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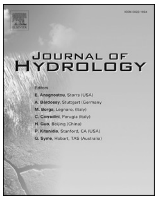

Research papers

Pi-VAT: A web-based visualization tool for decision support using spatially complex water quality model outputs

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ABSTRACT

Effective watershed management and protection of water resources from non-point source pollution require identification, prioritization, and targeting of pollutant source areas. Process-based hydrology and water quality models are powerful heuristic tools for land and water resources managers. However, because of their complexity, such models are often under-utilized as management prioritization and planning tools. In this paper, we present a prioritization, interactive visualization, and analysis tool (Pi-VAT) that is programmed to synthesize multi-scenario, multi-watershed outputs from process-based geospatial models. We demonstrate the utility of Pi-VAT to examine simulated hydrologic, sediment, and water quality response at the hillslope/hydrologic response unit (HRU) scale. We apply Pi-VAT to output from multiple watersheds and for multiple management scenarios and treatments from two geospatial models for watershed management: Water Erosion Prediction Project (WEPP) and Soil & Water Assessment Tool (SWAT). Pi-VAT was developed using the Shiny web application framework for the R programming language. In a matter of minutes, Pi-VAT can synthesize overwhelming amounts of output from process-based models into information useful for land and water resources managers. We illustrate the use of Pi-VAT to interactively identify, quantify, and visualize areas that are most susceptible to disturbance under different scenarios and provide a synthesis approach based on land use, soil type, and slope steepness. This approach guides land and water resources managers in prioritizing the areas of the watershed that provide the maximum reduction in pollutant loads while treating the least amount of area. Pi-VAT provides a flexible reactive platform for the development of decision support tools based on process-based models intended for watershed management and research applications.

1. Introduction

Water quality concerns from non-point source pollution (NPS) are a challenge for land and water resources managers. Effective management of NPS requires strategic targeting and prioritization of watershed areas for implementing best management practices (BMPs) (Diebel et al., 2008). Such targeting and prioritization typically consist of the identification of pollutant source areas and subsequent management to reduce water quality degradation (Daggupati et al., 2011; Easton et al., 2017).

Process-based hydrology and water quality simulation models have shown the capability to evaluate the potential effects of land management and climate scenarios on water quantity and quality. For example, a review of various process-based distributed watershed models by Wellen et al, (2015) reported that 83% of the reviewed scientific studies (257) published between the year 1992 and 2010 used one of these five models: Soil and Water Assessment Tool (SWAT), Integrated Catchment Model (INCA), Annualized/Agricultural Non-Point Source pollution model (AGNPS/AnnAGNPS), Hydrological Simulation Program - FORTRAN (HSPF), and Hydrologiska Byråns Vattenbalansavdelning (HBV). Such models can provide a link between management decisions

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and watershed response and provide a scientific basis for management decisions (Rode et al., 2010). The utility of these process-based models is not only to provide spatially explicit predictions of runoff and erosion but also to provide a deeper understanding of the key factors and dominant hydrologic processes and flow paths that drive the detachment and transport of sediment and associated pollutants (Brooks et al., 2015). Characteristically, such models have been successfully applied, predominantly by the scientific community for a management scenario-oriented impact assessment on water quality and quantity, to identify priority source areas, and to formulate management plans. For instance, the utility of the SWAT model has been widely demonstrated in the scenario-based evaluation of the efficacy of site-specific BMPs on water quality as well as in the targeting of BMPs placement for improving water quality (Briak et al., 2019; Daggupati et al., 2011; Easton et al., 2010; Liu et al., 2019; Merriman et al., 2019; Park et al., 2014; Xu et al., 2019). Similarly, the WEPP model has been successfully used for guiding watershed managers in the selection and placement of the BMPs in forested watersheds (Efta and Chung, 2014; Robichaud et al., 2007). It has also been applied for investigating the effectiveness of conservation management practices and targeted management in agricultural watersheds (Brooks et al., 2015; Pandey et al., 2009; Singh et al., 2011). Other models recognized in Wellen et al., (2015) were used to investigate sediment and nutrients response under alternative management scenarios as well as to identify priority areas for erosion control measures and to assess the BMPs effectiveness on nutrient loading (Abdelwahab et al., 2014; Ahn and Kim, 2016; Bastrup-Birk and Gundersen, 2004; Gudino-Elizondo et al., 2019; Luo et al., 2015; Zhang et al., 2020).

Despite this demonstrated usefulness, the use of process-based models by managers in “what if” scenario testing has been limited to date. Ease of use, extensive model setup and training requirements often form barriers to the adoption and effective use of process-based models in the planning process (Garen et al., 1999). There is also a strong need to disseminate the information generated by these models to stakeholders and decision-makers in a functional format. The recent evolution of web-based user interfaces for some models attempts to partly address these barriers. For example, SWATonline simplifies SWAT data querying as well as enables simple data visualizations (McDonald et al., 2019); The Hydrologic and Water Quality System (HAWQS) makes it easier to set up and run the SWAT model at the hydrologic unit codes (HUCs) 8 to 12 or larger scale and provides users with summary visualization capabilities and the ability to download an entire project to be used on a local computer (Yen et al., 2016). To enhance the use of process-based models in informed decision-making, an online watershed interface (WEPPcloud) has been developed to make use of the Water Erosion Prediction Project (WEPP) model across the US by watershed managers easier and more convenient (Dobre et al., n.d.). This interface was specifically developed for forestry applications as part of the Forest Service suite of models (https://forest.moscowfsl.wsu.edu/fswepp/) and its use recently has been extended to rangeland landscapes (WEPPcloud-RHEM) as well (Lew et al., n.d.).

Web-based user interfaces make the models more accessible and easier to use, but do not necessarily provide the data summaries and visualizations in a functional format to compare multiple watershed simulations of different management options and facilitate ‘what if’ scenario testing. To develop an action plan and ensure appropriate and effective management practices are implemented, managers need to understand the key hydrologic drivers and factors (soil type, land use/land cover, slope, and climate) involved in the transport of the pollutant and the sensitivity of these factors to pollutant transport. The amount of simulated output generated by process-based models especially when using the model to assess multiple management options over multiple years in unique land types within a watershed can be overwhelming. End-user (e.g., watershed managers) would require extensive training in geospatial analysis and modeling to process the output. In essence, process-based models are very useful tools for ingesting ‘Big Data’ as model input, however, they can also generate an equal amount of ‘Big Data’ that can be equally daunting for end-users to synthesize and extract useful knowledge for identifying and spatially prioritizing BMPs. A multiple scenario simulation from a hillslope or HRU based geospatial model for even a relatively small watershed and short daily weather time series can easily generate hundreds to thousands of targeting combinations (Fig. 1).

Integrating “what-if” scenario information with decision support tools would enable watershed managers to harness the potential of sophisticated, process-based models and truly aid in decision-making. Brooks et al. (2015) emphasized the need to connect science and management by improving process-based planning tools such that crucial information is available to planners to target areas in the landscape. Brooks et al. (2015) demonstrated the use of a simplified web interface consisting of post-processing algorithms built on top of the WEPP model to effectively support BMP assessment and planning.

