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Hydrologic response of artificially drained agricultural watersheds: insights from high-resolution integrated surface/subsurface simulations

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Abstract

Artificial drainage systems comprising subsurface networks of perforated pipes (tile drains) and engineered surface ditches are widely used to remove excess water from poorly drained agricultural regions. Artificial drainage lowers the water table by design but also has inadvertent effects on the watershed-scale hydrologic response with important implications for flood risk and nutrient exports. We investigated the effects of tile drains on watershed-scale hydrologic response in the Portage River, OH, Watershed using a high-resolution physically based integrated surface/subsurface hydrology model with recently developed capabilities to represent artificial drainage. Tile drains were found to enhance streamflow during times of low flow, generally consistent with previous studies. Streamflow flashiness was found to have a non-monotonic dependence on tile spacing with a minimum at intermediate spacings (∼50 m). Flashiness and the event hydrographs for small tile spacing were similar to the situation with no tiles, but flow paths from farm to stream were very different for those two end member cases, emphasizing the limitations of the stream hydrograph in characterizing hydrologic response. For typical tile spacings, peak flow can either be enhanced or attenuated by the presence of tiles, depending on the size of the event and the antecedent meteorological conditions. Tiles enhance peak flow when the event is below a threshold of ∼25 mm or when events arrive in dry conditions. Peak flow is reduced by tiles when events are large and arrive in conditions that are not overly dry. The dependence on event size and antecedent conditions is explained by differences in available storage and flow paths to the streams. These results provide additional insights into how tile drainage modulates event-scale hydrologic response, an important control on flood generation mechanisms and nutrient exports.

1. Introduction

Artificial drainage systems comprising subsurface networks of perforated pipes (tile drains) and engineered surface ditches are widely used to remove excess water from poorly drained agricultural regions. Tile drains re-route the excess water in crop rooting zones to the ditches and on to the stream network, resulting in improved crop yields, reduced yield variability, and improved trafficability of fields to farm machinery [1]. In the US, tile drainage is installed in 16% of agricultural land and over 30% of the Corn Belt [2], the U.S. Midwest region characterized by intensive row-crop agriculture. Moreover, tile drainage installation is intensifying to keep pace with rising crop prices, aging infrastructure, and more intense precipitation events [3].

Tile drainage affects watershed hydrology and downstream water quality by providing a more direct connection between the farm field and streams. In heavily tiled watersheds, a large fraction of watershed discharge originates from tile flow [4]. Tile drainage has been shown to short-circuit excess nitrate and dissolved phosphorous to streams, lakes and coastal areas resulting in large-scale eutrophication and harmful algal blooms [5–8]. However, the impacts of tile drainage on event-scale hydrologic response including large flooding events (i.e. peak flows) are far less understood and actionable.

Decades of research has concluded that the hydrologic impact of tile drainage depends on the interplay of soil, precipitation, tile design, and spatial scale as well as the flow metric of interest. Empirical studies have generally found that tiling increases lower flow regimes (e.g. base flow) in agricultural watersheds [9–12] and decreases the mean travel time of water from fields [6, 13]. However, Miller and Lyon [14] found that tiling decreases base flow in Ohio watersheds, while Adelsperger *et al* [15] found that tiling increases the duration and intensity of streamflow drought.

Even greater uncertainty exists regarding tile impact on larger flows. Recent empirical watershed scale studies in the Corn Belt have concluded that tile drains can both increase [13, 14] and decrease [9, 16] the 'flashiness' of hydrographs. Recent meta-analyses [16, 17] highlighted that soil type, drainage design, stream network, land use changes, and watershed slope must be controlled for in empirical studies of flashiness and may contribute to the conflicts. The influence of confounding factors and uncertainty increase with the peak flows that drive catastrophic flooding.

Several landmark reviews in the 1990s [8, 18, 19] concluded that in agricultural fields dominated by surface (subsurface) flow, tile drains reduce (increase) peak flows by routing flow through a slower (faster) tile flow path, contingent upon antecedent moisture and event size. However, these field scale results do not always translate to the watershed scale where flooding is experienced [e.g.18]. Unfortunately, few watersheds contain sufficiently long hydrologic records and adequate accounts of drainage activity and land use change to empirically detect changes in peak flow from tile drainage. Therefore, researchers must leverage hydrologic models to disentangle the effects of tile drainage on peak flows from other confounding factors (e.g. soil, climate, surface drainage).

