Understanding wetland hydrology and water quality through data/process based modelling

by

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Abstract

Rapid coastal development has led to loss/alteration of wetlands, streams, riparian vegetated areas and headwater areas that buffer coastal waterways from pollution. Small wetlands, besides being easily altered, have also shown to have higher capacity for nonpoint source amelioration. Consequently, the protection and restoration of small wetlands and their vegetated buffer systems are critical in regulating flows and enhancing water quality on the landscape. This requires good understanding of their functionality so that appropriate steps can be taken for their management and preservation. In Chapters 2, 3 and 4, this study evaluates headwater slope wetlands in Alabama's coastal plain using field data and process-based modeling, and in Chapter 5, improves existing relationships describing sediment removal by vegetated buffers through data-based modeling. Very little data exists for headwater slope wetlands (groundwater-fed wetlands above and alongside 1st order streams) in the region; to address this knowledge gap we observed hydrology and dissolved inorganic nitrogen (DIN) trends in select wetlands, addressed challenges associated with modeling their hydrology and lastly, identified nitrogen inputs pertinent to predicting nitrate export through a sensitivity analysis. Delineated watersheds were small (<2 km^2); flashy flows followed level of urbanization in the watershed, with the least altered wetland having stable and damped flows. Despite watershed alterations, wetlands still showed DIN load reductions ranging from 9% to 50%. One of the study wetlands showed unusually large flows, indicating the presence of a larger groundwater watershed relative to the extent the delineated surficial watershed; a common issue in coastal plain regions where topography is flat and water tables are shallow. Using this as a case study, we investigated different approaches of modelling flow using popular watershed model SWAT (Soil and Watershed Assessment Tool) as a simpler alternative to complex groundwater models. Since flows in SWAT are limited by watershed precipitation, simulated flows were several times smaller in magnitude than observed flows. Calibration approaches involved manual amplification of baseflow with a multiplier (E_{NASH} = 0.66), tweaking parameter RCHRGE_DP to allow extra water to be added to the system (E_{NASH} = 0.75), and incorporating ANN (Artificial Neural Network) with SWAT to further improve calibration performance (E_{NASH} = 0.88). These approaches provide managers and modelers useful tools to navigate similar flow calibration challenges in other groundwater dominant watersheds. Since data for models aimed at understanding wetland function are especially scarce for smaller wetlands (e.g., headwater slope wetlands), optimizing data collection to include only those most valuable for model predictions is a pressing need. Taking the case of nitrate, we conducted a sensitivity analysis to assess if detailing surface inputs of organic nitrogen and ammonia (whose fluxes are linked with nitrate) were necessary to predict nitrate export from study headwater slope wetlands. Nitrate export, modelled by model WetQual, showed negligible sensitivity to organic nitrogen and ammonia inputs. Perhaps low residence times in study headwater slope wetlands, which are typically gaining wetlands with no depressional storage, afforded too little time for N transformations to effect nitrate export leading us to conclude that organic nitrogen and ammonia input data at high

resolution are not as important as detailing nitrate inputs in low residence time, groundwater interacting wetlands such as headwater slope wetlands. Wetland management also involves revitalizing streamside vegetation which are crucial in mitigating nonpoint pollution, such as sediment pollution. With the objective of improving existing relationships describing sediment removal, we compiled data from 54 studies (including online BMP database) concerning sediment trapping by vegetated buffers and recorded buffer characteristics (such as buffer width, slope, area, vegetation type, sediment and runoff loading, runoff rates, residence time, roughness and sediment removal efficiency). An exponential regression model best described the relationship between sediment removal efficiency and volume ratio, residence time and width further (R^2 = 40.5%). This model was compared with performances derived from applying other sediment reduction regression models reported in literature namely those in White and Arnold (2009), Liu et al. (2008) and Zhang et al. (2010) to our database. Of these, only the model presented by White and Arnold (2009) was statistically significant presumably because of the inclusion of runoff reduction in their study. The results of this study point towards the importance of considering flow in buffer design.

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Chapter 1

Brief overview and justification for study

Water quality prediction has large implications on the environment, human health, and economy. In this regard, riparian zones and wetlands have only recently been acknowledged for the important role they play in improving water quality and regulating flows on the landscape. Historically wetlands were looked upon as 'unhealthy' lands (Amezaga et al. 2002) which allowed for the loss and destruction of >50% of U.S wetlands over the last century. Wetlands became the most degraded ecosystem, both within the U.S and on a global scale. Significant steps were taken in the late 1980s to preserve the remainder of America's wetlands, and to create and restore wetlands when feasible to increase the quality and quantity of the nation's wetland resource base (National Wetlands Policy Forum 1988).

Wetlands and riparian areas perform many important functions such as flood attenuation, improving water quality and improving biodiversity beside a host of other ecosystem services and functions. Strong relationships have been documented between water quality, water quantity and runoff with landscape characteristics within a watershed. Changes in land use can disrupt water budgets by changing the partitioning of precipitation between the different components of the water cycle such as evapotranspiration, runoff, and groundwater flow (Foley et al. 2005). Loss of native vegetation cover and increased impervious area cover causes increased surface runoff, flashiness in urban streams, reduced base flows, increased river discharges and initiate incision where stream power is high (Foley et al. 2005; Forman and Alexander 1998, Bledsoe and Watson 2001). Roads can block or redirect natural flows to the wetland, raising upslope water table and lowering that downslope (Forman and Alexander 1998). Agricultural runoff may contain large amounts of nutrients and sediment while runoff from heavily urban areas can contain excess nutrients from sewage pipes and fertilized lawns, sediment from construction sites, and oils, greases, and heavy metals, rubber fragments, sodium and sulfate and various other contaminants (Forman and Alexander 1998). High nutrient and sediment loading in surface waters within the watershed can ultimately compromise the quality and quantity of water reaching estuaries, bays and oceans through eutrophication, hypoxia, and degraded aquatic habitats. A classic example is presented by the Gulf of Mexico which has been facing numerous problems with eutrophication and hypoxia for years as a result of excessive nutrient loadings from the Mississippi River basin.

Despite acceptance of the socioeconomic and ecological importance of wetlands and riparian areas, their role has largely been ignored in watershed modeling and water resource planning, partly because of the complexity of processes that occur in them. Simple methods such as regression/statistical models, as well as process-based models are useful prediction tools to gain understanding of the influence of wetlands and riparian zones on overall watershed water and nutrient/sediment balances. While the former is limited in scope and sheds light on the relative significance of different processes and sources, the complexity of wetland processes generates a need for more sophisticated process-based dynamic models that can consider vegetation and soil fluxes, nutrient retention and interaction with surface water, groundwater, and soil (Hattermann et al. 2006). Integration of these complex wetland-scale models within larger watershed scale models such as SWAT (Soil and Watershed Assessment Tool) represents a difficult challenge since SWAT is associated with specific datasets which limits its transferability (Krysanova et al. 1998). However, ignoring wetland function in a watershed can grossly influence policy decisions with respect to pollution reduction and water quality improvement and the quantification of ecosystem services.

My dissertation will touch upon both modeling approaches for understanding wetland and riparian area influences on various aspects of hydrology and water quality as well as providing tools to better redirect wetland management and restoration efforts. Here the focus is on assessing a lesser studied wetland type in Alabama's coastal plain region, called the headwater slope wetland, to generate more understanding about its functional capacity in light of increasing urbanization in the region using process-based models such as SWAT and WetQual for hydrology and water quality prediction, while the other part of the dissertation will deal with improving data-based regression models for sediment removal by riparian buffers for better water quality prediction and management. The overall objective of my dissertation is to improve water quality prediction by incorporating the functional role of wetlands within a larger watershed context to aid in different water quality management objectives.

Overall Objectives

The broad objectives for my dissertation are as follows:

1. Evaluate the influence of increasing land use/land cover change on the functional capacity of headwater slope wetlands in Baldwin County, AL
2. Develop a data-based regression tool for sediment removal prediction from riparian buffers

Objective 1: ***Evaluate the influence of increasing land use/land cover change on the functional capacity of headwater slope wetlands in Baldwin County, AL***

In my first three chapters, I will focus on the evaluation of a lesser studied wetland type in Alabama's coastal plain region, called 'headwater slope wetland'. These are groundwater-fed forested wetlands that occur in the upper reaches (headwater areas) of 1st order streams (Barksdale et al. 2013). Headwater slope wetlands form the interface of terrestrial uplands and coastal creeks, and occur numerously in the U.S coastal plain region. Slope wetlands form where topographic features allow for subsurface flows from the surrounding landscape to intersect the surface resulting in consistently high water tables (Stein et al. 2004; Barksdale and Anderson 2015; Noble et al. 2007). They branch out into numerous creeks and extend throughout local watersheds as smaller streams and creeks which join larger drainage networks and ultimately flow into local bays and oceans. Cumulatively, headwater streams can account for over two-thirds of the total stream length in a river and at least 80% of the nation's stream network (Freeman et al. 2007; Meyer et al. 2003; Roy et al. 2009). They can also contribute ~55% of the water volume and 40% of nitrogen fluxes to 4th order streams (Alexander et al. 2007); as a result, hydrologic alteration of headwater wetland systems has the potential to impact ecological functions of the drainage networks at large scales (Freeman 2007). Because of their unique landscape position and their small size, they are highly vulnerable to watershed land use alterations.

Headwaters provide important ecosystem services such as habitat for aquatic life, nutrient uptake and cycling, downstream temperature regime regulation and mitigation of flows, sediment and nutrient fluxes (Roy et al. 2009). They have been shown to remove/transform over half of watershed load inputs of dissolved inorganic nitrogen (Peterson et al. 2001). Thompson et al. (2000) identified denitrification in estuarine headwaters as an important mechanism in reducing nitrate inputs to estuarine creeks. Observing the dense coastal stream networks of Baldwin County, as presented in Figure 1, and assuming a slope wetland at the headwaters and alongside each 1st order stream gives a visual picture of their sheer density on the landscape and the potential magnitude of their cumulative ecosystem function. Rapidly increasing population pressure in coastal areas has been an important stressor on coastal wetlands, including headwater wetlands - in Baldwin County (along the Gulf of Mexico in south Alabama), population increased by 42.9% from 1990 to 2000 and is expected to rise significantly in the future (BCPZD 2005). As a result, critical wetland habitat is continually being drained, dredged or altered to make way for agricultural or urbanized land use from native ecosystems which disrupts natural biogeochemical balances of the landscape as streams and rivers are no longer buffered from upland areas (Day Jr. et al. 2003). Headwater streams and wetlands are easily 'buried', i.e., redirected through channels, pipes, and ditches, or by directly paving over the stream (Elmore and Kaushal 2007) to make way for agricultural and urban development. Elmore and Kaushal (2007) reported a positive correlation between increasing impervious area cover and fraction of headwater streams buried, and that headwater streams were more likely to be buried than larger streams at every degree of urban development. Increased nutrient inputs into these headwater systems due to anthropogenic influences may overwhelm their capacity for nutrient transformation, and nutrients maybe transported to greater distances downstream in the drainage network (Peterson et al. 2001).

As the Gulf Coast continues to develop, groundwater driven headwater slope wetlands are likely to shift to more surface water driven systems, which can alter their hydrological, biogeochemical and physical characteristics and have far-reaching implications for downstream and coastal waters. Recent studies in Baldwin County, AL conducted by Barksdale et al. (2014) and Barksdale and Anderson (2015) reported flashier hydrologies and greatly altered species composition in headwater slope wetlands with higher watershed Curve Number (CN, which was used as a surrogate measure of watershed imperviosness) and landuse conversion. The main goal of this research is to expand on the body of knowledge regarding headwater slope wetland function in the region and giving valuable insights with regard to hydrology and water quality prediction in these systems to aid in their restoration and protection.

- In Chapter 2, I examine hydrology and nutrient trends in data collected from four headwater slope wetlands in Baldwin County AL.
- In Chapter 3, I assess the challenges of predicting flow for groundwater dominated hydrology in regions of low topographical relief, such as Alabama's coastal Plain region. Here, I focus on one of the study wetlands and use it as a case study to present different approaches of calibrating hydrology using commonly used watershed model, SWAT (Soil and Watershed Assessment Tool).
- In Chapter 4, I inquire whether detailed collection of surface water concentrations of Organic-N and Ammonia-N is pertinent to predicting nitrate export from these headwater slope wetlands through a sensitivity analysis involving watershed model SWAT and wetland model WetQual.

Objective 2: ***Develop a data-based regression tool for sediment removal prediction from riparian buffers***

Riparian ecotones form the transition zone between terrestrial and aquatic ecosystems. Water from terrestrial systems typically pass through this ecotone to reach the aquatic system, mainly through surface runoff, seepage, shallow subsurface flow, deep subsurface flow, and through drainage tiles (Vought et al. 1994). Naturally occurring riparian forests and streamside vegetation thus form a natural interface between uplands and aquatic processes (Sweeney and Newbold 2014). They not only intercept and purify pollutant-laden runoff, but also enhance the physical, chemical and biological characteristics of the riparian ecosystem that enable pollutant filtration and sequestration (Sweeney and Newbold 2014). Degradation of riparian vegetation in addition to non-point source pollutant export was identified as a significant stressor contributing to the deterioration of over 50% of stream and river length in the U.S (Sweeney and Newbold 2014).

Non-point source pollutants need to be tackled using several strategies: either pollutants can be managed at the source, or else, runoff should be intercepted to filter out nutrients and sediment before they reach surface waters (Vought et al. 1994; Ribaudo et al. 2001). The establishment and maintenance of vegetative filter strips (VFS) and riparian buffers have gained immense popularity as a cost-effective interception strategy for enhancing streamside ecosystem quality and water quality improvement by non-point source pollutant removal (Lowrance 1997; Mayer et al. 2003). Vegetative filter strips (VFS) are bands or areas of closely grown vegetation that receive and purify runoff from upslope areas such as croplands or pastures or other pollutant source areas (Dillaha et al. 1988). They perform a wide array of functions - they filter out sediments and nutrients from runoff, promote filtration, and increase retention time allowing for sediment deposition and lower velocity of runoff. A number of studies have documented effectiveness of vegetated filter strips. Le Bissonais et al. (2004) reported as much as 98% decrease in sediment concentration using a 6m wide grass strip. Duchemin and Hogue (2009) reported 87% decrease in total suspended solids using grass strips and 85% reduction in total suspended solids using mixed grass and tree buffer strips.

The maintenance of riparian buffers depends highly on understanding specific transport mechanisms through these ecosystems. Models are used to test different scenarios for reducing pollutant loads; however models used for this purpose are oftentimes too simplistic in their approach and may apply a simple user-defined reduction factor or empirical formula to simulate the effectiveness of the buffer strip (or BMP). Regression (statistical) models are a useful tool for water quality prediction and an important baseline for making management decisions regarding buffer maintenance and pollutant attenuation (Mayer et al. 2007).

- In Chapter 5, I compiled a database from peer reviewed literature and online BMP databases for buffer sediment control. This was used to develop regression-based relationships between sediment removal and buffer characteristics.

Chapters 2 – 5 have been organized as stand-alone chapters for ease of publication purposes. In Chapter 6, I summarize the major findings from each chapter and outline recommendations for future work.

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Figure 1. The triangles represent study headwater slope wetlands in Baldwin County, AL. Baldwin County has an extensive stream network; nearly each of the streams/creeks start out as headwater wetlands. This schematic is a good representation of the density of headwater wetlands in this region, and consequently a relative measure of their importance in water quality improvement and flow regulation.

Chapter 2

Hydrology and nitrogen trends in coastal plain headwater slope wetlands

Abstract

Rapidly increasing population pressure and land use conversion from forests to urban and agricultural uses in Alabama's coastal plain have been important stressors on coastal wetlands. Headwater wetlands are particularly vulnerable because of their small size; they are easily "buried" by altering water conveyance through ditching, tiling or directly paving over. Since headwater areas play a disproportionately high influence on watershed flow and nutrient fluxes (e.g., headwater streams contribute >40% of flow and nitrogen fluxes to fourth order streams), alterations to their functionality can have significant impacts downstream and in coastal waters. Here we examine flow and dissolved inorganic nitrogen (DIN) trends in four "headwater slope wetlands" across a range of watershed alterations. This wetland type exists as groundwater-fed wetlands above and alongside 1st order streams and occurs in high densities in the Alabama-Mississippi coastal plain region. Watershed sizes ranged from 0.5 – 1.8 km^2 and % imperviousness varied from 1.5 to 41.6%. Each wetland showed different hydrology and DIN trends. High levels of urban cover caused wetland hydrology to be flashy with increasing *RB* indices (flashiness index) corresponding to level of urbanization in the watershed. The wetland in the least altered watershed showed stable, persistent and damped flows with the highest baseflow contribution (>70%) compared with wetlands located further inland. Overall, observed DIN concentrations were low in the wetlands except for the wetland in a dominantly agricultural watershed. Despite watershed alterations, wetlands still showed DIN load reductions ranging from 9% to 50%. We also considered headwater slope wetlands cumulatively on a county level

by identifying all headwater slope wetlands in Baldwin County and delineating their watersheds. Overall, the county north of I-65 is more forested with wider and more complete stream networks, while south of I-10 is dominantly agricultural and/ urbanized with narrower and more fragmented stream networks. This was reflected in watershed land use, with currently % watershed area covered by agriculture varying from 3.3% north of I-65 to 44.1% south of I-10, and urban areas varying from 4% north of I-65 to 15.6% south of I-10. Density of headwater wetlands also decreased from 0.3 wetlands/km^2 to the north of I-10 to 0.2 wetlands/km^2 to the south of I-10. Findings from this study give preliminary understanding of the diversity of headwater slope wetland function in the region which will be critical towards their protection and restoration in the face of ever increasing development in Baldwin County.

Keywords: *Wetland, headwater slope wetlands, urbanization, coastal plain, Alabama, DIN*

1. Introduction

Wetland type, distribution and function varies widely with geology, climate, topography, hydrology, water quality and the degree of anthropogenic disturbance (Carter 1996). In the Alabama-Mississippi coastal plain, streams typically originate from forested groundwater fed slope wetlands in the headwater areas (Shaneyfelt and Metcalf 2014; Figure 1). These headwater slope wetlands, like other wetland types, maintain flows, store and transform carbon and nutrients, and support and maintain biodiversity (Nelson et al. 2011). Headwater areas have high levels of hydrological independence and ecological autonomy because of their location at the top of the drainage network (Lowe and Likens 2005). They have small contributing watersheds and processes in them are directly impacted by terrestrial inputs (e.g., nutrients, toxins, heavy metals) compared to larger streams, rivers and floodplain wetlands which are impacted by upstream networks and processes (Saunders et al. 2002; Lowe and Likens 2005). Moreover, wetlands associated with lower order streams such as headwater streams, affect nonpoint source amelioration to greater levels than floodplain wetlands further downstream (Brinson 1993; Rheinhardt et al. 1998). Headwater wetlands thus warrant significant protection efforts. Given the high density of coastal creeks in the Alabama-Mississippi coastal plain, the cumulative impacts on headwater slope wetland function are potentially significant; however, little information exists regarding their flow and nutrient attenuation functions in the region. This study presents baseline flow and nutrient data collected from four headwater slope wetlands in Baldwin County, AL, draining different land uses and situated at varying proximities from the coast.

Lowe and Likens (2005) aptly likens headwater streams to the alveoli of the lungs. Just as alveoli are the finest branches of the human lung and are units of primary gas exchange, headwater systems are the finest branches of the stream network and are most important in maintaining the functioning of the whole network (White and Crisman 2014). Headwater systems intercept runoff from terrestrial areas and their functioning is strongly tied to interactions with land use around them (Lowe and Likens 2005). This can have strong implications for wetland responses and downstream conditions, particularly for those in coastal watersheds. Rapidly increasing population pressure in coastal regions has been an important stressor on coastal wetlands - population of coastal counties along the Gulf of Mexico increased by 150% from 1960 – 2008 (Wilson and Fischetti 2010). Population in coastal Baldwin County, AL (along the Gulf of Mexico in south Alabama) increased by 42.9% from 1990 to 2000 (BCPZD 2005) and is expected to grow by 65% by 2040 (CBER 2017), making it the fastest growing county in Alabama. As coastal regions continue to develop, critical wetland habitat is often drained, dredged or altered to make way for agricultural or urban land use. Loss or alteration in wetlands can disrupt natural biogeochemical balances of the landscape as streams and rivers are no longer buffered from upland areas (Day Jr. et al. 2003).

Headwater systems are highly vulnerable to 'burial', i.e., redirected conveyance through pipes, ditches or directly paving over, because of their smaller size (Roy et al. 2009; Elmore and Kaushal 2008). Headwater streams are easily impounded to form ponds for recreational, residential and agricultural uses (Noble et al. 2007). Roads and impervious surfaces limit infiltration and groundwater recharge, intercept subsurface flows and interflow, and also funnel flow, nutrient and sediments rapidly to the waterbodies (Noble et al 2007). They can also incise headwater streams and result in a drawdown of the water table from immediately adjacent wetlands (Havens et al. 2004; Forman and Alexander 1998; Bledsoe and Watson 2001). Reduced infiltration and increased runoff velocity in urban areas can cause more frequent flood pulses and lower baseflows; consequently, hydrographs tend to be flashier in urban streams when compared to forested streams (Nagy et al. 2012; Havens et al. 2004; Forman and Alexander 1998; Bledsoe and Watson 2001). Elmore and Kaushal (2008) reported a positive correlation between increasing impervious area cover and fraction of headwater streams buried, and that headwater streams were more likely to be buried than larger streams at every degree of urban development. They also observed that headwater systems in coastal watersheds are more completely buried than those in upland areas due to higher population density along coastal plains than upland areas.

Since headwater wetlands and streams are highly connected to the conditions of their surrounding watershed, they can readily reflect alterations due to watershed development in their physical, chemical or biological responses (Schwartz 2010). Contamination of water resources occurs from increased nutrients, sediment, bacteria, heavy metals and other pollutants associated with increasingly dense urban populations, and land use changes to agriculture and urban sprawls (Nagy et al. 2012; Schwartz 2010). Fertilizers from lawns and crop fields, leaky sewers and sewage overflows, NOx emissions, etc., are some significant sources of nitrogen loading to headwaters in agricultural and urbanized watersheds (Wollheim et al. 2005). Compounded with hydrological changes resulting from land use alterations, pollutants are swiftly routed to water bodies along altered flow paths with reduced residence times (Wollheim et al. 2005). Wollheim et al. (2005) estimated 45% higher nitrogen loading in the urban head watershed compared to a forested head watershed of similar size.

Typically, headwater areas are sites of significant nutrient conversion and retention (Roberts et al. 2006) due to their diverse channel morphology, storage capacity and low discharge which allows them to retain and process large amounts of nutrients and organic matter from their watersheds (Weigelhofer 2017; Alexander et al. 2007). Peterson et al. (2001) reported that headwater streams retain and transform over 50% of inorganic nitrogen inputs from their watersheds. Thompson et al. (2000) identified denitrification in estuarine headwaters as an important mechanism in reducing nitrate inputs to estuarine creeks. Increased nutrient inputs into these headwater systems due to anthropogenic influences may overwhelm their capacity for storage or transformation, and therefore nutrients may be transported to greater distances downstream in the drainage network (Peterson et al. 2001).

Sanger et al. (2015) observed that health risks and flooding vulnerability in headwater regions became concerning when watershed impervious cover exceeded 10-30%. While watershed impervious cover of 10-20% is sufficient to observe adverse changes in physical and chemical environments, impervious cover exceeding 20-30% is sure to impair ecological processes in headwater creek systems (Sanger et al. 2015). Recent studies on headwater slope wetlands in coastal Alabama reported influence of surrounding land use on wetland water levels (Barksdale et al. 2014), which impacted forest structure and composition, soil conditions (Barksdale et al. 2014 and Barksdale and Anderson 2015) and amphibian distributions (Alix et al. 2014). Barksdale et al. (2014) reported headwater wetland hydrology changing to more surface water driven, flashy regimes with increase in the watershed Curve Number (a surrogate metric used to describe level of imperviousness and runoff in the watershed).

Amidst rapid rates of urban development and high levels of surface and groundwater interaction in coastal Alabama, there is much concern about nonpoint source pollution risk to both surface and groundwater resources. As priority areas in terms of their influence on the stream network, headwater slope wetlands have been frugally assessed for their flow characteristics and nutrient reduction function in the Alabama Coastal Plain. Our objectives for this study are to: 1) report baseline data regarding flow characteristics, as well as water quality reduction (DIN) for four headwater wetlands in Baldwin County, AL, and 2) delineate headwater slope wetlands across Baldwin County to get a general idea of their potential impact on the landscape. We hypothesized that wetlands that received runoff from agricultural and urban watersheds to have flashier, surface-water driven hydrology accompanied by higher nutrient concentrations and loads than those in more forested ones.

2. Materials and Methods

2.1 Site description

Data for this study was collected from four headwater slope wetlands located in Baldwin County, AL: New Foley wetland (NF) located at the headwaters of a smaller tributary to Owen’s Bayou, Old Foley wetland (OF) located at the headwaters of Graham Creek, Bay Minette wetland (BM) located at the headwaters of a tributary to Bay Minette Creek, and Stapleton wetland (ST) located at the headwaters of a tributary to Fish River (Figure 2). Wetlands OF and NF are located within the city of Foley, wetland BM in the city of Bay Minette, and wetland ST in the city of Stapleton. In order of proximity to the coast from closest to farthest, the wetlands are ordered from OF, NF, ST and BM.

These wetlands lie in Baldwin County, AL within the Southern Coastal Plain physiographic region, an area characterized by hot, humid summers and mild winters with mean annual temperatures of ~19ºC and precipitation of ~1676 mm (Robinson et al. 1996). Headwater wetlands in coastal Alabama occur at the headwaters of 1st order streams - they are typically groundwater fed and exist as braided channels along a gradual slope (Figure 1; Noble et al. 2007; Shaneyfelt and Metcalfe 2014). Following heavy rains, headwater wetlands maybe become inundated but rarely do they flood for extensive periods of time (Noble et al. 2007). Water moves slowly through the wetland collecting into small, braided channels that eventually converge into a single creek channel. Wetland soils are generally alluvial in nature while surrounding upland areas are typically comprised of sandy soils (Barksdale et al. 2014; McBride and Burgess 1964).

The study wetlands were selected to be comparable in watershed size, and display a range of land uses typical to the region. Watershed boundaries were delineated for the four wetlands using the Soil and Watershed Assessment Tool (SWAT-2012) through the ArcSWAT interface in ArcGIS 10.0. Watershed sizes were very small and ranged in size from 0.5 to 1.3 km^2 at discernible surface inflows and 0.5 to 1.8 km^2 at the discernible surface outflows (Table 1), which are typical for headwater wetlands. The four wetlands occur alongside 1st order stream reaches; OF and NF watersheds are located in the coastal plain lowlands at ~ 3-18m above MSL, while BM and ST watersheds are located further inland at elevations of ~ 64-84 m above MSL and 59 – 68m above MSL respectively. Wetland OF is located within the Graham Creek Nature Preserve and almost all of its watershed falls within the area of the preserve and is predominantly forested. NF, located just north of OF, is predominantly residential (~57%) with housing areas upstream, to the north and another proposed one to the south of the wetland. Also, a residential impounded lake drains into the NF wetland. The ST watershed is predominantly agricultural (dominated by peanut and cotton) upstream of the wetland with very little impervious cover. Wetland BM is predominantly an urbanized watershed with a mix of different urban land uses. It lies next to the Faulkner State Community College and receives a lot of runoff and debris from the college campus. A sediment detention pond and other construction on campus sometimes leads to large amounts of sediment entering the wetland channel causing flow obstruction periodically. Chinese privet (*Ligustrum sinense*), a highly invasive species, is a common sight along the stream. The inflow to the wetland is a concrete and riprap lined channel by the side of a parking lot.

Based on the National Land Cover Dataset (NLCD), nearly 84% of the BM watershed is classified as urban, followed by NF watershed with 45.6%, ST watershed with 5.7% and OF watershed with only 0.5% urban land use. Percent imperviousness was also derived in each watershed, defined as the percentage of the watershed that is impervious, by manually digitizing impervious cover in the watershed using 1m resolution aerial images photographed by the USDA-FSA Aerial Photography Field Office (downloaded from USDA Geospatial Data Gateway) (Table 1). The three watersheds were inspected in the field to verify conditions noted above.

2.2 Data collection

2.2.1 Hydrology monitoring

Hydrological data for the study wetlands were collected for varying time periods in 2013 and 2014 at discernible wetland inlets and outlets. Stage was measured every 15 min using InSitu Mini-Troll 500 pressure transducers and data loggers at discernible surface-water inlets and outlets to the wetland. Stage was associated with discharge measurements taken at the site at different times (~9 – 12 readings per transducer location) to develop stage-discharge relationships (i.e., rating curves). For each discharge measurement, surface water velocity and depth were measured every 10 cm across the channel width and used to calculate total stream discharge (based on USGS stream gauging guidelines, Rantz 1982). The surface water velocity was measured by using a Marsh-McBirney, Inc. Flo-Mate Model 2000 Portable Flowmeter.

A modified Manning's equation was used to generate estimates of discharge as a function of measured stage. Manning's formula can be described as

$$Q = 1/n\ AR^{(2/3)}\ \sqrt{S_0} \quad \text{(1)}$$

$$Q = kAR^{(2/3)} \quad \text{(2)}$$

where Q = flow (m^3/s), R = hydraulic radius, i.e. Area / Wetted Perimeter (m), S = slope, estimated as bedslope (S_0), n = Manning's roughness coefficient, A = Cross-sectional area, and $k=\sqrt{S_0}/n$. From channel dimensions, A, P and R were calculated and applied to observed stage-discharge data to calculate k values and eventually a k-h relationship was developed at each monitoring site. These k-h relationships were utilized in eqn (2) to calculate discharges which were then averaged to get daily estimates. This approach was adopted in order to incorporate channel roughness in discharge estimation. In instances when the k-h relationship seemed weak, we either modified the value of the power of R or used a direct stage-discharge relationship to calculate discharge.

To characterize stormflow flashiness, the Richards-Baker Flashiness Index (*RB*) (Baker et al. 2004) was calculated for storm flow events at each site, this is a dimensionless index used to characterize the degree of flashiness observed in the hydrograph as

$$RB = \frac{\sum_{i=1}^{n}|Q_i - Q_{i-1}|}{\sum_{i=1}^{n} Q_i} \times 1000 \quad \text{(3)}$$

where Q_i = discharge at daily time step i. *RB* indices were transformed by multiplying with 1000 for reporting purposes (Barksdale et al. 2014).

We also used the Web-based Hydrograph Analysis Tool (WHAT; Lim et al. 2005) to derive baseflows from observed daily flows at the transducer locations. WHAT was run using inbuilt $BFI_{\max}$ value (maximum value of long term ratio of base flow to total streamflow) of 0.80 for perennial streams with porous aquifers. Baseflow contribution (% *BF*) to total flow at each transducer location was then derived as

$$\%\ BF = \frac{\sum_{i=1}^{n} Q_{bf,i}}{\sum_{i=1}^{n} Q_i} \times 100 \quad \text{(4)}$$

where $Q_{bf,i}$ is the baseflow at the transducer location at daily time step i. Transducers were continually damaged at the ST wetland, and hence we did not have stage data (and flow estimates) for this wetland.

2.2.2 Water quality monitoring

Both grab samples and automated ISCO samples (ISCO 6712 Portable Sampler, Teledyne ISCO, Lincoln, NE) were collected to determine concentrations of Dissolved Inorganic Nitrogen (DIN) at discernible (and easily accessible on foot) surface water wetland inlets and outlets. Baseflow water quality was analyzed from grab samples taken periodically between August 2012 and May

2014. Water was collected in pre-washed polypropylene bottles and stored in an iced cooler until returning to the Weeks Bay Research Laboratory. Care was taken to ensure that sampling was done throughout the year and during baseflow conditions at least 2 days after rain events when the discharge peak after the storm had passed.

From December 2013 to May 2014, automated ISCO samplers were used to determine DIN concentrations during storm events. The ISCO samplers were installed at water quality sampling sites (wetland inlets and outlets) and were connected to the InSitu Mini-Troll 500 pressure transducers. In anticipation of an upcoming storm event, ISCOs were programmed to collect an aggregate stormwater sample. Each ISCO was individually programmed so that the amount of water sampled at each 15-min interval was proportionate to stream flow (gaged through stage level provided by the pressure transducer and by programming stormflows). Programmed relationships between stage data (surrogate for flow) and sample volume intake were developed for each sampling location based on rating curves and fitted to a linear relationship. Aggregate stormflow samples were collected in up to four pre-washed 3.7 L polyethylene bottles (total volume depended on stormwater duration). Samples were kept cool in the ISCO with ice, collected within 5 hours of the storm event, and transported for analysis at the Week's Bay Research Laboratory. Samples were analyzed for DIN using methodologies described in Rice et al. (2012). Thus event mean concentrations were derived for each storm event sampled. Stormflow DIN was collected for multiple storms to get a good picture of stormflow concentrations. Only grab samples measures exist for the ST wetland due to repeated fouling of transducers at the site. Significant differences between inlet and outlet concentrations at the wetlands were tested with Wilcoxon sign rank tests.

2.2.3 Wetland DIN loads

Grab samples were taken before transducers were deployed at the sites at some locations, which meant an absence of associated flow data. To reconstruct missing flows, we used the SWAT (Soil and Watershed Assessment Tool) model; observed flows were used to calibrate SWAT via the SWAT-CUP software, and calibrated flows, then, served to hindcast missing flows. SWAT models were created for the three wetlands with flow data (BM, OF and NF), and calibrated with SWAT-CUP using observed flows. The SWAT Calibration and Uncertainty Program (SWAT-CUP) is an automated calibration program designed for automatic calibration, uncertainty analysis and sensitivity analysis for SWAT models (Abbaspour et al. 2008). SWAT-CUP allows SWAT to be run using parameters propagated within a range of feasible upper and lower values. Refer to Neitsch et al. (2009) and Abbaspour et al. (2008) for descriptions of SWAT and SWAT-CUP, respectively. Performance measures such as the Nash Sutcliffe coefficient (E_{NASH}) and bias ratio (R_{BIAS}) were used to assess model fit based on the modified criteria presented in Kalin et al. (2010) for daily flow calibration. According to these criteria, a model has “very good” fit when $E_{\mathrm{NASH}} > 0.7$ and $R_{\mathrm{BIAS}} < 0.25$, “good” when $0.5 < E_{\mathrm{NASH}} > 0.7$ and $0.25 < R_{\mathrm{BIAS}} < 0.5$, “satisfactory” when $0.3 < E_{\mathrm{NASH}} > 0.5$ and $0.5 < R_{\mathrm{BIAS}} < 0.7$ and “unsatisfactory” when $E_{\mathrm{NASH}} < 0.3$ and $R_{\mathrm{BIAS}} > 0.7$. The “best” simulation with the highest E_{NASH} for predicted flow was used to fill in data gaps. Details about flow calibrations are presented in chapters 3 and 4. The “best” simulations for inflows had E_{NASH} values of 0.88, 0.75 and 0.44, and outflows had E_{NASH} values of 0.59, 0.61 and 0.70 at BM, NF and OF, respectively. Thus, missing flows were reconstructed to get continuous daily flow estimates from Jan 1, 2013 to May 1, 2014 for BM, NF and OF wetlands.

The USGS load estimator model (LOADEST; Runkel et al. 2004) was used to generate daily water quality time series in order to get a better picture of nutrient loading and load reductions in the wetlands. LOADEST generates a regression relationship using user-provided observed water quality and flow measurements (calibration dataset), using which it extrapolates daily loads from user-provided daily discharge. LOADEST gives the user the option of selecting a regression model for load estimation, or allowing the program to choose the best model from a set of predefined models. The choice was made based on the E_{NASH} values obtained on comparing load estimates with observed loads on days when both flow and nutrient concentrations were available. Thus, DIN loads at wetland inflows and outflows were derived for BM and NF wetlands. Since a good regression relationship using LOADEST was not achievable for OF outflow, DIN load reductions were not quantifiable using this method at OF wetland, probably because flows and concentrations were so low at this wetland. Instead DIN loads were calculated using flow-averaged baseflow and stormflow concentrations, $\overline{C_{bf}}$ and $\overline{C_{sf}}$, calculated as $\bar{C} = \frac{\sum CQ}{\sum Q}$, where C is the measured concentration (grab sample or ISCO sample concentration in mg/L) and Q is the associated daily flow estimate (m^3/s). $\overline{C_{bf}}$ was assigned to baseflows (flows corresponding to stage below which the ISCO was triggered), and $\overline{C_{sf}}$ was assigned to stormflows (flows corresponding to stage above which ISCO was triggered). For days with inlet and outlet data, flows and concentrations were multiplied at 15min intervals to yield loads which were then averaged over each day and summed to get total loads over the duration (days) for which the transducer was deployed.

Hence, DIN loads were derived from January 1, 2013 to May 1, 2014 for all wetland inlets and outlets. Since DIN loads at the inlets did not include loads entering the wetland area further downstream (of the inlet), the total load entering the wetland area had to be quantified by area-scaling DIN loads at the inlet. Thus, total inflow load was quantified as the sum of DIN loading at the discernible surface water inlet and loads from the remainder of the watershed, i.e., loads at discernible inlet scaled by area for the reminder of the watershed. The relative contributions of baseflow and stormflow to DIN loads at the inlets and outlets were calculated from median baseflow concentration (median of grab sample concentrations) and baseflow (derived from the WHAT tool) at the study wetlands.

2.3 Assessing headwater wetlands on a larger scale in Baldwin County, AL

To understand the cumulative effect of headwater slope wetlands on the water quality of coastal waters, it is necessary to prioritize headwater protection strategies. This requires location and assessment data for individual headwater slope wetlands to specify mitigation/protection efforts (U.S. EPA 2014). Here headwater slope wetlands were identified in Baldwin County and their watersheds, delineated. A 10m digital elevation model (DEM) for Baldwin County was used to generate flow paths with the National Hydrography Database (NHD) layer as a reference (DEM and NHD layers were downloaded from USGS's online Seamless Data Warehouse at https://datagateway.nrcs.usda.gov). This was done to determine stream order, as the NHD flow line layer does not have streams categorized by hierarchy of stream order. A threshold of 50 acres (0.202 km^2) drainage area was set to generate a high resolution stream network. The generated stream order network was then separated by order, and 1st order streams were exported as a separate layer. All 1st order streams were assumed to originate as slope wetlands in Baldwin County (Shaneyfelt and Metcalf 2014).

In ArcGIS 10.4, points were generated at the start of each 1st order stream. These points were used as outlet points for delineating head watersheds using the Spatial Analyst Hydrology toolset. The delineated watershed layer was superimposed with data from the National Wetlands

Inventory (NWI) (https://www.fws.gov/wetlands/data/mapper.html) as well as background aerial imagery to determine existence of wetlands within delineated watersheds. If the wetland didn't exist, or was buried or ditched by other land uses such as crop fields/drainage ditches/parking lot or some other land use, then that watershed polygon was eliminated from consideration.

This approach may have underestimated actual headwater slope wetland density, since in some cases: 1) the delineated 1st order stream may extend too far upstream to where the assigned outlet point for watershed delineation was affixed upstream of the actual headwater wetland causing the delineated watershed to completely miss the wetland, 2) the headwater wetland at the head of the 1st order stream has been drastically altered but remnants of the headwater wetland still exist downstream of the alteration which were not captured in the head watershed. Nevertheless, this approach yielded a useful rough approximation about the potential headwater wetland density and cumulative function on the landscape.

Relative cover of urban, agriculture and forested land was derived for each of the head watersheds using the latest NLCD dataset. General trends in head watershed land cover and their spatial distribution were assessed to understand potential and current threats to their headwater slope wetlands as Baldwin County continues to develop and urbanize. For each head watershed, land use areas classified under "Developed", "Forest" and "Agriculture" categories from NLCD land use classification were identified to get their extent within each watershed. Since two major interstates run East-West through Baldwin County, I-65 and I-10, we assessed trends in three categories - north of I-65, those between I-65 and I-10, and those south of I-10 towards the coast. These three regions are henceforth referred to as regions 1, 2 and 3 respectively; with 1 being farthest away from the coast and 3 being the closest.

3. Results

3.1 Hydrology

The hydrographs for the three wetlands are presented in Figure 3. Hydrological trends are consistent with proximity from the coast and degree of watershed urbanization. The hydrograph for BM, being farthest from the coast and with the highest amount of urbanized watershed, is dominated by surface flows with very little baseflow. On the other hand, the Foley wetlands have clearly observable baseflow contributions. Moreover, hydrological responses in OF are more stable and damped than the more urbanized NF right above it, consistent with what we expect to see in a reference wetland.

3.1.1 BM wetland

Observed flow data in the BM wetland were available for 252 days at the inlet (August 10, 2013 until May 1, 2014 with missing days) and for 473 days at the outlet (from January 1, 2013 until May 1, 2014 with missing days). The area received 1511 mm of rainfall in all of 2013 and 602 mm in 2014 (until May). Figure 3a presents the inflow and outflow hydrographs during the study period. On days when both inflows and outflows were available, observed flows at the inlet varied from 0 to 0.96 m^3/s and from 0 to 0.40 m^3/s at the outlet, with average flows of 0.04 m^3/s and 0.05 m^3/s respectively. Hydrology trends show an extremely flashy system in response to rain events, with barely any baseflow during other times. Calculated *RB* indices were highest at the BM wetland; values were 7.9 at the inlet to 17.5 at the outlet indicating a flashier outflow. Baseflows were less and contributed to 24% of the inflow and 28% of the outflow, indicating a surface flow dominated system. Runoff ratios (runoff : precipitation) of 0.8 were observed at the inlet and outlet respectively.

3.1.2 NF wetland

Observed flows at the NF wetland were available for 252 days at the inlet and outlet (from August 10, 2013 until May 1, 2014). The watershed received a total of around 1726 mm of precipitation during the study period. Observed inflow varied from 0.05 m^3/s to 0.95 m^3/s (average of 0.15 m^3/s) and outflow, from 0.06 m^3/s to 0.73 m^3/s (average of 0.18 m^3/s) (Figure 3b). The hydrograph (Figure 3b) shows some flashiness; *RB* indices decreased from 7.1 at the inlet to 4.6 at the outlet indicating a hydrologic damping effect of the wetland. Baseflow contributions are considerably higher when compared to the BM wetland and accounted for 67% of the inflow and 70% of the outflow. Runoff ratios for the period of observed data were abnormally large at 3.8 and 3.0 at the inlets and outlets respectively, indicating that runoff far exceeded precipitation at both locations. This anomaly is further investigated in Chapter 3.

3.1.3 OF wetland

Observed flows at the OF wetland were available for 315 days at the inlet and for 433 days at the outlet (from January 1, 2013 until May 1, 2014). During this time the watershed received 2876 mm of precipitation. Figure 3c represents the observed flows during the study period. To allow for comparison, we focused on days for which both inflow and outflow were available (315 days). Flows ranged from 0.01 to 0.13 m^3/s at the inlet (average of 0.07 m^3/s) and from 0.06 to 0.33 m^3/s (average of 0.1 m^3/s) at the outlet. Only 1.3% of the watershed draining into the OF wetland is impervious (road). The hydrographs for this wetland show much lower flows compared to the BM and NF wetlands with calculated *RB* indices of 1.0 at the inflow and 0.8 at the outflow. Flows at this site also show more and sustained baseflows compared to the previous wetlands; baseflows contributed 75% of the observed flows at the inlet and 74% at the outlet.

Runoff ratios for this wetland were 0.7 for both the inflow and outflow. Unlike the NF wetland, flows here are lower and damped (stable and less flashy) consistent with our understanding of a forested watershed on a coastal plain.

3.2 Observed concentrations and load reductions

The four wetlands exhibited large variations in DIN concentrations (Figures 3 and 4). Significant concentration reductions were observed at NF and ST wetlands based on Wilcoxon signed rank tests on measured data (significant at $p<0.1$). The ST wetland had the highest observed DIN concentration ranging from 0.01 to 1.64 mg/L (0.46 ± 0.25 mg/L) at the inlet and 0.002 to 0.62 mg/L (0.10 ± 0.07 mg/L) at the outlet (Figures 3d and 4). For days during which we had both inflow and outflow measurements, we observed average DIN concentration reduction of 67%. In the NF wetland, relatively higher overall DIN concentrations, 0.32 ± 0.06 mg/L at the inlet and 0.16 ± 0.03 mg/L at the outlet, were observed (Figure 4a) with DIN concentration reductions of 37% and 35% in baseflow and storm measurements (calculated for days when both inlet and outlet concentrations were available (Figure 4b). DIN concentrations at the BM wetland were low and averaged 0.06 ± 0.02 mg/L at the inlet and 0.06 ± 0.02 mg/L at the outlet after pooling all measurements (Figure 4a); baseflow DIN ranged from 0.06 ± 0.03 mg/L at the inlet to 0.05 ± 0.02 mg/L at the outlet, and stormflow DIN ranged from 0.06 ± 0.03 mg/L to 0.07 ± 0.04 mg/L (Figure 4b). In the most forested OF wetland, both incoming and outgoing DIN concentrations were low (0.05 ± 0.02 mg/L and 0.04 ± 0.01 mg/L respectively) (Figures 4a and 4b). Significant concentration reductions were not observed from DIN measurements at BM or OF wetlands.

Table 2 presents load reductions for the three wetlands, where load calculations for BM and NF wetlands were performed using the LOADEST software, and for OF using flow averaged baseflow and stormflow concentrations. All wetlands showed DIN load reductions;

BM, NF and OF reduced DIN loads by 9%, 49.7% and 21% respectively. Splitting by year, higher DIN reductions were observed at NF wetland with 51.8 % and 47.6% in 2013 (January – December, 2013) and 2014 (January – May, 2014) respectively, followed by OF wetlands with DIN reductions of 27.5% and 12.1% for the same time periods. The BM wetland showed DIN reduction of 31.8% in 2013, but exported 12.1% between January – May, 2014. Figure 5 shows the relative DIN contribution from baseflows and stormflows for the three wetlands. The BM wetland had the least baseflow load contributions of DIN amounting to 5.5% and 7.5% of the total DIN loads at the inlet and outlet i.e., >92% DIN loads contributed by stormflow. NF and OF wetlands had higher baseflow contributions of DIN; 25.6% and 23.6% of inlet and outlet DIN loads, respectively, were contributed by baseflow at NF wetland, while 14.3% and 35.6% were contributed by baseflows at OF wetland (stormflow loads amounting to 74-77% of total DIN loads at NF wetland and 64-86% at OF wetland).

3.4 Headwater slope wetlands and watersheds in Baldwin County

Using the Spatial Analyst Hydrology toolset, a total of 1569 watersheds for headwater slope wetlands were delineated in Baldwin County. This was reduced to a total of 1,143 based on data from NWI and background aerial imagery (Figure 6); 257, 495 and 391 watersheds were delineated in regions 1, 2 and 3 respectively. These delineated headwater areas constitute roughly 18% (735.33 km^2) of the total land area in Baldwin County (4118.1 km^2; obtained from US Census Bureau).

Of the total delineated watershed area, NLCD land use classified as “Developed” accounted for 7.4% and included developed high, medium and low density areas as well as developed open spaces. Forested and agricultural areas occupied 34.9% and 12.1%, respectively, while wetlands (classified as “woody” or “emergent”) accounted for 12.2% of the total watershed area. Thirteen watersheds had >60% urban cover ranging from 61% to 97%; of these five of them were situated in region 2 and the remaining eight in region 3. 1086 watersheds had 0-30% urban cover and included all 257 in region 1, 466 in region 2 and 354 in region 3. Forty-four watersheds had 30-60% urban cover with 21 in region 2 and 23 in region 3. Percentage of watershed area under urban cover and agriculture increased towards the coast in the three categories by 4%, 11% and 15.6% for the former and 3.3%, 3.3% and 44.1% for the latter in regions 1, 2 and 3 respectively. Percentage of watershed area under forest cover decreased steeply from 76.7%, 66.9% to 21% in regions 1,2 and 3 respectively.

Based on county land use, urban land cover increased steadily from approximately 2.4% in the region of Baldwin County north of I-65, to 5.4% between I-65 and I-10, to 14.3% south of I-10 (Figure 7). Percentage of land dedicated to agriculture, at 22.2%, was also highest south of I-10 compared with 2.2% and 1.9% north of I-65 and between I-65 and I-10 respectively (Figure 7). Figure 8 presents a snapshot of Baldwin County around I-10; here stream networks appear denser and wider with good connectivity from headwaters to the river mouth to the north of I-10, while in contrast, the region south of I-10 has stream/riparian systems that are fragmented with the narrower riverine networks. Regions 1 and 2 combined had a density of 0.3 headwater wetlands/km^2 which reduced to 0.2 headwater wetlands/km^2 in region 3.

Though we assumed a headwater slope wetland at the start of each 1st order stream, headwater areas of many first order streams didn’t yield in a delineation; either because superimposing with NWI layer showed no wetland at that location, or the headwater area was too small to be detected by this exercise. Hence, it is most likely that numbers of headwater wetlands in Baldwin County were underestimated and their true density is much larger.

4. Discussion

In this study, we examined baseline flow and DIN data obtained from 4 headwater slope wetlands (named BM, ST, NF and OF) in Baldwin County and quantified load reductions for three of four wetlands (BM, NF, OF). All the studied wetlands were forested; however, they all differed in the degree of urban development and agriculture within their watersheds. We expected wetlands closer to the coast to have higher water tables and consequently larger groundwater inputs to the wetlands. We also expected to see a shift in influence from groundwater to surface water with increasing levels of watershed urbanization and distance from the coast. From a nutrient perspective, we expected more watershed development (through agriculture and urbanization) to translate in higher DIN concentrations in the wetlands. While our expectations were reflected in monitored flows at the wetlands, they did not always hold for observed DIN concentrations.

Groundwater contributions to stream waters from these headwater slope wetlands were substantial and increased with proximity to the coast, from ~24-28% at BM to >70% at OF. This is consistent with other studies where reported contributions to streamflow from groundwater discharge wetlands range from 30% to >70% (Morley et al. 2011; Alexander et al. 2007). As expected, the wetland with the most forested watershed (OF) had very low flows with damped peaks, high baseflow contributions (% BF = 74-75%) and low concentrations (and consequently low loads) of DIN entering and leaving the wetland. The other wetlands, BM and NF, had more urban development within their watersheds and exhibited different hydrology and DIN-trends. The NF wetland had high flows with 67-70% contributed by baseflow. Flows here were flashier than OF (NF: RB > 4; OF: RB <1) but less so compared to BM (RB > 7) whose watershed was highly urban (42% impervious cover in BM watershed compared to 23% in NF watershed). High imperviousness in the BM watershed most likely explains the lack of persistent baseflow since imperviousness is known to reduce low flows and baseflow due to reduced infiltration and low groundwater recharge (Nagy et al. 2012; Havens et al. 2004; Forman and Alexander 1998; Bledsoe and Watson 2001). This might also explain the higher flashiness and low baseflow contributions observed in this wetland (% *BF* =24 – 28 %). This is consistent with results reported by Barksdale et al. (2013) who observed that headwater slope wetlands became increasingly surface water driven (flashy) with increase in watershed imperviousness (decrease in forested land cover). Or perhaps, the BM wetland acts more like a recharge pathway for groundwater than as a discharge, with water quickly percolating through the channel's sandy soils.

