LINKING DYNAMIC CONNECTIVITY AND HYDROLOGIC RESPONSE

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The dynamic connection and disconnection of water storages in landscapes is a key control on water and solute transport and transformation. However, the processes that control how and when landscapes connect to their streams are complex. Hydrologic connectivity, which often exhibits transient and threshold behavior, depends upon antecedent wetness and hydrologic forcing conditions which modify water fluxes through space and time. Further, the dominant controls on connectivity vary with landscape structure (i.e., natural topography, topology, and geology, as well as human modifications to drainage structure). Characterizations of hydrologic connectivity as a function of antecedent conditions, hydrologic forcing conditions, and landscape structure are needed to accurately predict hydrologic and solute responses as well as to assess their influence on associated ecosystem services.

In this body of work, I advance understanding of how dynamic hydrologic connectivity controls hydrologic response across a range of landscapes. I achieve this using a combination of field observations and numerical modeling. The first study explores how representing moisture-dependent, pore-scale hydrologic connectivity—a process called ecohydrologic separation—in a catchment-scale hydrologic model alters interpretations of stores, fluxes, and residence times of water and solutes. The following two chapters assess hydrologic connectivity dynamics in low-gradient landscapes of the Midwestern U.S. The second study explores how antecedent conditions control thresholds of runoff generation and nitrate export in tile-
drained agricultural fields using field observations and coupled water and nitrogen cycle simulations. The final study characterizes the spatial and temporal variability of flooding dynamics within topographic features of a minimally human-disturbed floodplain system, highlighting the role of floodplain channels in enhancing river-floodplain connectivity.

Overall, this research details conceptualizations of hydrologic connectivity in landscapes not commonly considered in current connectivity frameworks (low-gradient floodplains and intensively managed agricultural landscapes) and presents a novel representation of a moisture-dependent, hydrologic connectivity process and its ecological implications in a highly studied landscape (forested hillslopes).
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Chapter 1: Scope and context

1.1 The challenge of hydrologic prediction and hydrologic connectivity as a path forward

Nearly 50 years after the start of the International Hydrologic Decade, a global research initiative that launched the hydrologic sciences into a scientific discipline in its own right (Nace, 1980), and 20 years after the Prediction in Ungauged Basins of the International Association of Hydrological Sciences, which focused attention towards improving understanding of the processes underlying hydrologic function (Hrachowitz et al., 2013), hydrologists still struggle to accurately predict hydrologic responses to precipitation events. Fundamental to this problem is that watersheds are complex environmental systems characterized by heterogeneity of the land surface and subsurface, including factors like topography, soils, bedrock, and land cover (Jehn et al., 2021; Troch et al., 2009). This inherent structural complexity interacts with individual storm event characteristics and antecedent wetness, resulting in spatiotemporal variability of hydrologic stores and fluxes. Still, despite the uniqueness of all catchments and events, hydrologists find similarities in catchment responses and underlying mechanisms. These generalizable insights provide a path forward for transferring our understanding of hydrological processes between sites and events.

In particular, the concept of hydrologic connectivity has proved a useful tool for linking mechanisms and emergent response patterns across a range of environments and scales (Ali and Roy, 2009; Rinderer et al., 2018). While precise definitions vary, connectivity relates to the degree of hydrologic interactions between landscape elements. It is a dynamic property often described in terms of the magnitude, frequency, duration, and timing of water fluxes between
storages. In addition to providing a basis for conceptualizing catchment processes, hydrologic connectivity is the foundation for recently proposed frameworks for grouping and comparing runoff processes and emergent behavior across sites and scales (Ali et al., 2013; McDonnell, 2013; McDonnell et al., 2021). A primary reason connectivity has become such a crucial concept for understanding water movement is because emergent hydrologic response is scale-dependent and connectivity is a property that can be applied at all scales of interest (Lexartza-Artza and Wainwright, 2009).

1.2 Nonlinear hydrologic response and antecedent wetness controls

Hydrologic connectivity is intimately linked to nonlinear hydrologic responses observed in catchments nearly ubiquitously (Robinson et al., 1995; Sivapalan et al., 2002). Research in runoff generation across a range of landscapes supports that threshold responses (large changes in fluxes of water in response to small changes in wetness conditions) commonly reflect shifts in hydrologic connectivity (McGuire and McDonnell, 2010; Soulsby et al., 2015); a storage threshold within the landscape is reached, activating new flow pathways and enhancing connectivity with other parts of the landscape (McDonnell et al., 2021; Spence, 2007). Thus in contrast to assumptions of earlier work (e.g., Hewlett and Hibbert, 1967), a paradigm has emerged that runoff generation is not a smooth, continual function of storage accumulation/depletion, but is dictated by threshold-mediated connectivity (Spence, 2010). Further, regardless of whether the storages in question are soil pores (Klaus et al., 2013), bedrock depressions (Tromp-van Meerveld and McDonnell, 2006), or depressional wetlands (Leibowitz and Brooks, 2008), the amount of precipitation needed to meet critical storage
thresholds will vary according to how full storages are prior to a storm. Consequently, both
event precipitation and antecedent wetness are commonly identified as first order controls on
runoff volumes and timing (Detty and McGuire, 2010b; Meyles et al., 2003; Penna et al., 2011).

As noted above, storage thresholds can result from natural properties of a system, such as soil
moisture thresholds (i.e., field capacity) or geomorphic depression thresholds. However,
storage thresholds can also be built into landscapes by human modification. For examples,
storage reservoirs constructed to attenuate floods are often designed with overflow weirs or
spillways to release water during extreme floods. Less visible but pervasive in agricultural
landscapes are internal thresholds of subsurface drainage systems (commonly “tiles” or “tile
drains”) installed to maintain soil moisture conditions amenable to crop production. These
perforated pipes create physical thresholds in systems which alter connectivity between the
land surface, groundwater, and streams (Gedlinske, 2014; Kleinman et al., 2015; Macrae et al.,
2007). Regardless of whether storage thresholds are natural or human-made, the interplay
between storage thresholds, antecedent conditions, and event characteristics influences
emergent hydrologic responses.

1.3 Hydrologic connectivity influences material transport and ecosystem functions

Hydrologic connectivity is not only a key control on water transport but also the transport and
transformation of materials conveyed by water fluxes, including contaminants and essential
nutrients (Covino, 2017; Freeman et al., 2007). Linkages between upland water stores and
riparian zones are requisite for the transport of organic matter and inorganic nutrients to
stream networks (e.g., Detty and McGuire, 2010a; Jencso et al., 2010). Due to the heterogeneous distribution of nutrient storages in landscapes, nutrient export depends on the unique, connectivity-mediated flow pathways water takes en route to streams (Cirmo and McDonnell, 1997; Harms et al., 2019; Stieglitz et al., 2003). Further, biogeochemical signals at catchment outlets may reflect the dynamic connection, expansion, and contraction of source areas with distinct nutrient storages (McGlynn and McDonnell, 2003; Zimmer and McGlynn, 2018). While hillslope runoff generation primarily emphasizes lateral connectivity between hillslopes, riparian areas, and streams, connectivity in vertical and longitudinal dimensions also influences ecosystem processes. For example, the River Continuum Concept, one of the most influential theoretical frameworks in river ecology, relies on the notion of longitudinal connections between succeeding river sections that create progressive physical, chemical, and biotic gradients (Doretto et al., 2020; Vannote et al., 1980). Hyporheic exchanges via downwelling and upwelling represent vertical connections that influence stream ecosystems (Boulton et al., 2010; Franken et al., 2001; Wondzell, 2011). These exchange flows create unique habitats for a diversity of organisms and create strong chemical and physical gradients that facilitate solute processing, ultimately influencing water quality (Brunke and Gonser, 1997; Harvey et al., 2019).

In addition to spanning multiple dimensions, hydrologic connectivity can operate primarily unidirectionally (e.g., downstream or downslope transport processes) or multi-directionally (e.g., exchange fluxes). River corridor exchange—which encompasses multi-directional flows between surface waters, aquifers, riparian zones, and floodplains (Harvey and Gooseff, 2015)—
provides important water quality benefits by extending contact times with microbially active substrates (e.g., Battin et al., 2008; Brunke and Gonser, 1997; Dahm et al., 1998). As such, enhancing hydrologic connectivity via river corridor exchange is often the focus of river management strategies to maintain and restore river-floodplain systems (Buijse et al., 2002; Freitag et al., 2012). Hydrologic connectivity also occurs across spatial scales, creating a mosaic of nested hydrologic processes (Covino, 2017; Lexartza-Artza and Wainwright, 2009). Even small-scale connectivity processes can aggregate to larger-scale ecological effects. For example, the degree of interactions between macropores and soil matrix influences biogeochemical cycling and nutrient transport to streams (Asano et al., 2006; Franklin et al., 2021). Further, understanding mobility limitations between heterogeneously-sized soil pores is important for accurately predicting contaminant transport through porous media (e.g., Haggerty and Gorelick, 1995; Šimůnek et al., 2003).

1.4 Hydrologic connectivity and policy implications

U.S. federal regulations, such as the Clean Water Rule and the Navigable Waters Protection Rule (USDOD and USEPA, 2015; 2020), recognize the importance of hydrologic connectivity for the integrity of downstream waters and establish protection of wetlands, lakes, and ponds based on connectivity with navigable waterways and jurisdictional streams. Hydrologic connectivity, however, is a complex and dynamic property of environmental systems. It may or may not be easily observed (surface vs. subsurface flows), varies in magnitude over space and time, and occurs in multiple dimensions (Covino, 2017; Golden et al., 2017; Pringle, 2003). Thus although these rules aim to clarify the scope of the Clean Water Act, they have also raised
questions about which waters are protected (Alexander et al., 2018; Walsh and Ward, 2021). To inform rulemaking by federal agencies, the U.S. EPA conducted a comprehensive review summarizing current understanding of hydrologic connectivity (USEPA, 2015). The report shows that landscape features like streams, wetlands, and floodplains provide physical, chemical, and biological functions that affect downstream water quality, regardless of flow frequency and even when lacking surface water connections. However, despite demonstrating the myriad ways in which landscapes are connected and influence downstream waters, uncertainty remains regarding which waters should be regulated to effectively protect human health and ecological resources. This is reflected in continued rule-making efforts to redefine regulated waters and protect water resources (Biden, 2021; USDOD and USEPA, 2021). Developing effective policies and management necessitate understanding of the connectivity-mediated hydrologic mechanisms by which landscapes influence ecosystem functions. This includes identifying linkages between landscape structure, connectivity dynamics, and hydrologic function.

1.5 Summary of research efforts

The research presented in this dissertation advances understanding of controls on hydrologic connectivity, and how connectivity dynamics, in turn, mediate emergent hydrologic response. This is achieved using a combination of field observations and numerical modeling in a variety of landscapes and at reach- to catchment-scales. The first study (Chapter 2) explores how representing moisture-dependent, pore-scale hydrologic connectivity—a process called ecohydrologic separation—in a rainfall-runoff model of a headwater mountain catchment
influences interpretations of stores, fluxes, and residence times of water and solutes. Results demonstrate that omission of ecohydrologic separation from modeling frameworks alters expectations of internal catchment dynamics underlying ecosystem functions, including biogeochemical processing and plant water availability.

The following two chapters assess hydrologic connectivity dynamics in low-gradient landscapes of the Midwestern U.S. The second study (Chapter 3) investigates how antecedent conditions control thresholds of runoff generation and nitrate export in tile-drained agricultural fields using field observations and coupled water and nitrogen cycle simulations. Thus, this chapter focuses on how interactions between a human-made connectivity threshold (subsurface drainage tiles) and a natural connectivity threshold (soil moisture storage) control water and nutrient transport. I find that a tile outflow activation threshold emerges as a function of gross event precipitation, antecedent soil moisture, and antecedent below-tile groundwater moisture deficit. The third study characterizes the spatial and temporal variability of flooding mechanisms and inundation patterns within topographic features of a minimally human-disturbed floodplain system. Results highlight the role of floodplain feature networks in enhancing river-floodplain connectivity and demonstrate spatiotemporally complex dynamics of floodplain feature activation and dry-down.

The unifying goal of this research is to improve predictive understanding of how hydrologic connectivity controls the transport of water and associated materials through the environment. Chapter 5 provides a synthesis of the studies included in this dissertation, placing each in the
context of the entire body of work. Further, in this chapter I propose directions for future efforts to fill gaps limiting our ability to predict when and where hydrologic connectivity-mediated ecological functions occur.
1.6 References


USDOD, and USEPA (2021), Revised Definition of “Waters of the United States.”*, Federal Register*, 86, 69372-69450.


Chapter 2: Ecohydrologic separation alters interpreted hydrologic stores and fluxes in a headwater mountain catchment

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2.1 Abstract

Recent studies have demonstrated that compartmentalized pools of water preferentially supply either plant transpiration (poorly mobile water) or streamflow and groundwater (highly mobile water) in some catchments, a phenomenon referred to as ecohydrologic separation. The omission of processes accounting for ecohydrologic separation in standard applications of hydrological models is expected to influence estimates of water residence times and plant water availability. However, few studies have tested this expectation or investigated how ecohydrologic separation alters interpretations of stores and fluxes of water within a catchment. In this study, we compare two rainfall-runoff models that integrate catchment-scale representations of transport, one which incorporates ecohydrologic separation and one which does not. The models were developed for a second-order watershed at the H.J. Andrews Experimental Forest (Oregon, USA), the site where ecohydrologic separation was first observed, and calibrated against multiple years of stream discharge and chloride concentration. Model structural variations caused mixed results for differences in calibrated parameters and differences in storage between reservoirs. However, large differences in catchment storage volumes and fluxes arise when considering only mobile water. These changes
influence interpreted residence times for streamflow-generating water, demonstrating the importance of ecohydrologic separation in catchment-scale water and solute transport.

2.2 Introduction

The unsaturated root zone—the vegetation-accessible region between the earth’s surface and the groundwater table (Stephens, 1995)—is the primary node where precipitation is partitioned into terrestrial storage in catchments, either directly within the unsaturated zone or via groundwater recharge, indirect drainage to the stream, and evaporative fluxes (Savenije and Hrachowitz, 2017). This partitioning ultimately determines the pathways water takes to reach the catchment outlet, residence times within various stores, and the physical and chemical processes experienced during transport and storage. Many conceptual and mathematical models either treat the unsaturated zone as completely mixed or assume transport occurs via translatory flow (i.e., infiltrating precipitation displaces water previously stored in soil in a sequential order; Hewlett and Hibbert, 1967). However, work on ecohydrologic separation (the partitioning of less-mobile water available for transpiration by plants from more-mobile water that becomes streamflow; e.g., Brooks et al., 2010; Evaristo et al., 2016; Goldsmith et al., 2012; Hervé-Fernández et al., 2016) challenges these representations. Ecohydrologic separation, also referred to as the two water worlds hypothesis (Berry et al., 2017; McDonnell, 2014), conceptualizes the existence of several pools of water that have limited mixing, effectively representing the unsaturated zone as a location of parallel storage processes. Specifically, under dry conditions some infiltrating water bypasses small pores of the unsaturated zone while other infiltrating water is bound and stored in small pores. Evidence in
support of ecohydrologic separation is common in many catchments (see meta-analysis by Evaristo et al., 2015) and the conceptual model of ecohydrologic separation explains empirical data. However, we have limited understanding of how including this process in hydrologic models alters our interpretations of stores and fluxes of water at the scale of catchments.

Representation of ecohydrologic separation in hydrologic models could influence estimates of residence times and fluxes of water and solutes (Phillips, 2010; Sprenger et al., 2016; Sprenger et al., 2018) and thus challenge perceptions of dominant hydrologic processes operating within a catchment. For example, because the tightly bound water stored in the unsaturated zone is isolated from flow to streams, the volume of mobile water is expected to be smaller than would be expected from a one water world conceptualization in which all unsaturated water has the potential to generate streamflow. The reduced volume of mobile water should, therefore, result in more variable residence times of water and solutes in the unsaturated zone, with increased residence times for the immobile fraction of water and decreased residence times for the mobile fraction. Furthermore, hydrologic connectivity between subsurface reservoirs controls fluxes of water and solutes through the catchment, and thus stream solute and hydrologic response (Jencso et al., 2010; Jencso et al., 2009). Changes in residence times and fluxes of water from hillslopes to streams may alter the potential for associated biogeochemical reactions or weathering to occur within those zones. While this thought experiment suggests ecohydrologic separation will be important at the catchment scale, there are few examples which qualitatively demonstrate its impact on our understanding of stores and residence times of water.
Transport characteristics which reflect working definitions of the two water worlds hypothesis have been incorporated in a number of modeling studies, although the term may not have been explicitly used. For example, some studies assume groundwater recharge via preferential flow does not mix with unsaturated zone water and retains the chemical signature of precipitation (Birkel et al., 2014). Others have used hydrologic models to explore alternative explanations to the conceptualization of two isolated soil water pools to explain isotopic patterns, typically suggestive of a higher degree of mixing. Sprenger et al. (2016) invoked successive mixing of stored water with new rainwater in a soil physical model. Knighton et al. (2017) found that a combination of preferential and matrix flow best simulated unsaturated zone stable water isotopes in a lumped hydrologic model.

Recent publications have highlighted the influence mixing assumptions have on interpreting internal process dynamics and have advanced approaches for representing incomplete mixing (i.e., nonuniform sampling) associated with ecohydrologic separation. Several modeling studies use age-based methods to examine selective retention and release dynamics in catchments, in which sampling of storage for outflow is biased toward particular ages according to a StorAge Selection (SAS) function or a mixing coefficient (e.g., Benettin et al., 2013a; Benettin et al., 2013b; Botter et al., 2011; Harman, 2015; Hrachowitz et al., 2013; Rinaldo et al., 2015; van der Velde et al., 2012; van der Velde et al., 2015). This transfer function technique can indirectly account for different sources of mixing, including moisture-dependent variations in flow paths and temporal mixing.
dynamics between mobile and less mobile storages, but does not resolve internal catchment dynamics and treats the entire catchment as a single control volume. Still, some studies demonstrate how a SAS function approach can be applied to simulate selective sampling of younger water for transpiration (Harman, 2015; van der Velde et al., 2015; Wilusz et al., 2017). This is contradictory to the two water worlds hypothesis in that the youngest portion of water has the potential to bypass plant-available storage, meaning transpiration would not be selected from the youngest portion of catchment storage. Evaristo et al. (2019) observed that the ages of water taken up by roots are older than seepage to groundwater recharge by a factor of two in a mesocosm water tracing experiment.

Partial mixing in the root zone is less common in process-based models, but its importance in reproducing observed tracer patterns is increasingly recognized. Using a physically-based ecohydrologic model which tracks water isotopes and assumes full mixing in each soil layer, Kuppel et al. (2018) conclude that discrepancies between observed and modeled values reveal a need for incorporating partial mixing processes. Time-variable mixing has been represented in a small number of lumped models. For example, Hrachowitz et al. (2013) and van der Velde et al. (2015) compared model performance and water age distributions between a “complete mixing model,” used in most conceptual modeling studies, and a “dynamic partial mixing model,” in which a greater portion of new water bypasses passive (hydraulically inactive) storage under wetter conditions. Additionally, under high soil moisture conditions more water is routed to preferential flow pathways,
only partially mixing with matrix water (see also Hrachowitz et al., 2015). McMillan et al. (2012) investigate how mixing within the unsaturated zone can be parameterized by time-variable tracer data. They find that when separate state variables are used for tension and free storage reservoirs, the free storage becomes a very fast response store with low transit times. Here, we build upon these mixing approaches in order to explicitly represent ecohydrologic separation in a catchment-scale hydrologic model and assess its influence on water storage and residence times.

Both simple, lumped black box models (e.g., Soulsby et al., 2010; Speed et al., 2010) and more detailed process-based and spatially explicit hydrologic models (e.g., Maxwell et al., 2016) can be used to study stores and fluxes of water in catchments. Lumped conceptual models are comparatively simple, with data requirements scaling with model complexity to offset equifinality and the number of calibrated parameters minimized through a reduced-complexity structure that isolates dominant catchment processes (Fenicia et al., 2008b; Schoups et al., 2008; Young et al., 1996). Physically-based distributed models allow for greater spatial resolution, but over-parameterization renders inter-model comparison impractical because the degree of dissimilarity between model structures and processes represented make it difficult to identify the individual components that result in performance differences (Clark et al., 2015a; Clark et al., 2015b). The comparative advantages of lumped models for inter-model comparison make them suitable for incorporating ecohydrologic separation and comparing internal stores and fluxes across structurally different models.
The two water worlds hypothesis refers to a proposed explanation for observed ecohydrologic patterns, typically described by isotopic data. However, there lacks a precise definition of the processes which result in a range of observations that have been described under the two water worlds hypothesis (Berry et al., 2017). This flexible, evolving definition necessitates that authors place studies within the context of an ecohydrologic separation framework informed by previous studies. Here we identify key characteristics common with many descriptions of the two water worlds hypothesis, and thus use our own interpretations, to consider how dominant storages and their linkages might be organized in one possible model representation. A two water worlds model (2WW) has an architecture that incorporates two main features: 1) unsaturated storage that is hydrologically less connected to other catchment storages for at least part of the year and from which plants extract water, and 2) parallel transient storage processes by which some infiltrating precipitation bypasses tightly bound storage to generate streamflow and recharge groundwater. In contrast, in a one water world model (1WW), plants extract water from a pool that is fully connected to the catchment year-round.

The overarching goal of this study is to determine how including ecohydrologic separation in a lumped catchment model alters interpreted stores, fluxes, and residence times of water and solutes within a catchment. In reaching this goal of quantifying differences in internal dynamics, we are guided by three expectations. First, we expect the accuracy of 1WW and 2WW in predicting stream discharge will be similar because of a comparable
number of free parameters and the broad success of lumped representations in predicting discharge in the literature (Beven, 2011; Duan et al., 1992). Next, we expect 2WW will more accurately predict a seasonal stream chloride signal because ecohydrologic separation isolates the source of water for evapotranspiration, which generates chloride enrichment of the unsaturated zone during dry periods (Figure 2.1), from the source of water for stream discharge. Finally, we expect 2WW will decrease residence times for mobile, streamflow-generating water because new precipitation is able to bypass a portion of unsaturated storage while bound water remains in place; concurrently, residence times for the bound water fraction will increase, resulting in more variable residence times overall. To investigate alterations in stores, fluxes, and residence times of water, we developed two hydrochemical lumped rainfall-runoff models which incorporate the key features of 2WW and 1WW described above. The study location is a headwater catchment at the H.J. Andrews Experimental Forest (Oregon, USA), the site which motivated the two water worlds hypothesis (Brooks et al., 2010). Models are calibrated against stream discharge, as well as chloride concentrations to ensure adequate simulation of solute transport in addition to discharge dynamics. Previous studies at the site provide evidence in support that the ecohydrologic separation mechanism is operating in the catchment (Brooks et al., 2010). Thus, this study does not seek to identify 1WW or 2WW as a best or correct conceptual framework. Instead, we ask how our evolving conceptual model— informed by the findings of Brooks et al. (2010)—results in changes to our interpretation of the storage and transport of water and solutes at the catchment scale. Recent studies conducted in other catchments indicate that ecohydrologic separation is strongest in climates
with distinct dry and wet seasons (Geris et al., 2015) and the magnitude of ecohydrologic separation is temporally variable throughout the year (Hervé-Fernández et al., 2016; McCutcheon et al., 2017; Sprenger et al., 2017), such that the two water worlds hypothesis holds during the dry season but not during the wet season. Thus, in our analysis we particularly focus on alterations to water residence times and storage during the dry season when differences between 1WW and 2WW are potentially most relevant.

![Figure 2.1](image)

**Figure 2.1** Input time series of observed precipitation and estimated potential evapotranspiration ($E_p$) for the validation period (a). Chloride concentrations observed in precipitation and the stream over the validation period and average wet season stream chloride concentration over the study period (b). The blue shaded region highlights late dry season (Jul-Sep) trends.