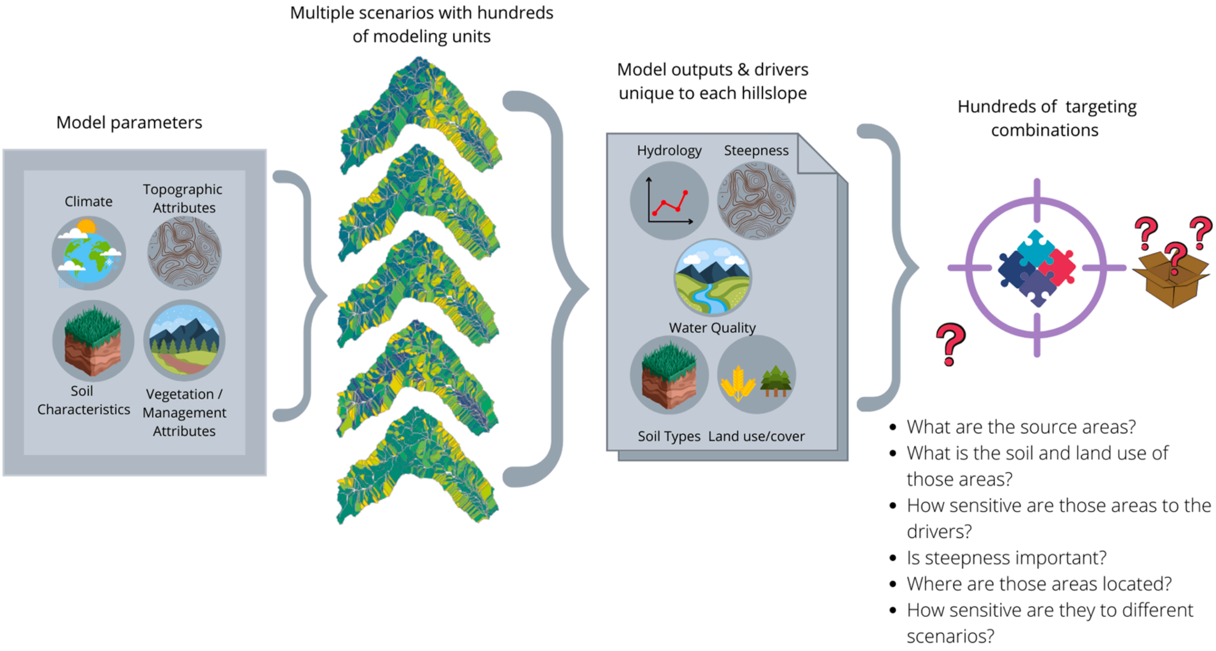
The number of commercial and open-source platforms for hosting online tools has led to an explosion in web-based applications and has provided an opportunity to develop geospatial decision support tools. For example, tools developed using Shiny, an open-source web application framework developed by the RStudio Team (R Core Team, 2021), have enabled the creation of interactive web applications that allow users to interact dynamically with the model simulations. Since its inception, the use of Shiny has increased steadily as evidenced by peer-reviewed papers through which specialists in academic fields disseminated knowledge to stakeholders (Kasprzak et al., 2020). While Shiny has been used across a diverse range of academic fields, to our knowledge, few peer-reviewed papers in the earth and environmental sciences have used the Shiny web application framework. For instance, Klein et al. (2017) developed the webXTREME tool to facilitate agroclimatic risk evaluation under climate change. WebXTREME has provided an important link between scientists and decision-makers. Whateley et al. (2015) used Shiny to develop a web-based decision support tool that provides an interactive environment to water managers and stakeholders to explore water supply system vulnerabilities to climate change. This tool, targeted at small-scale water supply systems, provides an opportunity for more dynamic and collaborative water resources management.

The objectives of this work were to develop a stand-alone, post-processing, interactive analysis, and visualization tool that can ingest complex, spatially distributed output from geospatial hydrologic models, and to demonstrate its use as a decision support tool for scenario-oriented planning and management. We developed the Prioritization-Visualization and Analysis Tool (Pi-VAT) that synthesizes tabular and map-based outputs for multiple watersheds and scenarios. We demonstrate the utility of the tool with watershed case studies using outputs from two of the most well-known hydrologic management models: WEPP and SWAT. We describe its development and demonstrate its use in evaluating and guiding land and water resources management decisions in three watershed case studies.

2. Methods

2.1. Interface implementation

Pi-VAT is an interactive tool developed for the identification and prioritization of pollutant hotspots and areas suitable for targeted management. Currently, Pi-VAT ingests output from two of the most widely used hydrologic models WEPP and SWAT using the Shiny web application framework for the R programming language (Beeley and Sukhdeve, 2018; Chang et al., 2021; R Core Team, 2021). Pi-VAT is deployed on the shinyapps.io server and can be accessed at https://cdeval.shinyapps.io/Pi-VAT/. The Pi-VAT source code can be found on the GitHub page of the tool (https://github.com/devalc/Pi-VAT). Pi-VAT requires users to have pre-computed scenario runs using either online or offline WEPP or SWAT interfaces. Information on summarizing and preparing multiple pre-computed scenarios for use in Pi-VAT is



- What are the source areas?
- What is the soil and land use of those areas?
- How sensitive are those areas to the drivers?
- Is steepness important?
- Where are those areas located?
- How sensitive are they to different scenarios?

Fig. 1. The “what-if” scenario testing and comparative analysis require further synthesis of the enormous datasets and resulting targeting combinations generated by process-based models.

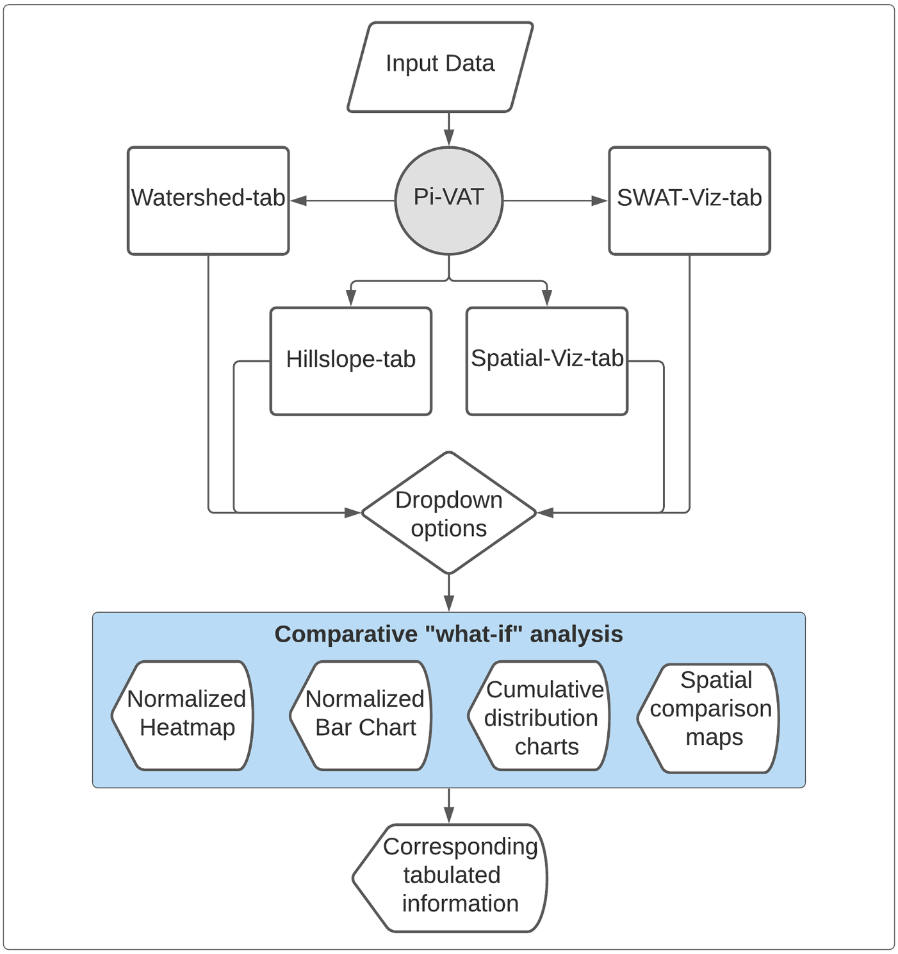


Fig. 2. General flow diagram of the comparative ‘what-if’ analysis in the Pi-VAT interface.