For higher elevations along the coastal plain, such as at the BM wetland, different forces might influence flow paths when compared to their lower elevation counterparts. Epps et al. (2013) documented strong relationships between water table elevations and runoff generation in lower coastal plain watersheds and observed that runoff response to rainfall depended on antecedent moisture conditions related with groundwater elevation. In the region, groundwater moves in the south/south-west direction from inland areas (~50m above MSL) to the lower marshlands at 0m above MSL (Murgulet and Tick 2013) resulting in significant discharges in the Wolf Bay watershed in which the Foley wetlands are situated (Beasley 2010). Consequently, depths to the water table may be greater around BM wetland (Robinson et al. 1996) which might cause the area of saturation around the stream to decrease (Epps et al. 2013) and wetland soils to reach surface saturation more intermittently than at NF and OF wetlands. The latter which, possibly due to their proximity to the coast, receive significant groundwater discharge from upland areas which may cause areas of saturation around the stream to increase and reach surface soil saturation all year round. This is reflected in consistent baseflows observed in the Foley wetlands and their lack thereof at the BM wetland. Moreover, ground-watershed boundaries in low relief areas do not always follow those of the surficial watershed and wetlands may receive groundwater flows from areas much larger than the delineated extent of the surface watershed (Winter et al. 2003; Nagy et al. 2012). This might explain why flows at the NF wetland exhibit runoff ratios >1; they probably receive groundwater flows from a much larger area than the delineated surface watershed. Observed flows at NF were also several orders of magnitude higher than OF despite the nearness of the sites to each other. Perhaps the presence of impoundments, both directly upstream of NF and at the headwaters of Owens Bayou to the north of NF adds additional groundwater through percolation to the NF system resulting in the higher flows. Hydrology at NF wetland has been further investigated in Chapter 3.

The highest DIN concentrations were observed at ST, followed by NF, BM and OF wetlands. The ST wetland reflected the highest concentrations, presumably an effect of the agricultural area upstream of the wetland. This agrees with findings from other studies such as Schaefer (2014), who also observed high nitrate concentrations in agricultural headwater streams. Elevated concentrations at NF wetland relative to OF and BM wetlands may have come from urban lawns in the watershed. The watershed also drains a small agricultural field (~9% of the watershed area) which may have contributed to the higher DIN concentrations in the inflow. DIN concentration reductions were consistently observed in the measured data for ST and NF wetlands. The BM wetland showed low DIN concentrations, probably because its watershed is predominantly non-residential, i.e., fewer sources of nitrogen such as lawns. Perhaps the BM wetland may show evidence of other forms of urban water quality footprints such as heavy metals, oils, etc., which were not analyzed during this study.

As hypothesized, the wetland with the most watershed imperviousness, i.e., BM, had the least DIN removal. Both NF and OF wetlands showed considerable DIN load reductions over the period during which they were evaluated. Temporary hydrologic storage in pools and side-channels could have enhanced uptake/transformation of DIN by increasing residence time (Angier and McCarty 2008; Ranalli and Macalady 2010). At the NF wetland, natural stream dams from fallen trees and snags were regularly observed. Minimal load reduction observed at the BM wetland could be a result of an extremely flashy hydrology where flows are quickly routed through the channel. This wetland often received sediment loads from construction sites adjacent to the wetland which obstructed water flow resulting in dammed pools in the channel which could explain higher DIN load reduction in 2013. DIN loads entering the wetlands ranged from 0.43 kg/day (1.73 kg/ha) at the BM wetland, 5.06 kg/day (32.6 kg/ha) at the NF wetland, to 0.29 kg/day (0.51 kg/ha) at the OF wetland. Loads at BM and NF are consistent with values reported by other studies such as Berkowitz et al. (2014) who documented values between 0.92 to 75.3 kg/ha from forested headwater streams in Virginia. Loading at the OF wetland is the least altered of the three wetlands, and perhaps closest represents reference loads in the region.

Since headwater slope wetlands are typically open, gaining systems (as opposed to depressional systems), outflows tend to be larger than inflows as was observed in NF and OF wetlands. DIN concentration reductions, then could be an effect of dilution; but quantified load reduction despite increase in discharge clearly points to DIN removal. DIN concentrations could be influenced by the degree and direction of groundwater upwelling, i.e., whether groundwater flows follow lateral or vertical gradients through the subsurface of the riparian zone (Lowrance et al. 1995; Jordan et al. 1993), and locations of upwelling zones with respect to the riparian zone and stream channels (Angier et al. 2005). All the wetlands had vastly different flows and DIN trends; but under natural circumstances wetlands would have low DIN concentrations and loads entering and leaving the wetland as observed at OF. As Baldwin County continues to urbanize rapidly along the coast as evidenced by land use maps (Figure 7), then headwater slope wetlands closest to the coast would be less equipped to deal with higher DIN loads (resulting from urban pollution) which could then easily be transported to the coast.

In general, coastal development is more prolific at topographical highs, for e.g., near watershed boundaries, to lower the chance of flooding. This directly coincides with headwater wetland function since they occupy similar landscape positions, i.e., at higher elevations within a watershed. From this study, the region south of I-10 had lesser density of headwater slope wetlands compared to the more forested (less altered) regions to the north of I-10; this decreased headwater wetland density along the coast is most likely a consequence of coastal development. Our attempts at headwater area delineation very likely underestimated their true density in the region; despite this, delineated headwater areas still accounted for a significant 18% of the county area. Headwater wetlands in heavily urbanized or agricultural watersheds may be functionally similar to BM, ST or NF wetlands and demonstrate altered surface-driven hydrology or transport high DIN loads. As more areas in the county undergo land use conversion, loss of hydrologic connectivity and the loss of functional headwater slope wetlands is bound to have an adverse impact on hydrology and nitrogen loads of entire stream networks, and consequently be greatly detrimental to coastal water quality. While individually headwater catchments contribute the lowest nitrogen loads among all steam orders, their cumulative loading is of similar magnitude to that originating from the incremental watersheds of higher order streams (Alexander et al. 2007).

5. Conclusions and next steps

Here we presented data from preliminary monitoring efforts in four headwater slope wetlands in Baldwin County, quantified DIN removal by these wetlands. We also attempted to identify the distribution of headwater slope wetland systems in the county and highlighted the trends in land use alterations within their watersheds. These were done as a preliminary step in addressing knowledge gaps in hydrology and water quality in coastal plain headwater slope wetland systems as well as to provide information to support decision makers set management priorities for restoration and management of these systems.

We acknowledge that there are some limitations to this study. For one, we monitored only at discernible surface water inlets and outlets of the wetlands; we were unable to monitor other potential sources of flow and nutrient to the wetlands, or zones of upwelling. As a result, our quantification of DIN loads at the inlets and outlets may be too simplistic in their ability to represent the actual uptake/transformation happening at the sites. The short duration of available data also constrained our ability to make generalizations about wetland function. Moreover, headwater slope wetlands occur at the head of coastal creeks and transition into riverine riparian areas along the length of the stream. Therefore, the outlets we monitored may or may not have captured the entire extent of the "headwater slope" wetland area. Another important shortcoming with the wetlands in altered watersheds is our assumption that the headwater slope wetland begins at the forested riparian area at the head of the stream, when in reality, the headwater slope wetland might have originally existed much farther upstream and was probably buried, i.e., we might not have captured the true headwater slope wetland. Head watersheds delineated were based on latest elevation maps, NWI and Google map imagery. This does not include headwater slope wetlands that have been lost to agriculture or urban development. Hence the historical extent of head watersheds would have occupied a much larger portion of Baldwin County. Given this large density of headwater slope wetlands and the diversity of their function, there is a need for their greater scrutiny in coastal Alabama.

Given the groundwater driven nature of these systems, there is also much uncertainty due to our limited understanding of the different hydrological flow paths and N removal processes. Further research involving quantification of subsurface inflows and outflows using piezometers and quantifying associated N concentrations to get a better picture of hydrological and nutrient budgets is required to reduce some of the uncertainties. Additional scrutiny regarding wetland biogeochemistry and interactions with hydrological processes will present a better picture regarding wetland function. In a hypothetical scenario involving unlimited funding and manpower resources to sustain a multi-year long-term project, limitations could be addressed by 1) selecting multiple study sites across a gradient of land use alterations within their watersheds at varying proximities to coast, 2) identifying major channels and smaller sub-channels in the wetlands through detailed ground-truthing in the field, 3) improving monitoring of surface waters by installing weirs and transducers to get improved rating curves to improve discharge estimations and to better program the automated ISCO water quality samplers, 4) improving groundwater measurements using multiple piezometers fitted with transducers, applied along transects and at different depths, both around and within the channels, to quantify horizontal and vertical gradients and water levels, 5) procuring weekly samples of water quality by hand as well as automated ISCO samplers, with increased frequency during and following storm events within and beneath channels, 6) sampling soil cores to better understand wetland soil properties, and 7) conducting tracer studies to accurately quantify residence times. With these data, we would not only reveal important information about hydrological and water quality characteristics but also potentially tease apart the influence of different processes, land use alterations and proximity to coast on wetland function. What we have presented through this study forms the beginnings of our understanding of this wetland type in coastal Alabama.

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Figures

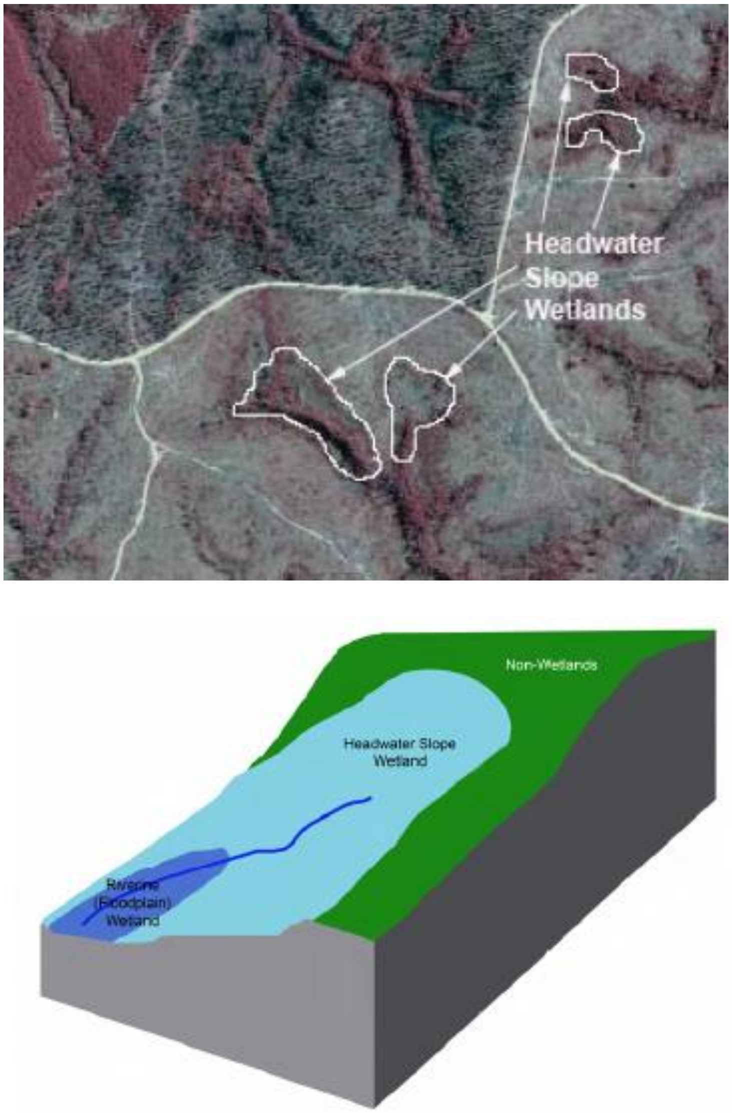


Figure 1. (Top) Aerial image of headwater wetlands in Gulf Coastal Plain.
(Bottom) Landscape position of headwater slope wetlands at the head of 1st order streams in the Gulf Coastal Plain. Both images have been borrowed from Noble et al. (2007).

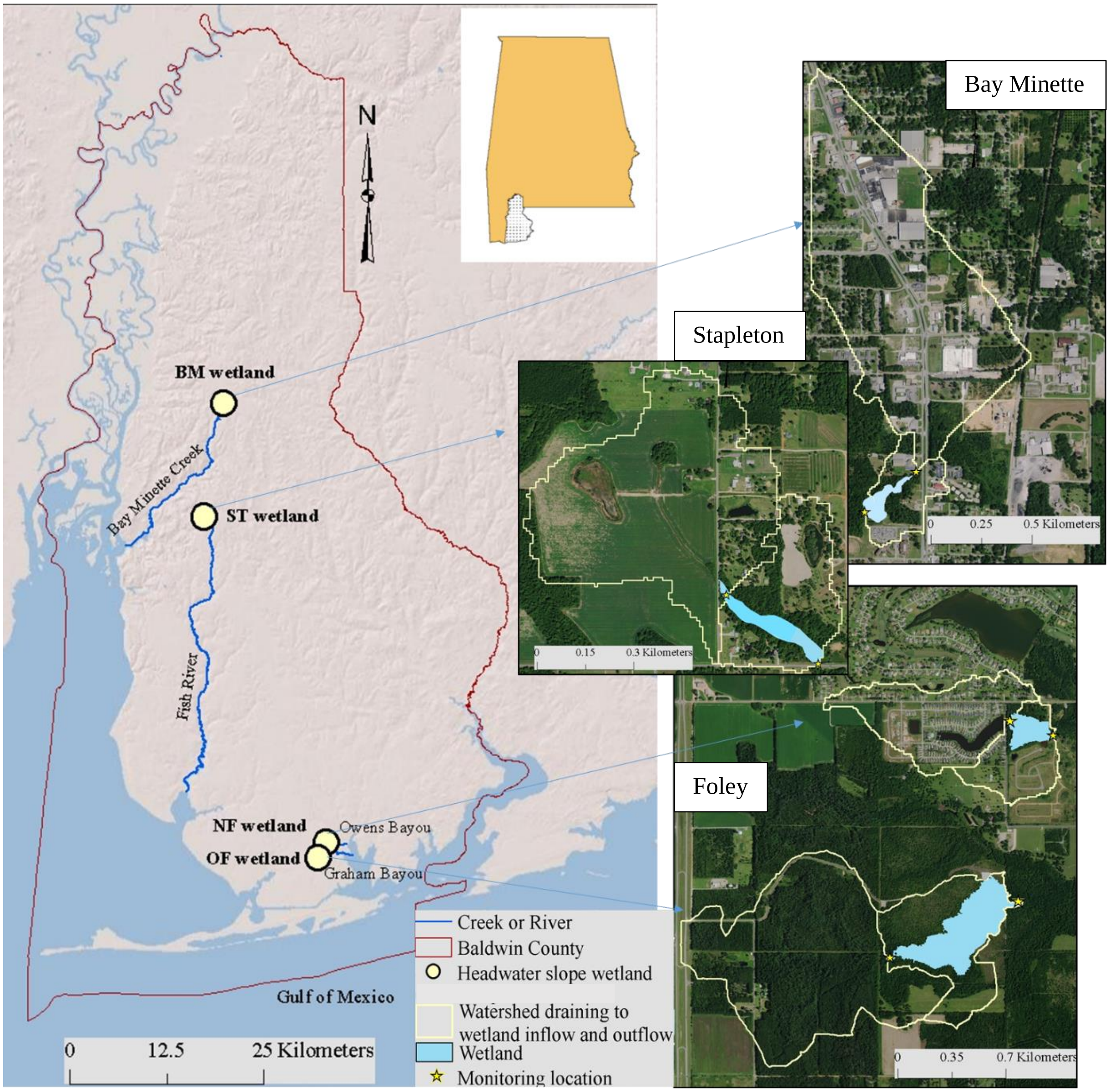


Figure 2. Location of study headwater slope wetlands in Baldwin County.

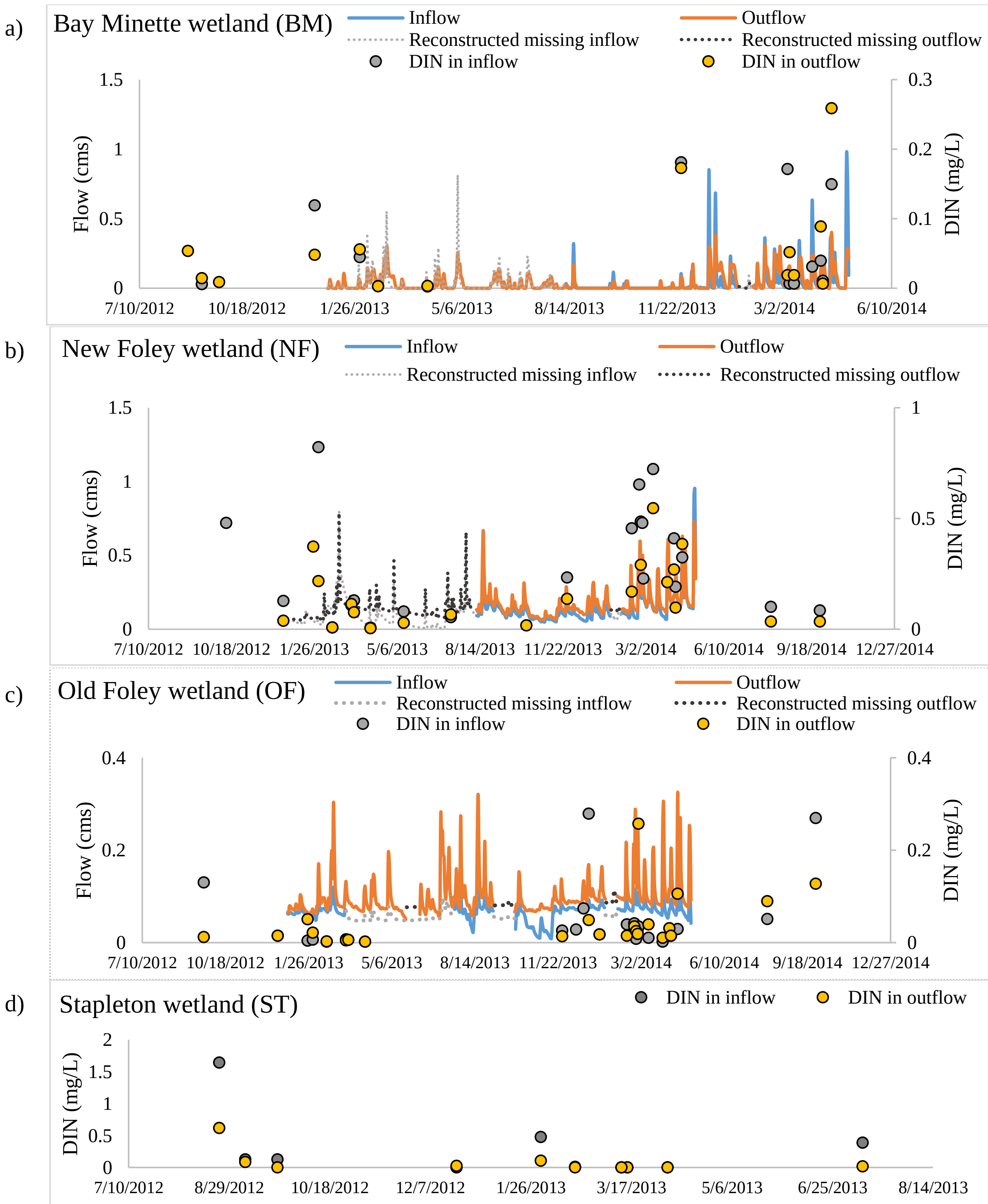
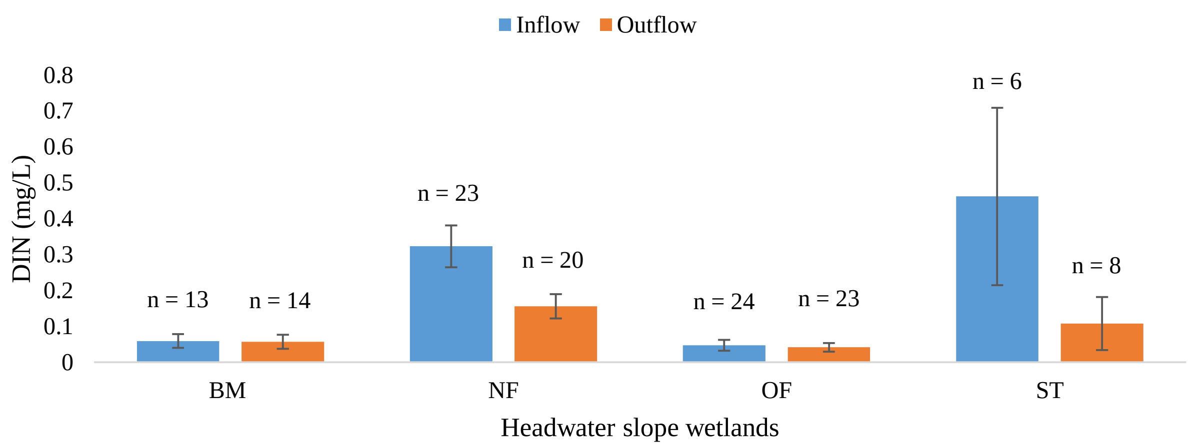


Figure 3. Observed flows and DIN concentrations at the headwater slope wetlands in Baldwin County AL. All data from Dec 2013 are ISCO collected observations – these were not available at ST wetland. Dashed lines indicate reconstructed flows where observed flows were missing.

(a)



(b)

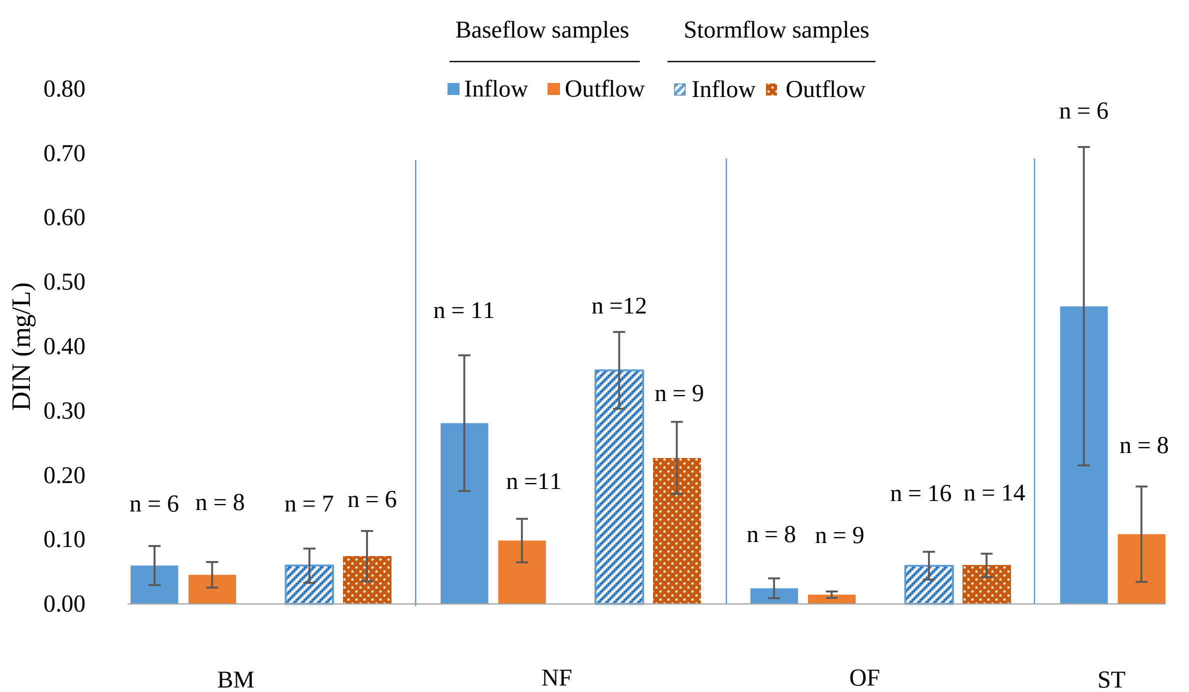


Figure 4(a) Average of measured DIN from pooled grab and automated samples ± standard error (mg/L) at the four study headwater slope wetlands. The number of measurements, including grab samples and automated samples, for each location is presented above the bar.
(b) Average of measured DIN ± standard error (mg/L) for the study headwater slope wetlands, each for grab samples and automated samples. Only grab sample data exists for the ST wetland.

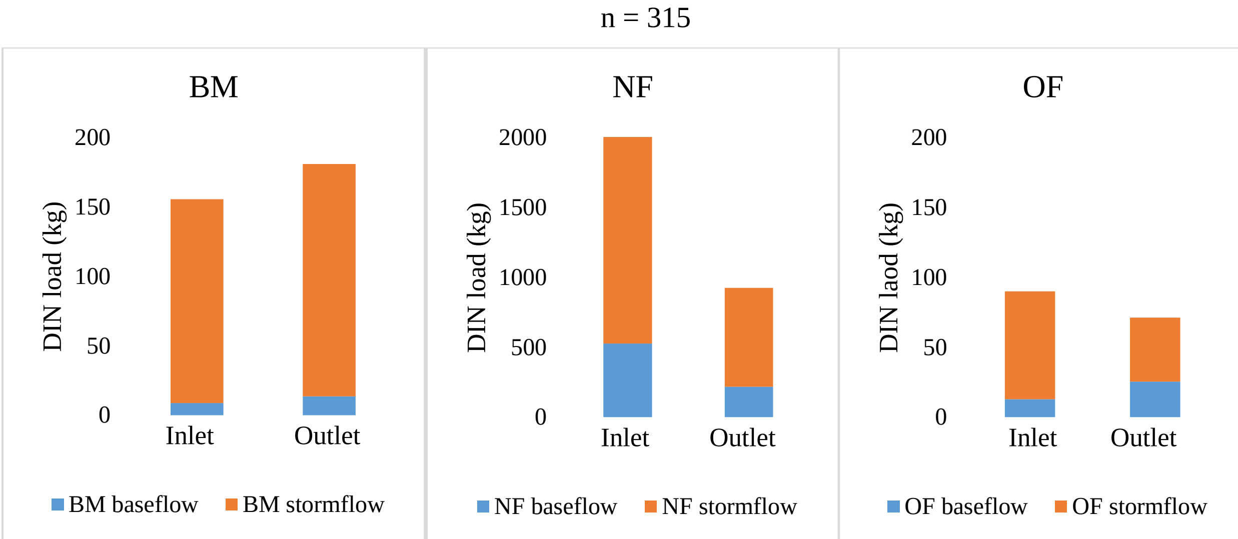


Figure 5. DIN loads contributed by baseflow and stormflow at the inlets and outlets of the study headwater slope wetlands. For comparison purposes, the calculations were done for the 315 days (January 2013 – May 2014) for which DIN loads for OF were calculated.

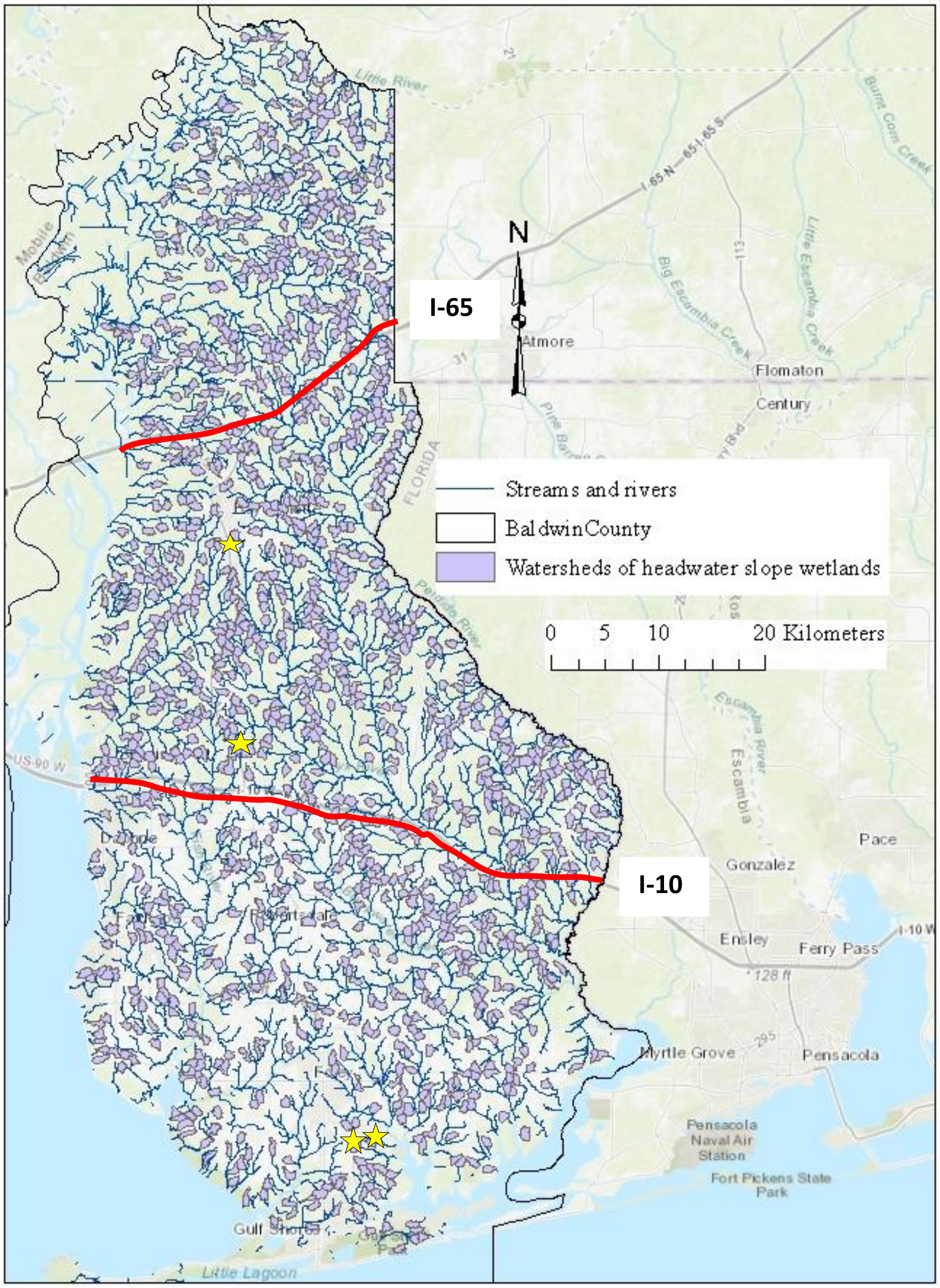


Figure 6. 1,143 delineated watersheds of headwater slope wetlands in Baldwin County AL. Data used for this exercise included 10m DEM, NHD layer, NWI layer and Google imagery for Baldwin County. The yellow stars indicate locations of study headwater slope wetlands.

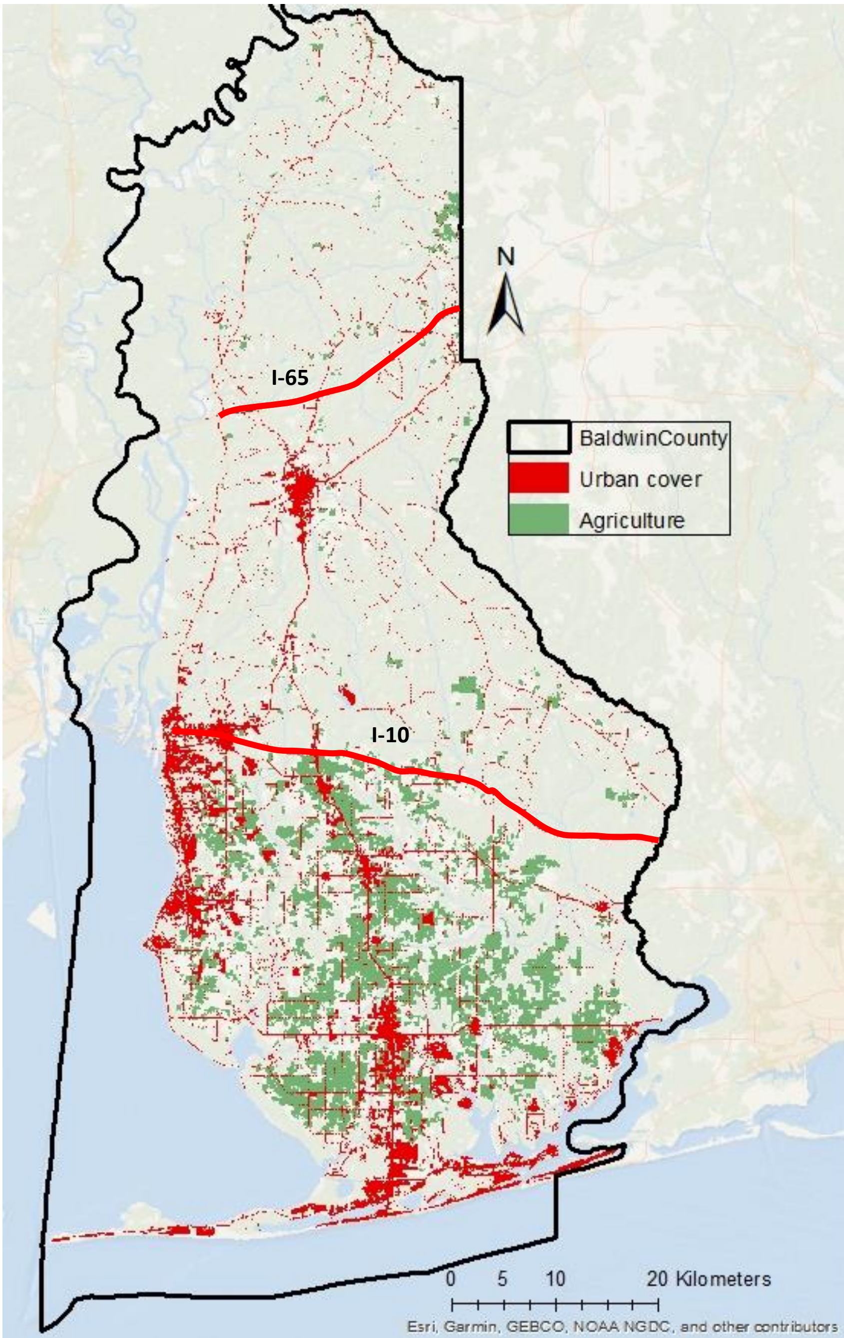


Figure 7. Distribution of urban cover and agriculture in Baldwin County. The region below I-10 has much of the agriculture and urban development in the county.

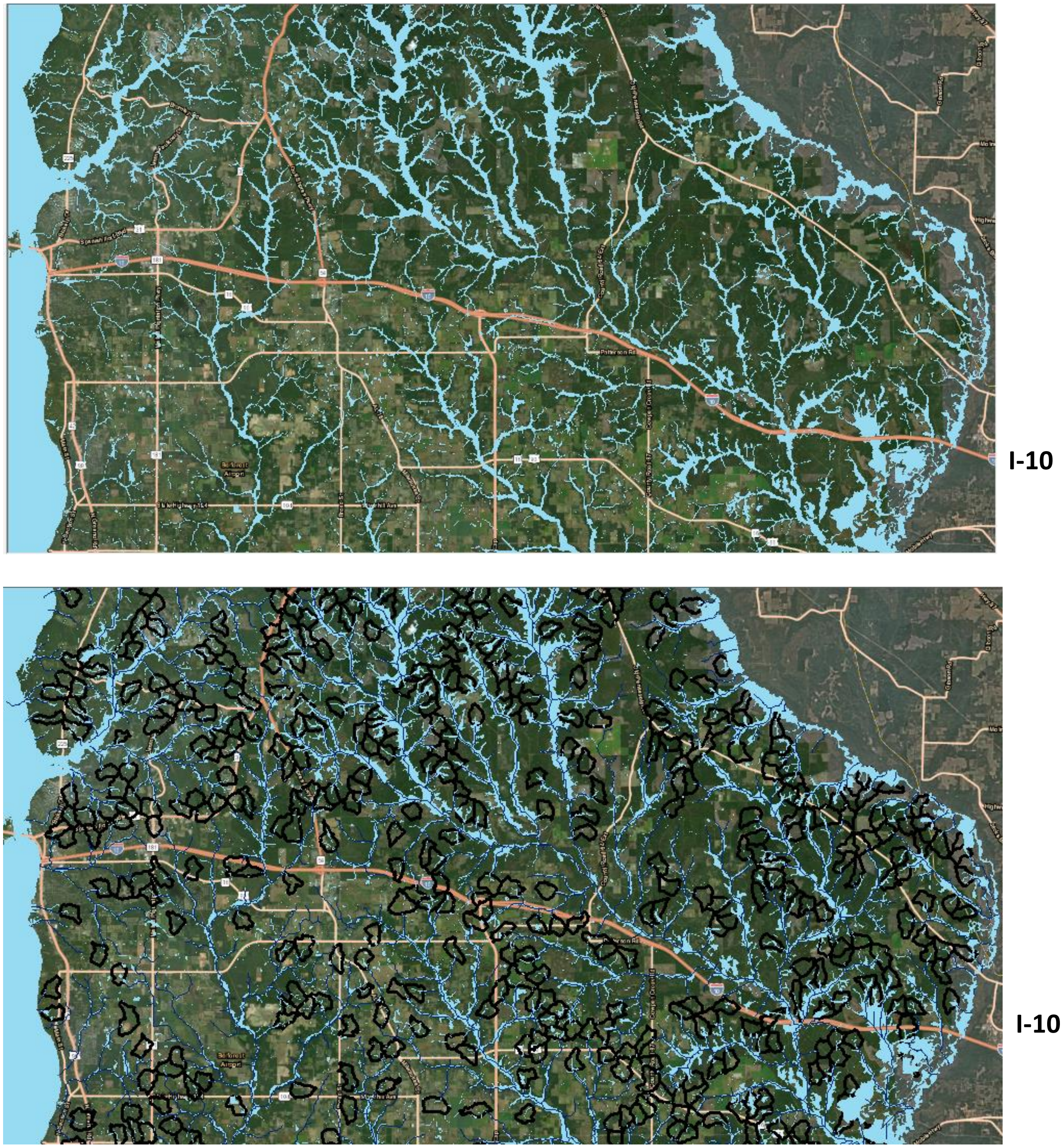


Figure 8. Snapshot of stream networks and delineated headwater catchments around I-10 in Baldwin County. Stream networks north of I-10 are wider and denser compared to stream networks south of I-10 due to increased agriculture and urban development south of I-10.

Tables

Table 1. Names and geographic coordinates of study headwater slope wetlands, their respective drainage areas, predominant land use and % imperviousness within the watershed

Name	Coordinates	Wetland area between discernible surface inflow and outflow (km^2)	Watershed area at discernible surface inflow (km^2)	Watershed area at discernible surface outflow (km^2)	Dominant land use in watershed	Impervious -ness in watershed (%)
Bay Minette wetland (BM)	30.855272°, -87.779157°	0.01	1.07	1.20	Mixed urban	41.6
Stapleton wetland (ST)	30.729401°, -87.800582°	0.01	0.40	0.54	Agriculture	5.6
New Foley wetland (NF)	30.354235°, -87.631394°	0.09	0.49	0.75	Residential	23.4
Old Foley wetland (OF)	30.342071°, -87.638012°	0.20	1.28	1.78	Forest	1.5

Table 2. Loads entering and leaving the study headwater slope wetlands, and the corresponding load reductions. Loads were quantified for BM and NF using the LOADEST software to generate loads after filling in missing bits of the hydrograph using SWAT and SWAT-CUP software. For OF loads were quantified by applying flow-averaged baseflow and stormflow concentrations to flows beneath and above the ISCO triggers for the duration of observed data

Site	Dominant land use	Duration (days)	Duration*	DIN in inflow (kg/day)	DIN in outflow (kg/day)	Load reduction (%)
Bay Minette (BM)	Mixed urban	483	January 2013 - May 2014	0.43 ± 0.08	0.39 ± 0.06	9.0
		362	2013	0.28 ± 0.06	0.19 ± 0.04	31.8
		121	2014	0.89 ± 0.24	0.99 ± 0.18	-12.1
New Foley (NF)	Residential	483	January 2013 - May 2014	5.06 ± 0.25	2.55 ± 0.13	49.7
		362	2013	3.46 ± 0.24	1.67 ± 0.10	51.8
		121	2014	9.88 ± 0.46	5.18 ± 0.30	47.6
Old Foley (OF)	Forested	315	January 2013 - May 2014	0.29 ± 0.01	0.23 ± 0.02	21.0
		209	2013	0.25 ± 0.01	0.18 ± 0.02	27.5
		106	2014	0.36 ± 0.02	0.32 ± 0.04	12.1

Chapter 3

Challenges calibrating hydrology for a small coastal plain watershed - a headwater wetland case study

Abstract

Modeling watersheds in coastal Alabama, USA, presents unique challenges pertinent to a low gradient coastal plain system including gentle slopes, high water table and significant groundwater interaction. Observed flow data from one such watershed draining into a headwater slope wetland in the city of Foley in Baldwin County, AL showed very high baseflow contribution leading to overall flows in excess of precipitation within the watershed: flows were 3.8 times precipitation during the study period. This larger groundwater contribution (compared to surface contribution) indicates that the ground watershed is much larger than the surficial watershed, an issue common in coastal plain regions where topography is flat and water tables are shallow. In this study we investigated approaches by which the Soil and Watershed Assessment Tool (SWAT), a ubiquitously used watershed model, could be used to predict and calibrate flow from a small watershed where groundwater input was so large that total flow exceeded precipitation. SWAT simulated flow for the watershed was limited by precipitation which is the major driver of SWAT's water budget, and consequently simulated flows were several times smaller in magnitude than observed flows. Thus, our first approach involved a separate baseflow and stormflow calibration followed by a manual magnification of baseflow. This yielded E_{NASH} = 0.66 and matched well with observed flow. Our next approach involved adapting SWAT to simulate upwelling groundwater discharge instead of deep aquifer losses. Assigning a negative value to parameter β_{deep}, instead of its default positive value, constrains the range of deep aquifer losses and produces groundwater-base recharge to the wetland; this calibration approach had higher E_{NASH} = 0.75. Finally, we also investigated the use of Artificial Neural Networks (ANN) in conjunction with SWAT in further improving the calibration performance. Calibration using SWAT calibrated flow with evapotranspiration and precipitation as inputs to ANN results in E_{NASH} = 0.88. The methods investigated in this study can be used to navigate similar flow calibration challenges in other groundwater dominant watersheds which can be very useful tool for managers and modelers alike.

Keywords: *Wetland, model, SWAT, headwater slope wetlands, urbanization, large ground watershed, high baseflow*

1. Introduction

The biogeochemical state or nutrient content of a drainage network is dictated by that of its headwaters which forms the beginning of water movement from uplands into streams (Brinson 1993). Headwater streams also comprise the highest proportion of stream miles (Rheinhardt et al. 1999; Leopold et al. 1964) which explains their disproportionately high influence in the drainage (Rheinhardt et al. 1999; Brinson 1993). Wetlands of headwater streams provide important ecosystem services such as habitat for aquatic life, nutrient uptake and cycling, clean drinking water, downstream temperature regime regulation and reduce loads of nitrogen, phosphorous and sediment to coastal waters (Rheinhardt et al. 1998; Roy et al. 2009). As a class, wetlands on lower order streams have higher capacity for water quality mitigation from nonpoint source pollution since channel flow in higher order downstream reaches does not come in contact with the floodplain wetland surface very often (due to infrequent overbank flooding) - this calls for greater scrutiny of wetland alterations on low order streams (Brinson 1993; Rheinhardt et al. 1998).

Forested, groundwater-fed headwater slope wetlands occur throughout the Alabama-Mississippi coastal plain at the headwaters of coastal creeks (Noble et al. 2007). Given their density on the landscape and their location at the interface of uplands and coastal creeks, these wetlands are likely to be extremely important in ameliorating runoff. However, headwater streams and associated wetlands have been severely altered in the Southeast, and data from headwater wetlands in the region are sparse (Rheinhardt et al. 1998). In coastal Alabama, increasing urbanization has caused critical wetland habitat to be drained, dredged or altered to make way for agricultural and urban development (Shaneyfelt and Metcalf 2014). Changes in watershed land use can disrupt water budgets by changing the partitioning of precipitation between the different components of the water cycle such as evapotranspiration, runoff, and groundwater flow (Foley et al. 2005). Roads and other impervious surfaces in the watershed can limit infiltration and groundwater recharge, obstruct or redirect natural flows to the wetland, incise headwater streams, result in a drawdown of the water table from immediately adjacent wetlands, and cause wetland hydrology to be dominantly surface-water driven (Havens et al. 2004; Forman and Alexander 1998; Bledsoe and Watson 2001). Previous studies on headwater slope wetlands in Alabama's coastal plain reported that surrounding land use influenced variations in water levels within headwater wetlands (Barksdale et al. 2014), which impacted forest structure and composition, soil conditions (Barksdale and Anderson 2015) and amphibian distributions (Alix et al. 2014). Though watersheds draining into headwater wetlands tend to be small (<1 sq. km (Gomi et al. 2002)), understanding the impact of human activities in these small head watersheds is critical to the restoration and management of headwater slope wetlands. In order to predict watershed impacts on headwater slope wetlands, models have to be applied and calibrated.

An important aspect of using models to simulate flow and water quality is ascertaining their accuracy (Gitau and Chaubey 2010). This is addressed by comparisons of model predictions with observed data and calibrating model parameters (i.e., fine-tuning model parameters either manually or automatically, through objective functions) to achieve a high degree of matching with the observed data; this exercise is only possible in gauged watersheds. Calibration is a required step in reproducing system behavior accurately since it is not possible to obtain reliable estimates for system behavior based on physical watershed characteristics alone due to inherent landscape heterogeneity and complex nature of hydrologic interactions (Wagener and Montanari 2011; Ssegane et al. 2003). The primary challenges for this are twofold: (1) models are essentially simpler representations of natural systems since it is not possible to account for the entire extent of real world complexity, and (2) models are defined by the values of their parameters. This can cause even highly complex models to fail in simulating watershed processes. A calibrated model can then be used to perform scenario analysis for different conditions of landscape, climate, etc. to provide us with a better understanding of the hydrologic conditions at that location. The assumption here is that future system responses are strongly conditioned by past observations and watershed responses (Ssegane et al. 2003; Gupta et al. 2003). This poses big challenges in ungauged watersheds, or where little data exists.

Another complexity is brought about by the influence of watershed size on the predictive ability of the model. In larger watersheds, the waterbody response may be driven by many landscape elements which are not spatially explicit, such as impervious surfaces within a watershed. However, as modelled watersheds get smaller, the significance of spatially explicit variables increases, e.g., spatial arrangement of the land uses or their individual management (Strayer et al. 2003). Disparities between surficial and ground watershed size in small watersheds can also introduce challenges to the model calibration process. Since ground watersheds cannot be observed from the land surface, defining their extent can be challenging (Winter et al. 2003). Additionally, groundwater flow systems of different magnitudes may be superimposed on one another, or the groundwater divides themselves may move in response to dynamic recharge and discharge conditions (Winter et al. 2003). These associations are further influenced by watershed size and their location within the groundwater flow system. For small watersheds located on terrains with high permeability and low regional topographic relief, as encountered in coastal Alabama, ground watershed area contributing water to the watershed can extend beyond the boundaries of the surficial watershed unless the watershed is situated on groundwater divides (Winter et al. 2003).

Subsurface processes are also difficult to observe or represent in watershed models because of the high level of soil/aquifer heterogeneity (Pechlivanidis et al. 2011). While the parameters of these processes maybe measured, they are prohibitive for use in larger watershed modeling since these are usually point scale measurements – for use in models these may be averaged or used at grid scales, which are larger than the scale of variations of these processes and as such do not capture catchment heterogeneity (Pechlivanidis et al. 2011). While there is consensus about the holistic existence of surface water and groundwater systems, these integrated systems are not very well developed in models (Zeng and Cai 2014; Sophocleous 2010).

A wide variety of models are utilized nowadays to understand hydrological and water quality responses to land use changes and environmental alterations. Watershed scale models such as the Soil and Watershed Assessment Tool (SWAT) have combined recent advancements in computational power with the use of Geographic Information Systems (GIS) technology to establish semi- to fully-distributed hydrologic models to better represent physical processes governing complex natural systems. Since SWAT allows for manipulations of land use, soils, slope and climate on watershed scales, its uses are extremely versatile; e.g., it can determine inputs to a wetland draining from a watershed, determine impacts of different land use practices on coastal waters, determine reference conditions for streams, etc. (Makareweicz et al. 2015). Moreover, it enjoys a great degree of support available through its various online user groups (Spruill et al. 2000). SWAT also has provisions for automated parameter calibration through the use of SWAT Calibration and Uncertainty Program, or SWAT-CUP, which enables sensitivity analysis, calibration and uncertainty analysis for SWAT models (Abbaspour et al. 2008). However, SWAT struggles with accurate groundwater predictions for reasons explained earlier. This study presents challenges in using the SWAT model to predict flows draining from a small groundwater dominated watershed into a headwater slope wetland in Alabama's coastal plain, as well as demonstrates easy to implement solutions to address these challenges.

Data-driven approaches such as the use of Artificial Neural Networks (ANN) are also being used extensively in hydrology modeling (Noori and Kalin 2016; Rezaienzadeh et al. 2015; Srivastava et al. 2006). ANNs are black-box models which can be trained to learn the relationships between inputs and outputs (including highly complex, multidimensional, nonlinear relationships) in a process without actually needing to delve into the physical characteristics of the process (Noori and Kalin 2016; Rezaienzadeh et al. 2015; Srivastava et al. 2006). ANNs, then provide a useful alternative for streamflow predictions while steering clear of issues affecting process-based models such as SWAT due to reasons such as large spatial scale, and complex but poorly understood processes (as described in previous paragraphs). ANNs may also be applied together with a watershed model to enhance streamflow prediction capabilities. Only one study to our knowledge has evaluated the use of ANN and SWAT together (Noori and Kalin 2016) to improve calibration ability. Our study also aims to add to the body of literature using ANN models in conjunction with SWAT to improve hydrological prediction ability.

The flow data utilized for this study was measured at the inlet to a headwater slope wetland in Foley, Alabama. Delineated surface watershed for this wetland was very small (0.49 km^2), and the flow data exhibited several peculiarities, the most important being that observed flow exceeded precipitation. Given the quality assurance and quality control of flow data, the only rational explanation is presence of another source of water besides rainfall. This led us to an interesting quandary: where was all this excess water coming from? Talking with local practitioners and other researchers didn't yield any explanations. Increasing the delineated watershed area to twice its current extent still didn't make up the difference in flows. This led us to believe that the groundwater component contributing to the wetland was a great deal larger than the surface flow component, as explained by Winter et al. (2003). If precipitation represents the maximum amount of water in the watershed, how does one model flows which exceed precipitation? The SWAT model has been criticized for its inability to accurately predict groundwater interactions: to remedy this deficiency, an integrated version of the SWAT model linking SWAT with groundwater model MODFLOW (SWAT-MODFLOW) was developed which links groundwater outputs from SWAT as inputs for MODFLOW (Guzman et al. 2015). However, this modeling approach is data, computation and expertise intensive, all of which may be too high of an investment for project goals in a small watershed. Instead, could we come up with an easier approach using just SWAT to model watershed flows when observed flows exceed precipitation in the watershed? Modelling flows which clearly reflect the presence of a larger ground watershed extent (relative to the surficial watershed), has not been confronted to our knowledge - this study aims to address this knowledge gap.

Our objectives for this study then target the use of SWAT, a fairly ubiquitously used watershed model, to predict flows for the watershed draining into the aforementioned headwater slope wetland. More specifically, our objectives for this study were: (1) to explore hydrological trends of the watershed outflows draining into a headwater slope wetland in coastal Alabama, (2) to apply different approaches of hydrology calibration using SWAT and (3) to test the use of ANN with SWAT to improve calibration performance. The study will yield useful modeling approaches in SWAT to model high groundwater systems such as the watershed used in this study as an alternative to more complex groundwater-surface water interaction models. Additionally, the study explores the use of Artificial Neural Networks (ANN) in improving flow calibration.