Earlier modeling studies leveraged conceptual field-scale models (e.g. DRAINMOD [20]) coupled with stream routing equations to explore the hydrologic effects of tile drainage in smaller agricultural watersheds (<100 km^2). These studies concluded that the field-scale peak flow reduction from tiles appear at the watershed outlet [8, 21–23] with notable exceptions in depressional lands that have surface inlets [24]. More recently, a series of papers explored the hydrologic impacts of tile drainage in Iowa from the field to the Cedar River Basin scale (16 870 km^2) using DRAINMOD coupled to linearized routing equations [25, 26]. The modeling studies confirmed that tile drains increase low flows and decrease peak flows (i.e. homogenize the hydrologic regime) for typical Iowa soil and weather conditions (neglecting surface inlets) up to a certain rainfall and antecedent moisture threshold, at which tiles have minimal effect [25]. The magnitude of peak flow reduction at the outlet was also found to be sensitive to tile spacing, drainage area, and tiling location within the watershed. Similarly, a SWAT model analysis found that tiles reduced peak flows in the Upper Red River Basin (17 000 km^2 [27];). However, an even larger scale study of the Upper Mississippi River Basin (492 000 km^2) and Ohio River Basin (531 000 km^2) with the National Water Model found that tile drainage led to a 14% increase in peak flows even though surface runoff decreased [28].

Most of the watershed scale modeling studies of tile drainage used semi-distributed models meaning they partition the landscape into subcatchments or hydrologic response units that are each described by a 'lumped parameter' response. Such semi-distributed models explicitly route water and nutrients through the stream network to determine watershed-scale response. However, the crucial connection between farm field and stream network is not explicitly resolved but implicitly represented through subgrid or 'parameterized' response functions, which, given the importance of farm-to-stream connectivity in determining hydrologic response, creates significant uncertainties. Semi-distributed models rely heavily on watershed-specific calibration to measured streamflows but the transferability of a highly calibrated model to new conditions is subject to significant uncertainties [e.g. 29, 30].

Fully resolved integrated surface/subsurface hydrologic models (ISSHMs) offer alternatives to semi-distributed models [e.g. 31]. ISSHMs explicitly resolve hydrologic states and fluxes by coupling 3D variably saturated subsurface flow, surface flow, and land surface biophysical processes [32, 33]. With increased availability of high-performance computing resources, robust parallelization methods and solution methods [34, 35], and community data products and workflow tools to define model inputs [36], ISSHMs have matured to the point where they can routinely be applied at the watershed scale. In a recent study, Bhanja *et al* [37] showed that the ISSHM Advanced Terrestrial Simulator (ATS) [38] performed well at reproducing streamflow and evapotranspiration observations in a diverse collection of catchments using only *a priori* information in the form of widely available community data products to define model inputs. Good performance without site-specific calibration and the fact that ISSHMs are built from component models that have each been extensively studied by the scientific community provide increased confidence in the transferability of ISSHMs, making them ideal for numerical experiments involving counterfactual conditions, like the removal of tile drains from a drained watershed to isolate the effect of tile drainage.

Applications of ISSHMs to artificially drained agricultural watersheds have largely been limited to relatively small catchments [39–42], mostly because of the computational challenges in representing drainage ditches and tile drains, small but hydrologically important features that require small mesh elements to resolve. However, that computational limitation was recently overcome by combining a new meshing strategy that explicitly represents drainage ditches combined with a physically based subgrid model for water removal to tile drains [43]. Implemented in the ATS code [38], the approach was demonstrated on the heavily drained Portage River, OH, Watershed (>1000 km^2). Without site-specific calibration, ATS with the new representation for artificial drainage produced reasonably accurate results for daily streamflow over multiple years and significantly outperformed a highly calibrated instance of the semi-distributed SWAT model.