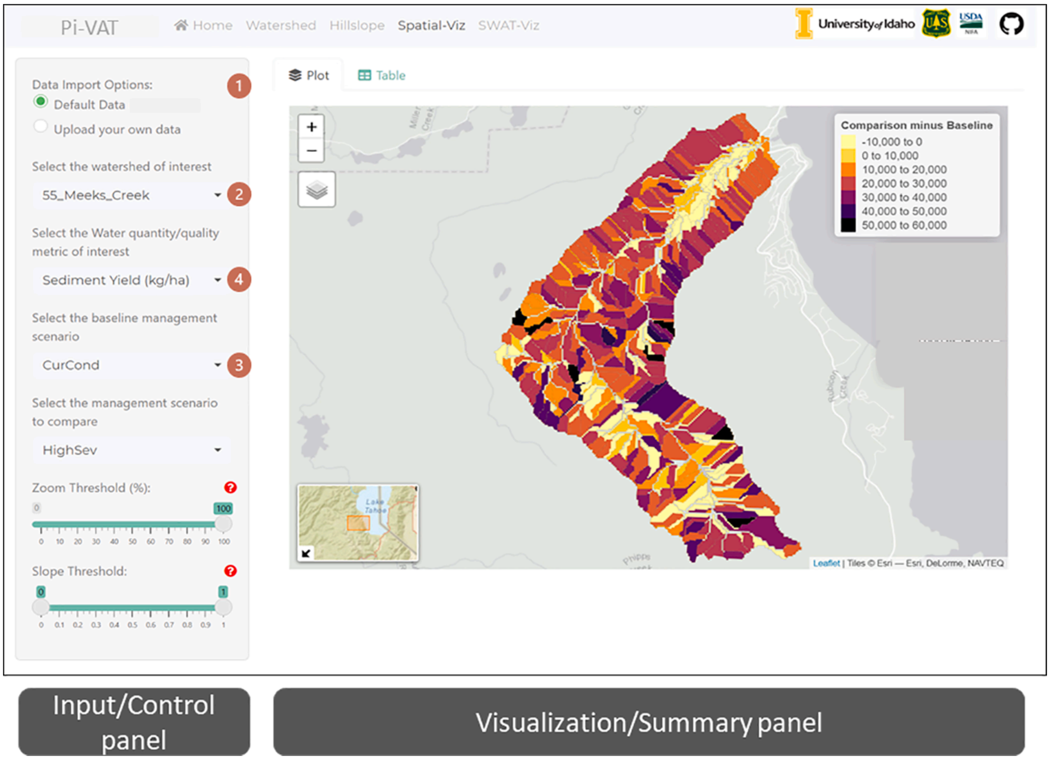
provided on the Pi-VAT's GitHub page.

2.2. Main interface components

The Pi-VAT interface intuitively guides the user through a "what-if" analysis from data input to dynamic visualization (Fig. 2). Each tab on the Pi-VAT user interface consists of two sections: the input/control panel and the visualization/summary panel as shown in Fig. 3. The visualization/summary panel was implemented using the R wrappers for the Plotly, Leaflet, and DataTables (Cheng et al., 2021; Sievert, 2020; Xie et al., 2021) making it fully interactive. The input/control panel contains four main options (denoted by numbers in Fig. 3) namely, data import options and three auto-populated dropdown menus for the watershed scenario, and the targeted water quality/quantity metric, respectively. The input panel provides users with the ability to upload output files from the hydrologic model, select water quality/quantity metrics of interest, and control visualization and data summaries by using the control buttons.

We specifically included synthesis products based on feedback from watershed managers for scenario-testing watershed applications. Three of the most common suggestions are to provide the ability to (i) compare impacts from different management options within a single sub-watershed; (ii) identify priority watersheds or hillslopes to implement a particular management practice; (iii) assess trade-offs from the implementation of particular management practice. In the first case, the user needs to have the ability to visualize and compare multiple treatments in a single watershed. In the second case, the user needs to be able to summarize and visualize differences across unique spatial units. In the third case, a manager may also want to better understand the implications of management options from multiple responses (e.g., reduced runoff and increased subsurface lateral flow) to identify whether a management practice may result in a positive environmental impact from one perspective but at the cost of creating another environmental problem from another perspective. In addition, a manager may want to identify the most sensitive areas in the landscape which give the greatest benefit from the application of a particular management practice (e.g., sediment reduction per unit area of the watershed treated). Furthermore, a manager may also want to ascertain unique soil, landscape, and climatic characteristics that make this identified landscape area very sensitive to the particular treatment. Managers can also be constrained by specific regulatory policies which limit the application of practice to a specific region (e.g., no logging timber on slopes > 30%). In this case, the manager would like to focus the analysis on treatable areas within the watershed. These management challenges are common to nearly all watershed studies (Brooks et al., 2015; Mulla et al., 2008; Rittenburg et al., 2015) and therefore we developed the tool (Pi-VAT) to address these objectives.

Specifically, Pi-VAT provides the ability to graphically compare differences in the magnitude of a certain simulated output (e.g., sediment yield) from multiple management scenarios on a single chart (Heatmap/Bar chart). For spatial analysis, the tool can map these differences in simulated output between two scenarios in a particular watershed. To identify watersheds sensitive to a particular management scenario, Pi-VAT also provides the option to generate charts and maps comparing the magnitude of a simulated output for a single management scenario across multiple watersheds. It provides the option to select and analyze single or multiple hydrologic response output variables. Pi-VAT also provides cumulative distribution figures which display the percent of the hydrologic or pollutant response output within a watershed vs the cumulative percent area from which the pollutant was generated within the watershed. Users can then use slider bars to filter the output and identify the areas which contribute the greatest source loading per unit area of the watershed. This is particularly useful where a manager might have limited financial resources which only allow the treatment of a small fraction of the watershed. Similar filter options have been implemented to narrow the analysis to a particular slope steepness range. For example, Pi-VAT allows users to select and only display output from areas having a slope steepness greater than and/or less than a certain minimum and/or maximum slope. To assist users in the identification of key factors and hydrologic drivers, Pi-VAT continuously updates downloadable output tables based on user-selected options which include not only multiple output hydrologic


Data Import Options: ①
● Default Data
○ Upload your own data

Select the watershed of interest ②
55_Meeks_Creek

Select the Water quantity/quality metric of interest ④
Sediment Yield (kg/ha)

Select the baseline management scenario ③
CurCond

Select the management scenario to compare
HighSev

Zoom Threshold (%): 0 – 100

Slope Threshold: 0 – 1

Fig. 3. Example of the spatial visualization (Spatial-Viz) tab of the Pi-VAT interface.

response variables but also key soil, topographic, and climatic input factors.

2.3. Site descriptions

We selected three case studies from three regions consisting of either a forest or an agricultural system: Lake Tahoe Basin (California/Nevada), Palouse (Washington), and WE-38 sub-watershed within the Mahantango Experimental Watershed (south-central Pennsylvania). We selected sub-watersheds in these regions based on the unique land uses and the associated land management and water quality concerns in each area. We first describe the sites, and in Section 2.4 describe the modeling scenarios.

