sediment loads in rivers and reservoirs, reduced soil fertility, and impaired long term sustainability of water resources. Soil erosion is especially significant in agricultural regions, where practices such as conventional tillage can increase soil loss, and in rapidly developing areas where land disturbance is common. These patterns show that erosion is a widespread process that requires systematic assessment and management (Montgomery, 2007; Pimentel et al., 1995a).

Soil erosion, sediment mobilization, transport, and deposition are major global impairments on freshwater quality, aquatic habitat condition, and reservoir and channel function (Fox et al., 2016; Syvitski et al., 2005). Sedimentation reduces storage capacity, shortens infrastructure service life, and increases the long-term operating cost of water supply systems. Suspended sediment also degrades water quality through turbidity and can transport nutrients, pesticides, and other sorbed contaminants. At the watershed scale, sediment generation is not spatially uniform. It depends on the combined effects of erosive rainfall, topography, land cover, soil erodibility, and hydrologic connectivity. As a result, a relatively small proportion of landscape units often contributes a disproportionately large share of total sediment exports.

This global pattern is strongly reflected in the United States, where sedimentation remains one of the most persistent water-quality challenges across both rural and urban systems (EPA,

2025). Streams, rivers, reservoirs, and lakes across the United States increasingly face sedimentation which remains one of the most critical water quality challenges in both rural and urban areas. Sediment from agricultural erosion, construction activities, and urban runoff degrades water quality by increasing turbidity, transporting nutrients and pesticides, and impairing aquatic habitat. Recent national-scale modeling estimated average water-driven soil erosion (sheet and rill) across the contiguous U.S. at $2.32 \text{ Mg ha}^{-1} \text{ yr}^{-1}$, with croplands contributing 44% of total soil erosion while occupying only 17% of land area (Shojaeezadeh et al., 2024). The highest erosion rates occur in intensively cultivated corn, soybean, and wheat regions. When gully and streambank erosion are considered, actual soil losses are likely higher (Fox et al., 2016) (Poesen et al., 2003a). In Kansas, sediment yields to reservoirs inferred from bathymetric surveys range from less than about 0.18 to more than $17.5 \text{ Mg ha}^{-1} \text{ yr}^{-1}$, reflecting strong variability among basins in land use, slope, and precipitation (Rahmani et al., 2018). These sediment loads have direct consequences for downstream cities such as Wichita, which relies on the Little Arkansas River and faces elevated water treatment costs due to upstream agricultural runoff contributions (Whittemore, 2012).

Sediment sources vary by land-use context, with agricultural areas primarily influenced by soil disturbance and urban areas by runoff from developed surfaces. These differences contribute to variability in sediment generation across watersheds and have direct implications for surface water management, particularly in mixed-use systems such as the Little Arkansas River watershed (LTAK).

To better understand and manage sediment transport, researchers commonly use watershed modeling approaches. Watershed models, such as SWAT and SWAT+, simulate hydrological and sediment processes by dividing the watershed into smaller units based on land use, soil, and topography (Arnold et al., 1998; Bieger et al., 2017a). This allows for detailed analysis of how

different parts of a watershed contribute to overall sediment yield. These models help identify areas that produce higher sediment, often referred to as critical source areas, and evaluate how different management practices can reduce sediment generation. Studies have shown that such models are effective tools for assessing the impact of land management and for supporting decision-making in watershed planning (Yang et al., 2011).

1.2 The Rural-Urban interface and Sedimentation

Sediment problems become most actionable when upstream sources and downstream beneficiaries are linked within a shared watershed system. This linkage is especially important in mixed rural–urban watersheds, where agricultural erosion upstream can directly affect downstream drinking-water treatment burden. Sedimentation poses substantial but varied threats across land-use settings in the United States. In rural areas, intensive agricultural practices such as conventional tillage and mono-cropping drive soil erosion through processes like sheet erosion (thin, uniform removal of soil), rill erosion (formation of small channels), and gully erosion (larger channels that cannot be removed by normal tillage). Sedimentation affects water quality in different ways depending on the land-use setting (Poesen et al., 2003b). These processes continue to impose substantial economic losses. For instance, erosion-induced depletion of the A-horizon in the U.S. Corn Belt is estimated to reduce crop yields by $6 \pm 2\%$ annually, translating to nearly $\$2.8 \pm \0.9 billion in economic losses per year (Thaler et al., 2021). In urban areas, impervious surfaces increase surface runoff, intensifying sediment transport. In mixed-use watersheds, the cumulative impact of these sources converges downstream. This creates a critical offsite problem where rural activities impact urban resources.

The LTAK provides an appropriate setting for studying off-site sediment control because it represents an upstream agricultural dominance and downstream municipal dependence. This

configuration creates a direct connection between field-scale erosion processes and city-scale water treatment outcomes. The study area therefore offers a practical context for evaluating whether sediment reductions can be achieved more efficiently through targeted BMP placement rather than uniform implementation. Additionally, the watershed is an indirect source of drinking water for the city of Wichita by contributing flow used for artificial recharge of the Equus Beds aquifer. Agricultural runoff contributes substantially to sediment loads in the river system(Whittemore, 2012). These loads increase the cost and complexity of water treatment and aquifer recharge operations, making targeted conservation practices important for maintaining water quality and long-term system sustainability.

1.3 Watershed Modeling and Off-Site BMP Programs

To address sediment issues, watershed management often rely on sediment transport modeling and integrated urban-rural partnerships.

1.3.1 Watershed modeling

Directly monitoring every field across a large watershed is logistically impractical. Therefore, process-based models are essential for identifying sediment sources areas (Arnold et al., 1998; Bieger et al., 2017a). Watershed-scale simulations, such as the Soil and Water Assessment Tool (SWAT+), allow researchers to model sediment dynamics, locate Critical Source Areas (CSAs), and evaluate the effectiveness of Best Management Practices (BMPs) before they are implemented(Arnold et al., 1998; Bieger et al., 2017a). However, most current studies view agricultural and urban sources in isolation, and few effectively prioritize the specific fields or Hydrologic Response Units (HRUs) that contribute the largest amounts of sediment (Sheshukov et al., 2016; Yang et al., 2011).

1.3.2 Integrated off-site BMP programs

The identification of these high-sediment areas supports the development of off-site BMP programs, which extend conservation measures beyond individual fields to the watershed scale. These programs are based on the principle that water quality objectives can be achieved more efficiently by implementing management practices at locations where they provide the greatest environmental benefit, rather than limiting interventions to on-site treatment.

At the policy level, such approaches are consistent with alternative or off-site stormwater management strategies, where regulatory frameworks allow the use of geographically separate locations to meet water quality requirements when equivalent or greater benefits are achieved (EPA, 2025).

These programs extend conservation measures beyond individual fields to the watershed scale. They function on the premise that it is often more cost-effective for downstream urban beneficiaries (like the City of Wichita) to invest in upstream rural conservation practices such as no-till, cover crops, or buffers rather than expanding water treatment infrastructure. Moore et al. (2019) emphasized that the success of such programs depends on bridging the urban, rural interface, where rural conservation practices directly influence urban water quality.

1.3.3 Problem statement and research focus

Despite the recognition of these issues, there is still limited research on how to operationalize off-site BMP targeting using field-scale sediment hotspot modeling. While modeling tools provide robust sediment reduction estimates, there is a gap in connecting these outcomes to practical policy mechanisms such as cost-share programs or incentives (Tian et al., 2020). A systematic study that prioritizes sediment-producing fields, generates efficiency maps for BMPs and connects these outcomes to watershed-scale management strategies is missing. This

research aims to bridge that gap by developing a practical, model-based approach for the LTAK (Lebon et al., 2022).

In practice, urban stormwater regulations often require developers to implement on-site BMPs to control sediment and pollutant loads; however, these practices are frequently expensive and spatially constrained within the boundaries. An alternative approach is the use of off-site BMP programs, where the municipalities and developers finance BMP implementation in upstream agricultural areas to achieve equivalent or greater water quality benefits. Such programs allow urban entities to pay for sediment reduction credit generated through rural practices, particularly when implemented in priority areas of the watershed (Moore et al., 2019). Evidence from the LTAK demonstrates that targeting upstream agricultural fields through off-site BMPs can provide a more effective watershed-scale solution compared to isolated on-site treatments. However, the success of these programs depends strongly on the ability to identify high-contributing sediment source areas and implement BMPs in a targeted manner, which remains insufficiently addressed in current research.

By identifying priority agricultural fields, this study supports the implementation of effective off-site BMP programs to protect downstream water resources. This need leads directly to the primary goal and specific objectives outlined in the following chapter.

Effective off-site BMP design requires both a reliable estimate of sediment generation and a defensible method for deciding where practices should be implemented. A practical targeting framework therefore needs three linked elements: process-based sediment estimation, spatial identification of high-contributing areas, and an efficiency measure that relates sediment reduction to treated area and field enrollment. This study connects modeled sediment heterogeneity with implementable watershed-scale targeting strategies.

The goal of this thesis is to develop and evaluate a process-based and spatially explicit strategy for reducing watershed sediment export through efficient BMP implementation in an off-site program context. The first objective is to quantify baseline sediment yield and its spatial heterogeneity across HRUs, subbasins, and fields. The second objective is to evaluate sediment reduction response under no-till and cover crops plus no-till scenarios across spatial scales. The third objective is to determine whether incorporating spatial information into field selection improves efficiency, where efficiency is defined as achieving a sediment reduction target with fewer treated fields and less treated area. Based on the spatially uneven nature of sediment generation, this study expects sediment sources to be concentrated, BMP response to be strongest in higher-yield units, and targeted selection strategies to outperform non-targeted selection in efficiency and stability. The following chapters present the modeling framework, scenario evaluation, and comparative assessment of selection strategies for off-site implementation.

Chapter 2 Main Goal and Objectives

The main goal of this study is to develop a spatially explicit framework using the SWAT+ model to identify and prioritize sediment sources and evaluate control strategies in the LTAK). The study aims to support the development of an Off-site BMP program that offsets sediment loads in the urban environment with water quality improvements in rural areas. The specific objectives can be defined as:

1. Develop and calibrate the SWAT+ model for the LTAK, compile, process, and integrate datasets including topography (DEM), soils, land use, management practices, and climate variables for accurate watershed representation.
2. Evaluate sources of sediment generation and identify spatial patterns of BMP effectiveness in the Little Arkansas River Watershed.
3. Prioritize agricultural fields for BMP implementation under an Off-site BMP program.

Chapter 3 Literature Review

3.1 Soil Erosion, Sediment Transport and Watershed Modeling Frameworks

Soil erosion and the subsequent sediment yield from agricultural landscapes represent a critical global environmental challenge, accelerating the decline of land productivity and degrading water resources (Dibaba et al., 2021). In watershed systems, excessive sediment delivery to streams not only degrades aquatic habitats but also significantly reduces the water quality, live storage capacity and life expectancy of downstream reservoirs (Dechasa et al., 2022). To mitigate these impacts, watershed managers require robust tools to identify erosion-prone areas and evaluate the potential effectiveness of conservation interventions before implementation. Because field monitoring of sediment losses across large, heterogeneous watersheds is often cost-prohibitive and labor-intensive, hydrological models have become essential tools for quantifying non-point source pollution and simulating watershed responses to management changes (Leh et al., 2018).

Among these tools, the Soil and Water Assessment Tool (SWAT) is widely recognized for its capability to simulate continuous-time hydrological processes in large, complex watersheds with varying soils, land use, and management conditions (J. G. Arnold et al., 2012a). SWAT divides a watershed into subbasins, which are further partitioned into HRUs, lumped land areas comprised of unique combinations of land cover, soil type, and slope (Lamba et al., 2016). This semi-distributed approach allows for the simulation of surface runoff, evapotranspiration, and sediment yield at a granular level, making it particularly suitable for agricultural watersheds where management practices vary spatially (Pandey et al., 2021).

A critical component of SWAT for sediment modeling is the Modified Universal Soil Loss Equation (MUSLE). Unlike the traditional Universal Soil Loss Equation (USLE), which relies on

rainfall energy, MUSLE utilizes a runoff energy factor to estimate sediment yield (Dechasa et al., 2022). By using runoff volume and peak runoff rate as the driving forces for erosion, MUSLE improves sediment prediction accuracy, particularly for individual storm events (Lee et al., 2025). The equation calculates sediment yield as a function of the runoff energy factor, soil erodibility, crop management, erosion control practices, and slope length and steepness (Nepal & Parajuli, 2022).

3.2 SWAT/SWAT+ for Sediment Estimation and Targeting

Watershed models are useful in this study not only because they estimate sediment yield, but also because they support spatial targeting of conservation practices. SWAT and SWAT+ can identify where sediment is generated, compare BMP scenarios, and rank fields or subareas based on their contribution to sediment load. This makes them effective tools for conservation planning in watersheds where management resources are limited (J. G. Arnold et al., 2012a; P. W. Gassman et al., 2007).

Douglas-Mankin et al. (2013) applied SWAT at the field scale to support conservation planning and demonstrated that modeled sediment loss can be translated into field-level BMP prioritization and funding allocation. Their study showed that targeting high contributing fields improves the efficiency of conservation investments compared to uniform implementation. Similarly, SWAT based studies have shown that spatially targeted BMP implementation significantly improves sediment reduction efficiency compared to uniform application. For example, Liu et al. (2017) demonstrated that identifying and prioritizing critical source areas leads to more effective watershed-scale sediment reduction and improved decision-making for BMP placement.

These studies collectively show that SWAT-based sediment modeling can be extended from watershed scale analysis to field level prioritization, supporting efficient BMP planning and decision-making.

3.3 Sediment Modeling and MUSLE Representation

Sediment yield within the watershed was simulated using the Modified Universal Soil Loss Equation (MUSLE) embedded in the SWAT+ modeling framework. MUSLE estimates sediment yield at the Hydrologic Response Unit level based on runoff energy (Williams & Berndt, 1972). The approach is suitable for agricultural watersheds where runoff intensity drives sheet and rill erosion.

$$Sed = 11.8. (Q_{surf} \cdot q_{peak} \cdot Area_{hru})^{0.56} \cdot K_{USLE} \cdot C_{USLE} \cdot P_{USLE} \cdot LS_{USLE} \cdot CFRG$$

Where,

Sed= sediment yield(tons)

Qsurf= surface runoff volume (mm H_2O / ha

Qpeak= peak runoff rate (cum/sec)

Areahru= HRU area(ha)

K_{USLE} = soil erodibility

C_{USLE} = cover and management

P_{USLE} = support practice

LS_{USLE} = topographic effect

CFRG = presence of coarse fragments

Surface runoff volume (Qsurf) and peak runoff rate (qpeak) represent the runoff energy available for soil detachment. Increased peak discharge increases sediment transport capacity. The soil erodibility factor (K_{USLE}) reflects inherent susceptibility, while the cover management factor

(CUSLE) represents vegetation cover and residue effects. The support practice factor (PUSLE) accounts for conservation practices, and the slope length steepness factor (LSUSLE) represents topographic influence. The coarse fragment factor (CFRG) reduces detachment where rock fragments protect the soil surface.

Sheet and rill erosion is a significant source of upland sediment loads in row-crop systems. MUSLE is suitable to represent these processes at the HRU scale, supported by the previous studies on sediment hotspot areas when the model was properly calibrated (Dibaba et al., 2021; Pandey et al., 2021). However, sediment outputs are sensitive to spatial resolution and HRU delineation thresholds (Lee et al., 2025).

Sediment yield was aggregated to annual totals to support prioritization analysis. Average annual sediment yield was calculated in tons per hectare per year. This metric standardizes sediment contributions across fields of varying size. Ranking based on sediment yield identifies fields contributing disproportionately to total watershed sediment load. Targeting high-yield fields improves BMP efficiency and cost-effectiveness (Abimbola, 2020; Dibaba et al., 2021).

Sediment outputs were extracted at HRU levels. HRU-level outputs support field-scale prioritization. The consistency between modeled sediment outputs and hydrologically calibrated conditions is necessary for defensible policy integration under off-site BMP trading frameworks. Sediment outputs were analyzed across three spatial scales: Hydrologic Response Unit (HRU), subbasin, and agricultural field. HRU-level outputs represent fundamental process units, while subbasin aggregation captures watershed-scale transport patterns. Field-scale estimates were derived by converting HRU-level sediment yield outputs into field level values. through spatial aggregation of HRUs to management-relevant units. This multi-scale structure enables identification of dominant sediment sources and supports target BMP prioritization.

3.4 Identification of Critical Source Areas (CSAs) and Field Prioritization

Effective watershed management relies on the accurate identification of areas contributing disproportionately high amounts of non-point source pollutants, commonly referred to as Critical Source Areas (CSAs) or hotspots. Research by (Abimbola, 2020) in the Big Sandy Creek watershed demonstrated that sediment and nutrient generation is spatially heterogeneous, their study confirmed that prioritizing interventions in identified pollution hotspots is significantly more cost-effective than random BMP placement.

However, a critical challenge in prioritization is the scale of analysis. Lamba et al., (2016) analyzed the Pleasant Valley watershed in Wisconsin and observed that while BMPs could reduce sediment loads by over 90% at the sub watershed level, these reductions often diminished to less than 15% at the watershed outlet. This discrepancy occurs due to in-stream processes, such as sediment resuspension and bank erosion, which can mask the benefits of upland conservation practices. Therefore, identifying CSAs requires a modeling approach that accounts for both upland sediment generation and the transport efficiency to the watershed outlet (Lamba et al., 2016).

Advancements in modeling techniques have increasingly moved toward higher spatial resolution to better capture field-level dynamics for prioritization. While traditional SWAT applications rely on generalized HRUs, recent studies emphasize the integration of precise field boundaries. (Merriman et al., 2018) successfully calibrated a field-scale SWAT model for the Alger Creek watershed by utilizing specific field boundaries rather than generic land use raster. Their findings indicated that defining HRUs by field boundaries, like the Common Land Unit (CLU) layer, significantly improved the accuracy of BMP simulations. This field-scale approach is essential for connecting modeling outputs to producer specific decision making.

3.5 Sediment Calibration, Validation, and Data Limitation

Independent sediment calibration is not always possible in agricultural watersheds because long term sediment observations are often limited. In SWAT and SWAT+, sediment prediction is strongly linked to runoff simulation because MUSLE uses runoff volume and peak runoff rate to estimate sediment yield. Therefore, many studies first establish satisfactory hydrologic calibration and then use the calibrated runoff conditions as the basis for sediment estimation and BMP comparison (J. G. Arnold et al., 2012a).

In this study, sediment calibration was not performed due to lack of observed sediment data. Instead, sediment outputs were derived from calibrated streamflow. This approach is consistent with SWAT based applications where runoff driven erosion processes dominate and is appropriate for evaluating relative differences in sediment yield and BMP performance (Admas et al., 2023).

Alternative sediment validation methods include outlet sediment calibration, sediment rating curves, and paired watershed analysis (D. N. Moriasi et al., 2007a). Sediment rating curves relate streamflow to sediment concentration, while paired watershed approaches compare treated and untreated basins. However, these methods require long-term sediment monitoring data, which were not available for this study.

Since this research focuses on upstream agricultural fields, downstream suspended sediment measurements may include additional contributions from channel processes and deposition and therefore may not directly represent field scale erosion. As a result, hydrologic calibration provides a suitable and physically consistent basis for sediment estimation and field prioritization within the SWAT+ framework.

3.6 No-till farming and Cover Crops as Modeled Best Management

Practices

This study focuses on no-till and cover crops because they directly affect the main processes that control sediment generation in row-crop systems, soil disturbance, residue cover, infiltration, and runoff (Jacobs et al., 2024). No-till reduces mechanical soil disturbance and maintains crop residue on the surface, which lowers detachment and runoff energy. Cover crops provide additional seasonal protection by increasing soil cover during otherwise exposed periods and improving soil structure, which enhances infiltration and reduces erosion potential (Blanco-Canqui, 2018; Daryanto et al., 2017).

Previous studies have demonstrated that no-till and cover crops are effective in reducing sediment loss in agricultural watersheds. A global meta-analysis by Blanco-Canqui, (2018) showed that no-till significantly reduces soil erosion by maintaining residue cover and improving soil stability. Similarly, Daryanto et al., (2017) found that conservation practices, including reduced tillage and cover crops, reduce runoff and sediment loss across a wide range of agricultural systems. These findings support the selection of no-till and cover crops as primary BMPs for sediment control in this study.

SWAT-based modeling studies further confirm that targeted implementation of these practices can significantly reduce sediment yield at watershed scale. For example, Yang et al. (2011) demonstrated that conservation practices applied to critical source areas resulted in substantial reductions in sediment export compared to uniform implementation. Similarly, Douglas-Mankin et al. (2013) showed that SWAT outputs can be used to prioritize high-contributing fields, improving the efficiency of BMP implementation. These studies support the

use of spatial targeting in combination with conservation practices to maximize sediment reduction.

However, literature also highlights important limitations. While no-till is effective for sediment reduction, it may increase dissolved phosphorus losses under certain conditions due to reduced soil mixing and nutrient stratification (Daryanto et al., 2017). This indicates that no-till is not universally beneficial for all water quality parameters. In the context of this study, which focuses on sediment reduction rather than nutrient transport, no-till remains an appropriate BMP.

Cover crops were not modeled as a standalone scenario in this study. Instead, they were evaluated in combination with no-till to represent an enhanced conservation condition. This combined approach reflects common agricultural practice, where cover crops are often implemented alongside reduced tillage systems to maximize soil protection. Previous studies have shown that combining conservation practices can produce greater reductions in sediment yield than individual practices alone (Blanco-Canqui, 2018; Yang et al., 2011). Therefore, evaluating both no-till and combined no-till with cover crops provides a realistic and policy-relevant representation of BMP performance.

Many structural and non-structural BMPs have been shown to reduce sediment losses in agricultural and urban systems. However, this study focuses on no-till and cover crops because they are directly represented through crop and management operations in SWAT+ and align with the agricultural conservation setting of the study watershed.

3.7 Off-Site BMP Programs and the Urban-Rural Policy Context

Off-site BMP programs are relevant in watersheds where downstream urban stakeholders depend on upstream rural land management for water quality protection. In agricultural

watersheds, a large portion of sediment originates from upstream cropland, while downstream municipalities bear the cost of water treatment. This creates a need for coordinated watershed scale management and supports the use of policy based approaches for nonpoint source pollution control (Carpenter et al., 1998).

In the LTAK, this issue is especially important because downstream water supply for the City of Wichita depends on reducing sediment generated from upstream agricultural areas. (Moore et al., 2019) describe the Wichita off-site BMP program as an urban rural partnership in which downstream beneficiaries support upstream conservation practices to achieve water quality goals more efficiently than relying solely on expansion of treatment infrastructure. This approach is based on the principle that reducing sediment at the source through agricultural management is often more cost-effective than removing sediment through engineered urban systems.

The sediment reduction target used in this study, 160 tons per year, is based on the structure of the Wichita off-site BMP program. This value reflects approximately 80 ha of annual development, an assumed sediment loading rate of 1 ton ha⁻¹ yr⁻¹, and a required 2:1 on site to offsite sediment reduction ratio (Moore et al., 2019). Under this framework, the required offsite reduction is calculated as:

$$\textit{Sediment Reduction Target} = 80 \text{ ha} \times 1 \text{ ton ha}^{-1}\text{yr}^{-1} \times 2 = 160 \text{ tons yr}^{-1}$$

This target provides a policy-relevant benchmark for evaluating whether upstream agricultural BMPs can offset sediment impacts from urban development.

Previous studies have demonstrated the effectiveness of BMPs in reducing sediment loads and have highlighted the importance of identifying critical source areas for targeted intervention (P. W. Gassman et al., 2007; Yang et al., 2011). However, most studies focus either on watershed-scale BMP performance or spatial identification of high-contributing areas. Few studies explicitly

connect SWAT based sediment modeling with a policy driven framework that translates watershed scale results into field level BMP prioritization under a defined sediment reduction target.

Achieving this target in practice requires spatially explicit modeling and field level prioritization. Watershed modeling outputs can be used to estimate sediment yield at the HRU and field levels and to quantify potential reductions under different BMP scenarios. Fields that contribute disproportionately high sediment loads can then be prioritized, as their management yields the greatest reduction per unit area. This approach forms the basis for a selection framework in which groups of fields are evaluated based on their ability to collectively meet or exceed the defined reduction target.

The success of such programs also depends on the development of scientifically defensible sediment reduction estimates that can be translated into implementation decisions. Sheshukov et al. (2016) demonstrated that SWAT-based outputs can be used to evaluate BMP effectiveness at subarea levels and to support ranking and selection of conservation practices. This linkage between process-based modeling and decision making is essential for operationalizing off-site BMP programs.

This gap is particularly important for off-site BMP programs, where implementation decisions depend on both physical effectiveness and policy constraints. The present study addresses this gap by integrating SWAT+-based sediment modeling, field scale prioritization, and a fixed sediment reduction target to support efficient and practical BMP allocation within an urban rural watershed context.

3.8 Research Gap and Study Contribution

Literature establishes several important foundations for this study. First, SWAT and SWAT+ are widely used for simulating runoff and sediment transport under different land management scenarios and have been validated across a range of agricultural watersheds (J. G. Arnold et al., 2012a; P. W. Gassman et al., 2007). Second, sediment generation is spatially heterogeneous, meaning that a relatively small portion of the landscape often contributes a large share of total sediment load, which supports the concept of Critical Source Areas and the need for targeted management (Daryanto et al., 2017).

Third, conservation practices such as no till and cover crops are effective for reducing soil erosion and sediment loss by improving soil structure and increasing surface cover. However, trade-offs such as increased dissolved phosphorus losses under no till conditions have also been reported, indicating that BMP performance depends on the specific water quality objective (Blanco-Canqui, 2018; Daryanto et al., 2017).

Fourth, watershed-scale management requires integration of upstream agricultural practices with downstream water quality outcomes. Agricultural nonpoint source pollution is a dominant contributor to sediment and nutrient loading in surface waters, which necessitates coordinated watershed-based management strategies linking land use and water quality (Carpenter et al., 1998).

Despite these advances, important gaps remain. Many studies evaluate BMP effectiveness at watershed or sub watershed scales but do not translate these results into field level prioritization frameworks. Similarly, while SWAT based studies demonstrate the benefits of targeting critical source areas, they often do not link sediment reduction outcomes to fixed policy targets such as

off-site sediment credit requirements or urban water quality goals. In addition, few studies integrate multiple components process based sediment modeling, field-scale prioritization, spatial targeting techniques, and random field selection within a single framework that supports decision making under real world implementation constraints.

The present study addresses these gaps by integrating SWAT+ sediment modeling with field-scale prioritization, spatial targeting methods, and a policy defined sediment reduction target. This approach provides a practical framework for linking watershed scale modeling outputs with field level BMP implementation strategies in support of off-site conservation programs.

Chapter 4 Materials

4.1 Study area

4.1.1 Physical and Hydrological Setting

The LTAK is in south-central Kansas and serves as a primary tributary to the Arkansas River at the northern boundary of the City of Wichita. The study area is defined within the spatial extent bounded by coordinates 98°14'14.766" W, 38°33'24.866" N and 97°11'22.53" W, 37°40'50.375" N. The watershed covers approximately 3,480 km² and spans portions of Harvey, McPherson, Rice, Marion, Reno and Sedgwick counties (Fluvial Sediment in the Little Arkansas River Basin, Kansas, 1966). The watershed boundary corresponds to HUC 11030012.

Topography transitions from rolling uplands in the northern smoky hill region to relatively flat alluvial plains in the southern Arkansas River lowlands. Elevation decreases from approximately 518m near the headwaters to 396m at the confluence with the Arkansas River, indicating a gradual downstream gradient that controls flow movement and sediment transport. The soils within the watershed are predominant derived from loess deposits and exhibit moderate erodibility, defined as the susceptibility of soil particles to detachment and transport under rainfall and runoff. Loess derived silt loam soils are particularly prone to detachment under high intensity rainfall due to their fine texture and weak structural stability, which increases erosion potential under surface runoff conditions (The Geologic Story of the Great Plains, 1980) Land use in the Little Arkansas River watershed is dominated by agricultural production; about 65% of the watershed area is in cultivated crops and pasture or hay (Scientific Investigations Report, 2023a). Major crops include wheat, corn, soybeans, and sorghum. Urban and suburban development is concentrated near the cities of Newton, Halstead, and northern Wichita. A total of 7% urban development and the remaining area of other landuse are shown in Table 1.

Data from long-term monitoring stations indicate that the Little Arkansas River contributes substantial sediment loads to the Arkansas River system. Historical USGS records reported average annual suspended sediment loads exceeding 300,000 tons at the Valley Center station (Fluvial Sediment in the Little Arkansas River Basin, Kansas, 1966). Recent observations continued to show elevated total suspended solids and nutrient concentrations (Scientific Investigations Report, 2023b). This is evidence that runoff and sediment transport from agricultural fields are major water-quality concern in the watershed.

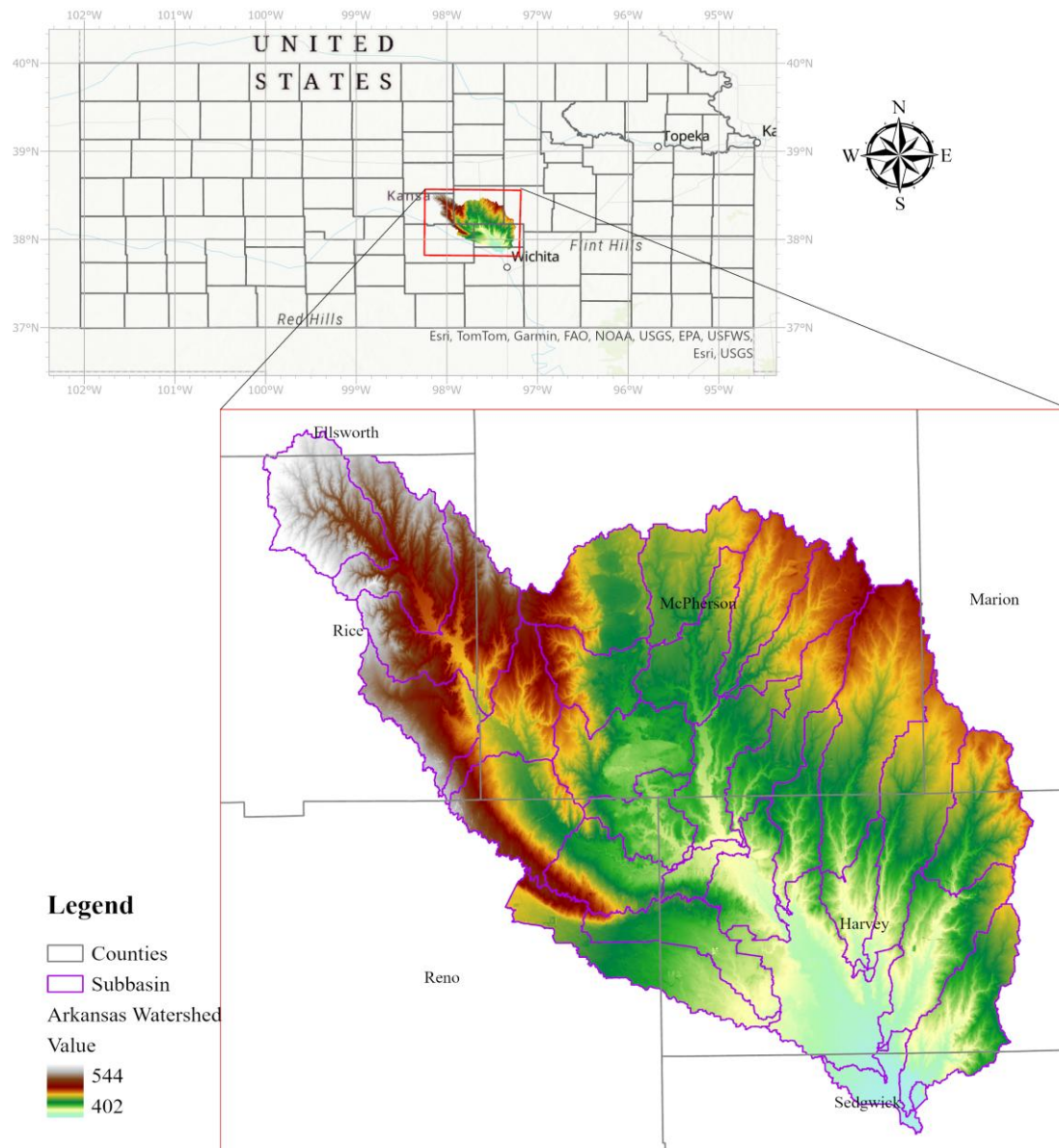


Figure 1 Location map of the Little Arkansas River Watershed in Kansas. Value in the legend represents the elevation in meter.

The watershed is hydrologically and economically important because it supplies source water for the City of Wichita’s Aquifer Storage and Recovery project. Surface water is diverted from the Little Arkansas River and used to recharge the Equus Beds Aquifer. Elevated sediment and nutrient concentrations increase treatment costs and affect long-term water supply sustainability. Watershed management plans under the Kansas Watershed Restoration and Protection Strategy identify sediment, nitrogen, and phosphorus as primary pollutants of concern

in the watershed (Devlin et al., 2011) Therefore, the watershed represents an agricultural and urban linkage where upstream land management decisions directly influence downstream municipal water quality.