Here, we use high-resolution ATS simulations with its new representations of artificial drainage [43] to develop new insights into the effects of tile drains on watershed hydrologic response. We use the Portage River Watershed (1024 km^2) in northwestern OH—a typical agricultural watershed with extensive subsurface drainage—for numerical experiments to investigate how tiles modulate low flows, flashiness, and event-based peak flows as a function of tile spacing, precipitation intensity, and antecedent conditions. Particular attention is given to quantifying how peak flow is affected by tiles for different event sizes and antecedent meteorological conditions. As noted above, results from previous studies that addressed these questions are subject to significant uncertainties because of the confounding effects of uncontrolled environmental conditions in empirical watershed analyses and the uncertainties associated with assumptions about farm-to-stream connectivity required for semi-distributed modeling. Our spatially resolved, physics-based simulations at high spatial resolution over a >1000 km^2 watershed avoid both those sources of uncertainty and make it possible to investigate the effects of tile drains on event-scale response in unprecedented detail.

2. Methods

2.1. Study area

The study domain for this analysis (figure 1) is the part of the Portage River Basin, the 1024 km^2 contributing area to the USGS gauge station at Woodville, Ohio. We will refer to this part of the domain as Portage Watershed for brevity. Landscapes in this region are poorly drained due to flat topography and low-permeability soils; therefore, the drainage is artificially enhanced using agricultural ditches and tile drains. For the study duration of 2010–2019, the mean annual precipitation is 1035 mm [Daymet, 44], evapotranspiration is 411 mm [SSEBop, 45], and discharge at the outlet is 442 mm.

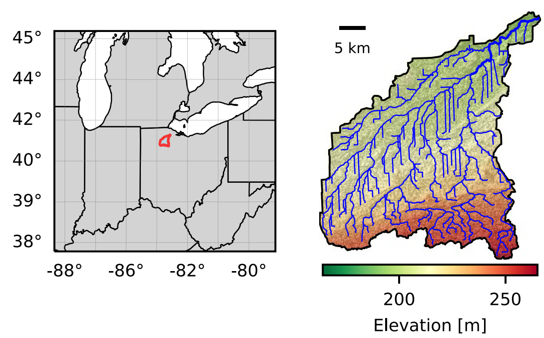

Figure 1. The Portage watershed (red polygon) situated in the Great Lakes Region (left); elevation heat map and river/ditch network for the portage watershed (right).

2.2. Integrated hydrology model

The analyses in this study are based on the numerical simulation campaign by Rathore *et al* [43], which used the new artificial drainage capabilities of ATS. The artificial drainage capabilities explicitly resolves streams and narrow drainage ditches with a mixed-polyhedral meshing strategy [46] that places long quadrilateral elements along the mapped streams/ditches with triangles in the rest of the domain (figure 2). The stream/ditch submesh was then hydrologically conditioned to ensure a fully connected stream network where every cell has a continuously downward path to the outlet. Such hydrologic conditioning improves representations of flow [47–49] by avoiding nonphysical ponding of water caused by noise in the DEM or by road embankments that appear in the DEM as flow obstructions but are in reality breached by culverts. The effects of subsurface tile drains were represented using a physically based subgrid model [43] based on Hooghoudt's drainage model [50, 51], a well-established model that is widely used at the farm scale [20]. It is important to note that Hooghoudt's drainage model is only used as a subgrid model to represent water removal through drains; ATS maintains a fully 3D representation of variably saturated flow in the subsurface coupled to 2D surface flow. Our multiscale implementation assigns a distributed water sink to the subcatchment associated with each reach in the stream/ditch network and distributes the resulting tile efflux to the associated reach, thus coupling subsurface tile drains to the surface water flow system.

Evaluation of our model for the Portage River Watershed is described in Rathore *et al* [43]. ATS-simulated hydrograph was in generally good agreement with streamflow gauge data as quantified by the Kling–Gupta efficiency (KGE) metric [52, 53] normalized in a nonstandard way to make it easier to interpret—that is, so that a value of 0 indicates the same predictive power as the timeseries mean and a