2.3.1. Lake Tahoe Basin

Lake Tahoe, despite being in an ultra-oligotrophic state(Coats et al., 2008; Hatch et al., 2001), has experienced long-term declining water clarity due to upland contributions of fine sediment and phosphorus (Sahoo et al., 2013). Previous research suggests that the primary productivity of the lake has been increasing by about 5% per year (Coats et al., 2008), and in the last five decades the Secchi depth of Lake Tahoe has decreased by about 10 m (Kerlin, 2017). Fire suppression in the Lake Tahoe basin during the 20th century has resulted in forest floor accumulation of duff and woody debris, which has increased the risk of frequent and more intense wildfires (Miller et al., 2010). Land managers in the basin are interested in comparing the impacts of wildfires and timber harvest on water quality to identify sensitive areas in the landscape for targeted management. In this case study, we used Pi-VAT to evaluate the effects of several forest treatments (thinning) and wildfire scenarios on sediment yield from multiple watersheds. We considered seven watersheds, with areas ranging between 4.1 km^2 and 110 km^2, and an average of 626 hillslopes in each watershed, and a total of 11 simulated scenarios ranging from forest treatments (such as thinning and prescribed fire) to wildfires. This amounts to 48,202 combinations of hillslopes along with the associated soils, land uses, and slope steepness that were evaluated for targeted management.

2.3.2. Palouse (Washington)

Conventional tillage management on the steep, hillslopes of the dryland wheat-based cropping systems within the Inland Pacific Northwest 'Palouse' region has caused excessive soil erosion. Aggressive tillage with low residual ground cover has left a degraded landscape. It was estimated that the topsoil was completely removed from 10% of the cropland and one-fourth to three-fourths was lost from 60% of the region (USDA, 1978). Subsoil horizons in the region can often include dense subsoil, calcium carbonate (B_k), argillic (B_{tb}), and fragipan (B_{txb}) soil horizons that lead to perched water tables, subsurface lateral flow, and saturation excess runoff processes (Brooks et al., 2012; McDaniel et al., 2008). Erosion rates can be reduced through the adoption of conservation tillage practices however the effectiveness varies by topography, soil type, and climate (Kok et al., 2009). In this watershed case study, we examine the effects of tillage management on the sediment yield within the Thorn creek (109 km^2) and Kamiache creek (40 km^2) watersheds located within the 381 to 457 mm mean annual precipitation zone in the Palouse. Soil and water conservation districts are interested in incentivizing conservation tillage practices on the hillslopes which contribute the greatest benefit to the cost ratio from the treatment application. These watersheds implement a three-year crop rotation consisting of winter wheat-spring barley-summer fallow. Each watershed has an average of 1590 hillslopes and a total of three simulated management scenarios resulting in 9,540 combinations. Three types of tillage systems were compared: a conventional tillage system (CT) with a chisel plow, a minimum or mulch tillage (MT) scenario, and a no-till system (NT).

2.3.3. WE-38 experimental sub-watershed

Managing the transport, delivery, and long-term legacy of excessive phosphorus loading from agriculturally dominated landscapes is a well-documented challenge particularly in the eastern US with a long history of dairy operations and impacts on soil chemistry (Kleinman et al., 2011; Sharpley et al., 2001, 1994; Stackpoole et al., 2019). Accurately identifying nutrient source areas, dominant delivery mechanisms, and the impact of management strategies on phosphorus loading is, therefore, an essential step to avoid long-term water quality impairment in downstream water bodies. WE-38 is a 7.3 km^2 first-order upland agricultural experimental sub-watershed, located within the larger 420 km^2 Mahantango Creek Experimental Watershed. It was established in 1976 by the USDA-Agricultural Research Service to better understand the water quantity and water quality implications of agriculturally-based farming systems in Pennsylvania and particularly for better understanding nutrient loading to Chesapeake Bay (Buda et al., 2011). WE-38 is known for its variable source area hydrology driven by topographic variability and perched water tables over fragipan subsoil horizons (Bryant et al., 2011). In the case of the WE-38 sub-watershed, we use Pi-VAT to examine the effects of varying soil phosphorus content, manure application, and tillage and cropping management on phosphorus and nutrient losses (Collick et al., 2015). We considered six sub-watersheds of WE-38 with a total of 1,286 HRUs and eight simulated management scenarios resulting in a 10,288 combination of HRUs that can be considered for targeted management.

2.4. Synthesis approach

Our synthesis approach demonstrates the application of Pi-VAT for multi-watershed, multi-scenario simulated results from WEPP and SWAT with a focus on targeting and prioritizing management. We demonstrate the utility of the tool rather than assess the accuracy or validate the model predictions because several previous validation studies already have shown the accuracy of WEPP (Boll et al., 2015; Brooks et al., 2016; Elliot et al., 2015; Srivastava et al., 2020; Srivastava et al., 2017) and SWAT (Collick et al., 2015; Easton et al., 2010, 2009; Xu et al., 2019) model predictions. To demonstrate the utility of Pi-VAT, we used WEPP model output for the Lake Tahoe and Palouse case studies generated using the WEPPcloud interface. For the Lake Tahoe test case, we considered the current conditions (CurCond) scenario as the baseline scenario and for the Palouse test case, we considered conventional till (CT) as the baseline scenario. For the WE-38 case study, we used SWAT-VSA model output (Easton et al., 2008) and considered the high rate, spring surface manure application scenario as the baseline scenario in the synthesis. From the target combinations described in each case study, we respond to land and water resources managers' desires to be able to identify which watershed and hillslopes to prioritize, and what treatment/management to implement to minimize water quality impacts. In the synthesis approach, we answer the following general targeting questions aimed at addressing the unique water quality problem in each case study described before:

a. Which watersheds are a major concern with respect to the pollutant of concern?
b. How sensitive is this watershed to the disturbances and changes in management practices?
c. What amount of the watershed needs to be treated to reduce the loading of the pollutant of concern?
d. Where are these source areas located in the watershed? How do they compare to the baseline scenario? What are the general driving factors in these areas?

3. Results

3.1. Lake Tahoe Basin

The Lake Tahoe Basin case study presents Pi-VAT usefulness for identifying critical source areas of sediment in forested environments with fire risk. A large amount of sediment yield and soil loss from both hillslopes and channels for the baseline scenario emerges from the Blackwood Creek watershed (41%) followed by the Ward Creek watershed (20%) (Fig. 4a, b). The sediment yield and soil loss are generally larger in the cases of fire scenarios, whereas these increases in the case of thinning management scenarios are comparatively small (Fig. 4c). The largest contribution of the total hillslope soil loss (54%) and the sediment yield (27%) across scenarios arises from the high severity (HighSev) fire scenario (Fig. 4d). In the case of the 85% thinning scenario (Thin85), this contribution of total hillslope soil loss and sediment yield across scenarios amounted to 2% and 4% respectively.