4.2 Datasets

4.2.1 Digital Elevation Model (DEM)

Topographic representation was derived from a 10 m resolution Digital Elevation Model obtained from the USDA–NRCS Geospatial Data Gateway (2024) (<https://datagateway.nrcs.usda.gov/>). Ten DEM tiles were mosaicked and projected to the NAD_1983_UTM_Zone_14N coordinate system to maintain spatial consistency. Flow direction, flow accumulation, and stream network layers were generated within QSWAT+. Slope was derived from the DEM and classified into two categories: 0–3% and >3%. The resulting elevation for the Little Arkansas River Watershed is shown in Figure 2.

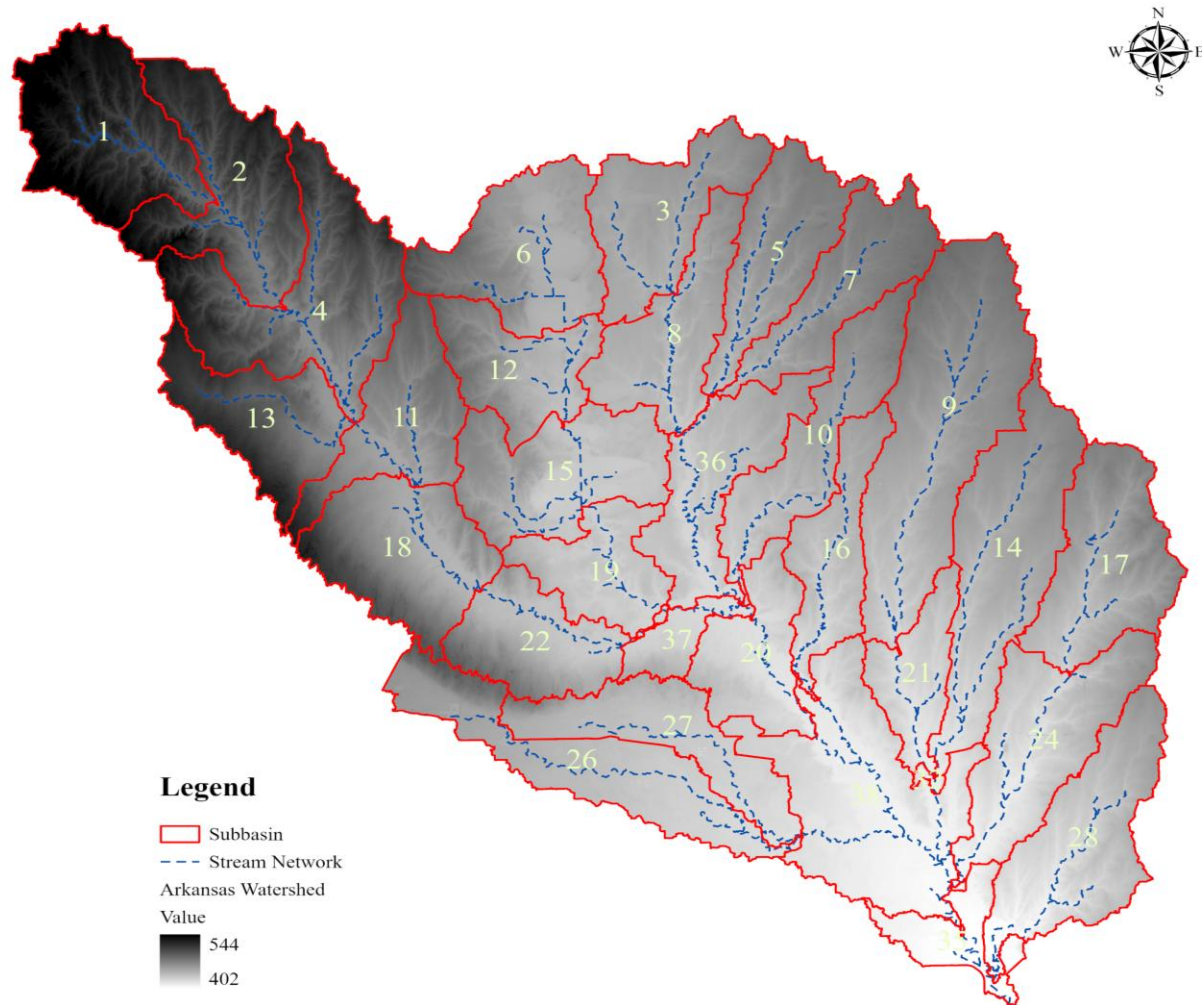


Figure 2 Digital Elevation Map of Little Arkansas Watershed. Value in the legend represents the elevation in meter.

4.2.2 Land Use and Land Cover (LULC)

Land use datas were obtained from the USDA NASS Cropland Data Layer (CDL)(<https://nassgeodata.gmu.edu/CropScape/>) which provides annual crop classification at 30 m spatial resolution. The spatial distribution of land use classes across the Little Arkansas River SWAT model domain is shown in Figure 3. The watershed is predominated characterized by agricultural land uses, with extensive coverage of winter wheat and pasture, along with corn and soybean cultivation. Non-agricultural classes, including urban areas, forest, and wetlands are

present but occupy relatively small portions of the watershed. The table lists the major LULC classes along with descriptive symbols.

Table 1 Percentage of land use area distribution of major LULC classes,

Land use	Symbol	Percent area
Agricultural Land Row Crops	AGR	8%
Irrigated Corn	CN	5%
Corn	CORN	10%
Forest	FRSD	3%
Grain sorghum	GRSG	4%
Irrigated Agricultural Land Row Crops	INDN	3%
Pasture	PAST	20%
Soybeans	SOYB	10%
Urban Area (medium developed)	URMD	7%
Winter wheat	WWHT	30%

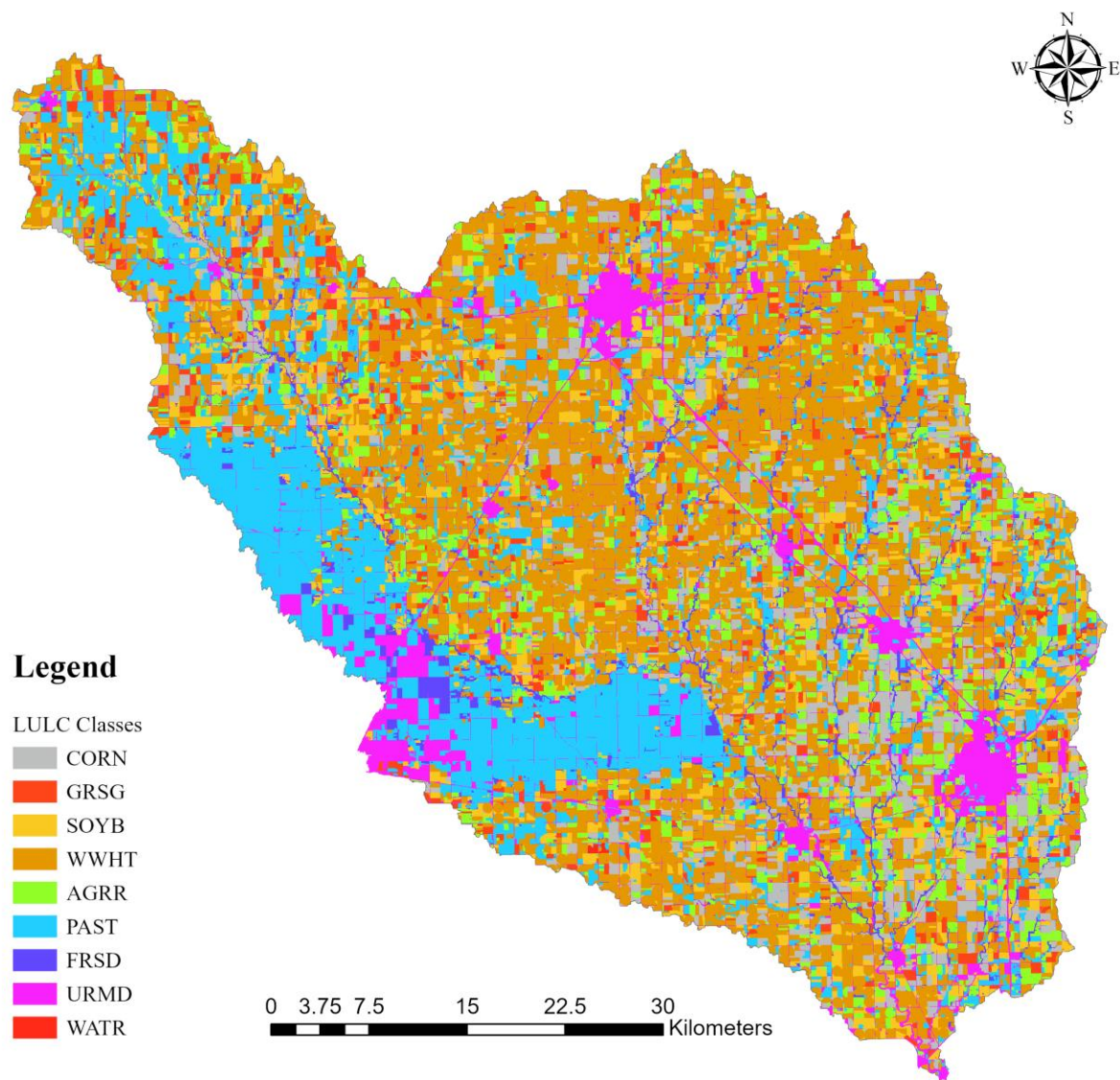


Figure 3 Land use map of the Little Arkansas Watershed.

Table 1 presents the proportional distribution of the land use classes. Winter wheat represents the largest share (30%), followed by pasture (20%), corn (10%), and soybean (10%). Other classes, including irrigated crops, grain sorghum (GRSG), and urban areas, contribute to smaller percentages. This distribution indicates that agricultural practices are the primary drivers of land surface conditions influencing hydrologic response and sediment generation.

4.2.3 Soil Dataset

Soil properties were obtained from the USDA Natural Resources Conservation Service (NRCS) State Soil Geographic Database (STATSGO2) (<https://sdmdataaccess.nrcs.usda.gov/>). The dataset provides key parameters, including hydraulic conductivity, bulk density, available water capacity, and soil texture required for SWAT+ model. Soil hydraulic properties influence infiltration, percolation, and runoff partitioning processes (J. G. Arnold et al., 2012a).

In addition, soil texture plays a critical role in controlling erosion processes by influencing soil detachability and transport potential. Soils with higher silt content are generally more susceptible to erosion due to lower cohesion, while clay-rich soils exhibit greater resistance to detachment but may generate higher runoff due to lower infiltration capacity. Sandy soil typically allows higher infiltration but can contribute to sediment transport under high flow conditions. The STATSGO2 dataset represents soil texture through associated hydraulic parameters such as erodibility and water retention, which are incorporated in the SWAT+ model to simulate spatial variability in erosion response. Table 2 shows the soil classification along with unique identification and hydrological group followed by Figure 4 which shows the soil map of LTAK obtained from STATSGO2.

Table 2 Soil Classification based on the STATSGO2 Source along with hydrological group

Name	hyd_grp	Texture
662818	B	L-WB
377988	C	GR-S- SR- GRX-COS GR-S
662820	D	FSL
662792	B	SIL
662760	C	SICL
662794	A	LFS
662767	C	SIL-SICL
662800	D	FSL
662799	A	LFS
662770	B	L-WB

662737	D	SIC
662739	B	FSL
662773	D	SICL
662774	D	SICL
662741	B	L-L
662740	B	SIL

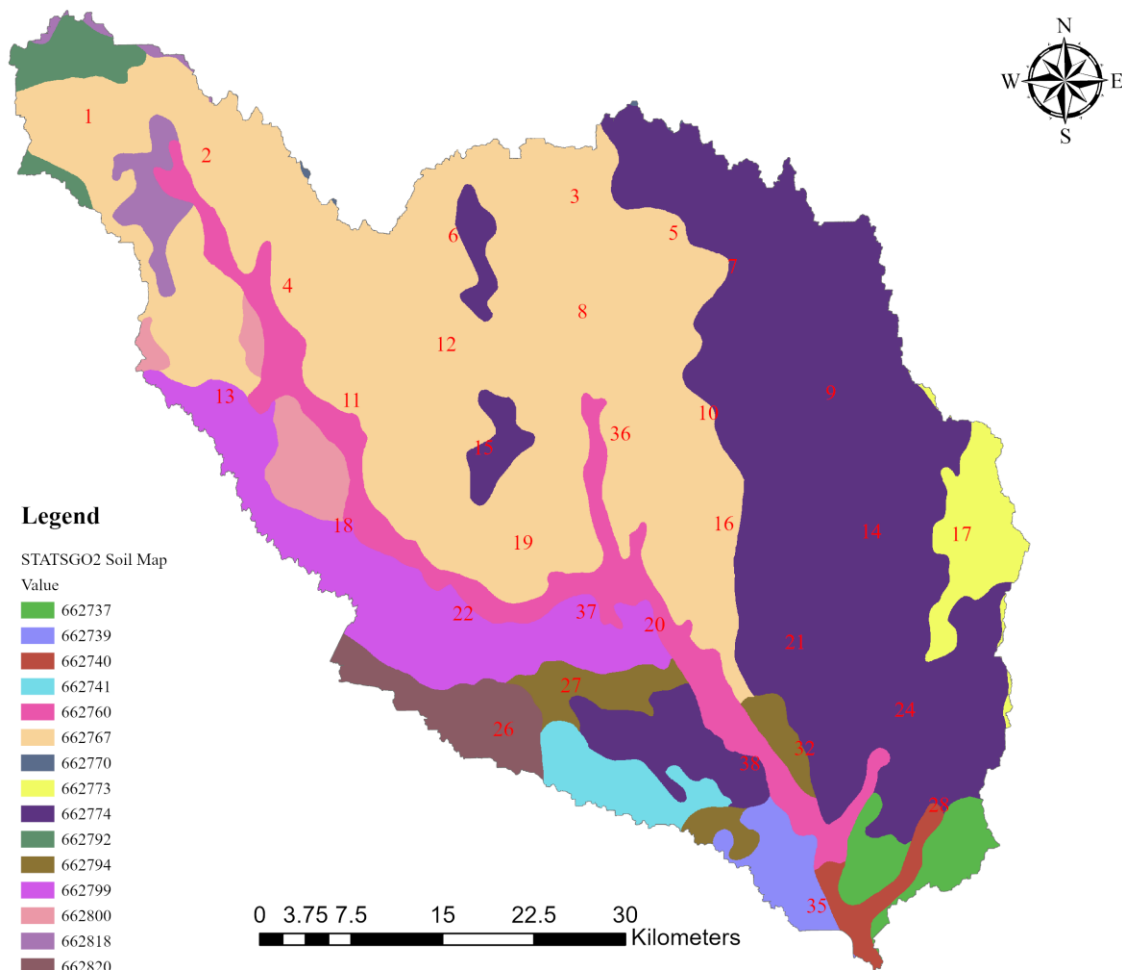


Figure 4 Map showing soil distribution

4.2.4 USGS Gauging Stations

Observed streamflow and sediment data were obtained from four USGS stations within the watershed. These stations included Alta (07143665), Halstead (07143672), Emma Creek

(07143665), and Sedgwick (07144200). These stations provide longitudinal coverage from upstream to downstream locations.

Table 3 Hydrological observation stations used for model calibration and validation

SN.	Station	USGS station	Lat	Long	Flow	Data
					(m ³ /s)	
1	ALTA MILLS, KS	7143665	38.11222	-97.59166	4.162	1994/01/01-2025/02/26
2	HALSTEAD, KS	7143672	38.02853	-97.54054	4.359	1995/05/01-2025/02/26
3	EMMA C AT SEDGWICK, KS	7144050	37.98517	-97.44573	1.364	2015/03/01-2025/02/26
4	SEDGWICK, KS	7144100	37.88306	-97.42416	8.582	1994/01/01-2025/02/26

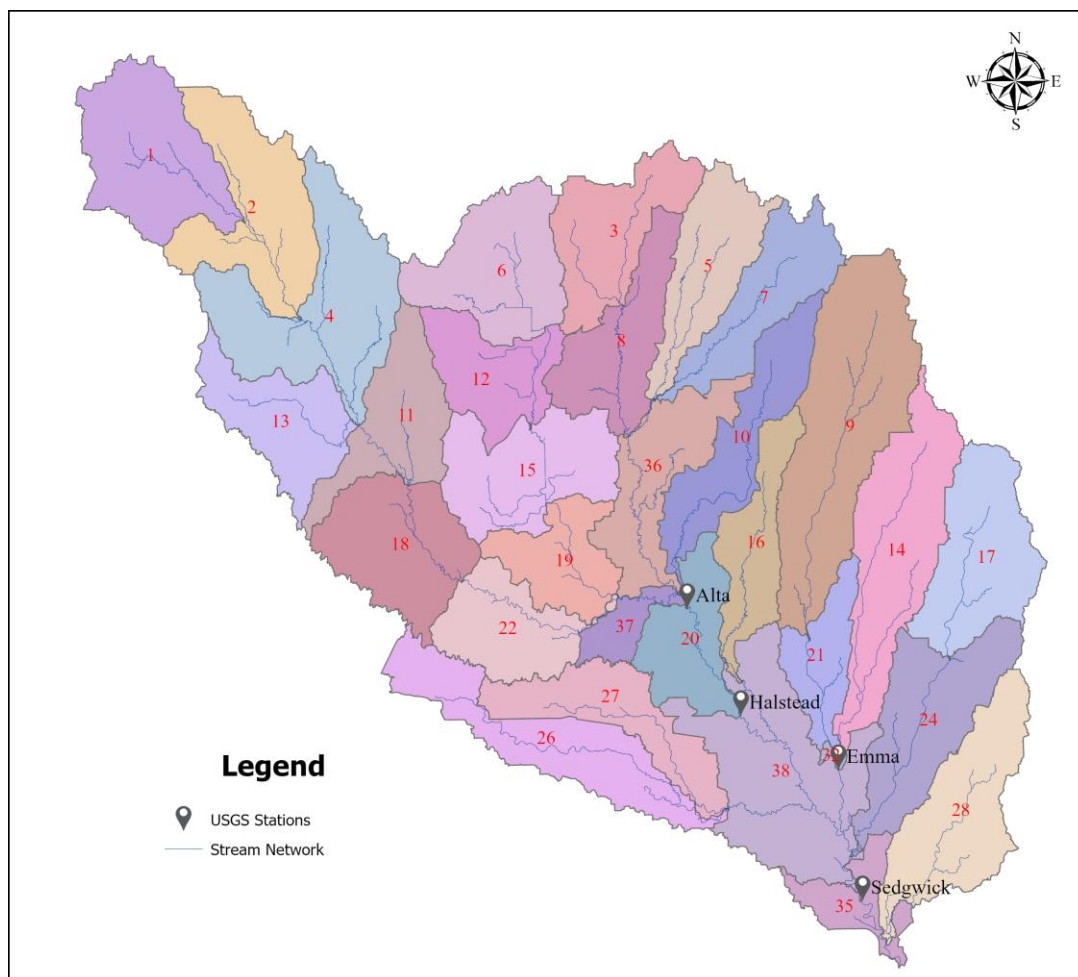


Figure 5 Subbasin delineation with stream network and USGS monitoring stations.

4.2.5 Field Boundary Layer (KARS Sub-CLU)

Agricultural field boundaries were obtained from the Kansas Applied Remote Sensing(KARS) sub-CLU dataset which provides field-level polygons derived from the USDA Common Land Unit (CLU) framework (Gao et al., 2017). The sub-CLU dataset represents actual farm management units, offering more realistic field boundaries compared to generalized land use layers. This improves spatial representation of Best Management Practice (BMP) implementation and evaluation(Merriman et al., 2018). In this study, the sub-CLU layer was used to convert HRU-level sediment outputs to field-level estimates through spatial intersection and aggregation, enabling direct linkage between modeled sediment yield and field-scale BMP application.

4.2.6 Weather Data

Climate data were obtained from the PRISM Climate Group (<https://prism.oregonstate.edu/explorer/>), which provides gridded datasets for precipitation and temperature at 4 kilometer resolution. The PRISM data were processed in ArcGIS Pro, where the watershed was delineated into HUC-12 subbasins and centroid points were generated for each unit. These centroids were used to extract PRISM grid values, ensuring that each subbasin was assigned representative climate inputs. The extracted datasets were subsequently formatted for integration into the SWAT+ model and used in the simulation framework.

In addition, daily precipitation and temperature observations were collected from USGS and NOAA Global Historical Climatology Network (GHCN) stations located within and near the watershed. Supplementary climate variables, including wind speed, solar radiation, and relative humidity, were incorporated to support evapotranspiration estimation and hydrologic flux simulation within SWAT+.

Chapter 5 Methodology

The methodology follows a structural workflow as illustrated in Figure 6, beginning with data preparation and SWAT+ model development, followed by stream flow calibration and validation using Nash Sutcliffe Efficiency (NSE), Kling Gupta Efficiency (KGE), and Percent Bias (PBIAS). Once satisfactory model performance was achieved, BMP scenarios including baseline, no-till (NT), and cover crops (CC) with no-till were simulated. The calibrated outputs were then used to evaluate sediment response and support spatial prioritization of critical sources areas.

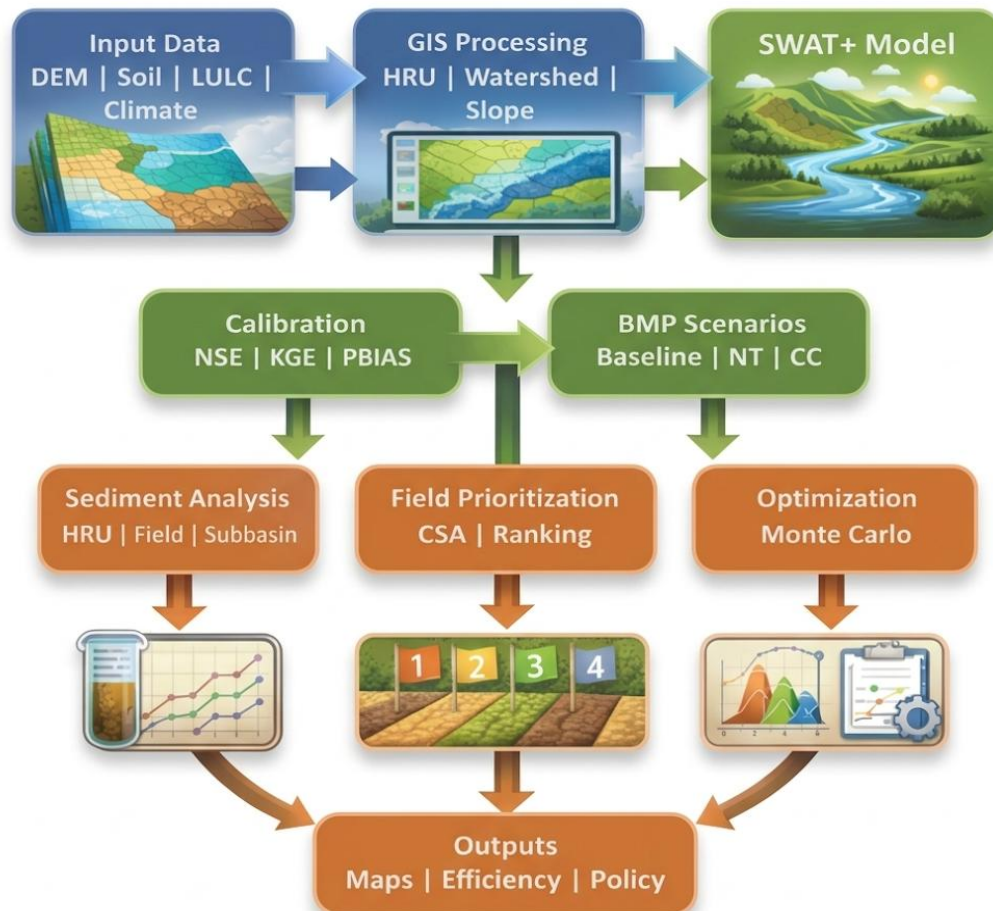


Figure 6 Schematic Diagram of Methodology

5.1 SWAT+ Model Development

Hydrological and sediment processes were simulated using the Soil and Water Assessment Tool Plus (SWAT+), the latest generation of the SWAT modeling framework. SWAT+ is a completely restructured, object-based version of SWAT that provides improved modularity, a more flexible spatial representation of landscape elements, and enhanced routing of water and constituents among hydrologic objects (Arnold et al., 2018; Bieger et al., 2017b). Model development was conducted using QSWAT+ 2.4.7 for watershed delineation and GIS preprocessing, SWAT+ Editor 2.3.3 for database configuration, and SWAT+ Toolbox v2.3 (Revision 60.5.7) for calibration, sensitivity analysis, and performance evaluation.

The DEM was used to derive flow direction, flow accumulation, and stream networks within QSWAT+. Watershed delineation followed HUC-12 boundary classification to ensure alignment with hydrologic unit coding. Minor depressions that produced artificial subbasin fragmentation were manually corrected. Smaller basins were merged to maintain hydrologic continuity. To address this, DEM-based stream paths were manually adjusted by bridging gaps in the drainage network to ensure proper connectivity and alignment with the outlet. The final delineation of the Little Arkansas River Watershed (HUC 11030012) produced 31 subbasins.

The subbasin area distribution presented in Table 4 indicates moderate spatial variability across the watershed. A total of 31 subbasins were delineated, with areas ranging from 266.50 ha (Subbasin 32) to 22,661.94 ha (Subbasin 9). Most subbasins fall within the range of approximately 8,000 to 14,000 ha or about 2–4% of the total watershed area. Subbasin 9 represents the largest unit, contributing 6.67% of the watershed, followed by Subbasin 38 (5.78%) and Subbasin 4 (5.22%). In contrast, several smaller subbasins, such as Subbasin 32 (0.08%) and Subbasin 37 (0.85%), contribute minimally to the total area. This variation reflects non-uniform watershed

partitioning and supports the need for subbasin-level analysis, as differences in area influence runoff generation and sediment yield across the watershed.

Table 4 Subbasin, area, and watershed percentage

Subbasin	Area (ha)	% of Watershed
1	14002	4.12
2	14033.7	4.13
3	10686.3	3.15
4	17728.5	5.22
5	9809.51	2.89
6	12576.2	3.7
7	9609.19	2.83
8	10109.5	2.98
9	22661.9	6.67
10	10556.6	3.11
11	9946.14	2.93
12	8424.05	2.48
13	9918.31	2.92
14	16273.7	4.79
15	12551.3	3.7
16	7904.68	2.33
17	12571.1	3.7
18	12510.2	3.68
19	7483.83	2.2
20	8070.06	2.38
21	5886.96	1.73
22	9017.24	2.66
24	13026.4	3.84
26	13128.3	3.87
27	9773.13	2.88
28	13473.9	3.97

32	266.5	0.08
35	4466.85	1.32
36	10596.8	3.12
37	2891.87	0.85
38	19613.4	5.78

Crop land use management was standardized across all agricultural HRUs to ensure controlled comparison among scenarios. All Cropland areas were assigned the corn_120 crop parameterization as the baseline condition. This uniform configuration eliminates variability associated with mixed crop rotations ensuring that differences in sediment yield reflect management changes rather than crop-type heterogeneity.

During HRU creation, land use, soil, and slope layers were overlaid to define unique Hydrologic Response Units (HRUs), which represent distinct combinations of physical and management characteristics influencing runoff and erosion processes (J. G. Arnold et al., 2012a). A total of 4,791 HRUs were defined across the 31 subbasins. The SWAT+ database was structured in SWAT+ Editor 2.3.3, where all model components, including land unit, channel, and management operations were linked together.

Management operations were assigned at the HRU level to represent different land-use categories. For cropland HRUs, a standardized corn_120 management schedule (Table 4) was applied as the baseline condition. Corn was selected because it represents a dominant crop type in the region and provides a consistent basis for evaluating sediment response under different management scenarios. This assumption ensures that variations in sediment yield are driven by management practices rather than crop-type differences.

In contrast, the “agrr” land-use class represents generic agricultural row crops within the SWAT+ database and does not correspond to a specific crop such as corn. Instead, it includes

generalized row crop characteristics and management operations used when detailed crop information is unavailable. In this study, the agr-related management schedules Table 7 and Table 8 , along with other crop rotations such as soybean and wheat Table 9 - Table 11, were included in the model database but were not used in the baseline simulation.

Grazing management was applied specifically to rangeland HRUs to represent livestock-induced soil disturbance. Grazing affects surface residue cover and soil compaction, which influence runoff generation and erosion processes. This management was implemented during the HRU parameterization stage based on land-use classification.

The crop management schedules used in the SWAT+ model are presented in Table 5-Table 11. These tables define the timing and sequence of operations, including tillage, planting, harvesting, irrigation, and fertilizer application for different land-use categories and crop rotations implemented in the study. **Note:** Operation codes (e.g., dkchmtl, fldcult) represent predefined SWAT+ management operations. Fertilizer applications and certain operations are simulated automatically using model-defined parameters and decision tables. This notation applies to all management schedules presented from Table 5 to Table 11.

Table 5 Corn management operations used in the SWAT+ model, including tillage, planting, harvesting, and fertilizer application for a two-year corn-soybean rotation.
Management schedule: Corn- soybean two-year rotation (corn_soyb_2yr_rot)

Year	Month	Date	Operation	Remarks
1	March	10	Tillage	Disk chisel (mulch tiller : dkchmtl)
	March	20	Tillage	Field cultivator (Ge 15 ft : fldcult)
	March	30	Tillage	Field cultivator (Ge 15 ft : fldcult)
	April	15	Tillage	Disk chisel (mulch tiller : dkchmtl)
	April	25	Planting	Corn

	September	20	Harvesting	Grain harvesting
Fertilizer application		Model set to apply fertilizer automatically		fert_stess_test5
2	March	15	Tillage	Field cultivator (Ge 15 ft : fldcult)
	March	30	Tillage	Field cultivator (Ge 15 ft : fldcult)
	April	15	Tillage	Disk chisel (mulch tiller : dkchmtl)
	May	20	Tillage	Field cultivator (Ge 15 ft : fldcult)
	May	25	Planting	Soybean
	October	2	Harvesting	Grain harvesting

Table 6 Irrigated corn management operations, including irrigation scheduling and automated decision-table-based tillage and planting operations.

Management schedule: Irrigated corn one year rotation (Irr_corn1_yr)

Year	Month	Date	Operation	Remarks
1	May	1	irrigation	sprinkler_med
	June	1	irrigation	sprinkler_med
	July	1	irrigation	sprinkler_med
	August	1	irrigation	sprinkler_med
	September	1	irrigation	sprinkler_med
	October	1	irrigation	sprinkler_med
Fertilizer application		Model set to apply fertilizer automatically		fert_stess_test3
Model set up to apply tillage automatically from decision table			Tillage	fall_plow12
Model set up to apply plant and harvest automatically from decision table			Planting and Harvesting	pl_hv_summer1(corn)

Table 7 Irrigated agricultural row crop management schedule, including irrigation timing and automated management operations.

Management schedule: Irrigated agricultural land row crop one year rotation (irr_agrr_1yr_rot)

Year	Month	Date	Operation	Remarks
1	May	5	irrigation	sprinkler_med
	June	5	irrigation	sprinkler_med
	July	5	irrigation	sprinkler_med
	August	5	irrigation	sprinkler_med
	September	5	irrigation	sprinkler_med
	October	5	irrigation	sprinkler_med
	November	5	irrigation	sprinkler_med
Fertilizer application		Model set to apply fertilizer automatically		fert_stess_test4
Model set up to apply tillage automatically from decision table			Tillage	fall_plow13
Model set up to apply plant and harvest automatically from decision table			Planting and Harvesting	pl_hv_summer1(agrr)

Table 8 Agricultural row crop management operations, including tillage and crop establishment practices.