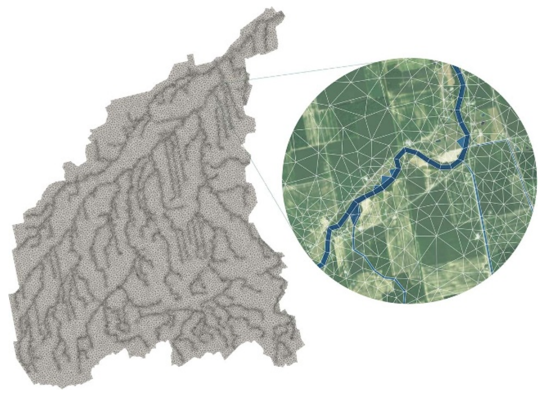

Figure 2. Stream-aligned mixed-polyhedral mesh for the Portage watershed, efficiently resolving narrow ditches and streams within the watershed-scale model. The circular callout provides a zoomed-in view of a confluence between a stream and ditches, displaying ponded depth from ATS simulations (blue), the ATS mesh (white lines), and a Google Earth image as the background.

value of 1 indicates a perfect match [37]. Without watershed-specific calibration, the modified KGE was 0.81, indicating a good match, and significantly better than the value (0.68) obtained with a highly calibrated instance of the SWAT model. Simulated soil-mositure patterns were similar to those of the SMAP-Hydroblocks product [54, 55]. Importantly, no catchment-specific calibration was used. That the ATS simulation was able to generally match stream hydrographs without calibration is important for studies like ours that involve counterfactual scenarios like removing all the tile drains from a watershed, as using heavily calibrated models outside conditions for which they are calibrated would have introduced significant uncertainties.

2.3. Numerical experiments

Eight new ATS simulations of the Portage watershed were used to study the effect of tile drains on watershed hydrology. The simulations used the same model setup as Rathore *et al* [43] except that the probablity of tiling in the with-tiles cases was assumed to be 100% instead of being spatially variable. The numerical experiments included a reference case with tile spacing of 15 m; variant cases with tile spacings of 30 m, 50 m, 100 m, 200 m, and 1000 m; and a case without tiles. The variable resolution mesh contained 1086 400 elements that ranged in size from 14.10 m^3 to 731 005.44 m^3. Model inputs for topography, soils properties, and land use were taken from community data products, as described in Rathore *et al* [43]. The 10 year simulation spanned the period from water year (WY) 2010 to WY 2019 after a multistep spinup process and were driven by meteorological data from the DayMet product [44].

Daily outputs from the simulations included stream discharge at the watershed outlet and spatially averaged values of evapotranspiration, depth to water table, and total quantity of water on the land surface including water in streams. Streamflow is expressed as specific discharge (i.e. volumetric discharge normalized by watershed area) in units of mm/day. Spatially resolved outputs including soil moisture content, depth of ponded water on the surface, and depth to the water table were recorded every 10 d.

2.4. Analysis of simulation outputs

Statistical properties of the stream hydrographs and depth to water table for the multiple cases were analyzed. Low-flow conditions were characterized by the exceedance probability at low flow and the annual baseflow index defined as the 7 d minimum flow normalized by the average flow in each year. The degree of day-to-day variability for each year was quantified by the Richard-Baker flashiness index [56] defined as $\frac{\sum_{i=1}^{n}|Q_i - Q_{i-1}|}{\sum_{i=1}^{n} Q_i}$ where Q_i and Q_{i-1} are mean daily flows (mm d^{-1}) for day i and $i-1$, respectively, and n is the number of days in a year.

To characterize response to precipitation events, a peak identification algorithm was used to identify individual events based on whether the discharge on a given day is greater than or equal to its six surrounding days (three on each side). We filtered out peak flows less than 0.25 mm d^{-1}. Peak flow reduction, the difference in peak flow without and with tiles, is a primary metric for the event-scale analysis. We used a support vector classifier [57] with a hinge loss to define a decision boundary that separates events by positive and negative peak flow reduction in the space of event size and antecedent aridity. The 4 d precipitation and snowmelt was used to characterize event size (mm). The 45 d standardized precipitation evapotranspiration index (SPEI) was used to characterize antecedent meteorological conditions [58]. The 45 d SPEI is the suitably normalized difference between precipitation and potential evapotranspiration over 45 days preceding each event and quantifies the meteorological water deficit (negative) or surplus (positive) during that period. We used the ATS-calcuated potential evapotranspiration in the SPEI.

For event-scale analyses, we introduced nine augmented events to represent large storms following dry antecedent conditions within the 10 year simulation record. These were created by selecting existing events with SPEI < -1.3. Precipitation for 5 of those events was scaled by a factor of 2.5 and an addition 4 events were scaled by a factor of 5. This augmentation expands coverage of the event size–SPEI feature space and allows exploration of conditions expected to become more frequent under future climate scenarios.