2. Materials and methods

2.1 Site description and hydrology monitoring

Data for this study was collected from a discernible inlet to a headwater slope wetland in Baldwin County, AL: New Foley wetland (30.354235°, -87.631394°) located at the headwaters of a smaller tributary to Owen's Bayou (Figure 1) within the city of Foley. Headwater slope wetlands in coastal Alabama occur above and alongside 1st order streams - they are typically groundwater fed and exist as braided channels along a gradual slope. Wetland soils are generally alluvial (Barksdale et al. 2014; McBride and Burgess 1964) and remain saturated or close to saturated throughout the year due to fairly stable water levels that are at or slightly below the ground surface (Noble et al. 2007). Land use in the watershed draining to the study wetland is predominantly residential, with residential areas to the north, west (upstream) and another proposed residential area to the south. A residential lake is also located directly upstream of the wetland which drains into the wetland through a concrete spillway. The watershed also comprises some agricultural area (Figure 1). The study area is characterized by hot, humid summers and mild winters with average annual temperatures of 19ºC and precipitation of 170 cm mostly evenly distributed throughout the year with peaks occurring in early spring and midsummer (Barksdale et al. 2014; Noble et al. 2007; Robinson et al. 1996).

Hydrological data was collected at the study wetland from August 2013 until December 2014. Stage was measured every 15 min using InSitu Mini-Troll 500 pressure transducers and data loggers at a discernible inlet to the wetland. Stage was associated with discharge measurements taken at the site at twelve different times to develop stage-discharge relationships (i.e., rating curves). Surface water velocity and depth were measured every 10 cm across the channel width and used to calculate average surface water discharge (based on USGS stream gauging guidelines, Rantz 1982). The surface water velocity was measured by using a Marsh-McBirney, Inc. Flo-Mate Model 2000 Portable Flowmeter.

A modified Manning's equation was used to generate estimates of discharge as a function of measured stage. Manning's formula can be described as

$$Q = \frac{1}{n} A R^{\frac{2}{3}} \sqrt{S_0} \quad \text{.......} (1)$$

$$Q = k A R^{\frac{2}{3}} \quad \text{.......} (2)$$

where Q = flow (m^3/s), R = hydraulic radius (m), S_0 = friction slope, estimated as bedslope, n = Manning's roughness coefficient, A = channel cross-sectional area, and $k = \sqrt{S_0}/n$. From channel dimensions, channel cross-sectional areas, wetted perimeters and hydraulic radius were calculated and applied to observed stage-discharge data to calculate k from eqn (2), and subsequently a k-h relationship was developed through regression. This k-h relationship was combined with eqn (2) to convert the measured stage time series at 15-min time intervals into discharge time series. The discharge time series at 15-min time interval were then used to estimate average daily streamflows.

2.2 SWAT and SWAT-CUP model descriptions

The Soil and Watershed Assessment Tool (SWAT) is a widely used watershed scale, process-based hydrologic model that was developed by the United States Department of Agriculture (Arnold et al. 1998; Cibin et al. 2013). It can operate on hourly, daily, monthly or annual scales, and has been used effectively for assessing nonpoint source pollution problems at different scales and environmental conditions all over the world (Cibin et al. 2013). SWAT divides the watershed into multiple subwatersheds which are further divided into hydrologic response units or HRUs - these represent percentages of the subwatershed area and are not identified visually within a SWAT simulation (Gassman 2007). SWAT defines multiple HRUs each having unique land use, soil and slope combinations. Hydrology is separated into the land phase and the routing phase of the hydrologic cycle - water to the main channel is determined by the land phase of the hydrologic cycle while the routing phase determines water from the channel network to the outlet. SWAT uses either the service curve number (CN) method or the Green & Ampt infiltration method to estimate surface runoff. Three methods are included for evapotranspiration estimation based on the number of inputs required – the Penmen-Monteith method, the Priestly-Taylor method and the Hargreaves method. Surface, lateral subsurface, and baseflow waters reaching the stream channels are routed either through Muskingum or variable storage coefficient method. The water budget is developed for each HRU, and then aggregated for the subbasin by a weighted average (Lam et al. 2010).

Water enters groundwater primarily through infiltration/percolation from land surfaces and seepage from surface water bodies (Neitsch et al. 2009). SWAT simulates two aquifers within each subbasin, a shallow aquifer which is unconfined and contributes baseflow to the reach or main channel of the subbasin, and a deep confined aquifer which contributes to streamflow somewhere outside the watershed. Below we describe the groundwater component of the SWAT model in more detail given its significant contribution to the study system.

SWAT calculates baseflow contribution to a channel on a given day as

$$Q_{gw,i} = Q_{gw,i-1}.\exp(-\alpha_{gw}.\Delta t) + w_{rchrg,sh}.(1 - \exp[-\alpha_{gw}.\Delta t]), \text{ if } aq_{sh} > aq_{shthr,q} \quad \text{.........} (5)$$

$$Q_{gw,i} = 0, \text{ if } aq_{sh} < aq_{shthr,q} \quad \text{.........} (6)$$

where, $Q_{gw,i}$ and $Q_{gw,i-1}$ are baseflow or groundwater flows into the main channel on days *i* and *i*-1 respectively (mm H_2O), Δt is the daily time-step ($\Delta t = 1\ day$), $w_{rchrge,sh}$ is the amount of recharge entering the shallow aquifer on day *i* (mm H_2O), aq_{sh} is the amount of water stored in the shallow aquifer at the beginning of day *i*, $aq_{shthr,q}$ is the threshold water level in the shallow aquifer for groundwater contribution to the main channel to occur (mm H_2O), and α_{gw} is the baseflow recession constant (a direct index of groundwater flow response to changes in recharge).

The amount of recharge entering the shallow aquifer, $w_{rchrge,sh}$ is a portion of the total aquifer recharge, w_{rchrg} after accounting for percolation to the deep aquifer which is lost from the system. This is represented as

$$w_{rchrge,sh} = w_{rchrg} - w_{deep} \quad \text{.........} (7)$$

where, w_{rchrg} is the total aquifer recharge on day *i* (mm H_2O), and w_{deep} is the amount of water percolating from the shallow aquifer to the deep aquifer on day *i* (which is essentially lost since it does not contribute to flows within that subbasin) (mm H_2O).

Default parameter ranges for calculating w_{deep} in the SWAT model ensures $w_{deep} \geq 0$ mm/day, *i.e.*, SWAT only assumes water loss from the shallow aquifer to the deep aquifer. The reverse scenario of discharge from the deep aquifer into the shallow aquifer is not considered.

Aquifer recharge, w_{rchrg} is comprised of water percolating past the lowest depth of the soil profile and bypass flow flowing through the vadose zone. An exponential decay weighting function is used to model recharge to the aquifers as

$$w_{rchrg,i} = (1 - \exp\left[-\frac{1}{\delta_{gw}}\right])\, w_{seep} + \exp\left[-\frac{1}{\delta_{gw}}\right] w_{rchrg,i-1} \quad \text{(8)}$$

where $w_{rchrg,i}$ is the amount of recharge entering aquifers on day *i* (mm H_2O), δ_{gw} is the delay time or drainage time of the overlying geologic formations which has been shown to remain somewhat constant within the same geomorphic area, w_{seep} is the total amount of water exiting the bottom of the soil profile on day *i* (mm H_2O), and $w_{rchrg,i-1}$ is the amount of recharge entering the aquifers on day *i*-1 (mm H_2O).

Parameters for the SWAT model can be calibrated through manual and automated methods – the former involves running SWAT model with manually modified deterministic values for parameters, while the latter allows the user to run SWAT models using parameters propagated within a range of specified feasible upper and lower values for parameters. An automated calibration software called SWAT Calibration and Uncertainty and Program (SWAT-CUP) was developed specifically to be used with SWAT in order to report uncertainty in the results by propagating parameter uncertainties (Abbaspour et al. 2008). Various SWAT parameters are identified for auto-calibration, through initial manual calibration as well as from literature. Parameter ranges are then propagated by Latin hypercube sampling using the SUFI-2 algorithm in SWAT-CUP (Abbaspour et al. 2008). Propagating parameter uncertainties results in uncertainties in the outputs which are represented as 95% probability distributions - calculated at

2.5% and 97.5% levels of the cumulative output distributions - also known as the 95% prediction uncertainty or the 95PPU. The goal of the SWAT-CUP calibration process is to have the 95PPU envelop most of the observations (measured data). The fit between simulation results, i.e., the 95PPU, and the observations is represented by two main factors - the *P*-factor and *R*-factor. The *P*-factor represents the percentage of observations enveloped by the 95PPU, and the *R*-factor is the thickness of the 95PPU band. No hard values exist for these values - for flow, a *P*-factor $\geq$ 0.7 and *R*-factor $\leq$ 1 are considered acceptable (Abbaspour et al. 2008). A few iterations (usually < 5) of multiple simulations (300-500 depending on the time it takes) are performed in SWATCUP, where initially the user starts out with larger parameter ranges which get smaller with each iteration. Various criteria such as coefficient of determination (R^2), Nash–Sutcliffe efficiency (E_{NASH}) (Nash and Sutcliffe 1970) and bias ratio (R_{BIAS}) (Salas et al. 2000) are used to measure the closeness of the model output and the observed data.

2.2.1 SWAT and SWAT-CUP model setup and data

The SWAT model was developed and applied for the watershed draining into the New Foley wetland. We used SWAT version SWAT-2012 through the ArcSWAT interface in ArcGIS 10.0 for all SWAT simulations. All the GIS data required for ArcSWAT setup was downloaded from the USGS's online Seamless Data Warehouse (https://datagateway.nrcs.usda.gov). The watershed boundaries for the wetland were delineated by ArcSWAT using elevation data obtained from the National Elevation Dataset (NED) DEM with a resolution of 1/3 arc-second (10m pixels) developed by USGS, and hydrography data from the National Hydrography Dataset (NHD). Hydrography was further modified and digitized to include headwaters with channel extensions to improve more accurate watershed delineation and streamflow routing in ArcSWAT

(Amatya and Jha 2011). The delineated watershed contributing to the discernible wetland inflow where the transducer was located had an area of 0.49 km^2 (49 ha).

Land use data was obtained from the 2011 National Land Cover Dataset (NLCD) and soil parameters were derived from the county level Soil Survey Geographic (SSURGO) dataset. Some classifications in the NLCD layer were edited slightly to reflect current land use in the watershed. About 45.6 % of the watershed area was classified urban. Slopes were divided into 3 % classes (1-3%, 3-6%, etc.). Threshold values of 5% were used for land use, soils and slope definition. Daily maximum and minimum temperature for the study period was available from a station in Robertsdale (station GHCND: USC00016988) in Baldwin County (Figure 1). Daily precipitation was obtained from NEXRAD data for a period from 2008 to 2014, and the Hargreaves method was used for calculation of potential evapotranspiration.

The study area received very high rainfall of ~380 mm between April 28 and May 1, 2014, and fluctuations in transducer data after these dates were highly variable and exaggerated. We believe that the sudden extreme rainfall may have affected the functioning of the transducer and caused it to produce faulty data. Consequently, these dates were excluded from the calibration. Since the duration of observed data was so small (<1 year), we did not split the data to perform validation – instead all the data was used for calibration alone. While the small duration of observed data are an important limitation to the study, it is not detrimental to the overall objectives of the study which are to present different approaches of dealing with challenging hydrology calibrations in a head watershed with extensive groundwater inputs which cannot be accounted for by the SWAT model.

Previously calibrated parameter values reported in Wang and Kalin (2011) for Magnolia River watershed, which is situated adjacent (in the northeast side) to the Wolf Bay watershed of which the study watershed is a part (Figure 2), were applied as starting values in the SWAT model for the study wetland (Table 1). Since the Magnolia River and Wolf Bay watersheds neighbor each other and have similar physical characteristics (soils, slope, geology), SWAT parameters calibrated for the Magnolia river watershed can be transferred to the Wolf Bay watershed (Wang and Kalin 2011). Literature has shown that model simulations require a long warmup period to accurately represent conditions being simulated such as antecedent moisture and initial groundwater table height which can influence predictions of streamflow and baseflows (Bosch et al. 2004; Wang and Kalin 2010; Kalin and Hantush 2006). The SWAT model was run for 7 years, with a warmup period of 5 years (2008-2012) prior to the 2-year period (2013-2014) of which the study period (8/10/2013 – 4/28/2014) is a part, to accurately initialize SWAT parameters.

SWAT-CUP requires that the default simulation (simulation that is fed into SWATCUP for calibration) not be too different from observed data. For this reason, some manual calibration was done (in addition to applying parameter values from Table 1) to ensure some parity between simulated and observed flows. Procedures explained in Neitsch et al. (2001) and personal communication with different SWAT users was used to adjust parameters for calibration. For baseflow dominated areas, parameters such as groundwater delay (GWDELAY), deep aquifer recharge coefficient (RCHRGE_DP) and baseflow alpha factor (ALPHA_BF) were adjusted, along with SCS curve number (CN2). Model parameters were calibrated at daily timescales for flow. Following manual calibration, around sixteen parameters influencing different aspects of surface and subsurface flows were chosen for SWAT-CUP auto-calibration from literature (Table 2). SWAT-CUP 2012 version 5.1.6 was used to conduct auto-calibration runs.

2.3 Coupled SWAT-ANN model description and setup

While hydrological models may be calibrated to some satisfying measure of performance ability, they may not always preserve all aspects of the hydrograph, i.e., not all simulated flow values will correspond to observed values (Vis et al. 2015). For example, a model might have a reasonably high value of the objective function (such as Nash–Sutcliffe efficiency which is a measure of the closeness of observed and simulated values), but fails in adequately capturing high- or low flow extremes which may be critical in predicting specific ecological responses (Vis et al. 2015). One way of dealing with this limitation, involves a step-wise coupled approach by first calibrating with SWAT through a process-based hydrological understanding of the system followed by black-box models such as Artificial Neural Networks (ANN) to improve the former calibration. A few studies have compared the ability of SWAT and ANN in predicting streamflow (Srivastava et al. 2006; Kim et al. 2012; Talebizadeh et al. 2010), but only one study to our knowledge has tested the utility of coupling SWAT and ANN for improved streamflow prediction (Noori et al. 2016). This study expands on the usefulness of SWAT-ANN coupled approach in improving hydrological calibration to better preserve key aspects of the streamflow hydrograph.

ANNs are black-box models where detailed understanding of the internal processes is not required to develop relationships between the inputs and outputs (Isik et al. 2013; Srivastava et al. 2006; Noori and Kalin. 2016). Many kinds of ANN exist, but the feed forward ANN is used most commonly in hydrological applications and consists of several nodes organized in layers. Between the input and the output layers, a number of user-defined hidden layers exist where most of the processing takes place. Input data are fed into the input layer, which communicates with nodes in the hidden layer(s), which then link to an output layer where the response of the

ANN model corresponding to each input data point is received (Srivastava et al. 2006). A process called training corresponds with the calibration process in traditional models (Srivastava et al. 2006). During training, the inputs together with the desired response (target response/observed data) is fed to the ANN model. The ANN model process is started with an initial random choice of weights, input data and target response and the model is allowed to compute responses which are compared with the desired response: this process is repeated in an iterative manner, each time adjusting the weights, until the desired subjective stopping criterion stopping criterion is reached. Training aims to minimize a predefined error function by searching for a set of connection strengths and threshold values so that ANN outputs are close or equal to the desired response/target (Kalin et al. 2010; Srivastava et al. 2006). Inputs are usually normalized to avoid differences in magnitudes and variance from interfering with the training process (Srivastava et al. 2006).

The size of the hidden layer and the number of neurons are important considerations in ANN development. There is no singular setup structure, rather trial and error is used to establish the optimum number of hidden layers and neurons (Isik et al. 2013). We varied the number of neurons in the hidden layer from 5 to 10 but restricted the number of hidden layers to 1 to avoid over-fitting with such limited data. We also used two different transfer functions to translate input signals to output signals – the log-sigmoid and the hyperbolic tangent sigmoid functions (Noori and Kalin 2016) - and picked the one which gave better results. We used SWAT calibrated streamflow together with precipitation and potential evapotranspiration (PET) calculated by the Hamon method (Hamon 1961) as inputs to the ANN model. The Hamon method calculates daily PET as a function of daily mean air temperature and hours of daylight, and has been shown to work favorably in the southeastern US (Lu et al. 2005; Noori and Kalin

2016). Here we checked to see if coupling ANN with SWAT calibrated streamflow would yield better calibration results than calibrating with SWAT alone. We used MATLAB R2016a version 9.0.0 for model construction and implementation. See Figure 3 for SWAT-ANN coupled model setup.

2.4 Performance measures and evaluation criteria

Model performances was measured using metrics such as coefficient of determination (R^2), Nash–Sutcliffe efficiency (E_{NASH}) (Nash and Sutcliffe 1970) and bias ratio (R_{BIAS}) (Salas et al. 2000). The coefficient of determination (R^2) is a measure of linear correlation between the two quantities, while the Nash–Sutcliffe efficiency statistic (E_{NASH}) is a measure of how the plot of observed versus simulated data deviates from the 1:1 line (i.e., perfect model). E_{NASH} values vary from $-\infty$ to 1 where 1 corresponds to the perfect model. The bias ratio (R_{BIAS}) in percentage measures the degree to which the forecast is under- or overpredicted – negative values indicate underprediction and positive values indicate overprediction (Salas et al. 2000).

Model performances for flow simulations were assessed based on the guidelines presented by Moriasi et al. (2007) for assessments of flow and nutrients at monthly time scales. Since our study is assessed at a daily time scale, the modified relaxed constraints in Kalin et al. (2010) were adopted for the purposes of this study:

Very Good: $E_{\mathrm{NASH}} \geq 0.7$; $|R_{\mathrm{BIAS}}| \leq 0.25$

Good: $0.5 \leq E_{\mathrm{NASH}} < 0.7$; $0.25 < |R_{\mathrm{BIAS}}| \leq 0.5$

Satisfactory: $0.3 \leq E_{\mathrm{NASH}} < 0.5$; $0. 5 < |R_{\mathrm{BIAS}}| \leq 0.7$

Unsatisfactory: $E_{\mathrm{NASH}} < 0.3$; $|R_{\mathrm{BIAS}}| > 0.7$

3. Results and calibration approaches

The hydrology at the watershed outlet showed distinctive trends consistent with ecological understanding of flow as a function of urbanization and coast proximity. As can be seen in Figure 4, observed flow had consistently high baseflow contribution. For the study period, observed flow at the watershed outlet ranged from 0.048 m^3/s to 0.95 m^3/s and averaged around 0.15 m^3/s.

SWAT simulations, after transferring parameters from the adjacent Magnolia River watershed, failed to simulate the magnitude of observed flows (R^2 = 0.52, E_{NASH} = -0.57, R_{BIAS} = -0.82; Figure 4). The figure indicates that the model simulations were able to capture trends but disproportionately (and consistently) underpredicts the magnitude. The watershed received a total of around 1726 mm of precipitation during the study period. It was, however, interesting to note that the sum of daily flows during this period equaled 6599 mm (depth calculated for ArcSWAT delineated watershed), which exceeded precipitation by a multiplier of 3.8, *i.e.,* streamflow ratio, or the percentage of precipitation converted to streamflow, was 3.8. So where was all this excess water coming from? For reasons described earlier, the only logical conclusion was the presence of a ground watershed larger in extent than the surficial watershed that ArcSWAT was failing to account for. Thus, the remainder of the results section is focused on the different approaches we used to calibrate a system with this unique hydrological behavior. As mentioned previously, extreme rainfall from April 28, 2014 seemed to have affected transducer functioning causing faulty and highly exaggerated fluctuations in the data - consequently, dates following April 28, 2014 were excluded from the calibration.

3.1 Approach 1 – Baseflow amplification

In this approach we followed a two-step calibration process where we separately calibrated baseflow trend and stormflow components. A magnification multiplier was then applied to the baseflow trend and added to the calibrated stormflow component to get total streamflow.

First, we partitioned observed streamflow into baseflow and stormflow components using the Web-based Hydrograph Analysis Tool (WHAT; Lim et al. 2005) using inbuilt BFI_{max} value (maximum value of long term ratio of base flow to total streamflow) of 0.80 for perennial streams with porous aquifers. On comparing observed baseflow and stormflow with that simulated by ArcSWAT (Figures 5 and 6), we observed that stormflow matched "satisfactorily" (R^2 = 0.59, E_{NASH} = 0.44, R_{BIAS} = -0.55), which was not the case for baseflows which greatly differed in magnitude or the match was "unsatisfactory" (R^2 = 0.28, E_{NASH} = -5.6, R_{BIAS} = -0.93). So we then constructed two SWAT models, one for baseflow and the other for stormflow.

In the baseflow model we manually adjusted different parameters to match the baseflow trend (not magnitude) by comparing GW_Q (groundwater contribution to streamflow) with observed baseflow. All parameters for Magnolia River watershed from Wang and Kalin (2011) mentioned in Table 1 were applied such as REVAPMN, which is the threshold depth of water in the shallow aquifer to occur, and ALPHA_BF which is the baseflow recession constant and indicates the groundwater flow response to changes in recharge. The parameters which were critical in matching baseflow trend were GW_DELAY which is the time required for water leaving the bottom of the root zone to reach the shallow aquifer, and RCHRGE_DP which is the deep aquifer percolation fraction. GW_DELAY was decreased to 1 day to mimic the high permeability of sandy soils in the coastal plain area where flow from the aquifer to the root zone is rapid (Bosch et al. 2004). We also decreased ALPHA_BF_D, which is the alpha factor for groundwater recession curve of the deep aquifer, from the default value of 0.01 (1/days) to 0. RCHRGE_DP was set to 0 (from default value of 0.05) which prevents percolation loss to the deep aquifer. Comparison of ArcSWAT simulated and observed baseflow trends now yielded a good match in trends (R^2 = 0.72; Figure 7). The magnification multiplier was determined by dividing averages of observed baseflow and trend calibrated baseflow (from ArcSWAT). Observed baseflow was on average, 13 times ArcSWAT calibrated baseflow. ArcSWAT simulated baseflow was amplified by multiplying with 13 and performing appropriate unit conversions to m^3/s. This magnified baseflow had a "very good" match with observed baseflow (R^2 = 0.72, E_{NASH} = 0.72, R_{BIAS} = 0.01).

A separate calibration was done for the stormflow component of observed streamflow. This calibration was done using SWAT-CUP software with 13 parameters concerned with both groundwater and surface water components (Table 2). Since SWAT's baseflow and groundwater parameters interact with each other, we didn't completely remove the baseflow parameters from this calibration. In any case, this does not affect actual baseflow estimates whose calibration was undertaken using a separate model. Three iterations of 500 simulations each were conducted - calibrated parameter ranges and the values for the best simulation are presented in Table 3. The best simulation from this calibration had a "good" match with observed stormflow (R^2 = 0.71, E_{NASH} = 0.62, R_{BIAS} = -0.5). ArcSWAT calibrated streamflow was calculated as the sum of amplified calibrated baseflow and calibrated stormflow, which yielded a "good" match with that of the observed streamflow (R^2 = 0.74, E_{NASH} = 0.67, R_{BIAS} = -0.14; Figure 8). While this approach resulted in a decent calibration, a look at the flow exceedance curve (Figure 8) shows that flows > 0.08 m^3/s are slightly but consistently underpredicted.

3.2 Approach 2 – Adjusting RCHRGE_DP to allow for groundwater discharge

In this approach, we evaluated the parameter RCHRGE_DP for its role in removing surface water by percolation to the deep aquifer. The default value of this parameter (fraction) is set to 0.05 and its range extends between 0 and 1. A positive RCHRGE_DP indicates shallow aquifer losses to the deep aquifer. However, in certain cases, the deep aquifer may recharge to the shallow aquifer which can be addressed by assigning a negative value to RCHRGE_DP. Tweaking this parameter in such a way has not been explored for the circumstances surrounding the watershed evaluated in this study.

In the SWAT manual (Neitch et al. 2009), water lost to deep aquifer is not contributed back to the stream. The fraction RCHRGE_DP (β_{deep}) controls the amount of water diverted from the shallow aquifer by percolation to the deep aquifer on a given day (Neitsch et al. 2009) as

$$w_{deep} = \beta_{deep}.w_{rchrg} \quad (9)$$

where, w_{deep} is the amount of water moving in the deep aquifer on a given day, β_{deep} is the aquifer percolation coefficient and w_{rchrg} is the amount of recharge entering both aquifers on the same day. Recharge to the shallow aquifer is then calculated as

$$w_{rchrge,sh} = r_{rchrg} - w_{deep} \quad (10)$$

where $w_{rchrge,sh}$ is the amount of recharge entering the shallow aquifer on the same day. If this is larger than the user specified threshold, then the shallow aquifer contributes baseflow to the reach (Neitsch et al. 2009). If the fraction β_{deep} is made negative, this implies a flow from the deep aquifer into the shallow aquifer since w_{deep} will be negative which in turn increases $w_{rchrge,sh}$ allowing for higher baseflow contribution from the shallow aquifer to enter the reach.

In this approach of streamflow calibration, we first manually manipulated SWAT parameters to ensure some match between the simulated and observed flows, following which we used SWAT-CUP to complete the calibration. Like in the previous approach, parameters from Wang and Kalin (2011) were first applied following which GW_DELAY was reduced to 1 and ALPHA_BF_D was changed to 0. Instead of a 2-step calibration like the previous approach, we changed RCHRGE_DP to -13 (rounding off the baseflow amplification multiplier from the previous approach). In order for this to work, ranges in the ArcSWAT database should be changed before applying negative RCHRGE_DP values in the model.

We then used SWAT-CUP to further calibrate the model. Three iterations of 500 simulations each were conducted - calibrated parameter ranges are presented in Table 4. The best streamflow simulation matched well with observed streamflow, and the 95PPU enveloped 84% of the observations (P-factor = 0.84, R-factor = 1.04, R^2 = 0.78, E_{NASH} = 0.75, R_{BIAS} = -0.03; Figure 9). From the flow exceedance curve in Figure 9, it can be observed that the hydrograph is mostly well preserved, except for low flows (< 0.1 m^3/s) which are slightly underestimated.

3.3 Approach 3 – ANN-SWAT Coupling

If accurately predicting low flows is an important concern, then the best simulation from the previous approach is slightly lacking (flow exceedance curve in Figure 9). To improve upon this limitation, previously calibrated streamflow from approach 2 was fed into ANN together with daily precipitation and PET as inputs. Due to the small calibration dataset (249 data points) and to maintain consistency with the different approaches, we used all of the data for training (or calibration) alone. Through trial-and-error, the ANN model with one hidden layer, 8 nodes and a log-sigmoid transfer function, predicted flows which had “very good” match with observed flows (R^2 = 0.89, E_{NASH} = 0.89, R_{BIAS} = -0.012; Figure 10). Coupling SWAT calibration with ANN in this hybrid approach much improved streamflow calibration compared to the previous approaches discussed in the study. From the flow exceedance curve in Figure 10, all aspects of the hydrograph are well estimated and the previously observed limitation of low flow underestimation has been resolved.

Sometimes process-based models, through advanced physical understanding of the system can allow for model calibration up until a certain point beyond which the model faces difficulties improving calibration, perhaps due to system complexity. The use of ANN allows further attempts at improving calibration without delving into the process details. Thus, ANN serves as a tool to improve upon deficiencies observed in SWAT simulated (and SWATCUP calibrated) flows.

4. Discussion and conclusions

In this study we explored different options for calibrating a very small head watershed in Alabama's coastal plain region draining into a headwater slope wetland which feeds Owen's bayou and eventually, Wolf Bay. This watershed exhibited unique characteristics most notably that flows exceeding precipitation - total precipitation and flows for the study period were 1726 mm and 6599 mm respectively – potentially due to high amounts of groundwater discharging at the watershed outlet. In general, models such as SWAT despite their capabilities show many deficiencies in modelling surface and groundwater interactions, which may be redeemed by using SWAT in conjunction with groundwater models such as MODFLOW. However, this comes with the added cost of increased complexity, heavy data requirements, technical expertise and computing prowess. Moreover, this level of integrated modeling may not be appropriate for the case at hand where very limited data are available and the watershed size is too small to warrant the use of very complex integrated models. In this study we evaluated the use of SWAT to tackle calibration of this groundwater-fed head watershed system with minimal observed data.

The three approaches evaluated for calibration had “good” to “very good” performance with $E_{\mathrm{NASH}} > 0.66$. In the first approach, baseflow and stormflow components were calibrated separately and summed to yield total streamflow: ArcSWAT simulated baseflow trend was matched to that observed and then manually amplified to the observed magnitude. The second approach involved attributing a negative value to the parameter RCHRGE_DP, which controls loss of surface water to the deep aquifer by percolation, to allow for recharge and discharge into streamflow instead. The calibrated range for this parameter from the SWAT-CUP calibration ranged from -13 to -20. Whether and how changing the value of RCHRGE_DP so far outside its range affects other aspects of streamflow and nutrient dynamics is unknown and worthy of future investigation. However, if hydrology calibration is the ultimate goal of the study, then tweaking RCHRGE_DP in this manner is a useful trick to be aware about. In this study we further attempted to improve hydrology calibration through the application of ANN in conjunction with SWAT. Feeding calibrated streamflow from ArcSWAT together with precipitation and ET to the ANN model resulted in a much improved performance with E_{NASH} of 0.88. Using ANN together with SWAT in this hybrid approach has the advantage of better calibration by letting ANN deal with complexities that we have less knowledge about and cannot be modeled while also incorporating a process-based hydrological understanding of the system through the SWAT model.

The study watershed is located at an elevation of 4 to 15 m above mean sea level where depth to water table is probably lower than 1.2 m below ground surface (Murgulet and Tick 2008). In parts of the Graham Creek Nature preserve immediately south of the study watershed, the water table was found to be as close as 12 inches below the ground surface (personal communication with Preserve manager). This indicates that high baseflows are natural to the system. However, baseflows may be still higher than natural conditions due to some upland contribution from an impounded lake in the residential area just upstream of the wetland. We suspect that percolation from the impounded lake have further raised the water table and contributed to groundwater discharge at the watershed outlet (Winter 2007), thus creating large parameter values for RCHRGE_DP.

Most headwater streams in Alabama originate from headwater slope wetlands (Shaneyfelt and Metcalf 2014). However, these systems are highly imperiled due to pressure from various land use activities such as transportation, construction, poorly planned residential and commercial developments, channel excavation, among others (Shaneyfelt and Metcalf 2014). These headwater slope wetlands, impacted to varying degrees by modifications to hydrological regimes and connectivity, will also exhibit differences in functioning along a gradient of land use pressure. Documenting existing hydrological trends of headwater slope wetlands and providing tools for hydrology calibration provides a very valuable tool for understanding impacts of watershed land use on wetland function, thus aiding in the understanding, protection and preservation of these systems. This study adds to that body of knowledge and gives managers useful tools for hydrology calibration in groundwater dominated wetlands when accurate predictions of hydrology are necessary.

5. Limitations and future steps

In this study we presented ways to model a complex hydrological trend with dominant groundwater input using relatively simple approaches involving the SWAT model. Given that watershed runoff to the NF wetland was >3X the precipitation, it is doubtful that any model would be able to simulate flows observed in this groundwater dominant system without the knowledge of detailed surface and subsurface hydrology and geology. In the absence of such detailed data, the approaches we present are useful alternatives to aid in management decisions, scenario analyses, or other pressing concerns which necessitates having a calibrated hydrological model. In no way do we deny the importance of using more relevant groundwater models to get a better handle on NF wetland hydrology; however, data presently available for the wetland do not support the application of groundwater models which tend to be highly data-intensive and require a lot of calibration, for e.g., to ascertain hydraulic conductivity of the soil layers. Another limitation is the absence of adequate data for validation. Since flow data at the wetland were limited, splitting the same into calibration and validation datasets were not possible. We acknowledge that model validation, as more data become available, would improve confidence in the calibration approaches presented in the study. In a hypothetical scenario involving unlimited funding and manpower resources to sustain a multi-year long-term project, limitations can be addressed by 1) improving monitoring of surface waters by installing weirs and transducers to get improved rating curves and discharge estimations, 2) improving groundwater measurements using multiple piezometers fitted with transducers, applied in transects and at different depths, both around and within the channels, to quantify horizontal and vertical gradients and water levels, and 3) conducting the study at multiple headwater slope wetlands across Alabama's lower coastal plain region to detect other wetland systems with similar hydrological characteristics. These data would not only enable validation of presented approaches but also support the application of improved models for flow prediction, as well as generate a greater understanding of the hydrological processes sustaining these wetland types. In any case, wetland management is an adaptive process which relies on existing data to make decisions which can be improved or altered as and when new data become available – until then, the approaches presented in this study provide a useful alternative to flow prediction in groundwater dominant systems.

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Figures

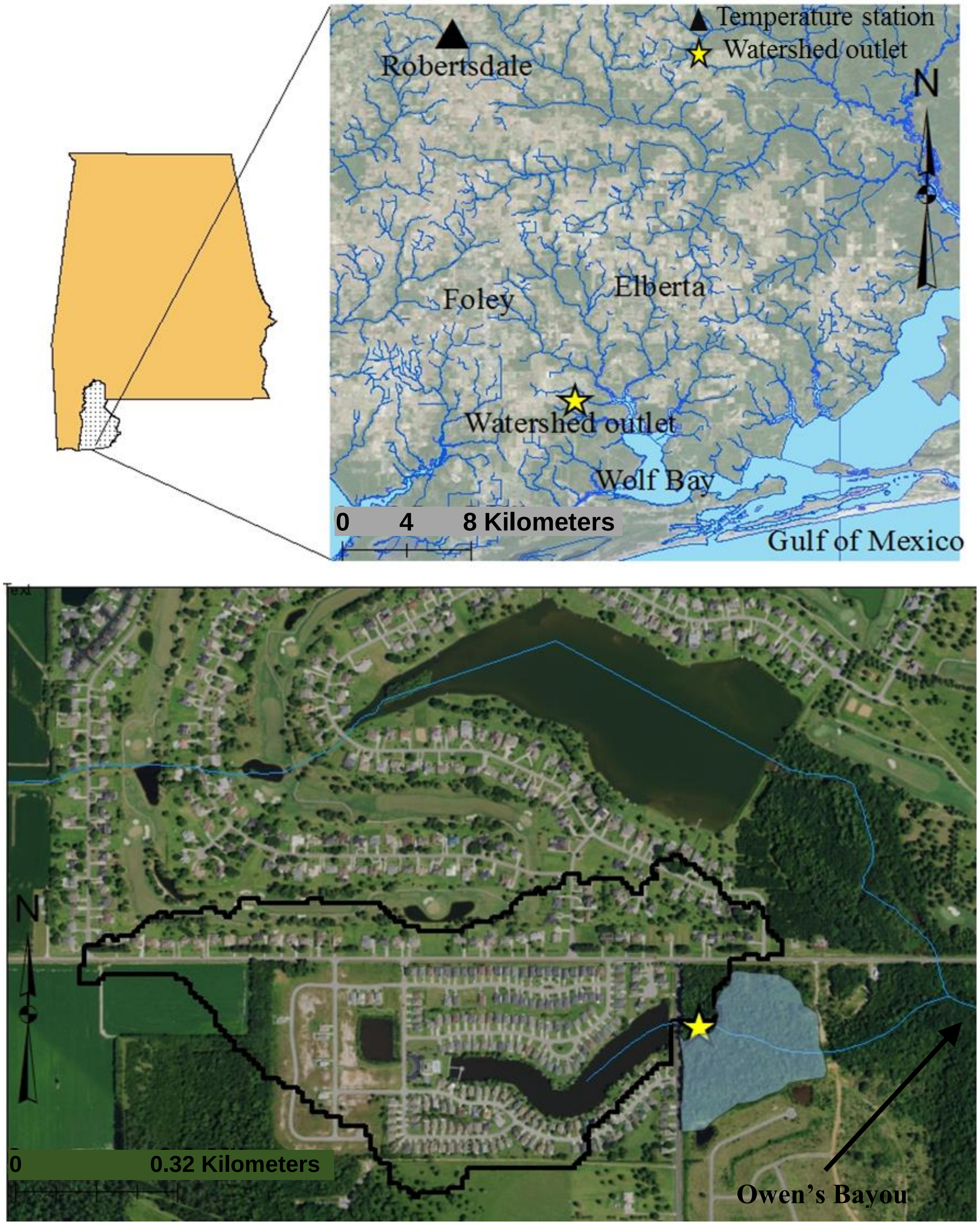


Figure 1. The head watershed used for this study drains into a headwater slope wetland that feeds a tributary to Owens's bayou. The watershed area is 0.49 km^2 with ~46% classified as urban

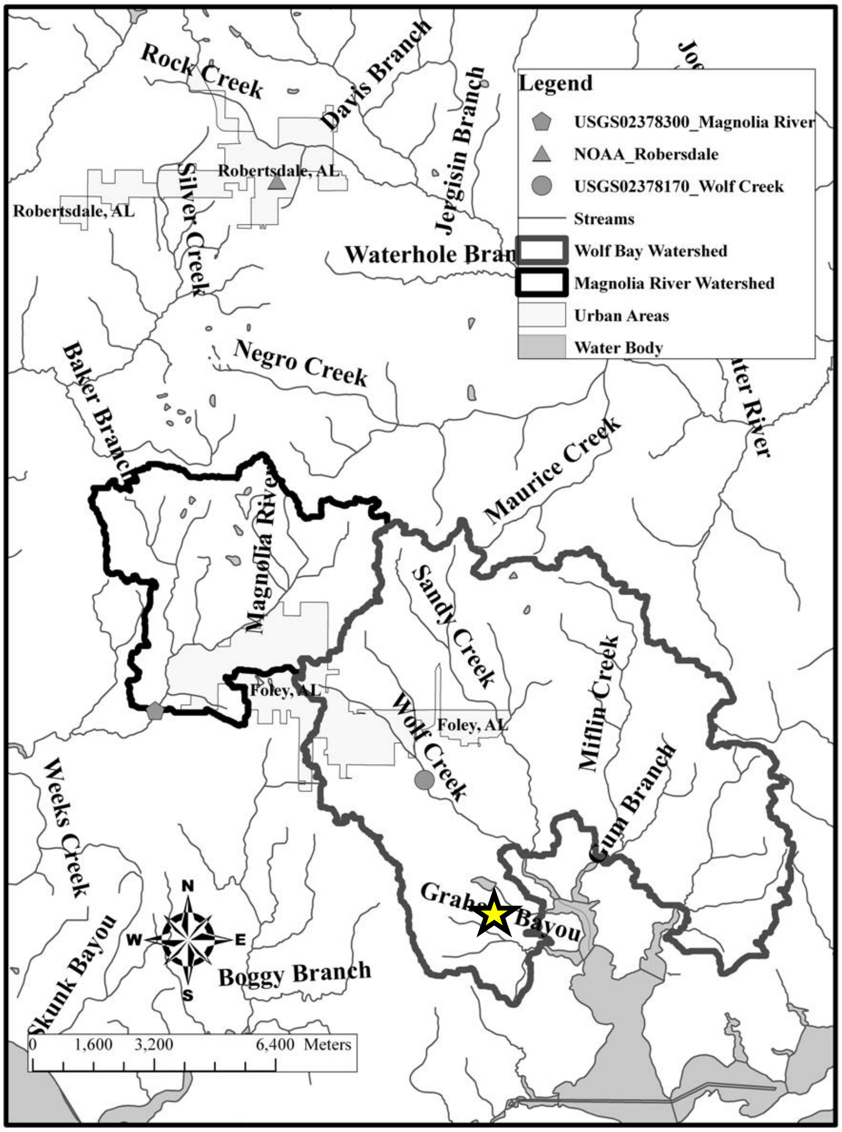


Figure 2. This image, borrowed from Wang and Kalin (2011), shows the spatial proximity of the Magnolia River watershed to the study watershed (represented by the yellow star). The study watershed is part of the Wolf Bay watershed which is situated adjacent to the Magnolia River watershed.

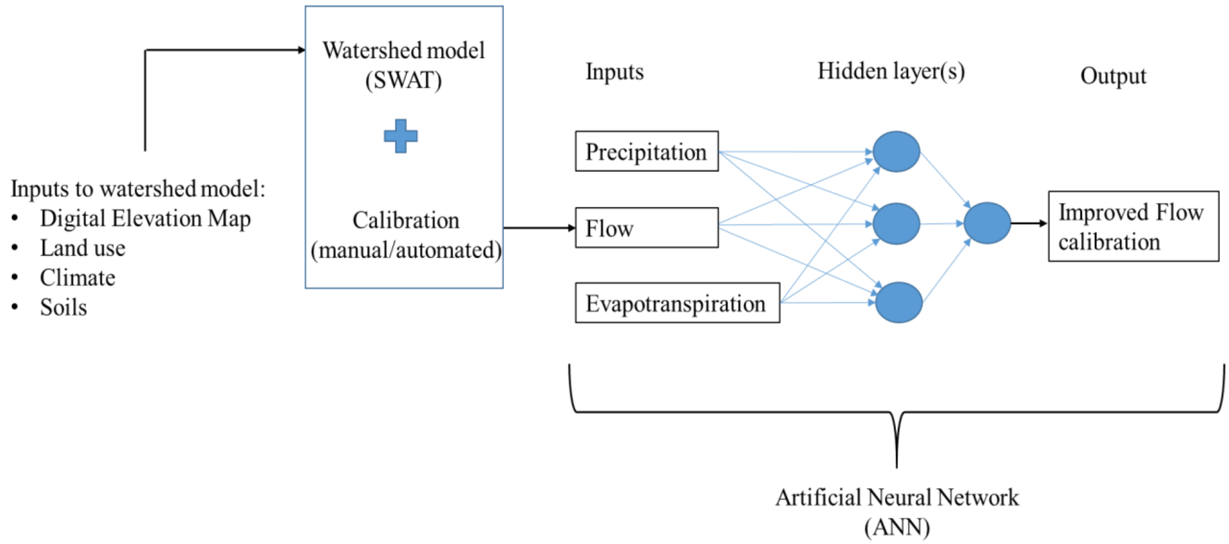


Figure 3. Conceptual framework of the coupled SWAT-ANN model.

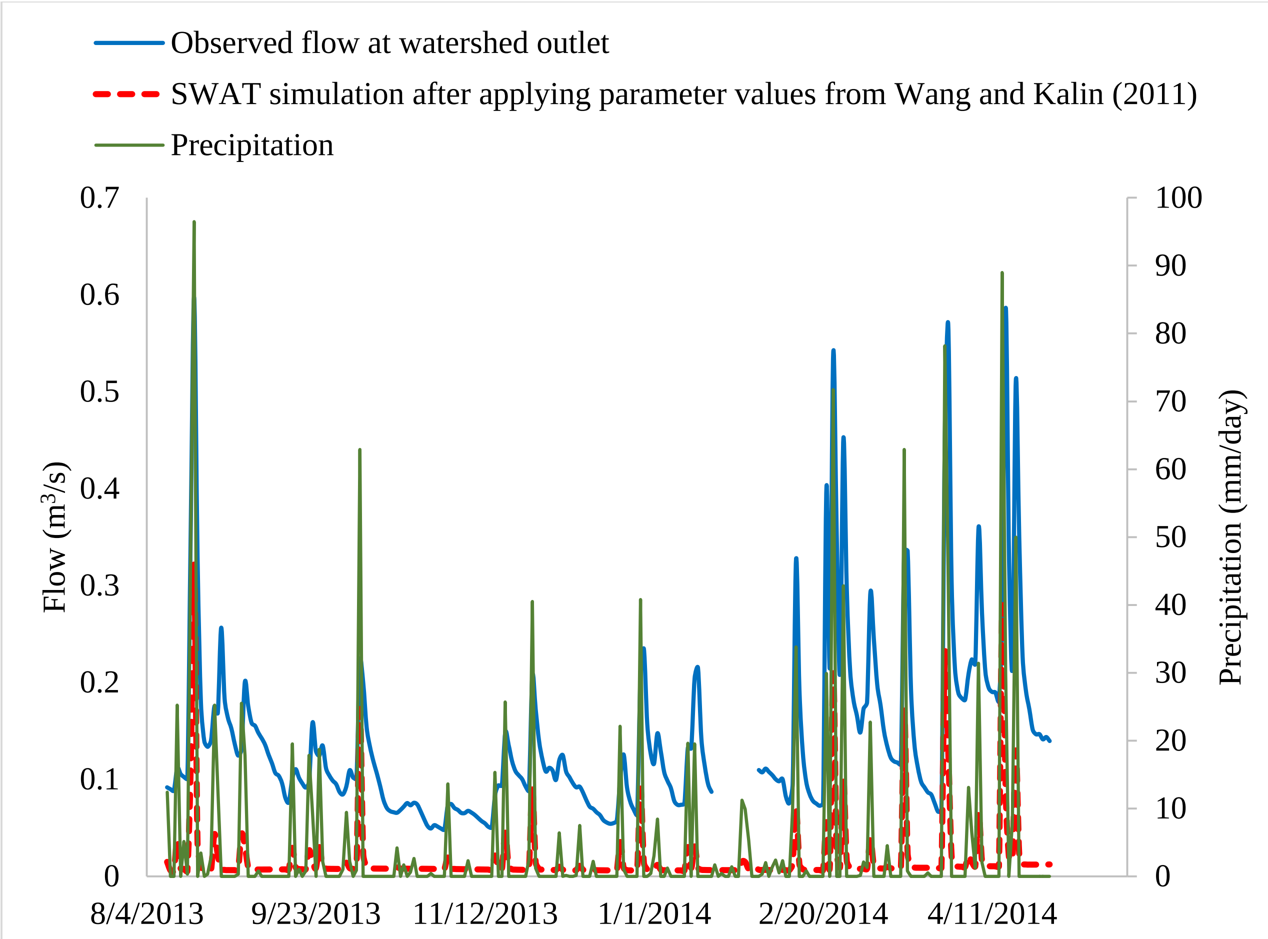


Figure 4. Comparisons between observed flow from the study watershed and SWAT simulated flow after applying parameters from Wang and Kalin (2011) for the same. From the figure, the magnitude of observed flow is many times larger than the SWAT simulation.