### 2.3 Site description and data

In this study we analyze data from Watershed 10 (WS10, 0.96 km²), a headwater catchment of the H.J. Andrews Experimental Forest located in the western Cascade Mountains of Oregon, USA. The catchment has been extensively studied over the last several decades, resulting in detailed site descriptions (Dryness, 1969; McGuire et al., 2005; Swanson and James, 1975;
Swanson and Jones, 2002). Watershed 10 has steep hillslopes (> 50%), narrow valley bottoms, and highly conductive soils (Dryness, 1969; Harr, 1977). These features, along with the presence of significant preferential subsurface flow paths, result in fast hydrologic responses to precipitation (McGuire and McDonnell, 2010). Bedrock is volcanic in origin, with andesitic and dacitic tuffs and coarse breccias as the parent materials for overlying soils of about 1 m thickness (Swanson and James, 1975). The forest is mainly coniferous with some deciduous species in the riparian zone. Elevations range from 461 to 679 m a.m.s.l. The region has a Mediterranean climate with wet, mild winters and dry, warm summers. During the study period (1-Jan-1989 to 31-Dec-2014), mean annual precipitation was 2200 mm, about 80% of which fell between October and April. Typically, highest precipitation occurs in late November and minimum precipitation occurs in late July, coinciding with minimum streamflow. Mean annual streamflow for WS10 was 1420 mm during the study period. Thus, annual evapotranspiration is estimated to be about 770 mm annually, or about 35% of precipitation. The catchment is at a sufficiently low elevation that major seasonal snowpack does not develop. Therefore, we do not include snow processes in our analysis, consistent with previous modeling studies of WS10 (Klaus et al., 2015; McGuire et al., 2007; Rodriguez et al., 2018).

Daily discharge values were obtained from a fixed trapezoidal flume located at the outlet of the catchment (H.J. Andrews station GSWS10). Stream water samples for chemistry were collected proportionally to streamflow at the gauge location as composite samples typically spanning three weeks, and samples were analyzed for chloride. Daily precipitation and temperature data to estimate potential evapotranspiration were obtained from a nearby climatic station located
below the outlet of WS10 (430 m a.m.s.l., H.J. Andrews station PRIMET). Precipitation samples
to be analyzed for chemistry were collected weekly from a bulk collector located at the same
elevation (H.J. Andrews collector RCADMN) and analyzed for chloride. Precipitation chloride
concentration has little systematic variation seasonally (Figure 2.1). However, high
concentration outliers, likely due to some evaporation prior to collection, resulted in general
over-estimation of stream chloride concentrations during the wet season when stream chloride
concentrations are low. As such, we use the approximate chloride concentration of stream
discharge during the wet season (0.1 mg L⁻¹) as a constant input concentration for precipitation.
We selected the study period based on availability of data for stream discharge, stream
chemistry, and precipitation.

2.4 Hydrologic model development

We developed two hydrologic models with the objective of reproducing the hydrograph and
chloride concentration timeseries within the stream draining WS10. One model includes
ecohydrologic separation characteristics (2WW; Figure 2.2b) and one does not (1WW; Figure
2.2a). Both 1WW and 2WW are lumped conceptual models that comprise interconnected
reservoirs that represent dominant physical processes affecting hydrologic and transport
response. We began with basic model structures and applied a flexible development approach
in which we progressively made modifications motivated by performance inadequacies and
knowledge of catchment characteristics (after Fenicia et al., 2008a; Fenicia et al., 2011).
Both the 2WW and 1WW models include four reservoirs: a plant available unsaturated storage reservoir, $S_{U1}$ (mm); a fast flow unsaturated reservoir supplying interflow, $S_{U2}$ (mm); a slow flow groundwater reservoir, $S_{GW}$ (mm); and a hydrologically passive solute mixing reservoir, $S_P$ (mm) (Table 2.1, Figure 2.2). We use a forward Euler numerical approximation at a daily time step to solve the equation set for all simulations. The models have a similar number of calibration parameters (6 for 1WW and 7 for 2WW) in order to minimize performance effects due to differences in the number of parameters (Perrin et al., 2001). Both models use the same underlying mathematical representations for hydrologic dynamics over a time step. Relevant state and flux equations are given in Table 2.2. The models differ only in how water and solutes are routed within a time step, primarily based on unsaturated storage being organized in serial (1WW) or parallel (2WW).

Figure 2.2 Model structures for (a) one water world (1WW) and (b) two water worlds (2WW). All water is mobile for 1WW, but plant available reservoir $S_{U1}$ in 2WW is isolated from outflow to the stream. The red line indicates chloride mass transfer between unsaturated reservoirs $S_{U1}$ and $S_{U2}$ in 2WW.
Table 2.1 Reservoir conceptualizations consistent between models

<table>
<thead>
<tr>
<th>Reservoir</th>
<th>Conceptualization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unsaturated Reservoir 1 (S\textsubscript{U1})</td>
<td>Slow flow unsaturated storage; plant available</td>
</tr>
<tr>
<td>Unsaturated Reservoir 2 (S\textsubscript{U2})</td>
<td>Fast flow unsaturated storage; preferential macropore flow</td>
</tr>
<tr>
<td>Groundwater Reservoir (S\textsubscript{GW})</td>
<td>Slow flow saturated storage</td>
</tr>
<tr>
<td>Passive Mixing Reservoir (S\textsubscript{P})</td>
<td>Storage available for mixing but hydrologically inactive; riparian zone and weathered groundwater below streambed elevation</td>
</tr>
</tbody>
</table>

Table 2.2 Water balance and flux equations for the models

<table>
<thead>
<tr>
<th>Reservoir</th>
<th>Storage Water Balance</th>
<th>Fluxes and State Equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unsaturated Reservoir 1 (S\textsubscript{U1})</td>
<td>( \frac{dS\textsubscript{U1}}{dt} = R\textsubscript{U1} - ET ) (E1)</td>
<td>( C\textsubscript{R} = \frac{1}{1+\exp\left(\frac{-S\textsubscript{U1}/S\textsubscript{U1max}^{+0.5}}{B}\right)} ) (E5)</td>
</tr>
<tr>
<td>Unsaturated Reservoir 2 (S\textsubscript{U2})</td>
<td>( \frac{dS\textsubscript{U2}}{dt} = R\textsubscript{U2} - Q\textsubscript{U} ) (E2)</td>
<td>( R\textsubscript{U1} = (1 - C\textsubscript{R})P ) (E6)</td>
</tr>
<tr>
<td>Groundwater Reservoir (S\textsubscript{GW})</td>
<td>( \frac{dS\textsubscript{GW}}{dt} = R\textsubscript{GW} - Q\textsubscript{GW} ) (E3)</td>
<td>( R\textsubscript{U2} = C\textsubscript{R}(1 - C\textsubscript{P})P ) (E7)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>( R\textsubscript{GW} = C\textsubscript{R}C\textsubscript{P}P ) (E8)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( ET = E\textsubscript{P} \min\left(1,\left(\frac{S\textsubscript{U1}}{S\textsubscript{U1max}}\right)^{\frac{1}{L\textsubscript{P}}}\right) ) (E9)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( S\textsubscript{U2,in} = S\textsubscript{U2} + R\textsubscript{U2}dt ) (E10)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Q\textsubscript{U} = S\textsubscript{U2,in}(1 - e^{-k\textsubscript{U}t})dt^{-1} ) (E11)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( S\textsubscript{GW,in} = S\textsubscript{GW} + R\textsubscript{GW}dt ) (E12)</td>
</tr>
</tbody>
</table>
Passive Mixing Reservoir (S_p)

\[
\frac{dS_p}{dt} = Q_U - Q_P \quad \text{(E4)}
\]

\[
Q_{GW} = S_{GW,in}(1 - e^{-K_{GW}})dt^{-1} \quad \text{(E13)}
\]

\[
Q_{Tot} = Q_P + Q_{GW} \quad \text{(E14)}
\]

Table 2.3 Comparison of key characteristics of unsaturated reservoir 1 (S_{U1}) for 2WW and 1WW models.

<table>
<thead>
<tr>
<th></th>
<th>Two Water Worlds</th>
<th>One Water World</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Hydrologic connectivity</strong></td>
<td>Protected storage, hydrologically disconnected; plants extract different water than supplies streamflow</td>
<td>Hydrologically connected to other reservoirs; plants extract from same water pool that supplies streamflow</td>
</tr>
<tr>
<td><strong>Adherence to translatory flow</strong></td>
<td>When catchment wetness is high, some precipitation bypasses S_{U1} and does not participate in translatory flow</td>
<td>All precipitation flows through S_{U1} and is displaced by newer water, as stated by translatory flow concept</td>
</tr>
<tr>
<td><strong>Solute tracer transport between S_{U1} and S_{U2}</strong></td>
<td>Chloride transported via solute mass transfer between S_{U1} and S_{U2}</td>
<td>Chloride transported to S_{U2} from S_{U1} with water via advection</td>
</tr>
<tr>
<td><strong>Moisture dependence</strong></td>
<td>Greater portion of precipitation routed to storage when dry</td>
<td></td>
</tr>
<tr>
<td><strong>Solute tracer concentration effects</strong></td>
<td>Where chloride is enriched via evapotranspiration</td>
<td></td>
</tr>
</tbody>
</table>

The 1WW model is a modified version of models presented by *Hrachowitz et al.* (2014)

Hrachowitz et al. (2014). The primary adaptation is the inclusion of a passive mixing reservoir because damping and delay of the interflow solute signal was determined to be a crucial process for reproducing stream chloride concentrations in both 1WW and 2WW. In the 1WW model, all infiltrating precipitation \( P \) (mm d\(^{-1}\)) is first mixed in the plant available unsaturated zone reservoir before draining to subsequent reservoirs within the same daily time step,
reflecting the sequential transport processes of transitory flow (Table 2.3). In contrast, in 2WW, water is partitioned in parallel between $SU_1$ and preferential flow paths to $SU_2$ and $SGW$ such that fast flow water does not mix with the hydrologically disconnected water stored in $SU_1$. The portion of infiltrating precipitation partitioned to $SU_1$ decreases with increasing wetness conditions.

2.4.1 Model structure

2.4.1.1 Solute transport

Chloride is assumed to be fully and instantly well-mixed throughout each storage volume. In general, chloride mass is routed through each storage according to:

$$c_{out} = \frac{c_{in} * R_{in} + m}{S}$$

in which $c_{out}$ (mg mm$^{-1}$) is the outflowing concentration, $c_{in}$ (mg mm$^{-1}$) is the inflowing concentrating, $R_{in}$ (mm d$^{-1}$) is the flux of water into the reservoir, $m$ (mg) is the chloride mass in the reservoir in the previous time step, and $S$ (mm) is the water storage after the addition of water inflows for the time step but before water outputs are subtracted for the time step.

2.4.1.2 Unsaturated reservoir 1

Storage $SU_1$ represents the portion of the unsaturated zone that is available to plants for transpiration, commonly considered the dynamic portion of the unsaturated zone (Savenije, 2016). Soil moisture within $SU_1$ controls numerous sub-surface processes, including water
partitioning between storage, evaporation, and interflow. In 2WW and 1WW, the amount of
daily observed precipitation that gets stored in $S_{U1}$ is determined by partitioning coefficient $C_R$
which is a function of $S_{U1\text{max}}$ (mm), a parameter that reflects the maximum slow flow
unsaturated storage capacity (Table 2.2). Coefficient $C_R$ is controlled by shape parameter $\beta$. For
high soil moisture conditions $C_R$ tends to 1, indicating that little precipitation $P$ is partitioned to
$S_{U1}$. Moisture in the unsaturated reservoir is depleted by evapotranspiration $ET$ (mm d$^{-1}$), which
increases linearly with soil moisture until it reaches a fractional threshold, $L_P$, of the maximum
storage capacity, above which it is equal to potential evapotranspiration $E_P$. In 2WW, water
fluxes to groundwater ($R_{GW}$) and water fluxes to unsaturated reservoir 2 ($R_{U2}$) are routed
directly to $S_{GW}$ and $S_{U2}$ without mixing with water in $S_{U1}$. In 1WW, all precipitation is mixed with
$S_{U1}$ prior to entering subsequent storages, reflecting the sequential transport processes of
translatory flow. While the difference in mixing results in differences in chloride fluxes to each
reservoir, the equations describing the volume of water which is ultimately routed to each
storage for each time step ($R_{U1}$, $R_{U2}$, and $R_{GW}$) remain the same for both 1WW and 2WW. The
characteristics of $S_{U1}$ in 2WW are consistent with what is referred to as “bound” or “poorly
mobile” water in the two water worlds conceptual model (Brooks, 2015; Evaristo et al., 2015).

Potential evaporation estimates are required to calculate daily evapotranspiration in the
models. Daily reference evapotranspiration $E_R$ (mm d$^{-1}$) was estimated using the Hargreave’s
equation (Hargreaves and Samani, 1985), which is based on differences between measured
values of daily maximum and minimum air temperature:

$$ (2) $$
\[ E_R = 0.0023(T_{\text{mean}} + 17.8)(T_{\text{max}} - T_{\text{min}})^{0.5}R_a \]

in which \( T_{\text{mean}} \) is mean daily temperature, \( T_{\text{max}} \) is maximum daily temperature, \( T_{\text{min}} \) is minimum daily temperature, and \( R_a \) is extraterrestrial radiation. \( E_R \) and \( R_a \) are in units of equivalent water evaporation and temperatures are in °C. Potential evapotranspiration \( E_P \) is assumed to be equal to \( E_R \).

### 2.4.1.3 Unsaturated reservoir 2

Storage \( S_{U2} \) is a fast-responding reservoir representing macropores that contribute to lateral preferential flow to the stream (i.e., interflow). The portion of precipitation that is routed to preferential flow via \( C_R \), which includes both vertical and lateral components, is further partitioned between interflow and groundwater recharge (\( R_{U2} \) and \( R_{GW} \)) according to a calibrated preferential recharge coefficient, \( C_p \). Outflow from the mobile unsaturated reservoir is linear with storage and characterized by a calibrated storage coefficient \( K_{U2} \) (d\(^{-1}\)). In 1WW, \( S_{U2} \) is hydrologically connected to \( S_{U2} \), thus mediating connectivity between \( S_{U1} \) and flow paths that supply streamflow. In 2WW, \( S_{U1} \) is hydrologically disconnected from \( S_{U2} \). The characteristics of \( S_{U2} \) in 2WW are consistent with the “mobile” water described in the two water worlds hypothesis.

For 2WW, water contained within \( S_{U2} \) can only be depleted through evapotranspiration, but chloride is exchanged between \( S_{U1} \) and \( S_{U2} \) without yielding a net transport of water via solute mass transfer. Chloride exchange between \( S_{U1} \) and \( S_{U2} \) is modeled as:
\[
\frac{dc_{U2}}{dt} = -\alpha \frac{S_{U1}}{S_{U2}} \cdot (c_{U2} - c_{U1})
\]

in which \(c_{U1}\) (mg/mm) and \(c_{U2}\) (mg/mm) are the chloride concentrations in \(S_{U1}\) and \(S_{U2}\) respectively, \(t\) is time (d\(^{-1}\)), and \(\alpha\) (d\(^{-1}\)) is the mobile-immobile exchange coefficient. The mass-transfer formulation used to exchange solutes between \(S_{U1}\) and \(S_{U2}\) is based on a standard first-order rate-limited mass transfer model (Haggerty and Gorelick, 1995) and enforces solute exchange proportional to the difference in concentration between the reservoirs.

### 2.4.1.4 Groundwater reservoir

The groundwater reservoir represents baseflow contributions to stream discharge. The portion of precipitation that is partitioned to \(S_{GW}\) depends on partitioning coefficients \(C_{R}\) and \(C_{P}\).

Outflow from \(S_{GW}\) is linear with storage and characterized by storage coefficient \(K_{GW}\) (d\(^{-1}\)). \(K_{GW}\) was determined to be 0.05 d\(^{-1}\) a priori through calculation of a master recession curve (MRC) that represents the baseflow recession of the catchment (Fenia et al., 2006). The technique includes concatenating a set of recession segments by shifting them in time so that the curves overlap, forming an MRC. The lower portion of the MRC, which is assumed to characterize baseflow, defines a line when extrapolated and plotted semi-log. The line decreases one log cycle in time \(1/K_{GW}\). In 1WW, flow paths to \(S_{GW}\) first mix with \(S_{U1}\) within the same time step. In 2WW, flow paths to \(S_{GW}\) bypass the bound unsaturated zone water represented by \(S_{U1}\) but mix with mobile unsaturated zone water of \(S_{U2}\).
2.4.1.5 Passive mixing reservoir

The damped and time-lagged response of tracer time series relative to hydrologic responses to precipitation provides insight into catchment transit times and suggests the presence of hydrologically inactive mixing volumes that cannot be inferred from discharge dynamics alone (Benettin et al., 2015; Birkel et al., 2011). These residual storages do not influence hydrologic responses but are critical to simulating chemical signatures and estimating temporal scales of solute transport and mixing. We conceptualize this passive storage to mainly represent the riparian zone and weathered bedrock below the elevation of the streambed at our study site. Outflow from SU2 is routed through a passive storage volume, SP, to reproduce the observed damped and lagged chloride response.

2.4.2. Model architecture decisions

Models were iteratively developed to better reflect dominant catchment behavior while maintaining parsimony, closely following the procedures of Fenicia et al. (2011) and Kavetski and Fenicia (2011). An interception reservoir and snow component were tested and removed after having minimal effect on model performance. Similarly, infiltration-excess overland flow routing was incorporated in the models but did not improve model performance. This result was anticipated because soils within H. J. Andrews Experimental Forest are highly porous and infiltration rates are sufficiently high (typically > 20 cm h⁻¹) that overland flow rarely occurs (Dryness, 1969; Jones, 2000). We also tested incorporating a groundwater passive reservoir, but preliminary calibrations suggested little groundwater storage so this value was set to 0, consistent with Rodriguez et al. (2018) who found this parameter to be unidentifiable for WS10.
The catchment is steep and mainly composed of thin soils (~1 m deep) over shallow bedrock (van Verseveld et al., 2008), limiting saturated storage. Previous studies indicate that groundwater dynamics in WS10 are dominated by fracture flow, and a highly fractured region within the upper meter of bedrock provides a pathway for rapid lateral subsurface stormflow (Gabrielli et al., 2012). A passive reservoir in series behind $S_{U_2}$, determined to be important for damping and lagging of the chloride signal, is expected to account for most saturated riparian storage.

Evapotranspiration was initially assumed to remove water and chloride from $S_{U_1}$ with chloride removal represented as a fraction, $J$, of the reservoir concentration (Benettin et al., 2015). Chlorine is a necessary micronutrient for proper biogeochemical functioning and metabolism in plants (Hänsch and Mendel, 2009); it is taken up in small quantities by roots and can accumulate in foliage (Berger et al., 2001; Likens, 2013). Because $ET$ represents the combined fluxes of both evaporation and transpiration, $J$ was expected to be small. Preliminary calibration of $J$ was close to zero, implying that evapoconcentration of chloride in pore water is more important to catchment solute dynamics than removal by plant uptake. This is in accordance with the strong seasonal chloride signal observed in the stream. To reduce the number of calibration parameters, $J$ was fixed at zero for all simulations presented in this study, thereby neglecting plant uptake of chloride.

Several studies indicate seasonal transience of ecohydrologic separation in some climates (Hervé-Fernández et al., 2016; McCutcheon et al., 2017; Sprenger et al., 2017), such that the
two water worlds hypothesis does not apply during the wet season when catchments exhibit
increased hydrologic connectivity between soil pores. As such, we tested 2WW models in which
we conditioned hydrologic exchange between SU1 and SU2 to be dependent upon soil moisture
in the unsaturated reservoir. However, the additional complexity of moisture-dependent mixing
was not adequately supported by the available data, resulting in a reduction in parameter
identifiability. Therefore, we elected to present fully 1WW and 2WW models. We note that in
some catchments these models might represent seasonal endmembers in which 1WW reflects
wet season dynamics and 2WW reflects dry season dynamics.

2.4.3. Model evaluation

Data from 1 January 1989 through 31 December 2014 were used as model input. These 26
years were identified to have all required input data for the model. The first year of data was
used for model warm-up and the following 12 years for calibration. The final 13 years were
used for model validation. A spin-up period was employed prior to all simulations by running
the model through the first 13 years of data 10 times in order to establish appropriate initial
values for state variables from meteorological data and input parameter values. Variables
spanning orders of magnitude were sampled from a logarithmic parameter space to ensure
equal coverage across all orders of magnitude (Kelleher et al., 2013; Ward et al., 2013; Ward et
al., 2017), and a Latin hypercube scheme was used to sample the parameter space. A total of
50,000 parameter sets were simulated for each model formulation.
We used a multi-objective calibration approach by first selecting a hydrologic behavioral set and subsequently selecting a subset of chloride transport behavioral models from this hydrologically acceptable set. Lumped conceptual models can have limited predictive power even after acceptable hydrologic calibration, suggesting poor representation of internal processes (Gupta and Sorooshian, 1983; Hrachowitz and Clark, 2017; McDonnell et al., 2007). Multi-objective calibration approaches using information orthogonal to stream discharge, such as solute concentrations, have been proposed to constrain subsets of models that can adequately reproduce multiple response dynamic signatures (Benettin et al., 2015; Hrachowitz et al., 2014; Kim et al., 2016). Using a sequential approach of first selecting baseline models based on hydrologic behavior alone allows assessment of the influence of the additional tracer constraints. We used the Nash-Sutcliffe efficiency of discharge (NSQ) and logarithmic values of discharge (LNSQ) for calibrating hydrologic parameters against daily discharge. The logarithmic transformation of discharge results in increased sensitivity to systematic model under- or over-prediction relative to non-transformed Nash Sutcliffe efficiency by increasing the influence of low flow values compared to peak values (Krause et al., 2005). Because the chloride time series is less dynamic, Nash-Sutcliffe efficiency (NSCl) was selected for transport calibration. First, we eliminated models with an NSQ below 0.6 from the pool of potential behavioral models. Of the remaining models, the 500 models with the highest LNSQ were retained for the hydrologic behavioral set (1% of models, 500 total parameter sets). From within the hydrologic behavioral set, models within the top 10% for NSCl were selected for the retained feasible solutions (50 total parameter sets). The best model solution was selected based on the best performance for chloride within the behavioral set.
2.4.4 Statistical analysis

Kruskal-Wallis tests were performed to test whether behavioral set performance, parameters, median water storage within reservoirs, and median daily mean residence times differ between model structures using a significance threshold of 0.05. We take p < 0.05 as an indicator that differences between models are unlikely to be attributable to chance alone (i.e., 95% certainty of differences). Hereafter, we use the terminology “statistical significance at the 95% confidence interval” as a shorthand for this interpretation. Additionally, percent differences (Δ) in medians were calculated using:

\[
\Delta_{1,2} = \frac{X_{1\mathrm{WW}} - X_{2\mathrm{WW}}}{(X_{1\mathrm{WW}} + X_{2\mathrm{WW}})/2} \times 100
\]

in which 1WW and 2WW subscripts indicate values of interest for 1WW and 2WW, respectively, and \(X\) represents a parameter of interest. Subscripts for \(\Delta\) indicate differences between 1WW and 2WW (1,2), 1WW and 2WW mobile water only (1,2M), or 2WW and 2WW immobile water only (2,2IM).

The hydrologic residence time distributions for all time steps and storages were determined by tracking individual parcels of water of a given age through the models. Daily mean water residence time distributions for individual reservoirs were created using the storage-weighted mean residence time for each day of all models, with a total of 9,131 days of simulation for each of the 50 behavioral models for both 2WW and 1WW. Probabilities of water parcels of
given ages in the unsaturated zone on each day of the year were determined by summing the water in storage on a particular day of the year over all years and all model runs (1300 samples used to construct each daily probability distribution); these were then normalized by the total amount of water in storage on a particular day of the year over all years and all model runs.