Management schedule agricultural land row crop one year rotation (agrr_1yr_rot)

Year	Month	Date	Operation	Remarks
1	March	10	Tillage	Disk chisel (mulch tiller: dkchmtl)
	March	30	Tillage	Field cultivator (Ge 15 ft: fldcult)
	April	15	Tillage	Field cultivator (Ge 15 ft : fldcult)
	April	25	Planting	agrr

	September	20	Harvesting	Grain harvesting
Fertilizer application		Model set to apply fertilizer automatically		fert_stess_test2

**Table 9 Soybean-grain sorghum two-year rotation management
schedule used in the SWAT+ model.**

Management schedule: soybean-grain sorghum two-year rotation(soyb_grsg_2yr_rot)

Year	Month	Date	Operation	Remarks
1	March	15	Tillage	Disk chisel (mulch tiller : dkchmtl)
	March	30	Tillage	Field cultivator (Ge 15 ft : fldcult)
	April	30	Tillage	Field cultivator (Ge 15 ft : fldcult)
	May	15	Tillage	Field cultivator (Ge 15 ft : fldcult)
	May	25	Planting	Soybean
	September	5	Harvesting	Soyb-grain
Fertilizer application		Model set to apply fertilizer automatically		fert_stess_test9
2	March	15	Tillage	Disk chisel (mulch tiller : dkchmtl)
	March	30	Tillage	Field cultivator (Ge 15 ft : fldcult)
	April	30	Tillage	Field cultivator (Ge 15 ft : fldcult)
	May	15	Tillage	Field cultivator (Ge 15 ft : fldcult)
	May	25	Planting	Grainsorghum
	September	10	Harvesting	grsg-grain

**Table 10 Winter wheat management schedule, including planting,
harvesting, and tillage operations.**

Management schedule: Winter wheat one-year rotation(wwht_1yr_rot)

Year	Month	Date	Operation	Remarks
1	June	15	Harvesting	Grain (wwht)
	July	15	Tillage	Disk chisel (mulch tiller : dkchmtl)
	July	30		Field cultivator (Ge 15 ft : fldcult)
	August	30	Tillage	Field cultivator (Ge 15 ft : fldcult)
	September	10	Planting	Winter wheat
Fertilizer application		Model set to apply fertilizer automatically		fert_stess_test10

**Table 11 Soybean–winter wheat three-year rotation management schedule used in the
SWAT+ model.**

Management schedule: Soybean-winter wheat three-year rotation(soyb_wwht_3yr_rot)

Year	Month	Date	Operation	Remarks
1	March	15	Tillage	Disk chisel (mulch tiller : dkchmtl)
	March	30	Tillage	Field cultivator (Ge 15 ft : fldcult)
	April	30	Tillage	Field cultivator (Ge 15 ft : fldcult)
	May	10	Planting	soybean
	September	20	Harvesting	Soyb-grain
2	July	30	Tillage	Disk chisel (mulch tiller : dkchmtl)
	August	30	Tillage	Field cultivator (Ge 15 ft : fldcult)
	September	10	Planting	Winter wheat

3	June	15	Harvesting	wwht-grain
Fertilizer application		Model set to apply fertilizer automatically		fert_stess_test6

The model simulated precipitation, runoff processes, infiltration, evapotranspiration, lateral flow, groundwater return flow, and sediment yield. The model was executed using QSWAT+ to generate time series outputs at HRU, LSU, and subbasin levels. A two-step calibration and validation procedure was employed. First, the model was calibrated by adjusting parameters to match simulated streamflow with observed data at four USGS monitoring stations. Second, the calibrated model was validated using an independent time period to assess its predictive performance without further parameter adjustment.

5.2 Model Input Data and Spatial Processing

Accurate representation of watershed processes requires consistent spatial and temporal datasets. Spatial preprocessing was conducted using QSWAT+ 2.4.7 within a GIS environment.

A 10 m Digital Elevation Model (DEM) was used to delineate watershed boundaries and stream networks. The DEM was further used to drive flow direction and flow accumulation. These layers were used to define stream networks based on an appropriate threshold that balances hydrologic representation and computational efficiency. Slope was also derived from the DEM and used in HRU definition and sediment calculations. Slope influences runoff velocity and contributes to the LS factor in the MUSLE equation, which directly affects sediment detachment and transport (J. G. Arnold et al., 2012b).

Soil properties were obtained from the STATSGO2 database including texture, hydraulic conductivity, bulk density, available water capacity, and organic carbon content. These properties control infiltration, percolation, and soil moisture storage, which influences runoff generation and

sediment yield. Hydraulic conductivity governs vertical water movement, while available water capacity determines soil water retention.

Land use was represented using the LULCD dataset and aligned with agricultural management classes. Land cover classification influences curve number assignment and USLE_C factors. Accurate crop representation is necessary for realistic residue and canopy cover simulation. Misclassification of land use introduces bias in sediment estimation (Pandey et al., 2021).

Hydrologic Response Units were defined by overlaying land use, soil, and slope layers. HRU threshold selection controls spatial aggregation. HRUs represent unique combinations of these attributes and serve as the basic computational units in SWAT+. A total of 4,791 HRUs were generated across 31 subbasins. This level of discretization was selected to preserve spatial variability and improve identification of high sediment-producing areas.

Climate data were obtained from PRISM within and near the watershed. Daily precipitation and temperature were the primary climate drivers. Additional inputs included wind speed, solar radiation, and relative humidity. Precipitation directly controls runoff generation and sediment detachment. Temperature influences evapotranspiration and soil moisture dynamics.

A continuous simulation period from 2000 to 2023 was selected to capture interannual variability. A warm-up period from 2000 to 2003 was applied to allow the model to stabilize internal state variables such as soil moisture, ground water storage, and channel conditions before analysis (J. G. Arnold et al., 2012a).

Input data quality was checked for missing values, consistency, and reasonable ranges prior to model execution.

5.3 Model Calibration and Sensitivity Analysis

Model calibration was conducted to minimize discrepancies between simulated and observed streamflow data. Calibration was performed using SWAT+ Toolbox v2.3 under project revision 60.5.7. A multisite calibration strategy was adopted to capture spatial variability in hydrologic response and to reduce parameter bias associated with single-outlet calibration (J. G. Arnold et al., 2012b).

The selection of calibration parameters was guided by prior SWAT and SWAT+ studies, as well as sensitivity analyses reported in the HAWQS (Hydrologic and Water Quality System) framework (HAWQS 2. 0, 2023). The HAWQS database identifies a set of hydrologic parameters that consistently exhibit high sensitivity in agricultural watersheds, particularly those controlling runoff generation, soil water balance, and groundwater response. These include CN2, ESCO, EPCO, ALPHA_BF, SOL_K, SOL_AWC, and SURLAG, which have been widely reported as dominant controls on streamflow simulation (Allen et al., 2015; D. N. Moriasi et al., 2007a; J. G. Arnold et al., 2012b). Based on these established findings, this study focused on a reduced set of physically interpretable and high-sensitivity parameters to ensure stable and efficient calibration.

Observed daily streamflow data were obtained from four USGS gauging stations located within the watershed. These stations included Alta (USGS 07143665), Halstead (USGS 07143672), Emma Creek (USGS 07143665), and Sedgwick (USGS 07144200). Multisite calibration reduces parameter bias that can occur when calibrating to a single outlet (J. G. Arnold et al., 2012a).

The SCS Curve Number parameter (CN2) was adjusted to regulate runoff generation potential. CN2 controls the partitioning of precipitation into runoff and infiltration and is consistently identified as one of the most sensitive parameters in SWAT-based hydrologic

simulations (D. N. Moriasi et al., 2007a; J. G. Arnold et al., 2012b). The calibrated CN2 adjustment was +2.26% relative to default values.

The soil evaporation compensation factor (ESCO) and plant uptake compensation factor (EPCO) were calibrated to improve soil moisture and evapotranspiration dynamics. ESCO regulates the depth distribution of soil evaporation, while EPCO controls plant water uptake from deeper soil layers. These parameters are commonly adjusted in SWAT calibration to improve water balance representation (J. G. Arnold et al., 2012b). The calibrated ESCO value was reduced to 0.14, and EPCO was increased to 0.82.

The lateral flow travel time (LAT_TTIME) and surface runoff lag coefficient (SURLAG) were calibrated to improve timing of subsurface and surface flow contributions. LAT_TTIME controls the delay in lateral flow movement, while SURLAG governs the rate of surface runoff routing. These parameters influence peak flow timing and hydrograph shape and are frequently identified as sensitive in watershed-scale studies (“Hydrologic and Water Quality Models,” 2015). The calibrated values were 168.15 days for LAT_TTIME and 3.66 days for SURLAG.

Soil hydraulic conductivity (SOL_K) and soil available water capacity (SOL_AWC) were adjusted to improve infiltration and soil water storage processes. SOL_K controls percolation rates, while SOL_AWC determines the water-holding capacity of soil layers. These parameters are critical for representing soil-water interactions and are commonly calibrated within literature-recommended ranges (D. N. Moriasi et al., 2007a). SOL_K was increased proportionally, while SOL_AWC was reduced by 18%.

Groundwater processes were represented using the baseflow alpha factor (ALPHA_BF) and the shallow aquifer threshold parameter (REVAP_MIN). ALPHA_BF controls the rate of groundwater recession, while REVAP_MIN governs upward water movement from the aquifer to

the root zone. These parameters influence baseflow contributions and long-term flow stability (Arnold et al., 2012). The calibrated values were 0.35 days for ALPHA_BF and 1.32 m for REVAP_MIN.

Calibration parameter bounds were defined based on a combination of HAWQS parameter ranges and literature reported calibration limits. These ranges ensure that parameter adjustments remain physically realistic while allowing sufficient flexibility to match observed hydrologic behavior. The selected bounds are consistent with previously published SWAT calibration studies and standard guidelines (D. N. Moriasi et al., 2007a; “Hydrologic and Water Quality Models,” 2015).

Model performance was evaluated using Nash–Sutcliffe Efficiency (NSE), Kling Gupta Efficiency (KGE), Root Mean Square Error (RMSE), Mean Square Error (MSE), and Percent Bias (PBIAS). NSE measures predictive accuracy relative to observed variance, while KGE evaluates correlation, variability, and bias simultaneously. PBIAS quantifies systematic overestimation or underestimation. Performance thresholds followed standard guidelines recommending NSE and KGE values greater than 0.50 and PBIAS within $\pm 25\%$ for satisfactory performance (D. N. Moriasi et al., 2007a).

Model performance metrics were evaluated across all stations to ensure that simulated streamflow adequately represented observed hydrologic behavior. Multisite calibration was used to maintain consistency in upstream and downstream flow dynamics. Establishing satisfactory hydrologic performance is necessary for subsequent sediment modeling, as sediment yield in SWAT+ is driven by runoff processes through the MUSLE formulation (J. G. Arnold et al., 2012b; Williams & Berndt, 1972).

Table 12 Selected SWAT+ calibration parameters and final calibrated values

Parameter	Unit	Level	Default value	Calib range	Calibration Method	Calibrated Value	Source
CN2	–	HRU	var	-30,30	% change	2.26	(HAWQS 2.0, 2023)
ESCO	–	HRU	0.95	0.01,1	replace	0.14	
EPCO	–	HRU	0.5	0.5,1	% change	0.82	
LAT_TTIME	days	HRU	0	90200	replace	168.15	
SURLAG	days	Basin	4	1,12	replace	3.66	
SOL_K	mm/hr	Soil	1	0,200	% change	81.26	
SOL_AWC	mm H ₂ O/m soil	Soil	0.04	-20,20	% change	-17.5	
ALPHA_BF	days	Aquifer	0.048	0.1,0.5	replace	0.35	
REVAP_MIN	m	Aquifer	3	0,2	replace	1.32	

5.4 Scenario Development and Parameterization

Three management schedules were developed within SWAT+ to represent baseline and conservation scenarios. Each schedule modifies tillage operations, residue management, and seasonal cover while maintaining identical crop growth parameters.

The baseline schedule (Corn_all_cropland_1yr_rot) represents conventional tillage corn production. Two tillage operations were performed prior to planting using tandem and field cultivator operations. Corn_120 was planted on May 1 and harvested on September 5. A post-harvest tillage operation was applied to represent additional soil disturbance following harvest. While the harvesting operation removes crop biomass, it does not modify soil structure or residue incorporation in the model. The post-harvest tillage operation therefore explicitly represents residue mixing and soil disturbance, which influences surface roughness, residue cover, and erosion processes.

The no-till schedule (No-till_corn_BMP1) eliminates all mechanical soil disturbance prior to planting. Corn planting and harvesting dates were maintained identical to baseline conditions. The combined no-till and cover crop schedule (NT-CC_Bmp30216) integrates no till operations with a winter wheat cover crop. Winter wheat was planted after corn harvest and terminated before the subsequent corn cycle. This configuration increases surface cover and reduces soil disturbance relative to the baseline condition.

Table 13 HRU-Level Management Schedules for Baseline and BMP Scenarios

Crop	Planting Date	Harvest Date	Fertilizer Application	Tillage Operations (Date – Type)
corn_120	1-Apr	5-Sep	Fert_stess_test2 (decision table)	April 15 – tandempl; April 29 – fldcult; September 17 – chispow
corn_120	1-Apr	5-Sep	Fert_stess_test2 (decision table)	No tillage (zerotill operations)
corn_120 + WWHT	Corn: April 1 / WWHT: September 9	Corn: September 5 / WWHT: April 27	Fert_stess_test2 (decision table)	No conventional tillage (zerotill throughout)

Note: Zero till represents a no-tillage operation in SWAT+, Fertilizer application (Fert_stess_test2) is implemented through SWAT+ decision tables, meaning that application timing and amount are controlled automatically by model defined rules rather than fixed scheduling. This configuration ensures consistent representation of management practices across simulation scenarios.

Parameter adjustments were applied to represent the physical effects of conservation practices on runoff generation and erosion processes. Reduced tillage and increased residue cover improve soil structure, enhance infiltration, and reduce surface runoff, which collectively decreases sediment detachment and transport (Dibaba et al., 2021; Pandey et al., 2021).

Key parameters used in scenario development include Curve Number (CN), which controls runoff generation; soil hydraulic conductivity (K), which governs infiltration capacity; available water capacity (AWC), which represents soil moisture storage; surface runoff lag coefficient (SURLAG), which controls runoff timing; the Universal Soil Loss Equation cover-management factor (USLE_C), which represents surface protection; and the support practice factor (USLE_P), which represents erosion control practices.

The simulation period extended from 2000 to 2023 with a three-year warm-up period to stabilize soil moisture, groundwater storage, and channel sediment conditions prior to analysis (J. G. Arnold et al., 2012a).

Curve numbers (CN) values were adjusted to represent differences in runoff potential under management conditions. Conventional tillage increases runoff potential due to soil disturbance, while no-till reduces runoff through improved infiltration and residue cover. Soil hydraulic conductivity (K) and available water capacity (AWC) were adjusted to represent changes in soil structure and moisture retention associated with management practices. These adjustments follow standard SWAT modeling approaches for representing land management impacts on hydrologic and erosion processes (Dibaba et al., 2021; J. G. Arnold et al., 2012b).

The USLE_C parameter was increased under baseline conditions (0.40) and reduced under conservation scenarios (0.30 for no-till and combined BMP) to reflect differences in surface residue protection. The USLE_P factor was maintained at 1.0 for conventional tillage and reduced

to 0.8 and 0.7 for no-till and combined scenarios, respectively, to represent conservation practices such as contour farming. Curve numbers were increased under baseline conditions and reduced under conservation scenarios across hydrologic soil groups A, B, C, and D to reflect differences in runoff response.

Model outputs were extracted at HRU, subbasin, and watershed outlet levels. Sediment yield differences between baseline and BMP scenarios were computed on an annual basis. Percent reduction and absolute sediment reduction were calculated for each HRU and used to support field-level prioritization under the off-site BMP framework.

summarizes the key parameter adjustments applied across baseline and BMP scenarios. Only parameters directly related to runoff generation, soil properties, and erosion processes were modified, while all other calibrated parameters were held constant to isolate the effects of management practices.

Table 14 summarizes the key parameter adjustments applied across baseline and BMP scenarios. Only parameters directly related to runoff generation, soil properties, and erosion processes were modified, while all other calibrated parameters were held constant to isolate the effects of management practices.

Table 14 Comparison of Default and Scenario-Specific Model Parameters for Conventional Tillage, No-Till, and Cover Crop BMPs.

Parameter	Default	Baseline (Conventional)	No-Till (BMP1)	Cover Crop (BMP2)	NT + CC
USLE_C	0.14	0.4	0.3	corn: 0.40; wheat: 0.03	corn: 0.30; wheat: 0.03
Biomass Energy Ratio	40	30	30	30	30

Harvest Index	0.55	0.4	0.4	0.4	0.4
PET Method	1	0	0	0	0
CN Method Flag	0	2	2	2	2
CN_A	73.63	78.63	75.63	78.63	75.63
CN_B	82.83	87.83	84.83	87.83	84.83
CN_C	89.99	94.99	91.99	94.99	91.99
CN_D	93.06	98.06	95.06	98.06	95.06
SURLAG (days)	3.66	5.66	5.66	5.66	5.66
Manning's n	0.06–0.12	conventional	reduced (no-till)	conventional	reduced
SOL_K	—	×0.5	×0.5	×0.5	×0.5
SOL_AWC	—	×0.5	×0.5	×0.5	×0.5
Slope Length	—	30	30	30	30
USLE_P	1	1	0.8	1	0.7

5.5 Critical Source Area Identification and Hotspot analysis

Effective sediment reduction strategies require identification of Critical Source Areas within the watershed. Critical Source Areas are defined as locations that contribute disproportionately to total sediment yield relative to their spatial extent (Dibaba et al., 2021). These areas generate high sediment loads due to combined effects of slope, soil erodibility, runoff intensity, and management practices. Targeting Critical Source Areas increases sediment reduction efficiency compared to uniform BMP implementation (Abimbola et al., 2020).

A targeted prioritization framework was developed to identify high-contributing areas. The framework integrates spatial ranking, clustering, hotspot identification, and stochastic selection to evaluate how spatial information improves implementation efficiency.

Average annual sediment yield was first computed at the Hydrologic Response Unit (HRU) level in units of tons per hectare per year. This metric standardizes sediment contribution across spatial units. HRUs were ranked in descending order based on sediment yield and subsequently aggregated to field units, which represent management-relevant decision units. High-ranking fields were interpreted as priority intervention zones. This ranking preserves spatial heterogeneity in erosion potential and forms the baseline prioritization layer.

To maintain consistency across all analyses, field units derived from HRU aggregation were used as the common spatial unit for clustering, hotspot analysis, and selection procedures. Clustering was incorporated within the framework to classify fields into sediment yield intensity groups, with detailed methodology provided in Section 5.7.

Spatial hotspot analysis was conducted using the Getis–Ord (G_i^*) statistic to identify statistically significant clusters of high sediment yield. The G_i^* statistic measures local spatial autocorrelation, where high values indicate spatial clustering of high-yield fields. Fields were classified into 90%, 95%, and 99% confidence levels, representing increasing statistical significance of hotspot intensity. These hotspot zones define spatially coherent high-contributing areas suitable for targeted BMP implementation.

Sediment reduction efficiency was quantified using both absolute and relative metrics. Absolute reduction was defined as the difference between baseline and BMP sediment yield (tons per year). Relative reduction was defined as the percentage decrease from baseline conditions. Efficiency is defined as the ability to achieve a predefined sediment reduction target using the minimum number of fields and minimum treated area. This definition provides a consistent basis for comparing alternative selection strategies.

Efficiency maps were generated to visualize the spatial distribution of sediment reduction potential. Fields with high baseline sediment yield and high absolute reduction under BMP scenarios were classified as high-priority candidates. These maps support transparent and spatially explicit decision-making for watershed management.

5.6 Field Selection Framework for Offsite BMP Program

A field selection framework was developed to evaluate the ability of rural BMP implementation to offset urban sediment contributions. The sediment offset target was defined based on the urban reduction requirement, with a representative value of 160 tons per year used for analysis. Field selection proceeds until the cumulative sediment reduction from selected fields meets or exceeds this target.

A Monte Carlo simulation framework was implemented to represent variability in field enrollment under realistic conditions. A total of 1000 independent simulation runs were conducted for each scenario. In each run, fields were randomly selected without replacement, and cumulative sediment reduction was tracked sequentially until the predefined target was achieved.

Field level sediment estimates were derived from HRU level model outputs. Initially, sediment yield rate ($\text{t ha}^{-1} \text{ yr}^{-1}$) was obtained at the HRU level from SWAT+ simulations. Total sediment load (t yr^{-1}) for each HRU was then calculated by multiplying the sediment yield rate by the HRU area. These HRU-level outputs were spatially intersected with field boundary data in ArcGIS to transfer sediment values to field units. The intersected polygons were subsequently dissolved by field boundaries to obtain aggregated field-level sediment load and yield rates. This process ensured that field selection reflects realistic management units rather than model discretization units.

For each simulation run, the number of selected fields and total treated area were recorded to evaluate selection performance. The framework evaluates three selection strategies with increasing levels of spatial information. The first strategy represents watershed-wide random selection, reflecting non-targeted enrollment conditions. The second strategy restricts selection to high-contributing subbasins, incorporating spatial prioritization at an intermediate scale. The third strategy integrates clustering and hotspot-based targeting to isolate statistically significant high-yield fields.

This hierarchical structure allows direct comparison of how spatial targeting improves efficiency and predictability. The framework links process-based sediment modeling with policy-based offset requirements where modeled sediment reductions provide quantitative support for BMP allocation decisions and enable evaluation of trade-offs between effectiveness and practicality.(Moore et al., 2019).

5.7 Multivariate clustering; K-means

To organize spatial heterogeneity in sediment yield and support field-level prioritization, a clustering approach was applied using the K-means algorithm. Clustering groups fields into homogeneous classes based on similar sediment yield characteristics, enabling differentiation between low-yield and high-yield regimes. K-means is an unsupervised learning algorithm that partitions observations into a predefined number of clusters by minimizing within cluster variance. Each field is assigned to the nearest cluster centroid, where the centroid represents the mean value of observations within that cluster. The algorithm minimizes the sum of squared distances between observations and their assigned centroids.

The clustering analysis was conducted using baseline field-level sediment yield rate ($\text{t ha}^{-1} \text{ yr}^{-1}$) derived from HRU aggregation. Sediment yield rate was selected because it normalizes

erosion intensity across fields of different sizes. The dataset exhibits strong right-skewness, characterized by a small number of high-yield fields and many low-yield fields.

The number of clusters (K) was selected to provide meaningful separation between sediment yield intensity levels while maintaining interpretability for management decisions. The resulting clusters represent discrete sediment yield intensity classes, typically corresponding to low, moderate, and high sediment-producing fields. High-yield clusters represent fields with disproportionately large contributions to total sediment load and are considered candidate areas for targeted BMP implementation. This classification is subsequently integrated with hotspot analysis to identify statistically significant high-contributing zones. By converting continuous sediment yield values into discrete classes, clustering provides a structured basis for linking model outputs to decision-making. This approach complements ranking by identifying groups of fields with similar erosion behavior and supports spatially targeted sediment reduction strategies.

Chapter 6 Results

6.1 Hydrological Model Performance (Calibration and Validation)

The performance of the SWAT+ model was evaluated using a combination of graphical diagnostics and statistical metrics across four gauging stations: Alta (Channel(ch) 94), Emma (Channel 123), Halstead (Channel 91), and Sedgwick (Channel 144). Model performance was assessed at daily and monthly timescales using hydrographs, scatter plots, flow duration curves (FDC), and cumulative flow comparisons. Statistical evaluation was conducted using the coefficient of determination (R^2), Nash–Sutcliffe Efficiency (NSE), Percent Bias (PBIAS), and Kling–Gupta Efficiency (KGE). NSE measures predictive efficiency relative to observed variance, while PBIAS quantifies systematic overestimation or underestimation of flow volume.

Figure 7 presents the multisite daily hydrograph for both calibration and validation periods, while Figure 8 to Figure 11 present detailed station-wise diagnostics including hydrograph comparison, scatter relationships, FDC behavior, and cumulative flow diagram.

Across all stations, the model reproduces the temporal dynamics of streamflow, including the occurrence and timing of flow events, under both calibration and validation conditions. Daily NSE values range from 0.50 to 0.71 during calibration and from 0.62 to 0.75 during validation. Monthly NSE values show substantial improvement, ranging from 0.70 to 0.79 during calibration and from 0.73 to 0.89 during validation, indicating strong representation of aggregated hydrological processes.

A key indicator of model reliability is the consistency between calibration and validation performance. Alta and Sedgwick exhibit stable or improved NSE and reduced bias during validation, indicating strong model transferability. In contrast, Emma and Halstead show notable

shifts in bias between periods, indicating sensitivity in runoff generation and flow partitioning processes.

The FDC analysis shows consistent agreement between simulated and observed flows in low and medium flow regimes across all stations. Deviations are concentrated in the upper tail of the distribution, indicating systematic difficulty in reproducing peak flows. This limitation is also reflected in scatter plots, where dispersion increases at higher discharge values.

Cumulative flow comparisons further confirm that long-term water balance is reasonably preserved at Alta and Sedgwick, while divergence is observed at Emma and Halstead during validation, consistent with observed bias shifts.

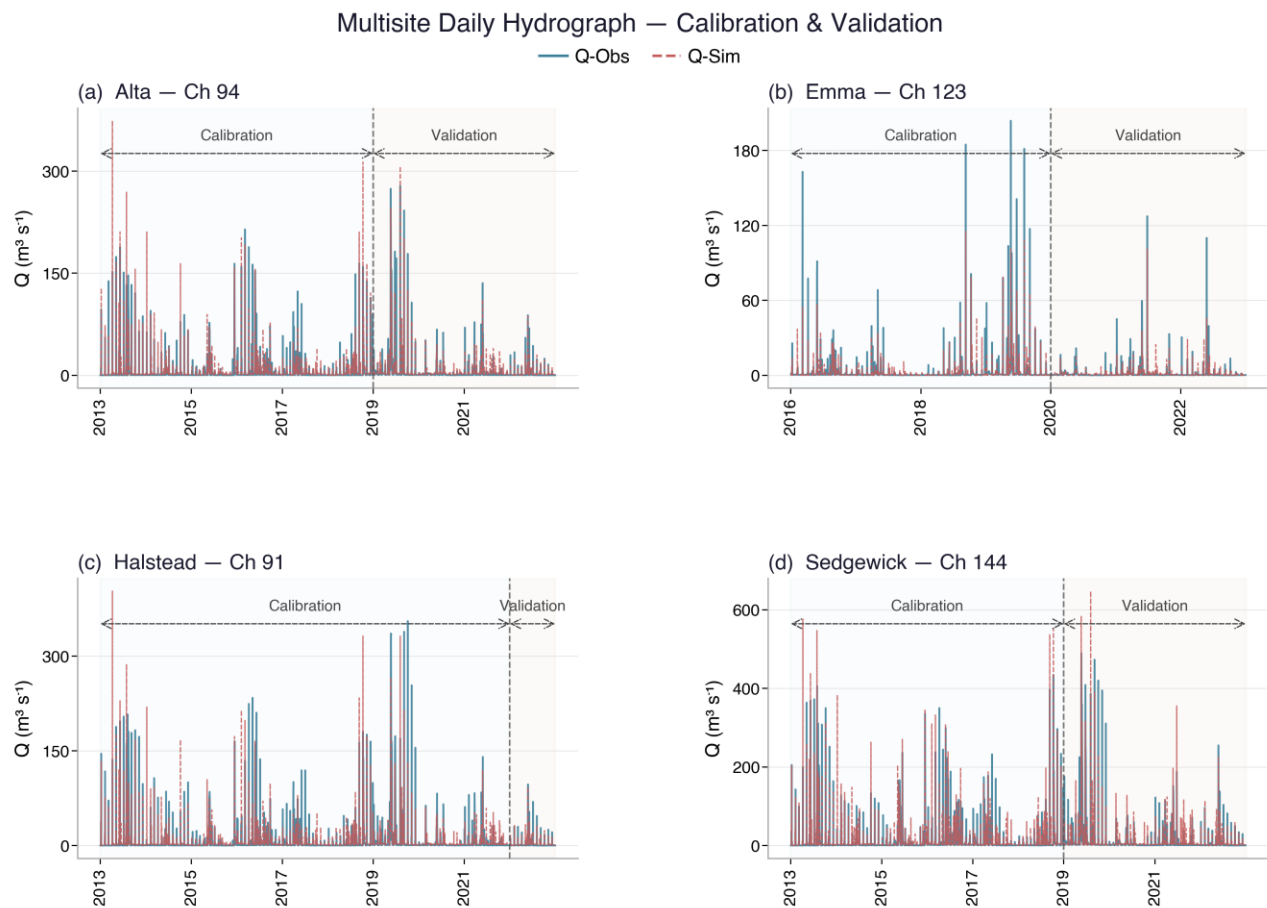


Figure 7 Multisite comparison of daily streamflow hydrographs and calibration statistics for Alta, Emma, Halstead, and Sedgwick.

A consolidated summary of calibration and validation metrics are presented in Table 15 and Table 16 to facilitate direct comparison across stations and temporal resolutions.

Table 15 Summary of daily and monthly calibration statistics for the four gauging stations.

Calibration										
Station	Period		Daily				Monthly			
	From	To	R ²	NSE	PBIAS	KGE	R ²	NSE	PBIAS	KGE
Alta	2013-01-01	2018-12-31	0.66	0.6	25.5	0.68	0.671	0.604	25.7	0.679
Emma	2016-01-01	2019-12-31	0.811	0.711	-15.7	0.546	0.879	0.786	-15.6	0.615
Halstead	2013-01-01	2021-12-31	0.518	0.505	1.1	0.672	0.742	0.701	1.2	0.632
Sedgewick	2013-01-01	2018-12-31	0.636	0.576	16.3	0.737	0.784	0.757	16.4	0.786

Table 16 Summary of daily and monthly validation statistics for the four gauging stations.

Validation										
Station	Period		Daily				Monthly			
	From	To	R ²	NSE	PBIAS	KGE	R ²	NSE	PBIAS	KGE
Alta	1/1/2019	12/31/2022	0.768	0.745	-1.4	0.697	0.914	0.819	-1.2	0.645
Emma	1/1/2020	12/31/2022	0.652	0.642	8	0.644	0.739	0.726	8.3	0.829
Halstead	1/1/2022	12/31/2022	0.652	0.641	32.3	0.54	0.971	0.89	32.5	0.668
Sedgewick	1/1/2019	12/31/2022	0.626	0.625	-4.7	0.718	0.878	0.795	-4.5	0.642

6.1.1 Performance at Station Alta

Alta demonstrates strong and consistent model performance across both calibration and validation periods Figure 8. Daily NSE improves from 0.60 during calibration to 0.75 during validation, while monthly NSE increases from 0.60 to 0.82. The hydrograph indicates accurate reproduction of flow timing in both periods, with improved peak alignment during validation. The scatter plot shows tighter clustering around the 1:1 line in validation compared to calibration, indicating improved predictive consistency. FDC analysis shows close agreement across most of the exceedance range, with minor deviation at high flows. The cumulative flow curve shows a clear improvement in

volume representation during validation, corresponding to a reduction in PBIAS from 25.5% (overestimation) during calibration to -1.4% during validation. This shift indicates improved water balance representation and confirms strong model transferability at this station.

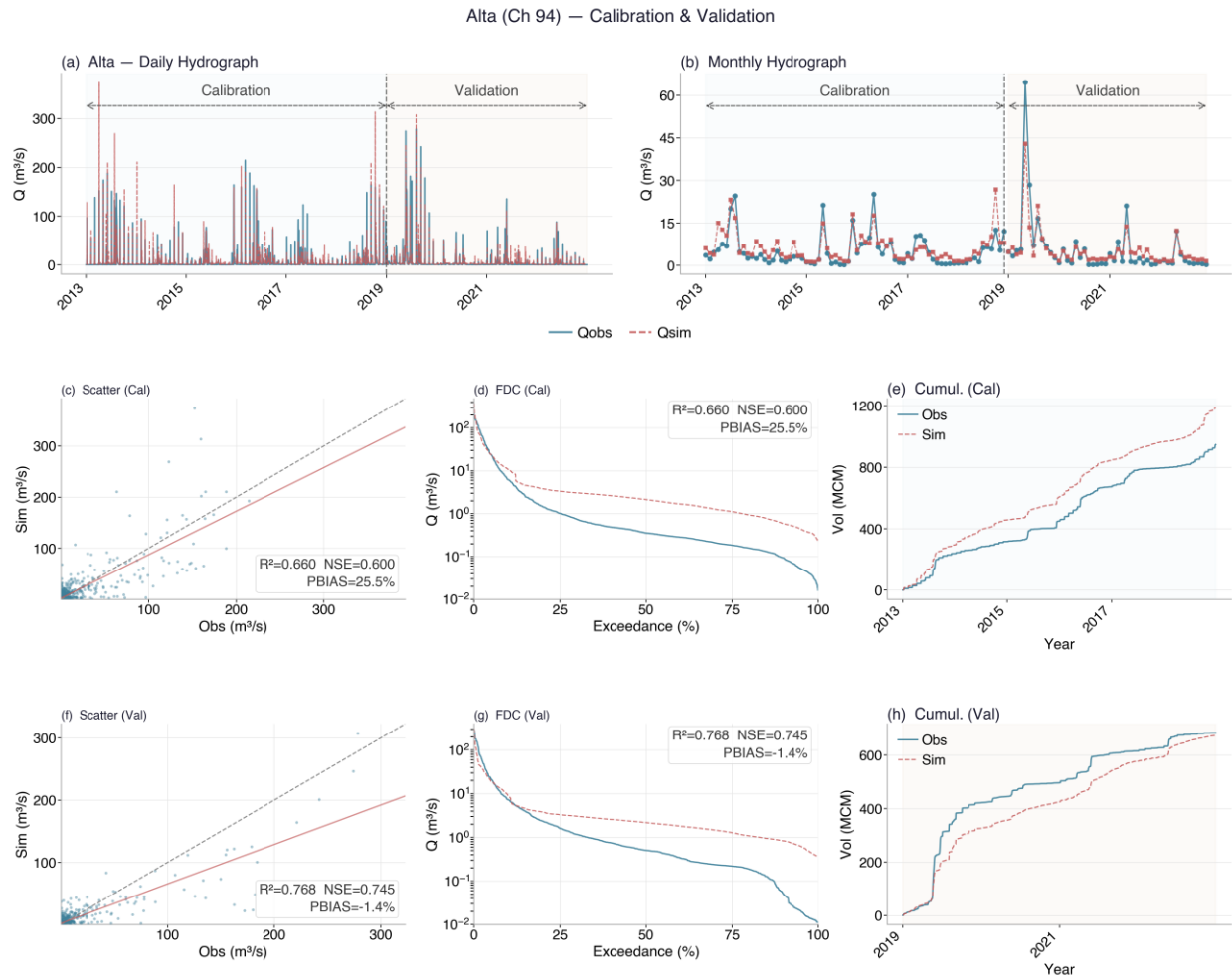


Figure 8 SWAT+ calibration and validation at Alta (Ch 94): hydrographs, scatter plots, FDCs, and cumulative flow comparisons.