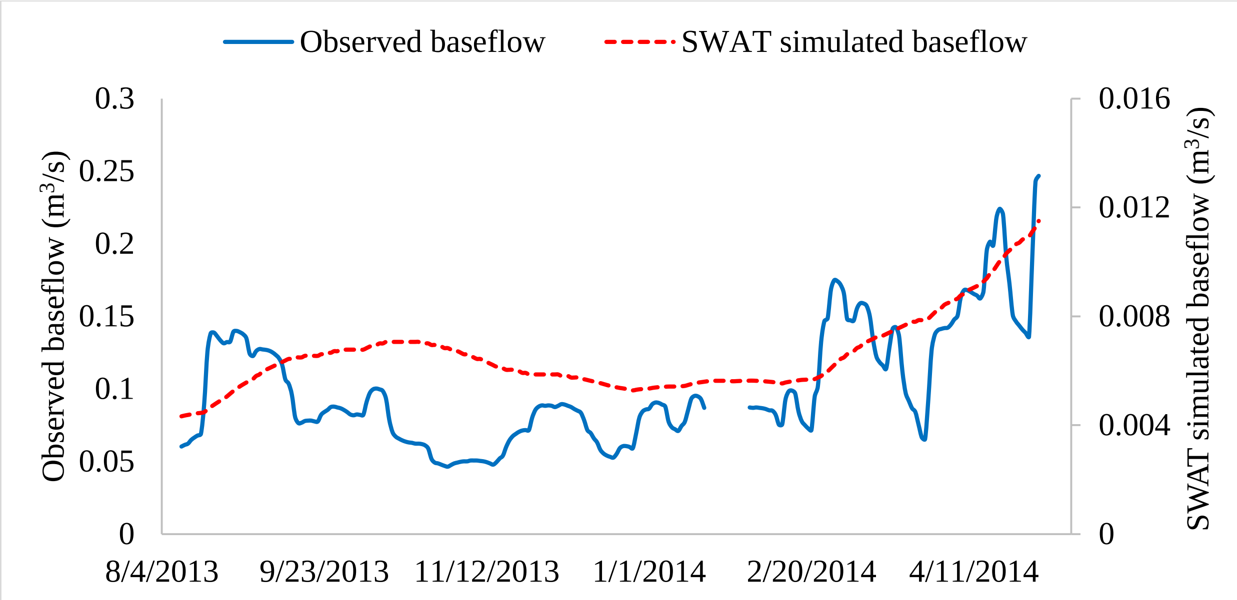


Figure 5. Comparisons between observed baseflow and SWAT simulated baseflow after applying parameters from Wang and Kalin (2011). From the figure, the magnitude of observed baseflow is many times larger than the SWAT simulation, and the trend is different as well (E_{NASH} = -5.6)

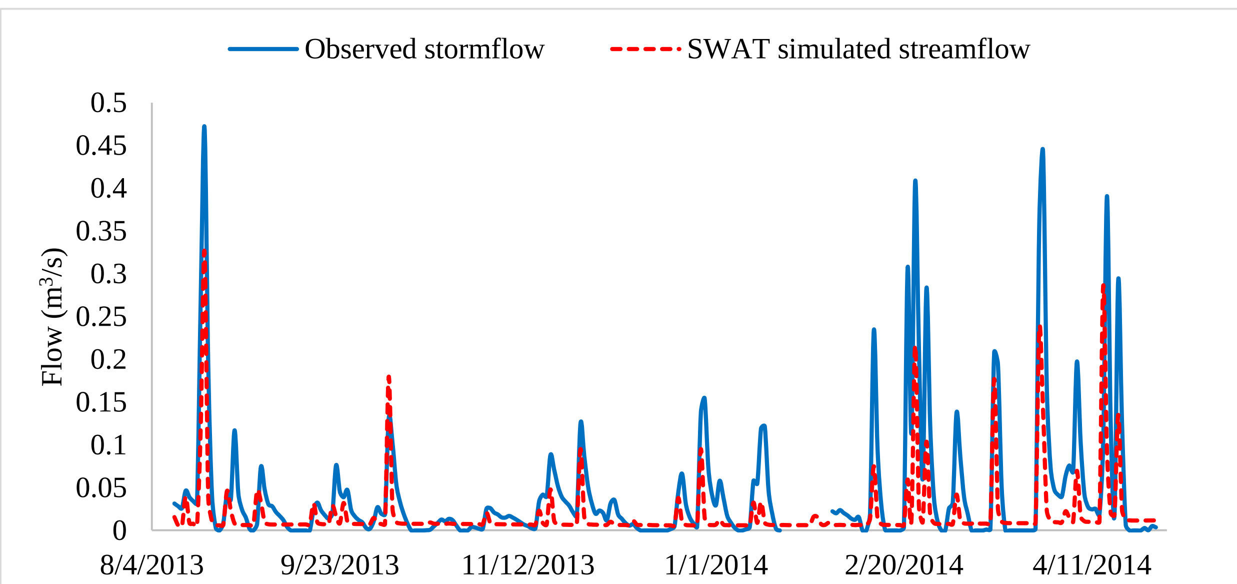


Figure 6. Comparisons between observed stormflow and SWAT simulated streamflow after applying parameters from Wang and Kalin (2011) for the same. From the figure, there is some parity between the magnitude of observed stormflow and SWAT simulated streamflow (E_{NASH} = 0.44)

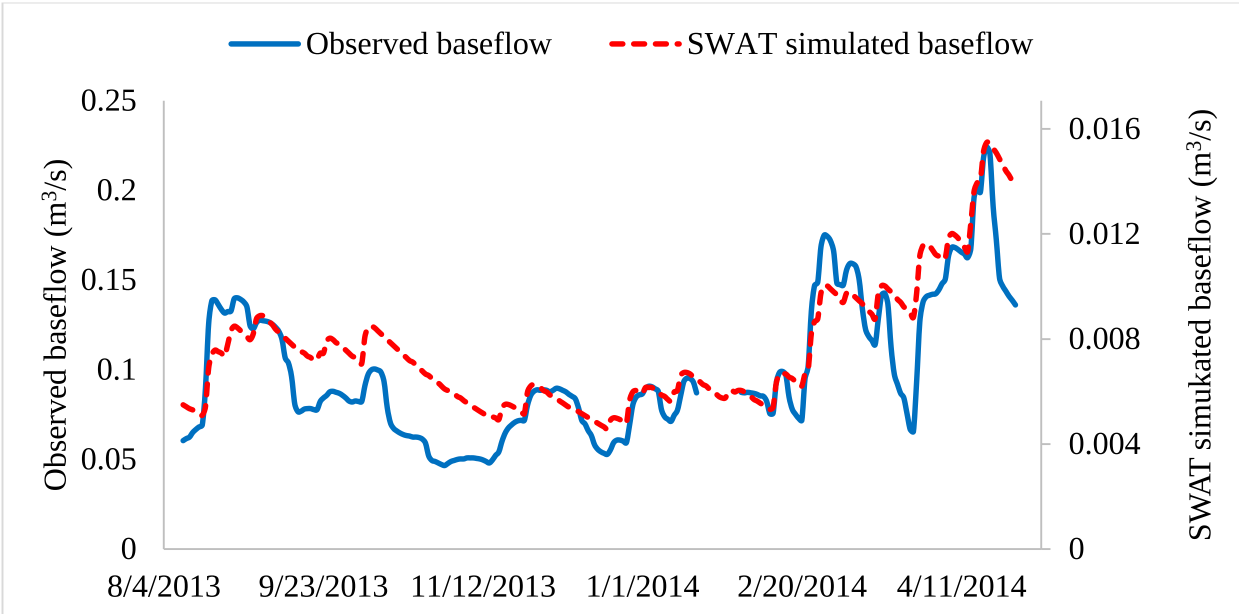
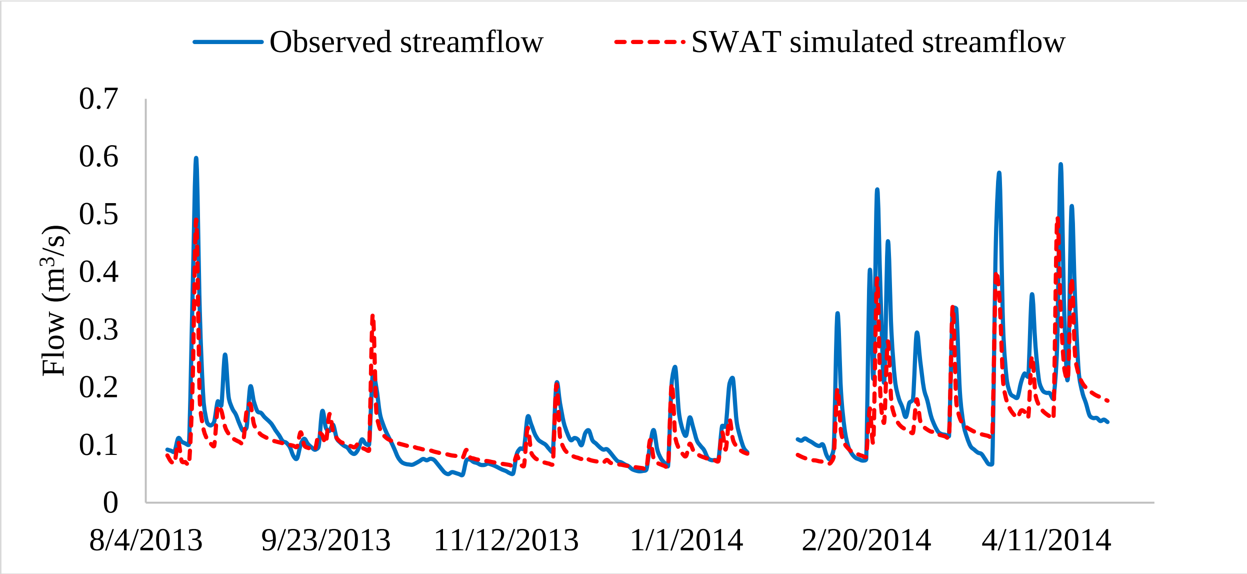


Figure 7. Comparisons between observed baseflow and SWAT simulated baseflow after manually calibrating the trend. Here SWAT baseflow trend was adjusted to match observed baseflow. On average, observed baseflow is about 13 times simulated baseflow. Hence, simulated baseflow was manually magnified by multiplied by 13 to match observed baseflow. This calibration procedure is described in Approach 1



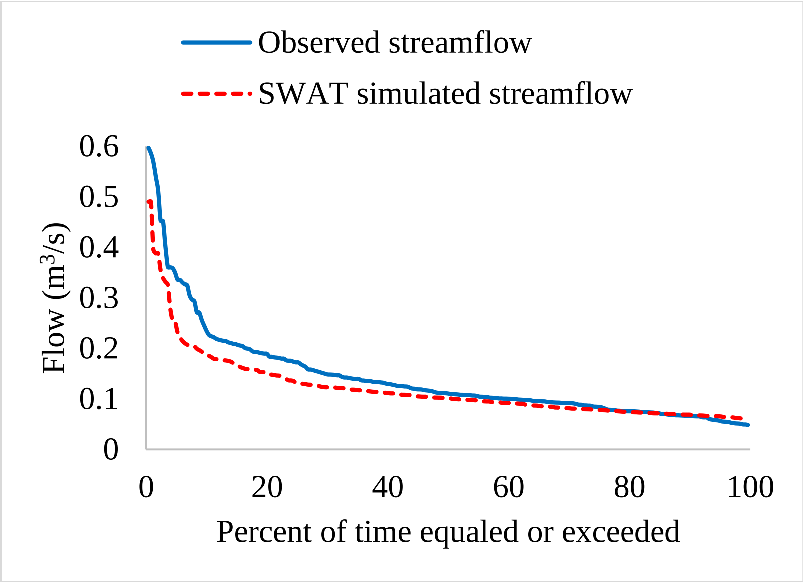
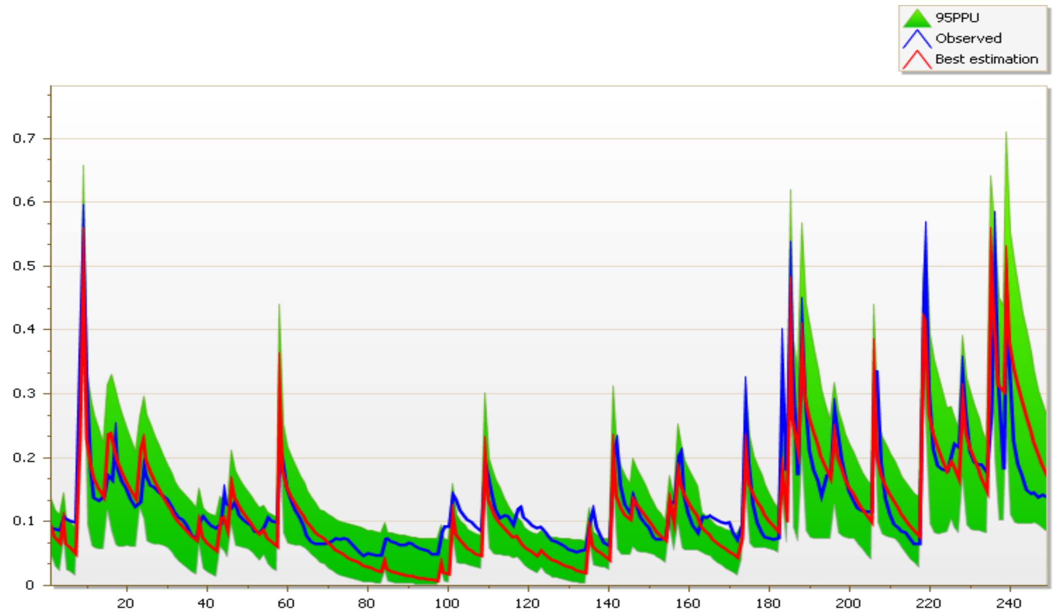


Figure 8 (top). This plot compares observed streamflow and SWAT calibrated streamflow from calibration Approach 1. Here SWAT flow was calibrated in two parts – (1) the trend of simulated baseflow was first matched to observed baseflow, following which a multiplier was applied to match the magnitudes, and (2) SWAT streamflow was calibrated to observed stormflow – and then (1) and (2) were summed. From the figure, the magnitude of observed flow has “very good” match with the SWAT simulation (E_{NASH} = 0.67)
Figure 8 (bottom). This plot compares the exceedance curves for observed and simulated flows



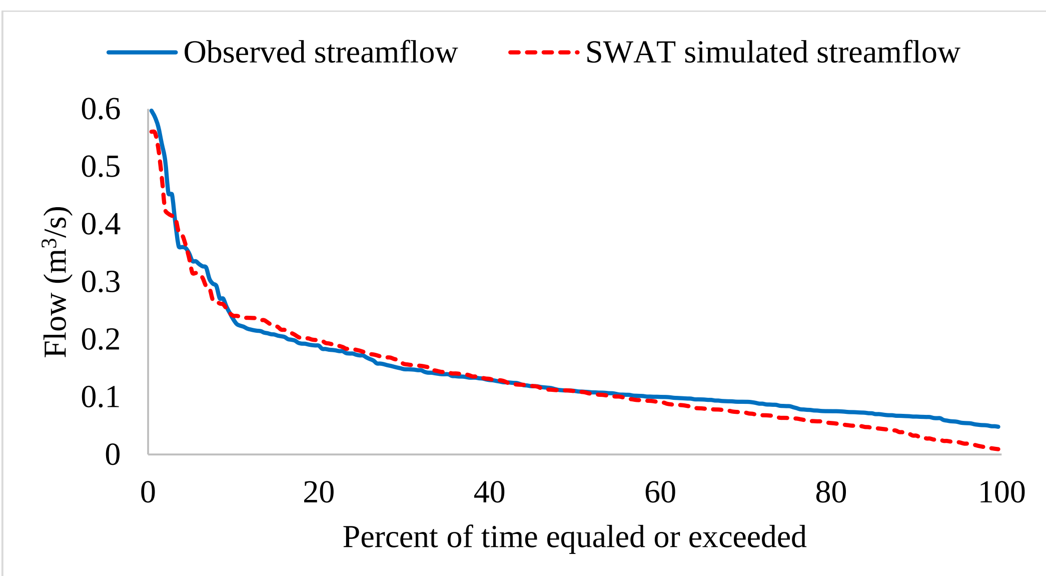
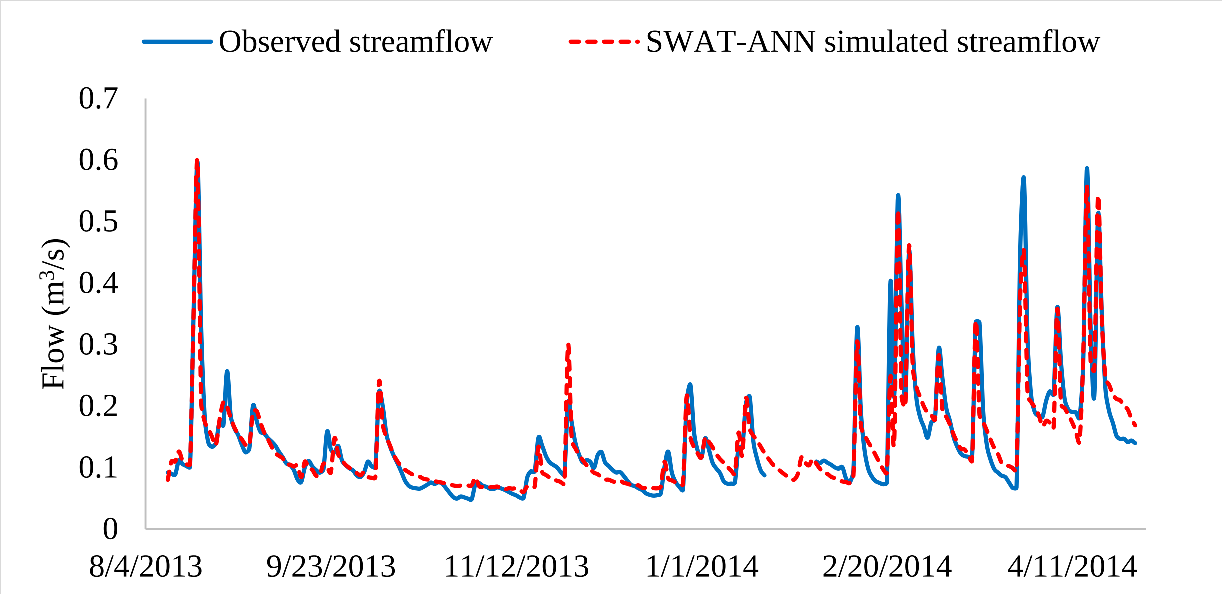


Figure 9 (top). The top figure includes SWAT-CUP results for calibrating flow using the approach that assigns a negative value for RCHRGE_DP parameter. Performance, in this case, was "very good" with $E_{NASH} = 0.75$. This is described in calibration Approach 2.
Figure 9 (bottom). This figure represents the comparison of flow exceedance curves for the "best simulation" from SWAT-CUP calibration, and observed flow.



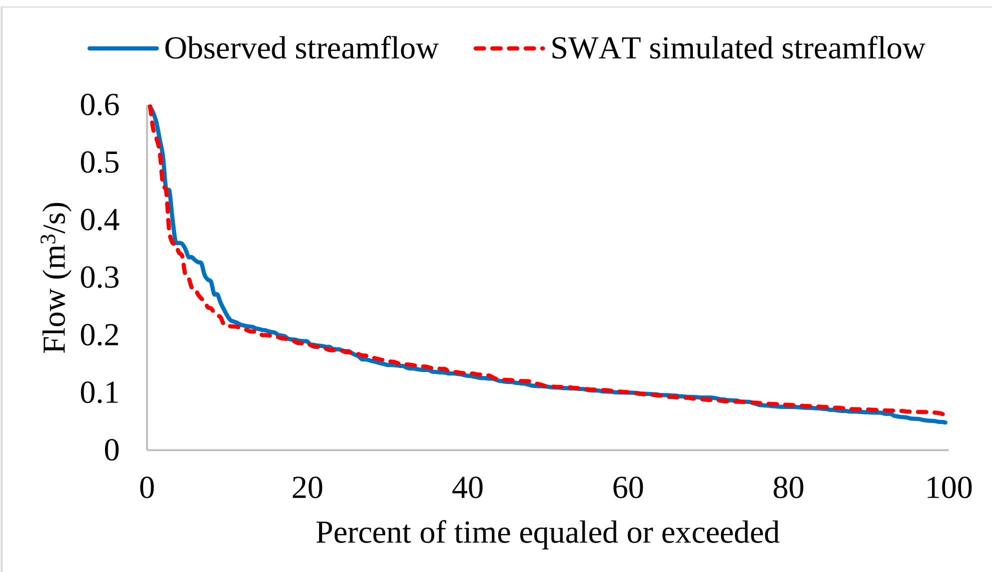


Figure 10 (top). Comparison of ANN simulated streamflow using SWAT calibrated flow, precipitation and PET as inputs, with observed inflow. The combination of SWAT-ANN yielded superior performance compared to using just SWAT with E_{NASH} = 0.88. This is described in calibration Approach 3.

Figure 10 (bottom). Exceedance curves for observed and SWAT-ANN predicted streamflow E_{NASH} = 0.88)

Tables

Table 1. Calibrated parameters for Magnolia River watershed, Baldwin County, AL from Wang and Kalin (2011)

Parameters	Default	Wang and Kalin 2010 Magnolia River watershed
CN2	Varies	+3*
ESCO	0.95	1
GW_DELAY	31	-
GWQMN	0	-
GWREVAP	0.02	-
SURLAG	4	1
SOL_AWC	Varies	-0.01*
REVAPMN	10	500
ALPHA_BF	0.048	0.015
CH_N2	0.014	0.114

* +/- sign indicates that parameter values are increased/decreased by adding/subtracting the given amount

Table 2. Parameters chosen from manual calibration and literature for inclusion in SWAT-CUP

Parameter	Parameter description	Location
CN2	Initital SCS runoff curve number for moisture condition II	.mgt
ALPHA_BF	Baseflow alpha factor (1/days)	.gw
GW_DELAY	Groundwater delay time (days)	.gw
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H_2O)	.gw
GW_REVAP	Groundwater revap coefficient which controls rate of water movement from shallow aquifer to the root zone	.gw
ESCO	Soil evaporation compensation factor	.hru
CH_N(2)	Manning's "n" value for the main channel	.rte
CH_K(2)	Effective hydraulic conductivity in main channel alluvium (mm/hr)	.rte
ALPHA_BNK	Baseflow alpha factor for bank storage (days)	.rte
SOL_AWC()	Available water capacity of the soil layer (mm H_2O)/mm soil)	.sol
SOL_K()	Saturated hydraulic conductivity (mm/hr)	.sol
SOL_BD()	Moist bulk density (Mg/m^3 or g/cm^3)	.sol
RCHRG_DP	Deep aquifer percolation fraction	.gw

Table 3. Final parameter ranges and the fitted values for the best simulation resulting from SWAT-CUP autocalibration with observed stormflow

Parameter_Name	Fitted_Value	Min_value	Max_value
1: r__CN2.mgt	0.015	-0.015	0.121
2: v__ALPHA_BF.gw	0.690	0.418	0.812
3: v__GW_DELAY.gw	0.362	0.001	2.527
4: v__GWQMN.gw	21.741	5.071	24.614
5: v__GW_REVAP.gw	0.199	0.134	0.200
6: v__ESCO.hru	0.842	0.796	0.887
7: v__CH_N2.rte	0.224	0.191	0.352
8: v__CH_K2.rte	32.122	0.010	43.114
9: v__ALPHA_BNK.rte	0.884	0.549	0.986
10: r__SOL_AWC(..).sol	-0.151	-0.240	0.048
11: r__SOL_K(..).sol	0.014	-0.116	0.370
12: r__SOL_BD(..).sol	-0.809	-0.855	-0.173
13: v__RCHRG_DP.gw	0.006	0.001	0.284

v__ means the existing parameter value is to be replaced by a given value
a__ means a given value is added to the existing parameter value
r__ means an existing parameter value is multiplied by (1+ a given value)

Table 4. Final parameter ranges and the fitted values for the best simulation resulting from SWAT-CUP autocalibration with observed flow, and assigning negative values for RCHRGE_DP

Parameter_Name	Fitted_Value	Min_value	Max_value
1: r__CN2.mgt	0.285	0.126	0.421
2: v__ALPHA_BF.gw	0.082	0.001	0.173
3: v__GW_DELAY.gw	0.563	0.001	3.104
4: v__GWQMN.gw	41.312	25.939	43.589
5: v__GW_REVAP.gw	0.094	0.026	0.101
6: v__ESCO.hru	0.952	0.916	0.985
7: v__CH_N2.rte	0.144	0.125	0.254
8: v__CH_K2.rte	131.781	85.332	142.185
9: v__ALPHA_BNK.rte	0.386	0.232	0.740
10: r__SOL_AWC(..).sol	-0.435	-0.441	-0.068
11: r__SOL_K(..).sol	0.241	-0.098	0.442
12: r__SOL_BD(..).sol	0.029	-0.217	0.134
13: v__RCHRG_DP.gw	-15.293	-19.559	-13.066

v__ means the existing parameter value is to be replaced by a given value
a__ means a given value is added to the existing parameter value
r__ means an existing parameter value is multiplied by (1+ a given value)

Chapter 4

Evaluating sensitivity of Nitrate-N export to Organic-N and Ammonia-N inputs in headwater slope wetlands

Abstract

Rapid coastal development has led to loss/alteration of wetlands, streams, and headwater areas that buffer coastal waterways from pollution. Small wetlands are more vulnerable to urban expansion because they can easily be altered by draining, ditching or paving over. From a water quality perspective, preserving and restoring multiple small wetlands on the landscape are critical since they have higher capacity for nonpoint source amelioration. Management efforts require good understanding of wetland function and often use models to predict impacts of land use on wetland function. However, models usually require multiple inputs at high resolution which agencies, who are typically strapped for funding and manpower resources, are unable to gather. Data for smaller wetlands are especially scarce. Hence there is a need to strategize data collection efforts by identifying data that would add most value to model predictions instead. Here, we consider the example of Nitrate-N export from small wetlands in coastal watersheds. From a process perspective, Nitrate-N fluxes are linked to cycles of Organic-N and Ammonia-N, hence the latter must be important to collect when trying to predict Nitrate-N export. But with limited resources to spare, does detailing Organic-N and Ammonia-N inputs add to Nitrate-N export prediction from small wetlands? We examined this question in three headwater slope wetlands in Baldwin County, AL using process-based wetland model, WetQual, to assess the sensitivity of Nitrate-N export to Organic-N and Ammonia-N inputs to these wetlands. Modeled Nitrate-N export showed negligible sensitivity to inputs in the headwater slope wetlands. We concluded that since headwater slope wetlands are groundwater fed gaining wetlands with no

depressional storage, they have low residence times and consequently less time for N transformations to effect Nitrate-N export. This study is significant because it tells us that collecting Organic-N and Ammonia-N input data at high resolutions is not as important as detailing Nitrate-N inputs in low residence time, groundwater interacting wetlands such as headwater slope wetlands.

Keywords: *small wetland, sensitivity, Nitrogen, Nitrate, headwater slope wetland, coastal plain Alabama*

1. Introduction

Wetlands and riparian areas perform many important functions such as flood attenuation, improving water quality and improving biodiversity beside a host of other ecosystem services and functions. However, wetlands have long borne the brunt of agriculture, urban development and population expansion; draining and destroying wetlands in the country (United States) were historically encouraged through political, financial and institutional incentives in the 1960s which resulted in widespread wetland loss to the order of 550,000 acres/year from the mid-1950s to the mid-1970s (Dahl and Allord 1996). However, rising awareness of wetlands as valuable areas that have an important role in regulating and enhancing environmental quality has allowed for the enactment of numerous programs for their restoration and maintenance (Dahl and Allord 1996). Even so, this protection oftentimes does not extend to/not enforced for the protection of small wetlands which are highly vulnerable to loss and modification by virtue of their size. From a water quality mitigation perspective, having multiple small wetlands on the landscape is more effective than a single large wetland since smaller wetlands have greater pollutant removal per unit area of wetland (NRC 2001). Moreover, wetlands along lower order streams have a higher potential for mitigating nonpoint source pollution than wetlands along higher order streams (floodplains) (Brinson 1999; Rheinhardt et al. 1998). Smaller wetlands thus deserve a lot of scrutiny to aid in their restoration as well as to better manage them at regional and local scales.

Models are used extensively to evaluate wetland function and to predict potential changes from proposed land use or climate alterations. But modeling wetlands involves several constraints from the large number of sites, the diversity of wetland types, to their highly dynamic ecological and hydrological responses and functions (Lee et al. 2015). Hence, most wetland models are site-specific and require a detailed understanding of site hydrology, and fine-scale surface and subsurface processes. Yet, data are almost always lacking for wetlands, specifically small wetlands which are largely defined by microtopography of their surroundings and their connection to groundwater and small streams (Lee et al. 2015). Usually, available data may describe morphometry and watershed characteristics, and sometimes even hydrologic data and water quality from limited monitoring (Walker 1982). Even then, coinciding flow and water quality measurements to quantify direct loading is hard to come by. When data is available, their accuracy is a major concern. This can pose significant challenges to agencies and those entrusted in maintaining regional and local water quality since the reliability of model outputs depends largely on the value of its parameters and the precision of its inputs.

Uncertainties in methodology and data are inherent to every model, and efforts are continuously underway to quantify them since they directly influence budgets and decision making (Glas et al. 2016; Loucks and van Beek 2017). Uncertainties in inputs can be reduced by collecting higher quality data more frequently. Since this poses a challenge for small wetlands, it would be useful to ask if measuring multiple inputs adds more value to model predictions over measuring just a few. The answer to this question could greatly help optimize resources and mitigate expenditures by monitoring a few key variables than wasting resources over measuring many variables that don't add any value in predicting model outputs. Identification of key variables can be accomplished by conducting a sensitivity analysis of model inputs where we explore and quantify the impacts of changes in model inputs on predicted model outputs (Loucks and van Beek 2017).

A sensitivity analysis describes the extent of change in models outputs in response to perturbation of model inputs, such as input data observations or model parameters. While uncertainty analyses and identification of important model parameters that influence model outputs through sensitivity analyses are frequently conducted, assessing sensitivity of input data is less prevalent in literature. Some examples of evaluating input data sensitivity include Oudin et al. (2005) who described the effects of different types of potential evapotranspiration inputs on rainfall-runoff model predictions, Cotter et al. (2003) who described the influence of resolution of elevation maps, land use and soils data on watershed model predictions, Howden et al. (2011) who evaluated how uncertainty in loads of fertilizer, animal, ploughing and crop uptake loads influence total catchment-N loads, Singh et al. (2011) who evaluated the effects of soil data resolution on identification of critical source areas of sediment within the watershed, Kalin and Hantush (2006) who explored the use of Next Generation Weather Radar (NEXRAD) data as an alternative to rain guage data in an eastern Pennysylvania watershed, and Cerco (1995) who evaluated the response of Chesapeake Bay to reductions in P and N loads. By assessing sensitivity of the model to its inputs, the minimum data requirements for improved model outputs can be gleaned (Glas et al. 2016). While valuable, this application of sensitivity analysis is not common in literature.

Coastal wetlands intercept runoff from upland terrestrial areas and represent very important ecosystems for the unique ecosystem services they provide such as nutrient and sediment retention leading to improved downstream (and coastal) water quality and flood attenuation. However, rapidly increasing population pressure in these coastal regions has been an important stressor on coastal wetlands, and this can have consequences for nonpoint source pollution amelioration. Approximately 50% of the world's human population lives within 100 km of the coastline (NRC 2000); population of coastal counties along the Gulf of Mexico increased by 150% from 1960 – 2008 (Wilson and Fischetti 2010), and by 60% in the Chesapeake Bay watershed between 1990 and 2000 (Kaushal et al. 2008; Jantz et al. 2005). As urban development continues to rise in these watersheds, associated hydrologic alterations (e.g., burial of headwaters by channeling, ditching or paving over, and loss of hydrologic connectivity between streams, wetlands and riparian areas due to increased impervious surfaces) may amplify export of Nitrate-N from small watersheds (Kaushal et al. 2008). Since concentrations of available N limit primary production in coastal waters, factors that increase N loading can have important impacts on coastal ecosystems (Caraco and Cole 1999).

Here we have as case studies, three headwater slope wetlands located at the headwaters of creeks in Alabama's coastal plain region (in Baldwin County, AL), for which we have hydrology (<1.5 years) and sporadic water quality measurements (Dissolved Inorganic Nitrogen, or DIN). Headwater slope wetlands are a common wetland type occurring at the headwater reaches of first order streams in Mississippi-Alabama coastal plain area (Noble et al. 2007). They are primarily groundwater-fed and remain saturated for most of the year. The headwater slope wetlands used in the study are located along a gradient of watershed urbanization and at varying proximities to the coast. These slope wetlands feed coastal creeks that discharge into systems that drain into the Gulf of Mexico. The Gulf of Mexico has long had issues with excessive Nitrate-N loading causing significant deterioration of coastal water quality, a problem that can be attributed to loss of wetlands and deteriorating hydrologic connectivity in watersheds draining to the coast (HTF 2015; Day Jr. 2003; Boesch et al. 2001), among others. While there is significant scientific consensus regarding the crucial role that small wetlands play in maintaining water quality and quantity and other ecological functions on the landscape (Freeman 2007; Meyer et al. 2003; Noble et al. 2007; Roy et al. 2009; Peterson et al. 2001), flow and water quality data for these systems are sparse. Yet, in order to address questions of wetland function, having data is crucial. Hence, in this study we aim to evaluate inputs that are sensitive to the prediction of Nitrate-N export in these systems.

From a process-based perspective, Nitrate-N transformation and export is tied to process cycles of Organic-N and Ammonia-N; Organic-N is converted to Ammonia-N through the process of ammonification or mineralization, which is then converted to Nitrate-N through nitrification. It makes sense, then, to perceive collection of Organic-N and Ammonia-N data as highly important to the prediction of Nitrate-N export. However, from a modeling perspective, is the prediction of Nitrate-N sensitive to Organic-N and Ammonia-N inputs? Or does this sensitivity vary between different kinds of wetlands? We used WetQual, a process-based wetland model (Hantush et al. 2012; Kalin et al. 2012) as a tool to evaluate the sensitivity of Organic-N and Ammonia-N in predicting Nitrate-N export from the Alabama headwater slope. The results from this study will be useful in optimizing data collection for model runs predicting Nitrate-N export from small wetlands.

2. WetQual model

WetQual presents a detailed process-based model for nutrient (nitrogen, phosphorous and carbon) retention, cycling and removal in flooded wetlands (See Hantush et al. 2012; Kalin et al. 2012; Sharifi et al. 2013). The model takes into account oxygen dynamics and its impacts on nitrogen cycling and release. A simple productivity model relates daily growth rate to daily solar radiation and annual plant growth; here free floating plant biomass such as phytoplankton are separated from rooted aquatic plants. The wetland is partitioned into two compartments; a free-water layer and a soil layer. The soil layer is divided into aerobic and anaerobic zones whose boundaries are variable in response to oxygen dynamics. The model accounts for ammonia volatilization losses in addition to transport, retention, uptake, nitrification, mineralization, denitrification and burial processes. Nitrification occurs in the aerobic layer of the soil while denitrification in the anaerobic layer beneath. N cycling in WetQual has been presented in Figure 1. The model uses forward difference approximation of time-derivatives for numerical integration. The following section is presented from Hantush et al. (2012).

In Wetqual, N dynamics in the water column is modelled as:

$$\phi_w \frac{d(V_w N_{ow})}{dt} = Q_i N_{owi} + a_{na} k_{da} a + a_{na} k_{db} f_{bw} b - \phi_w V_w k_{mw} N_{ow} - \nu_s \phi_w A N_{ow}$$

$$+ \nu_r \phi_w A (N_{or} + N_{os}) - Q_o N_{ow} + A f_{sw} S$$

$$\phi_w \frac{d(V_w N_{aw})}{dt} = Q_i N_{awi} + i_p A N_{ap} - \phi_w V_w f_N k_{nw} N_{aw} + \beta_{a1} A (N_{a1} - N_{aw}) + F_{N_a g}^{w}$$

$$- k_v \phi_w A (1 - f_N) N_{aw} + \phi_w V_w k_{mw} N_{ow} - Q_o N_{aw} - f_{aw} a_{na} k_{ga} a + A q_a$$

$$\phi_w \frac{d(V_w N_{nw})}{dt} = Q_i N_{nwi} + i_p A N_{np} + \phi_w V_w f_N k_{nw} N_{aw} + \beta_{n1} A (N_{n1} - N_{nw}) + F_{N_n g}^{w}$$

$$- f_{nw} a_{na} k_{ga} a - Q_o N_{nw} + A q_n$$

where N_{ow} is particulate organic nitrogen concentration in free water [ML^{-3}]; N_{aw} = [NH_4^+]+[NH_3] is total ammonia-nitrogen concentration in free water [ML^{-3}]; N_{nw} is nitrate-nitrogen concentration in free water [ML^{-3}]; O_w is oxygen concentration in free water [ML^{-3}]; *a* is mass of free floating plant [M *Chl a*]; *b* is mass of rooted plants [M *Chl a*]; N_{owi}, N_{awi}, and N_{nwi}, respectively, are concentrations of organic nitrogen, total ammonia nitrogen, and nitrate nitrogen in incoming inflow [ML^{-3}]; N_{a1} and N_{n1}, respectively, are pore-water concentrations of total ammonia nitrogen and nitrate nitrogen in oxygenated top soil layer (aerobic layer in Fig. 1) [ML^{-3}]; N_{or} is concentration of rapidly mineralizing organic nitrogen in wetland soil [ML^{-3}]; N_{os} is concentration of slowly mineralizing organic nitrogen in wetland soil [ML^{-3}]; N_{ap} and N_{np}, respectively, are concentrations of total ammonia nitrogen and nitrate nitrogen in precipitation [ML^{-3}]; q_a and q_n, respectively, are dry depositional rates of total ammonia nitrogen and nitrate [$ML^{-2}T^{-1}$]; v_s is effective settling velocity [LT^{-1}]; v_r is resuspension rate [LT-1]; *S* is rate of nitrogen fixation by microorganisms [$ML^{-2}T^{-1}$]; $F^w_{N_ag}$ and $F^w_{N_ng}$ are groundwater source/loss for total ammonia nitrogen and nitrate nitrogen respectively [MT^{-1}]; and f_N is the fraction of total ammonia in ionized form.

Soil organic nitrogen is modelled as

$$V_s\frac{dN_{or}}{dt} = f_r a_{na} k_{db} f_{bs} b + f_r v_s \phi_w A N_{ow} - v_r \phi_w A N_{or} - V_s k_{mr} N_{or} - v_b A N_{or} + f_r(1 - f_{sw})AS$$

$$V_s\frac{dN_{os}}{dt} = f_s a_{na} k_{db} f_{bs} b + f_s v_s \phi_w A N_{ow} - v_r \phi_w A N_{os} - V_s k_{ms} N_{os} - v_b A N_{os} + f_s(1 - f_{sw})AS$$

where N_{or} and N_{os} are defined above; v_b is burial velocity [LT^{-1}]; V_s = *HA* is volume of active sediment layer [L^3]; and *H* is thickness of active soil layer [L].

N dynamics in the aerobic soil layer is modelled as:

$$\phi V_1 R_s \frac{dN_{a1}}{dt} = -A\beta_{a1}(N_{a1} - N_{aw}) + F_{N_ag}^1 - f_{a1}a_{na}k_{gb}f_1 b - \phi A v_b N_{a1} - \phi V_1 f_N k_{ns} N_{a1} + A\beta_{a2}(N_{a2} - N_{a1}) + V_1 k_{mr} N_{or} + V_1 k_{ms} N_{os}$$

$$\phi V_1 \frac{dN_{n1}}{dt} = -A\beta_{n1}(N_{n1} - N_{nw}) + F_{N_ng}^1 + \phi V_1 f_N k_{ns} N_{a1} - A\beta_{n2}(N_{n1} - N_{n2}) - f_{n1}a_{na}k_{gb}f_1 b - v_b \phi A N_{n1}$$

where V_1 is volume of aerobic soil [L^3]; R_s is total ammonia retardation factor in wetland soil; ϕ is wetland soil porosity; N_{a2} is total ammonia-nitrogen pore-water concentration in lower anaerobic layer [ML^{-3}]; N_{n2} is nitrate-nitrogen pore-water concentration in lower anaerobic layer [ML^{-3}]; $f_1 = {l_1}/{(l_1 + l_2)}$ is volumetric fraction of aerobic soil layer; l_1 is thickness of aerobic soil layer [L]; l_2 is thickness of anaerobic soil layer [L]; $F_{N_ag}^1$ and $F_{N_ng}^1$ are, respectively, groundwater source/loss of total ammonia nitrogen and nitrate in the aerobic layer [MT^{-1}]; and m_s is soil bulk density [ML^{-3}].

N dynamics in the anaerobic soil layer is modelled as:

$$\phi V_2 R_s \frac{dN_{a2}}{dt} = -A\beta_{a2}(N_{a2} - N_{a1}) - \phi A v_b (N_{a2} - N_{a1}) + F_{N_ag}^2 + V_2 k_{mr} N_{or} + V_2 k_{ms} N_{os} - f_{a2}a_{na}k_{gb}f_2 b$$

$$\phi V_2 R_s \frac{dN_{n2}}{dt} = -A\beta_{n2}(N_{n1} - N_{n2}) - \phi V_2 k_{dn} N_{n2} - \phi A v_b (N_{n2} - N_{n1}) + F_{N_ng}^2 - f_{n2}a_{na}k_{gb}f_2 b$$

where N_{ag} is total ammonia-nitrogen concentration in ground water [ML^{-3}]; N_{ng} is nitrate-nitrogen concentration in ground water [ML^{-3}]; $f_2 = {l_2}/{(l_1 + l_2)}$ is volumetric fraction of reduced soil layer; V_2 is volume of anaerobic soil [L^3]; $F_{N_ag}^2$ and $F_{N_ng}^2$ are groundwater source/loss of total ammonia nitrogen and nitrate in the anaerobic layer [MT^{-1}]. For more information about parameters, their distributions and other information refer Hantush et al. (2012) and Kalin et al. (2012).

3. Study sites - Headwater slope wetlands in coastal Alabama:

Data was collected from three headwater slope wetlands located in Baldwin County, AL: NF (30.354235°, -87.631394°) located at the headwaters of a smaller tributary to Owen's Bayou, OF (30.342071°, -87.638012°) located at the headwaters of Graham Creek, and BM (30.855272°, -87.779157°) located at the headwaters of a tributary to Bay Minette Creek (Figure 2). Wetlands OF and NF are located within the city of Foley, and wetland BM in the city of Bay Minette. OF and NF feed into Graham Creek and Owen's Bayou respectively, which drain into Wolf Bay downstream. In order of proximity to the coast from closest to farthest, the wetlands are ordered from OF, NF and BM being the farthest away. Hydrology at these three wetlands were monitored at discernible surface water inlets and outlets from approximately 8 to 16 months in 2013 and 2014, with sporadic baseflow (14-22 samples) and stormflow DIN concentrations (13-20 samples) (Figure 3). As can be observed from Figure 2, the BM wetland drains a highly urban watershed and has the flashiest hydrology with very little baseflow (Figure 3). The NF wetland hydrology is also somewhat flashy but has a consistently high baseflow. In the most forested watershed, OF wetland has flows that are low and damped with consistent baseflows. DIN concentrations at all sites were quite low and load reductions were observed at all three wetlands (refer Chapter 2). Further details regarding headwater slope wetlands, and data collection can be found in Chapter 2.

Bathymetry data (stage, volume, area) for the wetlands were generated using the Storage Capacity Tool, a tool available through the Spatial Analysis toolbox in ArcMap Vers.10.4. This tool generates a table of water surface elevations and corresponding storage capacities for a given surface raster. A 3m DEM for Baldwin County (raster) and extents of the three wetlands (polygons) were used as inputs to the Storage Capacity Tool to compute wetland area and volume at 0.1m stage increments. Regression relationships between stage, area and volume were used to generate time series of wetland area and volume corresponding to observed stage at each wetland.

4. Sensitivity analysis using WetQual

4.1 Preparing flow data

Hydrographs for all three wetlands are presented in Figure 3. Flow data for the headwater slope wetlands have gaps which need to be filled since WetQual requires continuous time series of flow. For this purpose, flows generated by the Soil and Watershed Assessment Tool (SWAT) (Neitsch et al. 2009) and calibrated with observed data using SWAT Calibration and Uncertainty Program (SWAT-CUP) (Abbaspour et al. 2008) were used to fill in data gaps.

The SWAT model is a widely used watershed scale, process-based hydrologic model that was developed by the United States Department of Agriculture (Arnold et al. 1998) which can operate on daily, monthly or annual scales. Further details regarding SWAT can be referred from Neitsch et al. (2009). We used SWAT version SWAT-2012 through the ArcSWAT interface in ArcGIS 10.0 for all SWAT simulations. All the GIS data required for ArcSWAT setup was downloaded from the USGS's online Seamless Data Warehouse (https://datagateway.nrcs.usda.gov). Watershed boundaries for each of the wetlands were delineated using elevation data obtained from the National Elevation Dataset (NED) DEM developed by USGS, and hydrography data from the National Hydrography Dataset (NHD). While DEMs of 3m resolution (1/9 arc-second) were available only for OF and NF wetlands, DEMs of 10m (1/3 arc-second) resolution were available for all three wetlands. Hence, the 10m DEM was used to delineate the watershed and simulate flow at the BM wetland. Since model outputs did not differ between 10m and 3m DEMs at the NF wetland, results from the former were retained. At the OF wetland, however, model outputs were markedly different for the 3m DEM and these were retained. Hydrography was further modified and digitized to include headwaters with channel extensions to improve more accurate watershed delineation and streamflow routing in SWAT (Amatya and Jha 2011). Land use data was obtained from the 2011 National Land Cover Dataset (NLCD) and manually updated to reflect current land use in the watersheds. Soil parameters were derived from the county level Soil Survey Geographic (SSURGO) dataset. Slopes were divided into 3% classes (0-3%, 3-6%, 6-9%, etc.). Daily weather data was obtained from the National Weather Service's National Climatic Data Center stations closest to the wetlands. Daily maximum and minimum temperature for the study period was available from a station in Robertsdale (station GHCND: USC00016988) in Baldwin County (Figure 2) and daily precipitation for the wetlands was obtained from NEXRAD. HRUs were created using a 0-10 % overlay of landuse, soil and slope, and the Hargreaves method was used for calculation of potential evapotranspiration. Since the duration of observed data was short (≤ 1.5 years), we did not split the data to perform validation – instead all the data was used for calibration, intended to fill gaps in observed flow data.

The SWAT Calibration and Uncertainty Program (SWAT-CUP) was developed specifically to be used with SWAT in order to report uncertainty in the results by propagating parameter uncertainties (Abbaspour et al. 2008). Various SWAT parameters were identified for auto-calibration, through initial manual calibration as well as from literature. Parameter ranges were then propagated by Latin hypercube sampling using the SUFI-2 algorithm in SWAT-CUP (Abbaspour et al. 2008) and the outputs were represented as a 95% prediction uncertainty band (95PPU), bounded by the 2.5% and 97.5% levels of the cumulative distribution of the output variable. Basically, the 95PPU represents an envelope of possible solutions generated by the parameter ranges. Usually <5 iterations each of 300-500 simulations (depending on the time it takes) are conducted in SWAT-CUP, where the user initially starts out with larger parameter ranges which get smaller with each iteration.

SWAT models were set up for each of the study headwater wetlands. Previously calibrated parameter values reported in Wang and Kalin (2011) for Magnolia River watershed were used as starting parameter values in SWAT models for the Foley wetlands; this was done since the Magnolia River watershed is situated adjacent to the Wolf Bay watershed of which the Foley headwater slope wetlands are a part. Some manual calibration was done initially to ensure some parity between simulated and observed flows for all 3 study wetlands. For flashy systems, as observed in the BM wetland, parameters such as SCS curve number (CN2) were adjusted. For baseflow dominated wetlands such as OF and NF, parameters such as groundwater delay (GWDELAY), deep aquifer recharge coefficient (RCHRGE_DP) and baseflow alpha factor (ALPHA_BF) were adjusted, along with SCS curve number (CN2). For the OF and BM wetlands, activating the pond feature (.pnd) to account for wetland area in the SWAT subbasins improved flow prediction. Model parameters were calibrated at daily timescales for flow. For all wetlands, the parameter RCHRGE_DP was extended outside its default minimum of 0 to -50. This was done to allow for deep aquifer discharge into the shallow aquifer and consequently to baseflow (refer Approach 2 in Chapter 3 for more details).

Following manual calibration, around sixteen parameters influencing different aspects of surface and subsurface flows were chosen for auto-calibration from literature. We considered 13 – 18 parameters for automated calibration including ones that govern subsurface water response, surface water response, basin response and wetland response (if required). Depending upon the needs of autocalibration, variables were added or deleted from the initial set to achieve improved performance measures. Performance measures such as the Nash Sutcliffe Coefficient (E_{NASH}) (Nash and Sutcliffe 1970) was used to judge the closeness of SWAT simulations to observed flows. In all cases the "best" simulation for SWAT-CUP with the highest E_{NASH} was used to fill up gaps in flow data. Since flows for BM and OF wetlands (inflow and/outflow) are available from January 2013, missing data was filled to get continuous daily flows from January 1, 2013 until May 1, 2014. Both inflows and outflows for NF wetlands were available only from August 10, 2013; hence daily continuous flow with missing days filled were generated only from August 10, 2013 until May 1, 2014.

4.2 Preparing nutrient data and scenarios

We examined the sensitivity of Organic-N and Ammonia-N inputs on Nitrate-N export from the three wetlands using wetland model, WetQual as a tool. Inputs to WetQual include hydrology (inflow, outflow, groundwater recharge/discharge), bathymetry (stage, area, volume), climate (air temperature, precipitation, ET, wind speed), dissolved oxygen (DO), and nutrients entering the systems through inflows, groundwater and atmospheric deposition. Missing data in inflows and outflows for the headwater slope wetlands were reconstructed using the best simulation from SWAT-CUP results for flow calibration (January 1, 2013 – May 1, 2014 for BM and OF wetlands, and August 10, 2013 – May 1, 2014 for NF wetland). However, among input nutrient data at the headwater slope wetlands, only sporadic DIN concentrations were available to us (Figure 3). We used the LOADEST program (Runkel et al. 2004) to generate the daily DIN loading time series from which we computed daily DIN concentrations. LOADEST generates a regression relationship using user-provided observed water quality and flow measurements (calibration dataset), using which it extrapolates daily loads from user-provided daily discharge.

LOADEST gives the users the option of selecting a regression model for load estimation, or allowing the program to choose the best model from a set of predefined models. We relied on both options for the sites, depending on the E_{NASH} values obtained on comparing load estimates with observed loads on days when both flow and nutrient concentrations were available. Daily DIN concentrations were then calculated from the LOADEST generated DIN load estimates.

From the Alabama Department of Environmental Management (ADEM) water quality reports for stations along Bay Minette Creek and Wolf Creek (another creek in the Wolf Bay watershed close to NF and OF) (ADEM 2004, 2014, 2017a, 2017b), surface water DIN concentrations in the region are mainly dominated by Nitrate-N with very small levels of Ammonia-N; thus we used DIN as a proxy for Nitrate-N in the WetQual model for the headwater slope wetlands. Dissolved oxygen (DO) input was derived from SWAT-CUP outputs associated with flow calibration (which was used to fill up missing flows). Groundwater Nitrate-N concentration was set to a constant value as the average concentration of DIN in baseflow (represented by grab samples at the headwater slope wetlands). Atmospheric deposition data were derived from the National Atmospheric Deposition Program's website (NADP; http://nadp.slh.wisc.edu/data/NTN/). When available, water temperature was derived from the transducer used to measure stage at the wetlands' outflow; else water temperature from SWAT-CUP outputs were used. Time-series of groundwater recharge/discharge was calculated using simple mass balance at daily time-step.

Thirty scenarios of Organic-N and Ammonia-N concentrations were considered for each of the wetlands. Organic-N was varied as 0, 0.5,1, 2, 5 and 10X Nitrate-N concentrations, while Ammonia-N was varied as 0, 0.1, 0.25, 0.5 and 1X Nitrate-N concentrations. Water quality data reports for different watersheds in Alabama show that Ammonia-N concentrations rarely exceed

Nitrate-N in Alabama's Coastal Plain (ADEM 2004, 2014, 2017a, 2017b), while Organic-N can constitute a significant percentage of total nitrogen loads in southeastern rivers close to the coast (Scott et al. 2007); thus Organic-N was varied by a much larger range compared to Ammonia-N. Since DO values estimated by SWAT-CUP simulations were very small (<0.1 mg/L), we also included one scenario varying DO as 100X SWAT-CUP simulated DO, resulting in a total of 31 scenarios (Table 1). Parameter distributions from WetQual were informed from Kalin et al. (2012). Using these distributions, we generated 10,000 parameter sets. For each nutrient scenario, the pertinent inputs (hydrography, climate, nutrients) were fed into WetQual and Monte-Carlo simulations were performed by running WetQual one parameter set at a time thus yielding 10,000 time-series of Nitrate-N export for each scenario (Kalin et al. 2012). This was done for period from January 1, 2013 to May 1, 2014 for BM and OF wetlands, and from August 10, 2013 to May 1, 2014 for NF wetland – the period for which we have daily flow and other pertinent inputs. For each scenario, the 25th and 75th percentiles (C_{25} and C_{75}) and the median (C_M) of 10,000 Nitrate-N time-series were extracted from the Monte-Carlo simulations. These three time-series were compared among the different scenarios for each wetland and a sensitivity index, calculated as the average of a normalized measure of band width for each of the three measures, was used to assess sensitivity of Nitrate-N export to input Organic-N and Ammonia-N. The sensitivity index, *SI* was calculated as:

Sensitivity index, $SI = \frac{\sum(x_{max,i} - x_{min,i})}{\sum x_{md,i}} \times 100$

where x_{max}, x_{min} and x_{md} are the maximum, minimum and median values of Nitrate-N output at daily time-step, *i*, each for C_{25}, C_{75} and C_M to assess the sensitivity of C_{25}, C_{75} and C_M to input Organic-N, Ammonia-N and DO at the four wetlands, and *n* is the number of days simulated at each wetland.

We also thought it pertinent to test sensitivity of Nitrate-N predictions for the headwater slope wetlands under different scenarios of reduced flow rates as a way to understand how smaller flow rates, and consequently smaller loadings and higher residence times, would influence sensitivity of Nitrate-N exports to Organic-N and Ammonia-N inputs. To this end, we conducted WetQual runs using different hydrological scenarios where inflows were reduced by 20, 40, and 60%. Daily outflow, volume, area and stage corresponding to each reduced inflow scenario, to be used as inputs to WetQual, were generated using a combination of regression relationships and Artificial Neural Network (ANN) models developed from observed data at the wetlands. ANNs are black-box models where detailed understanding of the internal processes is not required to develop relationships between the inputs and outputs (Isik et al. 2013; Srivastava et al. 2006; Noori and Kalin 2016). Between the input and the output layers, a number of user-defined hidden layers exist where most of the processing takes place. Input data is fed into the input layer, which communicates with nodes in the hidden layer(s), which then link to an output layer where the response of the ANN model corresponding to each input data point is received (Srivastava et al. 2006).

First an ANN model, calibrated for observed outflow or stage, was created using daily net water input to the wetland (I) and antecedent water input calculated over three days' prior (I_3) as inputs. Daily net water input to the wetland, I, was calculated as

$$I_i = q_{in,i} + P_i - ET_i \; ; \; q_{in,i} = \frac{Q_{in,i}}{A}$$

where Q_{in} is the inflow [L^3T^{-1}], A [L^2] is the wetland area for h = 1m, P is the precipitation [LT^{-1}], ET is the evapotranspiration [LT^{-1}], and i is the daily time step. Antecedent water input calculated over three days' prior, I_3, was calculated as

$$I_{3,i} = I_{i-1}+I_{i-2}+I_{i-3}$$

where i-1, i-2 and i-3 refer to one day prior, two day prior and three day prior time steps. The calibration performance between ANN model prediction and observed data was measured using E_{NASH} (Nash and Sutcliffe 1970). In this way, an ANN model was created where outflow (or stage) was expressed as a function of I and I_3. The choice of outflow or stage depended on which calibration fully captured the range of the target. This ANN model was then applied to each reduced inflow scenario (20, 40 and 60% reduction in inflow) and corresponding outflow or stage was generated. Regression relationships, previously developed among bathymetry elements and observed outflow, were then used to reconstruct the other relevant hydrological and bathymetry inputs from the generated outflow/stage for each reduced inflow scenario. For each of the three hydrological scenarios at the three wetlands, all 31 scenarios (30 nutrient scenarios + 1 DO scenario) were run and *SI*s were calculated. We used MATLAB R2016a version 9.0.0 for ANN model construction and implementation.