2.5 Results

2.5.1 Parameter calibration and model performance

For model parameters to provide useful information, it is important that they are unique, optimal, robust solutions (Kelleher et al., 2013; Wagener et al., 2003; Ward et al., 2017). Model calibration resulted in identifiable values for calibrated parameters for both 1WW and 2WW (Figure 2.3, identifiability can be interpreted from steeper portions of the cumulative distribution and non-identifiable parameters appear linear across the calibration range). The levels of identifiability for the feasible solutions (post-selection based on chloride criteria) are higher than the initial hydrologic behavioral set, as indicated by a narrowing of the steep portion of the distributions. The identifiability range for some parameters, such as the maximum plant available unsaturated storage capacity $S_{U1max}$ and transpiration threshold $L_p$, are wider for 2WW than 1WW (Figure 2.3a and d).
Both models reproduce the features of the hydrograph well despite reduced-complexity structures (median $LNS_Q = 0.83$ and 0.82 for 1WW and 2WW calibration, Figure S2.1a-b; median $LNS_Q = 0.80$ for validation of both models, Figure 2.4a-b). The difference in median $LNS_Q$ between models for the calibration period is unlikely to be attributable to chance alone ($p = 0.01$), but the difference is not highly significant at the 95% confidence level and is small (0.01). This claim does not hold for the difference in median $LNS_Q$ over the evaluation period ($p = 0.93$), suggesting a higher degree of similarity. We also calculated $NS_Q$ (median $NS_Q = 0.73$ and 0.69 for 1WW and 2WW calibration period; median $NS_Q = 0.69$ and 0.67 for 1WW and 2WW validation). Reported values of $NS_Q$ are not significantly different at the 95% confidence level for either calibration ($p < 0.01$) or validation ($p = 0.01$). Both models under-estimate peak flows. It is not surprising that the

Figure 2.3 Identifiability of model parameters toward the objective functions. (a) maximum plant available unsaturated storage capacity $S_{U1max}$, (b) unsaturated reservoir 2 storage coefficient $K_{U2}$, (c) preferential recharge coefficient $C_P$, (d) transpiration threshold $L_P$, (e) runoff generation shape parameter $\beta$, (f) passive storage $S_P$, (g) mobile-immobile exchange coefficient $\alpha$. The black line is the preliminary hydrologic behavioral set and the blue and red lines are the retained feasible solutions for 2WW and 1WW, after implementing the selection procedure based on chloride concentration.
models reproduce the time series of flow similarly because they have the same underlying hydrologic equations. The small difference between the hydrologic performance range of 1WW and 2WW is due to the second calibration step, which eliminates models based on stream chloride performance.

The chloride objective function $NS_{Cl}$ shows acceptable model performance for 1WW and 2WW (median $NS_{Cl} = 0.78$ and 0.77 for 1WW and 2WW calibration, respectively; Figure 2.4c-d; median $NS_{Cl} = 0.77$ and 0.75 for validation, Figure S2.1c-d). Both models reproduce the pattern of seasonal chloride enrichment, including the timing and magnitude of oscillations. Similar to LNS$_Q$, the difference in median $NS_{Cl}$ over the calibration period is unlikely due to chance ($p < 0.01$), but the difference is small (0.02). The difference in median $NS_{Cl}$ is not significantly different at the 95% confidence interval between models.
for validation ($p = 0.31$). Overall, although there are some statistical differences between model evaluation criteria for discharge and chloride concentration for the calibration period, the magnitude of $p$-values relative to the significance threshold vary and median differences tend to be small, thus limiting their meaning in the context of this study. This could suggest that observed streamflow chloride concentration is not a strong predictor of unsaturated zone processes, such as ecohydrologic separation, in the catchment. Similarly, *Knighton et al.* (2017) observe minimal effects of unsaturated-zone percolation mixing on stream water isotopic signature and postulate that tracers in streamflow may not always be a strong feedback on internal catchment processes. *Kuppel et al.* (2018) observe some sensitivity of isotope tracers to unsaturated zone mixing processes, attributing the difference between the studies to a larger groundwater contribution at their site. Baseflow contributions in WS10 are relatively small, similar to the intermittent catchment studied by *Knighton et al.* (2017).

2.5.2 Comparing one- and two- water worlds parameters, storages, and residence times

Of the six calibration parameters common to both models, only two differ significantly between models at the 95% confidence level, $S_{U1max}$ and $C_P$ ($p < 0.01$, Figure 2.5). The magnitudes of percent differences are about 30% for both parameters. While the parameter range of $C_P$ is similar between models, the range of $S_{U1max}$ values in the 2WW behavioral set is about three times that of 1WW. The magnitudes of percent differences for the parameters that are not significantly different ($K_{U2}$, $S_P$, $L_P$, and $\theta$) range from 1% to
18%. When put in the context of calibration ranges, differences in parameters are not large.

Still, differences in parameters and solute routing result in variations in the simulated hydrologic function of the catchment (fluxes and stores of water). The medians of the mean simulated water storages for individual reservoirs $S_{U1}$ and $S_{GW}$ are unlikely due to chance ($p < 0.01$, Figure 2.6a and c), with differences of 21% and -29%, respectively.

Groundwater heights above bedrock during stormflow have been observed to be shallow in WS10 (10-15 cm, van Verseveld et al., 2008) and lie within the range of modeled groundwater storage during stormflow for both models when soil porosity is taken into account. Storage in fast flow reservoir $S_{U2}$ does not differ significantly between models ($p = 0.14$, Figure 2.6b). At the catchment scale we can compare differences between water
storage regardless of mobility, as well as compare mobile water volumes exclusively, which influence residence times (τ) of streamflow-generating water. Because all water is mobile in 1WW, these values are identical for total and mobile storage. For 2WW, mobile water storage (2WWM) excludes SU1 immobile storage (2WWIM) and unsaturated zone mobile water storage is equal to SU2. Unsaturated zone storage (SU1 and SU2) differs significantly between 1WW and 2WW for all water but is not highly significant at the 95% confidence level (p = 0.04, Figure 2.6d). Differences between 1WW and 2WWM are also unlikely to be attributable to chance (p < 0.01). While unsaturated zone storage for all water is larger for 2WW (Δ₁,₂ = 21%, 53 mm), mobile water unsaturated zone storage is smaller and the magnitude of the difference is much larger (Δ₁,₂𝑀𝑀 = −198%, −220 mm). Storage SU1 is two orders of magnitude larger than SU2 for both 2WW and 1WW (Figure 2.6a-b). Thus exclusion of SU1 from the mobile unsaturated storage volume for 2WW could be expected to result in a large negative difference in unsaturated zone mobile storage compared to 1WW. For total catchment storage (STot), the volumes of all water for 1WW (SU1, SU2, SGW, and SP) and 2WW (SU1, SU2, SGW, and SP) do not differ significantly (p = 0.10, Figure 2.6e). Mobile water volumes (SU2, SGW, and SP for 2WW) differ significantly at the 95% confidence interval (p < 0.01) and the magnitude of the difference is large (Δ₁,₂𝑀𝑀 = −137%, −233 mm).
Figure 2.6 Evaluation of behavioral set mean water storage. Subplots (a-c) compare storage between individual model reservoirs $S_{U1}$ (a), $S_{U2}$ (b), and $S_{GW}$ (c). Subplots (d-e) compare storage between one water world (1WW), combined mobile and immobile water of two water worlds (2WW), and mobile water of two water worlds (2WWM) for unsaturated storage $S_U$ (d) and total catchment storage $S_{Tot}$ (e). $\Delta_{1,2}$ = the difference between 1WW and 2WW storage and $\Delta_{1,2M}$ = the difference between 1WW and 2WW mobile water storage.

Due to large sample sizes, even small differences between distributions of daily mean residence times for behavioral model sets result in statistically significant differences ($p < 0.01$ for all reservoirs considered). Therefore, we proceed with interpreting only the magnitude of these differences when evaluating their importance. When considering all water stored in the unsaturated zone regardless of mobility, the 2WW median daily residence time is 102% (81 days) larger than 1WW (Figure 2.7a). However, in line with our expectations, when accounting for water mobility, the 2WW median residence time for mobile water (2WWM) is smaller than 1WW and the difference is -168% (-35 days). This is largely due to a smaller pool of mobile water in the 2WW unsaturated zone compared to 1WW. Furthermore, median residence time for 2WW immobile water is larger than 2WW total water but the difference is small ($\Delta_{2,2IM} = 2\%$, 3 days). On average, immobile water
makes up a larger portion of unsaturated zone storage for 2WW compared to mobile water (Figure 2.6); thus, the total unsaturated zone residence time distribution for 2WW is similar to that of the immobile fraction. The range of daily mean residence times for the total unsaturated zone is about four times larger for 2WW than 1WW.

Figure 2.7. Daily mean water residence time distributions for the behavioral model set for unsaturated storage \( S_U \) (a) and total storage \( S_{Tot} \) (b). Both plots show distributions for 1WW, 2WW (2WW all water), and 2WW\(_M\) (2WW mobile water). Plot (a) shows 2WW\(_{IM}\) (2WW immobile water). \( \Delta_{1,2} \) = the difference between 1WW and 2WW median daily residence times for all water, \( \Delta_{1,2M} \) = the difference between 1WW and 2WW median daily residence times for mobile water, and \( \Delta_{2,2IM} \) = the difference between 2WW all water and 2WW immobile water median daily residence times.

Similar to unsaturated storage, the median residence time for all water stored in the catchment for 2WW is larger than 1WW (74%, 55 days), consistent with observations of similar total water storage and modeled hydrographs. When considering only mobile water storage, 2WW median residence time is smaller than 1WW (-75%, -25 days; Figure 2.7b) and shows a bimodal distribution. This bimodal distribution is due to seasonal differences in residence times. During the wet season, a greater fraction of new precipitation is routed to \( S_{U2}, S_{GW}, \) and \( S_P \). This decreases residence times for the wet season relative to the dry season (Figure S2.2) when a smaller fraction of new precipitation is routed to these
reservoirs; instead, most new precipitation is stored in $SU_1$ under dry conditions. This moisture-dependent storage results in less seasonally-variable median residence times for $SU_1$. While seasonal differences in residence times hold for both 2WW and 1WW, the bimodal distribution is most apparent when considering only mobile water for 2WW because it excludes the more constant residence times of $SU_1$ and thus the seasonal shift makes up a larger percent difference (110% for 2WW$_M$ vs. 83% for 1WW and 43% for 2WW; Figure S2.2). Kuppel et al. (2018) found similar seasonal age variations in a small headwater montane catchment in Scotland using a fully distributed ecohydrologic model which incorporates tracking of water isotopes and age: hillslopes, which make up the majority of our study catchment, had median ages ranging from a week old during the winter to several months old during the growing season. The magnitude of these values are comparable to median residence times for total catchment 2WW$_M$ during the wet season (residence times of about 2 weeks) and 2WW or 2WW$_M$ during the dry season (residence times of several months). The range of daily mean residence times for the total catchment water is about twice as large for 2WW than 1WW.

In addition to comparing summary statistics for residence time distributions, we also calculated the time-variable residence time distributions for each day of the year (Figure S2.3 shows probabilities and Figure 2.8 shows cumulative probabilities). Residence times which correspond to precipitation during the wet season have high probabilities of being observed in storage, and residence times which correspond to the dry season inputs have low probabilities (Figure S2.3). Overall, probabilities tend to decrease as residence times
increase due to addition of younger water and continual depletion of water in storage. Water tends to be younger during the wet season, as indicated by a convergence of cumulative probabilities to 1 for shorter residence times compared to the dry season (Figure 2.8). The cumulative probability that a parcel of water is less than particular residence times (e.g., 5 days, 50 days, and 120 days; Figure 2.8d-f) is larger for 1WW than 2WW on all days of the water year when considering all water but is the opposite when considering only mobile water. For longer residence times, cumulative probabilities converge to 1 for both models (Figure 2.8f).

**Figure 2.8** Color denotes the probability a parcel of water in unsaturated storage is younger than a particular residence time (i.e., cumulative probability) on a particular day of the water year (Day 1 = October 1) for 1WW (a), 2WW (b), and 2WW\_M (mobile water). Red horizontal lines on a-c correspond to cumulative probabilities for residence times of 5 days (d), 50 days (e), and 200 days (f) throughout the water year. The blue shaded region indicates the late dry season (Jul-Sep).
2.6 Discussion

2.6.1 Representation of ecohydrologic separation

The 2WW model architecture we present is one realization of how ecohydrologic separation can be incorporated in a catchment-scale lumped model and is consistent with conceptual models of ecohydrologic separation. However, many process-specific questions remain in regards to 2WW. In this study, chloride transport through the unsaturated zone is conceptualized by assuming advective transport is limited to macropores, and transport between mobile and immobile zones is modeled using rate-limited mass transfer. Although the precise modes of mass transfer of solutes (e.g., dispersion, kinetic diffusion) have rarely been considered in isotopic studies, the isolated nature of water in 2WW necessitates a non-advective mechanism to mobilize concentrated chloride in $S_{U1}$ to mobile pathways to the stream, while not yielding a net transport of water. The incomplete displacement of preexisting water in soils by incoming water has long been recognized and represented in physically-based pore-scale models. For example, the mobile-immobile model of transport through heterogeneous porous media (Gerke and van Genuchten, 1993; van Genuchten and Wierenga, 1976) assumes that water in small pores is not directly connected to preferential flow paths to the stream, but is transported by first order diffusion between small and large pores. Similar conceptualizations have been applied to flow through porous media in fully saturated systems, commonly referred to as dual domain porosity (Goltz and Roberts, 1986; Haggerty and Gorelick, 1995; Singha et al., 2007). Although our model is not a mechanistic representation of pore-scale processes, we aim to represent the resultant behavior of similar processes at the
catchment scale. The simplified representation linking $S_{U1}$ and $S_{U2}$ in our model is consistent with mechanistic models of bound storage at smaller scales.

For the 2WW model, we assume that chloride transport between the mobile and immobile zones is independent of hydrologic forcing. However, we recognize that partial mixing of water between the mobile and immobile zones may be present under some hydrologic forcing conditions and soil textures. This is supported by studies showing that in some catchments ecohydrologic separation mechanisms are seasonal (Hervé‐Fernández et al., 2016; McCutcheon et al., 2017; Sprenger et al., 2017). Furthermore, it is expected that some portion of water is transported along the pressure head gradient between immobile and mobile pores to replace bound water taken up by plants (Berry et al., 2017; Gerke and van Genuchten, 1993) in addition to some solute transport via kinetic diffusion. Furthermore, Sprenger et al. (2018) found that accounting for isotopic exchange via water vapor in a two-pore domain model improved simulations of stable water isotopes in soils. Transport due to pressure head gradients between bound and mobile pores in the unsaturated zone is not represented in the 2WW model due to a lack of data to support representation of both chloride mass transfer and partial water exchange as a function of wetness conditions. Likewise, chloride transport via hydrologic exchange between $S_{U1}$ and $S_{U2}$ is represented in 1WW but mechanisms of chloride mass transfer are not. The addition of mechanisms must be balanced with the available data required to constrain models. In the future, calibration of 2WW lumped conceptual models using soil isotopic data (e.g., Birkel et al., 2010) could help to distinguish the balance between advective and
diffusive/dispersive transport processes, as well as the potential for moisture-dependent intermittent hydrologic connectivity between bound and mobile pores. Indeed, we expect that both mechanisms of solute mass transfer and water mixing would need to be incorporated to optimally model both chloride and isotopes in the catchment. The 2WW model we present represents the upper limit of differences we might observe if ecohydrologic separation were present year-round. In light of increasing data which supports seasonal transience of the ecohydrologic separation, it is plausible that both models hold for a single catchment during different times of the year; in such catchments, we would expect the 2WW model to better represent dry season dynamics whereas the 1WW model would better represent conditions under high antecedent rainfall when different sized soil pores become connected. However, we found that model performance did not improve when we added a moisture-dependent mixing mechanism between bound and mobile water, indicating that additional empirical data will be necessary to constrain the system.

The role of passive storage in ecohydrologic separation representation remains unclear. Passive storage has been conceptualized as the unsaturated storage below field capacity that is hydraulically inactive but available for mixing (Birkel et al., 2011). In some ways, the immobile portion of the unsaturated zone ($S_{UI}$) in 2WW represents the opposite: water that is hydraulically active, in that it comprises dynamic water storage and provides evapotranspiration fluxes, but which is not available for mixing with mobile water. Hrachowitz et al. (2013) implemented time-variable partial mixing between active and passive unsaturated storage, considering the potential importance of moisture-dependent
mixing between mobile and immobile storage on internal transport dynamics. Others have defined dual catchment storage conceptualizations which consist of direct storage, the fraction of the seasonally dynamic water volume which stream discharge is sensitive to, and indirect storage, which varies without directly influencing discharge (Carrer et al., 2019; Dralle et al., 2018). Dralle et al. (2018) interpret indirect storage volumes to consist of unsaturated storage held under tension in soils, moisture in weathered bedrock, and near-surface saturated storage which is eventually evapotranspired. These descriptions reflect some conceptualizations of passive storage, as well as incorporate aspects of the immobile storage volume $S_{U1}$; whereas immobile water comprises the majority of catchment storage in our study, Dralle et al. (2018) likewise determined that indirect storage comprised the majority of dynamic catchment storage. It has also been postulated that the distinction between passive and active storage in conceptual rainfall-runoff models may have implications for plant water availability (Birkel et al., 2011). In our study system, we conceptualize passive storage to mainly comprise the riparian zone and groundwater storage in weathered bedrock below the streambed elevation, resulting in placement of passive storage in serial arrangement with unsaturated reservoirs. As such, the passive storage reservoir lags and damps solute responses but does not interact with the plant water available reservoir or directly influence evapotranspiration rates. However, shallow groundwater table dynamics have been shown to strongly influence evapotranspiration in riparian zones and lead to discrepancies in modeled evapotranspiration (Kollet, 2009; Soylu et al., 2011). Consideration of the role of passive storage placement and mixing dynamics could have important implications for interpreted
water storage and residence times, as well as approaches for incorporating ecohydrologic separation in conceptual models. Furthermore, resolving distinctions between passive, indirect, and immobile storage volumes could inform mechanistic assessments of storage-discharge relationships and catchment-scale solute transport.

### 2.6.2. Identifiability and realism of the maximum plant available unsaturated storage capacity

Despite demonstrating adequate performance relative to the hydrologic objective function, the 2WW architecture reduced certainty in the estimation of $S_{U1max}$ as well as $L_p$. This indicates that additional calibration targets may be needed to reduce parameter identifiability issues when using a 2WW approach. Several methods have been used to independently estimate maximum root zone storage capacity, including (1) the mass curve technique (Gao et al., 2014), based on an engineering application for designing reservoirs; (2) soil-derived estimates based on the available storage between wilting point and field capacity (de Boer-Euser et al., 2016); and (3) a climate-based method which relies on the assumption that vegetation reserves a storage large enough to overcome drought conditions of a certain return period (de Boer-Euser et al., 2016). Furthermore, it is useful to consider the correspondence of parameter calibration to values estimated from other methods to assess confidence in a model’s correspondence to reality (Gharari et al., 2014; Kelleher et al., 2017). To investigate this, we used the climate-based method to estimate $S_{U1max}$ for comparison to the calibrated range for each model. This technique uses a simplified water balance model to estimate the required annual storages. Root zone
storage has zero moisture deficit during the wet period at the beginning of the simulation. Water deficit increases when transpiration exceeds net precipitation and excess precipitation is assumed to run off. A distribution of the yearly maximum deficits were used to determine the root zone storage capacity required for vegetation to bridge a drought of a 10 year return period, following (Gao et al., 2014). Using the same 26 year dataset of discharge and meteorological data for model calibration and validation, we estimated a root zone storage capacity of 480 mm. This value lies between the third quartile and upper limit for 2WW, but lies above the behavioral set range for 1WW (Figure 2.5a). This could indicate that 2WW model sets with $S_{U1max}$ close to this value better correspond to reality.

2.6.3 Ecohydrologic separation alters residence times and storages of water and solutes

Transport timescales are broadly recognized as a key control on biogeochemical function (Hill, 1990; Hrachowitz et al., 2016; Triska et al., 1989), because longer timescales allow more time for contact with biogeochemically active substrates in the landscape. Therefore, differences in residence times have implications for interpretations of reactive transport. As an example, we consider nitrification, an aerobic process that occurs in the unsaturated zone. The nitrification reaction rate constant in sandy loam soils has been reported to be on the order 1 d$^{-1}$ (McLaren, 1976) which corresponds to 99% removal by 5 days, assuming first-order kinetics. The probability that a parcel of water in the unsaturated zone is less than 5 days old is greater for 1WW than 2WW for all days of the year (Figure 2.8d), with the probability for 1WW being about 2 times larger than 2WW on average and about 3 times larger on average during the late
dry season (July-September). If using a 2WW model, we would interpret more complete nitrification occurs in the unsaturated zone as a whole compared to 1WW. Mobile water of 2WW, though, is about 4 times more likely on average to be less than 5 days old compared to 1WW. Consequently, using a 2WW model would result in the interpretation of lower total nitrification for the portion of water which supplies streamflow compared to 1WW. Thus, the differences in residence times for 2WW can substantially alter our expectations about biogeochemical processes operating in the watershed, and more generally how we would expect reactive transport to occur for many solutes or pollutants.

In addition to influencing water and solute transport, differences in where water is stored in the catchment alter interpretations of plant water availability. Although the difference in total catchment water storage is not significant between models (Figure 2.6e), the difference in storage is significant for the plant available reservoir $S_{U1}$ (21%, 52 mm, Figure 2.5a). Moreover, dry periods are of particular importance, not only because ecohydrologic separation has been observed to be strongest during the dry season, but dry periods also impart drought stress on plants. The percent difference in water storage in $S_{U1}$ is also greatest during the dry summer season (72%, 50 mm, Figure S2.4). To further demonstrate potential differences in plant water availability during dry periods, we compared cumulative distributions of plant available water storage (Figure 2.9). The 2WW model predicts more plant available water storage for all but the lowest 6.3% of days. The lower 25th percentile of $S_{U1}$ water storage is about twice as large for 2WW than 1WW (120.0 mm for 2WW versus 65.0 mm for 1WW). However, the lower 1st percentile of $S_{U1}$ is about three times larger for 1WW than 2WW (2.4
mm for 2WW versus 7.5 mm for 1WW). This indicates that although 2WW results in more plant available water storage for the driest 25% of days, this model results in more extreme low storage than 1WW. Alterations in dry period water storage within the plant available water pool for 2WW could have important implications for the expected resilience of ecosystems to environmental change.

2.7 Conclusions

In this study we demonstrated how incorporating ecohydrologic separation into a catchment-scale hydrologic model alters interpretations of the transport of water and solutes. In our goal of quantifying differences in internal functioning, we were guided by three expectations. First, we expected that the 2WW and 1WW models would predict stream discharge comparably well, but 2WW would more accurately predict seasonal enrichment in chloride. In line with expectations, the model formulations have similar performance metrics for stream discharge. However, both models also simulated the chloride timeseries similarly well. It is perhaps unsurprising that bulk water chemistry – which has been broadly reported and simulated for many years – did not necessitate adding the 2WW mechanism to improve model performance. Only with isotopic data did we update our conceptual model for storage and transport in the
unsaturated zone, which we show here has important consequences for how we understand catchments to store and release water and solutes.

We also expected that 2WW would result in an increased range of residence times in the unsaturated zone, with decreased residence times for mobile storage and increased residence times for immobile storage. In line with our expectations, 2WW increases the range of daily mean residence times in the unsaturated zone overall. Daily residence times for mobile water are shorter for 2WW, primarily due to a smaller mobile water volume compared to 1WW, and residence times for 2WW immobile water are longer relative to 1WW. Immobile storage makes up the majority of unsaturated storage for 2WW; therefore, daily mean residence times for the total unsaturated storage are also longer than 1WW overall. Despite mixed results for differences in calibrated parameters and water storages, meaningful differences in residence times and water availability emerge due to a combination of these differences and variations in 2WW and 1WW mobile water conceptualizations. Differences in unsaturated water storages and residence times between 2WW and 1WW also tend to be largest during the dry season, when ecohydrologic separation has been observed to be strongest.

