Spring 2018

Hydrologic and Nutrient Fluxes in a Small Watershed with Changing Agricultural Practices

Bridger Cohan
Western Washington University

Hydrologic and Nutrient Fluxes in a Small Watershed with Changing Agricultural Practices

By

Bridger Cohan

Accepted in Partial Completion
of the Requirements for the Degree
Master of Science

ADVISORY COMMITTEE

Dr. David Hooper, Chair

Dr. Benjamin Miner

Dr. Eric DeChaine

GRADUATE SCHOOL

Dr. Gautam Pillay, Dean

Master's Thesis

Bridger Cohan
May 7th, 2018

Hydrologic and Nutrient Fluxes in a Small Watershed with Changing Agricultural Practices

A Thesis
Presented to
The Faculty of
Western Washington University

In Partial Fulfillment
Of the Requirements for the Degree
Master of Science

by
Bridger Cohan
May 2018

Abstract

Many watersheds are subject to nonpoint-source inputs of nutrients from human activities, contributing to eutrophication of surface waters. The magnitude of these inputs is in turn dependent on the types of land use within a watershed, and on the specific land management strategies employed. Exact nutrient contributions resulting from particular management actions are difficult to identify, but field studies of nutrient fluxes through a waterway over time can shed light on the net impact of trends in land use and management. I investigated nutrient fluxes through upper Kamm Creek in northwest Washington State, to determine if historical changes in land management, responding to economic shifts and new legislation, had impacted nutrient export from the watershed. I measured streamflow and the concentrations of various forms of nitrogen and phosphorous between October 2015 and October 2016, and compared these measurements to data from a previous water quality study conducted from 1993-1998 on the same watershed. I found significantly higher nitrate fluxes, and significantly lower fluxes of mineral and total phosphorous, compared to the 1993-1998 sampling period. The increased annual nitrate flux resulted primarily from significantly increased summer flux relative to the historical data, while the phosphate and total phosphorous fluxes were significantly lower throughout the year in the current data. Mean nitrate concentration in the current data was high (8.8 +/- 0.17 mg N L^{-1}) and increased relative to the historical mean of 6.96 mg N L^{-1}. Current mean phosphate (0.009 +/- 0.0015 mg P L^{-1}) and total phosphorous (0.033 +/- 0.007 mg P L^{-1}) concentrations decreased relative to historical means by 0.03 and 0.04 mg P L^{-1}, respectively. Concentrations of all nutrient species varied seasonally in both current and historic data, but the trends of increased nitrate and decreased phosphorous concentrations held for most months. The relationships of all nutrient concentrations to streamflow were similar between sampling periods: nitrate concentrations decreased with streamflow, and phosphate and total phosphorous concentrations increased. Annual streamflow did not change compared to the previous sampling period, however streamflow was significantly higher during current summer months than previous summer months. Similar patterns, particularly for nitrate, did not occur on the nearby Nooksack River, which receives water from the study stream. The reduced phosphorous fluxes through Kamm Creek are consistent with the expected impacts of legislation that reduced the application of manure fertilizer between the sampling periods; the increased nitrate flux might result from increased inputs of nitrate-enriched groundwater, potentially in concert with shifts in crop types. Further understanding the relationships between specific land management changes and nutrient fluxes will help land managers trying to both maintain local agricultural productivity and improve water quality.

Acknowledgements

I sincerely thank the many people that have made this thesis possible by contributing their time, energy and resources. I would particularly like to thank my graduate adviser and chair of my thesis committee, Dr. David Hooper, for providing essential guidance on my project and thorough, insightful feedback on countless thesis drafts. Your expertise, generosity and patience are all deeply appreciated. I would also like to thank Dr. Benjamin Miner and Dr. Eric DeChaine, for their excellent advice and support while serving on my thesis committee. My research benefited greatly from Dr. David Schull and Ben Paulson in the Environmental Science Department, who provided much-needed advice and equipment for my stream water nutrient analyses. I am extremely grateful to Robin Matthews and Joan Vandersypen at the Institute for Watershed Studies, who conducted the initial research on which this study was based, and also provided quality control standards for my analyses. And, a tremendous thank you to the Biology Department Office and Stockroom staff, who were infallibly helpful and accommodating.