5. Results and Discussion

5.1 Flow calibration and reconstructing gaps in observed flow

Flows were calibrated using SWAT and SWAT-CUP software using observed flow data for the wetlands which were available (with data gaps) from January 1, 2013 - May 1, 2014 at BM and OF wetlands, and from August 10, 2013 to May 1, 2014 at the NF wetland. Calibrated parameter ranges and values for the “best” flow calibration using SWAT-CUP are presented in Table 2. Calibrated flows were used to fill in gaps in the observed flow data. All, except the inflow at OF had a high calibration performance with the best simulation having $E_{NASH} \geq 0.6$ (OF inflow calibration had $E_{NASH} = 0.4$). Given the high baseflows at NF, flow calibration was considerably challenging and was accomplished by manually manipulating the deep aquifer recharge factor, RCHRGE_DP, from its default positive value to a negative value to recover losses to the deep aquifer as contributions to baseflow. This is described in detail in Chapter 3. Following reconstruction of missing flows, BM and OF wetlands had continuous flow data from January 1, 2013 to May 1, 2014, and NF wetland from August 10, 2013 to May 1, 2014, for which period the sensitivity analysis was carried out.

From SWAT-CUP results, the most sensitive parameters at the 0.05 significance level for BM inflow included CH_K2 (effective hydraulic conductivity in the channel), ALPHA_BNK (baseflow alpha factor for bank storage), CH_N2 (Manning's n value for the main channel) and ESCO (soil evaporation compensation factor), and for BM outflow included CH_K2 and ALPHA_BNK. Since most of these parameters describe physical processes of the channel, it confirms the highly surface flow driven character of the wetland. A mix of surface flow and groundwater flow parameters were sensitive at the NF inflow and outflow giving further credence to the fact that hydrology here is influenced by both surface water and groundwater characteristics. The most sensitive parameters at the NF inflow were CN2 (SCS curve number), RCHRGE_DP (deep aquifer recharge factor), GW_DELAY (groundwater delay time), SOL_BD (soil bulk density), ALPHA_BF (baseflow alpha factor), and at NF outflow were CN2, RCHRGE_DP, ALPHA_BF and SOL_AWC (available water capacity of the soil). This is in contrast with the OF wetland where purely groundwater parameters were sensitive reflecting the entirely groundwater driven nature of the wetland. Parameters RCHRGE_DP, ALPHA_BF, and NDTARG (pond parameter describing number of days needed to reach target storage from current pond storage) were sensitive at OF inflow and outflow.

5.2 Sensitivity analysis

The *SI*s for the three wetlands for C_{25}, C_{75} and C_M of Nitrate-N outputs are presented in Figure 4. From the figure, all the study headwater slope wetlands had very low variation in Nitrate-N load outputs from changing Organic-N, Ammonia-N and DO inputs sensitivity (*SI* < 0.5%). Sensitivity of Nitrate-N export to fluctuations in each, Organic-N and Ammonia-N, are shown in Figure 5. While still extremely small, Nitrate-N export showed relatively higher sensitivity to changing Ammonia-N inputs compared with Organic-N inputs, perhaps because it can readily undergo nitrification to Nitrate-N. Changing DO also had negligible influence on Nitrate-N export (hence not presented separately in a figure or table). Sensitivities increased marginally with decreased flow rate scenarios in the headwater slope wetlands; the change was higher for OF wetland than for BM or NF wetlands (Figure 6). Possibly the flow reductions in NF and BM wetlands, whose flows are much larger than the OF wetland, were not enough to reap the benefits of increased residence time and effect N transformation. From this exercise we concluded that Nitrate-N predictions in headwater slope wetlands were insensitive to Organic-N, Ammonia-N and DO in the inflows, and consequently their lack of data thereof would not impact WetQual predictions of Nitrate-N. At this juncture, we paused to consider if these results applied to any other kinds of wetlands, primarily because flow and nutrient data from a vastly different wetland was available to us and performing a similar analysis sensitivity might be a useful way of double-checking and interpreting results. This wetland is a surface-water driven depressional wetland located, not at the headwaters, but near the mouth of Prospect Bay which is an inlet of the Chesapeake Bay in Maryland. Would the same sensitivity analysis results from the headwater slope wetlands hold for this wetland type? And how might that improve our understanding in context of the headwater slope wetlands?

The wetland, called Barnstable (BS), is located in the southern portion of Kent Island, a part of the Delmarva Peninsula in Maryland (Figure 7). The watershed is predominantly agricultural with some forested area. This wetland was restored from an artificially drained cropland by the Chesapeake Wildlife Heritage to improve wildlife habitat and mitigate pollutant loads from agricultural runoff (Sharifi et al. 2013). The BS wetland is purely surface-water fed since an impermeable clay layer was laid within 0.5m of the soil surface during restoration which blocks all groundwater exchanges and infiltration. The wetland was monitored for approximately two years for flow and water quality data from 1995 through 1997 (Figure 8; see Jordan et al. 2003) and was used to validate the wetland nutrient cycling model, WetQual, utilized in this paper (Hantush et al. 2012; Kalin et al. 2012; Sharifi et al. 2013). While parametric sensitivity and uncertainty has been assessed at this wetland previously, input data sensitivity has not.

All input data such as hydrology, bathymetry and water quality data were available for the depressional wetland in Maryland for a period of 2 years from 1995-1997. Since Nitrate-N data was measured on a weekly basis at the Maryland wetland, we converted it to daily values by assuming concentrations to remain constant over the week and missing data was filled by taking averages of the last available measurement before the gap and the first available measurement at the end of the gap (refer to Kalin et al. 2012). The same 31 scenarios considering variations in Organic-N, Ammonia-N and DO were applied to this wetland and Nitrate-N export was generated using WetQual in the same manner described for the headwater slope wetlands. At this site, however, Nitrate-N load export showed much higher sensitivity to surface water inputs of Organic-N and Ammonia-N with *SI* of 7.6-9.1% (Figure 9). Keeping all else the same between scenarios, Nitrate-N export concentrations were more sensitive to fluctuations in Ammonia-N (*SI*

= 8.2 to 9.2%) than Organic-N (*SI* < 2%) which followed similar trends as that observed at the headwater slope wetlands.

The differences in *SI*s between the headwater slope wetlands and the BS wetland could be due to several reasons. A major factor is the difference in bathymetry between the four wetlands. The BS wetland is a predominantly surface-water driven depressional wetland; all inputs enter via surface water and are retained in the wetland where nutrient transformations take place, until outflow stage exceeds 1m beyond which outflows occur. Average depth at the wetland is about 0.2 m and hydraulic detention time, calculated as the ratio of volume to inflow rate, is >1week though days with detention times as low as 0.5 days were reported (Jordan et al. 2003). The soils are silty loam with a clay impermeable aquiclude beneath effectively cutting off any groundwater interactions. The headwater slope wetlands, on the other hand, are riparian wetlands that occur above and alongside 1st order headwater streams. These wetlands have highly permeable soils and groundwater interactions are high; groundwater dominated the flow for over > 88% of the time at NF and OF, and ~35% of the time at BM (52% at the inflow and 19% at the outflow). Average flow depths were similar between the wetlands for the time period for which each of them was studied; 0.36m at BM, 0.27 m at NF, 0.33m at OF, and 0.2m at BS. However, while flows are stored in the depressional BS wetland, headwater slope wetlands are typically incapable of depressional storage because they lack closed contours (NRCS 2008). Outflows are continuous in the headwater slope wetlands with the deepest part of the wetlands occurring at the outflows. Headwater slope wetlands occur along a gradual slope and contribute flows and other material to the creeks. Water detention time is very small at these wetlands and averages 0.05 days at BM, 0.04 days at NF and 0.02 days at OF. However, this detention time considers only the main advection flow in the stream channel since sampling was done at the discernible flow channels entering and leaving the wetlands. It is widely reported that bulk of nutrient transformation and uptake in small riparian wetlands happens through transient storage, i.e., temporary hydrologic retention of stream water apart from the main advection flow in the stream channel (Ensign and Doyle 2005). However, this was not measured in this study.

Of the headwater slope wetlands, Nitrate-N export from the BM wetland showed higher sensitivity to changing N inputs. The BM wetland is situated at a much higher elevation compared to the Foley wetlands, as well as in the most urbanized watershed. The channel here is also more incised compared to the Foley wetlands. Of the three wetlands, water residence time associated with advection flow was relatively larger for this wetland (~0.04 days). The stream channel here went dry multiple times and did not have a consistent baseflow; it is possible that flows quickly percolated contributing to groundwater recharge here, or got trapped behind sediment accumulations in the channel which may have allowed for transient storage leading to prolonged contact between the water column and the streambed thus allowing favorable conditions for N transformations to take place. The presence of higher percentage of impervious surfaces within the BM watershed could have decreased groundwater input to the wetland leading to periodic discharge into the stream during storm events. The absence of constant groundwater Nitrate-N contributions combined with high propensity for transient storage due to sediment in the channel may have increased sensitivity of Nitrate-N export to varying Organic-N and Ammonia-N inputs. For both the Foley wetlands, constant groundwater input to the wetland, and consequently Nitrate-N input through this pathway, could have contributed to decreased water retention time and negligible sensitivity to varying N inputs. Very low Nitrate-N inputs, Organic-N and Ammonia-N inputs in the headwater slope wetlands could also have contributed to the low sensitivity indices observed in these wetlands.

6. Conclusions and limitations

The results of this study indicate that when predicting Nitrate-N export from small wetlands such as these in the study, details regarding Organic-N and Ammonia-N inputs are significant for surface fed depressional wetlands and not necessarily for groundwater fed systems. In the latter, it may be more important to accurately quantify all sources of Nitrate-N entering the system to improve predictions of Nitrate-N export from these systems. In these systems changes in Nitrate-N could be affected by elevated baseflows which add more Nitrate-N to the system, and instream processing in stagnant pools formed around natural stream dams (Angier and McCarty 2008). This is an important finding, because often detailed input data for running and calibrating models are missing. We show that when we are modeling Nitrate-N, having Ammonia-N and Organic-N data are not too critical for groundwater fed headwater slope wetlands, but very critical for surface water driven depressional wetlands.

We acknowledge that there are some limitations to this study, the most important of which is the uncertainties associated with the availability of data at the slope wetlands. Flows and DIN for the headwater slope wetlands were available only at discernible surface water inlets and outlets; given our limited resources we were unable to monitor other sources of flow and DIN to the wetlands. Being a groundwater dominant system, there may have been other hydrological flow paths that we failed to consider which, in turn, may have affected our quantification of daily DIN concentrations and loads entering the slope wetlands. However, without preliminary monitoring efforts it is challenging to foretell the extent of groundwater dominance or identify enough resources for hydrology/water quality monitoring at high resolution. Usually it is the understanding gained from preliminary monitoring efforts that informs subsequent data collection and study directions. The other potential limitation could be with our consideration of model WetQual to conduct the sensitivity analysis. Previous WetQual applications have involved depressional wetlands and not slope wetlands which could have influenced the results of the analysis. However, wetland models tend to be site-specific and data-intensive; given data limitations, WetQual seems suitable for the data resolution at hand. Also, there is a possibility that DIN concentrations at the slope wetlands were too low for WetQual to result in sensitive trends in quantified outputs. Further research involving quantification of subsurface inflows and outflows using piezometers and quantifying associated N concentrations to get a better picture of hydrological and nutrient budgets is required to reduce some of the uncertainties. What we have presented through this study offers suggestions to prioritize data collection efforts for modeling efforts and consequently aid in decision making with regard to management efforts. A validation of similar sensitivity analysis on slope wetlands in other areas with higher DIN concentrations would be useful to validate the results presented in this study.

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Figures

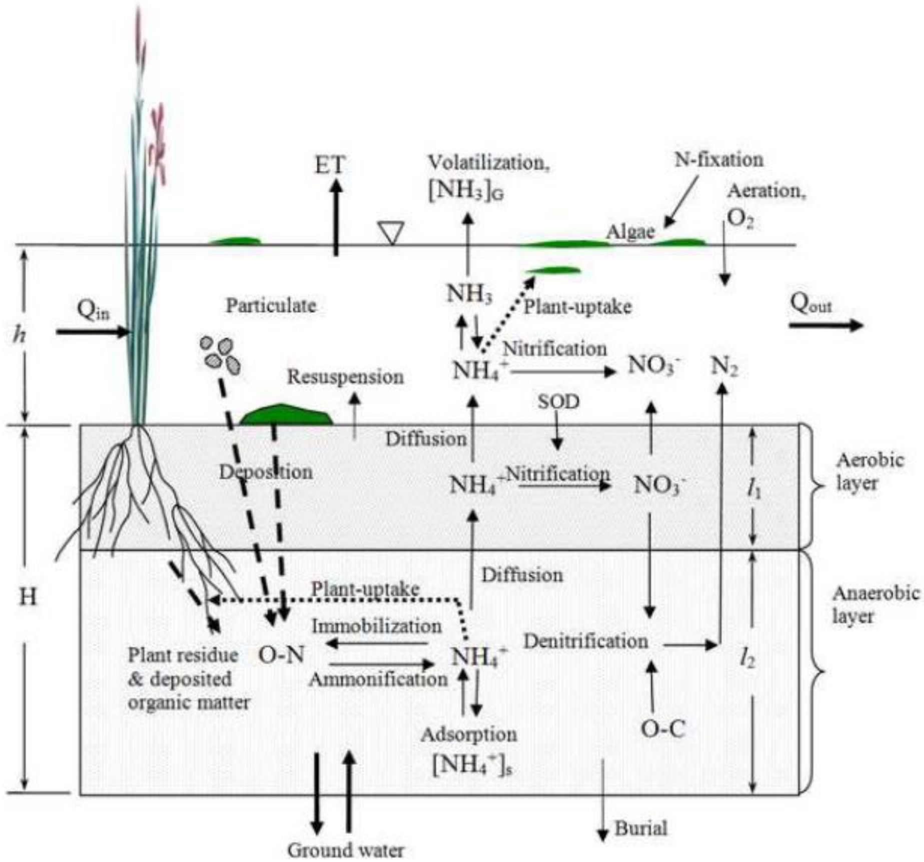

Figure 1. Nitrogen cycling and retention in WetQual model

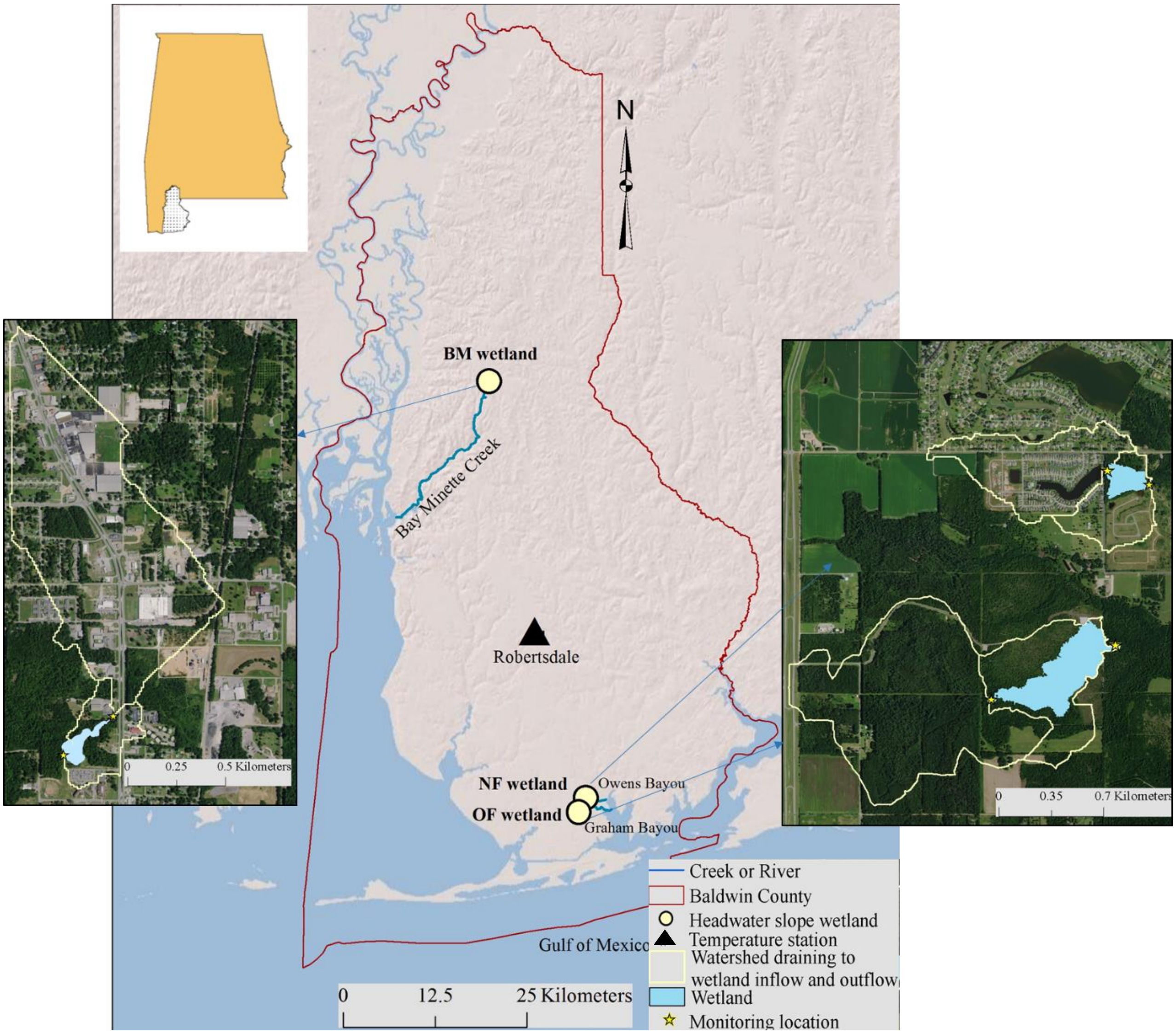

Figure 2. Study headwater slope wetlands in Baldwin County

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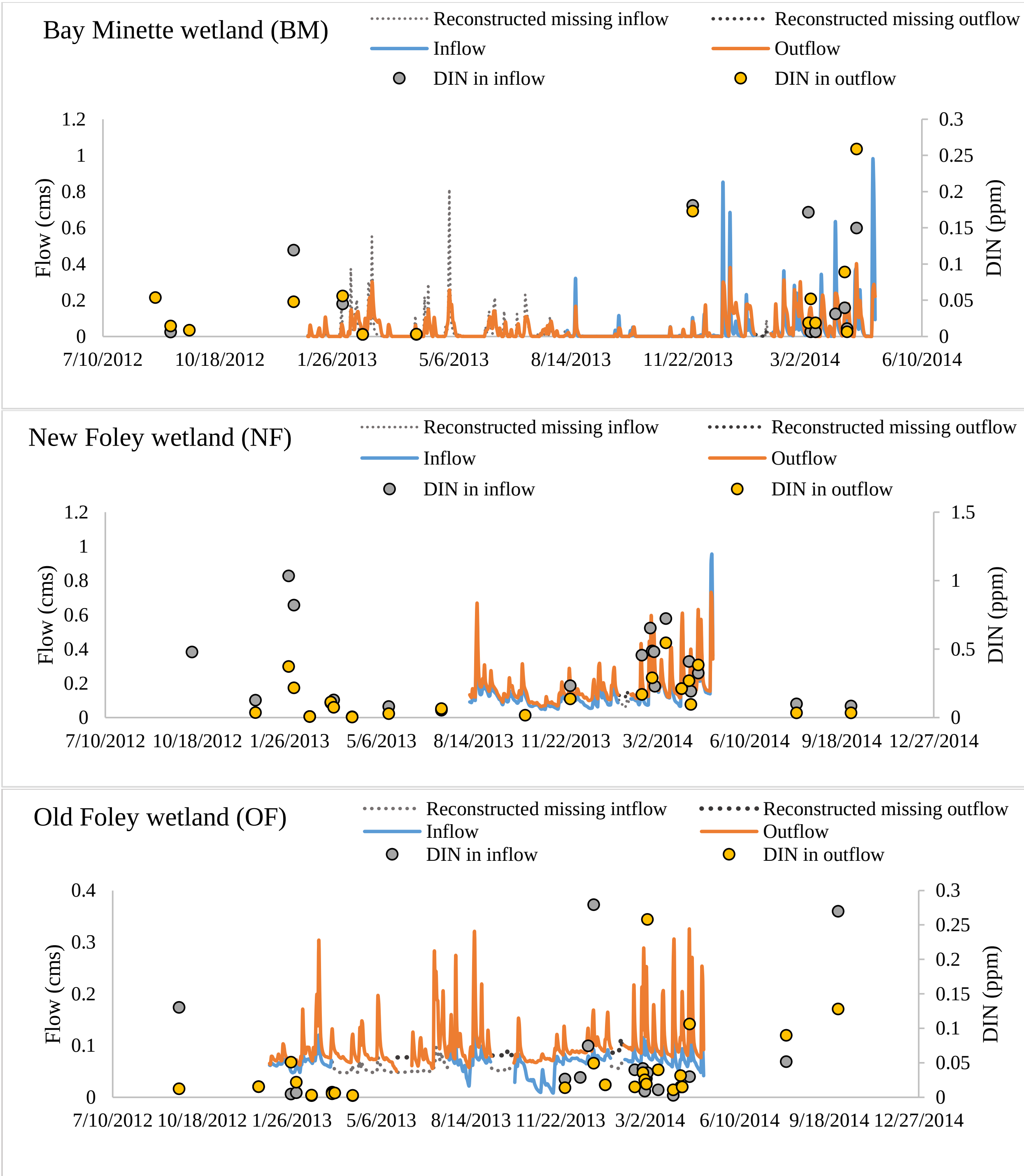

Figure 3. Observed flows and DIN concentrations at headwater slope wetlands in Baldwin County AL. All data before Dec 1 2013 consist of grab samples, and all after Dec 2013 consist of automated samples using ISCOs.

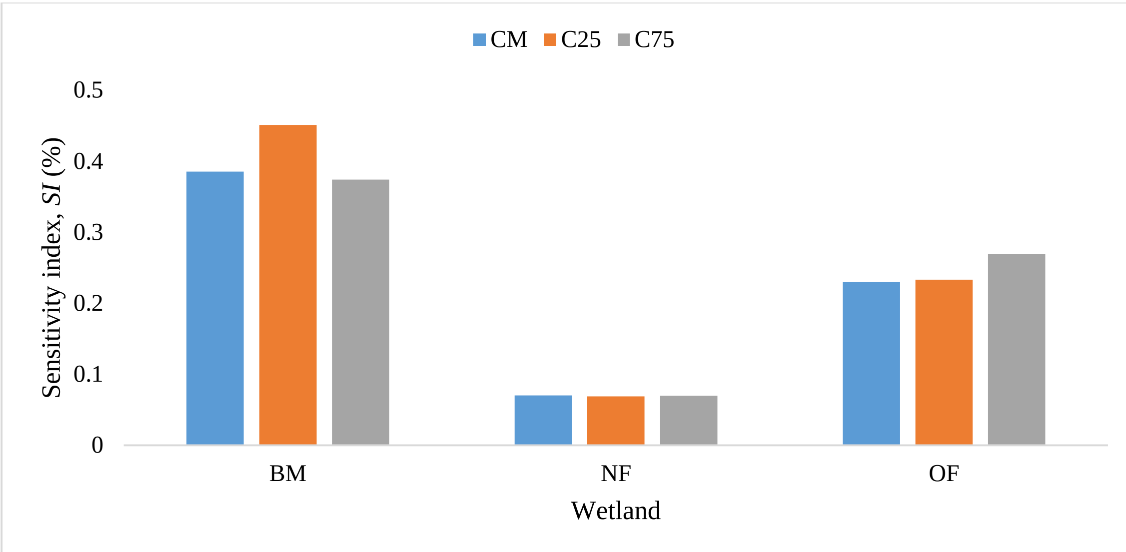

Figure 4. Sensitivity indices for Median (C_M), 25th percentile (C_{25}) and 75th percentile (C_{75}) of Nitrate-N load outputs generated by WetQual for varying inputs of Organic-N, Ammonia-N and DO in headwater slope wetlands in Alabama's coastal plain

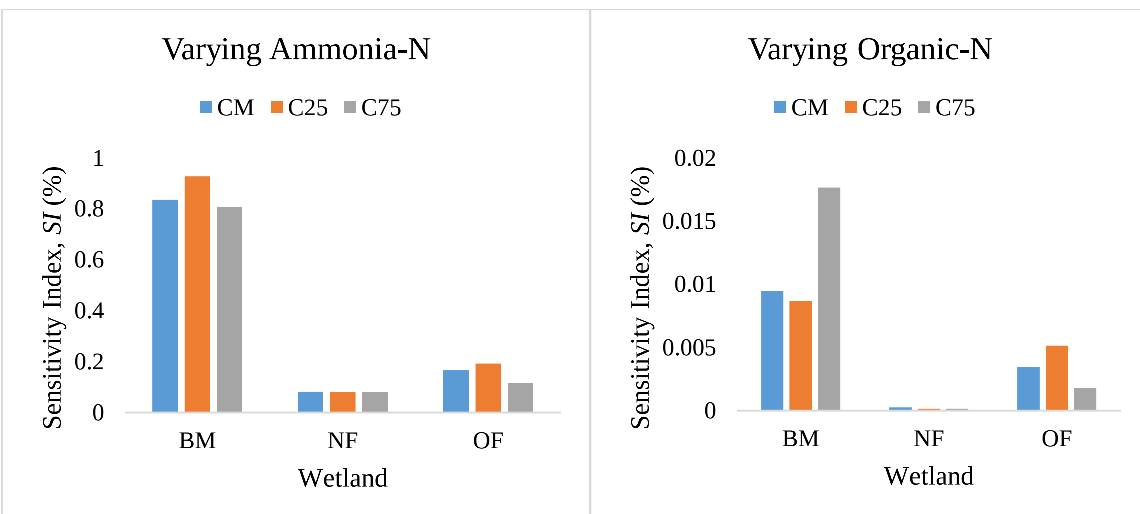

Figure 5. Sensitivity indices for Median (C_M), 25th percentile (C_{25}) and 75th percentile (C_{75}) of Nitrate-N concentration outputs from WetQual for varying inputs of Organic-N, Ammonia-N and DO in headwater slope wetlands in Alabama's coastal plain. The figure on the left presents *SI*s for scenarios varying only in their Ammonia-N input, while the figure on the right represents *SI*s for scenarios varying only in their Organic-N input. As can be observed, Nitrate-N export was relatively more sensitive to variations in Ammonia-N inputs than Organic-N inputs.

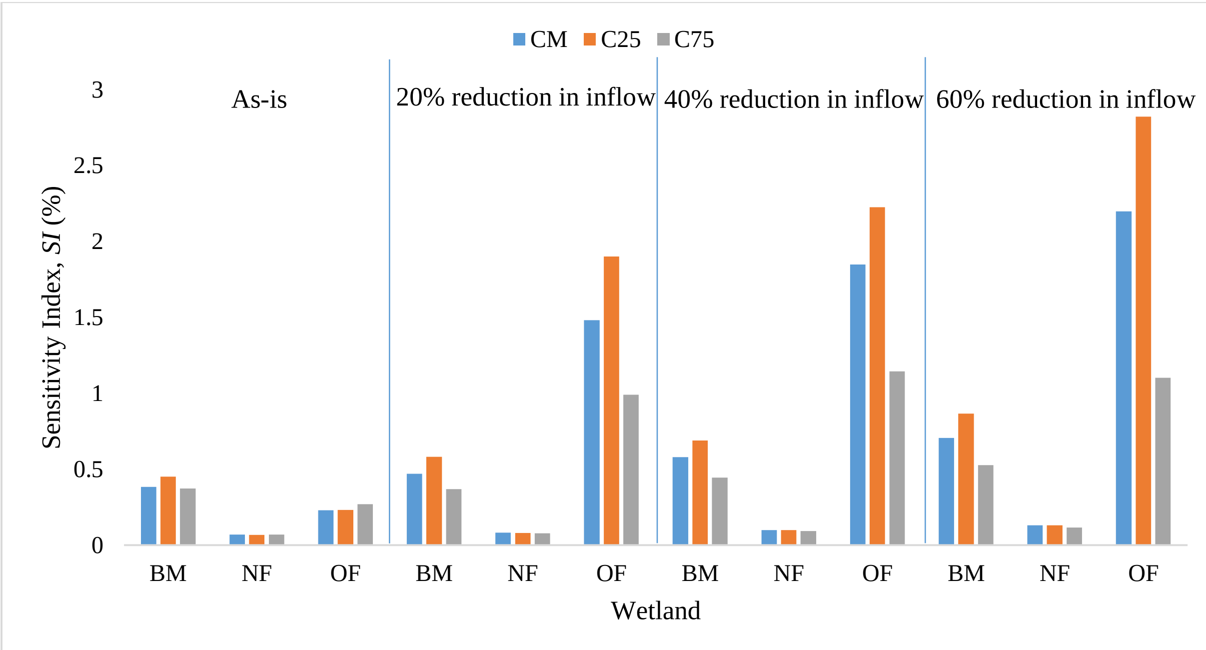

Figure 6. Sensitivity indices for Median (C_M), 25th percentile (C_{25}) and 75th percentile (C_{75}) of Nitrate-N load outputs from WetQual simulations for varying inputs of Organic-N, Ammonia-N and DO in headwater slope wetlands in Alabama's coastal plain for 20, 40 and 60% reductions in inflow. While *SI* for OF increases some with reduction in inflow, observed *SI* is still <3%.

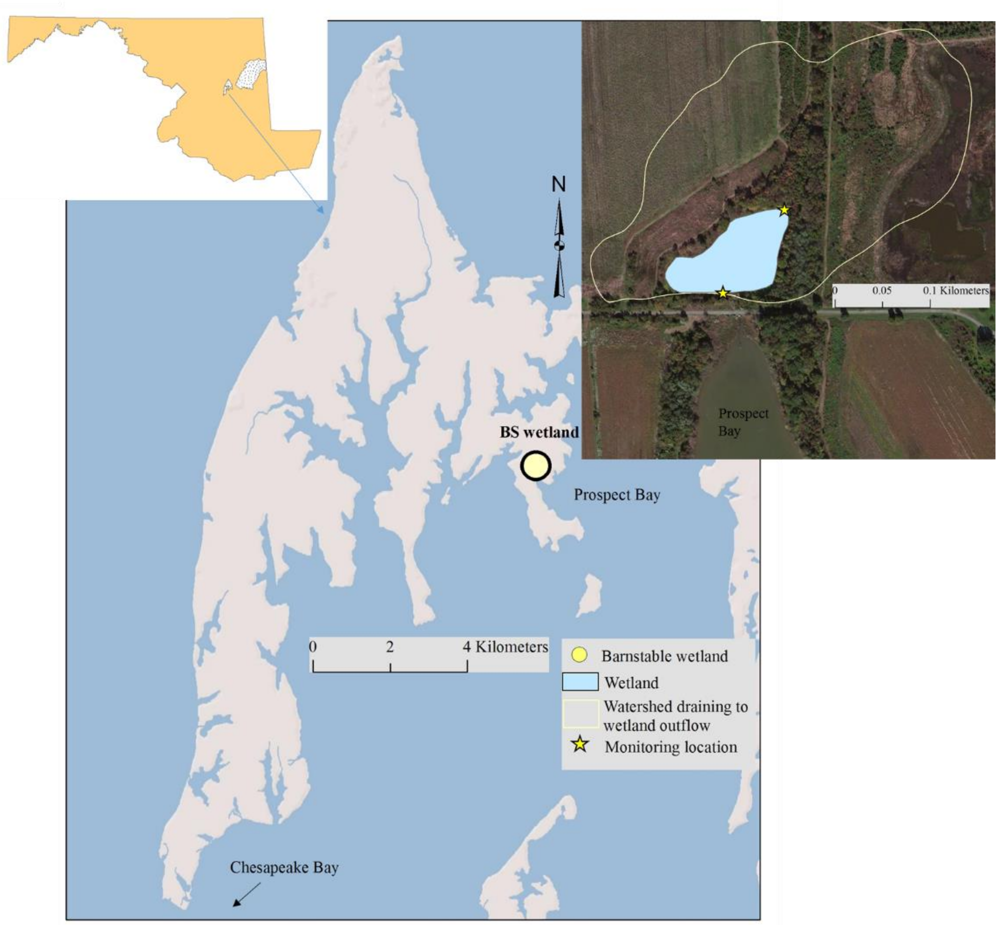

Figure 7. Barnstable (BS) wetland in Maryland. This is a depressional wetland

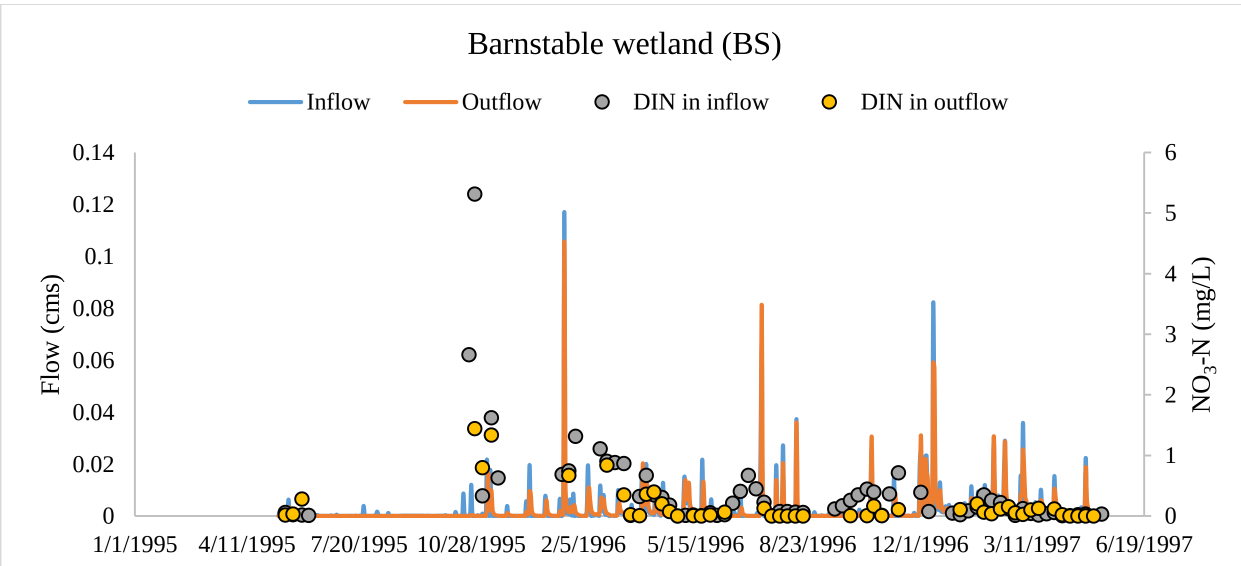

Figure 8. Observed flows and Nitrate-N concentrations at the Barnstable wetland (BS) in Maryland

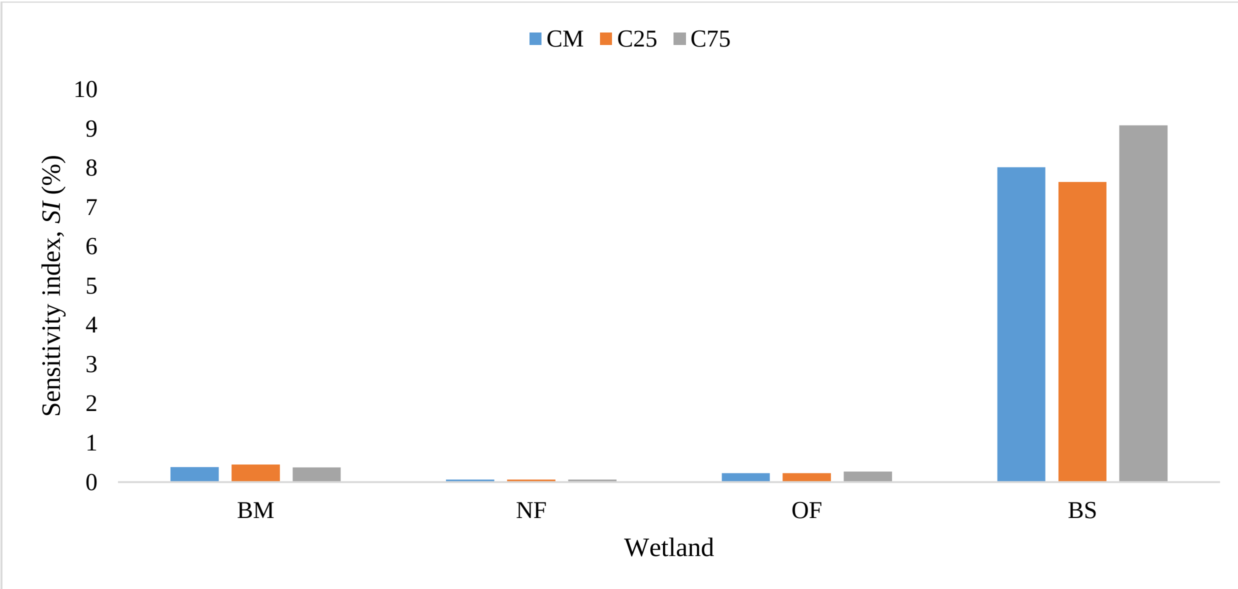

Figure 9. Comparison of sensitivity indices for Median (C_M), 25th percentile (C_{25}) and 75th percentile (C_{75}) of Nitrate-N outputs from WetQual simulations for varying inputs of Organic-N, Ammonia-N and DO in headwater slope wetlands in Alabama's coastal plain (BM, NF and OF) and a depressional wetland in Maryland (BS). From the calculated *SI*s, the BS wetland in Maryland is much more sensitive to varying Organic-N and Ammonia-N inputs than the headwater slope wetlands.

Tables

Table 1. Thirty-one input scenarios used to test the sensitivity of Nitrate-N export to inputs of Organic-N, Ammonia-N and dissolved oxygen (DO). Sensitivity analyses were conducted using WetQual model. These analyses were also repeated for different scenarios of reduced flows for the headwater slope wetlands.

		Organic N (ON) as fraction of Nitrate-N →					
		0	0.5X	1X	2X	5X	10X
Ammonia-N (AN) as fraction of Nitrate-N ↓	0	ON=0, AN=0	ON=0.5X, AN = 0	ON = 1X AN = 0	ON = 2X, AN = 0	ON= 5X , AN = 0	ON=10X, AN = 0
	0.1X	ON=0, AN=0.1X	ON=0.5X, AN=0.1X	ON=1X, AN=0.1X	ON=2X, AN=0.1X	ON=5X, AN=0.1X	ON=10X, AN=0.1X
	0.25X	ON=0, AN=0.25X	ON=0.5X, AN=0.25X	ON=1X, AN=0.25X	ON=2X, AN=0.25X	ON=5X, AN=0.25X	ON=10X, AN=0.25X
	0.5X	ON=0, AN=0.5X	ON=0.5X, AN=0.5X	ON=1X, AN=0.5X	ON=2X, AN=0.5X	ON=5X, AN=0.5X	ON=10X, AN=0.5X
	1X	ON=0, AN=1X	ON=0.5X, AN=1X	ON=1X, AN=1X	ON=2X, AN=1X	ON=5X, AN=1X	ON=10X, AN=1X
DO as fraction of DO from SWAT-CUP simulation	100X	ON=0, AN=0, DO=100X					

Table 2. Calibrated parameter ranges and fitted values for "best" simulation following flow calibration using SWATCUP at study headwater slope wetlands. The *P*-factor (% of observed data enveloped by 95PPU), *R*-factor (thickness of 95PPU) and E_{NASH} are indicators of calibration performance, where the factors indicate the performance of the 95PPU and the latter indicates performance of the "best" simulation. No hard numbers exist for what values the factors should be. *P*-factor>0.7 and *R*-factor ~1 are suggested for flow calibration. High E_{NASH} indicates good fit with observed data (Abbaspour et al. 2008)

Wetland	Location	Performance	Parameter_Name	Fitted_ Value	Min_ value	Max_ value
Bay Minette (BM)	Inflow	*P* – factor = 0.44	1:R__CN2.mgt	0.2112	-0.0304	0.3091
		R – factor = 0.26	2:V__ALPHA_BF.gw	1.1478	0.4340	1.3027
		E_{NASH} = 0.88	3:V__GW_DELAY.gw	124.0592	0.0100	272.6457
			4:V__GWQMN.gw	71.8229	0.0100	110.2088
			5:V__GW_REVAP.gw	0.1001	0.0200	0.1215
			6:V__ESCO.hru	0.9736	0.8651	0.9955
			7:V__CH_N2.rte	0.0675	0.0547	0.2183
			8:V__CH_K2.rte	13.5896	0.0100	68.4786
			9:V__ALPHA_BNK.rte	0.8288	0.3373	1.0000
			10:R__SOL_AWC(..).sol	0.5241	0.0664	0.5996
			11:R__SOL_K(..).sol	0.1802	-0.2977	0.7083
			12:R__SOL_BD(..).sol	0.1656	-0.1125	0.6635
			13:V__SURLAG.bsn	5.3977	0.0500	6.4545
			14:V__NDTARG.pnd	15.5417	11.0713	31.2387
			15:V__PND_K.pnd	0.7919	0.4506	1.3527
			16:V__RCHRG_DP.gw	0.4723	-0.2277	0.5911
	Outflow	*P* – factor = 0.14	1:R__CN2.mgt	0.1504	0.0036	0.2033
		R – factor = 0.23	2:V__ALPHA_BF.gw	0.5695	0.3509	0.7838
		E_{NASH} = 0.59	3:V__GW_DELAY.gw	587.4499	420.9120	771.5181
			4:V__GWQMN.gw	119.4230	54.0581	127.3646
			5:V__GW_REVAP.gw	0.0649	0.0596	0.1759
			6:V__REVAPMN.gw	155.7637	130.1761	443.4945
			7:V__ESCO.hru	0.9171	0.8600	0.9811
			8:R__OV_N.hru	-0.1163	-0.1166	0.0953
			9:V__SURLAG.hru	2.6356	1.1899	3.5535
			10:V__CH_N2.rte	0.3493	0.2310	0.4429
			11:V__CH_K2.rte	219.8718	124.0657	242.5887
			12:V__ALPHA_BNK.rte	0.9703	0.7172	1.0000
			13:R__SOL_AWC(..).sol	0.2128	-0.1568	0.2754
			14:R__SOL_K(..).sol	0.6854	0.2989	1.2691
			15:R__SOL_BD(..).sol	-0.0208	-0.1329	0.2559
			16:V__NDTARG.pnd	9.8967	1.0000	12.7838
			17:V__PND_K.pnd	0.3199	0.0000	0.3292

			18:V__RCHRG_DP.gw	0.2029	-0.0029	0.6176
New Foley (NF)	Inflow	*P* – factor = 0.84	1:R__CN2.mgt	0.2852	0.1259	0.4215
		R – factor = 1.04	2:V__ALPHA_BF.gw	0.0823	0.0010	0.1729
		E_{NASH} = 0.75	3:V__GW_DELAY.gw	0.5626	0.0010	3.1039
			4:V__GWQMN.gw	41.3123	25.9386	43.5892
			5:V__GW_REVAP.gw	0.0945	0.0258	0.1010
			6:V__ESCO.hru	0.9519	0.9163	0.9852
			7:V__CH_N2.rte	0.1436	0.1248	0.2542
			8:V__CH_K2.rte	131.7807	85.3318	142.1848
			9:V__ALPHA_BNK.rte	0.3857	0.2315	0.7403
			10:R__SOL_AWC(..).sol	-0.4349	-0.4405	-0.0683
			11:R__SOL_K(..).sol	0.2406	-0.0977	0.4419
			12:R__SOL_BD(..).sol	0.0287	-0.2174	0.1337
			13:V__RCHRG_DP.gw	-15.2932	-19.5595	-13.0659
	Outflow	*P* – factor = 0.76	1:R__CN2.mgt	0.3378	0.2939	0.4170
		R – factor = 0.74	2:V__ALPHA_BF.gw	0.0116	0.0010	0.0361
		E_{NASH} = 0.61	3:V__GW_DELAY.gw	0.1886	0.1021	0.6139
			4:V__GWQMN.gw	40.5962	39.6825	47.3605
			5:V__GW_REVAP.gw	0.0647	0.0517	0.0757
			6:V__ESCO.hru	0.9888	0.9804	1.0000
			7:V__CH_N2.rte	0.1758	0.1414	0.1764
			8:V__CH_K2.rte	153.7072	137.2320	156.9156
			9:V__ALPHA_BNK.rte	0.4214	0.3403	0.5118
			10:R__SOL_AWC(..).sol	-0.3983	-0.4798	-0.2450
			11:R__SOL_K(..).sol	0.1740	0.0464	0.2062
			12:R__SOL_BD(..).sol	0.1356	0.0174	0.1695
			13:V__RCHRG_DP.gw	-18.3424	-18.9908	-17.4433
Old Foley (OF)	Inflow	*P* – factor = 0.95	1:R__CN2.mgt	-0.1788	-0.1874	-0.1146
		R – factor = 3.01	2:V__ALPHA_BF.gw	0.0003	0.0002	0.0008
		E_{NASH} = 0.44	3:V__GW_DELAY.gw	728.3104	475.2162	737.4899
			4:V__GWQMN.gw	45.6854	24.8645	74.6356
			5:V__GW_REVAP.gw	0.1195	0.1000	0.2000
			6:V__ESCO.hru	0.9192	0.9000	1.0000
			7:V__CH_N2.rte	0.1694	0.1295	0.2388
			8:V__CH_K2.rte	23.5557	17.4981	25.4512
			9:V__ALPHA_BNK.rte	0.4141	0.3311	0.6406
			10:R__SOL_AWC(..).sol	0.1660	0.1108	0.2581
			11:R__SOL_K(..).sol	0.2817	0.0289	0.5361
			12:R__SOL_BD(..).sol	0.4139	0.2548	0.4712
			13:V__RCHRG_DP.gw	-5.8333	-6.0000	-2.0000

		14:V__NDTARG.pnd	6.8938	5.6392	16.8745
Outflow	*P* – factor = 0.82 *R* – factor = 0.68 E_{NASH} = 0.70	1:R__CN2.mgt	-0.1301	-0.1409	-0.1296
		2:V__ALPHA_BF.gw	0.0006	0.0005	0.0007
		3:V__GW_DELAY.gw	634.3761	495.0437	654.6455
		4:V__GWQMN.gw	48.8116	42.5454	48.8178
		5:V__GW_REVAP.gw	0.1038	0.0649	0.1198
		6:V__ESCO.hru	0.8649	0.8428	0.8976
		7:V__CH_N2.rte	0.2609	0.2410	0.3133
		8:V__CH_K2.rte	16.3606	16.0171	19.4185
		9:V__ALPHA_BNK.rte	0.5717	0.4664	0.5953
		10:R__SOL_AWC(..).sol	0.3556	0.2883	0.3568
		11:R__SOL_K(..).sol	0.9841	0.7070	0.9930
		12:R__SOL_BD(..).sol	0.3896	0.3567	0.3995
		13:V__RCHRG_DP.gw	-4.3412	-4.4873	-3.2592
		14:V__NDTARG.pnd	2.3590	1.5213	4.3228

Chapter 5

A secondary assessment of sediment trapping effectiveness by vegetated buffers

Abstract

Vegetated buffers and filter strips are a widely used Best Management Practice (BMP) for enhancing streamside ecosystem quality and water quality improvement by non-point source pollutant removal. This study explores the sediment removal ability of riparian buffers through a secondary analysis study. We compiled data from 54 studies (including data from an online BMP database) concerning sediment trapping by vegetated buffers. We recorded data regarding buffer characteristics such as buffer width, slope, area, vegetation type, sediment and runoff loading, runoff rates and sediment removal efficiency. Variables such as residence time and roughness were also calculated. We found that an exponential regression model describing the relationship between sediment removal efficiency by the buffer and volume ratio explained 36% of the variance. Adding the square of residence time increased the R^2 to 39.2%, while adding an exponential transformation of width further increased R^2 to 40.5%. The model was compared with other sediment reduction regression models reported in literature namely those in White and Arnold (2009), Liu et al. (2008) and Zhang et al. (2010). Of these only the model presented by White and Arnold (2009) was statistically significant presumably because of the inclusion of runoff reduction in their study. The results of this study point towards the importance of considering flow in buffer design.

Keywords – *buffer, filter strip, pollution, water quality, regression*

1. Introduction

Naturally occurring riparian forests and streamside vegetation play a critical role in intercepting and purifying pollutant laden runoff, but their degradation in addition with nonpoint source pollutant export has contributed to the deterioration of over 50% of stream and river lengths in the US (Sweeney and Newbold 2014). Sediment pollution can clog waterways, cause flooding, and reduce water quality for domestic uses (drinking, cooking), recreational uses and/or municipal and industry uses (Ribaudo et al. 1999). Sediment–laden water can destroy aquatic habitat by decreasing light-penetration in water, increasing water temperatures, reducing visibility of aquatic organisms, clogging fish gills, and by covering spawning areas and smothering aquatic biota (Cooper 1993; Ribaudo et al. 1999). The US EPA ranks siltation as the leading cause of pollution of streams and rivers in the United States (EPA 1998; Ribaudo et al. 1999).

Non-point source pollutants can either be managed at the source, or intercepted to filter out nutrients and sediment before they reach surface waters (Dillaha et al. 1989; Ribaudo et al. 2001). The establishment and maintenance of vegetative filter strips (VFS) and riparian buffers have gained immense popularity as a cost-effective interception strategy for mitigating water quality and improving riparian ecosystem quality by non-point source pollutant removal (Lowrance et al. 1997; Webber et al. 2010; Sweeney and Newbold 2014). Vegetative filter strips (VFS) are bands or areas of closely grown vegetation that receive and purify runoff from upslope areas such as croplands or pastures or other pollutant source areas (Dillaha et al. 1988). Vegetative filter strips and buffers perform a wide array of functions - they filter out sediments and nutrients from runoff by promoting processes such as infiltration, adsorption, plant uptake, sedimentation and pollutant degradation through numerous biogeochemical processes (Webber et al. 2010; Pinho 2008; Rahman et al. 2014). They prevent streambank erosion and improve habitat and biodiversity (Sweeney and Newbold 2014). A number of studies have documented effectiveness of vegetated filter strips for sediment trapping. Le Bissonais et al. (2004) reported as much as 98% decrease in sediment loads from a field using a 6m grass strip. Duchemin and Hogue (2009) reported total suspended solid load decreases of 87% using grass strips and 85% using mixed grass and tree buffer strips. Lee et al. (1999) documented 77% and 66% sediment load reduction from adjacent crop fields using 6m and 3m grass buffers respectively. Since vegetated buffers form an integral part of watersheds, either as on-site mitigation features in the form of grass hedges/vegetated filter strips at field (or other pollutant producing sites) edges or as end-of-pipe features such as riparian buffers, field and watershed scale models often need algorithms to better simulate hydrology and/or water quality through buffer systems. Hence there is a need to assess buffer effectiveness and/or load reductions from these systems through quantitative methods.