3. Results

3.1. Effect of tiles on depth to water table

Figure 3 shows snapshots of surface inundation with and without tile drainage during a storm event on

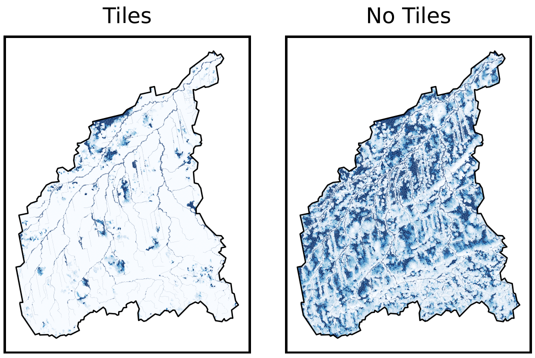

Figure 3. Surface inundation with and without tile drainage for a 10 March 2016 event. Panels show ATS-simulated ponded depth fields; blue cells indicate inundated areas. Tile drainage reduces both extent and intensity of inundation.

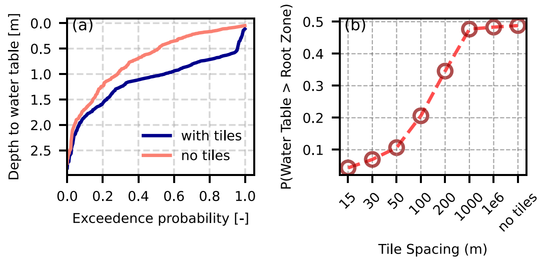

Figure 4. Exceedance probability for water table depth for the reference case with tiles and for the no-tiles variant (left); probability of the water table entering the root zone as function of tile spacing (right).

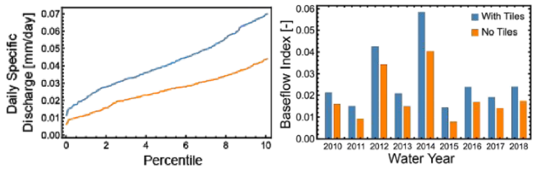

Figure 5. Hydrograph characteristics during low-flow periods: daily specific discharge with and without tiles for the lower 10 percentile (left); 7 d baseflow indices by water year (right).

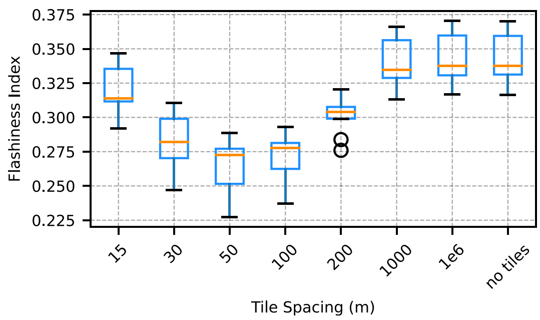

Figure 6. Impact of tile spacing on streamflow flashiness. Box plots show the distribution of annual flashiness index values for each tile spacing scenario. The orange line indicates the median.

10 March 2016, which produced 23.9 mm of cumulative precipitation and snowmelt over 4 d. In the with-tiles scenario, the stream network is clearly visible, with minimal inundation outside stream channels. The stream network is clearly visible in the with-tiles snapshots. Recall that stream locations and flows are prognostic in ISSHMs, arising from water flow and topography. The surface is mostly dry away from the streams in the reference case even during the storms as opposed to the no-tiles case where significant inundation is evident.

The probability distribution for depth to water table (all positions all times) with and without tiles is plotted in figure 4(a). The probability that the water table is in the rooting zone (<0.5 m) is about 5% with tiles and 50% without tiles, which is why tiles are implemented. The probability of the water table entering the root zone is sensitive to tile spacing (figure 4(b)), ranging from less than 5% when tile spacing is 15 m to nearly 50% for spacing greater than 1000 m, which behaves as if there were no tiles.