More than 80% of the total sediment yield in the Blackwood Creek watershed across three different scenarios comes from only 25% of the total hillslope area (Fig. 5a). In this 25% of the total hillslope area, the cumulative sediment yield increased from the baseline scenario by 195 Mg for the thinning scenario (Thinn85) and 1264 Mg for the low severity fire scenario (LowSev), respectively (Fig. 5c). The relative difference in sediment yield between the comparison scenario and the baseline scenario from all hillslopes in the Blackwood Creek watershed (Fig. 5b) and Fig. 5d shows the same for the top 25% of the total hillslopes contributing maximum sediment yield. Table A.1 lists the top 15 hillslopes with a maximum increase in sediment yield relative to the baseline scenario. For example, the highest absolute increase in sediment yield (25191 kg ha^{-1}) compared to the baseline scenario occurs from hillslope 2211 which is characterized as a melody rock outcrop soil and an average slope steepness of 42% (Table A.1). For each of these top 25% contributing hillslopes, Supplemental Table A.3 lists the sediment yield from the comparison scenario and its relative change from the baseline scenario along with the land use, soil characteristics, and slope description. Approximately 85% of these hillslopes have a steepness greater than 30%, and the majority of these soils are rock outcrop complexes or sandy loam soils.

3.2. Palouse

The Palouse case study presents Pi-VAT usefulness for identifying critical source areas of sediment of agricultural basins under different tillage intensities. Relatively large soil losses from both hillslopes and channels for the baseline scenario occur in the Thorn Creek watershed whereas relatively large sediment yield occurs from the Kamiache Creek watershed (Fig. 6a). Pi-VAT visuals indicated that the majority of the sediment yield in the region (67%) was generated from the Kamiache Creek watershed with a much smaller percentage (33%) generated from the Thorn Creek watershed (Fig. 6b). When compared across different management scenarios, the relative sediment yield and soil loss from the Kamiache Creek watershed occurs in the following order: CT > MT > NT (Fig. 6c). The largest contribution (40%) of the total hillslope soil loss and the sediment yield across scenarios arises from the CT practices (Fig. 6d), whereas the smallest contribution (25%) of the total hillslope soil loss and the sediment yield across scenarios arises from the NT practices (Fig. 6d).

About 80–85% of the total sediment yield in the Kamiache Creek watershed across the three different scenarios comes from only 15% of the total hillslope area (Fig. 7a). In this 15% of the total hillslope area, the cumulative sediment yield decreased by about 6 Mg and 11.5 Mg by switching from CT to MT and NT management practices, respectively (Fig. 7c). Fig. 7b shows the relative difference in sediment yield between the comparison scenario and the baseline scenario from all the hillslopes in the Kamiache Creek watershed, and Fig. 7d shows the same for the top 15% of the total hillslopes contributing maximum sediment yield. Table A.2 lists the top 15 hillslopes with a maximum increase in sediment yield relative to the baseline scenario. The highest absolute increase of 4.08 kg ha^{-1} from the baseline scenario occurs at hillslope 23 which has an average slope steepness of 17% and Chard silt loam soil (Table A.2). Supplemental Table A.4 lists the sediment yield from the comparison scenario and its relative change from the baseline scenario for these top 15% of the total contributing hillslopes. Generally, soil

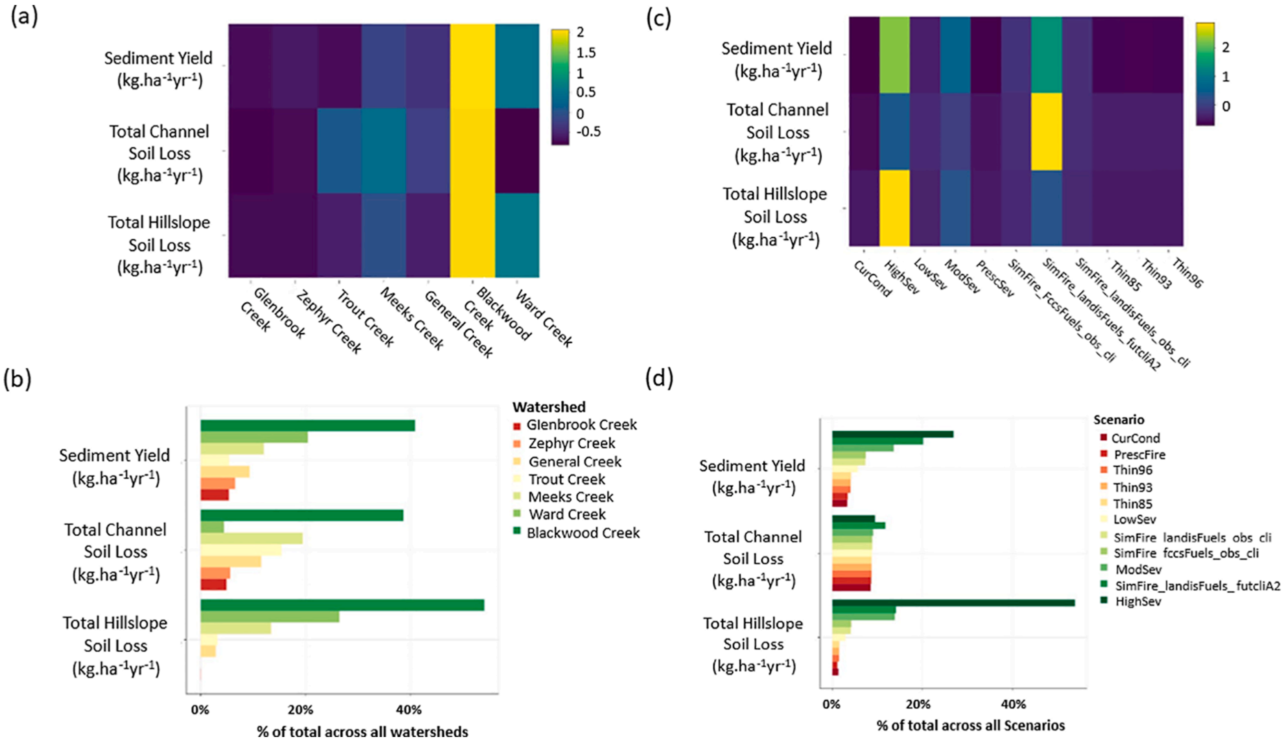


Fig. 4. Example application of synthesis approach in the Lake Tahoe basin. Relative normalized response in water quality/quantity metrics from (a) different watersheds for the current conditions (CurCond) baseline scenario and (c) different scenarios for Blackwood Creek watershed. Percent of total water quality/quantity metrics across (b) all compared watersheds for the baseline scenario and (d) all compared scenarios for Blackwood Creek watershed.