Regression (statistical) models are useful tools for water quality prediction and for making management decisions regarding buffer maintenance and pollutant attenuation (Mayer et al. 2007). Published literature has identified various factors affecting the load mitigation performance of vegetated buffers including buffer width, slope, area ratio (pollutant source area : buffer area) and hydrological flow conditions (Arora et al. 1996; Abu-Zreig et al. 2004; Boyd et al. 2003; Barfield et al. 1998l; Daniels and Gilliam 1996; Dillaha et al. 1989; Dosskey et al. 2008, 2011; Duchemin and Hogue 2009; Gharabaghi et al. 2006; Lee et al. 1999, 2000; Delectic and Fletcher 2005). A few studies have conducted meta-analysis assessments of sediment trapping-effectiveness by vegetated buffers. Liu et al. (2008) evaluated data from 31 studies and concluded that regardless of the area ratio of buffer to agricultural field, optimum sediment trapping was obtained when buffer width was 10m and had a slope of 9%. In a meta-analysis study by Zhang et al. (2010) buffer width alone captured 37% of the total variance in sediment removal efficiency. Here, a 30m buffer with slope ≈ 10% removed >85% of the sediment. These studies primarily evaluated buffer width and slope as design variables for predicting sediment reduction. While these are important design variables to consider for sediment reduction as well as for estimating costs related to buffer installation and maintenance (Dosskey et al. 2008), there is a need for evaluating buffer and slope impacts in light of various site conditions such as soil textures, vegetation types, and runoff loads that can significantly influence buffer efficiency.

Conducting secondary analysis studies on buffer efficiency can be quite daunting because of the variability in buffer parameterization across different studies. Quantifying loads and runoff with consistent dimensions and interpretation across experimental studies poses a significant challenge because of the large variations in site conditions in which the vegetative filter strip trials are tested. Sediment trapping efficiency (or sediment reduction) is represented by the following sediment mass balance equation:

$$R_m = \left\{\frac{M_{in}-M_{out}}{M_{in}}\right\} \times 100\ \% \quad \ldots\ldots (1)$$

where R_m is the percent removal efficiency, M_{in} is the sediment mass entering the buffer and M_{out} is the sediment mass leaving the buffer. However, there is a large variability in quantifying M_{in} and M_{out} across different studies. Some studies such as Dillaha et al. (1988, 1989) and Lee et al. (1989, 2000, 2003) compare a control erosion plot with a buffered erosion plot, where the dimensions of the erosion plots are the same in both cases. Other studies such as Uusi-Kämppä and Jauhiainen (2010), Tingle et al. (1998) and Thayer et al. (2012) compare different ratios of erosion plot and buffer with each other to determine % removal. Studies such as Abu-Zreig et al. (2004) strictly evaluate loads entering and leaving the buffer area. Consequently, the units in which loads have been calculated in the various studies differ. Most studies quantify loads as load per unit area. i.e., kg/ha, kg/m^2, tons/ha/yr, etc. However, significant portion of them do not specify the area over which the load was calculated. For some studies such as Lee et al. (2000) and Uusi-Kämppä and Jauhiainen (2010), the reported loads were over the entire area of the plot which included the erosion plot and the buffer. For other studies such as Abu-Zreig et al. (2004), the loads were reported over the buffer area only. This can cause inconsistencies in the reporting of the loads and calculation of sediment trapping efficiency. Moreover, many experimental approaches are used to generate runoff required for testing the effects of the buffer. One approach is to let natural rainfall generate runoff (Lee et al. 2003; Arora et al. 1996; Duchemin and Hogue 2009; Daniels and Gilliam 1996); which in many cases did not produce enough water for this purpose (Hay et al. 2006). Other approaches include simulated rain events (Barfield et al. 1998; Dillaha et al. 1989; Coyne et al. 1995; Chaubey et al. 1994), simulating inflows (Van Dijk et al 1996; Deng et al. 2011; White et al. 2007), or both (Schmitt et al. 1999). These create challenges in the quantification of inflows, runoff and rainfall, if measured at all. Meta-analysis studies have mostly overlooked these inconsistencies, which can have implications on the structure of the developed model.

Stand-alone models such as the process-based model vegetative strip model (VFSMOD; Munoz-Carpena and Parsons 2004) and Riparian Ecosystems Management Model (REMM; Lowrance et al. 2000) have been used to evaluate sediment reduction for different site designs and vice versa. For instance, Dosskey et al. (2008, 2011) used VFSMOD to develop graphical design aids for width and area ratio to achieve specific sediment reduction targets under broad range of agricultural site conditions. However, VFSMOD algorithms are complex and require detailed inputs and significant computing resources to run the models and interpret results, and as such are not used in site planning (Dosskey et al. 2008). Simpler mathematical models for buffer impacts based on theoretical equations, simplified mathematical abstractions, or regressions have been used within wider application models such as the Soil and Watershed Assessment Tool (SWAT). Earlier versions of SWAT considered a vegetated buffer model where trapping efficiency was solely a function of filter strip width (Nietsch et al. 2002). SWAT ver. 2012 considers an improved sediment reduction model where sediment trapping is a function of sediment loading to the buffer and runoff reduction actuated by the buffer. This model was developed by White and Arnold (2009) at the field scale using data from published literature, supplemented with data from VFSMOD simulations to deal with lack of inflow and runoff data. VFSMOD simulations were used to develop an empirical runoff reduction model in which runoff reduction is calculated as logarithm functions of runoff loading to the buffer and saturated hydraulic conductivity of the soils. A sediment reduction model was formulated based on measured data from 61 entries; here, sediment reduction was quantified as a function of sediment loading to the buffer and runoff reduction. They observed that sediment loading to the buffer alone accounted for 41% of the variability in buffer sediment trapping, which increased to 64% when runoff reduction was added to the model.

This study aimed to expand the dataset and develop a regression model while addressing the concerns in data quantification explained previously. The aim was to understand if this exercise would result in similarly sensitive parameters for buffer sediment trapping efficiency while using a larger dataset. We conducted a detailed secondary analysis of published studies on sediment trapping, evaluated the inflow and runoff conditions using different assumptions to glean realistic field relationships between buffer characteristics and trapping efficiency. Our specific objectives were to: 1) compile a database from published literature and online databases with detailed site-specific buffer characteristics such as width, and slope, soil texture, runoff and sediment loading, and reduction and runoff rates 2) construct a sediment reduction model using multi-regression analysis as a function of various design characteristics and 3) compare and asses aforementioned model performance to other published sediment reduction models for vegetated buffers. The overall objective is to obtain improved relationships that can be used at local scales to understand sediment trapping potential by vegetated buffers for water quality mitigation purposes.

2. Database compilation

Most studies on buffer sediment removal efficiency are limited to small-scale evaluation of filter strips, and/or site-specific assessment of riparian areas. Few studies have assessed the effectiveness of riparian buffers on a larger scale. A comprehensive dataset can allow us insight into generalizations about factors that are crucial for improving sediment removal and can greatly inform best management practices in areas where data are scarce. We searched for peer-reviewed literature using keywords *filter strip, vegetated buffer*, *riparian buffer*, *vegetated filter*, etc., alone or in combination to populate a Microsoft Excel® database with detailed information pertaining to sediment removal. Data was also obtained from an online stormwater BMP database (http://www.bmpdatabase.org/). We recorded detailed information about authors, buffer vegetation type, average slope, width, area, inflow and outflow loads, soil type, location, inflow and outflow volumes, and inflow and outflow rates. In addition to these attributes, we also recorded percentage sediment reduction (from eqn. 1) and source-buffer area ratio. We calculated percent sediment removal effectiveness in two ways depending on how data was provided: (1) as the percentage difference in loads between influent into and effluent out of the buffer, or (2) as the percentage difference in loads between edge of a cropland with no buffer and that with a test buffer (Figure 1). We considered data from both plot and field scale systems; however, most entries were from plot-scale experimental plots. A total of 361 data entries from 54 studies were compiled for the analysis (Appendix: Table 1A). Broadly, data were categorized as being "event-based", where the data reported was measured for short-term events such as individual storm events or simulated rainfall events, or as "long-term", where the measured data were reported as annual/multi-event/multi-year sums or averages. For the remainder of this paper, the terms 'vegetated buffer' or simply 'buffer' has been used to describe vegetated buffers, riparian buffers, vegetative filter strips (VFS), and vegetated hedges.

3. Measured variables influencing buffer sediment trapping performance

3.1 Buffer width, length, area

Many studies have evaluated the effect of buffer width on sediment trapping. The terms 'width' and 'length' of the buffer have been used interchangeably in the literature to describe buffer dimensions. In this study, buffer width is defined as the distance of the buffer parallel to runoff flow and buffer length as the buffer distance perpendicular to runoff flow. Since most studies included in this database are rectangular experimental plots, the buffer area is the product of the buffer length and width.

Intuitively sediment trapping increases with increase in buffer width. For instance, Dillaha et al. (1989) observed that increasing the buffer width from 4.6m to 9.1m increased sediment trapping efficiency by 14%. Coarser particles are easily trapped in the upper buffer while finer particles are harder to trap and are retained along the width of the buffer. However, at a certain buffer width, most of the sediment is effectively removed beyond which additional buffer width makes little difference (Zhang et al. 2010). A one-size-fits-all buffer width for optimum sediment trapping does not exist since buffer efficacy for trapping is influenced by multiple synergistic factors. For instance, buffers work better under the influence of shallow uniform flow than under concentrated flow conditions (Liu et al. 2008). Runoff velocity can also significantly influence trapping efficacy. Higher runoff velocities can reduce residence time within the buffer as well as cause erosion within the buffer causing more sediment at the buffer outflows, thus decreasing trapping efficiency.

3.2 Buffer slope

Sediment trapping efficiency is also affected by the slope of the buffer. As buffer slope increases, velocity of runoff increases potentially decreasing residence time and decreasing buffer efficacy. Gradual slopes, however, have been shown to increase trapping efficacy by facilitating laminar runoff flow through the buffer (Zhang et al. 2010). At steeper slopes the effect of decreased residence time and increasing flow channelization dominates causing efficiency to decrease. Dillaha et al. (1989) found that for the same buffer width, sediment trapping efficiency by the buffer increased as slope increased from 5% to 11% and decreased when slope increased to 16%. Zhang et al. (2010) identified a critical slope of 10% above which buffer efficacy begins to decrease. Liu et al. (2008) observed that a polynomial regression relationship best described the influence of slope on buffer trapping efficiency. In another study by Yuan et al. (2009), analysis of plots of buffer efficiency against buffer width revealed that buffers were less effective for slopes that were >5% than for slopes ≤5%.

3.3 Vegetation characteristics

The height and density of vegetation can influence buffer efficiency in trapping sediment. Dense vegetation can increase sediment deposition by decreasing water velocity of runoff. In this study, we categorized buffer vegetation as grass buffers (1), woody buffers (2) and mixed vegetation buffers (3). Grass buffers included buffers and filter strips that had mostly grasses, or stiff grass hedges, or crops (herbaceous vegetation). Woody buffers included filter strips and buffers that comprised of woody shrubs and/or trees. Mixed buffers included buffers and filter strips that comprised of mix of herbaceous and woody vegetation such as riparian buffer systems.

3.4 Residence time and Roughness

Residence time and roughness are important parameters that influence sediment retention within the buffer. Roughness, as used in this study, indicates above-ground obstacles to runoff and sediment flow contributed by vegetation density or by features that can hinder flow and increase sediment deposition. Increased residence time and roughness facilitates sediment deposition thus increasing sediment retention. However, most studies did not report residence time or roughness and very few studies measure roughness indicators such as vegetation height or vegetation densities. Hence, we included proxy terms to account for roughness and residence time as described below.

Expressions for residence time and roughness were determined by modifying the Manning's equation as described below.

Residence time can be expressed as

$$t = \frac{w}{u} = \frac{wLh}{Q} \quad \ldots\ldots (2)$$

where t is the residence time, w is the buffer width, u is the average runoff velocity, L is the buffer length perpendicular to flow, h is the height of flow, and Q is the average flow rate.

From Manning's equation for overland flow, we have

$$Q = \frac{(Lh)h^{\frac{2}{3}}\sqrt{s}}{n} = \frac{1}{n}Lh^{\frac{5}{3}}\sqrt{s} \quad \ldots\ldots (3)$$

where s is the buffer slope, and n is the Manning's coefficient.

Substituting for *h* from (3) in (2) we get an expression for residence time as

$$t = \frac{w^{0.6}n^{0.6}}{q^{0.4}s^{0.3}} \text{ ; where } q = \frac{Q}{wL}$$

$$t = n^{0.6}\left(\frac{w^{0.6}}{q^{0.4}s^{0.3}}\right)$$

$$t \propto \left(\frac{w^{0.6}}{q^{0.4}s^{0.3}}\right) \quad \text{(4)}$$

Substituting for *Q* from (3) in (2), we get

$$t = \frac{nw}{h^{\frac{2}{3}}\sqrt{s}}$$

$$t \propto \frac{w}{\sqrt{s}} \quad \text{(5)}$$

Flow velocity can also be represented as a function of flow depth *h*, gravitational constant *g*, bed slope *s* and channel roughness commonly described by the Darcy-Weisbach equation as

$$u = \sqrt{\left(\frac{8ghs}{f}\right)} \quad \text{(6)}$$

where *u* is the average flow velocity and *f* is the Darcy-Weisbach friction factor.

For laminar flow f = 16/*Re,* where *Re* = 4*uh/v* is the Reynold's number (and *v* is the kinematic viscosity). Substituting for *f* and *Re* in (6), we get

$$u = \frac{gh^2s}{2v}$$

Substituting for *u* = *Q/hL* from (2), we get an expression for *h* as

$$h = \sqrt[3]{\frac{2vQ}{gsL}} \quad \text{(7)}$$

Substituting (7) in (2) we get another expression for *t* as

$$t = \frac{wL}{Q}\sqrt[3]{\frac{2vQ}{gsL}}$$

$$t \propto \frac{wL^{2/3}}{s^{1/3}Q^{2/3}}$$

$$t \propto \frac{w^{1/3}}{s^{1/3}q^{2/3}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (8)$$

where $q = \frac{Q}{wL}$.

Right-hand-side expressions for residence time from (4), (5) and (8) were used as proxies for residence time. Equations (4) and (5) are applicable to turbulent flow conditions (since Manning's equation assumes turbulent flow conditions), and (8) for laminar flow conditions.

Manning's roughness $n = \frac{h^{\frac{5}{3}}L\sqrt{s}}{Q} = \frac{h^{\frac{5}{3}}\sqrt{s}}{qw}$

$$\mathrm{n} \propto \frac{\sqrt{s}}{qw} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (9)$$

From here we used $\frac{\sqrt{s}}{qw}$ as a surrogate variable for roughness.

By a similar analysis for laminar flow, we get Darcy's friction factor f $\propto \sqrt{s}$. Since (9) already considers proportionality to square root of buffer slope, we did not test this term explicitly in the model.

3.5 Area Ratio

Research has shown that area ratio, which is the ratio of the upland contributing area to the area of the vegetated buffer, significantly impacts sediment retention by the buffer (Dosskey et al. 2011; Webber et al. 2009, 2010; Boyd et al. 2003). The contributing area is a surrogate for the size of the runoff load and the buffer area is a surrogate for trapping effectiveness of the buffer (Dosskey et al. 2011). As area ratio increases, sediment trapping efficiency of the buffer decreases. Boyd et al. (2003) reported higher sediment reduction for 15:1 plots than 45:1 plots. However, site conditions such as soil texture, slope, and runoff rate can influence the area ratio-trapping efficiency relationship.

3.6 Soil texture

Soil texture and hydraulic conductivity can impact sediment reduction by influencing infiltration rates causing vegetated buffer strips on fine textured soils to exhibit lower trapping efficiencies than those on coarser sandy soils. Fine-textured soils exhibit lower infiltration rates, and can also produce more fine sediment that cannot easily be trapped by the buffer (Dosskey 2008).

Soil texture was reported in many ways in literature; some studies reported the soil series, while others, the percentage of sand, silt and clay. For the purposes of our meta-analysis, we categorized soil textural classes based on Hydrologic Soil Groups (HSG's) as well drained (type 1) which included sand, loamy sand and sandy loam soils, moderately well drained (type 2) which included silt loams and loams, low infiltration capacity (type 3) which included sandy clay loams, and very low infiltration capacity (type 4) which included clay loam, silty clay loam, sandy clay, silty clay and clay soils.

3.7 Sediment loads in runoff

Loads from the literature were converted to mass per buffer area after perusing them closely. We observed that while many studies reported loads in mass per unit area (kg/ha, kg/m^2, tons/ha), oftentimes they failed to report the area over which loads were expressed, or that information lacked clarity. Sometimes this metric was reported as mass over the VFS area, and other times as mass over the total area of erosion plot paired with a buffer (Figures 2a and 2b). For instance, Lee et al. (2000) compares the sediment retention of a switchgrass buffer with that of a mixed switchgrass-woody buffer for different simulated rainfall intensities and durations. Sediment loads are reported in kg/ha and include the loads transported from the bare cropland source area paired with either no buffer, a 4.1m switchgrass buffer, or a 16.3m wide switchgrass-woody buffer with the collectors located at the lower ends of these plots. Sediment loads from the bare cropland area is assumed to be loading into the buffers. Runoff volumes were converted to depth over the entire plot area (source plot with no buffer, or source plot + buffer as the case may be) (Figure 2a). In this case, we calculated sediment loading into the buffer as mass of sediment multiplied by source plot area, and sediment transported from the buffer as mass of sediment multiplied by total plot area (source plot + buffer). These loads entering and leaving the buffer were expressed in kgs/buffer area.

In some other studies such as Uusi-Kämppä and Jauhiainen (2010) (Figure 2b) and Tingle et al. (1998), the dimensions of the buffered and non-buffered plots are different. For studies such as these, the sediment loads leaving the non-buffered plot (reported as mass/source area) were multiplied with the source area to calculate the total load. This value was then scaled for the source areas of buffered plots to get a more accurate representation of sediment loading into the buffer. Similarly, the sediment loads exiting the buffer was calculated over the entire plot (buffer + source area) and then expressed over area of the buffer.

Where concentrations were reported, sediment loads were calculated by multiplying concentration and runoff volumes. Sediment trapping efficacy by the buffer was calculated as represented in eqn (1).

3.8 Inflow and outflow runoff volumes, flow rates

Runoff loading to the buffer combines several aspects of source area hydrology, precipitation and area ratio (White and Arnold 2009). In this study, runoff loading is expressed as total runoff volume from upslope contributing area divided by the VFS area. Similar problems were encountered with reporting runoff volumes as with sediment loads. In most cases runoff volumes were expressed as depth over the plot area, but oftentimes it was unclear if that included the source area and the buffer or just the buffer. We calculated runoff volumes entering the buffer as the runoff volume produced from the contributing source area, and scaled it as needed. Runoff volume exiting the buffer was calculated similarly.

Most meta-analysis studies do not include the effect of flow rate on the buffer's sediment retention capacity. Evaluating flow rate is critical to understand the functioning of a vegetated buffer system. Understandably so, these data are the hardest to come by. Several studies did not report runoff depths, or volumes. If they did, then flow rates were not reported. Studies have created runoff conditions by simulating rain events, or have evaluated buffer functioning during natural rain events. Some studies provide the hydrograph, while others report the time over which rainfall was simulated. In this study, we tried to extract information on runoff volumes and flow rates based on the quantitative and qualitative descriptions of the study. If hydrographs were provided, runoff volumes were divided by duration of inflows and outflows gleaned from the hydrograph to estimate average inflow and outflow rates. Else, if the study employed rainfall simulators, the duration of rainfall simulation was assumed to be duration of inflow and outflow. Runoff loading to the buffer did not include rainfall occurring directly in the buffer, but included inflows, simulated or from rainfall, occurring upslope of the buffer. Runoff from the buffer, however, included flows from rainfall occurring on the buffer as it is not possible to separate these components from the buffer outflows.

4. Statistical analyses

The compiled data (Appendix Tables 1A and 1B) was used to conduct statistical analyses and discern relationships between different factors influencing sediment removal efficiency, as well as to develop a regression model predicting sediment removal by the buffers. Several procedures and assumptions were adopted for conducting statistical analyses. Studies were grouped by vegetation type and soil types. Studies were also grouped by buffer width categories (0-5m, 5-10m, 10-20m and >20m). Box plots were created to visualize the distribution of buffer sediment trapping efficiency with vegetation types, soil types and width categories. Linear and nonlinear relationships between different buffer design characteristics with removal effectiveness were fitted to regression models and evaluated. Regression relationships between variables were also examined for potentially reconstructing missing data and avoid losing valuable information.

Manual stepwise regression (forward) approach was utilized using nonlinear regression fitting to construct a sediment reduction model using variables that we identified to be most relevant to buffer installation and maintenance. At every step, variables were added or discarded based on their goodness-of-fit measures such as R^2 and *AIC*. All analyses were performed using R version 3.1.3 (R Core Team 2013).

5. Results and discussion

5.1 General efficacy

The literature used for this analysis is summarized in Appendix: Table 1A and consists of 361 data entries from 54 studies, which includes data from the online BMP database. The table includes parameters related to buffer characteristics such as width, area, vegetation type, slope, area ratio of contributing source to buffer, soil type categories, flow volumes, and flow rates. Only entries associated with positive sediment removal were considered. Overall sediment removal efficiency varied from 0 to 100% with a mean removal of 77% and median removal of 83%. For data entries categorized as long-term, efficiency ranged from 0 - 100% with mean and median efficiencies of 75 and 79%, respectively. For the event-based category, the efficacies varied from 3.5 to 100% with mean and median efficacies of 78 and 84%, respectively.

5.2 Effect of vegetation type and soil drainage

The effect of vegetation type on buffer's sediment removal efficiency were statistically significant (Kruskal Wallis $H = 11.45$, df = 2, $p = 0.003$). From the boxplot in Figure 3 sediment trapping efficiency is significantly higher for grass buffers and mixed grass-woody vegetation than for woody vegetation-only buffers ($p < 0.05$; Wilcoxon rank sum test). However, of the studies considered, only 7 entries had woody-only vegetation and 44 had mixed vegetation while 310 entries had grass vegetation. Clearly there is a need for more data on woody and mixed buffers to get an effective comparison of their performance with respect to grass buffers. Median trapping efficacy for herbaceous buffers was similar to that of mixed vegetation buffers. These results are similar to those in Yuan et al. (2009) who, in their literature review and analysis, found both forested and grassy vegetation buffers to have similar sediment trapping efficiencies. However, a common observation is that much more information exists for grass buffers than mixed buffers, and there is a need for more detailed studies on mixed vegetation buffers. The effect of soil type on % sediment reduction was not statistically significant.

5.3 Effect of buffer width and slope

From the boxplot in Figure 4, buffer width significantly influences the buffer's sediment reduction efficiency (Kruskal-Wallis $H = 22.12$, df = 3, $p<0.001$), with the 10-20m buffer width achieving statistically higher sediment reduction than either the 0-5m, 5-10m or >20m width categories (Wilcoxon rank sum test $p < 0.001$).

Plotting % removal versus buffer width on a regression plot seemed very scattered with no clear trend. For greater visual clarity we calculated the average sediment removal for each value of buffer width and analyzed this plot to discern relationships. These trends were assessed for buffer widths between 1 to 40 m which included 95% of the data. Figure 5a shows the relationship between buffer sediment trapping efficiency and buffer width after pooling both event-based and longer-term data. From the plot, a polynomial regression model best describes the relationship (R^2 = 0.31). Figure 5b shows that the relationships between % sediment removal and buffer width are described by a polynomial relationship for grass buffers (R^2 = 0.31) and a logarithmic relationship for mixed buffers (R^2 = 0.31).

Yuan et al. (2009) observed that buffers were more effective for slopes >5% than for those with slope ≤ 5%. In our analysis we observed no clear relationship between width and removal for slopes ≤ 5%. Figure 6 shows the relationship between buffer width and average sediment removal for slopes > 5%. This relationship is best described using a polynomial relationship (R^2 = 0.25). Similar relationship was obtained for grass buffers with slopes >5%. Zhang et al. (2009) observed that a critical slope of 10% changed the relationship between slope and sediment reduction from positive negative. In this study we could not clearly identify any critical slope which influenced the direction of impact on sediment reduction by the buffer.

5.4 Volumes and Flow rates

Volume ratio (V_r), calculated as inflow volume divided by outflow volume, was used to evaluate the effect of runoff reduction on sediment reduction. Figure 7 shows the relationship between volume ratio and sediment removal by the buffer. The relationship is best explained using an exponential regression model (R^2 = 0.31); volume ratio, also a proxy for flow rate ratio in this study since volume and flow rate ratios were 99.9% correlated, is the best predictor for sediment removal yet in this study. These results are similar to those derived by White and Arnold (2009) where they observed that runoff reduction explained around 20% of the variability in their measured data.

Other variables including flow rates and volumes, area ratio, roughness and residence time parameters, sediment loading into the buffer did not present clear trends on plotting with sediment removal.

5.5 Sediment removal multiple regression model

For the purpose of developing a sediment reduction model only event-based data were considered which included 287 entries. Of these, flow rates could be calculated for fewer than 180 entries. To avoid losing valuable information for model development and to enable the inclusion of flow rate as a predictor in model construction, we attempted to reconstruct missing flow data based on univariate regression relationships with good fit (high R^2) between relevant variables. This included regression relationships between outflow rate and outflow volume ($Q_{out} = 14.7 * V_{out}$; $R^2 = 0.70$; $N = 161$) and that between ratios of flow rates and flow volumes (1:1 relationship with $R^2 = 1$, $N = 170$) (Appendix: Table 1B). Of these, we considered data for which buffer widths were < 40m, slopes under 40%, and studies where inflow volume was no more than 60X outflow volume, and for which outflow volumes were no more than 3X inflow volumes, i.e., $0.3 \leq V_{in}/V_{out} \leq 60$. These bounds were considered since most of the event-based data entries fell within these boundaries. Omitting entries with missing values and applying afore-mentioned conditions resulted in a total of 203 entries which were used to construct the sediment reduction model.

Factors considered for the model building process were buffer width (w), slope (s), sediment load per unit buffer area (L_{in}/A), inflow rate over unit buffer area (Q_{in}/A), average flow rate (Q_{av}), ratio of flow volumes (V_{in}/V_{out} or V_r), roughness factor (n), residence time factors (t_1, t_2 and t_3 from eqns 4, 5 and 8 respectively), and their square, log and exponential transformations. Predictors (or their transformations) were added in a stepwise forward manner to the nonlinear regression model based on the significance of their coefficients, overall R^2 and AIC values. R^2 varies from 0 to 1, and better model performance is indicated by a higher R^2. AIC is an indicator of model parsimony, and a lower AIC relative to other models is representative of a more parsimonious model.

The ratio of flow volumes (V_r) alone accounted for 36% of the variability in the observed data. Adding the square of residence time increased the R^2 to 39.2%, while adding an exponential transformation of width further increased R^2 to 40.5%. The final model (given below) has an acceptable R^2 of 40.5% (Table 1).

% Sediment reduction $R_m = 96.82 - 66.53 * e^{(-0.86*Vr)} - 0.014*t^2 - 2.26*10^{-11}*e^{(w)}$

where $V_r = V_{in}/V_{out}$, and $t = \left(\frac{w^{0.6}}{q^{0.4}s^{0.3}}\right)$ from eqn 4. From the sediment reduction plot in Figure 8, the model overpredicts for smaller values of observed reduction, but predicts higher values with greater precision.

Model performance was compared with that derived from applying other sediment reduction regression models developed in literature, such as those of White and Arnold (2009), Liu et al. (2008) and Zhang et al. (2009), to data entries in this study (Table 1). Of these only the model presented by White and Arnold (2009) was statistically significant. This model had the next highest R^2, with the Liu et al. (2008) and Zhang et al. (2009) models having much poorer performance. This could be because of the inclusion of runoff reduction in the White and Arnold (2009) model (calculated as $[(V_{in} – V_{out}) *100]/ V_{in}$) in their study). While the model in the White and Arnold (2009) study had a significant correlation between sediment loading and sediment reduction with their data (R^2 = 41%), our study did not present any significant relationship with sediment loading. This could be because of the larger number of entries considered for this study (203 entries) as opposed to 61 in the White and Arnold (2009) paper. Another reason for this difference could be the way in which we accounted for sediment loads and runoff volumes in this study.

For grass buffers (N = 161), V_r alone accounted for 46.5 % of the variability in the observed data. Adding the exponential function of width and the square root of average flow rate further increased the R^2 to 52.9%. The only other statistically significant model was the White and Arnold (2009) model (R^2 = 43%) The final sediment reduction model for mixed buffers (N = 36) included inflow rate and the volume ratio with an R^2 of 31.1% (Table 1) which was higher than the other models.

The results of this study point towards the importance of considering flow in buffer design. This is evident from the better fit obtained for models that considered flows versus those which didn't. However, the overall model accounted only for 40.5% of the total variance (and 53% of the variance for grass buffers). Several other factors may be responsible for the large percentage of unaccounted variation. This study only considers sediment removal under uniform sheet flow conditions. However, it is not possible to assure complete sheet flow conditions in these systems. Surface structure variations as a result of surface peaks and depressions in the flow path, differential infiltration capacities along the flow path, presence of vegetation and other organic matter, rainfall on the buffer, sediment deposition and erosion can cause convergence or divergence of flow. Moreover, sediment accumulation can change microtopography of the buffer aiding flow concentration (Gharabaghi et al. 2006). Studies such as Helmers et al. (2005) observed decline in buffer's sediment reduction with increase in flow convergence. Adjustments for flow concentration or divergence was not considered in this study. Factors such as vegetation height, density, shape and resilience can greatly influence the sediment deposition within the buffer. The denser the vegetation, more sediment can be trapped by the buffer. However, vegetation density could not be accounted for in this study, due to lack of reporting. Further research is needed as more information becomes available.

6. Conclusions

Sediment reduction by vegetated buffers are a consequence of synergistic influences of the physical dimensions of the buffer as well as their site-specific hydrological responses to local runoff/storm events. Very few models consider hydrological responses, understandably, because of the lack of detailed information reported in literature. This study includes a comprehensive database of 54 studies consisting of 361 entries which were used for evaluating the influence of various factors including the buffer's physical and hydrological characteristics on its sediment reduction capacity. Applying constraints to the database, 203 entries were used to construct a nonlinear sediment reduction model using stepwise forward regression approach. A regression equation considering the hydrological response of the buffer, included as the exponential transformation of ratio of flow volumes V_{in}/V_{out}, was observed to be the most influential factor in predicting sediment reduction capacity accounting for 36% of the variance in measured sediment reduction. Addition of terms considering residence time and width improved the performance to account for 40.5% of the variability in measured sediment reduction. The model developed during the course of this study outperformed existing models developed from similar work which considered fewer variables and/or which did not consider hydrological responses when applied to the data in this study – R^2 was slightly higher than a previously published model which included runoff reduction (White and Arnold (2009) sediment reduction model), and significantly higher than models which considered only physical characteristics (sediment reduction models in Liu et al. (2008) and Zhang et al. (2009)). The sediment reduction model from this study may be used in conjunction with other models when necessary. For instance, where runoff characteristics are lacking, models such as the VFSMOD derived runoff reduction equation from White and Arnold (2009) maybe used to calculate runoff reduction and used to determine the buffer's sediment reduction efficiency.

Presumably this model has many limitations. While effort was made to include data with uniform sheet flow, it is possible that this assumption was overlooked. For instance, buffer slopes intuitively influence runoff velocity and consequently flow conditions. Gradual slopes promote laminar sheet flow while steeper slopes can cause flow to concentrate leading to lesser sediment reduction. However, we did not find any relationship between slope and average flow rates in this study. Moreover, most of the data in the study comes from experimental plots, which many researchers suggest overestimate the real effectiveness of vegetated buffers (White and Arnold 2009). Experimental plots are typically tested over the short-term, and do not account for long-term sediment accumulation in the buffer that can decrease its sediment trapping efficiency (Sweeney and Newbold 2014). Another overlooked factor is rainfall on the buffer. This was deliberately overlooked in an attempt to compare apples-to-apples since studies showed much variation in how they initiated runoff, ranging from natural rain events on source and buffer, to rain events only on the contributing source area, to rainfall on entire areas together with sediment laden inflows, and so on. The intensity and duration of rainfall on the filters and antecedent soil moisture conditions can have a huge influence on the functional capacity of these buffer systems. This could have influenced our consideration of flow rates and flow volumes in the absence of detailed flow characteristics. Moreover, most experimental plots consider sediment delivery from smaller contributing areas, or small design storms (in case of simulated rainfall), when it is >10 year return interval storms that deliver most sediment over the long term (Sweeney and Newbold 2014).

A high level of uncertainty still exists regarding the required conditions for the installation of the optimum buffer. Nevertheless, this study provides a valuable insight into the conditions of several vegetated buffers systems through the extensive data compiled, as well as formulates a more complete secondary analysis model that includes the importance of hydrological considerations. The results of this study can prove useful to managers to effectively asses the effectiveness of site-specific buffers along with a comprehensive baseline to make management decisions regarding buffers and sediment control. However, it is important to note that this study considers only the sediment trapping efficiency of the buffer, and cannot be extended as to other aspects of ecosystem improvement such as temperature regulation, stream bank stabilization, or maintenance of riparian habitats and biodiversity.

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Figures

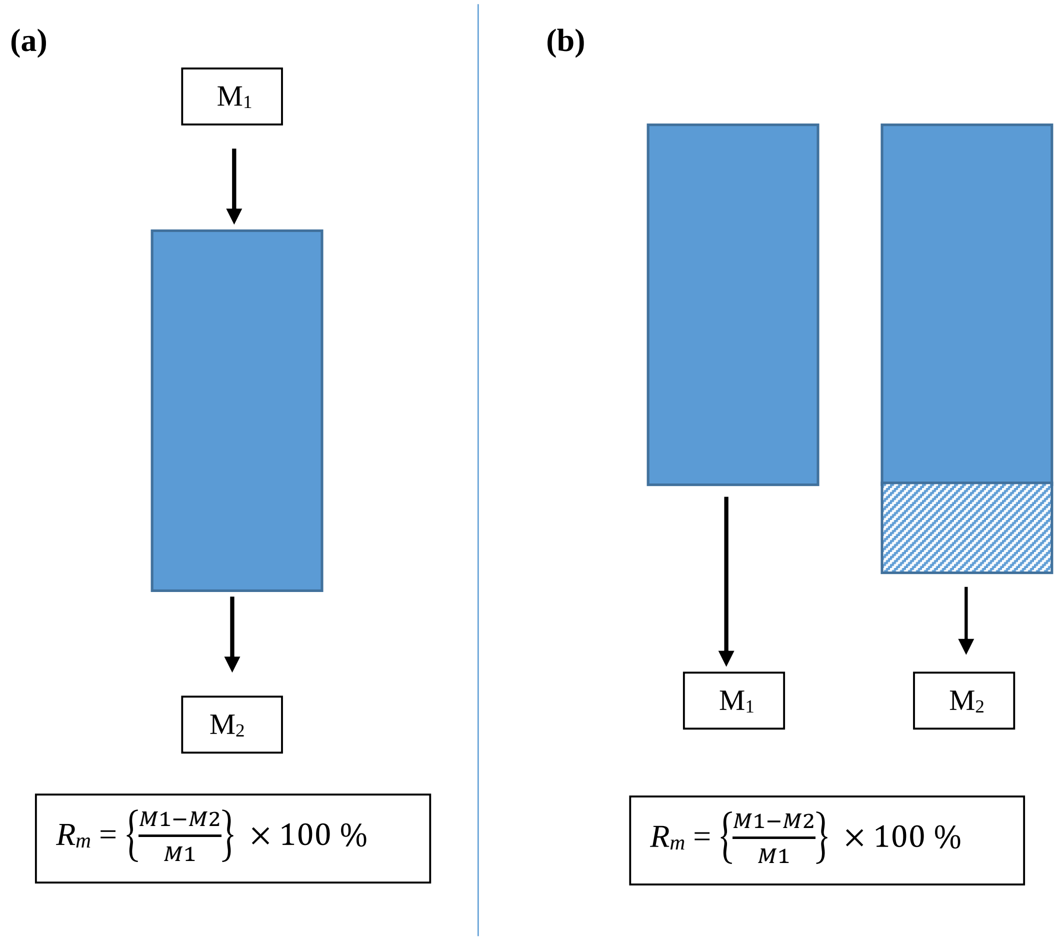

Figure 1. Percent sediment removal effectiveness was calculated in two ways depending on how data was provided. If load characteristics were reported for the buffer as presented in (a), then % removal (R_m) was calculated as the difference in loads between influent into (M_1) and effluent out of the buffer (M_2). If the study compared performances of control versus buffered sites and reported outflow load characteristics for these sites as presented in (b), then % removal (R_m) was calculated as the percentage difference in loads between edge of a cropland with no buffer (M_1) and that with a test buffer (M_2).

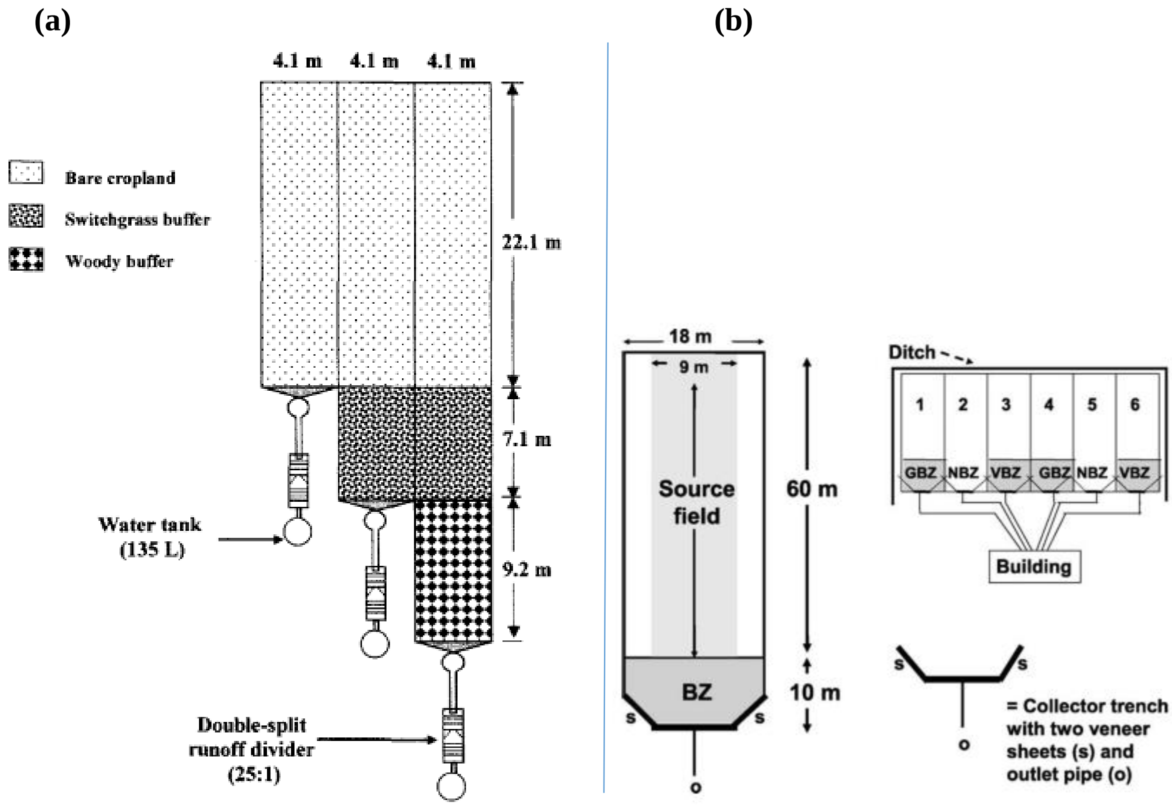

Figure 2(a). Experimental plot design in study by Lee et al. (2000) where sediment loads from the bare cropland area is assumed to be loading into the buffers and runoff volumes were converted to depth over the entire plot area (source plot with no buffer, or source plot + buffer as the case may be).

Fig. 2(b). Experimental plot design in study by Uusi-Kämppä and Jauhiainen (2010) where the dimensions of the buffered and non-buffered plots are different.

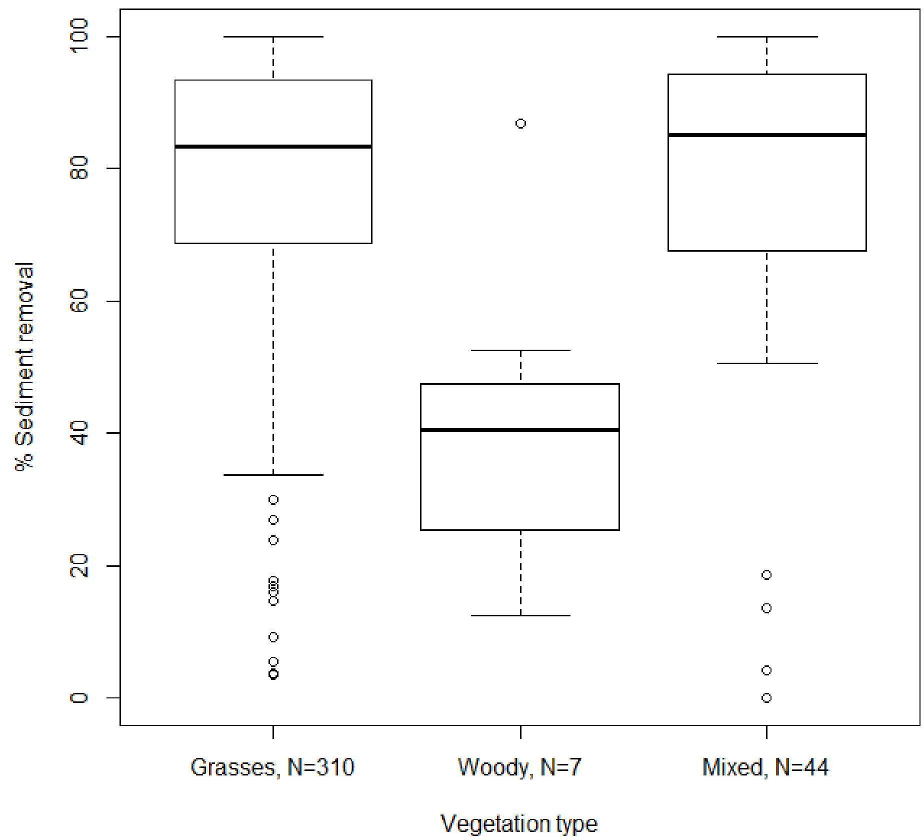

Figure 3. Boxplot of % sediment reduction for different vegetation types (grass, woody, mixed). The lower and upper boundary indicate the 25th and 75th percentile, while the bold line within the box indicates the median sediment removal for each vegetation type. Sediment reduction is higher for grass and mixed vegetation buffers and lower for woody vegetation buffers (Kruskal Wallis p = 0.003).

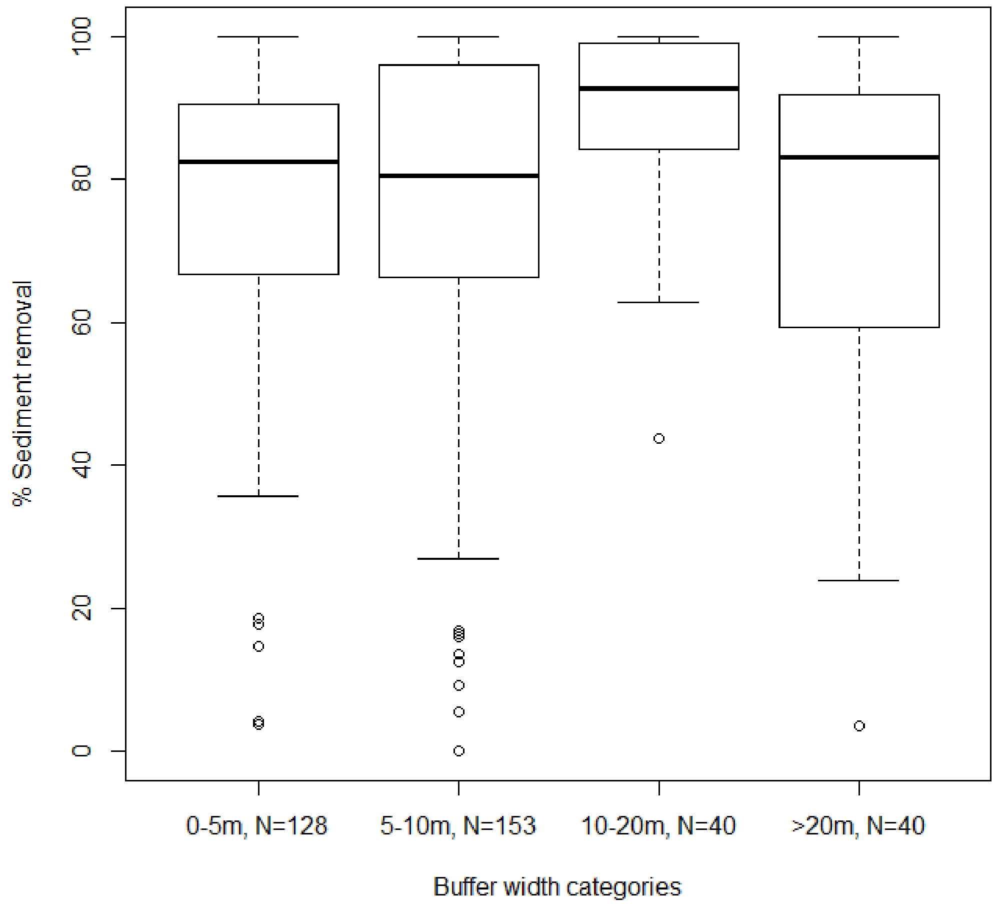

Figure 4. Boxplot of % sediment reduction for different width categories. The lower and upper boundary indicate the 25th and 75th percentile, while the bold line within the box indicates the median sediment removal for each width category. The bars above and below the box represent the 90th and 10th percentiles of sediment reduction respectively. Sediment reduction is highest for the 10m – 20m width category and significantly lower for the 0 – 5m, 5-10m and >20m width categories (Kruskal-Wallis p<0.001).

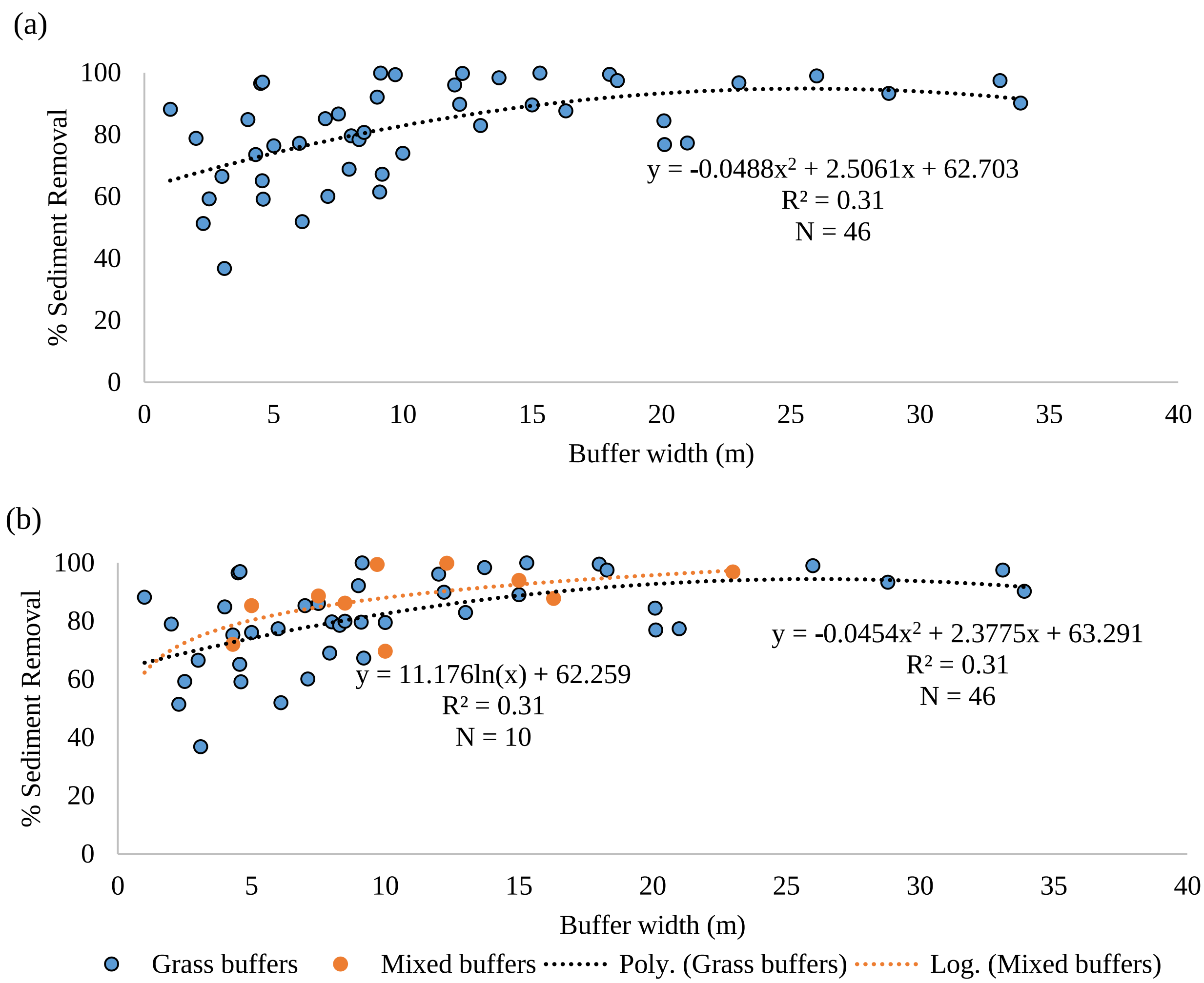

Figure 5a. Relationship between buffer sediment trapping efficiency and buffer width after pooling both event-based and longer-term data for buffers widths ≥ 1m. From the plot, a polynomial regression model best describes the relationship (R^2 = 0.31).
Figure 5b. Relationship between buffer sediment trapping efficiency and buffer width after pooling both event-based and longer-term data for grass buffers and mixed vegetation buffers for widths ≥ 1m. From the plot, a polynomial regression model best describes the relationship for grass buffers (R^2 = 0.31) and a logarithmic regression model best describes the relationship for mixed buffers (R^2 = 0.31).
*Each data point represents the average sediment reduction for each value of buffer width.

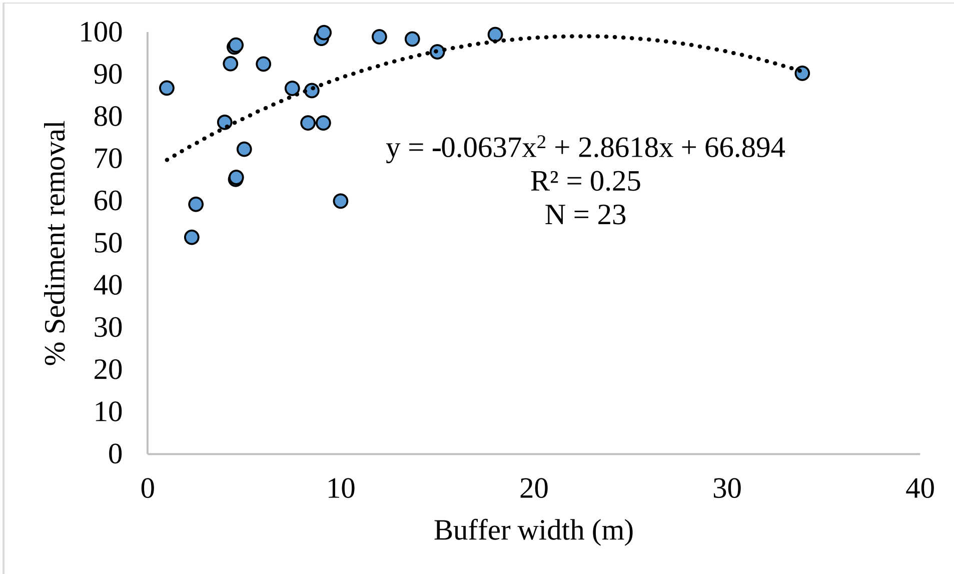

Figure 6. Relationship between buffer width and average sediment removal for slopes >5%. This relationship is best described by a polynomial relationship (R^2 = 0.25). Similar relationship was obtained for grass buffers with slopes >5%.