3.2. Effect of tiles on baseflow

Effects of tile drains on the water table are by design, but effects on the downstream flows are inadvertent and can have positive or negative consequences. For the 10 WYs of our study, annual average daily flows were increased by tiles by approximately 5% because of decreased evapotranspiration in the drier soils that result from tile drainage. It is important to note, however, that crop phenology is held fixed, and thus we are not including the indirect effects of tiles on evapotranspiration through changes in crop productivity. Effects on low-flow conditions are larger as shown by the greater specific discharge with tiles on the lower end of the flow duration curve (figure 5, left panel). The 7 d baseflow index—the lowest 7 d flow normalized by annual flow—is increased by tiles for all WYs (figure 5, right panel).

3.3. Effect of tiles on streamflow flashiness

The watershed flashiness index shows that tiles overall decrease flashiness. However, flashiness has a non-monotonic dependence on tile spacing (figure 6) with a minimum at 50 m. These watershed-scale results are consistent with previous field-scale DRAINMOD results [25] that identified an optimum tile spacing that reduced flashiness by creating subsurface storage to allow infiltration and reduce surface runoff, while keeping the tiles far enough apart to slowly release the flow. Consistency in trends between scales suggests that the imprint of field-scale processes in the watershed-scale response is not fully erased by finite routing time for water through the stream network.

Further exploration of how the watershed-scale response is influenced by tile spacing is provided in figure 7, which presents streamflow, infiltration, and

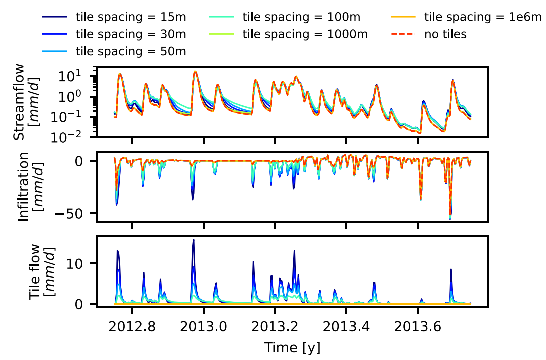

Figure 7. Impact of tile spacing on hydrograph recession, infiltration, and total tile outflow during wet (first half of water year) and dry (second half of water year) periods.

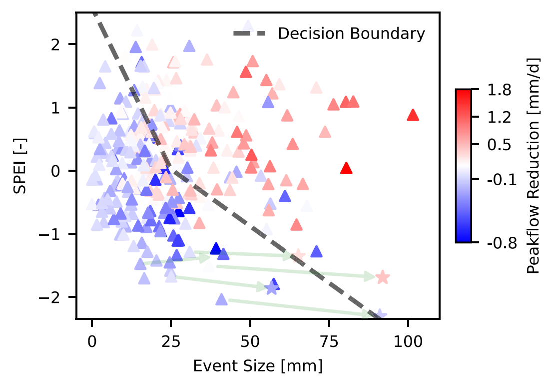

Figure 8. Precipitation events plotted as a function of event size and antecedent meteorological conditions, quantified by the standardized precipitation evapotranspiration index (SPEI). Points are color-coded by peak flow reduction (mm d^{-1}), calculated as the difference between peak flow without tiles and with tile drainage (15 m spacing). Red points represent events where peak flow is reduced by tiles; peak streamflow is enhanced for the blue events. Triangles denote original events; stars denote augmented events with precipitation scaled by a factor of 2.5. The feature space of event size and SPEI is divided into two distinct regions separated by a hinged decision boundary (dash line), derived using the support vector classification method.

tile flow for different tile spacings during WY 2013—a representative year used for visualization purposes. In the relatively wet first half of WY 2013, peak streamflows are slightly smaller and recession curves slower for tile spacing ∼50 m as compared with smaller or larger spacings, consistent with a lower Flashiness Index at intermediate spacings. At small spacing, flashy hydrographs are the result of rapid infiltration and flashy tile flows, whereas at large spacing or without tiles infiltration is minimal and flashy stream hydrographs can be attributed to surface flow. However, the flashiness-tile spacing relationship also depends upon antecedent conditions. All events result in infiltration and the hydrograph is much less sensitive to tile spacing in the relatively dry second half of WY 2013.