My thesis would not have been possible without the gracious contributions of time and expertise I received from many wonderful people in the agricultural research and conservation communities. In particular, I would like to acknowledge Lisa Wasko DeVetter, Chuck Timblin, Nichole Embertson, Chris Benedict, Barbara Carey, Jaehak Jeong and Luca Dora. I am also deeply indebted to APEX trailblazer and fellow lab member Drew Monks for all of his guidance and support. Crucial funding for this project was generously provided by the Thon and Fraser families, and the WWU Biology Department and the WWU Graduate School – thank you! My friends and family have encouraged me constantly, and prodded me when necessary, throughout my graduate experience and I am forever thankful. Finally, I am continually grateful to all of my fellow graduate students for their advice, support and friendship on this long journey.

Table of Contents

List of Tables and Figures

Body

Appendix A

Appendix B

Introduction

Human activities have dramatically increased the supply of nutrients to aquatic ecosystems worldwide (Vitousek et al. 1997, Carpenter et al. 1998, Lewis et al. 2011). While all aquatic ecosystems require nutrients to maintain biological productivity, an overabundance of nutrients such as nitrogen (N) and phosphorus (P) can cause extensive ecological damage to lakes, rivers and near-shore marine ecosystems through eutrophication (Carpenter et al. 1998, Diaz and Rosenberg 2008, Dodds et al. 2008, Chislock et al. 2013). Nonpoint-source inputs of N and P (generated by activities distributed throughout a basin, rather than by discrete sources) to waterways include atmospheric deposition, nutrients stored and transported by groundwater, and surface runoff carrying dissolved or suspended nutrients (Carpenter et al. 1998, Withers et al. 2014, Giri et al. 2016). The exact types and magnitudes of non-point source nutrient inputs depend on the specific nature of human activities in a watershed but given the spatially and temporally distributed nature of non-point nutrient sources, they can be difficult to quantify or attribute to specific practices (Braden and Segerson 1993, Cherry et al. 2012, Chen et al. 2018).

In agricultural watersheds, organic and mineral fertilizers are essential to maintain crop yields, but can become pollutants when they are applied in excess of crop demand, or at times when they are easily leached or otherwise exported (Van Es et al. 2004, Van Es et al. 2006, Hopkins et al. 2008). Nutrient export from agricultural landscapes also represents an economic inefficiency that reduces grower profit (Hopkins et al. 2008). Particular agricultural management practices, including crop types, irrigation methods, and the specific types, rates and timings of fertilizer application, can substantially impact nutrient loading to streams (Beaulac and Reckhow 1982, Sharpley et al. 1994, Ribaudo et al. 2001). These parameters may shift over time as the result of changes in agricultural input costs, crop values, grower guidelines, and environmental legislation, all of which in turn influence the implementation of best management practices (BMPs) (Makarewicz et al. 2009, Kaushal et al. 2014, Schlegel and Domagalski 2015). In addition, because nitrogen cycling is tied to different physical and biological processes from phosphorous cycling, measures intended to reduce export of one nutrient can fail to reduce, or even inadvertently boost, export of the other (Sims et al. 1998, Heathwaite et al. 2000, Chapin et al. 2011). Connections among general land usage, specific management practices, and stream nutrient fluxes are highly site-specific, and depend on a region's soils and use history (Sharpley et al. 1994, Withers et al. 2014). Due to these difficulties, many studies use models for source-attribution (Schaffner et al. 2009, Cavero et al. 2012, Niraula et al. 2013). However, models have inherent limitations (Borah and Bera 2004, Mulla et al. 2008), and even the best watershed models require high-quality data from the field for calibration and to confirm predictions (Chaubey et al. 2010, Daggupati et al. 2015). Therefore, *in situ* studies to investigate management–water quality relationships in a particular watershed are essential to instituting effective practices to reduce eutrophication.