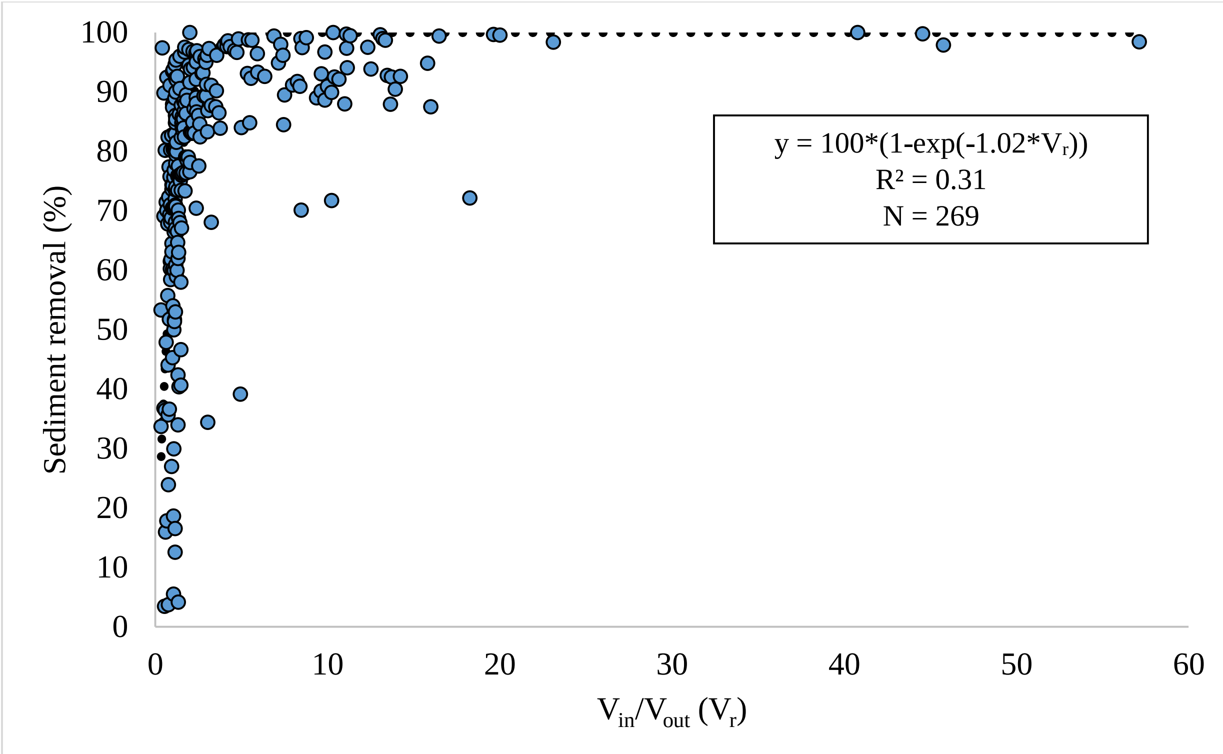

Figure 7. Relationship between volume ratio and sediment removal by the buffer for $0.3 \leq V_r \leq 60$. The relationship is best explained using an exponential regression model ($R^2 = 0.31$).

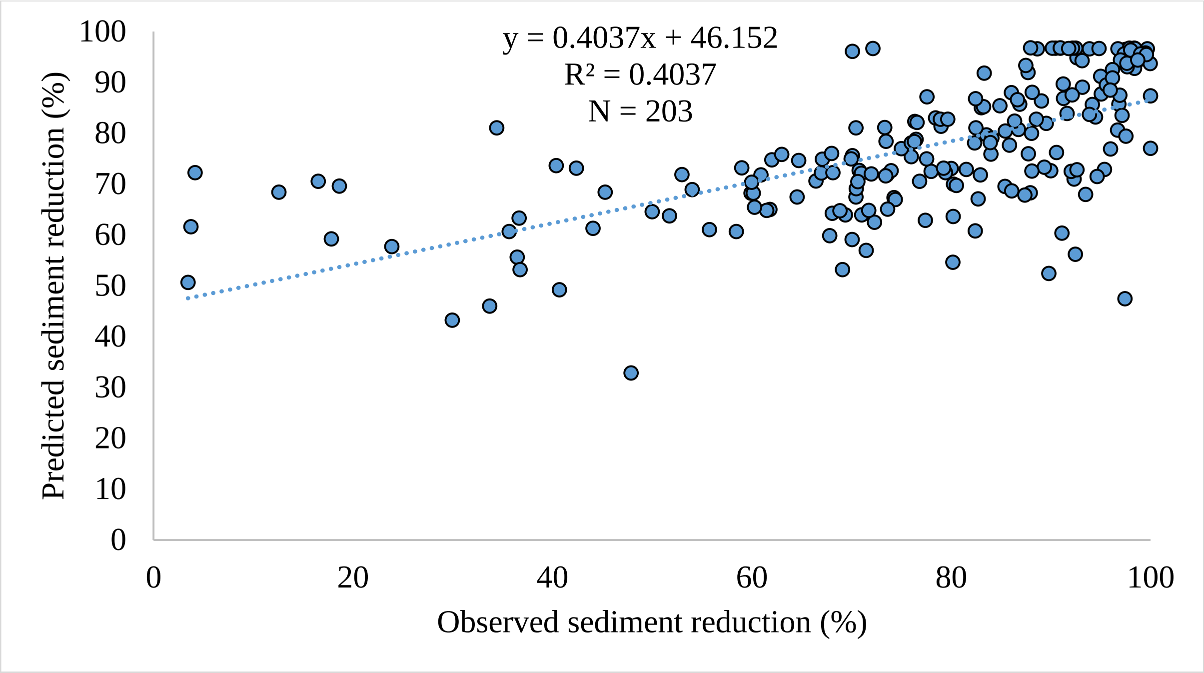

Figure 8. Plot of predicted sediment reduction (using model R_m = 96.82 - 66.53*e $^{(-0.86*Vr)}$ - 0.014*t_1^2 - 2.26*10^{-11}*e $^{(w)}$) versus observed sediment reduction.

Tables

Table 1. Nonlinear regression models for predicting % sediment reduction for the data presented in Appendix: Table 1B. Results are also presented for the application of other meta-analysis models to this data.

	This study	White and Arnold (2009)	Liu et al. (2008)	Zhang et al. (2010)
Full model	$a + b * \exp(c * V_r) + d * (t_1^2) + e * \exp(w)$	$a + b * L_{in}/A + c * (Rr\ \%)$	$a + b*(w) + c*(s) - d*(s^2)$	$k * (1 - \exp(-b * w)$
	a=96.82* (91.54 , 102.10)	a=70.08* (67.16 , 72.99)	a = 76.40* (68.24 , 84.55)	k = 77.43* (74.51 , 80.35)
	b=-66.53* (-85.07 , -48.00)	b=0.008 (-0.34 , 0.36)	b = -0.21 (-0.78 , 0.36)	b = 7.59 (-16.15 , 31.32)
	c=-0.86* (-1.20 , -0.52)	c=0.24* (0.19 , 0.29)	c = 48.97 (-140.37 , 238.31)	
	d=-0.014* (-0.03 , -7.19e-04)		d =32.17 (-926.67 , 991.02)	
	e=-2.26e-11* (-4.47e-11 , -4.35e-13)			
R^2	0.40	0.32	0.02	0.00
AIC	1715.51	1738.59	1814.94	1814.40
N	203	203	203	203
p-value	< 0.001	< 0.001	0.33	0.82
Grasses-only model	$a + b * \exp(c * V_r) + d * \exp(w) + e*\sqrt{Q_{av}}$	$a + b * L_{in}/A + c * (Rr\ \%)$	$a + b*(w) + c*(s) - d*(s^2)$	$k * (1 - \exp(-b * w)$
	a = 94.08* (89.89 , 98.27)	a =71.98* (69.24 , 74.72)	a = 78.24* (69.55 , 86.92)	k = 78.90* (75.83 , 81.96)
	b = -68.45* (-86.27 , -50.62)	b =-0.06 (-0.36 , 0.24)	b = -0.31 (-0.88 , 0.26)	b = 6.73 (-7.37 , 20.82)
	c = -0.94* (-1.28 , -0.60)	c = 0.24* (0.19 , 0.28)	c = 82.02 (-119.52 , 283.56)	
	d = -3.45e-11* (-5.09e-11 , -1.80e-11)		d = 278.95 (-735.34 , 1293.24)	
	e = 0.22e* (1.97e-03 , 0.45)			
R^2	0.53	0.43	0.02	0.00
AIC	1301.92	1329.85	1417.86	1416.89
N	161	161	161	161
p-value	< 0.001	< 0.001	0.38	0.71
Mixed-only model	$a + b * \exp(Q_{in}/A) + c*\log(V_r)$	$a + b * L_{in}/A + c * (Rr\ \%)$	$a + b*(w) + c*(s) - d*(s^2)$	$k * (1 - \exp(-b * w)$
	a = 69.33* (58.75 , 79.92)	a = 45.84* (22.67 , 69.01)	a = 64.32* (43.72 , 84.91)	a = 80.2960* (71.12 , 89.47)
	b = -0.01* (-0.01 , -0.002)	b = 24.47 (-4.02 , 52.95)	b = 1.18 (-1.10 , 3.45)	b = 0.53* (0.09 , 0.96)
	c = 23.78 (3.75 , 43.82)	c = 0.65* (0.25 , 1.05)	c = 10.67 (-438.76 , 460.09)	
			d =-222.59 (-2509.73 , 2064.55)	
R^2	0.31	0.25	0.07	0.03
AIC	313.41	316.61	326.19	323.68
N	36	36	36	36
p-value	0.002 **	0.009 **	0.49	0.30

* indicates significance at 0.05 level

Appendix:

Table 1A. Data on vegetated buffers physical and hydrological characteristics compiled for the study. Overall this included 361 entries (includes entries from online stormwater BMP database). Flow rates and volumes were either directly taken from the study or calculated from other available information reported in the study.

Study	Soil type	Veg. type	Width (m)	Area (m^2)	Slope (%)	Area ratio	Q_{in} (L/min)	Q_{out} (L/min)	V_{in} (m^3)	V_{out} (m^3)	L_{in} (kg/m^2)	L_{out} (kg/m^2)	Sediment removal (%)
Lee et al 1999	4	1	6	9.00	3	20.00	40.00	32.00	-	-	-	-	78.20
Lee et al 1999	4	1	6	9.00	3	20.00	40.00	31.00	-	-	-	-	74.80
Lee et al 1999	4	1	3	4.50	3	40.00	40.00	36.00	-	-	-	-	69.00
Lee et al 1999	4	1	3	4.50	3	40.00	40.00	35.00	-	-	-	-	62.00
Lee et al 2003	4	1	7	28.70	5	3.11	-	-	2.45	2.51	0.44	0.13	70.44
Lee et al 2003	4	1	7	28.70	5	3.11	-	-	0.82	0.72	0.18	0.04	80.25
Lee et al 2003	4	1	7	28.70	5	3.11	-	-	0.36	0.24	0.04	0.01	67.08
Lee et al 2003	4	1	7	28.70	5	3.11	-	-	2.08	1.07	16.67	0.92	94.49
Lee et al 2003	4	1	7	28.70	5	3.11	-	-	2.45	1.43	44.57	1.47	96.71
Lee et al 2003	4	1	7	28.70	5	3.11	-	-	0.82	0.48	4.82	0.12	97.52
Lee et al 2003	4	2	9.1	37.31	5	3.20	-	-	2.51	2.20	0.13	0.11	16.53
Lee et al 2003	4	2	9.1	37.31	5	3.20	-	-	0.72	0.63	0.04	0.03	12.56
Lee et al 2003	4	2	9.1	37.31	5	3.20	-	-	0.24	0.08	0.01	0.01	34.42
Lee et al 2003	4	2	9.1	37.31	5	3.20	-	-	1.08	0.79	0.92	0.55	40.38
Lee et al 2003	4	2	9.1	37.31	5	3.20	-	-	1.44	1.10	1.47	0.85	42.42
Lee et al 2003	4	2	9.1	37.31	5	3.20	-	-	0.48	0.16	0.12	0.02	86.88
Deng et al 2011	-	3	10	30.00	2	-	138.00	-	2.66	1.22	4.62	0.15	96.83
Deng et al 2011	-	3	10	30.00	2	-	138.00	-	2.94	1.22	7.94	0.24	96.92
Deng et al 2011	-	3	10	30.00	2	-	138.00	-	3.08	1.58	5.14	0.15	97.14
Deng et al 2011	-	3	10	30.00	2	-	228.00	-	3.08	1.72	4.87	0.51	89.56
Deng et al 2011	-	1	10	30.00	2	-	138.00	-	2.66	0.49	4.34	0.05	98.75
Deng et al 2011	-	1	10	30.00	2	-	138.00	-	2.66	0.63	4.38	0.06	98.60
Deng et al 2011	-	1	10	30.00	2	-	228.00	-	2.66	0.66	4.46	0.09	97.92

Deng et al 2011	-	1	10	30.00	2	-	138.00	-	2.94	0.61	8.36	0.09	98.90
Coyne et al 1995	2	1	9	41.40	9	2.50	29.35	4.27	2.79	0.32	6.86	0.06	99.13
Coyne et al 1995	2	1	9	41.40	9	2.50	48.38	6.17	4.62	0.55	13.87	0.14	98.96
Dillaha et al 1989	2	1	9.1	50.05	11	2.00	20.88	5.02	2.51	0.60	18.82	0.30	98.40
Dillaha et al 1989	2	1	9.1	50.05	11	2.00	38.50	17.46	4.62	2.09	20.63	1.21	94.16
Dillaha et al 1989	2	1	4.6	25.30	11	4.00	20.88	20.89	2.51	2.51	18.82	2.27	87.95
Dillaha et al 1989	2	1	4.6	25.30	11	4.00	38.50	48.49	4.62	5.82	20.63	4.66	77.41
Dillaha et al 1989	2	1	9.1	50.05	16	2.00	19.21	19.21	2.30	2.31	42.78	11.00	74.28
Dillaha et al 1989	2	1	9.1	50.05	16	2.00	27.59	47.60	3.31	5.71	47.20	29.99	36.47
Dillaha et al 1989	2	1	4.6	25.30	16	4.00	19.21	17.53	2.30	2.10	42.78	14.36	66.43
Dillaha et al 1989	2	1	4.6	25.30	16	4.00	27.59	41.04	3.31	4.92	47.20	38.79	17.82
Barfield et al 1998	2	1	4.57	20.89	9	4.84	50.61	5.94	6.07	0.71	103.00	2.62	97.46
Barfield et al 1998	2	1	4.57	20.89	9	4.84	77.23	7.85	9.27	0.94	258.00	8.44	96.73
Barfield et al 1998	2	1	4.57	20.89	9	4.84	76.92	3.92	9.23	0.47	55.70	0.18	99.68
Barfield et al 1998	2	1	4.57	20.89	9	4.84	75.08	6.00	9.01	0.72	67.40	4.13	93.87
Barfield et al 1998	2	1	9.14	41.77	9	2.42	26.86	0.23	3.22	0.03	26.60	0.02	99.93
Barfield et al 1998	2	1	9.14	41.77	9	2.42	58.18	5.14	6.98	0.62	212.00	1.10	99.48
Barfield et al 1998	2	1	9.14	41.77	9	2.42	35.88	0.00	4.31	0.00	19.60	0.00	100.00
Barfield et al 1998	2	1	9.14	41.77	9	2.42	3.94	0.10	0.47	0.01	21.50	0.00	100.00
Barfield et al 1998	2	1	13.72	62.70	9	1.61	73.83	5.19	8.86	0.62	28.40	2.09	92.64
Barfield et al 1998	2	1	13.72	62.70	9	1.61	96.95	5.88	11.63	0.71	361.00	2.06	99.43
Barfield et al 1998	2	1	13.72	62.70	9	1.61	5.08	0.00	0.61	0.00	0.98	0.00	100.00
Barfield et al 1998	2	1	13.72	62.70	9	1.61	41.10	3.98	4.93	0.48	10.30	0.00	99.98
Arora et al 1996	4	1	20.12	30.58	2	30.00	98.17	38.08	1.96	0.76	-	-	84.60
Arora et al 1996	4	1	20.12	30.58	2	30.00	98.17	75.23	1.96	1.50	-	-	75.90
Arora et al 1996	4	1	20.12	30.58	2	30.00	98.17	27.68	1.96	0.55	-	-	90.20
Arora et al 1996	4	1	20.12	30.58	2	15.00	49.08	15.14	0.98	0.30	-	-	91.10
Arora et al 1996	4	1	20.12	30.58	2	15.00	49.08	22.78	0.98	0.46	-	-	83.10
Arora et al 1996	4	1	20.12	30.58	2	15.00	49.08	29.82	0.98	0.60	-	-	88.40
McGregor et al 1999	2	1	0.5	2.00	5	43.20	-	-	3.46	2.92	12.10	3.54	70.77
McGregor et al 1999	2	1	0.5	2.00	5	43.20	-	-	4.15	3.62	41.47	7.07	82.95

McGregor et al 1999	2	1	0.5	2.00	5	43.20	-	-	4.32	4.24	128.74	38.01	70.47
McGregor et al 1999	2	1	0.5	2.00	5	43.20	-	-	3.54	4.60	114.91	31.82	72.31
Magette et al 1989	1	1	9.2	50.60	3	2.39	63.12	54.05	3.79	3.24	70.83	5.43	92.33
Magette et al 1989	1	1	9.2	50.60	3	2.39	37.71	42.61	2.26	2.56	9.45	1.87	80.22
Magette et al 1989	1	1	9.2	50.60	3	2.39	75.83	68.64	2.27	2.06	16.22	3.16	80.54
Magette et al 1989	1	1	9.2	50.60	3	2.39	58.89	67.50	1.77	2.02	6.62	1.92	71.03
Magette et al 1989	1	1	9.2	50.60	3	2.39	79.46	88.09	2.38	2.64	13.65	5.21	61.81
Magette et al 1989	1	1	9.2	50.60	3	2.39	65.74	91.52	1.97	2.75	8.32	2.68	67.83
Magette et al 1989	1	1	4.6	25.30	3	4.78	63.12	66.57	3.79	3.99	70.83	12.24	82.71
Magette et al 1989	1	1	4.6	25.30	3	4.78	37.71	43.16	2.26	2.59	9.45	3.64	61.51
Magette et al 1989	1	1	4.6	25.30	3	4.78	75.83	91.19	2.27	2.74	16.22	4.97	69.38
Magette et al 1989	1	1	4.6	25.30	3	4.78	58.89	72.66	1.77	2.18	6.62	4.20	36.66
Magette et al 1989	1	1	4.6	25.30	3	4.78	79.46	105.82	2.38	3.17	13.65	13.14	3.74
Magette et al 1989	1	1	4.6	25.30	3	4.78	65.74	88.76	1.97	2.66	8.32	4.65	44.07
W.J White et al 2007	2	3	10	50.00	1.5	32.00	144.00	100.97	13.00	9.12	27.30	8.74	68.00
W.J White et al 2007	2	3	10	50.00	1.5	32.00	151.00	108.49	13.00	9.34	19.76	4.74	76.00
W.J White et al 2007	1	3	10	50.00	6	32.00	160.00	111.45	13.00	9.06	25.22	6.31	75.00
W.J White et al 2007	1	3	10	50.00	6	32.00	173.00	114.21	13.00	8.58	30.03	7.21	76.00
W.J White et al 2007	1	3	10	50.00	6	32.00	196.00	168.86	13.00	11.20	29.90	14.05	53.00
W.J White et al 2007	1	3	10	50.00	6	32.00	197.00	150.17	13.00	9.91	25.74	9.78	62.00
W.J White et al 2007	1	3	10	50.00	11	32.00	200.00	163.43	13.00	10.62	33.80	13.86	59.00
W.J White et al 2007	1	3	10	50.00	11	32.00	156.00	133.21	13.00	11.10	33.80	9.80	71.00
W.J White et al 2007	1	3	10	50.00	11	32.00	206.00	176.56	13.00	11.14	30.55	10.08	67.00
W.J White et al 2007	1	3	10	50.00	11	32.00	188.00	138.73	13.00	9.59	30.55	11.30	63.00
W.J White et al 2007	1	3	10	50.00	16	32.00	167.00	117.80	13.00	9.17	28.99	1.16	96.00
W.J White et al 2007	1	3	10	50.00	16	32.00	167.00	140.42	13.00	10.93	34.19	3.42	90.00
W.J White et al 2007	1	3	10	50.00	16	32.00	176.00	152.36	13.00	11.25	30.29	8.48	72.00
W.J White et al 2007	1	3	10	50.00	21	32.00	196.00	161.62	13.00	10.72	38.09	7.62	80.00
W.J White et al 2007	1	3	10	50.00	21	32.00	203.00	172.32	13.00	11.04	22.23	4.89	78.00
Boyd et al. 2003	4	1	20.1	30.15	2	45.00	139.43	63.30	8.23	3.26	19.50	4.37	77.57
Boyd et al. 2003	4	1	20.1	30.15	2	15.00	48.91	20.93	2.74	0.92	6.49	0.57	91.27

Melville and Morgan 2001	1	1	1	3.00	5	6.00	2.14	0.14	0.10	0.01	0.17	0.01	94.83
Melville and Morgan 2001	1	1	1	3.00	5	6.00	4.45	0.10	0.20	0.00	0.23	0.00	97.89
Melville and Morgan 2001	1	1	1	3.00	5	6.00	3.58	2.38	0.16	0.11	0.24	0.06	73.48
Melville and Morgan 2001	1	1	1	3.00	5	6.00	2.14	0.02	0.10	0.00	0.17	0.00	98.16
Melville and Morgan 2001	1	1	1	3.00	5	6.00	4.45	0.19	0.20	0.01	0.23	0.00	98.37
Melville and Morgan 2001	1	1	1	3.00	5	6.00	3.58	0.06	0.16	0.00	0.24	0.00	98.43
Helmers et al 2005	2	1	13	195.00	1	-	-	-	111.24	149.67	152.31	26.79	82.41
Helmers et al 2005	2	1	13	195.00	1	-	-	-	61.35	109.02	14.60	2.90	80.16
Helmers et al 2005	2	1	13	195.00	1	-	202.98	263.97	111.72	132.65	18.56	1.65	91.11
Helmers et al 2005	2	1	13	195.00	1	-	-	-	189.00	155.10	144.42	26.70	81.51
Helmers et al 2005	2	1	13	195.00	1	-	-	-	186.66	156.66	535.05	109.95	79.45
Helmers et al 2005	2	1	13	195.00	1	-	-	-	143.81	149.96	355.74	91.13	74.38
Helmers et al 2005	2	1	13	195.00	1	-	-	-	268.50	232.16	267.48	70.71	73.56
Helmers et al 2005	2	1	13	195.00	1	-	-	-	106.80	87.38	16.25	1.29	92.06
Helmers et al 2005	2	1	13	195.00	1	-	336.61	325.11	215.84	182.49	50.16	7.32	85.41
Helmers et al 2005	2	1	13	195.00	1	-	752.32	741.84	155.96	122.70	146.01	10.76	92.63
Helmers et al 2005	2	1	13	195.00	1	-	-	-	138.69	78.54	346.91	72.86	79.00
Helmers et al 2005	2	1	13	195.00	1	-	-	-	126.86	59.88	161.40	27.38	83.04
Abu-Zreig et al 2004	2	1	2	2.40	2.3	-	51.32	38.49	2.93	2.19	0.01	0.00	70.10
Abu-Zreig et al 2004	2	1	2	2.40	2.3	-	35.70	11.78	2.29	0.75	0.01	0.00	83.32
Abu-Zreig et al 2004	2	1	2	2.40	2.3	-	46.78	40.23	2.76	2.37	0.01	0.00	68.13
Abu-Zreig et al 2004	2	1	5	6.00	2.3	-	42.89	24.02	2.75	1.54	0.01	0.00	76.36
Abu-Zreig et al 2004	2	1	5	6.00	2.3	-	51.83	32.65	3.27	2.06	0.01	0.00	83.54
Abu-Zreig et al 2004	2	1	5	6.00	2.3	-	46.25	27.75	2.96	1.78	0.01	0.00	86.76
Abu-Zreig et al 2004	2	1	5	6.00	2.3	-	39.90	21.55	4.03	2.18	0.01	0.00	78.43
Abu-Zreig et al 2004	2	1	10	12.00	2.3	-	44.21	3.98	3.10	0.28	0.01	0.00	97.37
Abu-Zreig et al 2004	2	1	10	12.00	2.3	-	34.34	12.71	3.13	1.16	0.01	0.00	93.18

Abu-Zreig et al 2004	2	1	10	12.00	2.3	-	41.27	16.51	3.43	1.37	0.01	0.00	86.05
Abu-Zreig et al 2004	2	1	15	18.00	2.3	-	55.70	23.39	4.40	1.85	0.01	0.00	89.07
Abu-Zreig et al 2004	2	1	15	18.00	2.3	-	53.31	12.26	4.43	1.02	0.01	0.00	97.65
Abu-Zreig et al 2004	2	1	15	18.00	2.3	-	52.24	33.43	3.97	2.54	0.01	0.00	85.85
Abu-Zreig et al 2004	2	1	5	6.00	5	-	47.18	26.42	3.68	2.06	0.01	0.00	86.36
Abu-Zreig et al 2004	2	1	5	6.00	5	-	48.96	20.56	4.70	1.97	0.01	0.00	88.13
Abu-Zreig et al 2004	2	1	5	6.00	5	-	47.11	28.74	4.24	2.59	0.01	0.00	85.45
Abu-Zreig et al 2004	2	1	5	6.00	2.3	-	54.44	32.12	4.90	2.89	0.01	0.00	82.47
Coyne et al 1998	2	1	4.5	20.70	9	4.00	51.52	17.62	3.09	1.06	0.00	0.00	95.00
Coyne et al 1998	2	1	4.5	20.70	9	4.00	41.40	5.68	2.48	0.34	0.00	0.00	98.00
Coyne et al 1998	2	1	9	41.40	9	1.50	44.18	9.60	2.65	0.58	0.00	0.00	97.00
Coyne et al 1998	2	1	9	41.40	9	1.50	47.35	3.58	2.84	0.22	0.00	0.00	99.00
Lee et al 1989	-	1	4.6	25.30	16	3.98	23.32	33.11	1.38	1.89	23.50	10.40	55.74
Lee et al 1989	-	1	9.1	50.05	16	2.01	23.32	40.94	1.38	2.21	23.50	6.70	71.49
Chaubey et al 1994	2	1	3	4.50	3	1.00	3.75	7.50	0.23	0.45	0.01	0.00	69.10
Chaubey et al 1994	2	1	6	9.00	3	0.50	3.75	11.25	0.23	0.68	0.01	0.00	53.34
Chaubey et al 1994	2	1	9	13.50	3	0.33	3.75	15.00	0.23	0.90	0.01	0.00	66.24
Chaubey et al 1994	2	1	15	22.50	3	0.20	3.75	22.50	0.23	1.35	0.01	0.00	62.72
Chaubey et al 1994	2	1	21	31.50	3	0.14	3.75	30.00	0.23	1.80	0.01	0.00	77.31
Young et al 1980	2	1	27.43	111.37	4	0.50	53.82	0.00	3.82	0.00	3.58	0.00	100.00
Young et al 1980	2	1	27.43	111.37	4	0.50	53.82	36.47	3.82	2.59	3.58	2.13	40.70
Young et al 1980	2	1	21.34	86.64	4	0.64	55.78	23.46	3.96	1.67	13.44	3.97	70.44
Young et al 1980	2	1	21.34	86.64	4	0.64	55.78	62.55	3.96	4.44	13.44	5.58	58.46
Young et al 1980	2	1	27.43	111.37	4	0.50	60.18	5.88	4.27	0.42	8.21	2.32	71.73
Young et al 1980	2	1	27.43	111.37	4	0.50	60.18	56.24	4.27	3.99	8.21	5.75	29.96
Young et al 1980	2	1	27.43	111.37	4	0.50	60.18	95.54	4.27	6.78	8.21	4.28	47.91
Young et al 1980	2	1	21.34	86.64	4	0.64	56.96	74.38	4.04	5.28	9.50	7.23	23.91
Young et al 1980	2	1	21.34	86.64	4	0.64	56.96	107.86	4.04	7.66	9.50	9.18	3.45
Van Dijk et al 1996	2	1	1	0.50	9.07	100.00	10.50	10.59	0.47	0.48	11.33	6.20	45.29
Van Dijk et al 1996	2	1	4	2.00	9.07	25.00	10.50	5.14	0.47	0.23	11.33	1.90	83.26
Van Dijk et al 1996	2	1	5	2.50	9.07	20.00	10.50	13.33	0.53	0.60	10.41	4.14	60.27

Van Dijk et al 1996	2	1	10	5.00	9.07	10.00	10.50	4.91	0.53	0.22	10.41	0.82	92.15
Van Dijk et al 1996	2	1	1	0.50	9.07	100.00	10.50	11.84	0.54	0.53	10.54	4.85	54.04
Van Dijk et al 1996	2	1	4	2.00	9.07	25.00	10.50	10.16	0.54	0.46	10.54	2.74	73.98
Van Dijk et al 1996	2	1	5	2.50	4	20.00	10.50	10.40	0.45	0.47	3.96	1.40	64.55
Van Dijk et al 1996	2	1	10	5.00	4	10.00	10.50	2.80	0.45	0.13	3.96	0.15	96.18
Van Dijk et al 1996	2	1	5	2.50	4.36	20.00	10.50	9.98	0.49	0.45	6.98	1.62	76.84
Van Dijk et al 1996	2	1	10	5.00	4.36	10.00	10.50	0.54	0.49	0.02	6.98	0.03	99.58
Van Dijk et al 1996	2	1	5	2.50	4	20.00	10.50	7.97	0.54	0.36	8.93	1.58	82.35
Van Dijk et al 1996	2	1	10	5.00	4	10.00	10.50	5.94	0.54	0.27	8.93	0.75	91.62
Van Dijk et al 1996	2	1	5	2.50	4.36	20.00	10.50	12.90	0.48	0.58	4.33	2.09	51.74
Van Dijk et al 1996	2	1	10	5.00	4.36	10.00	10.50	2.54	0.48	0.11	4.33	0.10	97.63
Lim et al 1998	2	1	6.1	14.64	3	2.00	48.80	73.20	2.93	4.39	0.15	0.04	70.07
Lim et al 1998	2	1	12.2	29.28	3	1.00	48.80	97.60	2.93	5.86	0.15	0.02	89.81
Lim et al 1998	2	1	18.3	43.92	3	0.67	48.80	122.00	2.93	7.32	0.15	0.00	97.43
Schmitt et al 1999	2	1	7.5	22.50	6.5	10.80	75.48	42.82	1.89	1.02	18.90	3.99	78.91
Schmitt et al 1999	2	1	15	45.00	6.5	5.40	75.48	14.24	1.89	0.35	18.90	1.30	93.12
Schmitt et al 1999	2	1	7.5	22.50	6.5	10.80	75.48	35.68	1.89	0.80	18.90	0.93	95.07
Schmitt et al 1999	2	1	15	45.00	6.5	5.40	75.48	13.58	1.89	0.34	18.90	0.24	98.73
Schmitt et al 1999	2	1	7.5	22.50	6.5	10.80	75.48	43.49	1.89	1.21	18.90	3.01	84.08
Schmitt et al 1999	2	1	15	45.00	6.5	5.40	75.48	27.15	1.89	0.66	18.90	0.84	95.57
Schmitt et al 1999	2	3	7.5	22.50	6.5	10.80	75.48	42.13	1.89	1.03	18.90	2.16	88.56
Schmitt et al 1999	2	3	15	45.00	6.5	5.40	75.48	35.70	1.89	0.93	18.90	1.16	93.87
Chaubey et al 1995	2	1	3.1	4.65	3	1.00	3.88	7.75	0.23	0.47	0.02	0.01	36.77
Chaubey et al 1995	2	1	6.1	9.15	3	0.51	3.88	11.50	0.23	0.69	0.02	0.01	33.70
Chaubey et al 1995	2	1	9.2	13.80	3	0.34	3.88	15.38	0.23	0.92	0.02	0.01	16.99
Chaubey et al 1995	2	1	15.2	22.80	3	0.20	3.88	22.88	0.23	1.37	0.02	0.01	43.73
Chaubey et al 1995	2	1	21.4	32.10	3	0.14	3.88	30.63	0.23	1.84	0.02	0.01	48.19
Lee et al 2000	4	1	7.1	29.11	5	3.11	8.15	7.48	0.98	0.90	0.31	0.12	59.94
Lee et al 2000	4	1	7.1	29.11	5	3.11	43.34	43.10	2.60	2.59	4.38	1.75	60.15
Lee et al 2000	4	3	16.3	66.83	5	1.36	8.15	2.89	0.98	0.35	0.31	0.03	89.36
Lee et al 2000	4	3	16.3	66.83	5	1.36	43.34	37.26	2.60	2.24	4.38	0.61	86.07

Mickelson et al. 2003	2	1	4.6	6.90	4.6	10.00	21.14	19.47	1.06	0.97	8.13	2.39	70.66
Mickelson et al. 2003	2	1	9.1	13.65	4.6	5.00	16.65	16.54	0.83	0.83	6.33	0.80	87.41
Hayes et al. 1984	2	1	28.8	86.40	2.86	0.17	698.40	117.72	83.81	14.13	-	-	93.30
Hayes et al. 1984	2	1	33.1	99.30	4.5	0.15	610.20	82.26	73.22	9.87	-	-	96.20
Hayes et al. 1984	2	1	33.1	99.30	4.5	0.15	529.20	39.60	63.50	4.75	-	-	98.70
Hayes et al. 1984	2	1	33.9	101.70	9.8	0.15	651.60	235.80	78.19	28.30	-	-	93.20
Hayes et al. 1984	2	1	33.9	101.70	15	0.15	651.60	291.60	78.19	34.99	-	-	87.20
Altadena Strip	-	1	7.925	-	3	-	-	-	73.17	51.51	3.66	0.88	76.07
Altadena Strip	-	1	7.925	-	3	-	-	-	151.13	144.70	17.68	3.47	80.36
Altadena Strip	-	1	7.925	-	3	-	-	-	61.42	63.68	2.76	1.02	63.13
Altadena Strip	-	1	7.925	-	3	-	-	-	62.38	55.95	3.24	1.57	51.70
Altadena Strip	-	1	7.925	-	3	-	-	-	49.81	36.64	2.34	0.73	68.70
Altadena Strip	-	1	7.925	-	3	-	-	-	180.32	168.12	16.59	4.03	75.68
Altadena Strip	-	1	7.925	-	3	-	-	-	90.05	70.31	4.41	1.48	66.54
Cerritos	-	1	20.12	-	2.1	-	-	-	115.87	87.61	8.23	5.43	33.97
Cerritos	-	1	20.12	-	2.1	-	-	-	57.26	51.20	5.90	2.87	51.39
Cerritos	-	1	20.12	-	2.1	-	-	-	88.41	15.91	10.34	0.80	92.31
Cerritos	-	1	20.12	-	2.1	-	-	-	100.78	52.73	13.61	2.85	79.07
Cerritos	-	1	20.12	-	2.1	-	-	-	31.71	8.41	9.99	1.61	83.92
Cerritos	-	1	20.12	-	2.1	-	-	-	32.73	10.11	4.84	1.55	68.07
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	45.16	19.25	4.52	0.15	96.59
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	60.69	43.45	5.70	0.78	86.29
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	19.01	10.80	1.44	0.30	79.06
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	9.87	6.67	0.38	0.20	46.65
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	25.63	22.77	2.15	0.36	83.08
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	66.57	44.71	2.13	0.89	58.02
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	11.22	11.91	0.36	0.26	27.00
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	12.00	5.96	0.60	0.13	78.15
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	4.24	7.12	0.14	0.11	15.98
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	6.72	5.99	1.41	0.16	88.96

San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	10.81	9.22	1.95	0.30	84.83
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	6.02	7.09	0.41	0.10	75.75
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	3.73	2.27	0.28	0.05	83.98
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	4.99	4.81	0.31	0.02	93.78
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	15.88	15.01	0.21	0.20	5.52
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	58.07	9.82	3.89	0.14	96.47
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	9.80	2.07	0.19	0.01	96.67
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	7.75	0.17	1.40	0.00	99.76
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	72.26	19.55	4.19	0.57	86.47
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	10.06	1.26	0.17	0.02	91.15
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	96.95	19.67	0.39	0.24	39.14
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	17.83	5.71	0.86	0.02	97.33
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	11.70	0.95	0.54	0.01	97.53
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	26.30	4.15	0.39	0.03	92.64
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	17.29	2.31	0.73	0.08	89.53
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	20.71	1.87	2.92	0.01	99.74
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	20.29	1.55	1.22	0.00	99.62
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	6.98	1.01	0.36	0.00	99.43
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	17.00	2.38	0.19	0.01	94.91
San Rafael RVTS 2	3	1	8.3	174.30	50	-	-	-	1.93	0.35	0.17	0.03	84.83
Westfield Level Spreader	-	1	44.8	1025.92	1.25	-	-	-	5.18	2.29	0.88	0.15	83.08
Westfield Level Spreader	-	1	44.8	1025.92	1.25	-	-	-	2.85	0.96	0.11	0.01	89.33
Westfield Level Spreader	-	1	44.8	1025.92	1.25	-	-	-	3.09	2.01	0.19	0.03	84.85
Angima et al.2002	2	1	1	2.50	20	8.00	-	-	0.03	0.00	2.20	0.25	88.64
Angima et al.2002	2	1	1	2.50	20	8.00	-	-	0.07	0.01	6.00	0.45	92.50
Angima et al.2002	2	1	1	2.50	20	8.00	-	-	0.09	0.01	9.20	0.88	90.49
Angima et al.2002	2	1	1	2.50	20	8.00	-	-	0.10	0.01	11.80	0.93	92.16
Angima et al.2002	2	1	1	2.50	20	8.00	-	-	0.24	0.02	36.60	3.60	90.16
Angima et al.2002	2	1	1	2.50	20	8.00	-	-	0.26	0.02	20.80	2.50	87.98

Angima et al.2002	2	1	1	2.50	20	8.00	-	-	0.34	0.04	21.00	1.90	90.95
Angima et al.2002	2	1	1	2.50	20	8.00	-	-	0.35	0.04	57.00	5.15	90.96
Angima et al.2002	2	1	1	2.50	20	8.00	-	-	0.14	0.02	28.60	2.35	91.78
Angima et al.2002	2	1	1	2.50	40	8.00	-	-	0.04	0.00	1.40	0.18	87.50
Angima et al.2002	2	1	1	2.50	40	8.00	-	-	0.06	0.00	5.20	0.38	92.79
Angima et al.2002	2	1	1	2.50	40	8.00	-	-	0.06	0.00	5.60	0.68	87.95
Angima et al.2002	2	1	1	2.50	40	8.00	-	-	0.06	0.01	11.40	1.15	89.91
Angima et al.2002	2	1	1	2.50	40	8.00	-	-	0.15	0.02	37.40	4.10	89.04
Angima et al.2002	2	1	1	2.50	40	8.00	-	-	0.16	0.01	17.80	1.05	94.10
Angima et al.2002	2	1	1	2.50	40	8.00	-	-	0.32	0.03	25.00	1.88	92.50
Angima et al.2002	2	1	1	2.50	40	8.00	-	-	0.19	0.03	41.80	6.48	84.51
Angima et al.2002	2	1	1	2.50	40	8.00	-	-	0.09	0.01	33.40	2.33	93.04
Parsons et al. 1994	1	1	4.3	17.20	1	8.60	48.06	14.79	1.30	0.40	5.70	0.70	87.72
Parsons et al. 1994	1	1	4.3	17.20	1	8.60	12.98	0.00	0.60	0.00	5.30	0.00	100.00
Parsons et al. 1994	1	1	4.3	17.20	1	8.60	37.64	51.33	2.20	3.00	12.90	8.30	35.66
Parsons et al. 1994	1	1	4.3	17.20	1	8.60	47.90	35.93	2.80	2.10	13.80	3.10	77.54
Parsons et al. 1994	1	1	4.3	17.20	1	8.60	84.59	65.07	1.30	1.00	10.20	3.60	64.71
Parsons et al. 1994	1	1	4.3	17.20	1	8.60	88.09	51.38	1.20	0.70	7.50	2.00	73.33
Parsons et al. 1994	1	1	4.3	17.20	1	8.60	14.85	16.82	1.50	1.70	9.40	3.00	68.09
Parsons et al. 1994	1	1	4.3	17.20	1	8.60	31.10	26.31	1.30	1.10	6.40	2.50	60.94
Parsons et al. 1994	1	1	4.3	17.20	1	8.60	23.92	16.75	1.00	0.70	5.30	0.50	90.57
Parsons et al. 1994	1	1	4.3	17.20	1	8.60	38.69	12.90	0.90	0.30	18.40	0.70	96.20
Parsons et al. 1994	1	1	8.5	34.00	1	4.35	48.06	18.48	1.30	0.50	5.70	1.00	82.46
Parsons et al. 1994	1	1	8.5	34.00	1	4.35	5.02	1.00	0.50	0.10	2.50	0.40	84.00
Parsons et al. 1994	1	1	8.5	34.00	1	4.35	12.98	6.49	0.60	0.30	5.30	0.00	100.00
Parsons et al. 1994	1	1	8.5	34.00	1	4.35	37.64	39.35	2.20	2.30	12.90	3.40	73.64
Parsons et al. 1994	1	1	8.5	34.00	1	4.35	47.90	51.33	2.80	3.00	13.80	4.30	68.84
Parsons et al. 1994	1	1	8.5	34.00	1	4.35	84.59	52.05	1.30	0.80	10.20	2.40	76.47
Parsons et al. 1994	1	1	8.5	34.00	1	4.35	88.09	36.70	1.20	0.50	7.50	1.00	86.67
Parsons et al. 1994	1	1	8.5	34.00	1	4.35	14.85	13.86	1.50	1.40	9.40	4.70	50.00
Parsons et al. 1994	1	1	8.5	34.00	1	4.35	31.10	23.92	1.30	1.00	6.40	1.70	73.44

Parsons et al. 1994	1	1	8.5	34.00	1	4.35	23.92	35.88	1.00	1.50	5.30	0.40	92.45
Parsons et al. 1994	1	1	8.5	34.00	1	4.35	38.69	0.00	0.90	0.00	18.40	0.00	100.00
Parsons et al. 1994	1	3	4.3	17.20	1	8.60	5.02	4.02	0.50	0.40	2.50	1.00	60.00
Parsons et al. 1994	1	3	4.3	17.20	1	8.60	-	-	0.40	0.30	2.40	2.30	4.17
Parsons et al. 1994	1	3	4.3	17.20	1	8.60	28.13	12.98	1.30	0.60	5.30	0.80	84.91
Parsons et al. 1994	1	3	4.3	17.20	1	8.60	-	-	0.60	0.30	4.70	1.10	76.60
Parsons et al. 1994	1	3	4.3	17.20	1	8.60	149.65	143.15	2.30	2.20	10.20	8.30	18.63
Parsons et al. 1994	1	3	4.3	17.20	1	8.60	38.69	38.69	0.90	0.90	18.40	1.20	93.48
Parsons et al. 1994	1	3	4.3	17.20	1	8.60	-	-	1.20	0.70	13.40	1.60	88.06
Parsons et al. 1994	1	3	4.3	17.20	1	8.60	-	-	0.60	0.40	4.90	0.60	87.76
Parsons et al. 1994	1	3	4.3	17.20	15	8.60	-	-	1.80	1.50	6.50	0.30	95.38
Parsons et al. 1994	1	3	4.3	17.20	15	8.60	-	-	0.80	0.70	14.90	0.80	94.63
Parsons et al. 1994	1	3	4.3	17.20	15	8.60	-	-	2.10	0.60	3.20	0.40	87.50
Parsons et al. 1994	1	3	8.5	34.00	15	4.35	-	-	1.30	0.50	17.30	0.70	95.95
Parsons et al. 1994	1	3	8.5	34.00	15	4.35	-	-	2.60	1.70	3.80	0.90	76.32
Parsons et al 1991	1	1	4.3	17.20	3.25	8.60	-	-	10.36	0.57	0.10	0.03	72.16
Parsons et al 1991	1	1	8.5	34.00	3.25	4.35	-	-	10.36	1.22	0.10	0.03	70.10
Delectic and Fletcher 2006	-	1	5	1.5	7.8	-	5.94	2.26	0.36	0.14	0.79	0.07	91.26
Delectic and Fletcher 2006	-	1	5	1.5	7.8	-	5.94	5.94	0.36	0.24	1.14	0.18	83.92
Delectic and Fletcher 2006	-	1	5	1.5	7.8	-	12.06	66.63	0.72	0.40	1.20	0.24	79.65
Delectic and Fletcher 2006	-	1	5	1.5	7.8	-	12.06	9.29	0.72	0.56	1.28	0.39	69.97
Delectic and Fletcher 2006	-	1	5	1.5	7.8	-	18.00	14.94	1.08	0.90	3.75	0.78	79.25
Delectic and Fletcher 2006	-	1	5	1.5	7.8	-	18.00	15.30	1.08	0.92	2.93	0.35	88.10
Lee et al 2003	4	1	7	28.70	5	3.11	-	-	0.88	0.48	5.32	0.54	89.86
Lee et al 2003	4	2	9.1	37.31	5	3.20	-	-	0.48	0.28	0.54	0.26	52.41
Rankins et al 2001	4	1	0.3	1.20	3	73.33	-	-	14.26	7.22	25.08	7.27	71.02
Rankins et al 2001	4	1	0.3	1.20	3	73.33	-	-	14.26	6.43	25.08	5.00	80.07
Rankins et al 2001	4	1	0.3	1.20	3	73.33	-	-	14.26	3.39	25.08	5.43	78.35

Rankins et al 2001	4	1	0.3	1.20	3	73.33	-	-	14.26	7.75	25.08	8.43	66.39
Mankin et al 2007	2	1	15.3	15.30	4	-	-	-	0.69	0.06	-	-	99.9
Mankin et al 2007	2	3	9.7	9.70	3.9	-	-	-	0.68	0.16	-	-	99.4
Mankin et al 2007	2	3	12.3	12.30	3.8	-	-	-	0.65	0.05	-	-	99.8
Barfield et al 1998	2	1	4.57	20.88	9	4.84	-	-	8.40	0.71	-	-	96.9
Barfield et al 1998	2	1	9.14	41.77	9	2.42	-	-	3.75	0.16	-	-	99.9
Barfield et al 1998	2	1	13.72	62.70	9	1.61	-	-	6.51	0.45	-	-	99.7
McGregor et al 1999	2	1	0.5	2.00	5	43.20	-	-	32.66	27.67	82.94	28.29	65.9
McGregor et al 1999	2	1	0.5	2.00	5	43.20	-	-	41.30	38.54	546.05	164.42	69.89
Webber et al. 2010	2	1	4.56	10.40	9.5	5.00	-	-	0.42	0.33	0.20	0.08	61.76
Webber et al. 2010	2	1	2.28	5.20	9.5	10.00	-	-	0.42	0.16	0.20	0.02	88.04
Webber et al. 2010	2	1	4.56	10.40	9.5	5.00	-	-	0.83	0.30	0.16	0.05	68.41
Webber et al. 2010	2	1	2.28	5.20	9.5	10.00	-	-	0.83	0.89	0.16	0.14	14.63
Webber et al. 2009	2	3	23	138.00	5	1.00	-	-	3.07	0.18	8.28	0.21	97.46
Webber et al. 2009	2	1	12	72.00	5	2.00	-	-	3.07	0.53	8.28	0.48	94.2
Webber et al. 2009	2	3	23	138.00	5	1.00	-	-	4.38	0.35	14.46	0.56	96.12
Webber et al. 2009	2	1	12	72.00	5	2.00	-	-	4.38	0.93	14.46	1.49	89.68
Wanyama et al. 2012	4	1	2.5	5.00	10	4.00	-	-	0.05	0.03	0.02	0.01	67.16
Wanyama et al. 2012	4	1	5	10.00	10	2.00	-	-	0.05	0.02	0.02	0.01	66.95
Wanyama et al. 2012	4	1	10	20.00	10	1.00	-	-	0.05	0.01	0.02	0.01	61.02
Wanyama et al. 2012	4	1	2.5	5.00	10	4.00	-	-	0.05	0.04	0.02	0.01	61.86
Wanyama et al. 2012	4	1	5	10.00	10	2.00	-	-	0.05	0.03	0.02	0.01	64.41
Wanyama et al. 2012	4	1	10	20.00	10	1.00	-	-	0.05	0.01	0.02	0.01	59.32
Wanyama et al. 2012	4	1	2.5	5.00	10	4.00	-	-	0.05	0.04	0.02	0.01	58.69
Wanyama et al. 2012	4	1	5	10.00	10	2.00	-	-	0.05	0.03	0.02	0.01	59.32
Wanyama et al. 2012	4	1	10	20.00	10	1.00	-	-	0.05	0.01	0.02	0.01	55.93
Wanyama et al. 2012	4	1	2.5	5.00	10	4.00	-	-	0.05	0.05	0.02	0.01	49.15
Wanyama et al. 2012	4	1	5	10.00	10	2.00	-	-	0.05	0.03	0.02	0.01	51.69
Wanyama et al. 2012	4	1	10	20.00	10	1.00	-	-	0.05	0.01	0.02	0.01	50.85
Hay et al. 2006	1	1	8.3	58.10	17	6.02	-	-	29.70	25.20	1.05	0.39	63.33

Uusi-Kamppa and Jauhiainen 2010	4	1	10	180.00	15	6.00	-	-	150.83	140.77	114.48	63.00	44.97
Uusi-Kamppa and Jauhiainen 2010	4	1	10	180.00	15	6.00	-	-	120.66	139.47	58.32	52.92	9.26
Uusi-Kamppa and Jauhiainen 2010	4	3	10	180.00	15	6.00	-	-	150.83	159.02	114.48	56.70	50.47
Uusi-Kamppa and Jauhiainen 2010	4	3	10	180.00	15	6.00	-	-	128.49	125.13	30.24	30.24	0
Uusi-Kamppa and Jauhiainen 2010	4	3	10	180.00	15	6.00	-	-	120.66	97.76	58.32	50.40	13.58
Sheridan et al 1999	4	1	8	320.00	3.5	33.33	-	-	63.24	27.90	1.60	0.36	77.5
Sheridan et al 1999	4	1	8	320.00	3.5	33.33	-	-	68.82	26.97	2.32	0.48	79.31
Sheridan et al 1999	4	1	8	320.00	3.5	33.33	-	-	76.26	21.39	1.12	0.20	82.14
Daniels & Gilliam 1996	1	1	3	-	4.9	28.00	-	-	-	-	-	-	59
Daniels & Gilliam 1996	1	1	6	-	4.9	14.00	-	-	-	-	-	-	61
Daniels & Gilliam 1996	1	1	3	-	2.1	28.67	-	-	-	-	-	-	45
Daniels & Gilliam 1996	1	1	6	-	2.1	14.33	-	-	-	-	-	-	57
Dickey & Vanderholm 1981	-	1	91	1092.0	0.5	1.00	-	-	2453.00	413.00	9076.10	411.35	95.5
Dillaha et al 1988	2	1	4.6	25.30	11	3.98	-	-	16.23	21.56	105.68	17.63	83.32
Dillaha et al 1988	2	1	9.1	50.05	11	2.01	-	-	16.23	18.34	105.68	7.54	92.87
Dillaha et al 1988	2	1	4.6	25.30	16	3.98	-	-	14.91	15.71	236.53	70.53	70.18
Dillaha et al 1988	2	1	9.1	50.05	16	2.01	-	-	14.91	22.17	236.53	43.70	81.52
Edwards et al 1983	-	1	30	135.00	2	-	-	-	0.36	0.36	3610.00	1800.00	50.14
Edwards et al 1983	-	1	60	270.00	2	-	-	-	0.36	0.38	3610.00	988.00	72.63
Schwer & Clausen 1989	2	1	26	275.60	2	-	-	-	0.01	0.00	235.64	2.48	98.95
Schellinger & Clausen 1992	4	1	22.9	174.04	2	3.69	-	-	1957.95	1397.54	294.82	118.17	59.92
Duchemin & Hogue 2009	2	1	5	25.00	3	6.00	-	-	25.52	21.85	137.99	18.12	86.87

Duchemin & Hogue 2009	2	3	5	25.00	3	6.00	-	-	25.52	21.66	137.99	20.39	85.22
Patty et al 1997	2	1	6	30.00	10	8.33	-	-	0.48	0.28	2.04E-05	2.53E-06	87.6
Patty et al 1997	2	1	12	60.00	10	4.17	-	-	0.48	0.22	2.04E-05	0	100
Patty et al 1997	2	1	18	90.00	10	2.78	-	-	0.48	0.03	2.04E-05	0	100
Patty et al 1997	2	1	6	30.00	7	8.33	-	-	0.46	0.07	4.93E-04	5.44E-06	98.9
Patty et al 1997	2	1	12	60.00	7	4.17	-	-	0.46	0.01	4.93E-04	3.70E-06	99.25
Patty et al 1997	2	1	18	90.00	7	2.78	-	-	0.46	0.00	4.93E-04	3.70E-07	99.92
Patty et al 1997	2	1	6	30.00	15	8.33	-	-	0.54	0.07	3.09E-04	2.87E-05	90.71
Patty et al 1997	2	1	12	60.00	15	4.17	-	-	0.54	0.04	3.09E-04	8.21E-06	97.34
Patty et al 1997	2	1	18	90.00	15	2.78	-	-	0.54	0.08	3.09E-04	4.80E-06	98.45
Tingle et al 1998	4	1	0.5	2.00	3	43.00	-	-	1.18	0.20	0.77	0.10	87.49
Tingle et al 1998	4	1	1	4.00	3	21.00	-	-	1.15	0.18	0.76	0.05	93.02
Tingle et al 1998	4	1	2	8.00	3	10.00	-	-	1.10	0.11	0.72	0.04	93.89
Tingle et al 1998	4	1	3	12.00	3	6.33	-	-	1.04	0.15	0.68	0.04	94.85
Tingle et al 1998	4	1	4	16.00	3	4.50	-	-	0.99	0.09	0.65	0.02	97.28
Le Bissonais et al. 2004	2	1	6	12.00	4.4	9.00	-	-	3.14	1.28	3.13	0.84	73.18
Le Bissonais et al. 2004	2	1	6	12.00	4.4	9.00	-	-	6.11	1.10	9.53	0.22	97.73

Table 1B. Entries categorized as 'event-based' that were used to construct the sediment reduction model. This included 287 entries from 33 studies (includes data from online stormwater BMP database), Missing data for flow rate were reconstructed using Q_{out} = 14.7 * V_{out} (R^2 = 0.7; N = 161) and V_{in}/V_{out} = Q_{in}/Q_{out} relationships. Factors considered for the model building process were buffer width (w), slope (s), sediment load per unit buffer area (L_{in}/A), inflow rate over unit area (Q_{in}/A), average flow rate ($Q_{av} = (Q_{in} + Q_{out})/2$), ratio of flow volumes (V_{in}/V_{out} or V_r), roughness factor (n), residence time factors ($t_1 \propto w^{0.6}/(q^{0.4} s^{0.3})$, $t_2 \propto w/\sqrt{s}$, $t_3 \propto w^{0.3}/(s^{0.3} q^{0.6})$; $q = Q_{av}/A$), and the square, log and exponential transformations of aforementioned variables.