3.4. Effect of tiles on peak flow

Finally, we focus on the hydrologic effects of tiles on event-based peak flows as function of event size and antecedent meteorological conditions represented by the SPEI (figure 8). Those two metrics of the meteorological forcing are largely predictive of whether tiles increase or decrease flows. Here, peakflow reduction is defined as the difference between peak flow without tiles and with tiles (in mm d^{-1}); positive values indicate attenuation due to tile drainage, while negative values indicate peak flow enhancement. Events that were scaled by a factor of 5 are not included in figure 8 but can be found in supplemental figure 1. Those events all showed peakflow reduction and fall to the right of the decision boundary. Including those events, our decision boundary analysis correctly separated positive from negative peakflow reduction 75% of the time. Generally, tile drainage reduces peak flows for larger precipitation events except when events occur after dry antecedent conditions and increases peak flow for smaller events and when events arrive in dry conditions. These trends are largely consistent with previous field [8, 18, 19, 25] and catchment-scale peak flow analyses [8, 21–23, 26]. Of the 25 events producing the largest streamflow, streamflow was reduced by tile drainage in 23 (median reduction of 5.3%, maximum reduction of 9.3%).

4. Discussion

4.1. Watershed-scale effects of tile drainage

Our finding that peak flow can either be enhanced or attenuated by the presence of tile drains, depending on the size of the event and the antecedent meteorological conditions as measured by 45 d SPEI, is qualitatively consistent with a field-scale conceptual framework initially proposed by Robinson and Rycroft [19] and extended by later studies [25, 26]. That conceptual model is based on differences in the storage capacity of the unsaturated zone and flow paths to the stream, as shown schematically in figure 9. For relatively small events or when events arrive in dry conditions, the predominant flow path to the stream is through shallow lateral flow in the no-tiles cases. An infiltration pulse must propagate laterally through the subsurface to affect streamflow and is attenuated by storage in a rising water table. Conversely, tiles limit the rise of the water table, thus reducing the ability of storage changes associated with water table rise to attenuate the infiltration pulse. Peak flow is enhanced by tiles as a result. When the precipitation event is large, overland flow is quickly triggered in the no-tiles case. The drier antecedent conditions of the soils when tiles are present provide more storage capacity to attenuate the infiltration pulse, thus reducing the peak flow.

Our results also provide insights into the question of ‘distribution’ effects raised by Robinson and

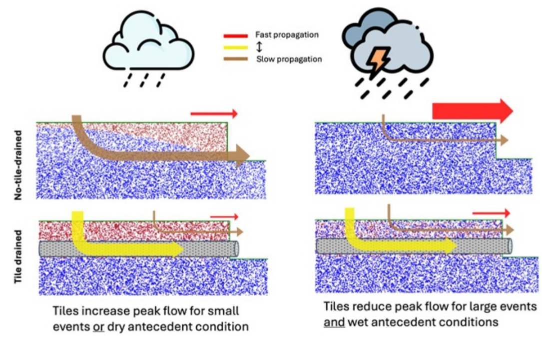

Figure 9. Schematics demonstrating different mechanisms for precipitated water to propagate to stream/ditch, and their contributions are controlled by event size and antecedent conditions. These factors determine the peak flow modulation by tile drains is dictated by event size and antecedent meteorological conditions.

Rycraft [19], who noted that synchronicity and routing of field hydrographs in the watershed have potential to lead to diminished or opposite effects in the outlet hydrograph. Our spatially explicit, high-resolution modeling shows that distribution effects are not large enough to eliminate the tile signal at the outlet. Thus, understanding gained from analysis of field-scale hydrographs is still relevant at the scale of the Portage River Watershed.

Our finding of a non-monotonic relationship between flashiness and tile spacing (figure 6) can also be explained by flowpath and storage differences. With very close tile spacing, the subsurface flow path to tiles is short and removes water quickly. As the tile spacing becomes large, the water table is able to rise significantly above the tile elevation, which makes it easier to trigger saturation excess overland flow and flashy hydrographs. Thus, the hydrographs at small and large spacings are flashier than at intermediate spacings, in agreement with the previous field-scale results [25]. The similar hydrographs for systems with very different flow paths underscores the limitations of the event hydrograph to characterize watershed response.