Rather than identify a best model, the goal of this study was to inform how the two water worlds hypothesis presented in isotopic studies has the potential to change interpretations of stores and fluxes of water at the catchment scale. In fact, these models might reflect seasonal endmembers of wet and dry condition dynamics in some catchments. Although we used simple models and calculations, we showed that accounting for this small-scale process alters internal
catchment dynamics. We used estimates to relate these differences in internal catchment functioning to timescales for nitrification and the availability of water for vegetation, demonstrating the relevance these changes to conceptual hydrologic models have on ecological processes. There remains uncertainty about the conditions under which representation of ecohydrologic separation is necessary in hydrologic models and how it should be conceptualized. We provide a hypothesis of how ecohydrologic separation can be incorporated in a lumped conceptual model, but expect appropriate representation will vary by model type and catchment and evolve as our understanding of ecohydrologic processes increases. These questions provide opportunities for further conceptual and quantitative investigations to address catchment-scale water and solute transport under ecohydrologic separation and to test representations of ecohydrologic separation in hydrologic models of contrasting systems.

**Notation**

- $P$ Precipitation, $mm \ d^{-1}$
- $ET$ Evapotranspiration, $mm \ d^{-1}$
- $E_p$ Potential evapotranspiration, $mm \ d^{-1}$
- $S_{U1}$ Storage in slow unsaturated reservoir, mm
- $S_{U2}$ Storage in fast unsaturated reservoir, mm
- $S_{GW}$ Storage in groundwater reservoir, mm
- $S_P$ Passive storage for fast unsaturated reservoir, mm
- $S_{U1\text{max}}$ Maximum slow unsaturated storage
- $R_{U1}$ Recharge of slow unsaturated reservoir
\(R_{U2}\) Recharge of fast unsaturated reservoir

\(R_{GW}\) Recharge of groundwater reservoir

\(Q_U\) Runoff from fast unsaturated reservoir, \(mm \, d^{-1}\)

\(Q_P\) Runoff from passive reservoir, \(mm \, d^{-1}\)

\(Q_{GW}\) Runoff from groundwater reservoir, \(mm \, d^{-1}\)

\(Q_{Tot}\) Total runoff, \(mm \, d^{-1}\)

\(C_R\) Runoff generation coefficient

\(C_P\) Preferential recharge coefficient

\(L_P\) Transpiration threshold

\(K_{U2}\) Storage coefficient of slow unsaturated reservoir, \(d^{-1}\)

\(K_{GW}\) Storage coefficient of groundwater reservoir, \(d^{-1}\)

\(\beta\) Shape parameter for \(C_R\)

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2.8 References


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2.9 Supplemental

**Figure S2.1** Observed (red) and modeled (blue) stream discharge (a and b) and stream chloride concentrations (c and d) with 95% confidence intervals over the calibration time period. Objective function values (LNS and NS) are for the solution with the best chloride performance (blue line) and 5/50 (bold)/95th percentiles of the retained feasible solutions. Asterisks indicate objective functions used for calibration (LNS$_Q$ and NS$_C$).
Figure S2.2 Daily mean water residence time distributions for total storage $S_{Tot}$ for the wetter months (Oct-June) and late dry season months (Jul-Sep). Plots show distributions for 1WW (a), 2WW (b, 2WW all water), and 2WW$_M$ (c, 2WW mobile water). $\Delta$ = the difference between median daily residence times for the wet months and the dry months.
**Figure S2.3** Color denotes the probability a parcel of water in unsaturated storage has a particular residence time on a particular day of the water year (Day 1 = October 1) for 1WW (a), 2WW (b), and 2WW_M (mobile water); dark blue diagonals represent ages corresponding to precipitation during the driest portion of the year (probability ≈ 0). Red vertical lines on a-c correspond to residence time probability distributions on Day 30 (d), Day 120 (e), and Day 210 (f). Distributions for 1WW and 2WW_M continue beyond the y-axis limit. The blue shaded regions indicate water which originated during the late dry season (Jul-Sep).
Figure S2.4 Evaluation of behavioral set average water storage for the late dry season (Jul-Sep). Subplots (a-c) compare storage between individual model reservoirs $S_{U1}$ (a), $S_{U2}$ (b), and $S_{GW}$ (c). Subplots (d-e) compare storage between one water world (1WW), combined mobile and immobile water of two water worlds (2WW), and mobile water of two water worlds (2WW_M) for unsaturated storage $S_U$ (d) and total catchment storage $S_{Tot}$ (e). $\Delta_{1,2}$ = the difference between 1WW and 2WW storage and $\Delta_{1,2M}$ = the difference between 1WW and 2WW mobile water storage.
Chapter 3: Antecedent conditions control thresholds of tile-runoff generation and nitrogen export in intensively managed landscapes

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3.1 Abstract

Threshold changes in rainfall-runoff generation commonly represent shifts in runoff mechanisms and hydrologic connectivity controlling water and solute transport and transformation. In watersheds with limited human influence, threshold runoff responses reflect interaction between precipitation event and antecedent soil moisture. Similar analyses are lacking in intensively managed landscapes where installation of subsurface drainage tiles has altered connectivity between the land surface, groundwater, and streams, and where application of fertilizer has created significant stores of subsurface nitrogen. In this study, we identify threshold patterns of tile-runoff generation for a drained agricultural field in Illinois and evaluate how antecedent conditions—including shallow soil moisture, groundwater table depth, and the presence or absence of crops—control tile response. We relate tile-runoff thresholds to patterns of event nitrate load observed across multiple storm events and evaluate how antecedent conditions control within-event nitrate concentration-discharge relationships. Our results demonstrate that an event tile-runoff threshold emerges relative to the sum of gross precipitation and indices of antecedent shallow soil moisture and antecedent below-tile groundwater moisture deficit, indicating that both shallow soil and below-tile
storages must be filled to generate significant runoff. In turn, event nitrate load shows a linear
dependence on runoff for most time periods, suggesting that subsurface nitrate export and
storage can be estimated using runoff threshold relationships and long-term average nitrate
concentrations. Finally, within-event nitrate concentration-discharge relationships are
controlled by event size and the antecedent tile flow state because these factors dictate the
sequence of flow path activation and tile connectivity over a storm event.

3.2 Introduction

Nonlinear responses in rainfall-runoff generation (i.e., small changes in catchment wetness
leading to large changes in streamflow) have been documented in catchments spanning
physiographic and climatic regions (e.g., Ali et al., 2013; Weiler et al., 2005). Nonlinear or
threshold changes commonly reflect activation of runoff mechanisms or hydrologic pathways
(e.g., Kirchner, 2009; McGuire and McDonnell, 2010; Soulsby et al., 2015; Spence, 2007).
Consequently, identifying threshold relationships provides insight into the dominant
mechanisms of delivery and sources of water to streams, as well as how the relative
importance of mechanisms evolves over timescales ranging from individual events to multiple-
year weather patterns. These responses control the transport and fate of water and solutes in
the landscape, including the timing and magnitude of export (e.g., Macrae et al., 2010; Stieglitz
et al., 2003) and the potential for biogeochemical transformation (e.g., Covino, 2017; McMillan
et al., 2018). While threshold patterns and associated mechanisms have been widely described
in forested hillslopes (e.g., Detty and McGuire, 2010; Farrick and Branfireun, 2014; James and
Roulet, 2007; Penna et al., 2011), comparable studies are lacking in intensively managed
landscapes (IMLs) despite their prevalence. Thus, our overarching objective is to characterize rainfall-runoff threshold relationships and their role in controlling the storage and export of water and solutes in IMLs.

Human intervention has profoundly changed catchment drainage structure and biogeochemical function of IMLs (Blann et al., 2009; Kumar et al., 2018). Throughout humid agricultural regions of the Midwestern U.S., Canada, and northern Europe, subsurface drainage systems (commonly ‘tile drains’ or ‘tiles’) are widely installed to maintain soil moisture conditions amenable to crop production. An estimated 56 million acres of U.S. farmland are tile-drained, about 14% of total U.S. cropland (USDA, 2017; Zulauf and Brown, 2019). Relative to undrained systems, tiles create a physical threshold that alters connectivity between the land surface, groundwater, and streams (Gedlinske, 2014; Kleinman et al., 2015; Macrae et al., 2019). Flow through tile drains may represent 40-95% of annual watershed discharge in IMLs (King et al., 2014; Macrae et al., 2007; Schilling and Helmers, 2008; Williams et al., 2015). Perhaps unsurprisingly, these dominant flow pathways for water also account for much of the nitrate, phosphorus, and pesticide loading to downstream waterways (e.g., Baker and Johnson, 1981; Buhler et al., 1993; King et al., 2015; Kladivko et al., 2001; Randall and Mulla, 2001; Saadat et al., 2018; Sims et al., 1998). Moreover, tiles are particularly important during storm events, when a disproportionate amount of annual nutrient loads are mobilized from landscapes to streams (Royer et al., 2006). Despite the widespread installation of tiles and their recognized role in transmitting water and solutes from the landscapes they drain, their role in controlling the timing, magnitude, and sources of runoff and nutrients is not well understood.
Two predominant models exist to describe tile-runoff generation, with contrasting implications for the storage, transformation, and export of water and nutrients from IMLs. One mechanism is based on infiltration in excess of a water holding capacity within the upper soil layers (Klaus et al., 2013), hereafter described as ‘top-down’ runoff generation. At the beginning of a storm, only a small amount of water reaches the tile via macropores, primarily event water. Once a soil water capacity threshold is reached, soil water contributions are activated and enter preferential flow paths, corresponding to a large increase in tile flow. This conceptual model suggests preferential flow through macropores directly connected to tile drains. It also predicts that tile flow consists primarily of pre-event water and nutrients displaced from the soil matrix of upper soil layers (Liu et al., 2020; Williams et al., 2018). A second, contrasting conceptual model for tile function is based on groundwater table dynamics, hereafter described as ‘bottom-up’ runoff generation. In this model, the potentiometric surface intersects the tile drain perennially (e.g., Schilling and Zhang, 2004), seasonally (e.g., King et al., 2014), or ephemerally (e.g., Kleinman et al., 2015). Consequently, tile flow is initiated in response to groundwater table rise after a storm event. While the two potential tile-runoff generation mechanisms differ, the models agree that a moisture-based threshold is necessary to explain the hydrologic function of tile-drained landscapes. Event response is ‘primed’ by either pre-event soil moisture or groundwater table elevation. For example, Lam et al. (2016) attributed seasonal differences in tile-runoff response to a threshold of soil moisture content in upper soil layers. Other field studies and conceptual models posit groundwater depth is an important
factor in tile-runoff generation, where below-tile storage must be filled to raise the groundwater table for bottom-up activation (Davis et al., 2014; Vidon and Cuadra, 2010).

In addition to controlling the hydrologic activation of tiles, antecedent conditions also influence the transport of nutrients associated with this runoff. At interannual timescales, IMLs exhibit chemostatic nitrate export regimes, with legacy sources providing a continuous supply of nitrogen (Basu et al., 2010; Van Meter et al., 2016). However at event timescales, stream nitrate concentrations often exhibit systematic variability in response to changing discharge (Duncan et al., 2017). Concentration-discharge (i.e., c-Q) relationships can be interpreted to infer changes in water sources (Chanat et al., 2002; Evans and Davies, 1998) and event activation thresholds for runoff mechanisms (Rose et al., 2018). Within-event c-Q commonly takes the form of hysteresis loops, whereby a clockwise rotational pattern occurs when discharge response lags solute response and a counterclockwise rotational pattern occurs when solute response lags discharge response. Liu et al. (2020) found that tile drain nitrate c-Q hysteresis patterns tended to be counterclockwise, consistent with predominantly counterclockwise nitrate c-Q observed in streams draining tiled agricultural watersheds (Blaen et al., 2017; Outram et al., 2016; Williams et al., 2018). In contrast, studies in agricultural watersheds which did not report the presence of tiles documented predominantly clockwise nitrate c-Q (Chen et al., 2012; Jiang et al., 2010), suggesting that tiles are a strong influence on transport processes controlling nitrate dynamics within tile-drained catchments.
While hysteretic behavior may show overall tendencies according to landscape type (Kincaid et al., 2020), c-Q dynamics can also vary dramatically between events in response to differences in antecedent conditions and storm characteristics (e.g., Davis et al., 2014). Antecedent wetness conditions and hydroclimatic variables (e.g., precipitation intensity and amount) interact to influence the evolution of hydrologic connectivity in the landscape during a storm, and this connectivity subsequently activates runoff pathways that control c-Q relationships. However, findings of how these factors influence hysteresis patterns in tile-drained catchments vary. For example, Blaen et al. (2017) found that an increase in counterclockwise hysteresis was associated with lower soil moisture in the week preceding an event and high rainfall intensity during events. In contrast, Williams et al. (2018) found that hysteresis was not significantly correlated with antecedent wetness or storm event size in a majority of watersheds studied, attributing the lack of correlation to consistent groundwater table rise or seasonal differences in nitrate availability.

In this study, we aim to identify how antecedent conditions control thresholds of tile-runoff generation, and, in turn, observed between- and within-event dynamics in nitrate export from the landscape. Building upon existing studies of IMLs that have primarily focused on either top-down or bottom-up tile-runoff generation mechanisms, we test three expectations. First, we expect a tile-runoff threshold to emerge relative to the sum of gross precipitation and an index of antecedent wetness. In other words, a defined volume of storage must be filled to activate significant tile-runoff. This volume will depend upon either (a) antecedent shallow soil moisture, indicating primarily top-down controls, or (b) antecedent below-tile groundwater
moisture deficit, indicating primarily bottom-up controls. Next, we expect that patterns of event nitrate load reflect runoff thresholds when evaluated over interannual timescales. Here, we assume a relatively chemostatic nitrate c-Q relationship at the scale of individual ‘tilesheds,’ such that event load has a linear dependence on event runoff. Finally, we expect antecedent wetness to control within-event nitrate c-Q relationships because threshold processes associated with runoff generation will be manifested in dynamic hydrologic connectivity in the landscape. To test these expectations, we use a combination of empirical data from a tile-drained field in the IML-Critical Zone Observatory and field-scale simulations of coupled water and nitrogen cycles using the Dhara model (Le and Kumar, 2017; Woo and Kumar, 2019).

3.3 Methods

3.3.1 Site Description

The study site is the Allerton Trust Farm which is part of the Intensively Managed Landscapes Critical Zone Observatory (IML-CZO) (Kumar et al., 2018; Wilson et al., 2018) located near Monticello, Illinois (40.0250, -88.6606, Figure 3.1). The region has a humid continental climate, with cold winters (average January temperature of -2°C) and warm summers (average July temperature of 23°C). Monticello receives an annual average precipitation of 1020 mm. Thunderstorms account for 50-60% of annual precipitation (Angel, 2003) in Illinois, and about half of thunderstorm days occur in the summer, although storms frequently occur during all seasons.
The site is located within the Upper Sangamon River Basin (USRB). The watershed is representative of the glaciated Midwest, characterized by low-gradient topography and poorly draining soils. Soil profiles at the study site reflect glacial deposition patterns, with very deep, poorly draining soils formed under loess, and bedrock depths 50–100 m below the surface. Soils within the monitored tile drainage network belong to the Ipava silt loam and Sable silt clay series (NRCS, 2020), and the field is nearly flat with land surface slopes ranging from 0 to 2%. The region has undergone significant anthropogenic changes over the last two decades. Prior to European settlement, the USRB was 90% prairie and 10% forest (IDNR, 1999), with forested portions mainly located in riparian zones. Today 90% of land use in the watershed is row crop agriculture, primarily corn and soybeans, and the majority of cropland is tile-drained. Wetlands historically covered about 40-50% of the land area but now make up less than 2% (IDNR, 1999; Rhoads et al., 2016), primarily due to the installation of tile drains and ditches which has artificially lowered the water table. Subsurface flows rather than direct surface runoff are the primary pathway by which water and
nutrients enter surface waters in the USRB (Demissie et al., 1996), and subsurface flows are mainly conveyed by tile drains (Botero-Acosta et al., 2018).

The farm is about 60 ha total, but the monitored tile network drains an estimated 10 ha based on analysis of aerial photography (Kratt et al., 2020). The drainage network consists of five individual 10-cm diameter perforated pipes, each about 400 m long and spaced 30 m apart, draining into a 10-cm diameter main that empties into a surface drainage ditch. The tiles are about 1–1.2 m below the land surface. The field is not irrigated, so the only water input is precipitation. An annual crop rotation of corn-soybean, a common practice in the Midwestern U.S., is used. During the study period, corn was planted in 2016, 2018, and 2020, and soybean was planted in 2017 and 2019. Prior to the monitoring period, anhydrous ammonia was applied in the fall of 2015 (Table 3.1). During the monitoring period, 32% urea and ammonium nitrate solution (UAN) was applied in the spring when corn was planted. In spring 2016, 2018, and 2020, 32% UAN was applied as an herbicide carrier in April prior to crop planting. In spring 2018 and 2020, 32% UAN was side-dressed in May after emergence. Each spring, the field was cultivated. During the fall after corn was planted, the field was chisel-plowed to cut and incorporate stalk residue into the soil to preserve soil organic matter and protect against erosion.
Table 3.1  Nitrogen fertilizer application at field site

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td><strong>Fall 2015</strong></td>
<td>179 kg N ha(^{-1}), anhydrous ammonia</td>
</tr>
<tr>
<td><strong>Spring 2016</strong></td>
<td>April: 50 kg N ha(^{-1}), 32% UAN applied as herbicide carrier</td>
</tr>
<tr>
<td><strong>Spring 2018</strong></td>
<td>April: 50 kg N ha(^{-1}), 32% UAN applied as herbicide carrier</td>
</tr>
<tr>
<td></td>
<td>May: 140 kg N ha(^{-1}), 32% UAN applied as side-dress</td>
</tr>
<tr>
<td><strong>Spring 2020</strong></td>
<td>April: 60 kg N ha(^{-1}), 32% UAN applied as herbicide carrier</td>
</tr>
<tr>
<td></td>
<td>May: 140 kg N ha(^{-1}), 32% UAN applied as side-dress</td>
</tr>
</tbody>
</table>

*UAN = urea and ammonium nitrate solution

3.3.2 Field and Laboratory Methods

Tile discharge, precipitation, and soil moisture were monitored throughout the 4-year study period at 15 minute intervals (April 2016 to June 2020). Tile discharge was measured within the tile main about 10 m from the outlet using a v-notch weir equipped with Decagon CTD-10 pressure transducers. Precipitation was measured using a Texas Electronics TR-525I tipping bucket rain gauge. Volumetric soil water content (VWC) was measured hourly at 5 cm and 20 cm depths using Decagon 5TE VWC dielectric soil moisture sensors installed in a grassed buffer strip near the tile drain outlet. A Teledyne ISCO 3700 was installed in the tile main near the outlet to automatically collect water samples during periods of tile flow. Samples were collected over a four year period: May–October 2016, February–July 2017, April–June 2019, and January–March 2020. After collection from the ISCO, water samples were filtered using 0.45 µm polypropylene filters and frozen until analysis. Nitrate (NO\(_3\)-N) concentrations were determined using ion chromatography.
3.3.3 Modeling Methods

To supplement field observations with a mechanistic simulation, we used the coupled surface-subsurface flow and soil-vegetation-atmosphere interaction model *Dhara* (*Le and Kumar*, 2017; *Woo and Kumar*, 2019) to simulate the hydrologic and biogeochemical dynamics of a parcel of tile-drained land. The model is used here as a heuristic, providing a basis for interpretation of the processes that are likely to underlie our field observations. The model was previously calibrated and validated for a tile-drained site in DeLand, Illinois that has similar soils, topography, and drainage infrastructure to Allerton Trust Farm and is also located within the USRB. A corn-soybean crop rotation is used at the site, and this rotation is also employed in model simulations. Compared to observed tile flow, simulated flow was muted during high peak flows, which also affected the accuracy of nitrogen loads at high flow. However, tile flow and nitrate loads captured the patterns of the observed data well overall, providing confidence in the use of the simulation results for process investigation. Refer to *Woo and Kumar* (2019) for a detailed description of the parameters and equations governing the model. A schematic diagram of *Dhara* is provided in Supplemental Information (Figure S3.1). A small number of alterations were made to the model application of *Woo and Kumar* (2019) to address the goals of this study. To simulate the groundwater table, the depth of the model was increased to 3.5 m, with the tile located at 1.2 m below the ground surface. While a horizontal mesh of 1.8 × 1.8 m was maintained, a finer vertical grid resolution of 0.1 m was employed to more accurately simulate the groundwater table and below-tile soil moisture. To account for the additional computational requirements of a finer grid and deeper domain, a smaller representative sub-domain consisting of 55 × 55 grid cells was simulated. Of this domain, the inner 50 × 50 grid
cells (90 × 90 m) were analyzed to reduce the effects of numerical boundary conditions. A weather generator was used to create a time series of precipitation as input for the model. Parameters for the weather generator were estimated using meteorological data observed between 1991 and 2010 and obtained from Weather Underground (http://www.wunderground.com). For the simulation, UAN fertilizer was applied at a rate of 15.2 g m⁻² in the spring prior to planting corn. Model output used in our analysis included hourly time series of soil moisture and tile discharge and daily time series of tile nitrate flux.

### 3.3.4 Storm event selection and hydrograph separation

In order to identify relationships between event tile-runoff and antecedent catchment wetness, we first defined a procedure for selecting the tile-runoff volume, gross precipitation, and antecedent moisture conditions associated with discrete storm events. Event selection followed one of two methods, depending on whether precipitation resulted in tile flow, and the same procedures were used for field and model data. If precipitation initiated a tile response, storm event runoff included the period between an initial increase in discharge until either discharge returned to approximately the initial value or increased in response to a different storm. Compound storm events (i.e., those with significant hydrograph overlap between multiple events) were omitted from the runoff threshold analyses. However, compound events were included in the within-event nitrate c-Q analyses, in which we investigated the influence of antecedent tile flow state on event-scale concentration dynamics and flow paths. Events in which snowmelt was expected to contribute to stormflow were also omitted in runoff threshold analyses due to uncertainties in the amount and timing of inputs. While tile flow at
the site mainly consisted of stormflow, tiles contributed some baseflow to the drainage ditch during wetter periods. As such, stormflow volumes were determined using the constant slope hydrograph separation method (Hewlett and Hibbert, 1967). For storms that resulted in a tile response, gross event precipitation was defined as the total precipitation that occurred up to one day prior to the initial tile storm response until the end of the tile storm response. For storms that did not initiate tile flow, gross event precipitation was calculated as total precipitation that occurred over a day or over consecutive days with precipitation. Gross precipitation over the considered time period had to exceed 1mm to be included in the analysis. Soil moisture values immediately preceding the considered precipitation time period were used to determine an antecedent soil moisture index (ASI), calculated as the total soil water content within the surface soil layer expressed as depth (mm). For this study, we consider the surface soil layer to be 0–0.3 m depth as an indicator of antecedent soil moisture conditions largely independent of groundwater dynamics. ASI is calculated as:

\[ ASI = \sum_{i=1}^{n} VWC_i \times D \]

where VWC\(_i\) is the volumetric water content (mm/mm) in the \(i^{th}\) sublayer, and D is the layer thickness (mm). We used \(n = 2\) sublayers, with the VWC for 0–5 cm soil depth estimated from the sensor at 5cm depth and VWC for 5-30 cm soil depth estimated from the sensor at 20 cm depth.
3.3.5 Tile-runoff relationships: calculations and data analysis

We analyzed relationships between storm event tile-runoff and wetness metrics to identify how antecedent wetness controls event tile-runoff. For field data, analyzed wetness metrics included gross precipitation ($P_{gross}$), ASI, and the sum of gross precipitation and ASI ($P_{gross} + \text{ASI}$). Model analysis included an additional metric of a below-tile groundwater moisture deficit ($GW_{def}$), calculated as the depth-equivalent unsaturated pore volume below the tile (mm). In other words, $GW_{def}$ represents the depth of water needed to raise the water table to the tile elevation and is calculated as:

$$GW_{def} = - \sum_{i=1}^{n} (VWC_S - VWC_i) \times D$$

where $VWC_i$ is the modeled volumetric water content (mm/mm) of the $i^{th}$ layer beneath the tile, $VWC_S$ is the volumetric water content of the soil at saturation (0.56 mm/mm), and $D$ is the layer thickness (100 mm). $GW_{def}$ has a negative value and decreases the overall wetness metric because it indicates a lack of moisture that must be overcome to initiate tile-runoff.