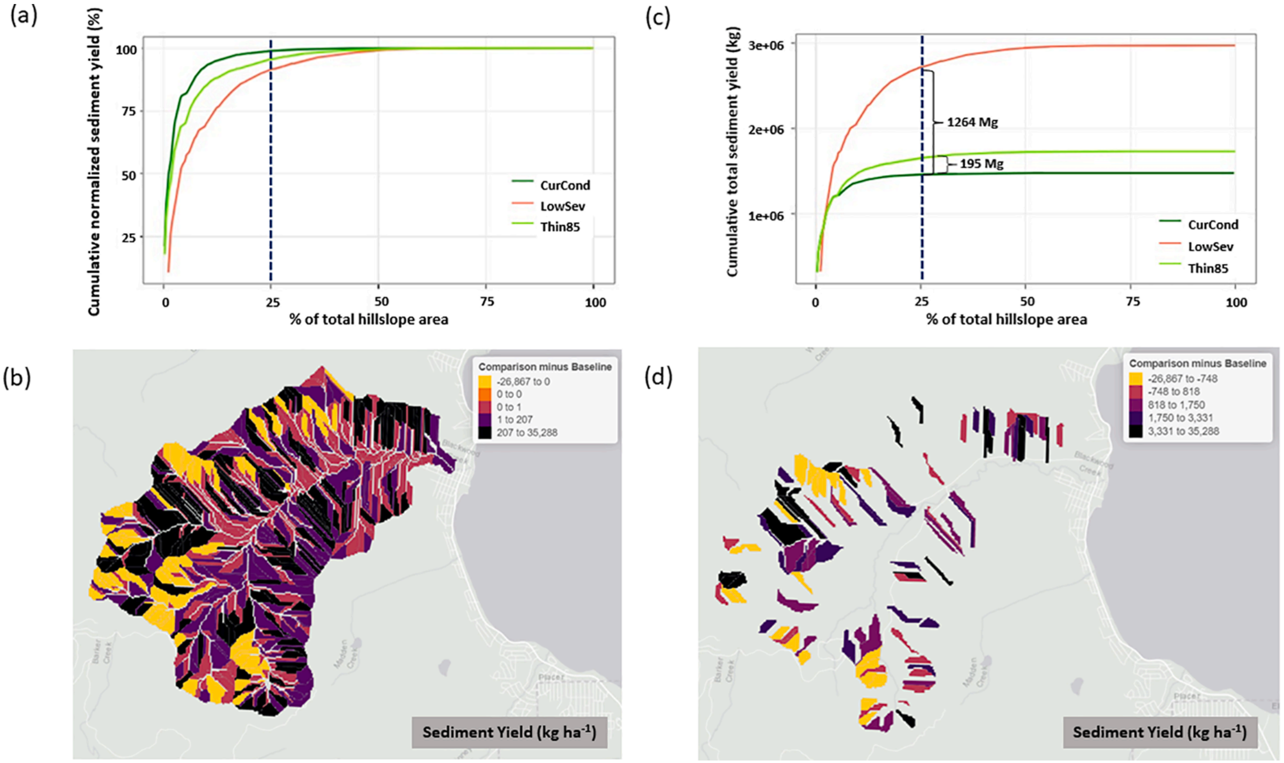


Fig. 5. Example application of synthesis approach in the Blackwood Creek watershed (Lake Tahoe basin): (a) cumulative normalized sediment yield (%) vs total hillslope area (%) for three scenarios; (b) difference plot (LowSev minus CurCond) for sediment yield (kg ha-1) from all hillslopes, where negative/positive values indicate a net decrease/increase in sediment yield (kg ha-1) ; (c) cumulative total sediment yield (kg) vs total hillslope area (%) for different scenarios; and (d) difference plot (LowSev minus CurCond) for sediment yield (kg ha-1) from the top 25% hillslopes with the largest contribution.

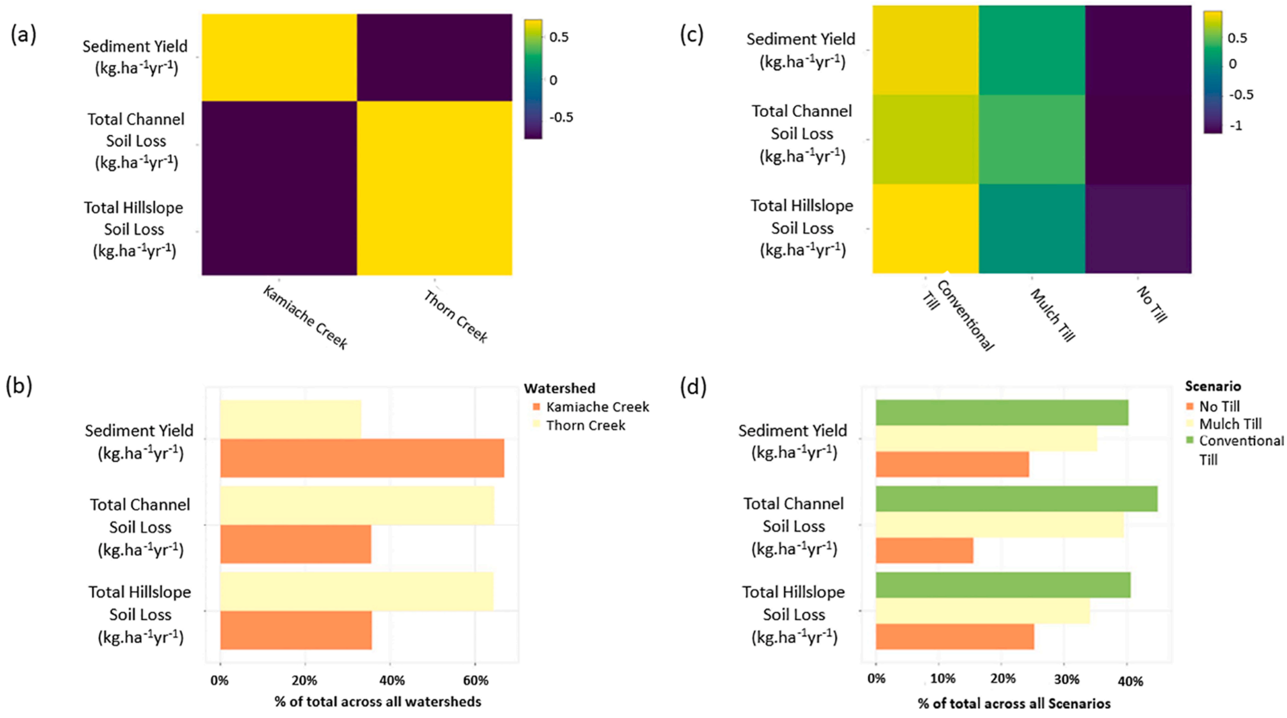


Fig. 6. Example application of synthesis approach in the Palouse. Relative response in water quality/quantity metrics from (a) different watersheds for the baseline scenario (CT); (c) different scenarios for Kamiache Creek watershed. Percent of total water quality/quantity metrics across all the compared: (b) watersheds for the baseline scenario; (d) scenarios for Kamiache Creek watershed.