6.1.2 Performance at Station Emma

Emma exhibits high calibration performance but reduced validation performance Figure 9. Daily NSE decreases from 0.71 during calibration to 0.64 during validation, while monthly NSE decreases from 0.79 to 0.73. The hydrograph shows consistent timing of flow events across both periods daily and monthly; however, peak magnitudes are less accurately reproduced during

validation. The scatter plot shows increased dispersion and deviation from the 1:1 line during validation, indicating reduced predictive accuracy. A clear bias reversal is observed, with PBIAS shifting from -15.7% (underestimation) during calibration to +8.0% (overestimation) during validation. The FDC confirms this transition, showing underestimation of higher flows during calibration and overestimation during validation. The cumulative flow curve shows divergence during validation, indicating inconsistency in volume representation. These results indicate that model performance at Emma is sensitive to temporal variability and does not fully generalize across periods.

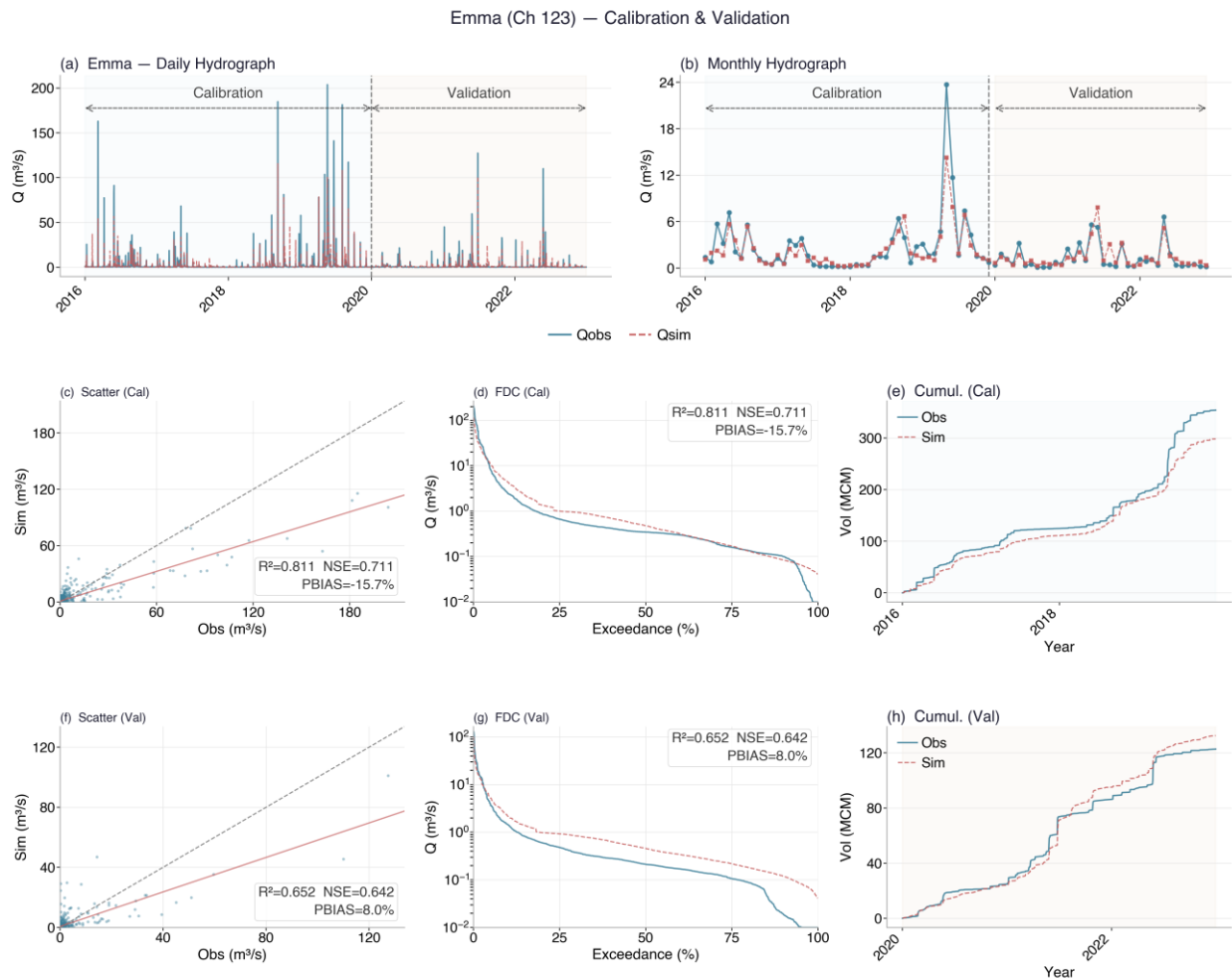


Figure 9 SWAT+ calibration and validation at Emma (Ch 123): hydrographs, scatter plots, FDCs, and cumulative flow comparisons.

6.1.3 Performance at Station Halstead

Halstead shows moderate calibration performance and improved NSE during validation Figure 10. Daily NSE increases from 0.51 to 0.64, and monthly NSE increases from 0.70 to 0.89. However, this improvement is accompanied by a substantial increase in bias. PBIAS shifts from 1.1% during calibration to 32.3% during validation, indicating strong overestimation of flow volume. The hydrograph shows that event timing is captured, but peak magnitudes are frequently overestimated during validation. The scatter plot confirms systematic deviation above the 1:1 line. FDC analysis shows reasonable agreement in low and medium flows but persistent overestimation in higher flows. The cumulative flow curve shows clear divergence during validation, confirming overprediction of total discharge. These results indicate that the improved NSE during validation reflects variance matching rather than accurate representation of water balance.

Halstead (Ch 91) — Calibration & Validation

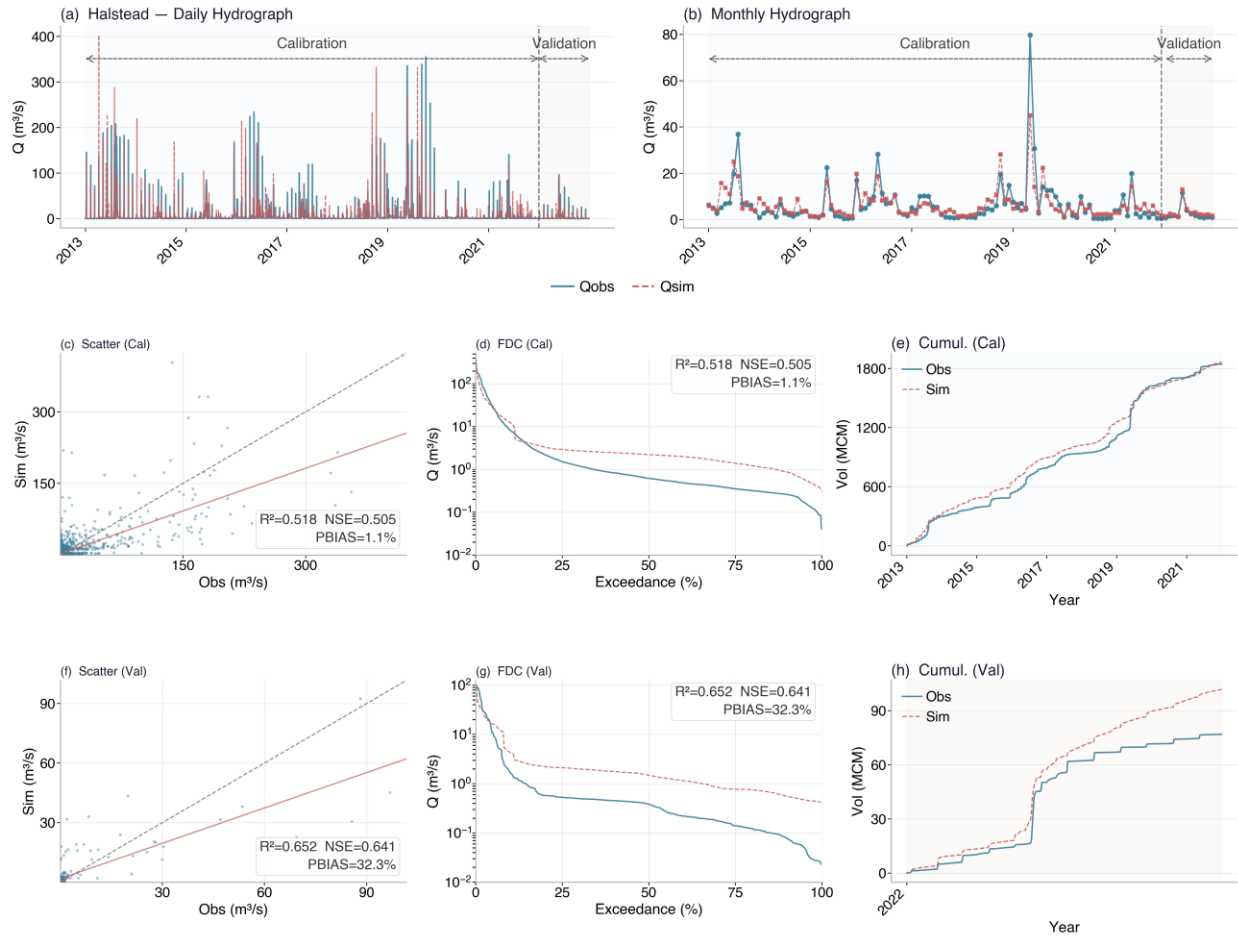


Figure 10 SWAT+ calibration and validation at Halstead (Ch 91): hydrographs, scatter plots, FDCs, and cumulative flow comparisons.

6.1.4 Performance at Station Sedgwick

Sedgwick demonstrates stable and balanced performance across both calibration and validation periods Figure 11. Daily NSE remains consistent (0.58 to 0.63), while monthly NSE improves from 0.76 to 0.80. The hydrograph shows consistent reproduction of both timing and magnitude of flow events. The scatter plots indicate stable predictive behavior across both periods. Bias is reduced from 16.3% during calibration to -4.7% during validation, indicating improved volume representation. The FDC shows strong agreement across the full range of

flows, with only minor deviations at extreme values. The cumulative flow curves confirm good agreement in total volume, particularly during validation. These results indicate stable hydrological process representation and strong model generalization.

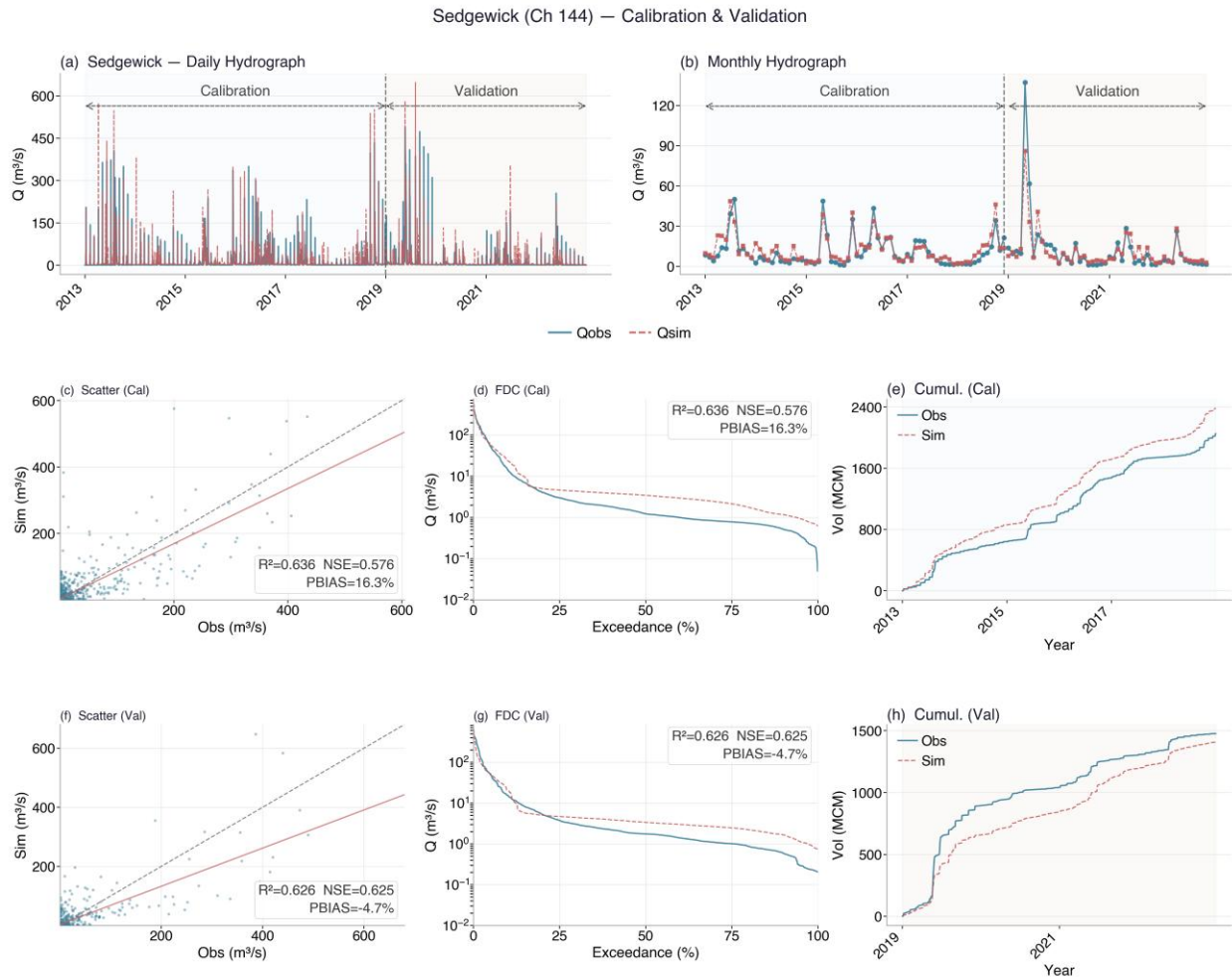


Figure 11 SWAT+ calibration and validation at Sedgewick (Ch 144): hydrographs, scatter plots, FDCs, and cumulative flow comparisons.

6.1.5 Hydrological model performance evaluation

The SWAT+ model demonstrates satisfactory performance across all stations, with consistent reproduction of flow dynamics at both daily and monthly timescales. Model performance improves at the monthly scale, indicating strong representation of seasonal

hydrological processes, which is commonly observed in watershed modeling due to temporal aggregation effects (D. N. Moriasi et al., 2007a).

Comparison between calibration and validation periods shows that model reliability depends not only on NSE but also on bias stability. Alta and Sedgwick demonstrate both stable NSE and improved bias, indicating robust performance. In contrast, Emma and Halstead stations show shifts in bias and variability, suggesting sensitivity in hydrological response and reduced transferability of calibrated parameters.

Across all stations, the model consistently captures low and medium flow conditions, while peak flow simulation remains limited. This behavior is typical in distributed hydrological models and is often associated with uncertainties in rainfall input, spatial heterogeneity, and flow routing processes (D. N. Moriasi et al., 2007a; J. G. Arnold et al., 2012b).

Overall, the achieved performance is sufficient for sediment modeling, as sediment transport in SWAT+ is primarily driven by runoff volume and flow energy through the Modified Universal Soil Loss Equation (MUSLE). Therefore, the calibrated model provides a reliable hydrological basis for sediment yield estimation and subsequent BMP scenario evaluation (J. G. Arnold et al., 2012b).

6.2 Sediment Yield Distribution across Spatial Scales and Management

Scenarios

This section examines the spatial distribution of sediment yield across three levels of aggregation Hydrologic Response Unit (HRU), field, and subbasin under three scenarios: baseline (conventional tillage), no-till (NT), and cover crops combined with no-till (NT+CC). Two complementary metrics are used: sediment yield rate ($\text{t ha}^{-1} \text{ yr}^{-1}$), which standardizes sediment production by area, and total sediment yield (t yr^{-1}), which represents absolute contribution.

6.2.1 HRU-Level Sediment Yield Distribution

At the Hydrologic Response Unit (HRU) level, sediment yield rate ($\text{t ha}^{-1} \text{ yr}^{-1}$) exhibits strong spatial heterogeneity, defined as the uneven distribution of values across individual HRUs. Under baseline conditions, the mean sediment yield is $3.26 \text{ t ha}^{-1} \text{ yr}^{-1}$, while the median is substantially lower at $1.06 \text{ t ha}^{-1} \text{ yr}^{-1}$, indicating a right-skewed distribution characterized by a limited number of high-yield HRUs. This pattern is visually evident in Figure 12, where localized areas of elevated sediment yield are embedded within predominantly low-yield regions

Fig H5 — HRU Sediment Yield Rate and BMP Effectiveness

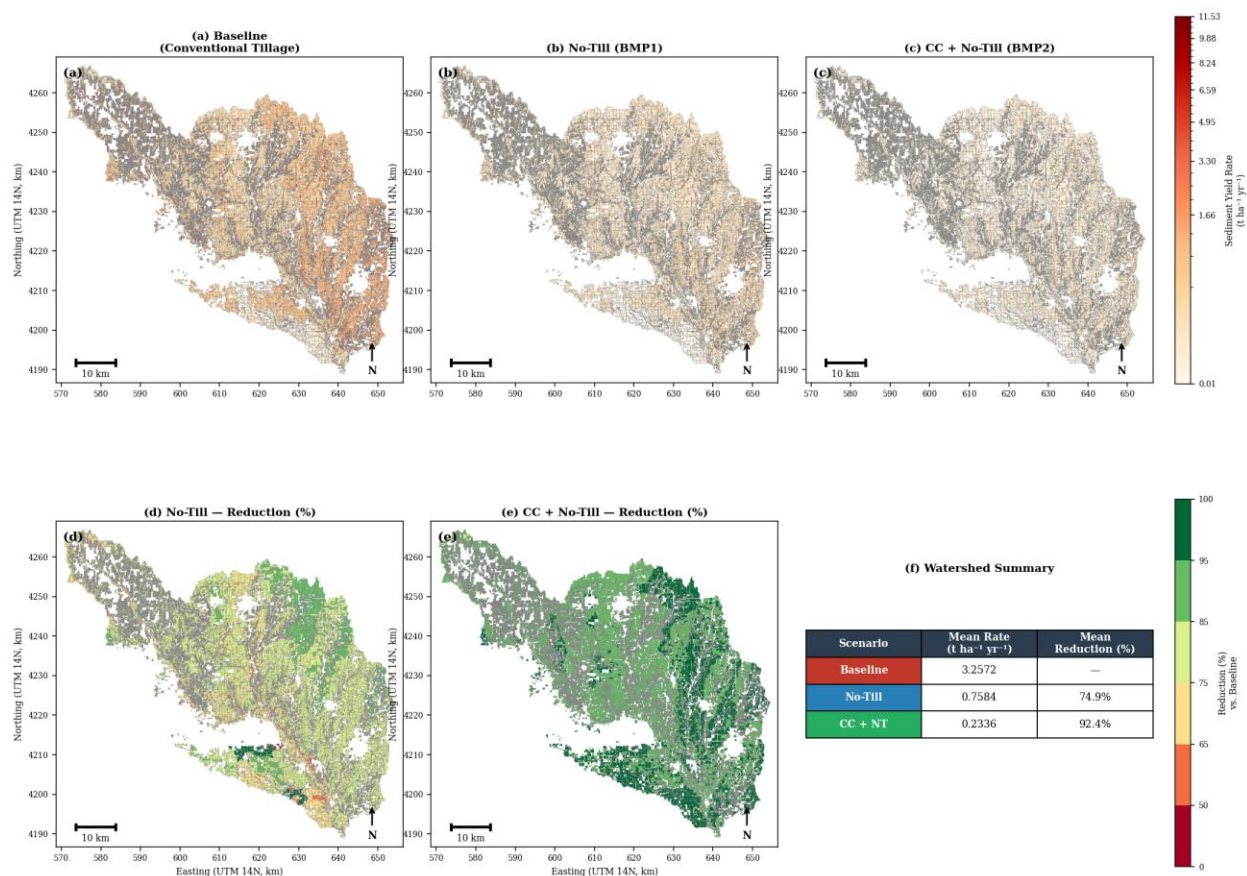


Figure 12 HRU-level sediment yield rate and percentage reduction across scenarios

Figure 12 presents HRU-level sediment yield rate and percentage reduction across scenarios. The spatial pattern remains consistent across scenarios, indicating that underlying controls such as slope and soil properties govern sediment generation at this scale. Differences across scenarios are primarily reflected in magnitude rather than spatial arrangement. To further characterize this pattern, the distribution of sediment yield across cropland HRUs ($n = 3,011$) is examined Figure 13 (a, b). The histogram shows a highly right-skewed distribution, where most HRUs produce low sediment yield while a small subset generates substantially higher values. The cumulative distribution further indicates that a limited fraction of HRUs contributes a large share of total sediment, confirming strong spatial inequality in erosion intensity.

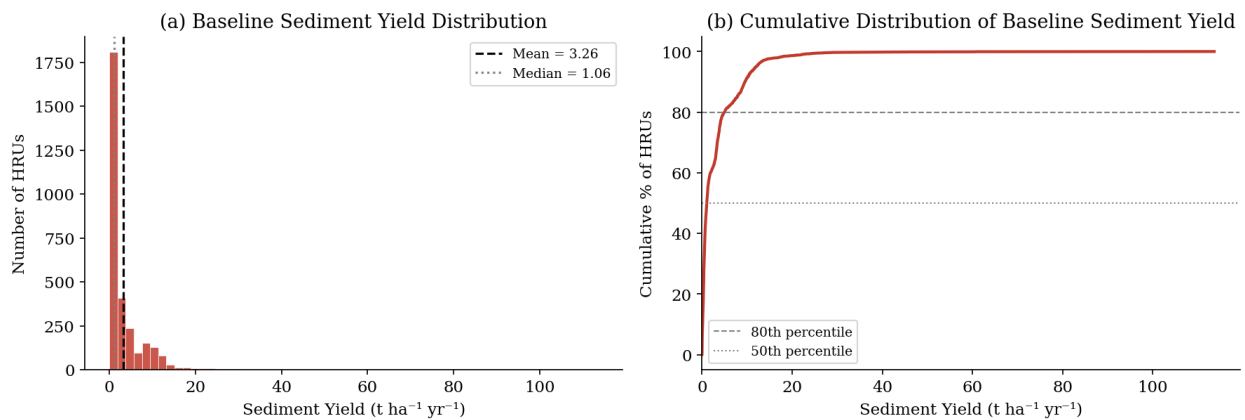


Figure 13 Baseline HRU sediment yield distribution: (a) histogram; (b) cumulative distribution.

Under the no-till scenario Figure 14(a, b), the distribution shifts substantially toward lower sediment yield values. The mean decreases to $0.76\ t\ ha^{-1}\ yr^{-1}$ and the median to $0.22\ t\ ha^{-1}\ yr^{-1}$, indicating a reduction in both central tendency and dispersion. The histogram shows a compression of the right tail, defined as a reduction in the frequency of high-yield HRUs, while the cumulative distribution becomes steeper at lower values, indicating that a larger proportion of HRUs contributes minimal sediment yield.

Little Arkansas River Watershed — No-Till Sediment Yield (BMP1)

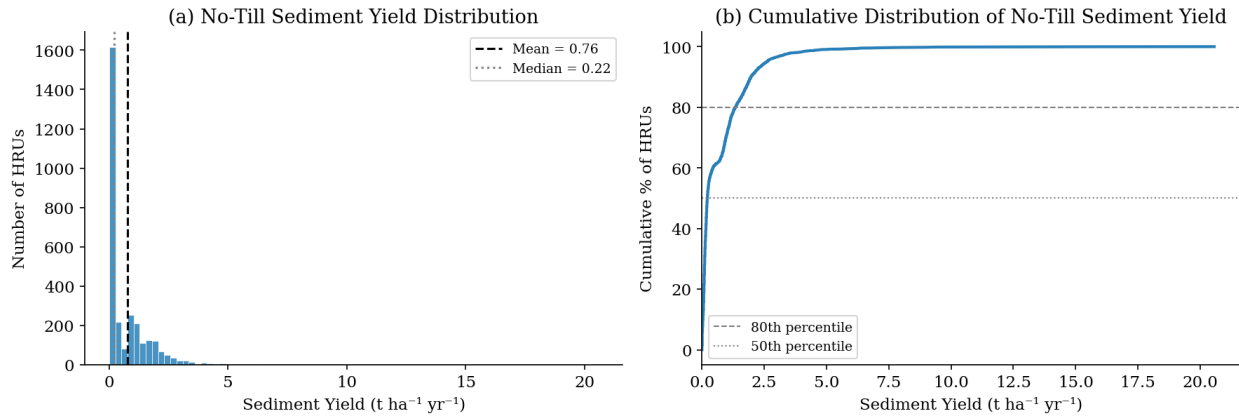


Figure 14 No Tillage sediment yield distribution: (a) histogram; (b) cumulative distribution.

Under the combined cover crop and no-till scenario Figure 15(a, b), the distribution shifts further toward near-zero values. The mean reduces to $0.23 \text{ t ha}^{-1} \text{yr}^{-1}$ and the median to $0.07 \text{ t ha}^{-1} \text{yr}^{-1}$, indicating a pronounced concentration of HRUs in the lowest yield range. The histogram shows a near elimination of the extreme right tail, while the cumulative distribution approaches saturation rapidly, confirming that the majority of HRUs produce negligible sediment yield.

Little Arkansas River Watershed — CC + No-Till Sediment Yield (BMP2)

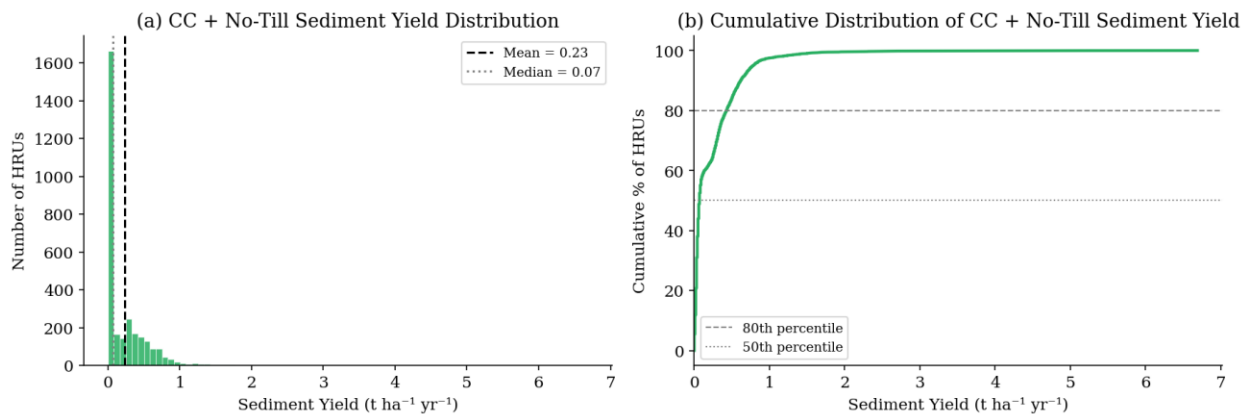


Figure 15 Cover Crops plus No Tillage HRU sediment yield distribution: (a) histogram; (b) cumulative distribution.

6.2.2 Field Level Sediment Yield Distribution

At the field level, sediment yield rate ($\text{t ha}^{-1} \text{ yr}^{-1}$) also exhibits strong spatial heterogeneity, defined as the uneven distribution of values across individual management fields. Under baseline conditions, the mean sediment yield is $1.34 \text{ t ha}^{-1} \text{ yr}^{-1}$, indicating that most fields contribute relatively low to moderate sediment yield, while a smaller subset of fields exhibits higher values. This pattern is clearly visible in Figure 16 (a,b,c), where localized zones of elevated sediment yield are embedded within predominantly low-yield areas.

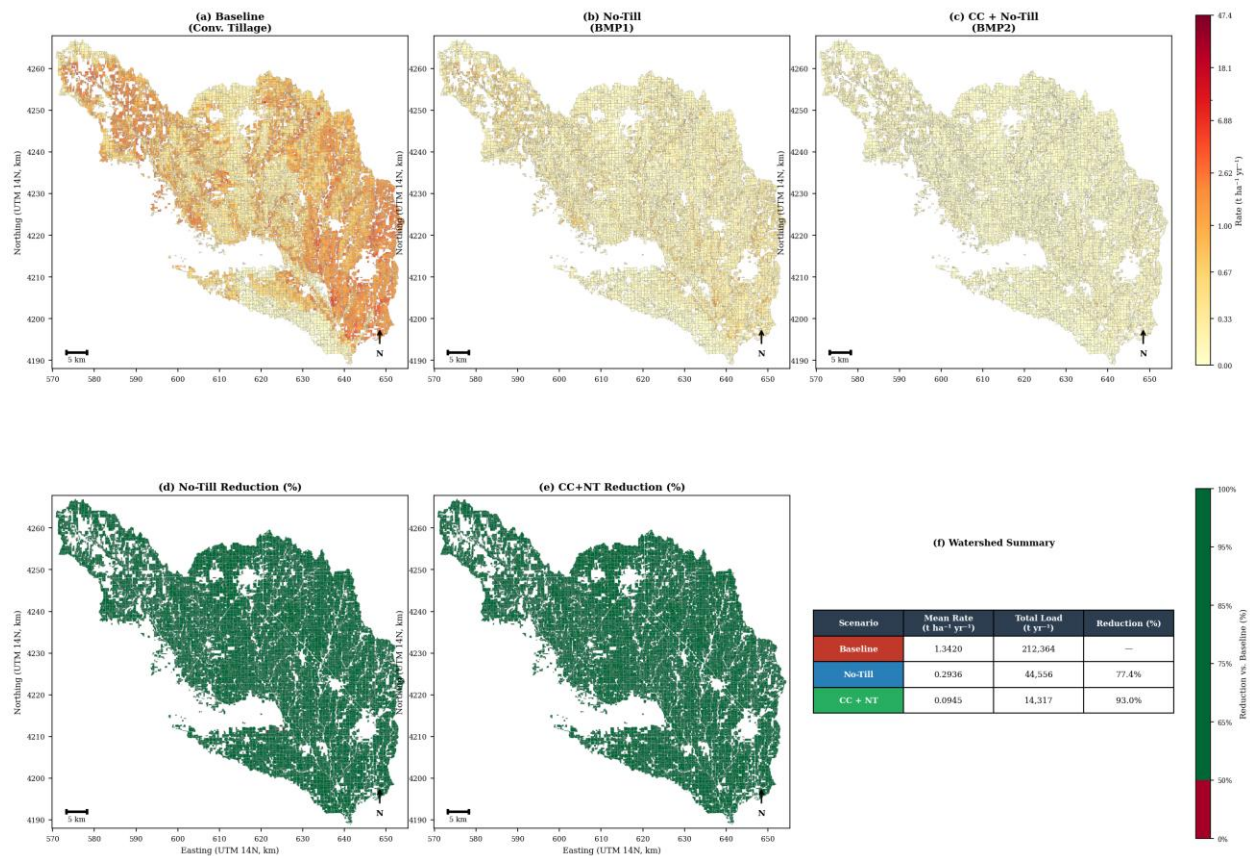


Figure 16 HRU-level sediment yield rate and percentage reduction across scenarios

Figure 16(d,e) presents the field-level percentage reduction across scenarios. The spatial pattern remains consistent across scenarios, indicating that underlying controls such as slope and soil

properties continue to govern sediment generation after aggregation to the field scale. Differences across scenarios are therefore primarily reflected in magnitude rather than spatial arrangement. The mean sediment yield decreases to $0.29 \text{ t ha}^{-1} \text{ yr}^{-1}$ under no-till and further to $0.09 \text{ t ha}^{-1} \text{ yr}^{-1}$ under the combined cover crop and no-till scenario, corresponding to average field-level reductions of approximately 77.4% and 93.0% compared to the baseline scenario, respectively. The reduction maps further show that these decreases are spatially widespread across the watershed, with greater reductions observed in fields that initially exhibited higher sediment yield, although a limited number of higher-yield fields persist under all scenarios. The reduction values reported at the field level represent mean percentage reductions across individual fields and therefore differ from HRU-level values due to differences in spatial aggregation.

6.2.3 Subbasin-Level Sediment Load Distribution and Source Area

Characterization

At the subbasin scale, total sediment load is derived by aggregating HRU-level sediment yield (tons per year) within each subbasin. The results indicate substantial variability across the 31 subbasins Figure 17 (a). Additionally results Figure 17(b) indicate that small number of subbasins dominate total sediment production, with Subbasin 9 contributing approximately 10.2% of the total baseline load, followed by Subbasins 28 and 17, each exceeding 7%. In contrast, several subbasins contribute less than 2% individually, indicating that sediment generation is highly uneven across the watershed.