In the absence of field observed below-tile moisture data to explore the effect of bottom-up controls, the antecedent groundwater table position was inferred from tile flow conditions and gross precipitation over the days leading up to the event. Similarly, previous investigations of nonlinear rainfall-runoff response have used proxies for inferring antecedent water storage when soil moisture observations were unavailable, including the duration of inter-storm dry
periods (Graham and McDonnell, 2010) and the amount of water input required for runoff to initiate (Ali et al., 2015). Here, storm events were categorized as “GW_{def} low,” indicating that the groundwater table was expected to be near the tile elevation such that the antecedent below-tile moisture deficit was near zero, if antecedent conditions met either of the following criteria: gross precipitation for the day prior to the event (i.e., 2 days prior to initial tile storm response) exceeded 20 mm or tile flow volume during the 6 days prior to the event exceeded 10 m$^3$. This procedure was implemented to exclude events in which the antecedent groundwater deficit was high but direct percolation to the tile resulted in a small amount of tile flow. If an event did not meet the above criteria, it was categorized as “GW_{def} high,” and the groundwater table was expected to be significantly lower than the tile such that antecedent below-tile moisture deficit was high. We also investigated how the presence or absence of crops affects event tile-runoff by categorizing storm events as occurring either during the growing season or during the non-growing season. Growing season events occurred when crops were present and water uptake was largest, during the months of June, July, August, or September. We expected that large seasonal fluctuations in water uptake and interception of precipitation in IMLs due to presence or absence of crops could pose an additional top-down moisture control on tile-runoff generation. During the growing season, a larger $P_{gross} + ASI$ value would be needed to initiate tile flow due to greater water uptake and interception by crops. Therefore, the runoff initiation threshold relative to $P_{gross} + ASI$ would be larger than during the non-growing season.
To identify potential thresholds within each group and compare threshold relationships between groups (e.g., $GW_{def}$ high versus $GW_{def}$ low), we used linear regression analysis to test for relationships between event tile runoff and wetness metrics for storm events exceeding a wetness value identified within each group. The value above which events were included in above-threshold regression was chosen using a binary logistic regression which modeled the probability of a storm event producing tile flow as a function of the wetness metric being considered. The response variable had two categories, either a storm produced tile flow or not. Storm events were included in the above-threshold linear regression if the they corresponded to a wetness metric at which the modeled probability that the storm would produce tile flow exceeded 0.5. The runoff threshold was estimated as the value at which the linear regression intercepted zero event tile-runoff.

### 3.3.6 Nitrate export: calculations and data analysis

Because our expectation that total event nitrate loads reflect runoff thresholds is based on the assumption of a chemostatic nitrate export regime at interannual timescales, we first examined the effect of discharge and time of sampling on nitrate concentrations using analysis of covariance (ANCOVA) and linear regressions. Field nitrate data were categorized into 5 seasonal time periods: Y1 Corn Spring/Summer (May–June 2016), Y1 Corn Summer/Fall (July–Oct 2016), Y2 Soy Spring/Summer (March–June 2017), Y3 Soy Spring/Summer (April–June 2019), and Y4 Winter (Dec 2019–March 2020). We expected that these time periods could reveal differences in nitrate concentration resulting from yearly/seasonal management decisions (e.g., fertilization, crop type). All statistical analyses were conducted in MATLAB, and we use a
significance threshold of 0.05. We performed the ANCOVA using the `anovan` function, including discharge as a covariate. This procedure enabled analysis of differences between time periods after the effects of discharge were removed. We followed with a Tukey post hoc test using the `multcompare` function to analyze the main effect of time period. We explored the effect of heteroscedasticity and deviations from normality by performing statistical analyses on log_{10}-transformed data and found no change in results (Table S3.1). As such, we report results of analyses performed on the non-transformed data. Based on the Tukey post-hoc test, we grouped time periods and performed linear regressions to determine the relationship between discharge and nitrate concentration. Slopes not significantly different from zero would support chemostasis over those time periods. Linear regressions were fit to total event nitrate load and event tile-runoff based on these groupings. We also performed linear regressions on modelled nitrate loads and event tile-runoff for comparison with field data.

Nitrate c-Q relationships were analyzed for field-observed data to evaluate how antecedent conditions influence within-event nitrate dynamics and infer runoff mechanisms. We selected only events in which we obtained nitrate samples throughout the hydrograph (at least 3 samples on the rising limb) and excluded compound events. Thus, 18 distinct storm events were included in the analysis. A similar analysis was not conducted on model data because the daily output of nitrate flux did not typically allow for multiple data points on the rising limb. To quantify event-based hysteretic behavior, we calculated hysteresis (HI) and flushing (FI) indices, which are described in detail in *Vaughan et al.* (2017) and adapted from *Lloyd et al.* (2016) and
Butturini et al. (2008). Both indices are based on values of either discharge or nitrate concentration normalized over the event to range between 0 to 1:

\[ Q_{i,\text{norm}} = \frac{Q_i - Q_{\text{min}}}{Q_{\text{max}} - Q_{\text{min}}} \]

(3)

\[ c_{i,\text{norm}} = \frac{c_i - c_{\text{min}}}{c_{\text{max}} - c_{\text{min}}} \]

(4)

where \( Q_i \) and \( c_i \) are the discharge and nitrate concentration values at the \( i \)th time step, \( Q_{\text{min}} \) and \( c_{\text{min}} \) are the minimum discharge and nitrate concentration values over the storm event, and \( Q_{\text{max}} \) and \( c_{\text{max}} \) are the maximum discharge and nitrate concentration values over the storm event. The normalization procedure enables comparison between storm events of different magnitudes. To calculate the hysteresis index, we first linearly interpolated \( c_{i,\text{norm}} \) to identify concentration values on both the rising and falling limbs at intervals of \( Q_{i,\text{norm}} \) (i.e., concentrations corresponding to a tile discharge value on both the falling and rising limbs). The hysteresis index was then calculated as:

\[ HI = \frac{\sum_{j=1}^{n}(c_{j,\text{rising}} - c_{j,\text{falling}})}{n} \]

(5)

where \( HI \) is the hysteresis index, \( c_{j,\text{rising}} \) and \( c_{j,\text{falling}} \) are the interpolated values of \( c_{i,\text{norm}} \) at the \( j \)th interval of \( Q_{i,\text{norm}} \) on the rising and falling limbs respectively, and \( n \) is the total number of intervals. For this study, we used \( n = 10 \) intervals. Values of \( HI \) range from -1 to 1, where
positive values indicate clockwise hysteresis (rising limb concentrations greater than falling limb on average) and negative values indicate counterclockwise hysteresis (rising limb concentrations less than falling limb on average). The magnitude of HI represents the strength of hysteresis. The flushing index, indicating the degree of flushing or dilution over the rising limb, was calculated as the difference between the normalized concentration at the time of peak event discharge and the normalized concentration at the beginning of the event. Similarly, FI values range from -1 to 1, with the magnitude representing the degree of flushing or dilution. Positive values indicate an increase in concentration on the rising limb (flushing), and negative values indicate a decrease in concentration on the rising limb (dilution). We consider HI and FI values within 10% of the index range (between -0.1 to 0.1) to be neutral, following Butturini et al. (2008) and Liu et al. (2020).

3.4 Results

3.4.1 Controls of antecedent conditions on tile-runoff: field data

Time series of tile discharge, shallow soil moisture, and precipitation data were used to investigate how antecedent conditions control event tile-runoff. A total of 157 storm events were analyzed, 45 of which resulted in tile-runoff. We found that event runoff depth correlated with gross precipitation ($r^2 = 0.28$, Figure 3.2b) but not antecedent soil moisture (Figure 3.2a). When gross precipitation and antecedent soil moisture were summed ($P_{\text{gross}} + \text{ASI}$), a threshold relationship emerged, and the above-threshold correlation was larger ($r^2 = 0.39$, Figure 3.2c) relative to the correlation with gross precipitation alone.
We performed additional analyses to explore whether antecedent below-tile moisture deficit and the presence of crops pose additional controls on tile-runoff response. If below-tile moisture deficit was an important control, we expected that $GW_{\text{def}}$ low events would have a strong linear correlation above the $P_{\text{gross}} + \text{ASI}$ threshold, but $GW_{\text{def}}$ high events would be overestimated by the above-threshold trendline for $GW_{\text{def}}$ low events. Overall, we found this to be the case: $GW_{\text{def}}$ low events showed a strong correlation above the $P_{\text{gross}} + \text{ASI}$ threshold ($r^2 = 0.79$, Figure 3.3a), whereas $GW_{\text{def}}$ high events showed more spread ($r^2 = 0.13$) and tended to be overestimated by the $GW_{\text{def}}$ low trendline. These data indicate that information on available below-tile storage is needed to predict storm event tile-runoff. We also expected that the presence of annual crops would pose an additional control on event tile-runoff. However, both growing season and non-growing season data showed considerable spread around the trend line (Figure 3.3b, “no crops” $r^2 = 0.42$ and “crops” $r^2 = 0.08$). The presence or absence of crops does not contribute additional information to ASI in explaining tile-runoff response.
3.4.2 Controls of antecedent conditions on tile-runoff: model data

In addition to field observations, hydrologic simulations of a tile-drained agricultural site provided 20 years of tile hydrologic response and additional below-tile soil moisture information to investigate how antecedent conditions control tile-runoff. We found that event runoff depth correlated with gross precipitation ($r^2 = 0.82$) but not ASI or $GW_{def}$ alone (Figure 3.4a, b, d). A threshold relationship emerged relative to $P_{gross}$ + ASI, with an above-threshold correlation of $r^2 = 0.85$ (Figure 3.4c). Similar to field data, the above-threshold correlation for $GW_{def}$ low events improved relative to all data ($GW_{def}$ low $r^2 = 0.94$ and all data $r^2 = 0.85$; Figure S3.2a). On average, the $GW_{def}$ low linear trend overestimated runoff for $GW_{def}$ high events. We
expected that adding the numeric below-tile groundwater moisture deficit ($GW_{\text{def}}$) to the catchment wetness metric would result in a clearer threshold trend with event tile-runoff. Indeed, we found that the runoff relationship with $P_{\text{gross}} + \text{ASI} + GW_{\text{def}}$ increased the above-threshold correlation ($r^2 = 0.90$) relative to $P_{\text{gross}} + \text{ASI}$. The above-threshold correlation relative to $P_{\text{gross}} + GW_{\text{def}}$ was similar to $P_{\text{gross}} + \text{ASI}$ ($r^2 = 0.85$). Thus, considering either $GW_{\text{def}}$ or ASI improves our ability to predict event tile-runoff using a threshold relationship. However, the strongest above-threshold trend emerges relative to an antecedent wetness metric which includes both ASI and $GW_{\text{def}}$, indicating that both are strong controls on tile-runoff initiation.

**Figure 3.4** Event tile-runoff for modeled storm events relative to (a) ASI, (b) $P_{\text{gross}}$, and (c) the sum of $P_{\text{gross}}$ and ASI (linear fit with intercept of 123 mm), (d) antecedent below-tile groundwater moisture deficit ($GW_{\text{def}}$) (e) the sum of $P_{\text{gross}}$ and $GW_{\text{def}}$ (linear fit with intercept of 27 mm), and (f) the sum of $P_{\text{gross}}$, ASI, and $GW_{\text{def}}$ (linear fit with intercept of 107 mm). Linear regressions for combined wetness indices are fit to values above a threshold wetness metric. n.s. = not significant.
3.4.3 Controls of antecedent conditions on total nitrate load across events

A total of 791 tile water samples were collected over about four years and analyzed for nitrate concentrations (Figure S3.3). ANCOVA results showed that there is a highly significant interaction between discharge and seasonal time period on nitrate concentration at the 95% confidence interval, $F(4,782) = 6.0, p < .001$ (Table S3.1), indicating that the effect of discharge on nitrate concentration depends on time period. A Tukey-Kramer post hoc test revealed that there is sufficient evidence that the adjusted mean nitrate concentrations are different between most groups ($p < .001$, Table S3.2) after controlling for discharge. This excludes the difference between Years 2 and 3 Soy Spring/Summer, which is not significant ($p = 0.88$).

However, while the magnitude of differences between Y1 Corn Spring/Summer and other time periods were large (14.4–18.4 ppm), differences were small between all other time periods (0.4–4.0 ppm). As such, we fit a linear regression through all data excluding Y1 Corn Spring/Summer, which was fit with a separate regression line (Figure 3.5a). The first trend line has an intercept of 9.3 ppm and small slope ($m = -0.001$), which is not meaningfully different than zero and indicates a chemostastic response at the interannual timescale. The fit through Y1 Corn Spring/Summer has a higher intercept of 25.8 ppm and more negative slope ($m = -0.004$), potentially indicating source limitation at higher flows. However, concentrations are also more sporadic over this period. Because nitrate concentrations during time periods other than Y1 Corn Spring/Summer exhibit similar nitrate concentrations and temporal invariance, the relationship between event nitrate load and event tile-runoff for these time periods are well approximated by a linear trend (Figure 3.5b, $r^2 = 0.98$). While Y1 Corn Spring/Summer is
not well approximated by the same trendline as other time periods, nitrate loads during this
time period are well approximated by a separate linear trend ($r^2 = 0.98$).

![Figure 3.5](image.png)

**Figure 3.5** (a) Relationships between observed NO$_3$-N concentration and tile discharge. Excluding Y1 Corn Spring/Summer which has higher NO$_3$-N concentrations overall, data exhibit similar concentrations and temporal invariance. (b) Observed event NO$_3$-N mass load plotted against event tile-runoff shows a strong linear relationship for most time periods, in accordance with the observed chemostatic nitrate export regime. Y1 Corn Spring/Summer is well approximated by a separate linear trendline. (c) Modeled event NO$_3$-N mass load plotted against event tile-runoff. Events with runoff less than 30 mm are well fit by a single linear trend. Events which exceed this threshold diverge into two trends, with those that occurred in the spring having higher event NO$_3$-N loads compared to events of the same size that occurred during other times of the year.

Model data similarly show larger event nitrate loads occurring in the spring compared to other times of the year (Figure 3.5c). However, whereas field-observed nitrate loads are elevated only during the Y1 Corn Spring/Summer time period, modeled nitrate loads are consistently elevated during the months of April and May regardless of crop type and associated management.

Nitrate loads are well approximated by a single linear trend for events with total tile-runoff below about 30 mm. Events which exceed this tile-runoff threshold diverge into two patterns:
events which occurred in the spring follow a trend with a larger slope (i.e., have higher nitrate loads for the same event size) compared to events which occurred during other seasons.

Figure 3.6 NO$_3$-N c-Q relationships for observed events. Arrows indicate hysteresis direction for events in which the hysteresis index (HI) magnitude is > 0.1.
3.4.4 Controls of antecedent conditions on nitrate concentration dynamics within events

Of the 18 events analyzed for c-Q relationships, 50% exhibited counterclockwise hysteresis, 17% exhibited clockwise hysteresis, and 33% were non-hysteretic (Figure 3.6). We did not observe a clear control of ASI or \(GW_{def}\) on HI, as would have been exhibited by a trend between HI and ASI or \(GW_{def}\). However, hysteretic behavior grouped by runoff event size and antecedent tile flow state (Figure 3.7). Larger events (> 150 m\(^3\) d\(^{-1}\) peak tile flow) which occurred when there was little to no tile flow at the onset exhibited strong counterclockwise hysteresis (events 3, 4, 11, 23 in Figures 3.6 and 3.7). Small events (< 150 m\(^3\) d\(^{-1}\) peak tile flow) tended to exhibit weak counterclockwise hysteresis to non-hysteretic behavior (events 6, 7, 9, 10, 14 – 17 in Figures 3.6 and 3.7). Larger events which occurred when the tile was still flowing from a previous event (i.e., a storm

![Figure 3.7 Storm hysteresis (HI, y-axis) and flushing (FI, x-axis) indices for NO\(_3\)-N. Numbers correspond to event numbers in Figure 3.6. Gray shaded regions indicate where indices are neutral (< 0.1). Hysteretic behavior grouped by runoff event size and antecedent tile flow state. Larger events which occurred when there was little to no tile flow at the onset of the event exhibited strong counterclockwise hysteresis. Small events exhibited weak counterclockwise hysteresis to non-hysteretic behavior. Larger events which occurred when the tile was still flowing from a previous event exhibited weak clockwise hysteresis to non-hysteretic behavior.](image)
occurred on the falling limb of another event) exhibited weak counterclockwise hysteresis to non-hysteretic behavior (events 1, 2, 5, 8, 12, 18 in Figures 3.6 and 3.7).

Storm events had a range of FIs, but the majority of events (67%) had FI > 0.1, indicating nitrate flushing (i.e., an increase in nitrate concentration over the rising limb). Overall, larger events with little to no antecedent tile flow and small events tended to show flushing effects while larger events with high antecedent tile flow showed more variable effects. However, although FI indicates a change in nitrate concentration between the start of an event and the time of peak discharge, the index does not take into account changes in concentration between those times. Visual analysis of nitrate concentration through time reveals inconsistent dilution/flushing over the rising limb. Tile hydrographs had steep rising limbs so water samples were mainly collected on the falling limbs. Of the four events exhibiting strong counterclockwise nitrate c-Q hysteresis, three had high sampling resolution on the rising limb (at least 5 samples). These correspond to an event during Year 1 Corn Summer/Fall (event 4) and two events during Year 3 Soy Spring/Summer (events 11 and 13). These events showed dilution over most of the rising limb prior to a rapid increase in nitrate concentrations before

![Figure 3.8 Example tile storm response for event with strong counterclockwise hysteresis. On the rising limb, a decrease in nitrate concentration corresponds with an increase in shallow soil water content until reaching a maximum. The inflection point suggests a threshold of soil water mobilization occurs at a water content of 31–32%.

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reaching peak discharge (Figures 3.8 and S3.4). The decrease in nitrate concentration corresponded with an increase in soil water content until reaching a maximum of about 31–32%, a value near field capacity for silt loam and silt clay soils.

3.5 Discussion

3.5.1 Antecedent catchment wetness controls tile-runoff thresholds

In our empirical and modeling studies, we find evidence for both top-down and bottom-up tile-runoff generation mechanisms. Our analysis of field-observed tile discharge, shallow soil moisture, and precipitation, in conjunction with modeled output including below-tile soil moisture, demonstrates that tile-runoff at the study site is a function of gross precipitation and both below- and above-tile storage controls. Tile-runoff response displays a threshold behavior similar to that observed in forested hillslopes, whereby runoff increases linearly with increasing $P_{\text{gross}} + \text{ASI}$ after a threshold value is exceeded; prior to the threshold, little runoff is produced in response to rainfall, resulting in an overall relationship reminiscent of a hockey stick shape. However, the above-threshold correlation is not as strong as has been observed in some forested catchments (Detty and McGuire, 2010; Farrick and Branfireun, 2014). This is potentially due to variation in the observational data set (e.g., number of storm events, available sensor data), intrinsic properties of the system, or the ability of the analysis to capture all relevant storage and runoff generation mechanisms in the tile-drained landscape. We also find that a similar tile-runoff threshold emerges relative to $P_{\text{gross}} + \text{GW}_{\text{def}}$. Moreover, including both ASI and $\text{GW}_{\text{def}}$ into the catchment wetness metric further improves the linear runoff relationship,
suggesting an additive effect of top-down and bottom-up moisture controls in regulating the tile flow threshold.

Instead of dominance by top-down or bottom-up runoff generation mechanisms, we find that both are important in our study system. In systems where both top-down and bottom-up moisture controls are present, we conceptualize that there is a soil moisture threshold that must be met in the shallow subsurface prior to significant transport to greater depths (Figure 3.9). Then, if a groundwater deficit is present, below-tile storage must be filled to raise the water table to the elevation of the tile to generate significant runoff. The outcome of this sequential filling of distinct, depleted storages in landscapes parallels that of the fill-and-spill concept initially used to explain threshold runoff behavior at the Panola hillslope (Tromp-van Meerveld and McDonnell, 2006a; b). There, depressions in bedrock topography must be filled before water can spill out and become hydrologically connected, generating significant lateral subsurface flow. Whereas the fill and spill mechanism described for the Panola hillslope is a bottom-up runoff generation process with implications for lateral connectivity, at our study site runoff generation is controlled by both top-down and bottom-up moisture, and the relevant storages are oriented vertically. Also in contrast to the steep hillslopes and shallow bedrock systems in many hillslope hydrology studies (e.g., Tromp-van Meerveld and McDonnell, 2006a; b), in tile-drained IMLs the water table boundary defines available bottom-up storage and varies temporally. Although the landscape structure and associated runoff generation mechanisms of low-gradient, tile-drained IMLs differs from that of steep, bedrock hillslopes, the conceptual filling and spilling of landscape storages and resultant threshold runoff behavior are
similar. Further, fill-and-spill was recently proposed as a framework to more broadly describe runoff generation processes by which landscape storages become progressively filled and connected (McDonnell et al., 2021). Another comparable bottom-up mechanism explaining threshold runoff response in untiled, minimally managed hillslopes is “transmissivity feedback” (Bishop, 1991; Kendall et al., 1999). Initially observed in till soils, this describes the process by which rapid lateral flow occurs when the groundwater table rises and encounters surficial soil layers of increasing hydraulic conductivity, often due to the presence of macropore networks. In intensively managed landscapes, the tile elevation threshold controlling lateral subsurface water transmission is analogous to the transmissivity feedback mechanism observed to generate nonlinear runoff response in some forested catchments. Although the water table in tile-drained landscapes is typically constrained too deep to encounter high conductivity shallow soil layers, tiles themselves impart a similar threshold runoff response.
Figure 3.9 Conceptual tile-runoff generation model for a scenario in which both top-down and bottom-up moisture controls are present. Brown indicates the soil matrix, the white box a preferential flow path, gray a tile drain, and light blue groundwater. Red indicates soil water and dark blue event water. A soil moisture threshold in the shallow subsurface must be met prior to significant transport to greater depths. Initially, water infiltrates the soil matrix and macropores at the beginning of the event, and a small amount of event water reaches the tile drain via preferential flow paths. Once the soil moisture threshold is reached, soil matrix water is mobilized and enters preferential flow paths. If a groundwater deficit is present, below-tile storage must be filled to raise the water table to the elevation of the tile to generate significant runoff. Counterclockwise nitrate c-Q hysteresis, observed during large events with little/no antecedent tile flow, reflects a shift from dilute event water in early runoff to nitrate-laden pre-event water after a soil moisture threshold is exceeded.

In addition to analyzing how antecedent wetness controls tile-runoff response patterns, we examined how distinct landcover regimes in IMLs influence runoff response. In agricultural landscapes dominated by annual crops, vegetation is typically present for periods that coincide with the growing season, resulting in large seasonal fluctuations in evapotranspiration (Sacks and Kucharik, 2011; Shaw, 1963). Therefore, we expected that vegetation could impart an additional top-down control on subsurface runoff in IMLs via fluctuations in water uptake and interception, with peak water use corresponding to critical crop growth stages (Al-Kaisi, 2000).
Further, there is evidence that in natural systems ecology and hydrology co-evolve in response to climate, establishing equilibrium conditions between vegetation and water availability to avoid water shortages (Eagleson, 1982; Gao et al., 2014; Troch et al., 2015). Due to these linkages between vegetation and root zone soil moisture, soil moisture runoff thresholds may closely reflect vegetation controls in minimally managed systems. In contrast, vegetation patterns in IMLs reflect continuous human manipulation and could act as an independent control on runoff patterns. However, we found no evidence that the presence or absence of crops contributes additional information to ASI in explaining tile-runoff response. This suggests that the influence of crop presence on tile-runoff thresholds is already reflected within the soil moisture metric. Our field data analysis, though, is limited due to the small number of events which produced large runoff during the growing season. In a study of forested headwater catchments at the Coweeta Hydrologic Laboratory, Scaife and Band (2017) similarly found little evidence that the \( P_{\text{gross}} + \text{ASI} \) runoff threshold value differed between the dormant and growing season. Nonetheless, their data demonstrate that runoff thresholds vary interannually, largely due to variation in runoff initiation thresholds between growing seasons, and they conclude that interannual runoff thresholds are influenced by ecohydrologic feedbacks with forest evapotranspiration rates.