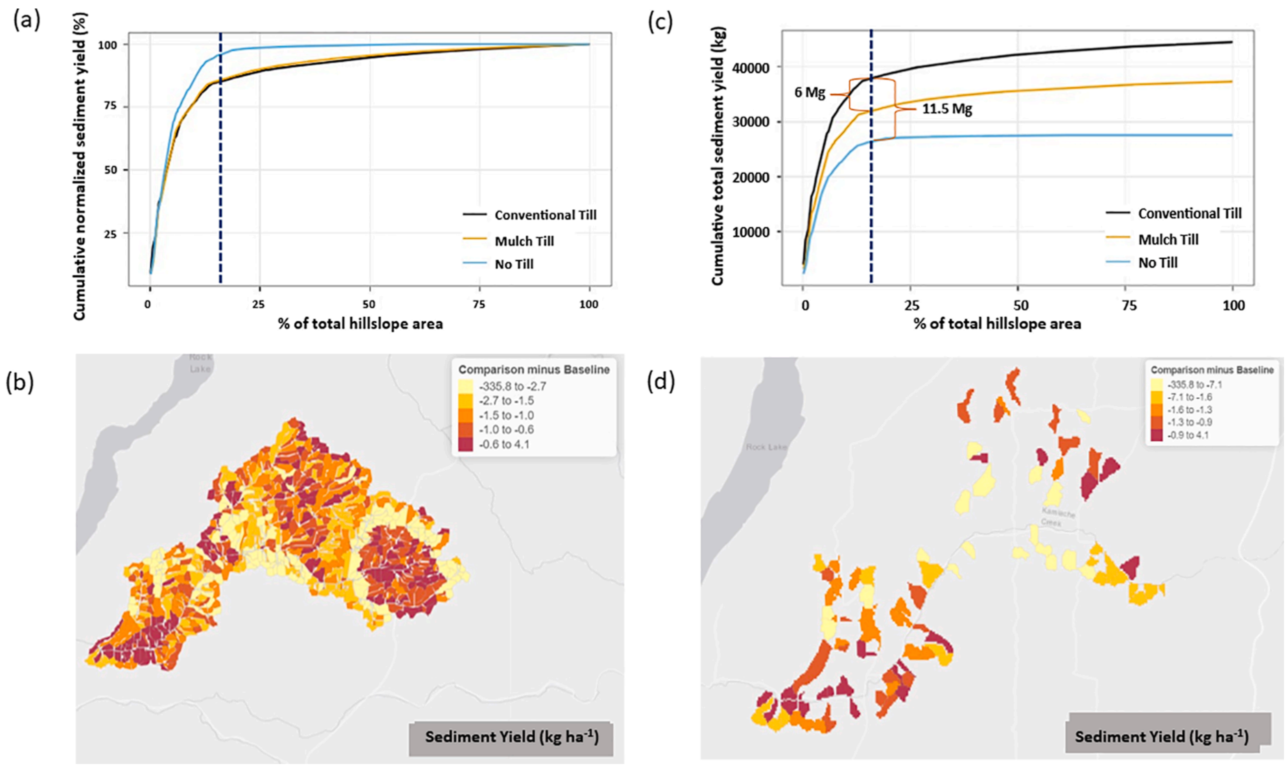


Fig. 7. Example application of synthesis approach in Palouse: (a) cumulative normalized sediment yield (%) vs total hillslope area (%) for different scenarios in for Kamiache Creek watershed; (b) difference plot (conventional till [CT] minus no till [NT]) for sediment yield (kg ha^{-1}) from all hillslopes in the Kamiache Creek watershed; (c) cumulative total sediment yield (kg) vs total hillslope area (%) for different scenarios in for Kamiache Creek watershed; and (d) difference plot (CT minus NT) for sediment yield (kg ha^{-1}) from the top 15% hillslopes that have the largest contribution in the Kamiache Creek watershed.

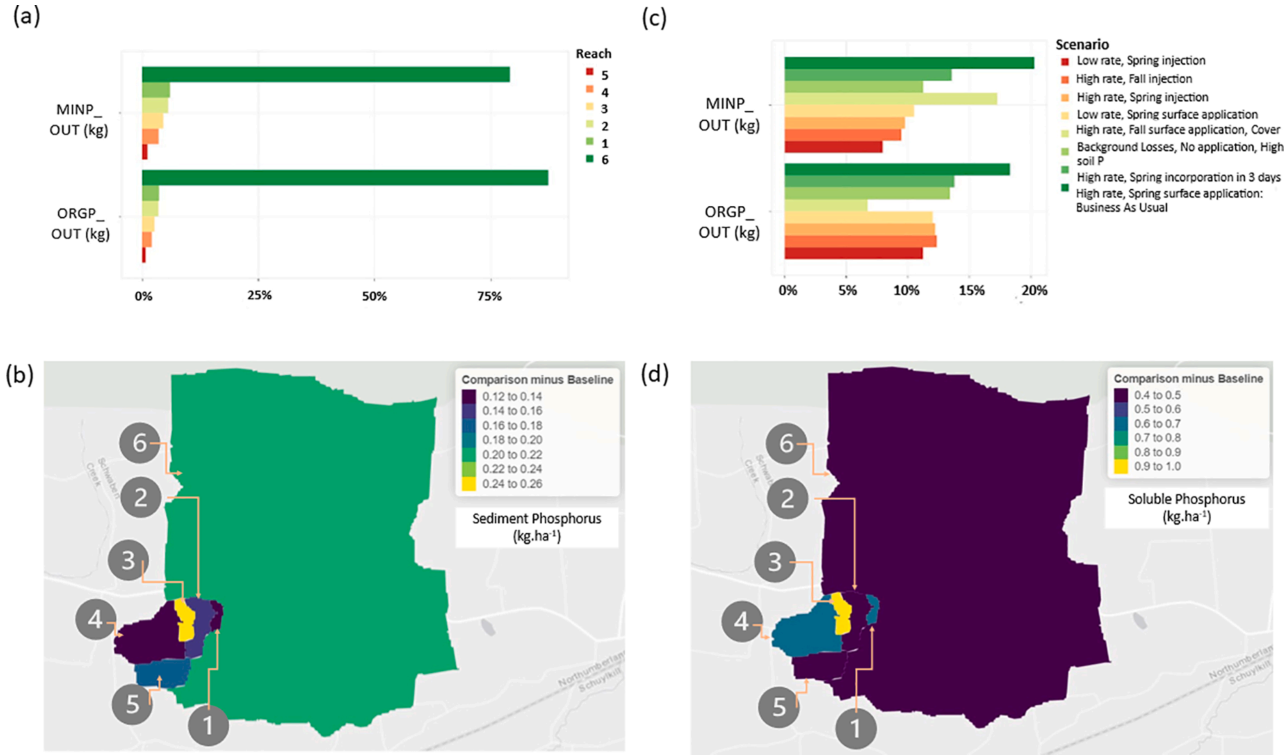


Fig. 8. Example application of the synthesis approach using SWAT in WE-38 experimental watersheds: (a) Mineral and organic phosphorus (kg) leaving the main channel for each subbasin; Difference plots (high rate, spring surface manure application [business as usual] scenario minus the background losses from high soil P with no manure application scenario) for (b) sediment phosphorus (kg ha^{-1}) and (d) soluble phosphorus (kg ha^{-1}) from all subbasin in the WE-38 watershed. (c) Mineral and organic phosphorus (kg) leaving the main channel for subbasin 3 across different scenarios.

erosion increased with slope steepness and slope length and was greatest where conventional tillage practices were employed in winter wheat-spring barley, summer fallow rotations in Chard silt loams which have dense calcium carbonate Bk horizon at ~ 90 cm below the soil surface.

3.3. *WE-38*

The Pi-VAT analysis of WE-38 indicates a phosphorus response to management which is sensitive to treatment and the form of the phosphorus transported. Mineral and organic phosphorus (kg) transported with water out of the reach decreases in the following reach order number 6 > 1 > 2 > 3 > 4 > 5 (Fig. 8a). However, when normalized by the area of each subbasin, the largest transport of mineral P attached to the sediment and soluble P into the reach occurs from subbasin 3 in the business-as-usual scenario (Fig. 8b and d). Also, for the same scenario, the amount of mineral P attached to the sediment transported into the reach decreases by subbasin in the following subbasin order number 3 > 6 > 5 > 2 > 4 > 1, and for the transport of soluble P decreases by the subbasin order number 3 > 1 > 4 > 2 > 5 > 6 (Fig. 8b and d). The highest mineral phosphorus (20%) and organic phosphorus (18%) transported through stream reach 3 compared across all the scenarios occur for the business-as-usual scenario. Whereas adopting a low-rate spring injection manure application method, the mineral phosphorus and organic phosphorus transport through stream reach 3 reduces to 8% and 11%, respectively. Reductions in organic (a), sediment (b), and soluble (c) phosphorus losses from corn silage land within subbasin 3 by converting from business-as-usual manure application methods to the high-rate spring injection method are displayed in Fig. 9. The reduction in phosphorus transport from an alternative or comparison management option/scenario relative to a baseline scenario along with the specific land use, soil type, and slope descriptions for organic, sediment, and soluble phosphorus output responses are listed in Supplemental Tables A.5–A.7, respectively.