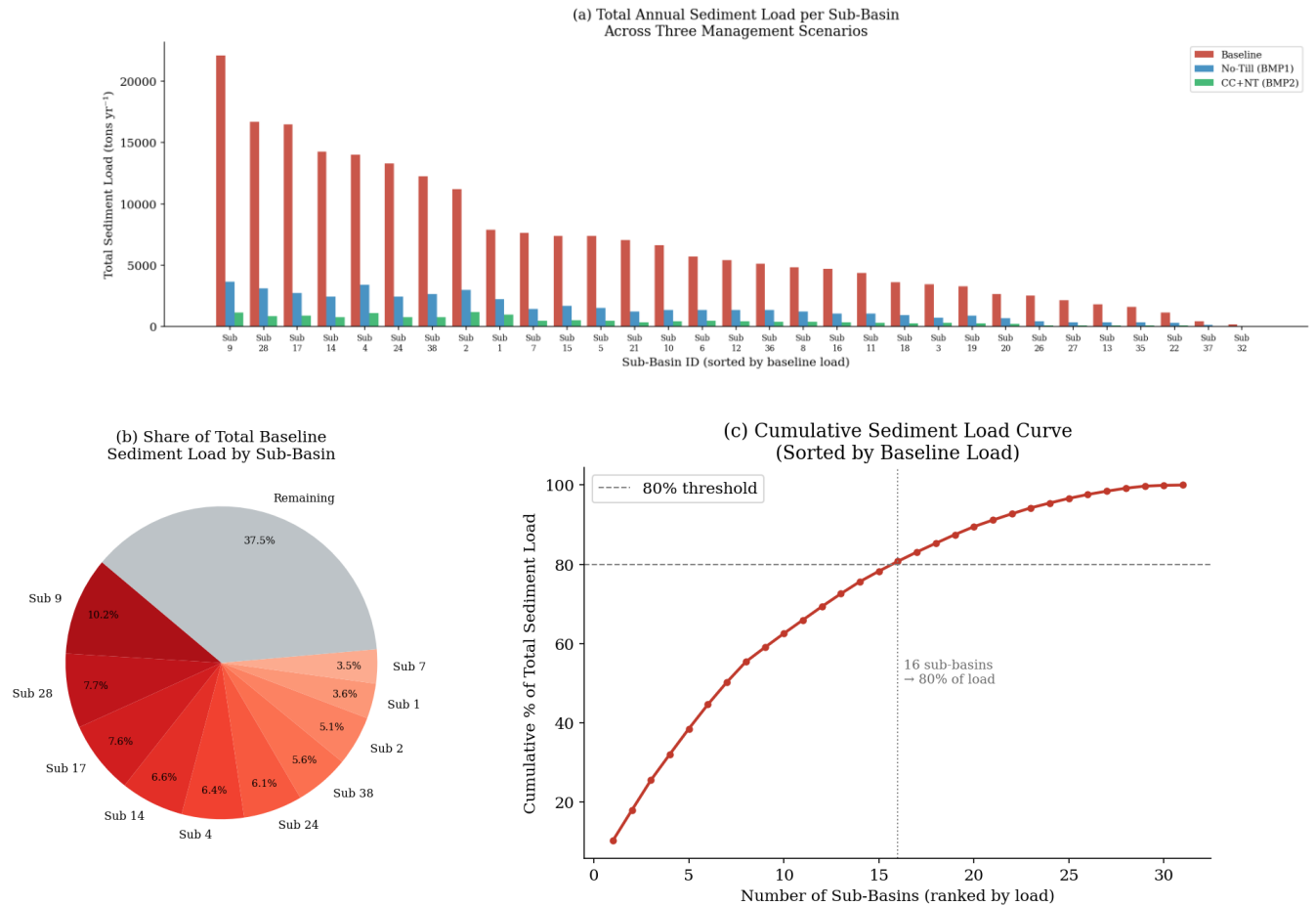


Figure 17 Subbasin-level sediment load distribution and concentration under scenarios.

The cumulative sediment load curve Figure 17 (c) further demonstrates this concentration. Approximately 16 out of 31 subbasins account for nearly 80% of the total sediment load. This reflects a concentration effect, defined here as the disproportionate contribution of a limited number of spatial units to the overall sediment yield. The presence of this effect indicates that watershed-scale sediment export is controlled by a subset of high-contributing subbasins rather than distributed uniformly.

Within individual subbasins, additional variability is observed among HRUs Figure 18 . High-yield subbasins exhibit wider interquartile ranges and multiple extreme values, indicating localized sediment-producing areas within the subbasin. In contrast, low yield subbasins display

more compact distributions with limited variability. This intra-subbasin heterogeneity highlights that not all HRUs within a high-contributing subbasin contribute equally to sediment export.

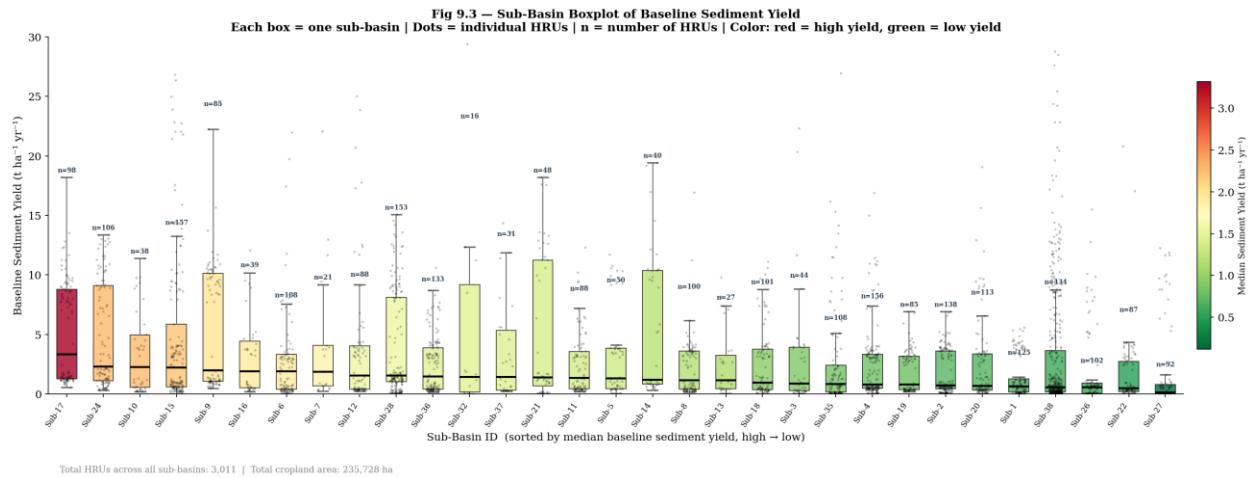


Figure 18 Sub-basin variability in baseline sediment yield across HRUs. Boxplots represent the distribution of sediment yield within each sub-basin, with individual HRUs shown as points and sub-basins ordered by median yield (high to low)

Spatial patterns of sediment yield further support these findings. The baseline sediment yield map Figure 19 shows that high sediment yield rates are concentrated in specific regions of the watershed, while large areas exhibit relatively low values. This spatial clustering corresponds to underlying physical controls. The slope-soil interaction analysis Figure 20 demonstrates that sediment yield increases systematically with both slope and soil hydrologic group. Areas with slopes greater than 8% and hydrologic group D soils exhibit the highest mean sediment yield ($36.99 \text{ t ha}^{-1} \text{ yr}^{-1}$), whereas nearly flat areas (0–1% slope) with hydrologic group A soils show minimal yield ($0.02 \text{ t ha}^{-1} \text{ yr}^{-1}$). This confirms that topography and soil infiltration characteristics jointly regulate erosion processes.

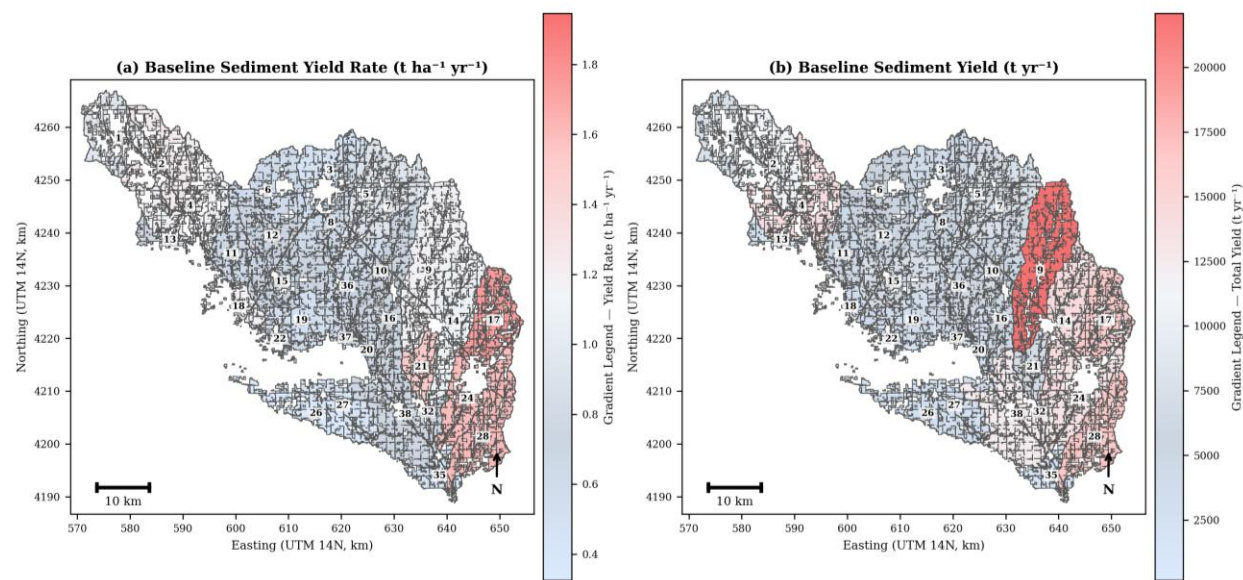


Figure 19 Distribution of baseline sediment yield in Subbasin (a) yield rate ($\text{t ha}^{-1} \text{yr}^{-1}$); (b) total yield (t yr^{-1}).

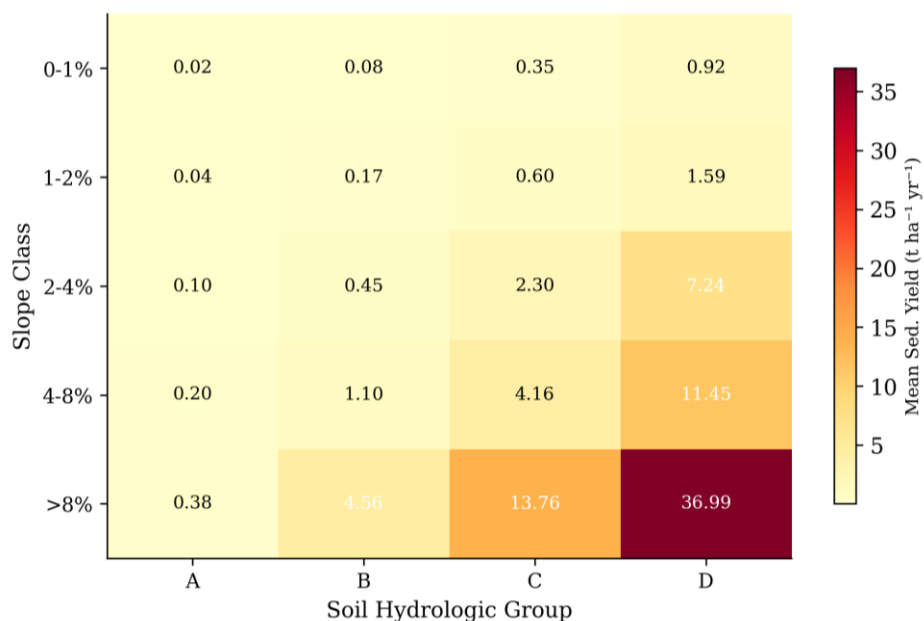


Figure 20 Mean baseline sediment yield ($\text{t ha}^{-1} \text{yr}^{-1}$) by slope class and soil hydrologic group.

Overall, the baseline results indicate that sediment generation is highly concentrated across spatial scales. A relatively small number of subbasins and localized high-yield HRUs contribute a dominant share of total sediment load, while most cropland areas generate comparatively low

sediment. This uneven distribution provides a clear basis for prioritizing targeted BMP implementation in high-contributing areas rather than applying uniform management across the watershed.

6.3 Sediment Response to BMP Scenarios

The analysis compares sediment yield under baseline (conventional tillage), no-till (BMP1), and cover crops combined with no-till (BMP2) scenarios. Sediment response is evaluated using both total sediment load (t yr^{-1}) and sediment yield rate ($\text{t ha}^{-1} \text{yr}^{-1}$) to distinguish between watershed-scale impact and unit-level response.

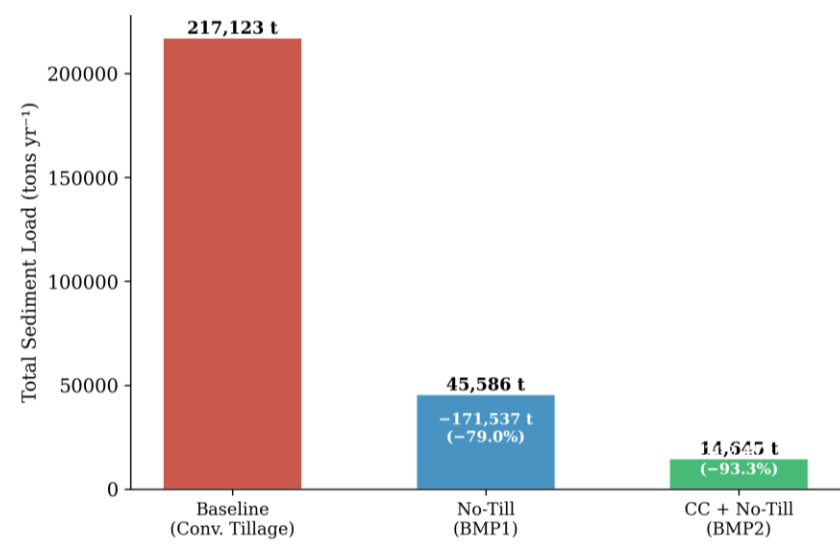


Figure 21 Watershed Total Sediment Load and Absolute Reduction by BMP Scenarios

Figure 21 presents watershed-scale sediment response. The baseline condition produces a total sediment load of $217,123 \text{ t yr}^{-1}$. The no-till scenario reduces this to $45,586 \text{ t yr}^{-1}$, corresponding to an absolute reduction of $171,537 \text{ t yr}^{-1}$ (79.0%). The combined BMP further reduces sediment load to approximately $14,645 \text{ t yr}^{-1}$, representing a reduction of 93.3% relative to baseline. These results indicate that both BMPs are effective, with the combined practice providing substantially greater reduction than no-till alone.

At the subbasin level, reductions vary in magnitude across the watershed. Subbasins with higher baseline sediment loads exhibit the largest absolute reductions following BMP implementation. For example, Subbasin 9 shows a reduction exceeding 18,000 t yr⁻¹ under no-till and over 20,000 t yr⁻¹ under the combined BMP. This indicates that high-contributing areas offer greater potential for absolute reduction, although relative effectiveness varies due to differences in slope, soil properties, and land management.

The percentage reduction analysis Figure 22 shows that no-till achieves reductions generally in the range of 70–85% across most subbasins, while the combined BMP consistently achieves reductions exceeding 90% in nearly all areas.

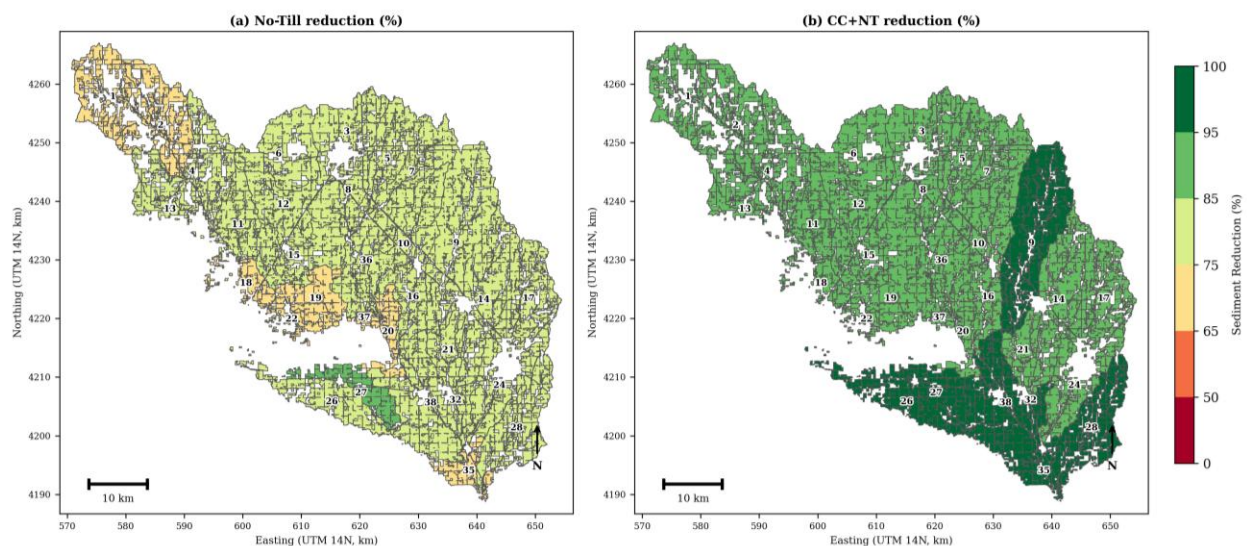


Figure 22 Subbasin-level BMP effectiveness showing percent sediment reduction under BMP scenarios

Spatial patterns of sediment reduction Figure 24 confirm these results, showing a transition from high-yield regions under baseline conditions to substantially reduced levels under BMP scenarios, with the most pronounced reductions observed under the combined practice. While reductions are widespread, localized variability persists, reflecting spatial heterogeneity in watershed characteristics.

At the HRU level, sediment yield distribution further illustrates BMP effectiveness Figure 23. Under baseline conditions, the distribution is highly skewed with a long upper tail, reflecting the presence of high-yield outliers. The no-till scenario compresses this distribution by reducing both median and extreme values, while the combined BMP shifts the distribution toward near-zero values, indicating substantial reduction in variability and suppression of high-yield areas.

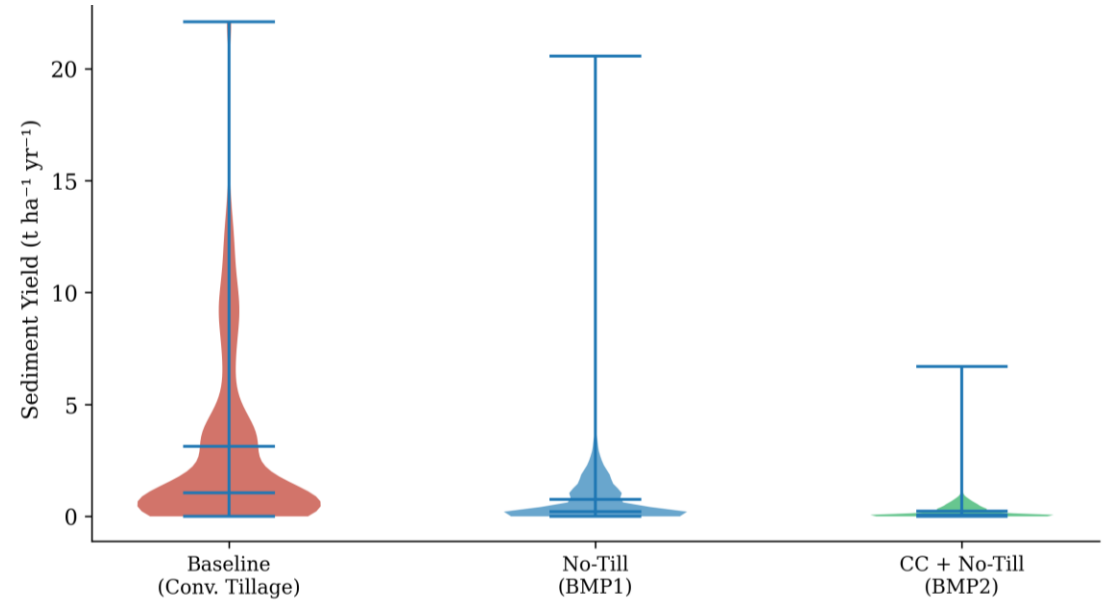


Figure 23 Violin Plot showing HRU-Level Sediment Yield Distribution

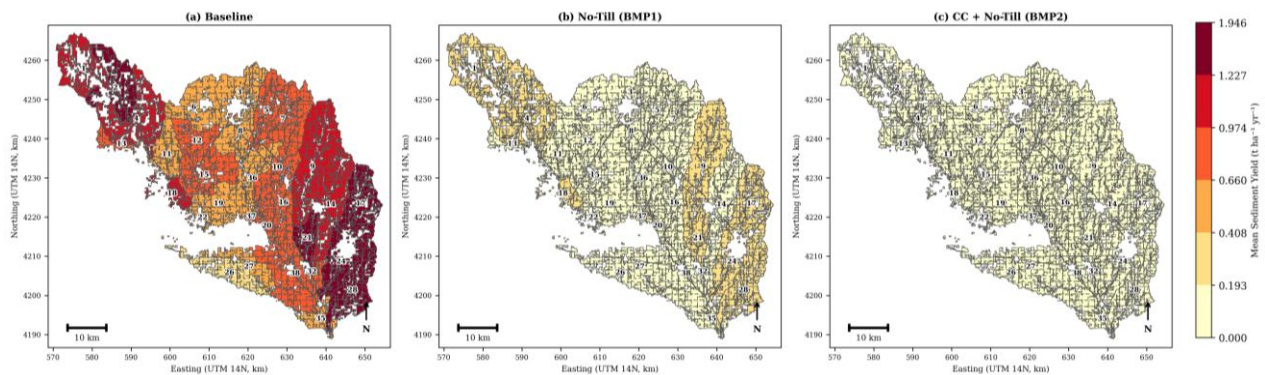


Figure 24 Sediment Yield Distribution across Subbasin

Overall, BMP implementation leads to substantial reductions in sediment yield across all spatial scales. No-till provides significant reduction in sediment load, while the addition of cover crops results in further improvement in both total load reduction and reduction of high-yield areas.

6.4 Identification of Priority Areas

The baseline analysis demonstrated that sediment generation in the watershed is highly concentrated within a limited number of subbasins. Building on this observation, priority intervention areas were identified to support targeted implementation of best management practices (BMPs).

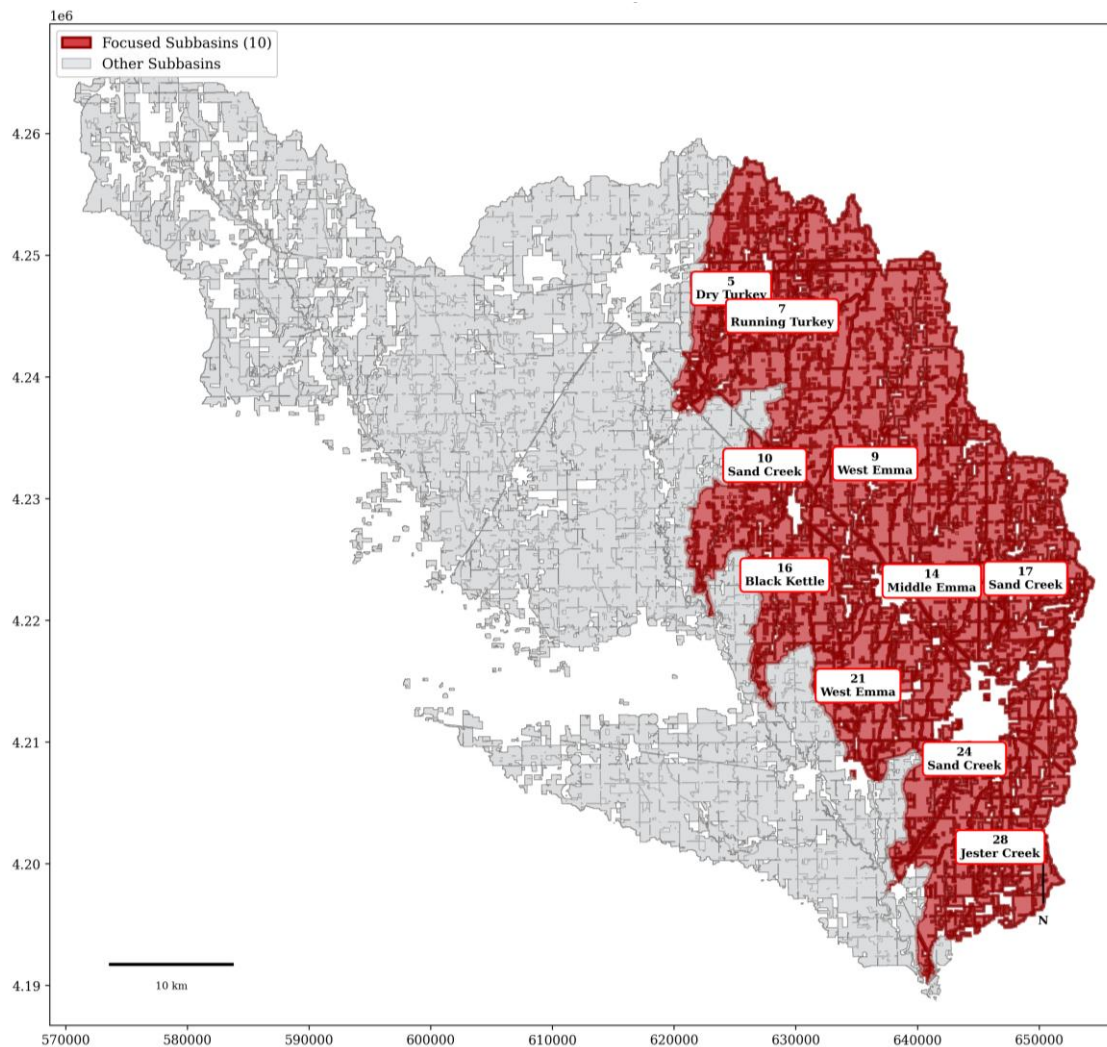


Figure 25 Map highlighting high Sediment Yielding Subbasins

Figure 25 shows the spatial distribution of selected sediment yielding subbasins. Subbasins were initially ranked based on total sediment contribution under baseline conditions (t yr^{-1}). The final selection included Subbasins 5, 7, 9, 10, 14, 16, 17, 21, 24, and 28. In addition to ranking based on total sediment contribution, expert judgment was applied to refine the selection by considering slope, land use, and soil characteristics. Subbasins with steeper slopes, higher proportions of agricultural land, and soils prone to erosion were prioritized, while also ensuring spatial representation across the watershed. This approach balances sediment contribution with underlying physical drivers of erosion and supports practical implementation of BMPs.

The selected subbasins are primarily concentrated in the eastern and southeastern portions of the watershed, indicating that high sediment producing areas are spatially clustered rather than uniformly distributed. Figure 25 provides spatial context for these selected zones and illustrates the reduction from the full watershed to targeted regions.

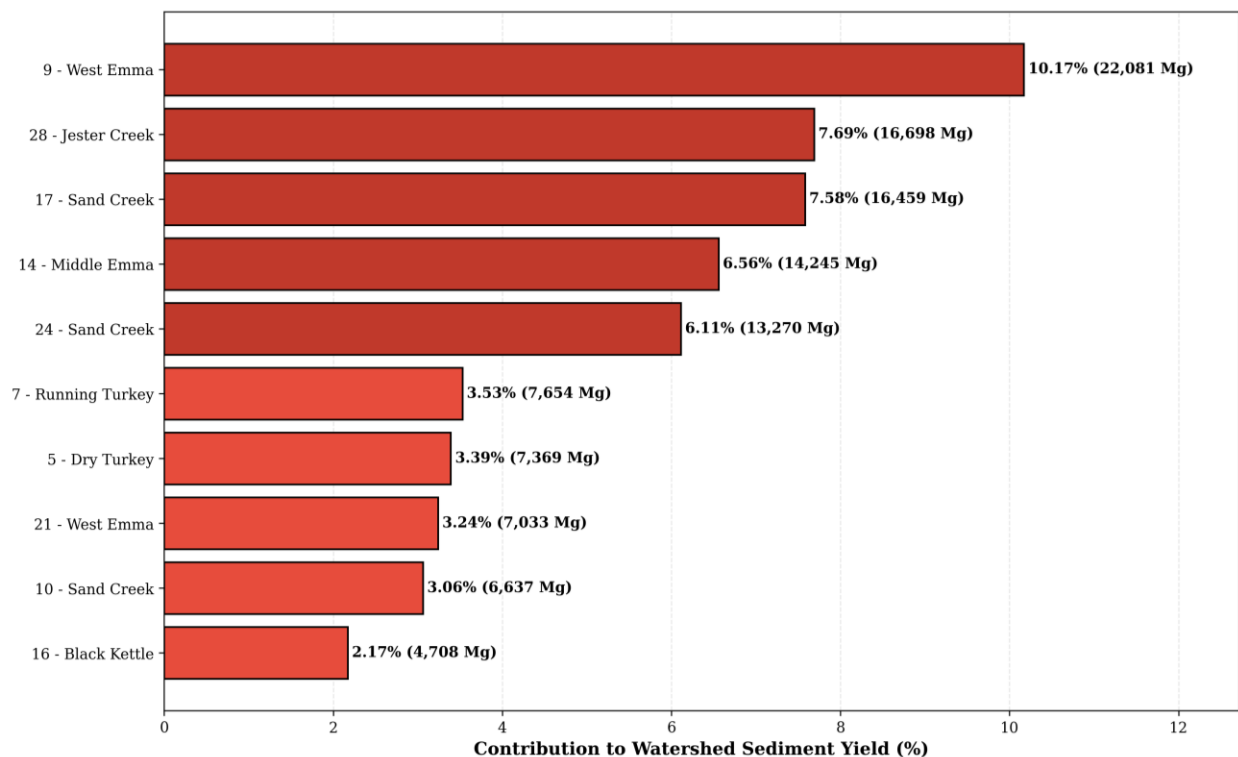


Figure 26 Bar plot Contribution of selected subbasins to total watershed sediment yield BL

The relative contribution of the selected subbasins is presented in Figure 26. Subbasin 9 contributes the largest share of total sediment load (10.17%), followed by Subbasins 28 (7.69%) and 17 (7.58%). Additional subbasins such as 14 (6.56%) and 24 (6.11%) also contribute substantially, while the remaining selected subbasins contribute between 2% and 4%. Together, these subbasins account for a significant portion of total watershed sediment load.

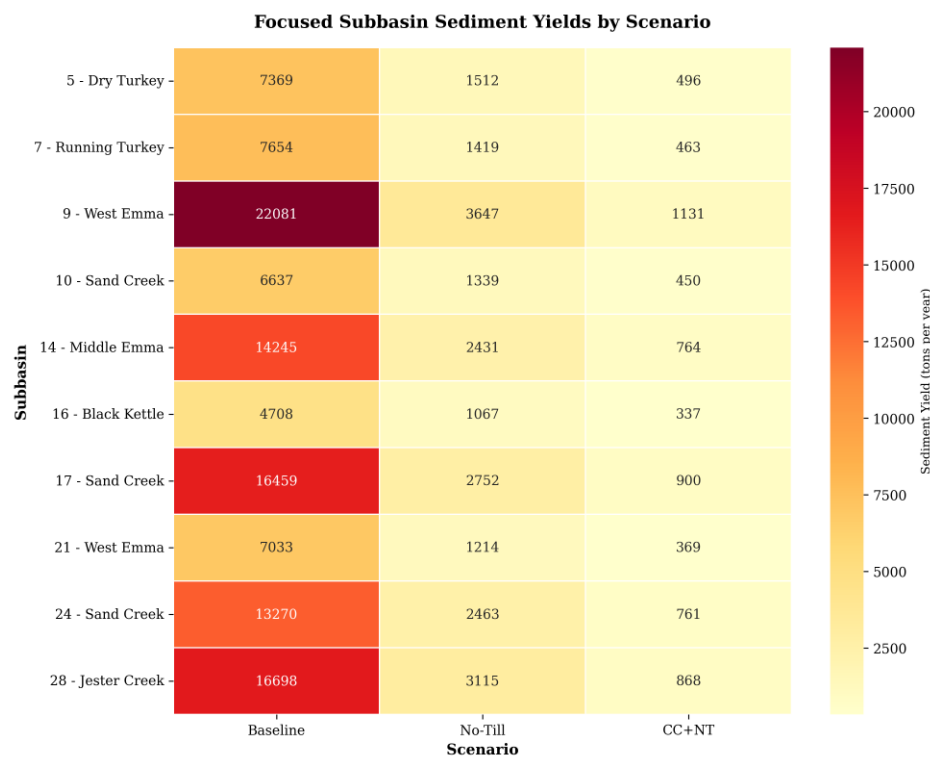


Figure 27 Sediment yield across selected subbasins under baseline, no-till (BMP1), and CC+NT (BMP2) scenarios.