### 3.5.2 Antecedent catchment wetness controls nitrate export thresholds

For most time periods, patterns of field-observed event nitrate load reflect tile-runoff thresholds. This relationship arises because tileshed-scale nitrate c-Q is relatively chemostatic when evaluated over multiple events and interannual timescales, leading to a linear
dependence of load on runoff. Therefore, the tileshed is primarily transport-limited at the interannual timescale, and nitrate export is controlled by the same factors that dictate event tile-runoff: gross precipitation and antecedent catchment wetness, including both shallow soil moisture and below-tile moisture deficit. An exception to the dominant relationship occurred during Y1 Corn Spring/Summer when nitrate concentrations were higher than other times. This time period, consisting of events in May and June, was distinguished from others in regard to the combination of management and wetness conditions. Events occurred during a rainy period directly following nitrogen fertilizer application. Despite elevated concentrations, nitrate c-Q is still relatively chemostatic during Y1 Corn Spring/Summer such that event nitrate load and runoff show a linear relationship separate from other time periods. Modeled data, in comparison, show that nitrate load is consistently elevated for large events during April and May relative to comparable events during other months, and this occurred regardless of crop and associated management (fertilizer was applied only during corn years). Like field observations, the periods of elevated nitrate export also show a separate, relatively linear relationship with runoff. However, this occurs only above a threshold event runoff of about 30 mm. Below this value, event nitrate load shows a consistent linear dependence on runoff, suggesting that the threshold runoff value corresponds to activation of hydrologic pathways which source variable nitrate loads throughout the year. Within field data, all events from Y1 Corn Spring/Summer exceed a comparable threshold (~300 m³), preventing further analysis of field data. Taken together, our empirical and model-based results indicate that event nitrate export could be estimated using runoff threshold relationships and long-term average nitrate concentrations (e.g., estimating tile-runoff based on site properties and multiplying this by the
average nitrate concentration to calculate load). While this approach would be specific to the threshold relationship at a given site, it is a plausible basis to reconstruct past loading, estimate future responses, or make estimates at unmeasured sites on the basis of similar soil and management characteristics. This could prove useful for predicting nitrate loading from legacy nitrate stores, particularly in the face of increased implementation of conservation practices and precision fertilizer application to reduce nitrogen flushes during large rain events. Still, we note that interactions between management and hydroclimatic variables can overwrite dominant patterns during extreme periods, such as rain shortly after fertilizer application, which is particularly troublesome given that most nitrogen mass is mobilized during a relatively small number of these events (Royer et al., 2006).

In addition to controlling nitrate loading to downstream waterways, tile-runoff thresholds modulate the accumulation of nitrate in groundwater. Tiles reduce recharge of high nitrate concentration soil water to deeper groundwater by providing direct flow paths to streams that bypass deeper groundwater (Rodvang and Simpkins, 2001). While the mere presence of tiles is expected to influence spatial variations in groundwater contamination across IMLs (Power and Schepers, 1989), emergent runoff thresholds within drained landscapes reveal conditions leading to nitrate storage versus export. For example, a below-threshold event which mobilizes soil water and nitrate but does not raise the groundwater table to intersect the tile would primarily result in storage of nitrate in groundwater. Conversely, an above-threshold event with low antecedent groundwater deficit would result in greater nitrate export. Thus threshold
relationships could provide a tool for predicting both the storage and delivery of water and nitrate in IMLs.

3.5.3 Within-event nitrate c-Q reflects threshold of soil water mobilization

Within-event nitrate c-Q relationships show substantial variation between events, primarily explained by runoff event size and tile flow state at the onset of the event (Figure 3.7). Hysteretic behavior, in conjunction with these identified controls, provides insight into tile water source activation and transport mechanisms during storm events. The most common nitrate c-Q relationship we observed was counterclockwise hysteresis (50% of events), consistent with studies examining nitrate c-Q in tile flow (Liu et al., 2020) and streams draining tiled watersheds (Blaen et al., 2017; Outram et al., 2016; Williams et al., 2018). This dominant pattern is attributed to a shift from primarily event water in early runoff (typically dilute in nitrate) to nitrate-laden pre-event water sourced from the soil matrix on the falling limb (Kennedy et al., 2012; Liu et al., 2020; Williams et al., 2018; Woo and Kumar, 2019). Klaus et al.’s (2013) two-phase conceptual flow model, based on a series of tracer experiments, further suggests that the water source transition results from a moisture-based mobilization threshold within upper soil layers. Early in a storm, a small amount of tile flow is generated via macropores, mainly consisting of event water. After a threshold near-saturation moisture is reached within upper soil layers, soil water contributions activate and enter vertical preferential flow paths, and tile flow consists of mainly soil water. While soil water that reaches the saturated zone likely mixes with a small amount of older groundwater, we expect the shallow
saturated zone is stratified (*Fenelon and Moore, 1998; Jiang and Somers, 2009*) such that tile flow resembles recent soil water.

In our data, the transition from event to soil water is reflected by strong counterclockwise hysteresis during large events which occurred when there was little to no tile flow at the event onset (Figure 3.9). We expect that during small events, the threshold of soil water mobilization was not reached so c-Q shows weak to no counterclockwise hysteresis (Figure S3.5). Likewise, large events that occur when the tile is already flowing (i.e., when the tile is initially connected to the water table) do not reflect the transition from event to soil-derived water because tile water is already composed of primarily pre-event water at the beginning of an event. Thus, tile flow exhibits non-hysteretic behavior or weak clockwise hysteresis. Although the tight coupling between tile flow and nutrient load observed in this study indicates that nitrate dynamics were primarily transport-limited, the latter behavior may indicate nitrate source exhaustion when consecutive storm events occurred. Further, while small events observed in this study tended to occur when there was little to no tile flow, we expect that small events which occur when the tile is flowing prior to the event would similarly exhibit weak to no hysteresis, following the same rationale described above.

In addition to hysteretic behavior, we also analyzed nitrate flushing or dilution over the rising limb. Although the majority of events had an overall flushing effect (FI > 0.1), rising limbs often exhibited periods of both dilution and flushing. This is evident in the three events with strong counterclockwise hysteresis (i.e., those capturing the transition from event to pre-event water)
in which high sampling resolution was achieved over the rising limb (events 4, 11, and 13; Figures 3.8 and S3.4). An initial period of nitrate dilution is followed by a period of flushing. The decrease in nitrate concentration corresponds with an increase in soil moisture prior to both reaching an inflection point. This relationship suggests that the source of tile drain water shifted once a water storage threshold was exceeded, further supporting interpretation of counterclockwise hysteresis as the result of a soil moisture mobilization threshold. For all events, the inflection point occurred when shallow soil water content exceeded 31–32% soil water content. We expect that this soil water content represents the threshold of soil water mobilization within soils at the site. The initial decrease in nitrate concentrations may result from event water depleting nitrate stored within preferential flow paths or on the soil surface. Another potential explanation for the initial decrease in concentration is that water was transported faster than nitrate could be dissolved or mobilized. After the soil moisture threshold is reached, soil matrix water and associated nitrate mobilize, resulting in a rapid increase in nitrate. The threshold of soil water mobilization occurred prior to peak tile discharge, 1–2 hours after the initial increase in tile discharge.

3.6 Conclusions

In this study, we investigated how antecedent conditions control thresholds of tile-runoff generation and nitrate loads between events, as well as nitrate c-Q relationships within events. First, we expected a tile-runoff threshold would emerge relative to the sum of gross precipitation and an antecedent catchment wetness index reflecting either shallow soil moisture, indicating top-down runoff generation, or below-tile groundwater moisture deficit,
indicating bottom-up runoff generation. Instead, we found that the most distinct runoff threshold and linear response emerged as a combination of both top-down and bottom-up controls, quantified as the sum of gross precipitation, antecedent soil moisture index (ASI), and below-tile groundwater moisture deficit ($GW_{def}$). Moreover, our results demonstrate a simple additive effect of below- and above-tile storage in determining the threshold of tile-runoff initiation.

Next, we expected that event nitrate load would reflect runoff threshold relationships. We found this to be the case for most of the study period, with the exception of a two-month period when wet conditions directly followed fertilizer application and led to elevated nitrate export. Therefore, although interactions between management and hydroclimatic variables can overwrite dominant patterns, under most conditions export of accumulated nitrate is controlled by the same factors controlling tile-runoff and can be accurately predicted using runoff threshold relationships. Finally, we expected that antecedent wetness conditions would control within-event nitrate c-Q relationships. While we did not observe a clear control of ASI or $GW_{def}$ on HI, we found that hysteretic behavior grouped by antecedent tile flow state and runoff event size. Our results suggest that these factors are the dominant controls on event-scale nitrate c-Q because they determine the sequence of flow path activation and tile connectivity over a storm event. Further, the relationship between nitrate concentration and soil water content timeseries indicate a threshold of soil water mobilization, a key mechanism underpinning event-scale nitrate dynamics.
Understanding the hydrologic functioning of tile-drained IMLs is critical to developing accurate predictions of downstream water quality, particularly in the context of a changing climate and continued intensive agriculture to meet growing demands. This study contributes to this area of research by developing a simple model for tile-runoff generation based on the additive effects of top-down and bottom-up moisture controls. Our results suggest that tile-runoff threshold relationships are a promising framework for predicting the storage and delivery of water and nitrate in IMLs under varying antecedent conditions. Catchment classification based on threshold runoff response characteristics has been proposed as a basis for developing a unified hydrologic theory to advance predictive understanding of runoff response as a function of physical controls and climate (Ali et al., 2013). Intensively managed agricultural landscapes comprise a distinct physiographic category, commonly characterized by subsurface drainage, low-gradient topography, anthropogenic nutrient inputs, and transpiration regimes modulated by the seasonal presence or absence of crops. While site-specific variations in tile depth and spacing, soil, climate, and management will influence the slope and intercept of the threshold relationship, this framework can be applied across tile-drained landscapes to support watershed management. Parallel to the approach of using representative hydrologic response units to scale mechanistic understanding at one scale to integrated basin-scale responses (Buttle, 2006), the concept of ‘representative unit tilesheds’ could be used to aggregate individual contributions to larger-scale predictions.

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Figure S3.1 (Upper left) Schematic representation of a coupled 3-dimensional ecohydrological and biogeochemical model, *Dhara*, which is adopted and modified from *Drewry et al.* [2010a; b], *Le and Kumar* [2017], and *Woo and Kumar* [2017; 2019]. (Upper right) 1-dimensional multilayer approach is used to estimate canopy interception, evaporation, transpiration, and atmospheric carbon assimilation [*Drewry et al.*, 2010a; b]. (Lower) Schematic representation of organic carbon and nitrogen and inorganic nitrogen
processes for the first soil layer, implemented in *Dhara*. Details of the soil nutrient age and concentration sub-models and their coupling to the ecohydrological dynamics are provided by [Woo et al., 2014] and [Woo and Kumar, 2016; 2017; 2019], including equations and parameters.

**Figure S3.2** Modeled tile event runoff relative to the sum of antecedent soil moisture index (ASI) and gross event precipitation ($P_{gross}$). (a) Events grouped by either “$GW_{def}$ low” or “$GW_{def}$ high” conditions as an indicator of antecedent below-tile groundwater moisture deficit. (b) Events grouped by either “crops” (months of June, July, August, or September) or “no crops” (all other months). Linear regressions are fit to values above a threshold moisture metric.
Figure S3.3 (a) Observed daily precipitation ($P_{\text{daily}}$). (b) Observed tile discharge and NO$_3$-N concentrations. Collected water samples are categorized into five seasonal time periods.

Table S3.1 Summary of a one-way ANCOVA for the effects of discharge, time period, and their interactions on NO$_3$-N concentration. Bottom shows results of test performed on log$_{10}$-transformed NO$_3$-N concentrations.

<table>
<thead>
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<th></th>
<th>d.f.</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
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<tr>
<td>Discharge</td>
<td>1</td>
<td>8.5</td>
<td>p = 0.004*</td>
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<tr>
<td>Time period</td>
<td>4</td>
<td>916.5</td>
<td>p &lt; 0.001**</td>
</tr>
<tr>
<td>Time period * discharge</td>
<td>4</td>
<td>6.0</td>
<td>p &lt; 0.001**</td>
</tr>
</tbody>
</table>

$log_{10}$-transformed [NO$_3$-N]

<table>
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<th></th>
<th>d.f.</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discharge</td>
<td>1</td>
<td>10.9</td>
<td>p &lt; 0.001**</td>
</tr>
<tr>
<td>Time period</td>
<td>4</td>
<td>595.1</td>
<td>p &lt; 0.001**</td>
</tr>
<tr>
<td>Time period * discharge</td>
<td>4</td>
<td>12.5</td>
<td>p &lt; 0.001**</td>
</tr>
</tbody>
</table>

* indicates a significant difference (p < 0.05)

** indicates a highly significant difference (p < 0.001)
Table S3.2 Pairwise comparisons from Tukey-Kramer post-hoc tests for the ANCOVA test for effects of discharge, time period, and their interactions on NO₃-N concentration. Mean differences and 95% confidence intervals are for mean NO₃-N concentrations adjusted for discharge.

<table>
<thead>
<tr>
<th>Group 1</th>
<th>Group 2</th>
<th>Mean Difference [ppm]</th>
<th>Low limit 95% CI [ppm]</th>
<th>Upper limit 95% CI [ppm]</th>
<th>p-value</th>
</tr>
</thead>
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<tr>
<td>Y1 Corn Spring/Summer</td>
<td>Y1 Corn Summer/Fall</td>
<td>14.4</td>
<td>13.8</td>
<td>15.1</td>
<td>p &lt; 0.001**</td>
</tr>
<tr>
<td>Y1 Corn Spring/Summer</td>
<td>Y2 Soy Spring/Summer</td>
<td>16.8</td>
<td>16.0</td>
<td>17.6</td>
<td>p &lt; 0.001**</td>
</tr>
<tr>
<td>Y1 Corn Spring/Summer</td>
<td>Y3 Soy Spring/Summer</td>
<td>16.4</td>
<td>15.3</td>
<td>17.4</td>
<td>p &lt; 0.001**</td>
</tr>
<tr>
<td>Y1 Corn Spring/Summer</td>
<td>Y4 Corn Winter</td>
<td>18.4</td>
<td>17.6</td>
<td>19.3</td>
<td>p &lt; 0.001**</td>
</tr>
<tr>
<td>Y1 Corn Summer/Fall</td>
<td>Y2 Soy Spring/Summer</td>
<td>2.3</td>
<td>1.5</td>
<td>3.2</td>
<td>p &lt; 0.001**</td>
</tr>
<tr>
<td>Y1 Corn Summer/Fall</td>
<td>Y3 Soy Spring/Summer</td>
<td>1.9</td>
<td>0.9</td>
<td>3.0</td>
<td>p &lt; 0.001**</td>
</tr>
<tr>
<td>Y1 Corn Summer/Fall</td>
<td>Y4 Corn Winter</td>
<td>4.0</td>
<td>3.1</td>
<td>4.9</td>
<td>p &lt; 0.001**</td>
</tr>
<tr>
<td>Y2 Soy Spring/Summer</td>
<td>Y3 Soy Spring/Summer</td>
<td>-0.4</td>
<td>-1.6</td>
<td>0.8</td>
<td>p = 0.88</td>
</tr>
<tr>
<td>Y2 Soy Spring/Summer</td>
<td>Y4 Corn Winter</td>
<td>1.7</td>
<td>0.7</td>
<td>2.7</td>
<td>p &lt; 0.001**</td>
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<tr>
<td>Y3 Soy Spring/Summer</td>
<td>Y4 Corn Winter</td>
<td>2.1</td>
<td>0.9</td>
<td>3.2</td>
<td>p &lt; 0.001**</td>
</tr>
</tbody>
</table>

* indicates a significant difference (p < 0.05)

** indicates a highly significant difference (p < 0.001)
Figure S3.4 Tile storm response for all events with strong counterclockwise hysteresis. On the rising limb, a decrease in nitrate concentration corresponds with an increase in soil water content within the upper 0.3 m until reaching a maximum near saturation. The inflection point suggests a threshold of soil water mobilization occurs at a water content of 31–32%.
Figure S3.5 Conceptual flow model for tile-runoff generation, adapted from Klaus et al., 2013. Brown indicates the soil matrix, the white box a preferential flow path, gray a tile drain, and light blue groundwater. Red indicates soil water, dark blue event water, violet to magenta mixed water. For large events with little to no antecedent tile flow (a), water infiltrates the soil at the beginning of the event, and a small amount of event water reaches the tile drain via preferential flow paths. With increasing storage, pre-event soil matrix water enters preferential flow paths and mixes with event water. Strong counterclockwise hysteresis reflects the transition from event to pre-event water. For events which occur when the tile is flowing (b and d), tile water is already composed of primarily pre-event water at the beginning of the event so nitrate c-Q does not reflect the source transition. For small events (c and d), the threshold of soil water mobilization is not reached so nitrate c-Q similarly does not reflect the source transition.
Chapter 4: Empirical evidence of activation mechanisms for ephemeral floodplain features in a lowland meandering river system

4.1 Abstract

Floodplains along low-gradient, meandering river systems commonly contain a diversity of geomorphic features, ranging from enclosed depressions to morphologically-connected channels. These topographically low, ephemerally-flooded features (i.e., floodplain features) inundate prior to river water overtopping all banks, enhancing river-floodplain connectivity for moderately high flow stages. Predicting when and where ecological functions occur in floodplains requires understanding the dynamic hydrologic processes of floodplain features, including inundation and exchanges processes. In this study, we use high spatial and temporal frequency monitoring of floodplain feature intermittency and surface water and groundwater levels at a site in central Illinois to characterize flooding mechanisms (i.e., water sourcing) and inundation patterns across feature locations and between storm events. Our results highlight spatially and temporally complex dynamics of floodplain feature activation and dry-down. Initial inundation was commonly characterized by dynamic contributions from direct precipitation, groundwater, and antecedent floodwater. These initial floodwaters accumulated in non-contiguous sections of floodplain features and ultimately mixed with river-derived water, suggesting that floodplain features are hotspots for perirheic zone formation. The dominant inundation mechanisms observed at monitored locations varied as a function of feature location, antecedent wetness, and event characteristics. Finally, surficial interactions between rivers and floodplain channels differed between channel types and varied over flooding events.
Whereas multi-connection channels at the site facilitated flow-through conditions, single-connection channels primarily functioned as sinks of river-derived water to the floodplain with short source periods.

4.2 Introduction

Far from pipes that passively convey water and solutes downstream (Bencala, 1993; del Giorgio and Pace, 2008), rivers are complex systems in which spatial and temporal variations in channel characteristics (e.g., topographic features, land surface gradients, variable hydraulic conductivity) and dynamic forcing (e.g., discharge, lateral and longitudinal hydraulic gradients, groundwater inflow/outflow) interact to yield complex 3-dimensional and time-variable connectivity (Findlay, 1995; Malard et al., 2002; Wohl, 2017). The resulting material and energy exchanges between rivers and off-channel surface and subsurface waters define the river corridor (National Research Council, 2002; Harvey and Gooseff, 2015), a concept which expands the frame of reference of river systems beyond their banks, underscoring the influence of rivers on surrounding environments as well as adjacent landscapes on downstream flows. Floodplains are recognized as key components of river corridors (Amoros and Bornette, 2002; Wohl, 2021), with floodplain-river connectivity an important factor regulating downstream water quality and sustaining river-floodplain ecosystems. Like river channels, floodplains themselves exhibit complexity of form and dynamics (Hughes, 1980), with their hydrologic functioning (i.e., water storage, flow pathways, and residence times) subject to heterogeneity in geomorphology, meteorological conditions driving dynamics, and sources of water present on the floodplain at a given place and time. Just as there are numerous physical processes that govern the pathways
and transport times of precipitation through hillslopes to streams, floodwaters are subject to a host of processes that influence transport and fate during floodplain inundation and flood recession. Although floodplains are known to be ecologically important (Gordon et al., 2020; Opperman et al., 2010; Tockner and Stanford, 2002), we have limited understanding of hydrological processes occurring at floodplain reach-scales and consequently little ability to predict when and where important ecological functions occur. Thus, the objective of this study is to characterize the spatial and temporal variability of inundation dynamics across floodplain features and between storm events in a low-gradient floodplain system.

At the reach-scale, floodplains have historically been conceptualized as flat, featureless expanses which exist in a binary state of either dry or flooded above some threshold river stage (Riley, 1972; Williams, 1978; Wolman and Leopold, 1957). Facilitated by the onset of high-resolution remotely-sensed topographic data in recent years, there has been increased recognition that contrary to this depiction, a diversity of topographic elements span low-gradient floodplains (Czuba et al., 2019; David et al., 2017; Dunne and Aalto, 2013; Lewin and Ashworth, 2014; Trigg et al., 2012), arising due to varied erosional and depositional processes. Ephemerally-flooded, topographic lows (i.e., floodplain features) may occupy geomorphic features such as swales, point bars, scroll bars, and sloughs, and generally range from enclosed depressions to morphologically-connected linear elements (Lewin and Ashworth, 2014). On one end of this continuum are geographically isolated floodplain depressions which provide ecosystems services largely dependent on their relative lack of connectivity to permanent water bodies, including the provision of breeding habitats to support local biodiversity (Colburn
et al., 2008; Semlitsch and Skelly, 2008) and water quality benefits as effective biogeochemical reactors (Marton et al., 2015). Although they lack permanent surface water connections, these temporary pools are by no means hydrologically or biogeochemically disconnected from nearby waters (Cohen et al., 2016). In addition to forming episodic surface connections with other floodplain features and the river channel during some flood events (Leibowitz and Brooks, 2008), such isolated pools can provide groundwater recharge as well as receive groundwater discharge (Winter and LaBaugh, 2003). On the other end of the river-floodplain connectivity continuum are features that create breaks in the main channel banks, providing a direct pathway for river-derived water to flow onto floodplains prior to overtopping all banks and thus enhancing river-floodplain connectivity for moderately high flow stages (Lindroth et al., 2020). In particular, extensive networks of ephemerally-flooded channels, shown to be prevalent in meandering river-floodplain systems (David et al., 2017; Xu et al., 2020), have garnered attention for their role in conveying surface flows.

In one example, Czuba et al. (2019) demonstrate the continuum of lateral river-floodplain connectivity that occurs over a range of flow stages in a meandering river system, with a focus on how these connections influence surface water exchange fluxes and residence times. They document floodplain channel inundation 19 days per year on average for the East Fork White River in Indiana, highlighting that ephemeral floodplain channels play a role in transport and fate beyond extreme events. Such dynamic surface water conditions in floodplain channels can also be expected to exert considerable influence on groundwater, with hydraulic head differences driving multi-directional groundwater-surface water exchange. Similar to streams,
floodplain channels presumably experience gaining and losing conditions, but few, if any, studies have investigated when and where these conditions occur within networks.

Regardless of feature type, increased interest in the connectivity and function of floodplain features coincides with a concerted effort to answer similar questions in the context of intermittent and ephemeral streams. Estimated to comprise more than 50% of the global river network, intermittent and ephemeral streams can be hotspots of biogeochemical transformation but have only been rigorously studied in recent decades (Burrows et al., 2017; Datry et al., 2014; Gómez-Gener et al., 2021). Likewise, river network expansion via episodic floodplain channel inundation may have basin-scale biogeochemical effects, but ephemeral floodplain channels are under-studied, even compared to their perennial counterparts in larger floodplain systems (e.g., Mertes et al., 1996; Trigg et al., 2012).