4.2. Spatially explicit models and watershed counterfactual experiments

Empirical watershed studies that compare hydrographs from stream gauges in tiled and non-tiled watersheds attempt to control for the effects other watershed characteristics, which typically requires aggregating heterogeneous characteristics into single watershed values that may not contain sufficient information to isolate the effect of tile drainage. These uncertainties are likely exacerbated when looking at larger peak flows, as these are under-sampled and more sensitive to the spatial heterogeneity of the run-off generation processes. This likely explains the lack of consistent results on effects of tile drainage on peak flows [8, 18, 19].

Creating counterfactual watershed models is an attempt to address these confounding environmental factors. However, to date most modeling studies used semi-distributed models that require significant calibration, which increases uncertainty when extrapolating to counterfactual conditions. Our high-resolution physics-based ATS modeling approach directly incorporates these confounding variables to create physics-based counterfactual numerical experiments. The fact that the ATS simulations require minimal calibration gives us confidence that the model is capturing the relevant physical processes at the necessary scales, so that modifying the underlying features such as tile drainage will give a physically realistic basin response.

Future work should include ATS simulations of larger watersheds with different soils and topography to further explore scaling and physiographic controls of the hydrologic response of tile-drained watersheds. ATS can also be used to explore sensitivities to scenarios such as land-use/land-cover change, surface drainage modifications, future climate, and drainage intensification.

4.3. Implications for adverse effects of tile drainage

Our simulations show that tile drainage can reduce peak flows of larger events that can contribute to flooding especially when those events arrive in wet conditions. For the 25 largest events by streamflow, the median and maximum reduction are 5.3% and 9.3%, respectively, which aligns well with previous results at similar watershed scales [26, 27]. However, the reductions in peak flows seen at the scale of the Portage River Watershed may not be the same magnitude or even sign at larger scales [28] as the peak flow effects at the larger scale are driven by the aggregation of flow from multiple events over longer temporal windows [26].

The installation of tile drainage is intensifying across the United States since the 1990s [28]. Our results indicate that installing more tile at narrower spacing may increase flashiness (figure 6), which has negative implications for downstream water quality as flashiness is a control on nutrient and sediment transport.

We find that tiles increase lower flows in the Portage River Watershed. These lower flows have been cited extensively as major sources of nutrient export leading to eutrophication in lakes, streams and the Gulf of Mexico [5–8]. Additionally, the intensification of lower flows drives adverse changes to river sediment budgets and geomorphology [59]. Future ATS simulations coupled with reactive and sediment transport models could provide additional insights into the drivers of these adverse impacts.

5. Conclusions

We configured a new high-resolution multiscale model for flow in agricultural watersheds to study how tiles affect flow in the Portage River Watershed (1024 km^2). The Portage River Watershed is typical of large agricultural watersheds with poorly draining soils and extensive tile drainage.

We found that tiles greatly increased low flow, while decreasing higher flows to a lesser extent. This homogenization of the hydrologic regime led to decreased streamflow flashiness that is consistent with most previous watershed studies. Flashiness has a non-monotonic dependence on tile spacing with a minimum at c. 50 m. Flashiness and the event hydrographs for small tile spacing were similar to the case with no tiles. However, flow paths from farm to stream were very different, with overland flow dominating event response in the no-tiles case and tile-flow in the densely tiled case. The similar hydrographs for systems with very different flow paths underscores the limitations of the event hydrograph to characterize watershed response. The non-monotonic dependence of flashiness on tile spacing suggests that ongoing intensification of tile drainage in the Corn Belt may have the unintended consequence of increasing flashiness, with negative implications for downstream water quality.

We find that the 4 d event size and 45 d SPEI are highly predictive of whether tile drainage increases or decreases peak flow. Tiles enhanced peak flow when the 4 d event size is below a threshold that depends on SPEI. The dependence of peak flow changes on event size and SPEI are explained by field-scale surface and subsurface flow alterations mediated by increased subsurface storage capacity and efficiency.

Overall, our ATS simulations overcome uncertainties associated with confounding variables that plague statistical analyses and over-fitting of semi-distributed models to provide high-resolution evidence of tile drainage effects on watershed hydrology. The reduced need to for calibration in ATS makes counterfactual numerical experiments at the watershed scale possible, which has a broad range of potential applications to better understand how farming practices like tile drainage impact water quantity and quality downstream. An important next step is to use ATS's reactive transport capabilities [60] in studies similar to this one to gain new insights into watershed-scale nutrient transport.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.15485/2539863.

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