								Residence time parameters				
Study	Width (m)	Slope (%)	Q_{in}/A (L/min/m²)	Q_{av} (L/min)	V_r	L_{in}/A (kg/m²)	L_{out}/A (kg/m²)	t_1	t_2	t_3	Roughness, n	Sediment removal (%)
Lee et al 1999	6.00	3.00	4.44	36.00	1.25	-	-	4.82	34.64	2.32	0.01	78.20
Lee et al 1999	6.00	3.00	4.44	35.50	1.29	-	-	4.85	34.64	2.34	0.01	74.80
Lee et al 1999	3.00	3.00	8.89	38.00	1.11	-	-	2.36	17.32	1.12	0.01	69.00
Lee et al 1999	3.00	3.00	8.89	37.50	1.14	-	-	2.37	17.32	1.13	0.01	62.00
Lee et al 2003	7.00	5.00	1.25	36.37	0.98	0.44	0.13	7.18	31.31	4.43	0.03	70.44
Lee et al 2003	7.00	5.00	0.42	11.25	1.14	0.18	0.04	11.48	31.31	9.70	0.08	80.25
Lee et al 2003	7.00	5.00	0.19	4.41	1.52	0.04	0.01	16.69	31.31	18.09	0.21	67.08
Lee et al 2003	7.00	5.00	1.07	23.19	1.94	16.67	0.92	8.60	31.31	5.99	0.04	94.49
Lee et al 2003	7.00	5.00	1.25	28.48	1.71	44.57	1.47	7.92	31.31	5.22	0.03	96.71
Lee et al 2003	7.00	5.00	0.42	9.49	1.71	4.82	0.12	12.29	31.31	10.86	0.10	97.52
Lee et al 2003	9.10	5.00	0.99	34.61	1.14	0.13	0.11	9.52	40.70	5.96	0.03	16.53
Lee et al 2003	9.10	5.00	0.28	9.89	1.14	0.04	0.03	15.72	40.70	13.73	0.09	12.56
Lee et al 2003	9.10	5.00	0.09	2.34	3.05	0.01	0.01	28.00	40.70	35.95	0.39	34.42
Lee et al 2003	9.10	5.00	0.42	13.68	1.37	0.92	0.55	13.81	40.70	11.06	0.07	40.38
Lee et al 2003	9.10	5.00	0.57	18.62	1.31	1.47	0.85	12.20	40.70	9.01	0.05	42.42
Lee et al 2003	9.10	5.00	0.19	4.67	3.05	0.12	0.02	21.22	40.70	22.65	0.20	86.88
Deng et al 2011	10.00	2.00	4.60	100.59	2.18	4.62	0.15	7.93	70.71	3.54	0.00	96.83
Deng et al 2011	10.00	2.00	4.60	97.70	2.40	7.94	0.24	8.03	70.71	3.61	0.00	96.92
Deng et al 2011	10.00	2.00	4.60	104.40	1.95	5.14	0.15	7.82	70.71	3.46	0.00	97.14
Deng et al 2011	10.00	2.00	7.60	177.55	1.79	4.87	0.51	6.32	70.71	2.43	0.00	89.56
Deng et al 2011	10.00	2.00	4.60	81.79	5.40	4.34	0.05	8.62	70.71	4.07	0.01	98.75

Deng et al 2011	10.00	2.00	4.60	85.34	4.22	4.38	0.06	8.47	70.71	3.95	0.01	98.60
Deng et al 2011	10.00	2.00	7.60	142.41	4.01	4.46	0.09	6.90	70.71	2.81	0.00	97.92
Deng et al 2011	10.00	2.00	4.60	83.32	4.82	8.36	0.09	8.56	70.71	4.02	0.01	98.90
Coyne et al 1995	9.00	9.00	0.71	16.81	8.77	6.86	0.06	11.04	30.00	8.47	0.08	99.13
Coyne et al 1995	9.00	9.00	1.17	27.28	8.45	13.87	0.14	9.09	30.00	6.13	0.05	98.96
Dillaha et al 1989	9.10	11.00	0.42	12.95	4.16	18.82	0.30	12.53	27.44	10.73	0.14	98.40
Dillaha et al 1989	9.10	11.00	0.77	27.98	2.21	20.63	1.21	9.21	27.44	6.42	0.07	94.16
Dillaha et al 1989	4.60	11.00	0.83	20.89	1.00	18.82	2.27	5.23	13.87	3.94	0.09	87.95
Dillaha et al 1989	4.60	11.00	1.52	43.49	0.79	20.63	4.66	3.90	13.87	2.42	0.04	77.41
Dillaha et al 1989	9.10	16.00	0.38	19.21	1.00	42.78	11.00	9.56	22.75	7.28	0.12	74.28
Dillaha et al 1989	9.10	16.00	0.55	37.60	0.58	47.20	29.99	7.31	22.75	4.65	0.06	36.47
Dillaha et al 1989	4.60	16.00	0.76	18.37	1.10	42.78	14.36	4.92	11.50	3.79	0.12	66.43
Dillaha et al 1989	4.60	16.00	1.09	34.32	0.67	47.20	38.79	3.83	11.50	2.50	0.06	17.82
Barfield et al 1998	4.57	9.00	2.42	28.28	8.52	103.00	2.62	4.54	15.23	3.03	0.05	97.46
Barfield et al 1998	4.57	9.00	3.70	42.54	9.84	258.00	8.44	3.86	15.23	2.31	0.03	96.73
Barfield et al 1998	4.57	9.00	3.68	40.42	19.64	55.70	0.18	3.94	15.23	2.39	0.03	99.68
Barfield et al 1998	4.57	9.00	3.59	40.54	12.51	67.40	4.13	3.93	15.23	2.38	0.03	93.87
Barfield et al 1998	9.14	9.00	0.64	13.54	116.35	26.60	0.02	12.19	30.47	9.89	0.10	99.93
Barfield et al 1998	9.14	9.00	1.39	31.66	11.32	212.00	1.10	8.68	30.47	5.61	0.04	99.48
Barfield et al 1998	9.14	9.00	0.86	17.94	-	19.60	0.00	10.89	30.47	8.20	0.08	100.00
Barfield et al 1998	9.14	9.00	0.09	2.02	40.78	21.50	0.00	26.10	30.47	35.16	0.68	100.00
Barfield et al 1998	13.72	9.00	1.18	39.51	14.22	28.40	2.09	11.92	45.73	7.27	0.04	92.64
Barfield et al 1998	13.72	9.00	1.55	51.42	16.48	361.00	2.06	10.73	45.73	6.10	0.03	99.43
Barfield et al 1998	13.72	9.00	0.08	2.54	-	0.98	0.00	35.75	45.73	45.32	0.54	100.00
Barfield et al 1998	13.72	9.00	0.66	22.54	10.32	10.30	0.00	14.92	45.73	10.57	0.06	99.98
Arora et al 1996	20.12	2.00	3.21	68.12	2.58	-	-	14.22	142.27	5.88	0.00	84.60
Arora et al 1996	20.12	2.00	3.21	86.70	1.30	-	-	12.91	142.27	5.00	0.00	75.90
Arora et al 1996	20.12	2.00	3.21	62.92	3.55	-	-	14.67	142.27	6.19	0.00	90.20
Arora et al 1996	20.12	2.00	1.61	32.11	3.24	-	-	19.20	142.27	9.70	0.01	91.10
Arora et al 1996	20.12	2.00	1.61	35.93	2.15	-	-	18.36	142.27	9.00	0.01	83.10

Arora et al 1996	20.12	2.00	1.61	39.45	1.65	-	-	17.69	142.27	8.46	0.01	88.40
McGregor et al 1999	0.50	5.00	25.38	46.81	1.18	12.10	3.54	0.46	2.24	0.26	0.02	70.77
McGregor et al 1999	0.50	5.00	30.46	57.08	1.14	41.47	7.07	0.42	2.24	0.23	0.02	82.95
McGregor et al 1999	0.50	5.00	31.73	62.89	1.02	128.74	38.01	0.41	2.24	0.22	0.01	70.47
McGregor et al 1999	0.50	5.00	26.02	59.78	0.77	114.91	31.82	0.42	2.24	0.22	0.02	72.31
Magette et al 1989	9.20	3.00	1.25	58.59	1.17	70.83	5.43	10.23	53.12	6.12	0.02	92.33
Magette et al 1989	9.20	3.00	0.75	40.16	0.88	9.45	1.87	11.89	53.12	7.87	0.02	80.22
Magette et al 1989	9.20	3.00	1.50	72.23	1.10	16.22	3.16	9.40	53.12	5.32	0.01	80.54
Magette et al 1989	9.20	3.00	1.16	63.19	0.87	6.62	1.92	9.92	53.12	5.82	0.02	71.03
Magette et al 1989	9.20	3.00	1.57	83.77	0.90	13.65	5.21	8.86	53.12	4.82	0.01	61.81
Magette et al 1989	9.20	3.00	1.30	78.63	0.72	8.32	2.68	9.09	53.12	5.03	0.01	67.83
Magette et al 1989	4.60	3.00	2.49	64.84	0.95	70.83	12.24	4.91	26.56	2.86	0.02	82.71
Magette et al 1989	4.60	3.00	1.49	40.44	0.87	9.45	3.64	5.93	26.56	3.92	0.02	61.51
Magette et al 1989	4.60	3.00	3.00	83.51	0.83	16.22	4.97	4.44	26.56	2.41	0.01	69.38
Magette et al 1989	4.60	3.00	2.33	65.77	0.81	6.62	4.20	4.88	26.56	2.83	0.01	36.66
Magette et al 1989	4.60	3.00	3.14	92.64	0.75	13.65	13.14	4.26	26.56	2.25	0.01	3.74
Magette et al 1989	4.60	3.00	2.60	77.25	0.74	8.32	4.65	4.58	26.56	2.54	0.01	44.07
W.J White et al 2007	10.00	1.50	2.88	122.48	1.43	27.30	8.74	9.81	81.65	4.81	0.01	68.00
W.J White et al 2007	10.00	1.50	3.02	129.74	1.39	19.76	4.74	9.58	81.65	4.63	0.01	76.00
W.J White et al 2007	10.00	6.00	3.20	135.72	1.44	25.22	6.31	6.21	40.83	2.83	0.01	75.00
W.J White et al 2007	10.00	6.00	3.46	143.60	1.51	30.03	7.21	6.07	40.83	2.72	0.01	76.00
W.J White et al 2007	10.00	6.00	3.92	182.43	1.16	29.90	14.05	5.52	40.83	2.32	0.01	53.00
W.J White et al 2007	10.00	6.00	3.94	173.59	1.31	25.74	9.78	5.63	40.83	2.40	0.01	62.00
W.J White et al 2007	10.00	11.00	4.00	181.72	1.22	33.80	13.86	4.61	30.15	1.90	0.01	59.00
W.J White et al 2007	10.00	11.00	3.12	144.61	1.17	33.80	9.80	5.05	30.15	2.22	0.01	71.00
W.J White et al 2007	10.00	11.00	4.12	191.28	1.17	30.55	10.08	4.51	30.15	1.84	0.01	67.00
W.J White et al 2007	10.00	11.00	3.76	163.36	1.36	30.55	11.30	4.81	30.15	2.04	0.01	63.00
W.J White et al 2007	10.00	16.00	3.34	142.40	1.42	28.99	1.16	4.54	25.00	1.98	0.01	96.00
W.J White et al 2007	10.00	16.00	3.34	153.71	1.19	34.19	3.42	4.40	25.00	1.88	0.01	90.00
W.J White et al 2007	10.00	16.00	3.52	164.18	1.16	30.29	8.48	4.29	25.00	1.80	0.01	72.00
W.J White et al 2007	10.00	21.00	3.92	178.81	1.21	38.09	7.62	3.82	21.82	1.55	0.01	80.00

W.J White et al 2007	10.00	21.00	4.06	187.66	1.18	22.23	4.89	3.75	21.82	1.50	0.01	78.00
Boyd et al. 2003	20.10	2.00	4.62	101.36	2.52	19.50	4.37	12.05	142.13	4.46	0.00	77.57
Boyd et al. 2003	20.10	2.00	1.62	34.92	2.97	6.49	0.57	18.45	142.13	9.08	0.01	91.27
Melville and Morgan 2001	1.00	5.00	0.71	1.14	15.81	0.17	0.01	3.62	4.47	5.18	0.59	94.83
Melville and Morgan 2001	1.00	5.00	1.48	2.28	45.75	0.23	0.00	2.74	4.47	3.26	0.30	97.89
Melville and Morgan 2001	1.00	5.00	1.19	2.98	1.50	0.24	0.06	2.46	4.47	2.73	0.23	73.48
Melville and Morgan 2001	1.00	5.00	0.71	1.08	109.43	0.17	0.00	3.70	4.47	5.37	0.62	98.16
Melville and Morgan 2001	1.00	5.00	1.48	2.32	23.11	0.23	0.00	2.72	4.47	3.22	0.29	98.37
Melville and Morgan 2001	1.00	5.00	1.19	1.82	57.13	0.24	0.00	3.00	4.47	3.79	0.37	98.43
Helmers et al 2005	13.00	1.00	8.38	1916.25	0.74	152.31	26.79	7.44	130.00	2.38	0.00	82.41
Helmers et al 2005	13.00	1.00	4.62	1251.28	0.56	14.60	2.90	8.82	130.00	3.16	0.00	80.16
Helmers et al 2005	13.00	1.00	1.04	233.47	0.84	18.56	1.65	17.26	130.00	9.68	0.01	91.11
Helmers et al 2005	13.00	1.00	14.24	2527.24	1.22	144.42	26.70	6.66	130.00	1.98	0.00	81.51
Helmers et al 2005	13.00	1.00	14.06	2521.51	1.19	535.05	109.95	6.66	130.00	1.98	0.00	79.45
Helmers et al 2005	13.00	1.00	10.83	2157.52	0.96	355.74	91.13	7.09	130.00	2.20	0.00	74.38
Helmers et al 2005	13.00	1.00	20.23	3677.06	1.16	267.48	70.71	5.73	130.00	1.54	0.00	73.56
Helmers et al 2005	13.00	1.00	8.05	1426.12	1.22	16.25	1.29	8.37	130.00	2.90	0.00	92.06
Helmers et al 2005	13.00	1.00	1.73	330.86	1.18	50.16	7.32	15.02	130.00	7.67	0.01	85.41
Helmers et al 2005	13.00	1.00	3.86	747.08	1.27	146.01	10.76	10.84	130.00	4.46	0.00	92.63
Helmers et al 2005	13.00	1.00	10.45	1595.45	1.77	346.91	72.86	8.00	130.00	2.69	0.00	79.00
Helmers et al 2005	13.00	1.00	9.56	1371.48	2.12	161.40	27.38	8.50	130.00	2.97	0.00	83.04
Abu-Zreig et al 2004	2.00	2.30	21.38	44.90	1.33	0.01	0.00	1.46	13.19	0.63	0.00	70.10
Abu-Zreig et al 2004	2.00	2.30	14.88	23.74	3.03	0.01	0.00	1.88	13.19	0.96	0.01	83.32
Abu-Zreig et al 2004	2.00	2.30	19.49	43.51	1.16	0.01	0.00	1.48	13.19	0.64	0.00	68.13
Abu-Zreig et al 2004	5.00	2.30	7.15	33.45	1.79	0.01	0.00	4.10	32.97	1.91	0.01	76.36
Abu-Zreig et al 2004	5.00	2.30	8.64	42.24	1.59	0.01	0.00	3.73	32.97	1.64	0.00	83.54
Abu-Zreig et al 2004	5.00	2.30	7.71	37.00	1.67	0.01	0.00	3.93	32.97	1.79	0.01	86.76
Abu-Zreig et al 2004	5.00	2.30	6.65	30.72	1.85	0.01	0.00	4.24	32.97	2.02	0.01	78.43

Abu-Zreig et al 2004	10.00	2.30	3.68	24.10	11.11	0.01	0.00	9.34	65.94	4.76	0.01	97.37
Abu-Zreig et al 2004	10.00	2.30	2.86	23.52	2.70	0.01	0.00	9.43	65.94	4.84	0.01	93.18
Abu-Zreig et al 2004	10.00	2.30	3.44	28.89	2.50	0.01	0.00	8.69	65.94	4.22	0.01	86.05
Abu-Zreig et al 2004	15.00	2.30	3.09	39.54	2.38	0.01	0.00	11.49	98.91	5.13	0.01	89.07
Abu-Zreig et al 2004	15.00	2.30	2.96	32.79	4.35	0.01	0.00	12.39	98.91	5.81	0.01	97.65
Abu-Zreig et al 2004	15.00	2.30	2.90	42.83	1.56	0.01	0.00	11.13	98.91	4.87	0.00	85.85
Abu-Zreig et al 2004	5.00	5.00	7.86	36.80	1.79	0.01	0.00	3.12	22.36	1.39	0.01	86.36
Abu-Zreig et al 2004	5.00	5.00	8.16	34.76	2.38	0.01	0.00	3.20	22.36	1.44	0.01	88.13
Abu-Zreig et al 2004	5.00	5.00	7.85	37.92	1.64	0.01	0.00	3.09	22.36	1.36	0.01	85.45
Abu-Zreig et al 2004	5.00	2.30	9.07	43.28	1.69	0.01	0.00	3.70	32.97	1.61	0.00	82.47
Coyne et al 1998	4.50	9.00	2.49	34.57	2.92	0.00	0.00	4.14	15.00	2.62	0.04	95.00
Coyne et al 1998	4.50	9.00	2.00	23.54	7.28	0.00	0.00	4.82	15.00	3.38	0.06	98.00
Coyne et al 1998	9.00	9.00	1.07	26.89	4.60	0.00	0.00	9.15	30.00	6.19	0.05	97.00
Coyne et al 1998	9.00	9.00	1.14	25.47	13.21	0.00	0.00	9.35	30.00	6.42	0.05	99.00
Lee et al 1989	4.60	16.00	0.92	28.21	0.73	23.50	10.40	4.15	11.50	2.85	0.08	55.74
Lee et al 1989	9.10	16.00	0.47	32.13	0.62	23.50	6.70	7.78	22.75	5.17	0.07	71.49
Chaubey et al 1994	3.00	3.00	0.83	5.63	0.50	0.01	0.00	5.06	17.32	4.00	0.05	69.10
Chaubey et al 1994	6.00	3.00	0.42	7.50	0.33	0.01	0.00	9.03	34.64	6.60	0.04	53.34
Chaubey et al 1994	9.00	3.00	0.28	9.38	0.25	0.01	0.00	12.38	51.96	8.54	0.03	66.24
Chaubey et al 1994	15.00	3.00	0.17	13.13	0.17	0.01	0.00	18.04	86.60	11.37	0.02	62.72
Chaubey et al 1994	21.00	3.00	0.12	16.88	0.13	0.01	0.00	22.84	121.24	13.46	0.02	77.31
Young et al 1980	27.43	4.00	0.48	26.91	-	3.58	0.00	33.81	137.15	22.73	0.03	100.00
Young et al 1980	27.43	4.00	0.48	45.15	1.48	3.58	2.13	27.49	137.15	16.10	0.02	40.70
Young et al 1980	21.34	4.00	0.64	39.62	2.38	13.44	3.97	22.53	106.70	13.66	0.02	70.44
Young et al 1980	21.34	4.00	0.64	59.17	0.89	13.44	5.58	19.19	106.70	10.46	0.01	58.46
Young et al 1980	27.43	4.00	0.54	33.03	10.23	8.21	2.32	31.15	137.15	19.83	0.03	71.73
Young et al 1980	27.43	4.00	0.54	58.21	1.07	8.21	5.75	24.83	137.15	13.59	0.01	29.96
Young et al 1980	27.43	4.00	0.54	77.86	0.63	8.21	4.28	22.11	137.15	11.20	0.01	47.91
Young et al 1980	21.34	4.00	0.66	65.67	0.77	9.50	7.23	18.41	106.70	9.76	0.01	23.91
Young et al 1980	21.34	4.00	0.66	82.41	0.53	9.50	9.18	16.81	106.70	8.39	0.01	3.45
Van Dijk et al 1996	1.00	9.07	21.00	10.55	0.99	11.33	6.20	0.61	3.32	0.29	0.01	45.29

Van Dijk et al 1996	4.00	9.07	5.25	7.82	2.04	11.33	1.90	2.74	13.28	1.42	0.02	83.26
Van Dijk et al 1996	5.00	9.07	4.20	11.91	0.88	10.41	4.14	2.89	16.60	1.34	0.01	60.27
Van Dijk et al 1996	10.00	9.07	2.10	7.70	2.38	10.41	0.82	6.88	33.20	3.59	0.02	92.15
Van Dijk et al 1996	1.00	9.07	21.00	11.17	1.01	10.54	4.85	0.59	3.32	0.28	0.01	54.04
Van Dijk et al 1996	4.00	9.07	5.25	10.33	1.18	10.54	2.74	2.45	13.28	1.18	0.02	73.98
Van Dijk et al 1996	5.00	4.00	4.20	10.45	0.96	3.96	1.40	3.89	25.00	1.93	0.01	64.55
Van Dijk et al 1996	10.00	4.00	2.10	6.65	3.57	3.96	0.15	9.33	50.00	5.21	0.02	96.18
Van Dijk et al 1996	5.00	4.36	4.20	10.24	1.09	6.98	1.62	3.83	23.95	1.90	0.01	76.84
Van Dijk et al 1996	10.00	4.36	2.10	5.52	20.00	6.98	0.03	9.79	47.89	5.73	0.02	99.58
Van Dijk et al 1996	5.00	4.00	4.20	9.23	1.49	8.93	1.58	4.09	25.00	2.09	0.01	82.35
Van Dijk et al 1996	10.00	4.00	2.10	8.22	2.00	8.93	0.75	8.57	50.00	4.52	0.01	91.62
Van Dijk et al 1996	5.00	4.36	4.20	11.70	0.82	4.33	2.09	3.63	23.95	1.74	0.01	51.74
Van Dijk et al 1996	10.00	4.36	2.10	6.52	4.17	4.33	0.10	9.16	47.89	5.13	0.02	97.63
Lim et al 1998	6.10	3.00	3.33	61.00	0.67	0.15	0.04	4.79	35.22	2.27	0.01	70.07
Lim et al 1998	12.20	3.00	1.67	73.20	0.50	0.15	0.02	8.90	70.44	4.02	0.01	89.81
Lim et al 1998	18.30	3.00	1.11	85.40	0.40	0.15	0.00	12.56	105.66	5.44	0.01	97.43
Schmitt et al 1999	7.50	6.50	3.35	59.15	1.84	18.90	3.99	5.17	29.42	2.56	0.01	78.91
Schmitt et al 1999	15.00	6.50	1.68	44.86	5.35	18.90	1.30	11.54	58.84	6.15	0.02	93.12
Schmitt et al 1999	7.50	6.50	3.35	55.58	2.37	18.90	0.93	5.30	29.42	2.66	0.01	95.07
Schmitt et al 1999	15.00	6.50	1.68	44.53	5.60	18.90	0.24	11.58	58.84	6.18	0.02	98.73
Schmitt et al 1999	7.50	6.50	3.35	59.49	1.56	18.90	3.01	5.16	29.42	2.55	0.01	84.08
Schmitt et al 1999	15.00	6.50	1.68	51.31	2.87	18.90	0.84	10.94	58.84	5.62	0.02	95.57
Schmitt et al 1999	7.50	6.50	3.35	58.80	1.84	18.90	2.16	5.18	29.42	2.57	0.01	88.56
Schmitt et al 1999	15.00	6.50	1.68	55.59	2.04	18.90	1.16	10.59	58.84	5.33	0.01	93.87
Chaubey et al 1995	3.10	3.00	0.83	5.81	0.50	0.02	0.01	5.16	17.90	4.04	0.05	36.77
Chaubey et al 1995	6.10	3.00	0.42	7.69	0.34	0.02	0.01	9.09	35.22	6.60	0.03	33.70
Chaubey et al 1995	9.20	3.00	0.28	9.63	0.25	0.02	0.01	12.52	53.12	8.57	0.03	16.99
Chaubey et al 1995	15.20	3.00	0.17	13.38	0.17	0.02	0.01	18.14	87.76	11.38	0.02	43.73
Chaubey et al 1995	21.40	3.00	0.12	17.25	0.13	0.02	0.01	23.07	123.55	13.52	0.02	48.19
Lee et al 2000	7.10	5.00	0.28	7.82	1.09	0.31	0.12	13.47	31.75	12.53	0.12	59.94
Lee et al 2000	7.10	5.00	1.49	43.22	1.01	4.38	1.75	6.80	31.75	4.01	0.02	60.15

Lee et al 2000	16.30	5.00	0.12	5.52	2.83	0.31	0.03	35.55	72.90	36.29	0.17	89.36
Lee et al 2000	16.30	5.00	0.65	40.30	1.16	4.38	0.61	16.05	72.90	9.64	0.02	86.07
Mickelson et al. 2003	4.60	4.60	3.06	20.31	1.09	8.13	2.39	4.09	21.45	2.26	0.02	70.66
Mickelson et al. 2003	9.10	4.60	1.22	16.60	1.01	6.33	0.80	8.76	42.43	5.12	0.02	87.41
Hayes et al. 1984	28.80	2.86	8.08	408.06	5.93	-	-	11.72	170.30	3.56	0.00	93.30
Hayes et al. 1984	33.10	4.50	6.15	346.23	7.42	-	-	12.56	156.04	3.93	0.00	96.20
Hayes et al. 1984	33.10	4.50	5.33	284.40	13.36	-	-	13.59	156.04	4.48	0.00	98.70
Hayes et al. 1984	33.90	9.80	6.41	443.70	2.76	-	-	9.22	108.29	2.63	0.00	93.20
Hayes et al. 1984	33.90	15.00	6.41	471.60	2.23	-	-	7.92	87.53	2.19	0.00	87.20
Altadena Strip	7.92	3.00	-	915.71	1.42	3.66	0.88	-	45.75	-	-	76.07
Altadena Strip	7.92	3.00	-	2172.69	1.04	17.68	3.47	-	45.75	-	-	80.36
Altadena Strip	7.92	3.00	-	918.83	0.96	2.76	1.02	-	45.75	-	-	63.13
Altadena Strip	7.92	3.00	-	869.12	1.11	3.24	1.57	-	45.75	-	-	51.70
Altadena Strip	7.92	3.00	-	634.94	1.36	2.34	0.73	-	45.75	-	-	68.70
Altadena Strip	7.92	3.00	-	2559.11	1.07	16.59	4.03	-	45.75	-	-	75.68
Altadena Strip	7.92	3.00	-	1177.75	1.28	4.41	1.48	-	45.75	-	-	66.54
Cerritos	20.12	2.10	-	1494.49	1.32	8.23	5.43	-	138.82	-	-	33.97
Cerritos	20.12	2.10	-	796.54	1.12	5.90	2.87	-	138.82	-	-	51.39
Cerritos	20.12	2.10	-	766.17	5.56	10.34	0.80	-	138.82	-	-	92.31
Cerritos	20.12	2.10	-	1127.42	1.91	13.61	2.85	-	138.82	-	-	79.07
Cerritos	20.12	2.10	-	294.70	3.77	9.99	1.61	-	138.82	-	-	83.92
Cerritos	20.12	2.10	-	314.66	3.24	4.84	1.55	-	138.82	-	-	68.07
San Rafael RVTS 2	8.30	50.00	3.81	473.07	2.35	4.52	0.15	2.94	11.74	1.31	0.03	96.59
San Rafael RVTS 2	8.30	50.00	5.11	764.83	1.40	5.70	0.78	2.43	11.74	0.95	0.02	86.29
San Rafael RVTS 2	8.30	50.00	1.60	218.92	1.76	1.44	0.30	4.00	11.74	2.19	0.07	79.06
San Rafael RVTS 2	8.30	50.00	0.83	121.53	1.48	0.38	0.20	5.06	11.74	3.24	0.12	46.65
San Rafael RVTS 2	8.30	50.00	2.16	355.44	1.13	2.15	0.36	3.30	11.74	1.59	0.04	83.08
San Rafael RVTS 2	8.30	50.00	5.61	817.28	1.49	2.13	0.89	2.36	11.74	0.91	0.02	58.02
San Rafael RVTS 2	8.30	50.00	0.95	169.83	0.94	0.36	0.26	4.43	11.74	2.60	0.09	27.00
San Rafael RVTS 2	8.30	50.00	1.01	131.86	2.01	0.60	0.13	4.90	11.74	3.07	0.11	78.15
San Rafael RVTS 2	8.30	50.00	0.36	83.45	0.60	0.14	0.11	5.88	11.74	4.17	0.18	15.98

San Rafael RVTS 2	8.30	50.00	0.57	93.30	1.12	1.41	0.16	5.63	11.74	3.87	0.16	88.96
San Rafael RVTS 2	8.30	50.00	0.91	147.10	1.17	1.95	0.30	4.69	11.74	2.86	0.10	84.83
San Rafael RVTS 2	8.30	50.00	0.51	96.23	0.85	0.41	0.10	5.56	11.74	3.79	0.15	75.75
San Rafael RVTS 2	8.30	50.00	0.31	44.07	1.64	0.28	0.05	7.60	11.74	6.38	0.34	83.98
San Rafael RVTS 2	8.30	50.00	0.42	72.01	1.04	0.31	0.02	6.24	11.74	4.60	0.21	93.78
San Rafael RVTS 2	8.30	50.00	1.34	226.87	1.06	0.21	0.20	3.94	11.74	2.14	0.07	5.52
San Rafael RVTS 2	8.30	50.00	4.89	498.62	5.91	3.89	0.14	2.88	11.74	1.27	0.03	96.47
San Rafael RVTS 2	8.30	50.00	0.83	87.15	4.74	0.19	0.01	5.78	11.74	4.05	0.17	96.67
San Rafael RVTS 2	8.30	50.00	0.65	58.21	44.55	1.40	0.00	6.80	11.74	5.30	0.26	99.76
San Rafael RVTS 2	8.30	50.00	6.09	674.28	3.70	4.19	0.57	2.55	11.74	1.04	0.02	86.47
San Rafael RVTS 2	8.30	50.00	0.85	83.18	7.97	0.17	0.02	5.89	11.74	4.18	0.18	91.15
San Rafael RVTS 2	8.30	50.00	8.17	856.52	4.93	0.39	0.24	2.32	11.74	0.88	0.02	39.14
San Rafael RVTS 2	8.30	50.00	1.50	172.87	3.12	0.86	0.02	4.40	11.74	2.57	0.09	97.33
San Rafael RVTS 2	8.30	50.00	0.99	92.88	12.33	0.54	0.01	5.64	11.74	3.88	0.16	97.53
San Rafael RVTS 2	8.30	50.00	2.22	223.60	6.34	0.39	0.03	3.97	11.74	2.16	0.07	92.64
San Rafael RVTS 2	8.30	50.00	1.46	143.93	7.50	0.73	0.08	4.73	11.74	2.90	0.10	89.53
San Rafael RVTS 2	8.30	50.00	1.75	165.80	11.09	2.92	0.01	4.47	11.74	2.64	0.09	99.74
San Rafael RVTS 2	8.30	50.00	1.71	160.44	13.07	1.22	0.00	4.53	11.74	2.70	0.09	99.62
San Rafael RVTS 2	8.30	50.00	0.59	58.72	6.88	0.36	0.00	6.77	11.74	5.27	0.25	99.43
San Rafael RVTS 2	8.30	50.00	1.43	142.28	7.15	0.19	0.01	4.75	11.74	2.92	0.10	94.91
San Rafael RVTS 2	8.30	50.00	0.16	16.75	5.48	0.17	0.03	11.19	11.74	12.16	0.89	84.83
Westfield Level Spreader	44.80	1.25	0.07	54.85	2.26	0.88	0.15	117.62	400.70	107.83	0.05	83.08
Westfield Level Spreader	44.80	1.25	0.04	28.00	2.96	0.11	0.01	153.92	400.70	168.83	0.09	89.33
Westfield Level Spreader	44.80	1.25	0.04	37.40	1.54	0.19	0.03	137.09	400.70	139.20	0.07	84.85
Angima et al.2002	1.00	20.00	0.19	0.26	9.85	2.20	0.25	4.01	2.24	7.75	4.32	88.64
Angima et al.2002	1.00	20.00	0.42	0.57	13.71	6.00	0.45	2.93	2.24	4.60	1.97	92.50
Angima et al.2002	1.00	20.00	0.55	0.74	13.93	9.20	0.88	2.64	2.24	3.85	1.51	90.49
Angima et al.2002	1.00	20.00	0.56	0.77	10.67	11.80	0.93	2.59	2.24	3.75	1.45	92.16
Angima et al.2002	1.00	20.00	1.40	1.93	9.62	36.60	3.60	1.80	2.24	2.03	0.58	90.16

Angima et al.2002	1.00	20.00	1.55	2.12	11.00	20.80	2.50	1.73	2.24	1.91	0.53	87.98
Angima et al.2002	1.00	20.00	1.99	2.78	8.40	21.00	1.90	1.55	2.24	1.59	0.40	90.95
Angima et al.2002	1.00	20.00	2.06	2.83	10.00	57.00	5.15	1.54	2.24	1.58	0.40	90.96
Angima et al.2002	1.00	20.00	0.81	1.14	8.24	28.60	2.35	2.22	2.24	2.89	0.98	91.78
Angima et al.2002	1.00	40.00	0.21	0.28	16.00	1.40	0.18	3.16	1.58	5.83	5.63	87.50
Angima et al.2002	1.00	40.00	0.38	0.50	13.47	5.20	0.38	2.50	1.58	3.94	3.13	92.79
Angima et al.2002	1.00	40.00	0.34	0.46	13.65	5.60	0.68	2.60	1.58	4.21	3.46	87.95
Angima et al.2002	1.00	40.00	0.38	0.52	10.24	11.40	1.15	2.48	1.58	3.89	3.07	89.91
Angima et al.2002	1.00	40.00	0.89	1.24	9.35	37.40	4.10	1.75	1.58	2.17	1.28	89.04
Angima et al.2002	1.00	40.00	0.92	1.25	11.14	17.80	1.05	1.74	1.58	2.16	1.27	94.10
Angima et al.2002	1.00	40.00	1.88	2.58	10.41	25.00	1.88	1.30	1.58	1.33	0.61	92.50
Angima et al.2002	1.00	40.00	1.10	1.57	7.45	41.80	6.48	1.59	1.58	1.85	1.01	84.51
Angima et al.2002	1.00	40.00	0.55	0.76	9.64	33.40	2.33	2.12	1.58	3.00	2.08	93.04
Parsons et al. 1994	4.30	1.00	2.79	31.42	3.25	5.70	0.70	7.51	43.00	5.05	0.01	87.72
Parsons et al. 1994	4.30	1.00	0.75	6.49	-	5.30	0.00	14.11	43.00	14.45	0.06	100.00
Parsons et al. 1994	4.30	1.00	2.19	44.48	0.73	12.90	8.30	6.53	43.00	4.01	0.01	35.66
Parsons et al. 1994	4.30	1.00	2.79	41.92	1.33	13.80	3.10	6.69	43.00	4.17	0.01	77.54
Parsons et al. 1994	4.30	1.00	4.92	74.83	1.30	10.20	3.60	5.31	43.00	2.83	0.01	64.71
Parsons et al. 1994	4.30	1.00	5.12	69.73	1.71	7.50	2.00	5.46	43.00	2.97	0.01	73.33
Parsons et al. 1994	4.30	1.00	0.86	15.83	0.88	9.40	3.00	9.87	43.00	7.98	0.03	68.09
Parsons et al. 1994	4.30	1.00	1.81	28.71	1.18	6.40	2.50	7.78	43.00	5.36	0.01	60.94
Parsons et al. 1994	4.30	1.00	1.39	20.33	1.43	5.30	0.50	8.93	43.00	6.75	0.02	90.57
Parsons et al. 1994	4.30	1.00	2.25	25.79	3.00	18.40	0.70	8.12	43.00	5.76	0.02	96.20
Parsons et al. 1994	8.50	1.00	1.41	33.27	2.60	5.70	1.00	14.50	85.00	9.61	0.01	82.46
Parsons et al. 1994	8.50	1.00	0.15	3.01	5.00	2.50	0.40	37.90	85.00	47.66	0.13	84.00
Parsons et al. 1994	8.50	1.00	0.38	9.74	2.00	5.30	0.00	23.71	85.00	21.80	0.04	100.00
Parsons et al. 1994	8.50	1.00	1.11	38.49	0.96	12.90	3.40	13.68	85.00	8.72	0.01	73.64
Parsons et al. 1994	8.50	1.00	1.41	49.62	0.93	13.80	4.30	12.36	85.00	7.36	0.01	68.84
Parsons et al. 1994	8.50	1.00	2.49	68.32	1.63	10.20	2.40	10.88	85.00	5.95	0.01	76.47
Parsons et al. 1994	8.50	1.00	2.59	62.39	2.40	7.50	1.00	11.28	85.00	6.32	0.01	86.67
Parsons et al. 1994	8.50	1.00	0.44	14.35	1.07	9.40	4.70	20.30	85.00	16.84	0.03	50.00

Parsons et al. 1994	8.50	1.00	0.91	27.51	1.30	6.40	1.70	15.65	85.00	10.91	0.02	73.44
Parsons et al. 1994	8.50	1.00	0.70	29.90	0.67	5.30	0.40	15.13	85.00	10.32	0.01	92.45
Parsons et al. 1994	8.50	1.00	1.14	19.35	-	18.40	0.00	18.01	85.00	13.80	0.02	100.00
Parsons et al. 1994	4.30	1.00	0.29	4.52	1.25	2.50	1.00	16.30	43.00	18.40	0.09	60.00
Parsons et al. 1994	4.30	1.00	0.34	5.14	1.33	2.40	2.30	15.48	43.00	16.88	0.08	4.17
Parsons et al. 1994	4.30	1.00	1.64	20.55	2.17	5.30	0.80	8.90	43.00	6.70	0.02	84.91
Parsons et al. 1994	4.30	1.00	0.51	6.61	2.00	4.70	1.10	14.00	43.00	14.28	0.06	76.60
Parsons et al. 1994	4.30	1.00	8.70	146.40	1.05	10.20	8.30	4.06	43.00	1.81	0.00	18.63
Parsons et al. 1994	4.30	1.00	2.25	38.69	1.00	18.40	1.20	6.91	43.00	4.40	0.01	93.48
Parsons et al. 1994	4.30	1.00	1.02	13.95	1.71	13.40	1.60	10.39	43.00	8.68	0.03	88.06
Parsons et al. 1994	4.30	1.00	0.51	7.34	1.50	4.90	0.60	13.43	43.00	13.31	0.05	87.76
Parsons et al. 1994	4.30	15.00	1.54	24.24	1.20	6.50	0.30	3.70	11.10	2.44	0.06	95.38
Parsons et al. 1994	4.30	15.00	0.68	11.02	1.14	14.90	0.80	5.07	11.10	4.12	0.14	94.63
Parsons et al. 1994	4.30	15.00	1.79	19.83	3.50	3.20	0.40	4.00	11.10	2.78	0.08	87.50
Parsons et al. 1994	8.50	15.00	0.56	13.22	2.60	17.30	0.70	9.31	21.95	7.21	0.12	95.95
Parsons et al. 1994	8.50	15.00	1.12	31.58	1.53	3.80	0.90	6.57	21.95	4.04	0.05	76.32
Parsons et al 1991	4.30	3.25	8.85	80.26	18.25	0.10	0.03	3.62	23.85	1.83	0.01	72.16
Parsons et al 1991	8.50	3.25	4.48	85.08	8.46	0.10	0.03	6.99	47.15	3.47	0.01	70.10
Delectic and Fletcher 2006	5.00	7.80	3.96	4.10	2.63	0.53	0.05	3.78	17.90	2.05	0.02	91.26
Delectic and Fletcher 2006	5.00	7.80	3.96	4.96	1.49	0.76	0.12	3.50	17.90	1.80	0.02	83.92
Delectic and Fletcher 2006	5.00	7.80	8.04	9.35	1.82	0.80	0.16	2.72	17.90	1.18	0.01	79.65
Delectic and Fletcher 2006	5.00	7.80	8.04	10.67	1.30	0.85	0.26	2.58	17.90	1.08	0.01	69.97
Delectic and Fletcher 2006	5.00	7.80	12.00	16.47	1.20	2.50	0.52	2.17	17.90	0.81	0.01	79.25
Delectic and Fletcher 2006	5.00	7.80	12.00	16.65	1.18	1.95	0.23	2.16	17.90	0.80	0.01	88.10

Chapter 6

Conclusion

Wetlands and riparian areas provide several crucial ecosystem functions such as hydrology and water quality regulation on the landscape. However, agriculture and urban development has propagated globally at the expense of wetlands, streams and riparian ecosystems, largely altering their flows, nutrient retention, species composition and other biotic and abiotic characteristics, which have detrimental impacts on the many ecosystem services that we rely on. Studies show that smaller wetlands afford larger nutrient removal, and that for the same wetland size the removal of small wetlands corresponded to a greater loss in wetlands nutrient removal potential (Cheng and Basu 2017). While smaller systems display a disproportionately large role in nutrient cycling, they are also the most vulnerable to human alteration owing to their small size.

To better direct restoration and management efforts of small wetland systems and their riparian zones, there needs to be an improved understanding of their functioning across landscape positions. This study is aimed at furthering knowledge regarding small slope wetlands occurring in headwater areas in the Gulf coastal plain region, as well as providing decision makers with tools to model hydrology and water quality to aid in restoration of small wetlands and riparian areas.

In Chapter 1, the overall premise of the study and its motivation are presented. Here, I outlined two main objectives. These objectives and their findings are summarized in the following paragraphs.

Objective 1: ***Evaluate the influence of increasing land use/land cover change on the functional capacity of headwater slope wetlands in Baldwin County, AL***

Three chapters were dedicated to this objective. Here I addressed gaps in knowledge about headwater slope wetlands in Baldwin County, AL; these are groundwater fed wetlands and exist above and alongside 1st order streams in the region. Despite their numerous occurrence in the Alabama-Mississippi coastal plain, they have been sparsely studied in the region.

In Chapter 2, I investigated trends in field data collected from four headwater slope wetlands to make observations regarding their function in context of watershed land use and proximity to the coast. I found that:

- Hydrological flashiness increased with rising imperviousness in the watershed; the flashiest flows were observed in the BM wetland located in the most urbanized watershed while the most damped flows were observed in the OF wetland located in least urbanized watershed.
- Baseflow contributions in the study wetlands increased with proximity to the coast. Consequently, the wetland in the most urbanized watershed (BM wetland) exhibited surface flow dominated hydrology compared with the other wetlands near the coast which were strongly baseflow dominated. This could result from a multitude of factors such as (1) decreasing wetland elevation towards the coast, (2) groundwater discharge near the coast from upland areas, and (3) decreasing urban cover in the study watersheds towards the coast.
- One study wetland, NF, located proximate to the coast demonstrated large flows with very high runoff ratios, which were too large to have originated entirely within the extent of the delineated surficial watershed. We concluded that this excess flow was either a result of (1) a ground watershed that was much more extensive than the surficial watershed, an issue

commonly encountered in low topographical relief coastal plain areas, and (2) increased percolation from an upstream residential impoundment.

- Despite the presence of watershed alterations, headwater slope wetlands in this study showed considerable DIN load reductions.
- This capacity for nutrient retention may be overwhelmed as Baldwin County continues to urbanize. Currently most agriculture and urbanization in Baldwin County is contained to the south of I-10 along the coast which has caused fragmentation of stream networks with narrowing of riparian areas when compared with networks to the north of I-10. This study affirms the worthiness of headwater slope wetlands to be managed and restored to enhance their ecosystem functions.

Chapter 3 is a methods study focused on watershed flows draining into the inlet of the NF wetland. Here, I addressed the challenge of calibrating flows draining a small watershed fed by a ground watershed much larger than the surficial watershed. Although groundwater models can be used for this purpose, their complexity and large data requirements make their application a challenge with limited data. As an alternative, I suggested tweaks to the SWAT model, a popularly used watershed scale model in which watershed (surficial) precipitation is the major driver of the water budget to accommodate extra flows originating from a potentially larger ground watershed. The approaches I used were:

- Calibrated surface flow and baseflow components separately in which baseflow calibration involved a manual magnification of the baseflow
- Reversed the default positive value of SWAT parameter, RCHRGE_DP (which controls flow to the deep aquifer) to a negative value which returns water lost to the deep aquifer to the baseflow thus adding more water to streamflow

- Used ANN models to improve upon deficiencies observed in flow calibrated from the above approach

In Chapter 4, I addressed the usefulness of conducting sensitivity analyses as a way to prioritize data collection to only those that make a meaningful change to modelled outputs. This would be beneficial to data collection efforts in small wetlands such as headwater slope wetlands where data are usually sparse, due to limited financial and manpower resources, which in turn makes modeling them a challenge. Since nitrate pollution is a serious concern in coastal watersheds, I performed a sensitivity analysis using wetland model WetQual, to ask if Nitrate-N export from headwater slope wetlands required detailed data on Organic-N and Ammonia-N data inputs. In this study I found:

- Nitrate-N predictions in headwater slope wetlands were insensitive to Organic-N, Ammonia-N and DO in the inflows, and consequently their lack of data thereof would not impact WetQual predictions of Nitrate-N. This could be attributed to the fact that headwater slope wetlands tend to be open gaining systems and consequently have low residence times, when considering the main advection flow through stream channel, which may not afford enough time for N transformations to take place.
- Detailing Nitrate-N inputs through multiple sources maybe more important than Organic-N and Ammonia-N in predicting Nitrate-N export using WetQual in headwater slope wetlands.

Objective 2: ***Develop a data-based regression tool for describing sediment removal by vegetated buffers***

In Chapter 5, I focused on sediment removal by vegetated buffers. Here I compiled a database of sediment removal by vegetated buffers from literature and an online database to improve upon existing regression relationships through a secondary analysis with the aim of improving water quality prediction from riparian buffers. Data such as physical buffer characteristics were related to observed sediment removal and I found that:

- An exponential regression model including volume ratio, square of residence time and width best described sediment removal by vegetated buffers.
- On applying three other existing regression models from literature to the database I compiled, only the model described by White and Arnold (2009) was statistically significant presumably because of the inclusion of runoff reduction in their study. This points towards the importance of considering flow in buffer design.

Future directions

While this study contributes to knowledge relevant to greater understanding of headwater slope wetland and riparian zone function, it was also limited by the lack of proper long term data which needs to be addressed in future research. Below I outline some directions for future studies to glean more about wetland and riparian zone function such as:

- Monitor hydrology and water quality across a larger range of headwater slope wetlands to investigate if trends resulting from this study hold.
- Monitor subsurface flows and zones of upwelling in these slope wetlands and investigate the diversity of nutrient uptake/removal across the wetland area.
- Investigate and describe the influence of quality, quantity, species composition of the riparian zone in sediment and nutrient removal in context of surface and subsurface flow paths into the wetland.
- Quantify flows and water quality amelioration potential to the north and south of I-10 to get a clear picture of impacts across a range of land use alterations.

- Investigate more wetlands such as NF that exhibit disproportionately high runoff ratios and the physio-topographical zones they occur to improve upon hydrology calibration approaches.
- Armed with information from above, quantify cumulative impact of headwater slope wetland impact on watershed scale on an incremental basis.

References

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