The selected subbasins also exhibit substantial reduction potential under BMP implementation Figure 27. Across all selected subbasins, sediment loads decrease under both no-till and combined cover crops and no-till scenarios. For instance, Subbasin 9 reduces from 22,081 t yr⁻¹ under baseline conditions to 3,647 t yr⁻¹ under no-till and further to 1,131 t yr⁻¹ under the

combined BMP. Similar reductions are observed across all selected subbasins, indicating that these areas not only contribute significantly to sediment generation but also respond effectively to management practices.

The selection of these subbasins results in a substantial reduction in the spatial extent of analysis. While the full watershed includes more than 27,318 fields, the selected subbasins reduce the candidate pool to approximately 11106 fields. This reduction is critical for subsequent optimization, as it enables targeted evaluation of BMP implementation while maintaining focus on high-impact areas.

Overall, the results show that sediment generation is concentrated within a limited subset of subbasins, and that these areas exhibit strong response to BMP implementation. The identified subbasins form the basis for the selected subbasin scenario evaluated in the subsequent Monte Carlo analysis.

6.5 Cluster-Based Characterization of Baseline Sediment Yield Rate

The results from Sections 6.2 and 6.3 indicate that sediment contribution is concentrated within a limited subset of fields. To formalize this pattern, clustering analysis is applied to the baseline sediment yield rate ($\text{t ha}^{-1} \text{ yr}^{-1}$), grouping fields into distinct sediment yield intensity classes.

The overall distribution of the baseline sediment yield rate shows that most fields are associated with low sediment yield values, while only a small subset exhibits high values. This supports the need for classification-based analysis.

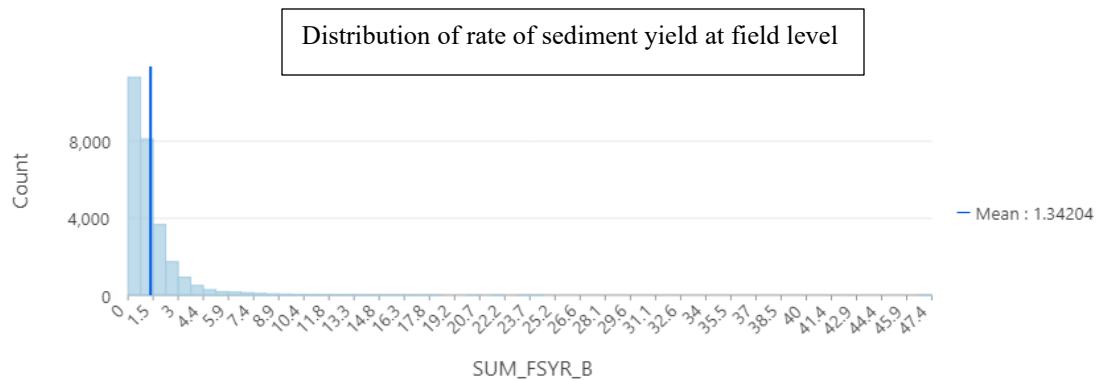


Figure 28 Distribution of baseline field-level sediment yield

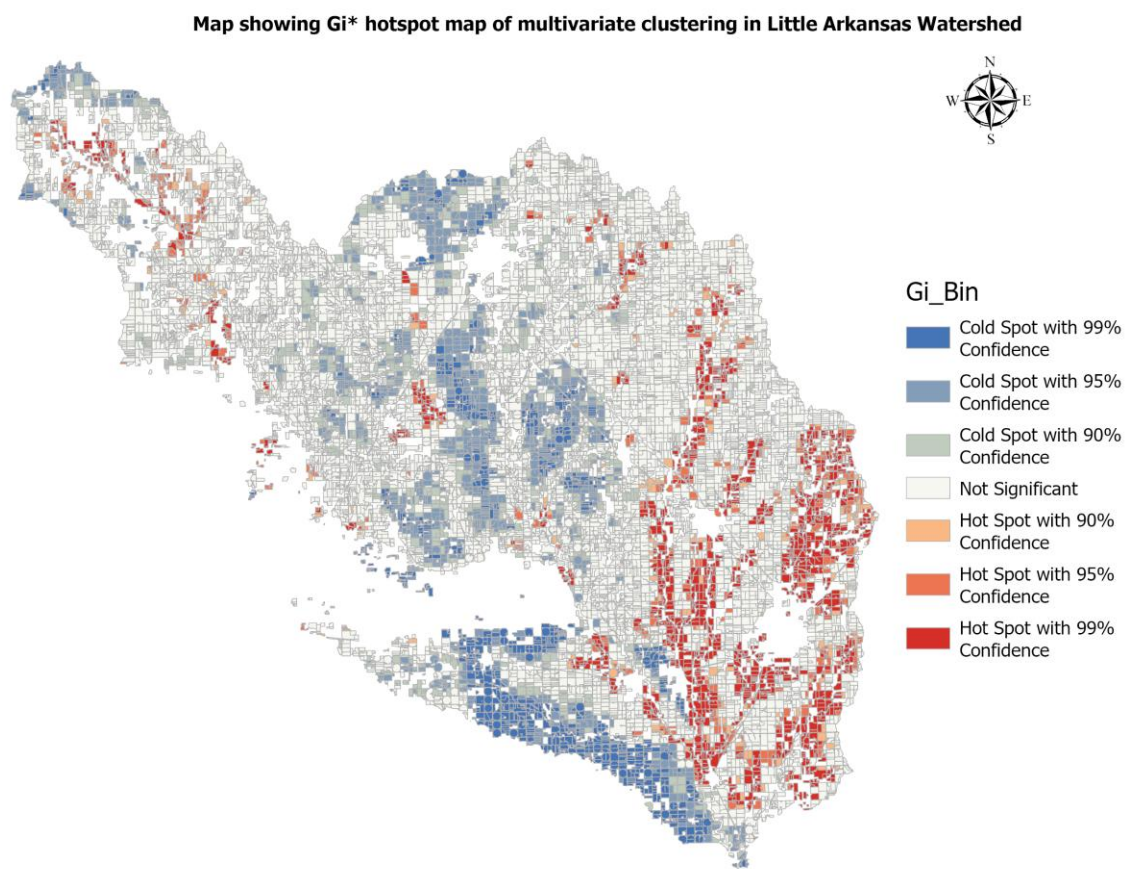


Figure 29 Getis–Ord Gi* statistic hotspot analysis of sediment yield clustering, showing statistically significant hot spots and cold spots across the watershed at multiple confidence levels.

The clustering results show a clear imbalance in the number of fields across clusters. Most of the fields are grouped within lower-yield clusters, while progressively fewer fields belong to higher-yield clusters.

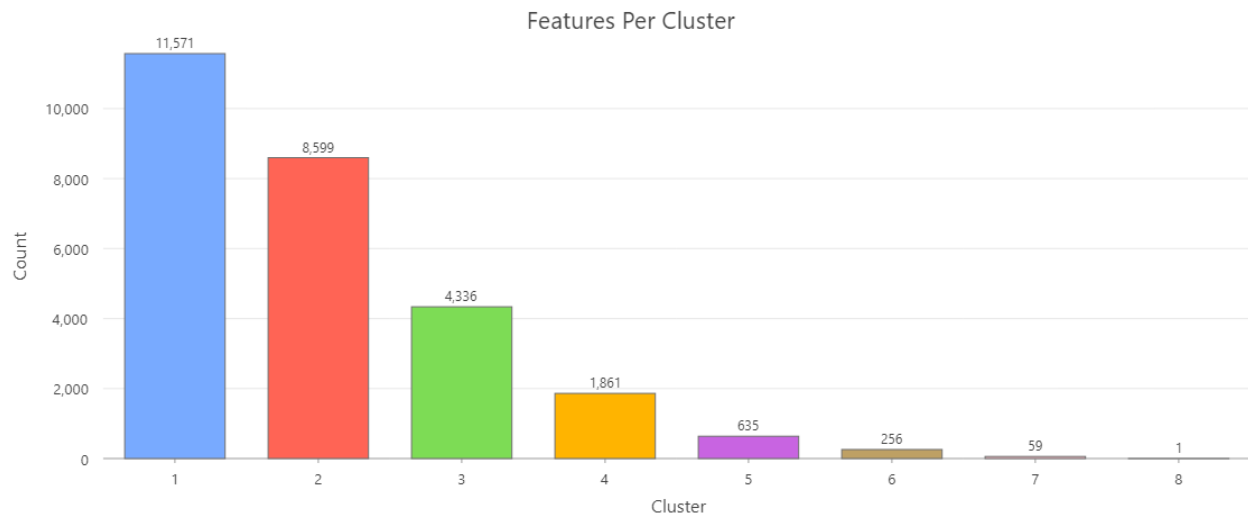


Figure 30 Number of fields in each cluster.

Cluster-wise comparison shows a consistent increase in sediment yield magnitude across clusters. Higher clusters represent fields with substantially elevated sediment yield rates, and the separation between clusters is clearly observed.

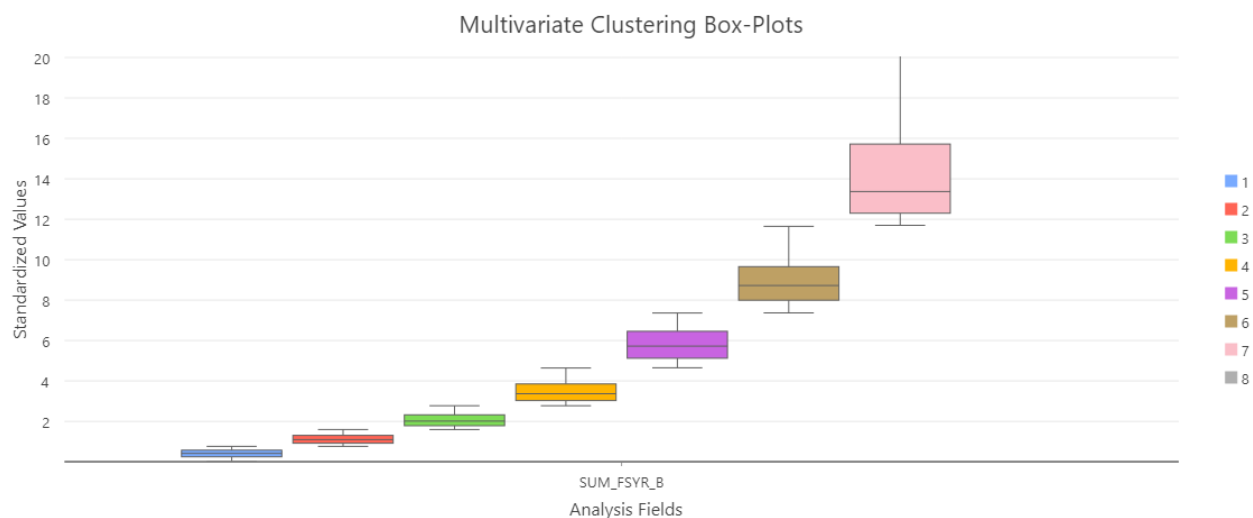


Figure 31 Boxplots of sediment yield rate across clusters

To incorporate spatial structure, hotspot analysis is performed using the Getis–Ord G_i^* statistic. Fields are classified into 90%, 95%, and 99% confidence levels representing increasing statistical significance of hotspot presence. The distribution of sediment yield across these hotspot classes shows a clear increase with confidence level. Fields within the highest confidence class exhibit the highest sediment yield rates, confirming that spatial hotspots correspond to the highest sediment-contributing fields.

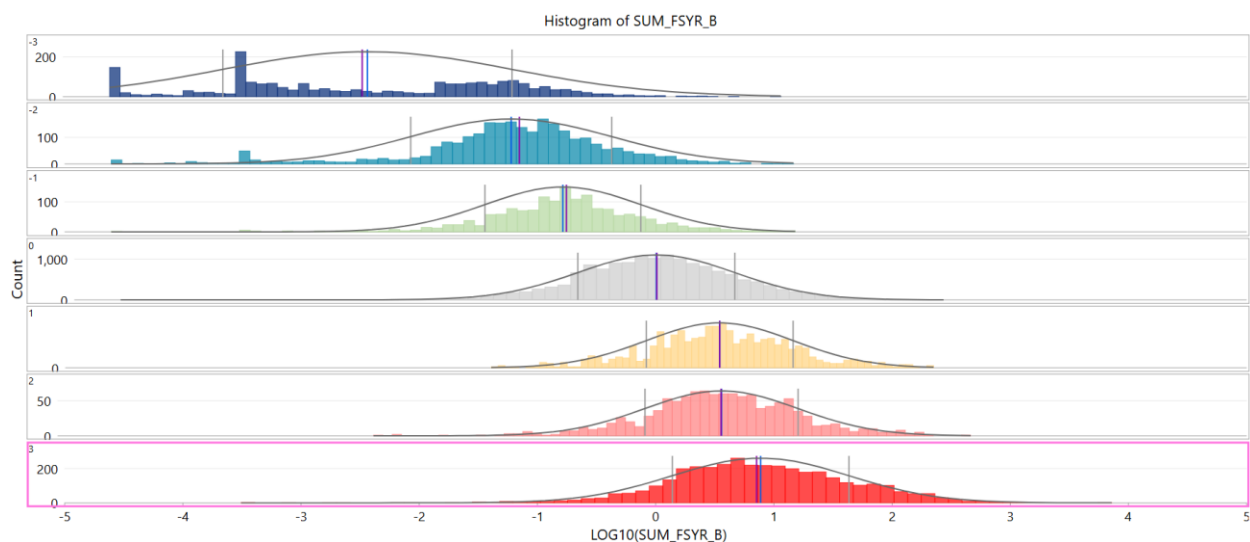


Figure 32 Distribution of sediment yield (SUM_FSYR_B) by G_i^* hotspot classification

6.6 Monte Carlo Field Selection for Targeted BMP Implementation

6.6.1 Scenario 1: Watershed-Wide Field Selection

To evaluate the feasibility of achieving a predefined sediment reduction target using non-targeted implementation, a Monte Carlo simulation framework was applied across all available cropland fields in the watershed ($n = 27,318$). In this scenario, fields were randomly selected without spatial prioritization until a target sediment reduction between 160 and 165 t yr^{-1} was

achieved. This approach establishes a baseline level of efficiency against which targeted strategies can be compared.

The underlying field population exhibits substantial variability in size Figure 33. The distribution of available field areas is highly right-skewed, with a median field size of approximately 2.82 ha and a long tail extending to larger fields. This indicates that most fields are relatively small, while a limited number of large fields contribute disproportionately to total area. This variability directly influences the selection process, as larger fields can contribute more rapidly to cumulative sediment reduction.

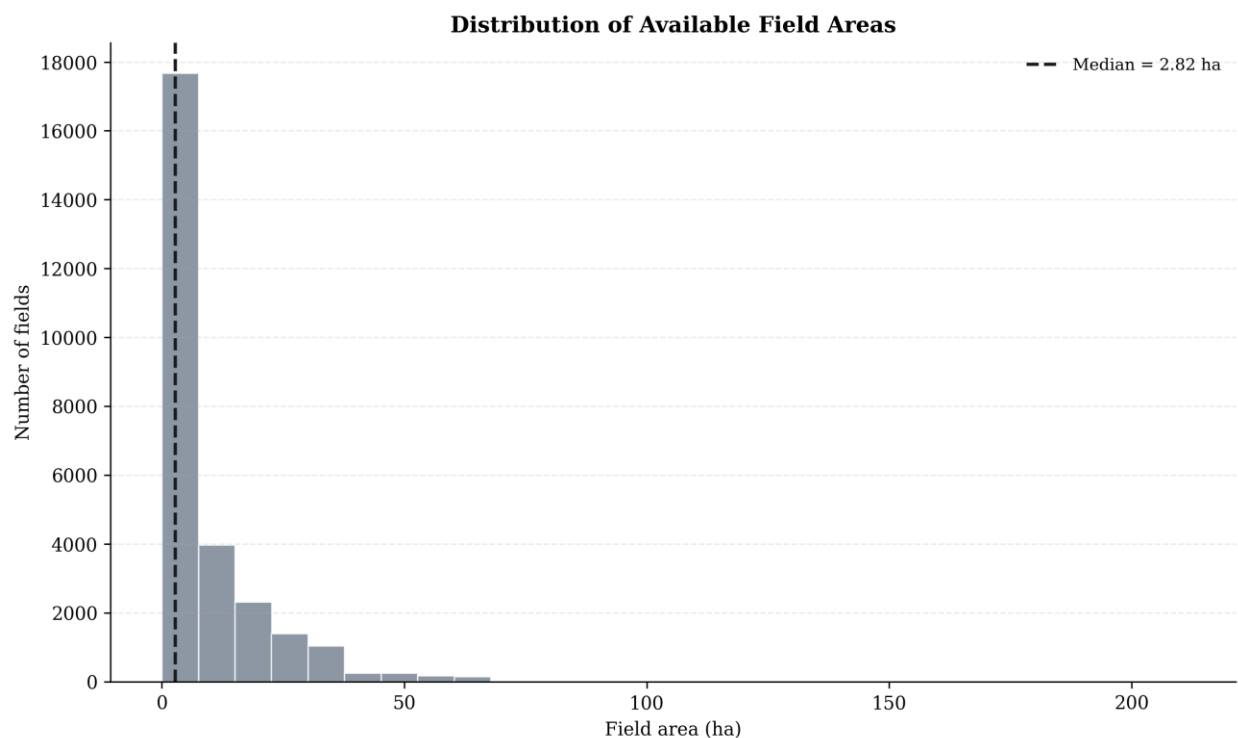


Figure 33 Distribution of field areas (ha)

The Monte Carlo results show that the number of fields required to achieve the target reduction varies across simulation runs Figure 34. Under the no-till scenario, the median number of selected fields is approximately 23, while under the combined cover crop and no-till scenario, the median decreases to approximately 20 fields. The interquartile range indicates moderate

variability, with some runs requiring fewer than 15 fields and others exceeding 30 fields. This variability reflects the stochastic nature of random selection, where the sequence in which fields are selected affects, the cumulative reduction achieved.

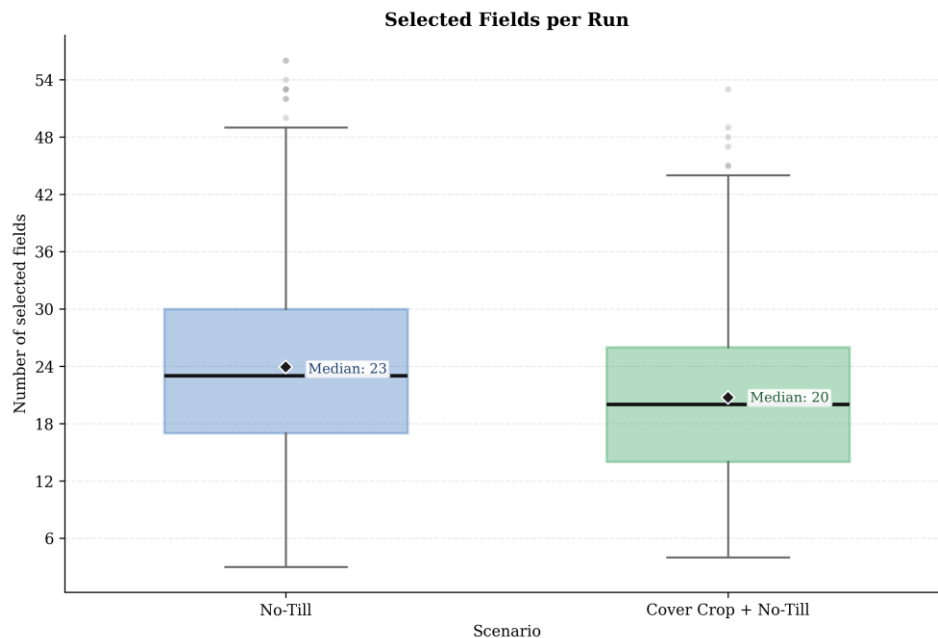


Figure 34 Boxplot showing selected fields per run under BMP scenarios.

The distribution of selected field areas Figure 35 further indicates that both scenarios rely on a mix of small and large fields. The median selected field size is approximately 7.33 ha for no-till and 7.19 ha for the combined BMP, which is substantially larger than the median size of available fields. This suggests that larger fields are more likely to be included in successful selections, as they contribute more efficiently toward the reduction target.

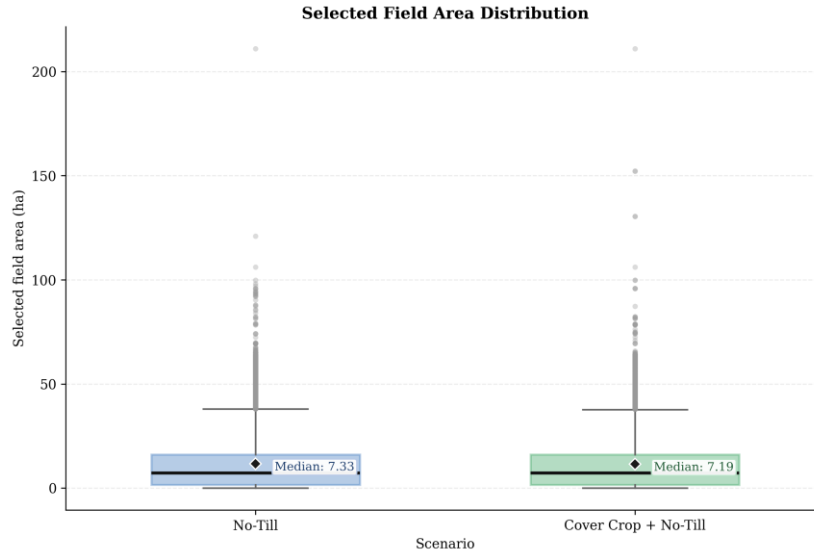


Figure 35 Box plot showing selected fields area per run under BMP scenarios.

At the aggregate level, the total area required to meet the reduction target also varies across runs Figure 36 . The median total selected area is approximately 219 ha for no-till and 188 ha for the combined BMP. This reduction in required area under the combined BMP reflects its higher effectiveness per unit area, allowing the target to be achieved with fewer fields and lower total land area.

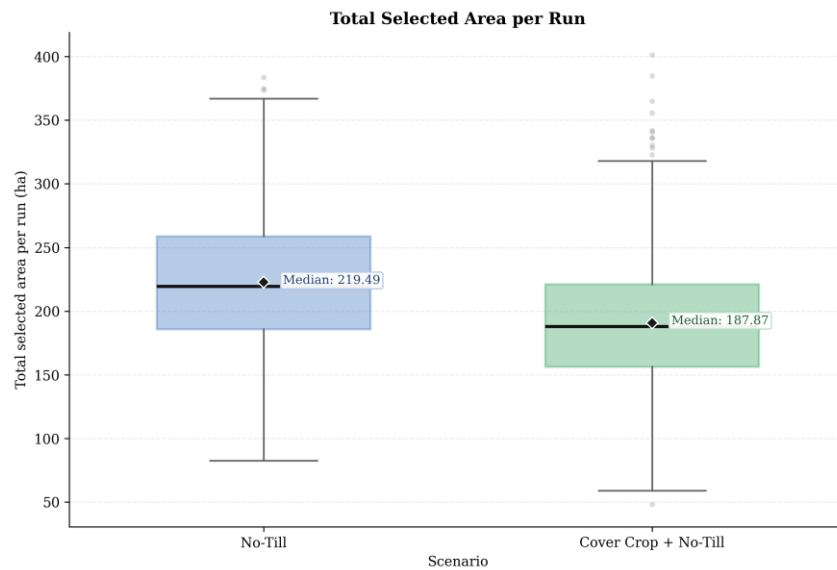


Figure 36 Box plot showing Total selected field area per run (ha) under no-till and cover crop + no-till scenarios.

The relationship between total selected area and the number of fields per run is illustrated in Figure 37. A clear positive relationship is observed, indicating that larger total selected areas generally correspond to a higher number of selected fields. However, the spread of points shows that similar reduction targets can be achieved through different combinations of field sizes, highlighting the role of variability in field characteristics.

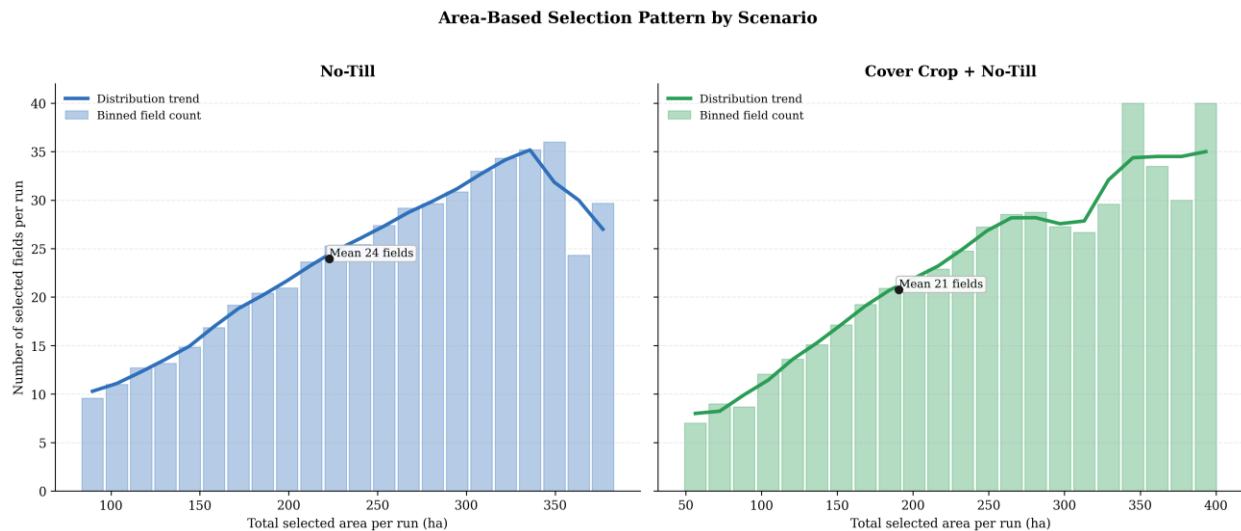


Figure 37 Relationship between total selected area and number of selected fields per run under BMP scenarios

Overall, the results of Scenario 1 demonstrate that the sediment reduction target can be achieved through random field selection, but with notable variability in both the number of fields and total area required. The combined cover crops and no-till scenario consistently require fewer fields and less area compared to no-till alone, indicating higher efficiency. However, the absence of spatial prioritization results in a broader and less controlled selection process, which may not be optimal for practical implementation. These results provide a baseline for evaluating the benefits of targeted field selection in subsequent scenarios. The observed variability indicates that random selection does not guarantee consistent efficiency, motivating the need for spatially targeted selection approaches.

6.6.2 Scenario 2: Selected Subbasins

To evaluate the effect of spatial prioritization, the Monte Carlo framework was applied to a restricted set of fields located within selected high-sediment-yield 10 subbasins ($n = 11,106$). These subbasins were identified through prior analysis based on their contribution to total sediment load. Unlike Scenario 1, this configuration represents a targeted implementation strategy, where the selection pool is spatially constrained to areas with higher sediment generation potential.

The distribution of available field areas within the selected subbasins Figure 38 remains right skewed, with a median field size of approximately 2.90 ha. This distribution is consistent with the watershed-wide pattern observed in Scenario 1, indicating that the underlying field size characteristics are similar despite spatial filtering. However, the concentration of fields within high yield subbasins increases the likelihood that randomly selected fields contribute more effectively to sediment reduction.

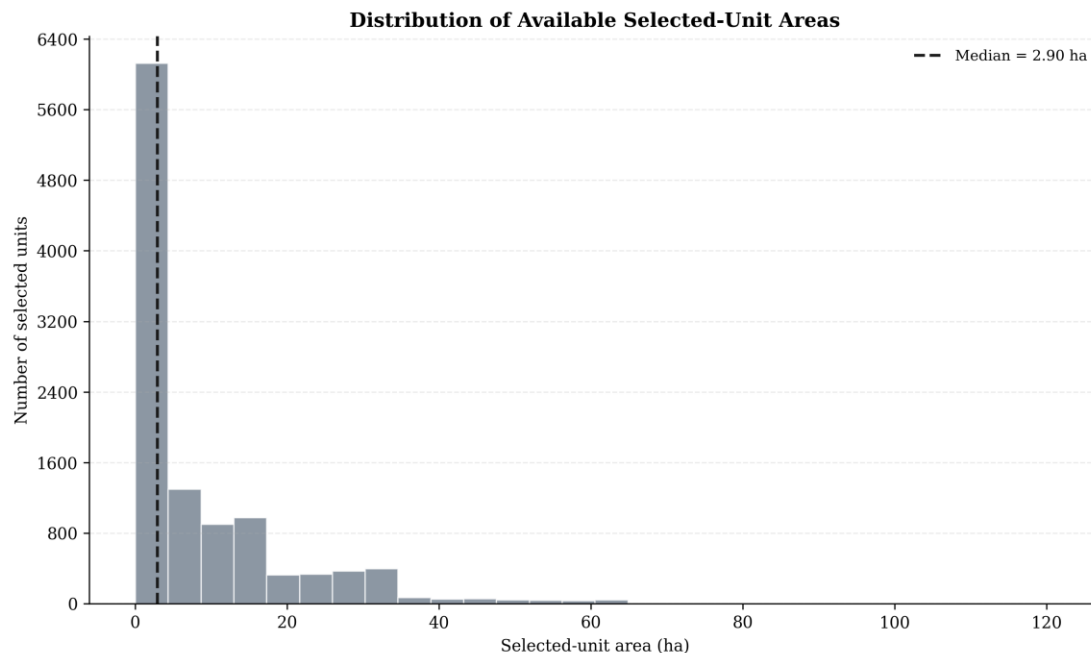


Figure 38 Distribution of selected-unit areas (ha) in selected Subbasins

The number of fields required to achieve the target reduction is lower compared to Scenario 1. Figure 39. The median number of selected fields is approximately 17 under the no-till scenario and 15 under the combined cover crop and no-till scenario. This represents a reduction relative to Scenario 1 (medians of 23 and 20, respectively), indicating improved efficiency due to spatial targeting. The variability across runs remains present, but the interquartile range is narrower, suggesting more consistent outcomes.

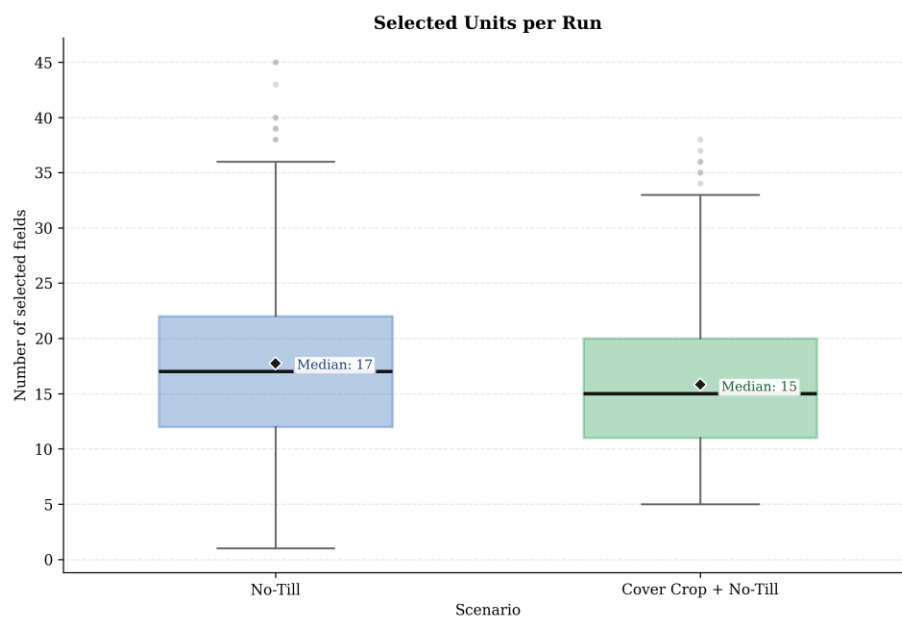


Figure 39 Boxplot showing Distribution of selected fields per run under BMP scenarios in selected Subbasin

The distribution of selected field areas Figure 40 shows median values of approximately 7.61 ha for no-till and 7.75 ha for the combined BMP. These values are comparable to those observed in Scenario 1, indicating that the selection process continues to favor relatively larger fields. However, the improved efficiency in this scenario is not driven by field size alone, but by the higher sediment yield associated with fields in the selected subbasins.

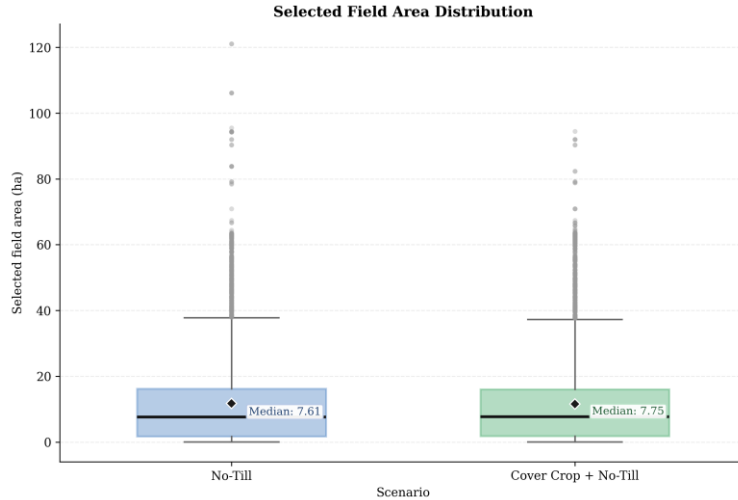


Figure 40 Boxplot showing Distribution of selected field area per run under BMP scenarios for selected subbasins

At the aggregate level, the total area required to meet the sediment reduction target is substantially lower than in Scenario 1 Figure 41. The median total selected area is approximately 165 ha for no-till and 145 ha for the combined BMP, compared to 219 ha and 188 ha in Scenario 1. This reduction in required area demonstrates that targeting high yield subbasins enables more efficient allocation of conservation practices.