The number of geomorphic connections between a floodplain channel and the main river channel may be a key control on hydrologic behavior at the feature-level. David et al. (2017) outlines two main floodplain channel types: (1) chute channels formed from headward erosion or enlargement of swales, typically shorter channels with a single morphologic connection to the main river; and (2) long, coherent channels that provide down-valley flow and span multiple meander wavelengths. This latter channel type often has multiple morphologic connections and forms when preexisting topographic lows, such as meanders, become connected via differential erosion. From a hydrologic perspective, floodplain channels with multiple prominent river connections facilitate flow-through conditions during floods. While there will be some
groundwater-surface water exchange as water is conveyed through these channels (Helton et al., 2012a; b), under high flow conditions much of the water entering the floodplain channel upstream presumably returns to the main channel downstream within relatively short time periods. In contrast, single-connection floodplain channels would be expected to discharge river-derived water to diffuse, backwater zones of floodplains during the rising limb of storms. Consequently, these pathways would lead to longer residence times, as well as a higher likelihood of recharging groundwater or being evapotranspired. Single-connection floodplain channels may also accommodate reverse flow, in which floodplain water from backwater zones would drain to the main river during storm falling limbs. These interactions between residence times and bi-direction exchange processes ultimately dictate whether floodplains are sources or sinks of nutrients and pollutants (BryantMason et al., 2013; Jones et al., 2014; Tockner et al., 1999).

Understanding the mechanisms by which floodplains retain, export, and transform water and solutes requires consideration of how feature morphology, antecedent conditions, and storm event characteristics interact to control both water sourcing and subsequent transport processes. Commonly, river-sourced water comprises only a portion of floodwaters on floodplains; groundwater, direct precipitation, runoff from nearby slopes, antecedent water from prior floods, and local tributary water can also contribute floodplain water (Mertes, 1997; Pinel et al., 2020). The area where differentially sourced floodwaters mix, termed the perirheic zone, can have high chemical and sediment concentration gradients and thus can influence nutrient transformation and hydrogeomorphic patterns. Recent studies have emphasized
temporal (Jones et al., 2014) and spatial (Berezowski et al., 2019) dynamics of the perirheic zone. Given their varied topographic positions and role in conveying flow, floodplain features are expected to influence both the location and timing of perirheic zone formation. For example, floodplain channels convey river-derived water to more isolated depressional regions of floodplains, likely to contain differentially-sourced or antecedent floodwater. Inundation mechanisms, and thus water-sourcing, in floodplain channels themselves may vary with antecedent conditions (e.g., groundwater table elevation and the presence of antecedent floodwater) and position on the floodplain (e.g., elevation, proximity to river or valley sides that convey runoff).

In this study, we use empirical evidence from a lowland meandering river-floodplain system in central Illinois to investigate spatial and temporal patterns of inundation in floodplain features of different typologies, including floodplain channels with single and multiple river channel connections and isolated depressions. We ask: (1) how variable are inundation timescales as a function of floodplain feature type and location?; (2) what controls patterns of inundation timing and duration?; (3) what inundation mechanisms can be inferred to occur in floodplain features and how do they vary as a function of floodplain location, antecedent wetness, and event characteristics?; (4) How does floodplain channel flow direction vary across flooding events? To this end, we use a combination of surface water and groundwater monitoring at select locations and high spatial frequency monitoring of the presence or absence of floodwater within floodplain features. Together, these data provide a comprehensive depiction of the spatiotemporal patterns of floodwater intermittency and linkages between groundwater and
surface water levels from which we can infer inundation mechanisms and dynamics across flood events. Such observations are a first step towards understanding the hydrologic functioning of floodplain features and ultimately aggregating their influence across larger spatial scales to predict transport and transformation through river-floodplain networks.

4.3. Methods

4.3.1 Site description

The study site is a 4-km reach of the upper Sangamon River, a primary tributary of the Illinois River, and adjacent floodplain (Figure 4.1a). The monitored area covers about 1 km² of floodplain and river corridor. The site is located within Allerton Park, a protected natural area near Monticello, Illinois which contains bottomland/floodplain and upland forest, and is a core research site of the ClNet: Critical Interface Network. The region has a humid continental climate with hot summers and cold winters. Monticello receives an annual average precipitation of 1,020 mm.

Allerton Park together with the adjacent Upper Sangamon River Land and Water Reserve comprise one of the largest remaining forests in central Illinois. The upland forest is primarily oak-hickory in composition (Boggess and Geis, 1967; Bretthauer et al., 2007), and the bottomland forest is dominated by silver maple (Bell, 1974; Chueng and Brown, 1995). Although the study site is located within minimally disturbed, old-growth floodplain forest, the surrounding landscape has undergone significant anthropogenic changes in recent centuries. Prior to European settlement, the Upper Sangamon River Basin was 90% prairie and 10% forest
(IDNR, 1999), with forests primarily in riparian zones. Today 90% of land use is row crop agriculture. Consequently, floodwaters are nutrient-rich due to high fertilizer inputs in the watershed (Brown and Peterson, 1983).

**Figure 4.1** Field site location along the Sangamon River near Monticello, IL (a). Aerial photograph depicts forested landcover of immediate study region and primarily agricultural land use of surrounding watershed. Monitored floodplain features outlined and labeled (b): multi-connection channels (M1 & M2), single-connection channels (S1 and S2), and depressions (D1 and D2).

Within the study area, the Sangamon River is a 5th-order stream according to the Horton-Strahler system (Stall and Fok, 1968). It is 20–30 m wide and meanders through a valley about 0.5 km wide. Floodwaters typically exceed river banks within the park several times per year, with most flooding occurring during the winter and spring (January–June). Floodwaters are constrained by distinct valley sides. Floodplain soils are primarily Sawmill silty clay loam (NRCS, 2022), deep and poorly drained soils formed in alluvium. Prominent topographic features at the
site include floodplain channels, both those with single and multiple morphologic connections with the main river channel, and isolated depressions.

4.3.2 Field monitoring

The hydrologic dynamics of floodplain features of varying morphologies and topologies were monitored using a combination of intermittency loggers and water level loggers (Figure 4.2). While hydrologic connectivity of floodplain features varies through time, surface water connectivity at moderate flood stages—when floodplain channels are inundated but floodwaters have not overtopped all banks—provides a geomorphically-relevant method for characterizing feature archetypes. Instrumented features include floodplain channels which have multiple surficial connections with the main river channel at moderate flood stages (Figure 4.1b, Features M1 and M2), secondary channels with one surficial connection to the main river channel at moderate flood stages (Features S1 and S2), and depressions located near the end of a channel feature (Feature D1), and geomorphically isolated from other floodplain features under moderate flood levels (Feature D2). We also monitored several locations within a non-channelized backwater wetland, formed from a meander scar which filled with sediment (“backwater wetland” on Figure 4.1b).

Stream Temperature, Intermittency, and Conductivity (STIC) loggers were installed to monitor the occurrence of surface water at 60 discrete locations on the floodplain every 10 min over a 2.5-year period (June/July 2018–December 2020). Built by modifying HOBO Pendant Temperature/Light sensors (Chapin et al., 2014), STICs provide electrical conductivity
measurements that can be used as proxies for water presence/absence at the sensor elevations (here, slightly above the ground surface). For this study, STIC locations were considered inundated when electrical conductivity measurements diverged from the dry response (raw signal \(\approx 0\)). Inundation was characterized by a sustained signal above zero, clearly distinguished from sporadic fluctuations of electronic noise or direct precipitation/moisture on the sensor. Examples of raw STIC electrical conductivity data and descriptions of how sensors were tested are provided in Supplemental Information (Figure S4.1). STICs were deployed primarily along the centerline of the floodplain channels and bottom of depression features described above. Given the placement of STIC sensors along the ground surface, STIC data were used to characterize temporal and spatial dynamics of the initial presence of surface water on the floodplain (i.e., wet-up), the timing of the last presence of floodwater during late flood recession (i.e., dry-down), and the duration of flooding at each location. While STIC loggers occasionally malfunctioned or were inaccessible due to flooding, inundation data for were available for at least 50% of the study period for the 60 locations used in this study.
Surface water and shallow groundwater levels were analyzed for a 1.5-year period (July 2019–December 2020) of 15-min interval data using HOBO U20 Water Level Loggers. Sixteen shallow wells (3–6 m deep) were installed at higher floodplain elevations near floodplain features to monitor changes in the near-surface water table, with the lower 1.5 m screened for all wells. Surface water was monitored at several locations along the centerline of each floodplain channel and at the bottom each of the two depression features, totaling 15 floodplain surface water monitoring locations. Co-located groundwater and surface water loggers at 11 sites were used to inform hydrologic dynamics and exchange processes within and between features. River stage in the main channel was monitored 0.4 km upstream of the study reach to relate floodplain dynamics to pre-storm river conditions. A Trimble S6 Robotic Total Station was used to record the relative elevations of monitoring equipment. For most of the study period, precipitation was measured 2-km from the park using a Texas Electronics TR-525I tipping bucket rain gauge. However, due to vandalism of instrumentation in May 2020, we use precipitation measured with a Meter ECRN-100 rain gauge at a site near Champaign, IL, about 30-km away from the floodplain site, for the final months of the study.

4.3.3 Flood event selection and characterization

To compare floodplain hydrologic dynamics spatially and between events, 11 distinct flooding events were identified over the 1.5-year water level monitoring period (Figure 4.3a). Only
events which resulted in a floodplain surface water level response were considered in the analysis. Metrics of event characteristics and antecedent conditions were calculated for each identified event, including gross event precipitation, peak event river stage, antecedent river stage, change in river stage over the event, and antecedent inundation (Figure 4.3b). We consider gross event precipitation to be the total precipitation between a start time identified via visual inspection of precipitation and river stage time series and the time of peak event river stage. Antecedent river stage was identified as the river stage immediately preceding an increase in river stage for each event. Change in river stage is calculated as the difference between peak river stage and antecedent river stage. Antecedent inundation was calculated as the percentage of STIC locations with antecedent floodwater present prior to the start of the event.
4.3.4 Wet-up timescale and inundation duration analysis

For each event, we calculated the wet-up timescale as the time between the maximum 15-min event precipitation and the time of inundation at each STIC location for each event. If a location became inundated prior to the time of maximum event precipitation, this value is negative. Because no local precipitation was recorded for Event 5, we calculate its wet-up timescale from
the time of initial increase in river water level to include in comparisons of wet-up timescale variation but not comparisons of medians. A total of 44 STIC sensor locations were used for the wet-up timescale analysis, selected due to continuous datasets across events. Because antecedent floodwater occurred at some floodplain locations prior to each event and some locations did not inundate during all events, the total number of wet-up timescale values calculated for each event varies between 9 and 40 locations. Kruskal-Wallis tests were performed to determine whether wet-up timescales differed between events using a significance threshold of 0.05. Wet-up timescale metrics were used to compare inundation timing across locations for the 11 events identified during the water level monitoring period.

Linear regression analysis was used to test for relationships between wet-up timescales within events and expected controls on inundation at each location. Because large differences in mean wet-up timescales between events could obscure within-event trends, for this analysis we use a normalized wet-up timescale based on deviations of individual locations from the mean wet-up timescale for all sensors during that event. A relationship with elevation would indicate that local topography was a strong control on inundation and that initial floodwaters were likely due to groundwater rise or accumulation of overland flow in low areas; a relationship with distance from the nearest river connection along the channel centerline would indicate floodplain network expansion away from the river and river-sourced floodplain water; a relationship with distance from the valley wall would indicate that runoff from nearby slopes was a primary contribution to initial flooding. Distance from the nearest river connection along the channel centerline was determined for locations with an evident channel flow path to the river, and
thus excluded STIC locations in the isolated basin and backwater wetland. While we report the $r^2$ value for all calculations, we proceed with interpretation of an $r^2 < 0.3$ to indicate no relationship, $0.3 \leq r^2 < 0.5$ to indicate a weak relationship, $0.5 \leq r^2 < 0.7$ to indicate a moderate relationship, and $r^2 \geq 0.7$ to indicate a strong relationship.

We also used linear regression to test for relationships between the percent time each of the 60 STIC locations was inundated over the monitoring period and the expected inundation controls of elevation, distance from the nearest river connection along the channel centerline, and distance from the valley wall. Because differences in dry-down timing between locations tended to be much larger than differences in wet-up timing, percent time inundated mainly reflects dry-down dynamics. Therefore, we expected a relationship between percent time inundated and elevation would indicate that the falling groundwater table was a primary control on dry-down timing such that low spots stayed wet longer, and a relationship with distance from the nearest river connection along the channel centerline would indicate floodwater drainage to the river was a primary control on dry-down timing. Further, Kruskal-Wallis tests were performed to test whether percent time inundated differs as a function of floodplain features type.

**4.3.5 Water level analyses**

Trends in groundwater and surface water levels have been used widely to interpret interactions between groundwater and surface water stores (Kalbus *et al.*, 2006). In one recent study *Brookfield et al.* (2017) used temporal variations in river response functions, which indicate the
relationship between the response of groundwater levels and a change in river stage, to interpret water sources and changes in flow mechanisms between a river and aquifer. Here, we use direct groundwater-surface water level (GW-SW) relationships for each pair of co-located water level loggers to characterize hydrologic dynamics and infer inundation mechanisms. Although analyzing hydraulic gradients between groundwater and surface water provides a direct method to infer groundwater-surface water exchange, process interpretations in low-gradient environments can be sensitive to small inaccuracies in land surface and water level elevation measurements (Cain and Hensel, 2018). Given that differences in water levels between co-located monitoring locations were often very small, evaluating the relationship between temporal groundwater-surface water level variations offers an analysis technique less prone to inaccuracies in absolute vertical measurements. Thus, GW-SW relationships serve as a valuable proxy that provides novel insight into flow mechanisms and water sources.

We expected to observe one of three GW-SW relationships at each floodplain location, with patterns explained by different hydrologic dynamics during flood event rising limbs. With surface water level oriented on the x-axis and groundwater level on the y-axis, GW-SW relationships would show either clockwise hysteresis (initial floodplain surface water response lags groundwater response), counterclockwise hysteresis (initial floodplain groundwater response lags surface water response), or no hysteresis (surface water and groundwater level responses are simultaneous) for each event (Figure 4.4). Clockwise hysteresis would indicate groundwater forcing (i.e., floodwater at the location was initially groundwater-sourced). We expected groundwater sourcing to be most common at more isolated locations, including the
depressions and channel locations furthest from the river. Inundation via river-derived surface flows would be most delayed at these sites, allowing time for regional groundwater tables to intersect the land surface. Counterclockwise hysteresis would indicate surface water forcing, either as floodwater was sourced from the river or overland flow of direct precipitation. We expected river-sourcing to be most common in channel locations nearer the river, and direct precipitation/overland flow to occur during the most extreme precipitation events. We expected synchronous groundwater and surface water response would be most common for events in which antecedent catchment wetness was high (e.g., high antecedent river levels and antecedent flooding) because hydrologic connectivity would already be high and groundwater and surface water levels tightly coupled. In addition to the three simple hysteresis patterns described above, more complex dynamics are also possible. For example, events may exhibit clockwise to counterclockwise (C-CC) figure-eight hysteresis (initial floodplain surface water response lags groundwater response and then groundwater response lags surface water response). When hysteretic relationships are present during events with larger changes in river stage, GW-SW relationships become linear at higher water levels. This linear portion of GW-SW response corresponds to when groundwater wells, located at higher elevations than the floodplain features, become flooded.

Finally, to infer the flow direction through each floodplain channel over the course of a flood event, the hydraulic gradient was calculated between the most upstream and downstream surface water monitoring locations for the multi-connection floodplain channels and between the locations nearest and furthest from the river for the single-connection floodplain channels.
Times in which the surface water logger locations were hydrologically disconnected via surface flows, determined from dry STIC sensors located between the two water level monitoring locations, were not included in the analysis.

<table>
<thead>
<tr>
<th>Behavior</th>
<th>Description</th>
<th>Inferred Inundation Mechanism</th>
</tr>
</thead>
<tbody>
<tr>
<td>clockwise (C)</td>
<td>Initial floodplain surface water response lags groundwater response at location (groundwater forcing).</td>
<td>Common for isolated depression -&gt; Floodwater contributions are likely initially groundwater-sourced.</td>
</tr>
<tr>
<td>counter clockwise (CC)</td>
<td>Initial groundwater response lags floodplain surface water response at location (surface water forcing).</td>
<td>Most common behavior observed for throughout floodplain feature locations and events -&gt; Initial floodwater contributions are likely primarily river-sourced or direct precipitation/overland flow at location.</td>
</tr>
<tr>
<td>C-CC figure-eight</td>
<td>Initial floodplain surface water response lags groundwater at location and then groundwater response lags surface water at location.</td>
<td>Common in mid-channel locations and the near-channel depression during events with low antecedent wetness and high gross event precipitation -&gt; Early in event groundwater levels rise rapidly due to recharge from high intensity precipitation, potentially leading to initial floodwater contributions that are groundwater-sourced. Later transition to floodwater contributions that are primarily river-sourced or direct precipitation/overland flow.</td>
</tr>
<tr>
<td>no hysteresis</td>
<td>Surface water and groundwater responses is simultaneous</td>
<td>Common for locations near the river -&gt; Indicates strong influence from nearby river channel and that flood waters contributions are primarily river-sourced at location.</td>
</tr>
</tbody>
</table>

**Figure 4.4** GW-SW relationships and inferred mechanisms
4.4 Results

4.4.1 Wet-up timescales and inundation duration

The normalized wet-up timescale over all events and locations did not correlate with the expected controls of elevation, distance from the nearest river connection along the channel centerline, or distance from the valley wall ($r^2 < 0.1$ in all cases; Figure 4.5b–d).

Wet-up timescales varied between events (Figure 4.5a). Events with larger changes in river water level (Figure 4.3b; Events 1, 3, 9, and 10) tended to have mean wet-up timescales near zero (mean of -0.7 to 0.2 days) and small spread (standard deviation of 0.1 to 0.3 days). An exception is Event 8, which had a lower mean (-3.4 days) and greater standard deviation (0.5 days) than other large events. Wet-up timescales for events with small to moderate changes in river water level (Events 2, 4, 6, 11) tended to have larger mean wet-up timescales (1.7-3 days) and greater standard deviations (0.6 to 0.7 days). Like Event 8, Event 7 was characterized by a lower mean (-2.0 days) and greater standard deviation (0.8 days) compared to other events with a similar change in river stage. Precipitation during both of these events mainly occurred in 2 distinct pulses, with the maximum precipitation occurring in the second pulse. Event 5 had the greatest standard deviation (2.5 days) and is also the only event in which no local precipitation was recorded.
Across the 60 floodplain locations where the presence of surface water was monitored, inundation duration ranged from 30 to 93% of the monitored period (Figure 4.6) and had a median of 61%. Percent time inundated showed a weak correlation with elevation ($r^2=0.40$) but no relationship with distance from the nearest channel connection or distance from the valley wall ($r^2 < 0.1$ in all cases; Figure 4.7b–d). Feature type was not a strong control on percent time inundated (Figure 4.7a). Based on a posthoc analysis, two groupings were observed ($p < 0.01$). The first group included Features S2 and M1, which had the largest mean inundation (66% and 68%). Feature S2 was also included in the second grouping which included S1, M2, D1, and D2 (56%, 55%, 56% and 53%, respectively).
Figure 4.6 Percent time inundated at floodplain feature locations.

Figure 4.7 Boxplots representing percent time inundated medians and interquartile ranges across the monitored locations for each floodplain feature (a). Letters above boxplots indicate statistical differences in medians according to Kruskal-Wallis tests. Note that while each channel feature has numerous inundation monitoring locations (n=8–22 sensors), each basin feature had one (n=1 sensor). Percent time inundated and linear regressions relative to
4.4.2 Groundwater-surface water level dynamics

Overall, GW-SW relationships across locations and events were dominated by counterclockwise hysteresis, indicating activation by surface water and subsequent rising of the floodplain groundwater table (Figure 4.8; 61% across all events and monitored locations). Lower proportions of clockwise hysteresis (7%), C-CC hysteresis (18%), no hysteresis (13%), and no hydrologic response (2%) were also observed. GW-SW relationships varied by floodplain location and event characteristics (Figures 4.8 and 4.3). As expected, the isolated depression (Location i) showed primarily clockwise hysteresis. The near-channel depression (Location h), however, displayed a mix of mainly counterclockwise and C-CC figure-eight hysteresis, with only one event showing clockwise hysteresis. For floodplain channel locations, dominant GW-SW relationships tended to group by proximity to the river (i.e., near-river or mid-channel locations) rather than by channel type (i.e., single-connection vs. multi-connection channel locations). Near-river channel locations (Locations a, b, d, and f) displayed primarily a mix of clockwise hysteresis (59%) and no hysteresis (34%), whereas mid-channel locations (Locations c, e, g, j, k) displayed a mix of clockwise hysteresis (76%) and C-CC hysteresis (20%).

While counterclockwise hysteresis was observed across events, C-CC hysteresis occurred most commonly during events with low antecedent wetness conditions and high gross event precipitation, leading to a large change in river stage (e.g., Events 1, 8, and 9). Patterns of no hysteresis most commonly occurred for events with more moderate changes in river stage (e.g.,
Events 2, 3, 4, 5, and 7). Two instances of no water level response were observed during Event 5, the event in which no local precipitation was recorded. This occurred in the isolated depression and a mid-channel location.

Figure 4.8 Pie charts display the proportion of each GW-SW hysteresis pattern observed at floodplain feature locations. The inset displays proportions of GW-SW relationships across all locations. Letters representing locations correspond to Figure 4.3b. While counterclockwise hysteresis dominated floodplain channels, the isolated depression showed primarily clockwise hysteresis. Within floodplain channels, other GW-SW relationships observed tended to group by proximity to the river, with mid-channel locations exhibiting more clockwise to counterclockwise figure-eight (C-CC) hysteresis and channel locations near the river more commonly exhibiting no hysteresis.
4.4.3 Floodplain channel surface flow

For the single-connection floodplain channels, surface water hydraulic gradients were primarily away from the river (positive values, Figure 4.9a), indicating surface flows directed from the river onto the floodplain. Negative hydraulic gradient, indicating flow from the floodplain to the river, occasionally occurred for short periods of time during floodplain wet-up and dry-down. In single-connection channel S2, hydraulic gradients drop to near-zero around the time of peak river stage prior to increasing again during the falling limb. Hydraulic gradients for the multi-connection channels were always in the downstream direction (Figure 4.9b). Similar to S2, there is little water flow through the multi-connection channels around peak river stage.

**Figure 4.9** Floodplain channel surface water hydraulic gradients. For single-connection channels, positive values indicate flow away from the river. For multi-connection channels (b), positive values indicate flow in the downstream direction. Numbers designate the flood event number and correspond to Figure 4.3a.
4.5 Discussion

4.5.1 Spatial and temporal variability in floodplain feature wet-up and dry-down

Spatially and temporally complex dynamics of floodplain feature activation and dry-down were present at our study site. Within-event wet-up timescales do not trend with expected controls of elevation, distance from the nearest river connection along the channel centerline, or distance from the valley wall (Figure 4.5b–d). Instead, we hypothesize that within such low-gradient environments, microtopography influences locations where initial floodwaters accumulates within features. Further, interactions with antecedent wetness conditions and event characteristics result in inconsistency in wet-up patterns, obscuring relationships with expected controls. These results suggest that initial floodwater is commonly comprised of non-contiguous sections of accumulated precipitation—or, when antecedent floodwater is present, a mixture of antecedent floodwater and direct precipitation. Given the placement of STIC sensors along the ground surface, this initial floodwater may comprise shallow depths of a few centimeters. The importance of initial flooding via infiltration excess overland flow may also explain why larger flooding events, typically characterize by greater precipitation volumes, tended to have mean wet-up timescales near zero and small spread (Figure 4.5a).

In contrast to wet-up timescales, percent time inundated shows a relationship with elevation ($r^2=0.40$; Figure 4.7b). Because differences in dry-down timing between locations tend to be much larger than differences in wet-up timing, percent time inundated mainly reflects dry-down dynamics. The relationship between percent time inundated and elevation suggests that the groundwater table is coincident with floodplain surface water elevations during late
recession periods and that water table relaxation is a primary control on dry-down patterns. However, the relationship with elevation is weak. This may be due to spatial variation in water table depth across the study site (groundwater depths varied as much as 1.3 m between floodplain locations), the presence of discontinuous or perched water tables, or structural heterogeneity within the floodplain aquifer. Further, factors such as local topography, the presence of vegetation, and seasonal variations in evapotranspiration may explain the spread of inundation duration with the factors analyzed.