4. Discussion

In each of the case studies, Pi-VAT was able to ingest large output files from multiple watersheds for multiple management scenarios. Synthesis results very clearly identify not only the greatest hydrologic response to treatment but also where the pollutant was generated, the type of pollutant which was most sensitive, and knowledge on key factors and characteristics (soil type or topographic) of the most sensitive landscape positions. This type of scenario comparison and detailed synthesis is cumbersome as these hydrologic models are developed to provide output for one scenario at a time. Comparison of multiple scenarios in WEPP, for example, often requires a user to upload output files into spreadsheets or use programming languages such as R which is very time-consuming and complicated for typical land managers who would like this type of comparative analysis. Pi-VAT significantly reduced the time and complexity of such comparative analyses allowing the managers to carry out the 'what-if' analysis in a matter of minutes.

In all three case studies, we saw that the effectiveness of management practices was not equal across a landscape suggesting that targeted management strategies rather than blanketed management would be successful and will likely be cost-effective. This is a well-known and documented finding for large watershed management studies (Walter et al., 2000). Here, however, we showed that Pi-VAT can quickly visualize this using modeling output especially when a land manager may be trying to convince stakeholders and investors of implementing a targeted management approach. Not only was Pi-VAT able to show where targeted responses to management will occur in these watersheds, but the tool also quickly provided the location and characteristics of the targeted locations as well as the hydrologic responses in the dominant hydrologic flow paths. In particular, for WE-38, we see that the phosphorus response to treatment varied by the delivered form of phosphorus. Pi-VAT was able to show that this varied response by the delivered form of phosphorus was also associated with the hydrologic pathways. For instance, the spatial patterns of sediment-bound phosphorus were similar to that of the runoff from the HRUs.

We demonstrated using Pi-VAT that comparative visualization and analysis can help identify pollutant source areas for prioritizing targeted management. For all three cases, Pi-VAT's comparative analysis was able to directly identify locations in the landscape where the greatest relative unit decrease in the response of the pollutant of concern occurred from the application of different management practices. For example, generally in the Lake Tahoe and Palouse analysis, we found that specific soil types with restrictive soil horizons were often the most sensitive to treatments. In the Lake Tahoe case study, land types characterized as having steep slopes with rock outcrops and gravelly sandy loam soils had the potential to generate high to very high surface runoff. In addition, these land types were often identified as landscape positions having the greatest sensitivity to alternative management practices.

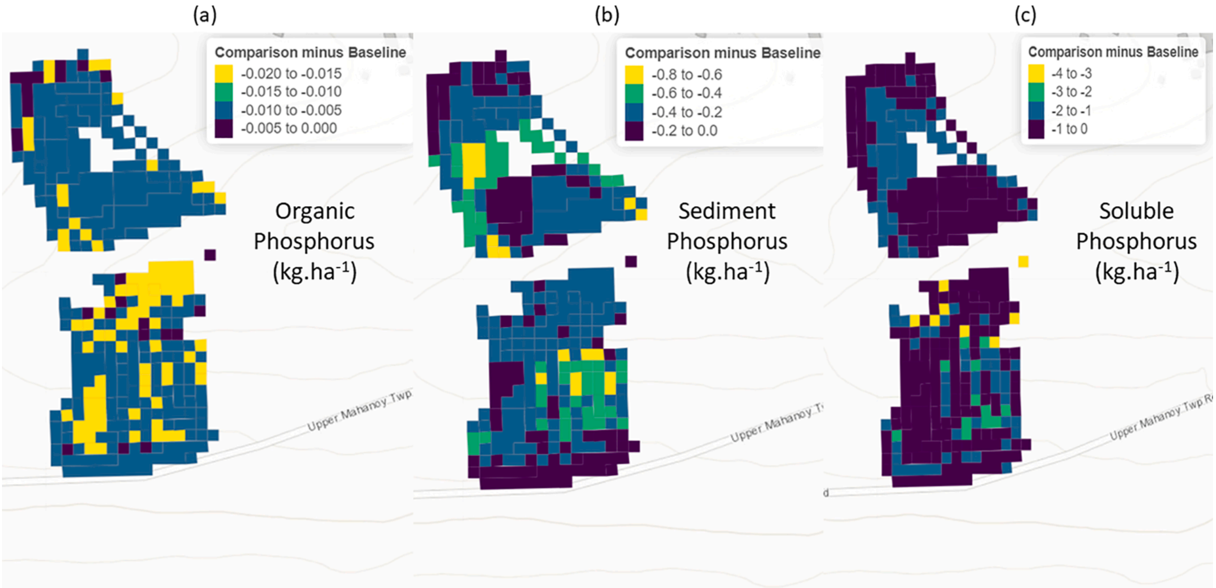


Fig. 9. Difference plots (high rate, spring surface manure application [business-as-usual] scenario minus the high-rate spring manure injection scenario) for organic phosphorus (a), sediment phosphorus (b), and soluble phosphorus (c) from corn silage land cover in subbasin 3.

Given the abundance of process-based hydrology and water quality models coupled with the increased use of data-driven analytics, the broader opportunities for the hydrologic community to integrate models with decision tools are vast and yet unrealized (Guswa et al., 2014). Such integration would enable land and water resources managers to harness the potential of these sophisticated models in decision-making. With the three case studies, we demonstrated the potential utility of Pi-VAT, as a standalone tool, in bridging the barriers in the use of two commonly employed sophisticated hydrology and water quality models (WEPP and SWAT) for management prioritization. By making the results available to managers in an interactive and functional format, Pi-VAT has the potential to assist watershed managers in using the physically based models more regularly alongside their current planning process and effectively communicating the implications of proposed managements.

5. Conclusions

Land and water resources managers are interested in the optimal use of conservation dollars to protect water resources from NPS sediments, nutrients, and other water quality issues associated with land management practices. This requires identifying, prioritizing, and targeting critical source areas for implementing conservation management practices. Process-based models that account for the relevant physical processes are powerful tools and can be effective for prioritization and targeted watershed management provided the outputs from these models are made available to the managers in a more functional format. We demonstrate the use of Pi-VAT to interactively identify, quantify and visualize the areas that are most susceptible to disturbance and change in management. We provide a synthesis approach based on land use, soil type, and slope steepness such that the synthesized data and visuals can aid managers in identifying watersheds/subbasins of concern; evaluating the sensitivity of these watersheds/ subbasins to land management practices; quantifying and isolating source areas for treatment/management and understanding factors driving hydrologic and water quality response. We demonstrate the utility of Pi-VAT in facilitating a better understanding of the critical pollution source areas and in devising an action plan. The simplicity and accessibility of this web-based interactive tool along with compatibility to process both WEPP and SWAT-based outputs can greatly support watershed planning using complex process-based models. The tool was developed such that it can be potentially quickly modified to ingest output from any model that can provide tabular files from spatial modeling units represented by geospatial maps and therefore has the potential to be widely adopted as a decision support tool for multiple applications.

CRediT authorship contribution statement

Chinmay Deval: Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing – original draft, Writing – review & editing, Project administration. **Erin S. Brooks:** Conceptualization, Methodology, Supervision, Resources, Writing – review & editing. **Mariana Dobre:** Data curation, Methodology, Supervision, Funding acquisition, Resources, Writing – review & editing. **Roger Lew:** Data curation, Writing – review & editing. **Peter R. Robichaud:** Methodology, Supervision, Writing – review & editing. **Ames Fowler:** Data curation, Writing – review & editing. **Jan Boll:** Writing – review & editing. **Zach M. Easton:** Data curation, Writing – review & editing. **Amy Collick:** Data curation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2022.127529.

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