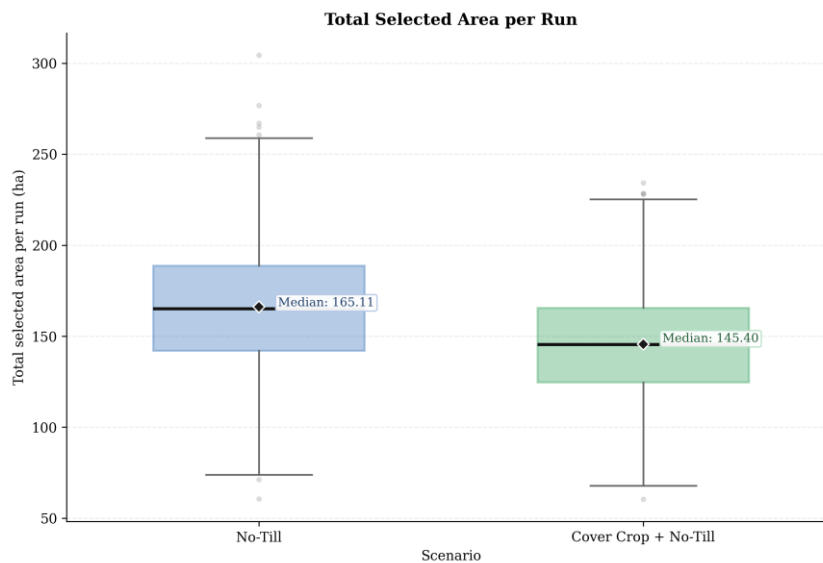


Figure 41 Boxplot showing Total selected field area per run (ha) under no-till and cover crop + no-till scenarios for selected subbasin

The relationship between total selected area and the number of fields per run Figure 42 continues to show a positive association. However, for a given reduction target, fewer fields and lower total area are required compared to the watershed-wide selection case. The mean number of selected fields per run is approximately 18 for no-till and 16 for the combined BMP, further confirming the efficiency gains achieved through spatial prioritization.

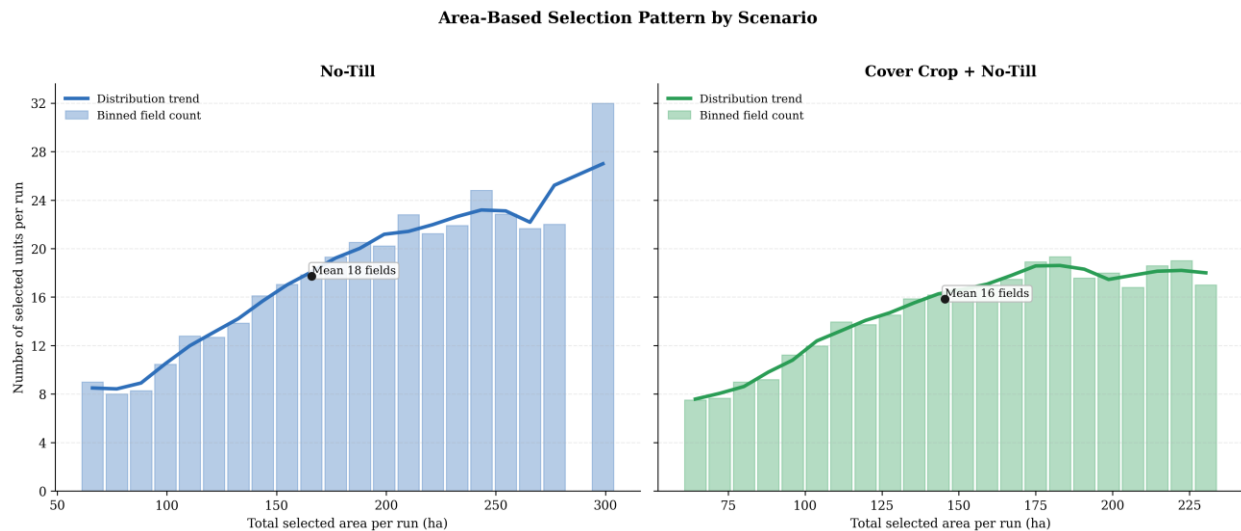


Figure 42 Relationship between total selected area and number of selected fields per run under BMP scenarios for selected subbasin

Overall, Scenario 2 demonstrates that restricting the selection pool to high yield subbasins significantly improves the efficiency of achieving sediment reduction targets. Both the number of fields and the total area required are reduced, while variability across simulation runs is also moderated. The combined cover crops and no-till scenario continue to outperform no-till alone, requiring fewer fields and less area. These findings indicate that spatial targeting at the subbasin level provides a substantial advantage over non-targeted watershed-wide implementation.

6.6.3 Scenario 3: Cluster and Hotspot-Based Targeted Field Selection

To further refine spatial prioritization, the Monte Carlo framework was applied to a subset of fields identified through clustering and hotspot analysis within the previously selected subbasins. This scenario represents the most targeted implementation strategy, where field selection is restricted to areas exhibiting the highest sediment yield intensity based on statistical clustering and hotspot classification. Specifically, only fields associated with high-confidence hotspot classes (90%, 95%, and 99% significance levels) were included, ensuring that the selection pool is concentrated in areas with the greatest potential for sediment reduction.

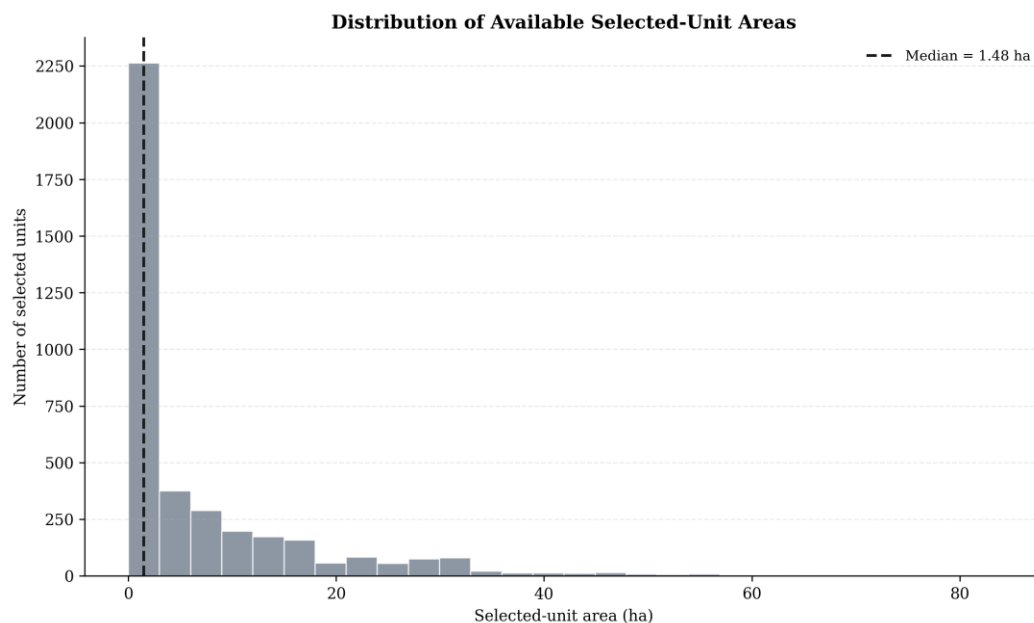


Figure 43 Distribution of selected-unit areas (ha) in identified hotspots

The distribution of available field areas within these targeted zones Figure 43 remains right skewed, like Scenarios 1 and 2. However, the reduced selection pool reflects a higher concentration of hydrologically critical fields. The median field size is slightly lower than in the previous scenarios (approximately 1.48 ha), indicating that hotspot regions consist of a larger number of

smaller but high-impact fields. This confirms that sediment contribution is not solely driven by field size but by spatial location and underlying erosion processes.

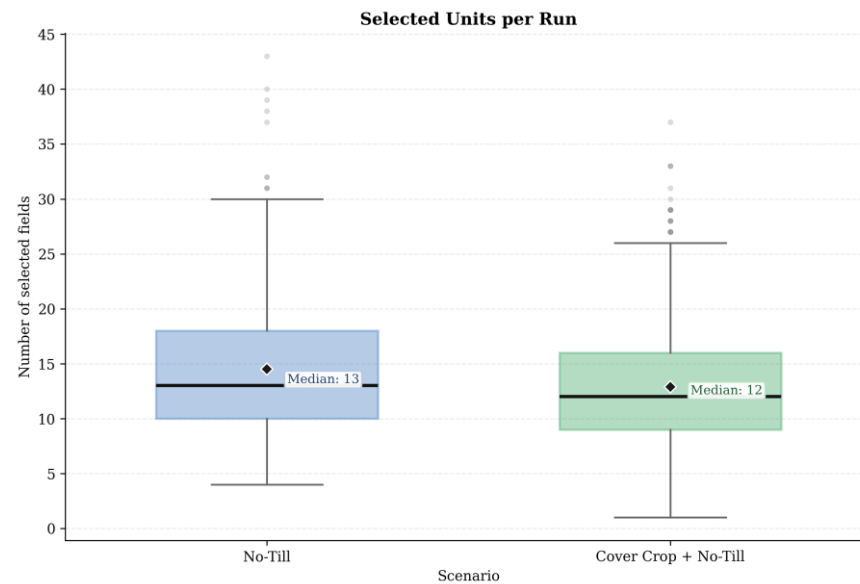


Figure 44 Boxplot showing Distribution of selected fields per run under BMP scenarios in selected Subbasin

The number of fields required to achieve the sediment reduction target is further reduced compared to Scenario 2 Figure 44 . The median number of selected fields is approximately 13 under the no-till scenario and 12 under the combined cover crop and no-till scenario. This represents a clear improvement relative to Scenario 2 (medians of 17 and 15, respectively), indicating that clustering-based targeting enhances selection efficiency. The variability across simulation runs is also reduced, demonstrating greater consistency in achieving the target when selection is restricted to high-priority zones.

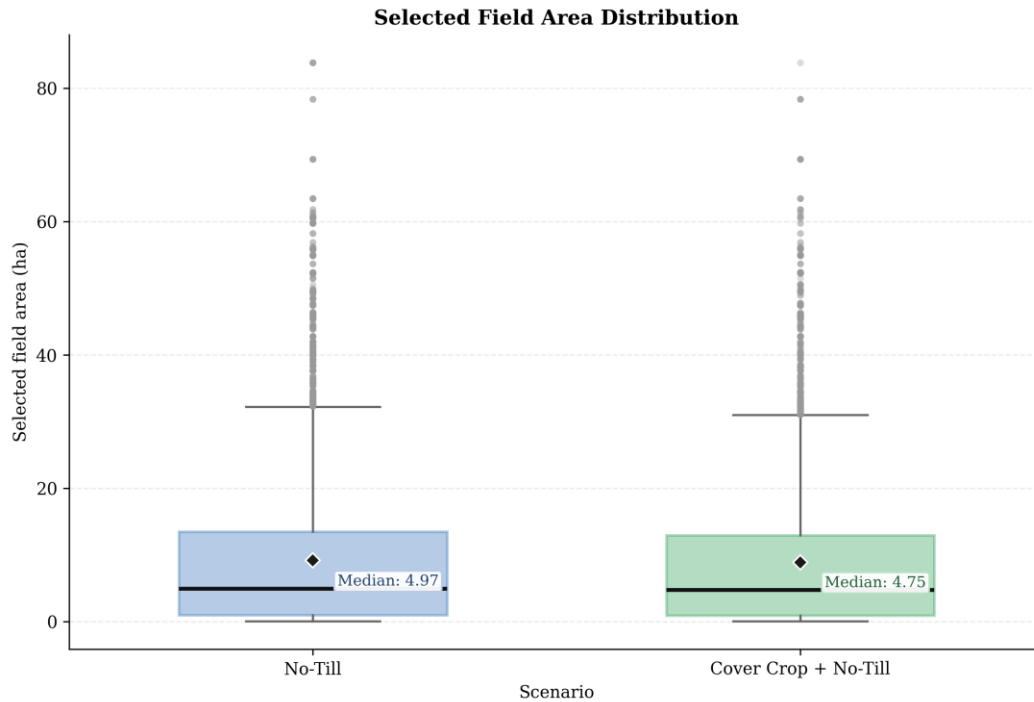


Figure 45 Boxplot showing Distribution of selected field area per run under BMP scenarios for in identified hotspots

The distribution of selected field areas indicates median values of approximately 4.97 ha for no-till and 4.75 ha for the combined BMP Figure 45. These values are lower than those observed in Scenarios 1 and 2, confirming that effective sediment reduction in this scenario is achieved through the selection of smaller but more impactful fields. This shift reflects the influence of spatial prioritization, where field effectiveness is governed by sediment yield intensity rather than area alone.

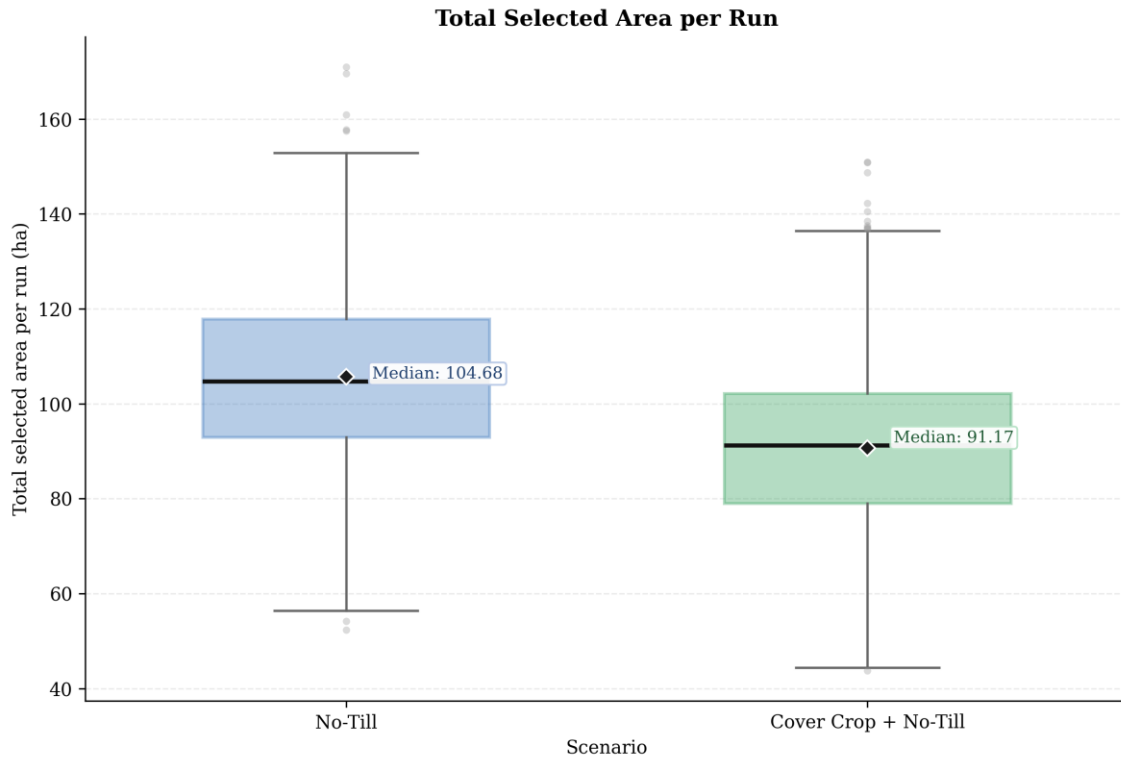


Figure 46 Boxplot showing Total selected field area per run (ha) under no-till and cover crop + no-till scenarios for selected subbasin in identified hotspot

At the aggregate level, the total area required to meet the sediment reduction target is significantly reduced Figure 46. The median total selected area is approximately 105 ha for no-till and 91 ha for the combined BMP. Compared to Scenario 2 (165 ha and 145 ha) and Scenario 1 (219 ha and 188 ha), this represents the highest level of efficiency among all scenarios. The reduction in required area directly reflects the concentration of high-yield fields within hotspot zones.

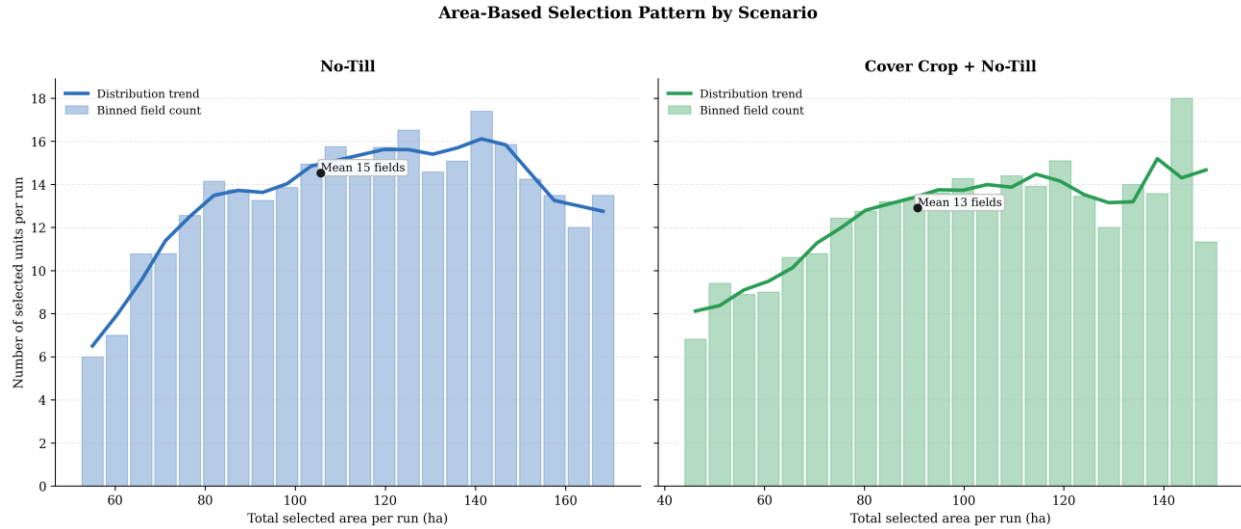


Figure 47 Relationship between total selected area and number of selected fields per run under BMP scenarios for selected subbasin in identified hotspot

The relationship between total selected area and the number of fields per run remains positive, indicating that larger selected areas correspond to a higher number of fields Figure 47. However, for a given reduction target, substantially fewer fields and lower total area are required compared to both previous scenarios. The mean number of selected fields per run is approximately 15 for no-till and 13 for the combined BMP, further supporting the efficiency gains achieved through clustering-based prioritization.

Overall, Scenario 3 demonstrates that integrating clustering and hotspot analysis into the field selection process yields the most efficient outcomes. By restricting implementation to statistically significant high-yield areas, both the number of fields and total area required to achieve the sediment reduction target are minimized. The combined cover crop and no-till scenario continue to outperform no-till alone, consistently requiring fewer fields and less area. These findings establish clustering-based targeting as the most effective strategy among the evaluated approaches and directly build upon the priority intervention framework developed in Section 6.4.

6.6.4 Comparative Summary of Selection Strategies

The three selection strategies evaluated in this study demonstrate a clear progression in efficiency as spatial information is increasingly incorporated into the field selection process. Efficiency is defined here as the ability to achieve the predefined sediment reduction target (160–165 t yr⁻¹) using the minimum number of fields and the minimum total area.

The watershed-wide random selection approach (Scenario 1) represents a non-targeted baseline. Although the target reduction is consistently achieved, the results exhibit substantial variability in both the number of selected fields and total area required. Median values indicate that approximately 23 fields (no-till) and 20 fields (cover crop + no-till) are required, with corresponding total areas of approximately 219 ha and 188 ha, respectively. This variability reflects the stochastic nature of random selection and the absence of control over field-level sediment contribution.

Restricting the selection pool to high-contributing subbasins (Scenario 2) improves efficiency by incorporating spatial prioritization at the subbasin scale. The median number of selected fields decreases to approximately 17 (no-till) and 15 (combined BMP), while the median total area decreases to approximately 165 ha and 145 ha. This improvement is attributed to the concentration of higher sediment-yield fields within the selected subbasins, which increases the likelihood that randomly selected fields contribute more effectively to the reduction target. Variability across simulation runs is also reduced, indicating more consistent outcomes compared to Scenario 1.

Further refinement through clustering and hotspot-based targeting (Scenario 3) yields the highest level of efficiency. By restricting selection to statistically significant high-yield fields, the median number of selected fields decreases to approximately 13 (no-till) and 12 (combined BMP),

with corresponding total areas of approximately 105 ha and 91 ha. This represents a substantial reduction relative to both Scenario 1 and Scenario 2. The improved performance is driven by the explicit identification of fields with the highest sediment yield intensity, ensuring that each selected field contributes maximally toward the reduction target. The reduced variability across runs further indicates that hotspot-based targeting produces more stable and predictable outcomes.

Across all scenarios, the combined cover crop and no-till practice consistently outperform no-till alone, requiring fewer fields and less total area to achieve the same reduction target. This confirms that increased surface protection and reduced soil disturbance enhance sediment reduction efficiency at the field scale.

Overall, the results establish a clear hierarchy of selection strategies. Random selection provides a feasible but inefficient baseline. Subbasin-level targeting improves efficiency by leveraging spatial concentration of sediment sources. Clustering and hotspot-based targeting provide the most effective approach by directly identifying and prioritizing the highest contributing fields. These findings demonstrate that integrating spatial analysis with process-based modeling substantially improves the efficiency and practicality of off-site BMP implementation.

Chapter 7 Discussion

7.1 Sediment Generation patterns

The results show that sediment generation is not uniformly distributed across the watershed. A small number of subbasins and fields contribute a large share of total sediment load. This concentration is observed at both the subbasin and HRU levels, where high-yield areas form distinct clusters. These patterns indicate that erosion processes are strongly controlled by local conditions such as slope, soil properties, and land use.

At the HRU level, the distribution of sediment yield is highly skewed, with a long upper tail representing a limited number of high-yield units. This indicates that most areas contribute relatively low sediment, while a small subset drives overall watershed sediment export. Similar spatial concentration has been reported in watershed studies identifying critical source areas, where a small proportion of land contributes a large share of sediment export (Merriman et al., 2018; P. W. Gassman et al., 2007).

7.2 Effectiveness of BMP scenarios

The results demonstrate that both no-till and combined no-till with cover crops significantly reduce sediment yield across all spatial scales. No-till alone produces substantial reductions, while the addition of cover crops further enhances sediment control.

At the watershed level, total sediment load decreases by approximately 79% under no-till and more than 93% under the combined BMP. Similar trends are observed at field and HRU levels, where both median and extreme sediment values decrease under BMP implementation.

The greater effectiveness of the combined BMP reflects the complementary role of residue retention and soil cover. No-till reduces soil disturbance, while cover crops provide additional protection against rainfall impact and runoff. These combined effects result in improved erosion

control compared to single-practice implementation. Similar findings have been reported in Midwestern agricultural watersheds, where conservation practices reduce sediment yields by 60–90% depending on site conditions (Lamba et al., 2016; Nepal & Parajuli, 2022).

The selection of no-till and cover crops in this study is based on their widespread adoption and demonstrated effectiveness in reducing soil erosion in row-crop systems. These practices are commonly recommended in conservation programs because they directly influence soil disturbance, residue cover, and runoff processes, which are key drivers of sediment generation.

7.3 Spatial targeting and priority areas

The identification of high-contributing subbasins shows that sediment generation is spatially clustered rather than randomly distributed. Selected subbasins account for a large share of total sediment load while representing a smaller portion of the watershed area.

The selection process, based on sediment contribution and refined using slope, land use, and soil characteristics, ensures that priority areas reflect both observed sediment output and underlying erosion drivers. This approach improves the reliability of targeting by linking model results with physical watershed conditions.

Within selected subbasins, further refinement using clustering separates fields into groups based on sediment yield intensity. The results show a strong imbalance, where most fields belong to low-yield groups, while a small number of fields fall into high-yield clusters. This indicates that sediment contribution is concentrated within a limited subset of fields, and that selecting fields without considering this structure would include many low-impact areas.

In addition to clustering, Gi* hotspot analysis was used to identify statistically significant high-yield areas. The results show that high sediment yield fields are spatially coherent and form distinct hotspot regions. Higher hotspot confidence levels correspond to higher sediment yield,

indicating that hotspot analysis effectively captures areas of concentrated erosion risk. This provides an objective method to identify priority intervention zones based on spatial patterns rather than only total sediment contribution.

The combination of subbasin screening, clustering, and hotspot analysis provides a multi-level targeting approach. Subbasin selection reduces the spatial domain, clustering separates fields based on sediment intensity, and hotspot analysis identifies spatially connected high-yield areas. Together, these steps reduce the number of candidate fields while maintaining high sediment reduction potential.

At the field level, sediment results derived from HRU outputs show similar concentration patterns, where a limited number of fields contribute a large share of sediment load. This confirms that high-yield areas remain dominant even after aggregation from HRUs to fields. Since BMPs are implemented at the field scale, this representation provides a direct link between model results and practical management decisions.

7.4 Implications for off-site BMP Implementation

The results show that sediment reduction can be achieved more efficiently by focusing on a limited number of high-contributing subbasins and fields rather than applying BMPs uniformly across the watershed. This targeted approach reduces the number of fields and total areas required to meet reduction goals, improving implementation feasibility.

The stepwise selection approach used in this study, subbasin screening followed by field level targeting using clustering and Gi* hotspot analysis, provides a clear and implementable pathway for BMP placement. Subbasin selection reduces the spatial domain, while clustering and hotspot analysis identify high-yield fields within those areas. This structure improves both efficiency and consistency in field selection.

No-till and cover crops were selected as the primary BMPs because they directly influence the key processes controlling sediment generation, including soil disturbance, surface cover, and runoff. No-till reduces soil disruption and maintains residue on the surface, which decreases soil detachment and runoff potential. Cover crops provide additional ground cover and improve soil structure, further reducing erosion risk. These practices are widely recommended in conservation programs and have been shown to significantly reduce sediment yields in agricultural watersheds (Lamba et al., 2016; Merriman et al., 2018; Nepal & Parajuli, 2022).

The results also show that combining no-till with cover crops achieves greater sediment reduction than no-till alone. This indicates that both location and practice selection play an important role in improving implementation efficiency. The magnitude of reduction observed in this study is consistent with previous studies in Midwestern agricultural systems, where sediment reductions of 60–90% have been reported under conservation practices (Lamba et al., 2016; Nepal & Parajuli, 2022). These findings support the use of combined BMPs to maximize sediment reduction outcomes.

The use of a uniform corn management system across all cropland areas provides a consistent basis for comparing BMP performance. However, actual agricultural systems include multiple crops and rotations, which may influence sediment response. Despite this simplification, the results clearly show relative differences between BMP scenarios and identify high-contributing areas. Therefore, the findings remain useful for guiding BMP placement, particularly in prioritizing locations rather than predicting exact sediment values.

The results support off-site BMP programs, where upstream agricultural practices are used to reduce sediment impacts on downstream systems. The findings provide direct guidance for BMP policy design by supporting targeted, area efficient implementation strategies rather than uniform

watershed-wide adoption. This approach aligns with conservation frameworks that prioritize high impact areas to maximize environmental benefits while minimizing implementation effort and cost.

7.5 Limitations

Sediment prediction in SWAT+ depend strongly on hydrologic simulation because sediment generation is driven by runoff energy through the Modified Universal Soil Loss Equation (MUSLE) (J. G. Arnold et al., 2012a). Therefore, uncertainty in runoff directly affects sediment estimates.

In this study sediment calibration was not performed due to lack of observed sediment data. Instead, sediment outputs were obtained from calibrated streamflow. This approach is commonly used in data limited watersheds and is physically consistent for agricultural systems dominated by sheet and rill erosion (J. G. Arnold et al., 2012a). However, this introduces uncertainty in absolute sediment values.

Comparison with literature indicates that the model is likely to provide conservative estimates. Reported average erosion rates in the United States are approximately $2.32 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ (Shojaeezadeh et al., 2024), while studies in agricultural regions often report values up to $2\text{-}10 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ (Montgomery, 2007; Pimentel et al., 1995b). The modeled baseline values in this study ($3.26 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ at HRU level) fall within this range but do not capture the higher extremes reported in field or watershed-scale studies.

Similarly, Kansas based sediment yield estimates range from <50 to $>5,000 \text{ t mi}^{-2} \text{ yr}^{-1}$ (Scientific Investigations Report, 2018), which correspond to a wide variability in erosion processes. The model outputs in this study align with the lower to moderate range of these values.

This difference is expected because SWAT+ primarily represents upland erosion and does not fully capture gully, channel, and extreme event driven processes.

Despite these differences in magnitude, the spatial patterns observed in this study are consistent with theory and previous studies. High sediment yield areas correspond to combinations of slope, soil erodibility, and runoff potential, which supports the reliability of the model for identifying critical source areas (P. W. Gassman et al., 2007). Comparison with regional programs such as WRAPS also shows similar spatial prioritization patterns, further supporting the validity of the results for decision making.

Alternative sediment validation methods include sediment rating curves and paired watershed analysis (D. N. Moriasi et al., 2007b). These methods require long-term observed sediment data, which was not available. In addition, downstream suspended sediment measurements include channel and deposition effects and therefore do not directly represent upstream field-scale erosion. Since this study focuses on upstream agricultural fields, hydrologic calibration provides a suitable basis for sediment estimation.

A uniform corn management system was applied across all Cropland areas to maintain consistency in BMP comparison. This assumption simplifies actual agricultural conditions and does not capture crop diversity or rotation practices, which may influence sediment generation.

The analysis is based on long-term average conditions and does not explicitly evaluate extreme rainfall years. Since sediment generation is often driven by high-intensity storm events, this may underestimate peak sediment export.

The identification of hotspot areas assumes that spatial patterns of sediment generation remain stable over time. Any changes land use, climate variability, and management practices may alter these patterns in reality.

Selection efficiency was evaluated based on the number of fields and treated area rather than economic cost. While area-based metrics provide useful insights, actual BMP implementation depends on financial cost, incentives, and farmer participation.

From a policy perspective, the model may underestimate the actual amount of sediment, so the exact values should be used with caution. However, the model is still reliable for comparing different areas and BMP scenarios. This means it can effectively identify high impact areas and help decide where BMPs should be implemented. For practical use, BMP programs should combine model results with field monitoring and update decisions over time to account for uncertainty.

Chapter 8 Conclusion and Future Research

This study developed a process-based and spatially explicit framework to identify, evaluate, and prioritize sediment sources in the Little Arkansas River watershed using the SWAT+ model. The model was constructed using detailed topographic, soil, land use, and climate data, and calibrated using multi-site streamflow observations to ensure reliable hydrologic representation. Sediment yield was estimated at multiple spatial scales, including HRU, subbasin, and field levels, and then translated into field-based outputs to support management decisions. Different agricultural management scenarios, including conventional tillage, no-till, and cover crops, were simulated to evaluate sediment reduction performance. A field prioritization framework was developed by combining sediment yield ranking, hotspot identification, clustering, and Monte Carlo-based selection methods. This framework was used to assess how targeted selection improves efficiency in achieving a defined sediment reduction goal within an Off-site BMP program.

The results confirm that sediment generation is highly uneven across the watershed, with a small number of fields contributing a large share of total sediment yield. This spatial concentration supports the concept of Critical Source Areas and highlights the importance of targeted intervention rather than uniform treatment. Conservation practices, particularly no-till and the combined no-till with cover crop scenario, showed clear reductions in sediment yield due to increased surface cover and reduced soil disturbance. The analysis also demonstrates that incorporating spatial information into field selection significantly improves efficiency, allowing sediment reduction targets to be achieved with fewer fields and less treated area. Among the evaluated strategies, targeted approaches based on high-yield fields and hotspot zones consistently outperformed random selection in both effectiveness and stability. These findings provide a

practical basis for designing cost-effective Off-site BMP programs that link upstream agricultural management with downstream water quality benefits.

Despite these contributions, several limitations remain and provide direction for future research. The current study used a single crop type (corn_120) across all cropland areas to maintain consistency in modeling. Future work can include multiple crop types such as soybeans, grain sorghum, and other regionally relevant crops to better represent agricultural variability. The inclusion of winter crops and crop rotation systems would improve representation of year-round soil cover and erosion processes.

The analysis in this study was based on long-term average annual conditions and does not explicitly capture extreme rainfall events. Future research should focus on event-based and extreme-year analysis to better understand sediment response during high-impact periods, which are often responsible for a large portion of total sediment transport.