While the ephemeral and intermittent nature of low-gradient floodplain channels resembles ephemeral and intermittent streams, the spatially variable wet-up and dry-down dynamics of the monitored low-gradient floodplain channel network differ from those of steep, headwater stream networks. Headwater mountain streams predominantly expand longitudinally in the upstream direction and contract longitudinally in the downstream direction in response to changes in stream discharge (e.g., Ward et al., 2018; Zimmer and McGlynn, 2017; 2018), although non-contiguous sections of dry or wet streambed often persist in some locations. Both intermittent and ephemeral headwater streams and floodplains are effective bioreactors that regulate downstream water quality (Gómez-Gener et al., 2021; Gordon et al., 2020; Lane et al., 2022; Roley et al., 2012). However, it is unknown how these differing patterns of wet-up and dry-down influence factors controlling solute transport and biogeochemical processing, including the asynchronous integration of water and solute fluxes as isolated fragments reconnect and the structure and function of microbial communities responding to dynamic environmental conditions.
Although initial wet-up and dry-down comprise only a fraction of the total time of inundation, these periods could be particularly important for the biogeochemical processing within floodplain feature networks. Alternating wet-dry periods have been shown to increase denitrification due to paired nitrification-denitrification resulting from cycles of oxic-anoxic conditions and due to the pulsed release of nutrients during soil re-wetting (e.g., Baldwin and Mitchell, 2000). Our data show high variability in both the frequency and duration of inundation across floodplain feature locations. Such variability should lead to hot spots and hot moments of peak biogeochemical activity (McClain et al., 2003) within floodplain feature networks and influence the overall biogeochemical functioning in these systems. For example, while wet-dry cycles lead to increased nitrogen cycling, complete drying may lead to death of bacteria and decrease in microbial activity (Amalfitano et al., 2008; Baldwin and Mitchell, 2000). Saturated sediments of the hyporheic zone of intermittent streams have been shown to act as a refuge for microbes during drought (Febria et al., 2012; Harjung et al., 2019; Lewandowski et al., 2019), supporting enhanced nutrient turnover rates upon rewetting. Likewise, discontinuous patches of floodwater that remain for much of the year may similarly provide refuge for microbes and extend optimal conditions for anaerobic processing. Thus, knowledge of the spatial and temporal heterogeneity of floodplain inundation and subsequent integration of water and solute fluxes during flooding is critical to understanding the hydrologic and biogeochemical function of floodplain features.
4.5.2 Flooding mechanisms are controlled by location, antecedent wetness, and event characteristics

Whereas STIC sensor binary wet/dry data reveals spatial patterns of initial inundation timing and duration within a horizontal plane, water level data provides information on vertical flooding dynamics. Surface water level measurement locations were several centimeters above near-ground surface STIC measurements. Thus, water level and STIC data provide complimentary information on flooding dynamics over the course of a flood. Specifically, groundwater-surface water level (GW-SW) relationships during flood events provide insight into how floodplain feature inundation mechanisms vary by location, event characteristics, and antecedent wetness conditions (Figure 4.4).

Counterclockwise hysteresis was the most commonly observed GW-SW pattern across locations and events, indicating a strong influence of surface water forcing on hydrologic dynamics, particularly in channel locations. While it is difficult to distinguish between river-sourced or direct precipitation-sourced water using GW-SW analysis alone, we expect that for large events this pattern is primarily the result of a dominance of river-sourced floodwater contributions (i.e., flooding from the river to the floodplain via breaks in channel banks). This is because the hysteretic portion of the GW-SW relationships (i.e., prior to broader floodplain inundation beyond topographically low floodplain features indicated by linear relationship) commonly spans a water level changes up to 0.5-m. Such an increase in surface water levels over a single event would require an unrealistically large volume of overland flow from the surrounding landscape. Therefore, we find it more plausible that the overall relationship during large events
is primarily driven by river dynamics. However, STIC analysis indicates that accumulated precipitation is an important source of initial floodwaters, albeit potentially at shallow depths. Thus, counterclockwise hysteresis likely results from a combination of floodwaters derived initially from smaller amounts of infiltration excess overland flow that are subsequently augmented by overbank contributions from the river.

While counterclockwise hysteresis is the most commonly observed GW-SW relationship, other patterns were observed. No hysteresis was common at near-river channel locations, indicating synchrony in groundwater level changes in response to fluctuating river stage. This pattern mainly occurred during events with high antecedent wetness (high antecedent inundation and river stage). Although soil moisture was not monitored during this study, this may suggest that high soil moisture is important for this observed tight coupling of groundwater and surface water dynamics, which would be consistent with studies of other systems (e.g., Cain et al., 2022; Jencso et al., 2009; McGlynn et al., 2004).

Groundwater forcing was most common for the isolated depression, the most geomorphically isolated location monitored in the study. However, we had also expected clockwise hysteresis to be observed in the moderately isolated location of the near-channel depression and channel locations further from the river. Instead, in addition to counterclockwise hysteresis these locations exhibited C-CC figure-eight hysteresis, indicating initial groundwater forcing and later surface water forcing. This pattern was primarily observed during events with a large change in river stage, the result of low antecedent wetness conditions and high gross event precipitation.
We expect that high intensity precipitation leads to rapid groundwater level rise, increasing the likelihood of groundwater-sourced floodwater contributions towards the beginning of the rising limb. Later during the rising limb, river stage rise exceeds groundwater table rise and these locations experience surface water forcing. As this pattern was most commonly observed during large events for which STIC data indicate accumulated precipitation as another important early source of floodwaters, we expect surface water level measurement elevations were too high to capture early, shallow dynamics when antecedent floodwaters were not present.

While river-sourced contributions dominate floodplain responses over the course of a flood, our results demonstrate that a substantial portion of early floodwater within the floodplain feature network was comprised of antecedent floodwater, direct precipitation, and groundwater. These data suggest that floodplain features may be hotspots of perirheic zone formation in channelized floodplains. They also suggest that the formation and dynamics of perirheic zones in highly channelized floodplains differs from that of less-channelized floodplains. For example, Berezowski et al. (2019) found that in a temperate zone floodplain system with fen wetlands, the active perirheic zone primarily formed as a front along the river’s edge which migrated further onto the floodplain and then back toward the river. In contrast, our data suggests that the perirheic zone forms primarily near floodplain topographic features rather than as a front along the river. Thus, at our site the perirheic zone occurs in more spatially variable patches across the floodplain, including locations far from the river where floodplain channels convey river water. Further, whereas previous studies of perirheic zone
formation processes have tended to focus on large river-floodplain systems (e.g., Jones et al., 2014; Mertes, 1997), our study demonstrates the relevance of feature-scale processes on perirheic zone formation within a moderate-sized river-floodplain system. As smaller rivers make up a greater extent of total river length (Leopold et al., 1964), understanding the dominant processes contributing to the occurrence of perirheic zone formation in their floodplains is critical for understanding the role of perirheic zones across the entire river-floodplain network.

4.5.3 Floodplain feature functioning: sinks or sources of matter

Floodplain channel hydraulic gradients reveal complex surficial river-floodplain interactions over the course of flood events, as well as distinctions between the hydrologic functioning of single-connection and multi-connection floodplain channels. Single-connection channels monitored in this study predominantly conveyed flow onto the floodplain. During high flow conditions, these channels drain into a non-channelized backwater wetland in the northeastern portion of the study site. While the wetland connects to the river during extreme floods, it is relatively isolated from the river under moderate flooding and is expected to be a primary site for groundwater recharge. Thus during moderate flood levels, the single-connection channels at our site primarily functioned as net sinks of river water to the floodplain, which was ultimately stored in backwater wetlands. Moreover, this water flux would be associated with both dissolved and suspended materials delivered from the river to the floodplain.
Although single-connection channel hydraulic gradients were towards the floodplain for the majority of the rising limb, peak river stage, and falling limb, hydraulic gradients indicating flow from the floodplain to the river (i.e., “reverse flow”) were recorded for shorter periods during early wet-up and late dry-down. Reverse flow during wet-up occurred for events with a high percent antecedent inundation (e.g., Events 3, 4, and 7), with the exception of Event 5 which had no local precipitation. Therefore, we expect that wet-up reverse flow occurs when overland flow during precipitation rapidly increases water levels of antecedently flooded channels, reconnecting flooded fragments with the river prior to river stage exceeding floodplain water levels. Reverse flow during dry-down presumably results from floodplain channel surface water levels lagging declines in river stage. As noted above, floodplain channel water levels are expected to be tightly coupled with groundwater levels during dry-down. Groundwater contributions to floodplain features would maintain residually high surface water levels during the late falling limb compared to the river. Thus, water draining from floodplain channels to the river during recession would be a combination of high residence time floodwater and what was recently groundwater. While periods of reverse flow in single-connection channels are relatively short, they could be important times for floodplain sourcing of pollutants to rivers. Although flooding tends to increase nitrogen removal, long-residence time water and anaerobic conditions can lead to enhanced release of phosphorous from floodplains (Amarawansha et al., 2016; Loeb et al., 2008). For example, Jones et al. (2014) found greater accumulation of soluble reactive phosphorous (SRP) and dissolved organic matter (DOM) in a relatively disconnected backwater wetland compared to a flow-through wetland. They surmise that during periods of high river-floodplain connectivity, much of the accumulated SRP and DOM is flushed
downstream. Since much of the water that drains from the single-connection floodplain channels at our study site is antecedent floodwater with long residence times, it is probable that reverse flows similarly export accumulated solutes.

In contrast to single-connection channels that primarily function as sinks of river-derived water and solutes to the floodplain with short source periods, our data indicate that multi-connection channels function as flow-through systems in which water enters the channel at the upstream connection and exits at the downstream connection. However, like streams, multi-connection floodplain channels can alter the quality of return flows by delaying downstream transport relative to the main river channel (Czuba et al., 2019), increasing the benthic surface area to water volume ratio (Ensign and Doyle, 2006), and enhancing floodplain surface-subsurface exchange (Krause et al., 2007). In addition to differences in the timing and directionality of river-floodplain exchange between floodplain channel types, mean residence times are presumably shorter for water entering multi-connection floodplain channels compared to single-connection channels. However, it is unclear how these differences in residence times influences biogeochemical functioning. For example, although greater residence times lead to increased nitrogen removal from a parcel of water, nitrogen removal is commonly limited by transport onto the floodplain (Forshay and Stanley, 2005; Jones et al., 2014). Overall, our data highlight that differentiation of whether a floodplain section is a net source or a sink is confounded by high spatial and temporal variation in the directionality of connectivity and timescales influencing biogeochemical processing. As floodplain channels are the primary conduits for flow to and from the floodplain during moderate flooding, understanding of
differences in feature-scale hydrologic functioning is needed to accurately develop water, nutrient, and sediment budgets in channelized floodplain systems.

4.6 Conclusions

The Sangamon River floodplain demonstrates the complexity of inundation patterns and mechanisms that can occur across floodplain feature networks. Although there is a strong influence of overbank flooding on hydrologic response over the course of a flood, initial feature inundation is characterized by dynamic contributions from direct precipitation, groundwater, and antecedent floodwater that accumulate in non-contiguous sections designated by local topography. Eventually these isolated fragments connect and mix with river-derived water. The role of differentially-sourced water on initial flooding suggests that floodplain features are hotspots for perirheic zone formation, and thus may be important sites for biogeochemical transformation on floodplains. Inundation mechanisms varied as a function of location, antecedent wetness, and event characteristics. Whereas floodplain channel locations were dominated by surface water forcing overall, an isolated depression was exclusively characterized by initial groundwater forcing. During large events with low antecedent wetness conditions, floodplain channel locations further from the river and a near-channel depression showed an early period of groundwater forcing followed by a dominance of surface water forcing as flooding progressed. Finally, floodplain channels were characterized by spatial and temporal variation in flow direction. Whereas multi-connection channels at the site facilitated flow-through conditions, single-connection channels primarily functioned as sinks of river-derived water and associated materials to the floodplain with short sink periods. Given that
floodplain channels are the primary pathways for water to and from the floodplain during early and late flooding, these feature-scale processes must be taken into account to predict when and where floodplains are sources or sinks of water and dissolved and suspended materials.

River-floodplain connectivity is increasingly the focus of river corridor management strategies including the attenuation of flood peaks and removal of excess nutrients (Buijse et al., 2002; Freitag et al., 2012), and a basis for regulations aimed at protecting watersheds and drinking water (USDOD and USEPA, 2015; 2020). Overall, our data demonstrate that floodplain feature networks enhance river-floodplain connectivity at moderate flood stage and control hydrologic dynamics and water-sourcing across flooding events. Thus, floodplain channels are important considerations in the context of maintaining and restoring floodplains and regulatory decisions. Further, our study site is located within a relatively undisturbed forest of an otherwise highly agricultural landscape, where riverine flows are characterized by elevated nutrients loads from fertilization (Brown and Peterson, 1983). Targeted restoration of floodplains along waterways with higher nutrient concentrations has been proposed as a cost-effective investment for nutrient removal (Gordon et al., 2020). Further, in a study conducted in the neighboring state of Indiana, floodplain channels were primarily found in systems with high meandering rates and predominantly agricultural land use (David et al., 2017), common characteristics of low-gradient, alluvial river systems of the agricultural Midwestern U.S. Thus in addition to the added water quality benefits within these landscapes, the distribution of floodplain channel networks may provide additional opportunities for development strategies that incorporate these natural floodplain features. More generally, we add to the body of literature showing that spatial
heterogeneity underpins floodplain functioning in unmanaged river corridors (Wohl, 2021). While inundation patterns and mechanisms will vary by site-specific characteristics (hydraulic conductivity, floodplain feature density, vegetation), we expect the broader implications of our results are applicable across topographically complex floodplains.

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4.7 References


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4.8 Supplemental

Figure S4.1 Example raw electrical conductivity signal (a) for 7 STIC loggers across two example events (E1 and E2) that occurred over a month in 2018. Example data includes wet-up and dry-down periods for each event. Examples show wet-up and dry-down periods. STIC locations were considered inundated when electrical conductivity measurements diverged from the dry response (raw signal $\approx 0$). Relative spatial distribution of STIC sensors (b) in single-connection channel 1 (S1) and depression 1 (D1), with wet-up order for each event indicated by numbers to the right. Colors in S4.1b correspond to sensor colors in S4.1a.

STIC logger testing

Stream Temperature, Intermittency, and Conductivity (STIC) loggers were built by modifying HOBO Pendant Temperature/Light sensors following the methods of Chapin et al. (2014). After modification and prior to field deployment, STICs were deployed and submerged in water several times to test that the sensors were responsive to inundation and drying (i.e., saturated response differed from the dry air response raw signal $\approx 0$). Further, STICs were submerged in 1 m of water for 1 day to test for leaks in housings.
Chapter 5: Conclusions

5.1 Synthesis of results

Predicting water and material transport through landscapes requires developing meaningful conceptualizations linking emergent hydrologic response with internal mechanisms. As a property that arises across scales and sites, hydrologic connectivity provides a framework for characterizing how the interplay of landscape architecture, antecedent conditions, and storm event characteristics leads to dynamic flow path activation and complex, nonlinear hydrologic response patterns. The field monitoring and numerical modeling studies presented in this dissertation (Chapters 2–4) advance predictive understanding of the how dynamic hydrologic connectivity manifests in several different types of landscapes to control transport.

The study presented in Chapter 2 explores how representing ecohydrologic separation—the compartmentalization of poorly mobile water supplying plant transpiration from highly mobile water supplying streamflow and groundwater—in a catchment-scale hydrologic model alters interpretations of water and solute storage and transport. Simulated stream discharge and chloride concentration were similar for the model that incorporated ecohydrologic separation and the model that did not. Further, total catchment water storage was similar between models. However, large differences in simulated storages and fluxes of mobile water between models altered interpreted residence times of streamflow-generating water, influencing expectations for the reactive transport of solutes. Further, differences in where water is stored (immobile vs. mobile pools) altered interpretations of the availability of water for vegetation.
Taken together, these results demonstrate the potential relevance of a moisture-dependent, small-scale hydrologic connectivity processes when making catchment-scale interpretations. Whereas Chapter 2 focuses on a natural hydrologic connectivity process in a headwater mountain catchment, Chapter 3 addresses the occurrence of threshold-mediated hydrologic connectivity in a low-gradient, human-modified agricultural landscape. I investigate how antecedent conditions control thresholds of tile-runoff generation and nitrate loads between events, as well as nitrate concentration-discharge (c-Q) relationships within events. Empirical data and hydrologic modeling revealed a tile-runoff generation activation threshold emerged as a function of the sum of gross precipitation, antecedent shallow soil moisture, and antecedent below-tile groundwater moisture deficit. These results indicate an additive effect of two storage thresholds in generating subsurface runoff in tile-drained landscapes—a shallow soil moisture threshold and a below-tile groundwater moisture threshold controlled by the tile depth. Event nitrate load showed a linear dependence on runoff, suggesting that subsurface nitrate export and storage can be estimated using runoff threshold relationships and long-term average nitrate concentrations. Finally, within-event nitrate concentration-discharge relationships were controlled by event size and antecedent tile flow state because these factors dictate the sequence of flow path activation and tile connectivity over a storm event. This study shows the importance of threshold-mediated connectivity in water and nutrient export in intensively managed, tile-drained landscapes.

Chapter 3 considers the continuum of floodplain-river connectivity induced by the ephemeral inundation of floodplain topographic features, including secondary channels and depressions.
In this study I use high spatial and temporal frequency monitoring of floodplain feature intermittency and surface water-groundwater level relationships to characterize inundation patterns and flooding mechanisms across feature locations and between storm events. Results highlight spatially and temporally complex dynamics of floodplain feature activation and dry-down. Initial inundation was commonly characterized by dynamic contributions from direct precipitation, groundwater, and antecedent floodwater. These initial floodwaters accumulated in non-contiguous sections of floodplain features and ultimately mixed with river-derived water, suggesting that floodplain features are hotspots for perirheic zone formation. The dominant inundation mechanisms observed at monitored locations varied as a function of feature location, antecedent wetness, and event characteristics. Finally, surficial interactions between rivers and floodplain channels differed between channel types and varied over flooding events. Whereas multi-connection channels at the site facilitated flow-through conditions, single-connection channels primarily functioned as sinks of water and solutes onto the floodplain with short source periods to the river. Overall, these results highlight complex river-floodplain surface connectivity dynamics, as well as complex floodplain feature surface water-groundwater connectivity.

5.2 Future research directions

There are several recommendations for future work based on the studies presented here, particularly building upon the conceptualizations developed in Chapters 3 and 4. The techniques used to identify tile runoff mechanisms in Chapter 3 have historically been applied to pristine, forested hillslopes. However, my results suggest that identifying runoff threshold
relationships is a promising method for predicting the storage and delivery of water and nitrate in intensively managed landscapes. These traditional hillslope hydrology techniques could be similarly applicable in other landscapes in which humans have modified drainage structure, including urban landscapes and different agricultural systems. Further, catchment classification based on connectivity and threshold runoff response characteristics have been proposed as a basis for advancing predictive understanding of runoff response as a function of physical controls and climate (Ali et al., 2013; McDonnell, 2013; McDonnell et al., 2021). Despite typically being omitted from such classifications and comparisons of catchment response, my results suggest that human-modified landscapes could similarly be classified under schemes based upon connectivity and threshold runoff response characteristics. Thus, a future efforts should seek to test how runoff threshold relationships manifest across diverse landscape types and can be incorporated into generalizable classification schemes.

The conceptual models of hydrologic connectivity and water sourcing presented in Chapters 3 and 4 could be further constrained using water isotope analysis. Stable isotopes of hydrogen (\(^2\text{H} \text{ or D for deuterium} \)) and oxygen (\(^{18}\text{O} \)) have a long history of use in hydrology and have proved useful for characterizing water flow paths, sources, and age (Kendall and McDonnell, 2012; McGuire and McDonnell, 2007). As the elemental basis for water molecules, they are ideal tracers because they naturally occur in abundance and are transported in the same way as water. Stable isotopic composition commonly differs between precipitation, surface water, and groundwater at a particular location. Thus, if the isotopic signature of each contributing water source is known, mixing models can be applied to determine the relative contribution from
each (Kalbus et al., 2006; Klaus and McDonnell, 2013). In Chapter 3, threshold tile-runoff relationships across events and c-Q relationships within events are used to infer flow paths and water sourcing to tile drains. Isotopic analysis would enable further differentiation between event water, soil matrix water, shallow groundwater, and deeper groundwater contributions over the course of a storm. The analysis would also provide a parallel line of evidence to test the conceptual model of tile-runoff generation.

Likewise, the conceptual model of floodplain feature activation presented in Chapter 4 would benefit from water isotope analysis. In this study, we used spatiotemporal patterns of floodwater intermittency and linkages between groundwater and surface water levels to infer inundation mechanisms and floodplain water sources. Isotopic analysis would provide complimentary information that could be used to estimate the relative contributions of precipitation, river water, and groundwater to floodplain water over the course of a flood. These data would be particularly helpful for differentiating between river-sourced and direct precipitation-sourced flood water since that could not be accomplished through water level relationship analysis alone.

Further, while our data suggest that floodplain features are hotspots of perirheic zone formation and therefore biogeochemical processing, this has not been directly tested. Collecting flood water samples for biogeochemical analyses (e.g., nitrate, phosphorous, and organic matter concentrations) over the course of a flood would shed light on the biogeochemical response of floodplain features to flooding. However, given that floodplains are
dynamic environments, accessing sampling locations during floods can be challenging. Automatic samplers, including both passive siphon samplers and active electronic samplers, provide a means for sampling at controlled intervals without the need to be at the sampling location (Chapin, 2015; Diehl, 2008; Graczyk et al., 2000). However, samples for analysis of biogeochemical parameters commonly have hold times of hours to days (Burke et al., 2002; Moore and Locke, 2013; USEPA, 1974). Because high flood waters commonly remain on the floodplains for weeks, floodplains present challenging environments for retrieving water samples within an appropriate timespan for biogeochemical analysis, particularly during the rising limb of storms. As such, future work aimed at understanding floodplain feature biogeochemical dynamics would require consideration of methods to safely and effectively collecting high frequency water samples during floods.

The field-based observations presented in Chapter 4 provide novel insights into hydrologic processes occurring in floodplain features and represent a first step towards understanding how topographically complex floodplain systems function hydrologically. A question which has emerged from this empirical work is, what are the magnitudes of groundwater-surface water exchange fluxes and residence times of floodplain features? Further, how do these fluxes and timescales influence the biogeochemical transformation potential of floodplain features and compare to that of well-studied exchange processes of hyporheic exchange beneath submerged bedforms and through meanders and alternate bars? This information is necessary to identify processes that dominate river corridor exchange under varying hydrology and develop a predictive understanding of where ecosystem functions like nutrient removal occur in
river-floodplain networks. While field methods such as tracers can provide insight into flow pathways and timescales at feature-scales (Harvey and Gooseff, 2015; Tetzlaff et al., 2015), hydrologic models are a useful tool for quantifying exchanges fluxes and residence times as well as aggregating over larger scales. Thus, a valuable next step would be to develop a floodplain hydrologic model, informed by field observations of inundation dynamics, to simulate surface and subsurface hydrology and quantify floodplain groundwater-surface water exchange and residence times.

The research presented in this dissertation sheds light on internal hydrologic connectivity processes that influence the storage and release of water. The insights gained from these studies enhance our predictive understanding of dominant hydrologic connectivity controls, when and where important hydrologic connections occur, and how connectivity dynamics ultimately influence hydrologic response. Although hydrologic connectivity manifests in different ways across landscapes and scales, these findings help to build a foundation to further develop the concept of connectivity and provide approaches for transferring conceptualizations of hydrologic connectivity to new sites and situations. Ultimately, this work supports improved understanding of process-based hydrologic connectivity relevant for environmental management.
5.3 References


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Threshold changes in tile drain storm runoff are controlled by antecedent conditions. American Geophysical Union Meeting (2019). San Francisco, CA.
Dynamic hydrologic connectivity controls transport of water and solutes through Midwest landscapes. Intensively Managed Landscapes Critical Zone Observatory Meeting (2019). Champaign-Urbana, IL.

Multi-scale observation of time-variable surface and subsurface interactions of an Intermittent urban stream. *European Geophysical Union Meeting* (2016). Vienna, Austria.


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