Model calibration in this study was limited to streamflow due to insufficient observed sediment data. Future studies should prioritize the collection and use of sediment observations to enable independent sediment calibration, which would improve the accuracy and reliability of sediment predictions.

Further improvements can be achieved by integrating remote sensing data to capture vegetation dynamics, land-cover changes, and spatial variability in watershed conditions. This approach can enhance model representation and improve identification of sediment source areas over time.

Finally, this study evaluated BMP effectiveness based on achieving a fixed sediment reduction target using area-based efficiency metrics. Future research should incorporate economic cost data and cost effectiveness analysis to evaluate tradeoffs between sediment reduction and

implementation cost. Including financial and policy constraints will improve the applicability of the framework for real-world BMP planning and decision-making.

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Appendix A : Monte Carlo Random Selection Analysis Scripts

Purpose: This appendix presents the Python scripts used to perform Monte Carlo random selection of agricultural management units at three spatial levels: (1) individual crop fields (Appendix A-I), (2) selected subbasins (Appendix A-II), and (3) hotspot-targeted selected subbasins (Appendix A-III). The objective of each simulation was to identify combinations of management units whose cumulative sediment reduction reaches a target of 160 t/yr (accepted window: 160–165 t/yr) under two conservation scenarios — No-Till (NT) and Cover Crop + No-Till (CC+NT) — over 1,000 \

1. Appendix A-I — Field-Based Random Selection
2. Appendix A-II — Selected Subbasin Random Selection
3. Appendix A-III — Hotspot-Targeted Selected Subbasin Random Selection

Appendix A-I — Field-Based Random Selection

Source notebook: `Field_Reduction_MonteCarlo_Reconstructed.ipynb`

Spatial unit: Individual crop fields

Input data: `Field_Int_SY_final.csv`

Step 1 — Imports

```
import os
from pathlib import Path
from collections import Counter
import numpy as np
import pandas as pd
```

Step 2 — User-Defined Variables

All parameters that may need adjustment are collected here. No changes are required further down in the script.

```
# — Paths —————
BASE DIR = (r"C:\Users\srija\OneDrive - Kansas State University"
            r"\1. MASTERS\Research\Thesis MS Srijana"
            r"\3 GraphsMaps\GraphPlots\Field Based")
INPUT CSV = os.path.join(BASE DIR, "Field Int SY final.csv")

# Output sub-folders (created automatically)
OUT ROOT = os.path.join(BASE DIR, "RandomSelection Results Reconstructed")
RUNS DIR = os.path.join(OUT ROOT, "Runs")           # one CSV per run
SUMMARY DIR = os.path.join(OUT ROOT, "Summary")      # per-scenario & combined summaries
FREQ DIR = os.path.join(OUT ROOT, "Frequency")      # selection-frequency tables

# — Simulation parameters —————
N_RUNS = 1000 # number of Monte Carlo runs per scenario
```

```

TARGET          = 160.0    # sediment reduction target (t/yr)
TARGET MIN      = 160.0    # lower bound of acceptance window (t/yr)
TARGET MAX      = 165.0    # upper bound of acceptance window (t/yr)
TARGET TOL      = 1e-6     # numerical tolerance for exact-target check
RANDOM SEED      = 42       # reproducibility seed
MAX ATTEMPTS PER RUN = 250  # max shuffle attempts before raising an error

# — Beam-search repair parameters —————
REPAIR TAIL SIZE = 40      # near-boundary selected fields eligible for re-swap
REPAIR LOOKAHEAD = 24     # unselected fields considered during repair
REPAIR BEAM WIDTH = 3000  # maximum states kept per beam-search step
REPAIR SCALE     = 100    # integer scaling factor (= 0.01 t resolution)

# — Gap-filler filter —————
# Fields whose individual reduction is below this quantile of their scenario's
# eligible pool are excluded from the frequency table to avoid inflating counts.
GAP FILLER QUANTILE = 0.25

# — Input column names —————
COL FIELD ID = "LALULC CLU" # unique field identifier
COL AREA     = "SUM Fld hru Ar" # field area (area units)
COL BASELINE = "SUM FSY BL ton" # baseline sediment yield (t/yr)
COL NT       = "SUM FSY NT ton" # No-Till sediment yield (t/yr)
COL CCNT     = "SUM FSY CN ton" # Cover Crop + No-Till sediment yield (t/yr)

# Candidate column names for an optional subbasin identifier in the CSV
SUBBASIN CANDIDATES = [
    "Subbasin", "SUBBASIN", "Subbasin ID", "SubbasinID",
    "Subbasin No", "Subbasin no", "subbasin", "SUBBASIN ID",
]

```

Step 3 — Create Output Folders

```

for p in [OUT ROOT, RUNS DIR, SUMMARY DIR, FREQ DIR]:
    Path(p).mkdir(parents=True, exist_ok=True)

```

Step 4 — Load and Prepare Input Data

```

df = pd.read_csv(INPUT_CSV, encoding="utf-8-sig")

# Validate required columns
required_cols = [COL FIELD ID, COL AREA, COL BASELINE, COL NT, COL CCNT]
missing = [c for c in required_cols if c not in df.columns]
if missing:
    raise ValueError(f"Missing required columns: {missing}")

# Coerce numeric types and drop rows with missing values
for c in required_cols:
    df[c] = pd.to_numeric(df[c], errors="coerce")
df = df.dropna(subset=required_cols).copy()
df[COL FIELD ID] = df[COL FIELD ID].astype(int)

# Attach subbasin column if present in the CSV
subbasin_col = next((c for c in SUBBASIN CANDIDATES if c in df.columns), None)
if subbasin_col is None:
    df["Subbasin"] = pd.NA
    subbasin_col = "Subbasin"

# Compute sediment reduction per field per scenario

```

```

df["reduction NT"] = (df[COL BASELINE] - df[COL NT]).astype(float)
df["reduction CCNT"] = (df[COL BASELINE] - df[COL CCNT]).astype(float)

# Keep only fields with a positive reduction (eligible for selection)
df nt = df.loc[df["reduction NT"] > 0,
               [COL FIELD ID, COL AREA, subbasin col, "reduction NT"]].copy()
df ccnt = df.loc[df["reduction CCNT"] > 0,
                [COL FIELD ID, COL AREA, subbasin col, "reduction CCNT"]].copy()

print(f"Total fields after cleaning : {len(df):,}")
print(f"Eligible NT fields           : {len(df nt):,}")
print(f"Eligible CC+NT fields        : {len(df_ccnt):,}")

```

Step 5 — Monte Carlo Core Functions

```

def choose best index(cum values, target min, target max, tol):
    """
    Identify the first index in the cumulative-reduction array that satisfies
    the acceptance rule:
        1. Exact match to target min within numerical tolerance tol
        2. Closest value inside the window [target_min, target_max]
        3. None – no valid prefix found
    Returns (index, rule_label).
    """
    exact_idx = np.where(
        np.isclose(cum values, target min, atol=tol, rtol=0.0)
    )[0]
    if len(exact_idx) > 0:
        return int(exact_idx[0]), "exact_160"

    window_idx = np.where(
        (cum values >= target min) & (cum values <= target max)
    )[0]
    if len(window_idx) > 0:
        best = window_idx[np.argmin(np.abs(cum_values[window_idx] - target_min))]
        return int(best), "within 160 165"

    return None, "no valid prefix 160 165"

def score total(total, target):
    """
    Beam-search scoring function (lower = better).
    Strongly penalises totals outside [TARGET_MIN, TARGET_MAX].
    """
    abs_dev = abs(total - target)
    hard overshoot = max(total - TARGET_MAX, 0.0)
    hard undershoot = max(TARGET_MIN - total, 0.0)
    return abs dev + 30.0 * hard overshoot + 10.0 * hard undershoot

def refine selection indices(perm, reductions, cum perm, base idx,
                             target, target_min, target_max,
                             tail size, lookahead, beam width, scale):
    """
    Beam-search repair step.

    Starting from a greedy prefix (or from scratch if base idx is None),
    explores integer-approximated subset sums of a small candidate window
    to find a feasible selection whose total lies in [target min, target max].

    Parameters

```

```

-----
perm      : permutation of field indices for this run
reductions : array of per-field reduction values
cum perm   : cumulative reductions along the permutation
base idx   : last index of the greedy prefix (None if no prefix found)
target     : ideal target (160 t/yr)
target min  : lower acceptance bound (160 t/yr)
target max  : upper acceptance bound (165 t/yr)
tail size   : number of tail fields eligible for re-swap
lookahead   : number of extra fields considered beyond the prefix
beam width  : maximum states retained at each beam step
scale       : integer rounding factor for subset-sum approximation

Returns
-----
selected positions : array of field indices forming the refined selection
tag                : string label describing how the solution was found
"""
n = len(perm)

if base idx is None:
    mandatory count = 0
    opt end  = min(n, max(lookahead, tail size))
    base tag = "repair from start"
else:
    base total = float(cum perm[base idx])
    if target min <= base total <= target max:
        return perm[:base idx + 1].copy(), "baseline within 160 165"

    mandatory count = max(0, (base idx + 1) - tail size)
    while (mandatory count > 0 and
           float(cum perm[mandatory count - 1]) > target max):
        mandatory count -= 1

    opt end  = min(n, base idx + 1 + lookahead)
    base tag = "repair from prefix"

mandatory positions = perm[:mandatory count]
mandatory sum = (float(reductions[mandatory positions].sum())
                 if mandatory count > 0 else 0.0)

optional positions = perm[mandatory count:opt end]
if len(optional positions) == 0:
    return np.array([], dtype=int), "no refine window"

vals int = np.maximum(
    np.round(reductions[optional positions] * scale).astype(int), 0
)

# Beam search over integer subset sums
states = {0: 0} # {cumulative sum int: bitmask of selected optionals}
for i, v in enumerate(vals int):
    new states = dict(states)
    bit = 1 << i
    for s int, mask in states.items():
        ns = s int + int(v)
        if ns not in new states:
            new states[ns] = mask | bit
    ranked = sorted(
        new states.items(),
        key=lambda kv: _score_total(mandatory_sum + kv[0] / scale, target),

```

```

    )
    states = dict(ranked[:beam width])

best = best meta = None
for s int, mask in states.items():
    total = mandatory sum + s int / scale
    abs dev = abs(total - target)
    if np.isclose(total, target min, atol=TARGET TOL, rtol=0.0):
        pr, tag = (0, abs dev), f"{base tag}->refined exact 160"
    elif target min <= total <= target max:
        pr, tag = (1, abs dev), f"{base tag}->refined within 160 165"
    else:
        continue
    if best is None or pr < best:
        best, best meta = pr, (mask, tag)

if best meta is None:
    return np.array([], dtype=int), f"{base tag}->no valid 160 165"

best mask, best tag = best meta
selected optional = [optional positions[i]
                      for i in range(len(optional positions))
                      if (best mask >> i) & 1]
return (np.concatenate([mandatory positions,
                        np.array(selected optional, dtype=int)]).astype(int),
        best tag)

def run_scenario(scenario name, data, reduction col, rng):
    """
    Run N RUNS Monte Carlo iterations for one scenario.

    Each iteration:
    1. Randomly permutes eligible fields.
    2. Scans the cumulative-reduction prefix for a value in [160, 165].
    3. Applies beam-search repair if a valid prefix is not found directly.
    4. Saves a per-run CSV to RUNS DIR/<scenario name>/.
    5. Accumulates summary statistics and per-field selection counts.

    Parameters
    -----
    scenario name : "NT" or "CCNT"
    data          : DataFrame of eligible fields for this scenario
    reduction col : column name for the per-field reduction values
    rng           : numpy Generator (seeded)

    Returns
    -----
    summary df      : DataFrame with one row per run
    frequency counter : Counter mapping field ID to selection count
    """
    if len(data) == 0:
        raise ValueError(f"No eligible fields for scenario {scenario name}.")

    scenario runs dir = os.path.join(RUNS DIR, scenario name)
    Path(scenario runs dir).mkdir(parents=True, exist ok=True)

    field ids = data[COL FIELD ID].to numpy()
    areas = data[COL AREA].to numpy(dtype=float)
    reductions = data[reduction col].to numpy(dtype=float)

    red_col_name = f"Sed_Red_{scenario_name} (tons/yr)"

```

```

rate col name = f"Sed Red Rate {scenario name} (tons/yr per area-unit)"
cum col name  = f"Cumulative Sed Red {scenario name} (tons/yr)"

summary rows      = []
frequency counter = Counter()

for run id in range(1, N RUNS + 1):
    found valid      = False
    selected positions = np.array([], dtype=int)
    base rule = refined rule = ""

    for i in range(MAX ATTEMPTS PER RUN):
        perm      = rng.permutation(len(data))
        cum perm = np.cumsum(reductions[perm])

        base idx, base rule = choose best index(
            cum perm, TARGET MIN, TARGET MAX, TARGET TOL
        )
        candidate positions, refined rule = refine selection indices(
            perm, reductions, cum perm, base idx,
            TARGET, TARGET MIN, TARGET MAX,
            REPAIR TAIL SIZE, REPAIR LOOKAHEAD,
            REPAIR BEAM WIDTH, REPAIR SCALE,
        )
        candidate positions = np.array(candidate positions, dtype=int)
        if len(candidate positions) == 0:
            continue
        if TARGET MIN <= float(reductions[candidate positions].sum()) <= TARGET MAX:
            selected positions = candidate positions
            found valid      = True
            break

    if not found valid:
        raise RuntimeError(
            f"No valid selection found for run {run id} ({scenario name}) "
            f"after {MAX ATTEMPTS PER RUN} attempts. "
            "Consider increasing MAX ATTEMPTS PER RUN, REPAIR BEAM WIDTH, "
            "or REPAIR LOOKAHEAD."
        )

    total reduction = float(reductions[selected positions].sum())
    total area      = float(areas[selected positions].sum())
    n selected      = int(len(selected positions))

    # Build per-run output DataFrame
    run df = pd.DataFrame({
        "Run ID":      run id,
        "Field ID":     field ids[selected positions],
        "red col name": reductions[selected positions],
        "Area (area-unit)": areas[selected positions],
        "Selection order": np.arange(1, n selected + 1, dtype=int),
    })
    run df[rate col name] = np.where(
        run df["Area (area-unit)"] > 0,
        run df[red col name] / run df["Area (area-unit)"],
        np.nan,
    )
    run df[cum col name] = run df[red col name].cumsum()

    frequency counter.update(run df["Field ID"].tolist())

```

```

file name = (f"run {run_id:04d} sum{total_reduction:.2f}"
             f" n{n_selected:03d}.csv")

run df.to_csv(
    os.path.join(scenario_runs_dir, file name),
    index=False, float_format="%.6f",
)

summary_rows.append({
    "Run ID":          run_id,
    "Scenario":        scenario_name,
    "Number of fields": n_selected,
    "Total reduction": total_reduction,
    "Total selected area": total_area,
    "Target reduction": TARGET,
    "Accepted range min": TARGET_MIN,
    "Accepted range max": TARGET_MAX,
    "Deviation from target": abs(total_reduction - TARGET),
    "Overshoot amount": max(total_reduction - TARGET, 0.0),
    "Undershoot amount": max(TARGET - total_reduction, 0.0),
    "Output file name": str(Path("Runs") / scenario_name / file name),
    "Selection rule":    f"{base_rule}->{refined_rule}",
})

if run_id % 100 == 0:
    print(f" {scenario_name}: completed {run_id}/{N_RUNS} runs")

return pd.DataFrame(summary_rows), frequency_counter

```

Step 6 — Run Monte Carlo Simulations

```

rng = np.random.default_rng(RANDOM_SEED)

summary_nt, freq_nt = run_scenario("NT", df_nt, "reduction_NT", rng)
summary_ccnt, freq_ccnt = run_scenario("CCNT", df_ccnt, "reduction_CCNT", rng)

summary_all = pd.concat([summary_nt, summary_ccnt], ignore_index=True)

# Save summary CSVs
summary_nt.to_csv(
    os.path.join(SUMMARY_DIR, "MC run summary NT.csv"),
    index=False, float_format="%.6f",
)
summary_ccnt.to_csv(
    os.path.join(SUMMARY_DIR, "MC run summary CCNT.csv"),
    index=False, float_format="%.6f",
)
summary_all.to_csv(
    os.path.join(SUMMARY_DIR, "MC run summary.csv"),
    index=False, float_format="%.6f",
)

# Constraint verification
print("Constraint check - all totals must be within [160, 165] t/yr:")
print(f"  Min : {summary_all['Total_reduction'].min():.4f}")
print(f"  Max : {summary_all['Total_reduction'].max():.4f}")
print(f"  All valid : {(summary_all['Total_reduction'] >= TARGET_MIN) &
(summary_all['Total_reduction'] <= TARGET_MAX)}.all()}")

```

Step 7 — Selection Frequency Table

```

def build_freq_table(freq_counter, eligible_df, reduction_col, scenario_runs):
    """
    Build a ranked frequency table for fields selected across all runs.

    Columns produced:
        Field ID            - unit identifier
        Selection count      - number of runs in which the field was chosen
        Selection frequency - Selection count / N RUNS
        Reduction value     - individual field reduction (t/yr)
        Contribution score  - Selection frequency x Reduction value

    Fields below the GAP FILLER QUANTILE of their scenario's eligible
    reduction distribution are excluded from the table.
    """
    freq_raw = pd.DataFrame({
        "Field ID":      list(freq_counter.keys()),
        "Selection count": list(freq_counter.values()),
    })
    freq_raw["Selection frequency"] = freq_raw["Selection count"] / scenario_runs

    lookup = eligible_df[[COL_FIELD_ID, reduction_col]].copy()
    lookup.columns = ["Field ID", "Reduction value"]
    freq_merged = freq_raw.merge(lookup, on="Field ID", how="left")

    # Remove gap-filler fields (below GAP FILLER QUANTILE)
    min_reduction = eligible_df[reduction_col].quantile(GAP_FILLER_QUANTILE)
    freq_merged = freq_merged[
        freq_merged["Reduction value"] >= min_reduction
    ].copy()

    freq_merged["Contribution score"] = (
        freq_merged["Selection frequency"] * freq_merged["Reduction value"]
    )
    return (freq_merged.sort_values("Contribution score", ascending=False)
            .reset_index(drop=True),
            min_reduction)

freq_nt_df, min_red_nt = build_freq_table(
    freq_nt, df_nt, "reduction_NT", N_RUNS
)
freq_ccnt_df, min_red_ccnt = build_freq_table(
    freq_ccnt, df_ccnt, "reduction_CCNT", N_RUNS
)

freq_nt_df.to_csv(
    os.path.join(FREQ_DIR, "Field Selection Frequency NT.csv"),
    index=False, float_format="%.6f",
)
freq_ccnt_df.to_csv(
    os.path.join(FREQ_DIR, "Field Selection Frequency CCNT.csv"),
    index=False, float_format="%.6f",
)
pd.concat([freq_nt_df.assign(Scenario="NT"),
           freq_ccnt_df.assign(Scenario="CCNT")],
          ignore_index=True).to_csv(
    os.path.join(FREQ_DIR, "Field Selection Frequency Combined.csv"),
    index=False, float_format="%.6f",
)

print(f"NT gap-filler threshold (25th pct): {min_red_nt:.4f} t/yr")
print(f"CCNT gap-filler threshold (25th pct): {min_red_ccnt:.4f} t/yr")

```

Appendix A-II — Selected Subbasin Random Selection

Source notebook: `Selected_Subbasin_Reduction_MonteCarlo_Reconstructed.ipynb`

Spatial unit: Selected subbasin composite units

Input data: `Selected_Subbasin_Final_Final.csv`

The algorithm is identical to Appendix A-I. Only the paths, column names, and output directory differ.

Step 1 — Imports

```
import os
from pathlib import Path
from collections import Counter
import numpy as np
import pandas as pd
```

Step 2 — User-Defined Variables

```
# — Paths —
BASE_DIR = (r"C:\Users\srija\OneDrive - Kansas State University"
            r"\1. MASTERS\Research\Thesis MS Srijana"
            r"\3_GraphsMaps\GraphPlots\Selected_SuB_Analysis")
INPUT_CSV = os.path.join(BASE_DIR, "Selected Subbasin Final_Final.csv")

OUT_ROOT = os.path.join(BASE_DIR, "Selected Subbasin RandomAnalysis Output")
RUNS_DIR = os.path.join(OUT_ROOT, "Runs")
SUMMARY_DIR = os.path.join(OUT_ROOT, "Summary")
FREQ_DIR = os.path.join(OUT_ROOT, "Frequency")

# — Simulation parameters —
N_RUNS = 1000 # number of Monte Carlo runs per scenario
TARGET = 160.0 # sediment reduction target (t/yr)
TARGET_MIN = 160.0 # lower bound of acceptance window (t/yr)
TARGET_MAX = 165.0 # upper bound of acceptance window (t/yr)
TARGET_TOL = 1e-6 # numerical tolerance for exact-target check
RANDOM_SEED = 42 # reproducibility seed
MAX_ATTEMPTS_PER_RUN = 250 # max shuffle attempts before raising an error

# — Beam-search repair parameters —
REPAIR_TAIL_SIZE = 40 # near-boundary selected units eligible for re-swap
REPAIR_LOOKAHEAD = 24 # unselected units considered during repair
REPAIR_BEAM_WIDTH = 3000 # maximum states kept per beam-search step
REPAIR_SCALE = 100 # integer scaling factor (= 0.01 t resolution)

# — Gap-filler filter —
GAP_FILLER_QUANTILE = 0.25

# — Input column names —
COL_FIELD_ID = "UID" # unique subbasin unit identifier
COL_AREA = "Sum_sel_ha" # selected area (ha)
COL_BASELINE = "base total" # baseline sediment yield (t/yr)
COL_NT = "nt_total" # No-Till sediment yield (t/yr)
COL_CCNT = "ccnt total" # Cover Crop + No-Till sediment yield (t/yr)

SUBBASIN_CANDIDATES = [
    "CONCATENAT", "Concatenated Subbasins",
    "Subbasin", "SUBBASIN", "Subbasin ID", "SubbasinID",
    "Subbasin_No", "Subbasin_no", "subbasin", "SUBBASIN_ID",
```

```
] 
```

Step 3 — Create Output Folders

```
for p in [OUT_ROOT, RUNS_DIR, SUMMARY_DIR, FREQ_DIR]:
    Path(p).mkdir(parents=True, exist_ok=True)
```

Step 4 — Load and Prepare Input Data

```
df = pd.read_csv(INPUT_CSV, encoding="utf-8-sig")

required_cols = [COL_FIELD_ID, COL_AREA, COL_BASELINE, COL_NT, COL_CCNT]
missing = [c for c in required_cols if c not in df.columns]
if missing:
    raise ValueError(f"Missing required columns: {missing}")

for c in required_cols:
    df[c] = pd.to_numeric(df[c], errors="coerce")
df = df.dropna(subset=required_cols).copy()
df[COL_FIELD_ID] = df[COL_FIELD_ID].astype(int)

subbasin_col = next((c for c in SUBBASIN_CANDIDATES if c in df.columns), None)
if subbasin_col is None:
    df["Subbasin"] = pd.NA
    subbasin_col = "Subbasin"

df["reduction_NT"] = (df[COL_BASELINE] - df[COL_NT]).astype(float)
df["reduction_CCNT"] = (df[COL_BASELINE] - df[COL_CCNT]).astype(float)

df_nt = df.loc[df["reduction_NT"] > 0,
               [COL_FIELD_ID, COL_AREA, subbasin_col, "reduction_NT"]].copy()
df_ccnt = df.loc[df["reduction_CCNT"] > 0,
                 [COL_FIELD_ID, COL_AREA, subbasin_col, "reduction_CCNT"]].copy()

print(f"Total units after cleaning : {len(df):,}")
print(f"Eligible NT units           : {len(df_nt):,}")
print(f"Eligible CC+NT units         : {len(df_ccnt):,}")
```

Steps 5–7 — Core Logic, Simulation, and Frequency Table

*The functions `choose_best_index`, `score_total`, `refine_selection_indices`, `run_scenario`, and `build_freq_table` are identical to those in **Appendix A-I, Steps 5 and 7**. Copy them here without modification.*

>

Note: In `run_scenario`, update the area column label to `"Area (ha)"` and the rate label to `"(tons/yr/ha)"` to reflect the subbasin-level schema. The field identifier key in the output DataFrame is `"Field_Code"`.

```
# --- Paste choose best index, score total, refine selection indices,
#      run scenario, and build freq table from Appendix A-I here ---

# Execute simulations
rng = np.random.default_rng(RANDOM_SEED)

summary_nt, freq_nt = run_scenario("NT", df_nt, "reduction_NT", rng)
summary_ccnt, freq_ccnt = run_scenario("CCNT", df_ccnt, "reduction_CCNT", rng)
```

```

summary all = pd.concat([summary nt, summary ccnt], ignore index=True)

summary nt.to csv(
    os.path.join(SUMMARY DIR, "MC run summary NT.csv"),
    index=False, float format="%.6f",
)
summary ccnt.to csv(
    os.path.join(SUMMARY DIR, "MC run summary CCNT.csv"),
    index=False, float format="%.6f",
)
summary all.to csv(
    os.path.join(SUMMARY DIR, "MC run summary.csv"),
    index=False, float format="%.6f",
)

# Frequency tables
freq nt df, min red nt = build freq table(
    freq nt, df nt, "reduction NT", N RUNS
)
freq ccnt df, min red ccnt = build freq table(
    freq ccnt, df ccnt, "reduction CCNT", N RUNS
)

freq nt df.to csv(
    os.path.join(FREQ DIR, "Field Selection Frequency NT.csv"),
    index=False, float format="%.6f",
)
freq ccnt df.to csv(
    os.path.join(FREQ DIR, "Field Selection Frequency CCNT.csv"),
    index=False, float format="%.6f",
)
pd.concat([freq nt df.assign(Scenario="NT"),
           freq ccnt df.assign(Scenario="CCNT")],
           ignore index=True).to csv(
    os.path.join(FREQ DIR, "Field Selection Frequency Combined.csv"),
    index=False, float format="%.6f",
)

print("Constraint check – all totals must be within [160, 165] t/yr:")
print(f" All valid: {(summary all['Total reduction'] >= TARGET_MIN) &
(summary_all['Total_reduction'] <= TARGET_MAX)}.all()}")

```

Appendix A-III — Hotspot-Targeted Selected Subbasin Random Selection

Source notebook: `Hotspot_Subbasin_Reduction_MonteCarlo_Reconstructed.ipynb`

Spatial unit: Hotspot-targeted selected subbasin composite units

Input data: `hotspot_selected10_final.csv`

Units in this analysis were pre-filtered through spatial hotspot analysis (Getis-Ord Gi*) to retain only the top-tier high-sediment subbasin clusters. The Monte Carlo algorithm and all parameters are identical to Appendix A-II; only the input file and output folder differ.

Step 1 — Imports

```

import os
from pathlib import Path
from collections import Counter
import numpy as np
import pandas as pd

```

Step 2 — User-Defined Variables

```
# — Paths —————
BASE_DIR = (r"C:\Users\srija\OneDrive - Kansas State University"
            r"\1. MASTERS\Research\Thesis MS Srijana"
            r"\3_GraphsMaps\GraphPlots\Hotspot_Field_RandomAnalysis")
INPUT_CSV = os.path.join(BASE_DIR, "hotspot_selected10_final.csv")

OUT_ROOT = os.path.join(BASE_DIR,
                        "Hotspot_Selected_Subbasin_RandomAnalysis_Output")
RUNS_DIR = os.path.join(OUT_ROOT, "Runs")
SUMMARY_DIR = os.path.join(OUT_ROOT, "Summary")
FREQ_DIR = os.path.join(OUT_ROOT, "Frequency")

# — Simulation parameters —————
N_RUNS = 1000 # number of Monte Carlo runs per scenario
TARGET = 160.0 # sediment reduction target (t/yr)
TARGET_MIN = 160.0 # lower bound of acceptance window (t/yr)
TARGET_MAX = 165.0 # upper bound of acceptance window (t/yr)
TARGET_TOL = 1e-6 # numerical tolerance for exact-target check
RANDOM_SEED = 42 # reproducibility seed
MAX_ATTEMPTS_PER_RUN = 250 # max shuffle attempts before raising an error

# — Beam-search repair parameters —————
REPAIR_TAIL_SIZE = 40 # near-boundary selected units eligible for re-swap
REPAIR_LOOKAHEAD = 24 # unselected units considered during repair
REPAIR_BEAM_WIDTH = 3000 # maximum states kept per beam-search step
REPAIR_SCALE = 100 # integer scaling factor (= 0.01 t resolution)

# — Gap-filler filter —————
GAP_FILLER_QUANTILE = 0.25

# — Input column names —————
COL_FIELD_ID = "UID" # unique hotspot unit identifier
COL_AREA = "Sum sel ha" # selected area (ha)
COL_BASELINE = "base_total" # baseline sediment yield (t/yr)
COL_NT = "nt_total" # No-Till sediment yield (t/yr)
COL_CCNT = "ccnt_total" # Cover Crop + No-Till sediment yield (t/yr)

SUBBASIN_CANDIDATES = [
    "CONCATENAT", "Concatenated Subbasins",
    "Subbasin", "SUBBASIN", "Subbasin_ID", "SubbasinID",
    "Subbasin No", "Subbasin no", "subbasin", "SUBBASIN ID",
]
```

Step 3 — Create Output Folders

```
for p in [OUT_ROOT, RUNS_DIR, SUMMARY_DIR, FREQ_DIR]:
    Path(p).mkdir(parents=True, exist_ok=True)
```

Step 4 — Load and Prepare Input Data

```
df = pd.read_csv(INPUT_CSV, encoding="utf-8-sig")

required_cols = [COL_FIELD_ID, COL_AREA, COL_BASELINE, COL_NT, COL_CCNT]
missing = [c for c in required_cols if c not in df.columns]
if missing:
```

```

        raise ValueError(f"Missing required columns: {missing}")

for c in required_cols:
    df[c] = pd.to_numeric(df[c], errors="coerce")
df = df.dropna(subset=required_cols).copy()
df[COL_FIELD_ID] = df[COL_FIELD_ID].astype(int)

subbasin_col = next((c for c in SUBBASIN_CANDIDATES if c in df.columns), None)
if subbasin_col is None:
    df["Subbasin"] = pd.NA
    subbasin_col = "Subbasin"

df["reduction_NT"] = (df[COL_BASELINE] - df[COL_NT]).astype(float)
df["reduction_CCNT"] = (df[COL_BASELINE] - df[COL_CCNT]).astype(float)

df_nt = df.loc[df["reduction_NT"] > 0,
               [COL_FIELD_ID, COL_AREA, subbasin_col, "reduction_NT"]].copy()
df_ccnt = df.loc[df["reduction_CCNT"] > 0,
                 [COL_FIELD_ID, COL_AREA, subbasin_col, "reduction_CCNT"]].copy()

print(f"Total hotspot units after cleaning : {len(df):,}")
print(f"Eligible NT units                  : {len(df_nt):,}")
print(f"Eligible CC+NT units                : {len(df_ccnt):,}")

```

Steps 5–7 — Core Logic, Simulation, and Frequency Table

*All functions and execution code are identical to **Appendix A-I, Steps 5–7**. Copy them here and run with the hotspot data loaded above. Output is saved to*

Hotspot_Selected_Subbasin_RandomAnalysis_Output/.

```

# --- Paste choose_best_index, _score_total, refine_selection_indices,
#       run_scenario, and build_freq_table from Appendix A-I here ---

# Execute simulations
rng = np.random.default_rng(RANDOM_SEED)

summary_nt, freq_nt = run_scenario("NT", df_nt, "reduction_NT", rng)
summary_ccnt, freq_ccnt = run_scenario("CCNT", df_ccnt, "reduction_CCNT", rng)

summary_all = pd.concat([summary_nt, summary_ccnt], ignore_index=True)

summary_nt.to_csv(
    os.path.join(SUMMARY_DIR, "MC_run_summary_NT.csv"),
    index=False, float_format="%.6f",
)
summary_ccnt.to_csv(
    os.path.join(SUMMARY_DIR, "MC_run_summary_CCNT.csv"),
    index=False, float_format="%.6f",
)
summary_all.to_csv(
    os.path.join(SUMMARY_DIR, "MC_run_summary.csv"),
    index=False, float_format="%.6f",
)

# Frequency tables
freq_nt_df, min_red_nt = build_freq_table(
    freq_nt, df_nt, "reduction_NT", N_RUNS
)
freq_ccnt_df, min_red_ccnt = build_freq_table(
    freq_ccnt, df_ccnt, "reduction_CCNT", N_RUNS
)

```

```

)

freq nt df.to csv(
    os.path.join(FREQ DIR, "Field Selection Frequency NT.csv"),
    index=False, float format="%.6f",
)
freq ccnt df.to csv(
    os.path.join(FREQ DIR, "Field Selection Frequency CCNT.csv"),
    index=False, float format="%.6f",
)
pd.concat([freq nt df.assign(Scenario="NT"),
           freq ccnt df.assign(Scenario="CCNT")],
           ignore index=True).to csv(
    os.path.join(FREQ DIR, "Field Selection Frequency Combined.csv"),
    index=False, float format="%.6f",
)

print("Constraint check - all totals must be within [160, 165] t/yr:")
print(f" All valid: {(summary_all['Total reduction'] >= TARGET_MIN) &
(summary_all['Total_reduction'] <= TARGET_MAX)}.all()}")

```