Eutrophication from nonpoint-source nutrient pollution is a major conservation focus in the Pacific Northwest, including Water Resources Inventory Area 1 (WRIA1, Figure A1) in Whatcom County, northwest Washington State (Sharpley et al. 1994, Dowd et al. 2008, Carey 2013, Beeler and Mitchell 2017). Lowland areas of WRIA1 have a history of heavy agricultural use (Burrows and Bretz 2011), and previous local studies (Matthews and Vandersypen 1998, Whatcom County Ag Watershed Project 2014) identified livestock manure and chemical fertilizers added to cropland as key nonpoint inputs of nutrients to waterways, in agreement with findings from other regions (Wang 2006, Dowd et al. 2008). Several pieces of legislation have influenced BMPs in WRIA 1 over the past two decades, with the intention of improving water quality. These include The Washington State Dairy Nutrient Act (1998) and the Whatcom County Manure Nutrient Management Act (1998). These acts were passed to reduce manure fertilizer use in Whatcom County, and, in particular, the practice of applying liquid manure to bare ground after the harvest. This manure easily ran off into small waterways (Chuck Timblin, WCD, personal communication, 2017), and from there to the Nooksack River, the primary waterway in WRIA 1 (Butler et al. 2007). The lower Nooksack River Basin contains much more agricultural land than the heavily forested upper drainage and is therefore more influenced by changes in management practices. Manure runoff also contributed to nitrate contamination of the Sumas-Blaine Aquifer underlying much of the Nooksack Watershed (Carey 2013, Carey et al. 2017), and to closures of downstream shellfish beds at Portage Bay due to fecal coliform contamination (Freimund et al. 2015). In 2005, the Whatcom County Critical Areas Ordinance (CAO) was passed to encourage BMP implementation on local farms to limit nutrient and fecal coliform inputs to streams. Specific BMP's, such as cover crops or conservation tillage, may also lead to decreased erosion and associated fluxes of nutrients, particularly P (Wang et al. 2015, Cooper et al. 2017). However, despite some declines in nutrient fluxes through the lower Nooksack River, Portage Bay, after a period of improvement, continues to experience periodic contamination and closures from fecal coliform (Freimund et al. 2015).

Changes in land use and crop types, often driven by economic forces, may also contribute to changes in nutrient loading. Berry crop cultivation has increased dramatically in the Nooksack Drainage, while hay and pastureland acreage has decreased (Table 1) (Burrows and Bretz 2011). Berry production is one potential, but unverified, source of nitrate contamination in local waterways (Erickson 1998, Matthews and Vandersypen 1998, Zebarth et al. 1998). Nutrient management guidelines for berry crops recommend different fertilizer application methods

TABLE 1. Area (Ha) and percentage (*italics*) of upper Kamm Creek's watershed covered by development, native forest and four crop categories in 1998 and 2015, ordered by percentage change in watershed area between the observation dates. Due to 1998 data constraints, the 'Grass' category includes pasture, hay fields and fallow grasslands. Data obtained from USDA National Agricultural Statistical Service.

	1998	**2015**	**% Change**
Blueberry	6.4	56.4	
	1.6%	*14.6%*	*12.9%*
Developed	7.1	28.5	
	1.8%	*7.4%*	*5.5%*
Caneberry	18.5	34.9	
	4.8%	*9.0%*	*4.2%*
Forest	65.3	71.2	
	16.9%	*18.4%*	*1.5%*
Corn	45.0	27.6	
	11.6%	*7.1%*	*-4.5%*
Grass	244.6	168.3	
	63.2%	*43.5%*	*-19.7%*

compared to graminoid crops (mineral vs. manure, respectively), with lower rates of P application (Table A1); in practice, actual applications vary widely among individual growers, fields and years (Chuck Timblin, WCD, personal communication, 2016). Differences in nutrient uptake are important variables in determining nutrient exports as well, with certain crops and cultivars absorbing a larger percentage of applied fertilizer (Fageria et al. 2008). For example, blueberry plants selectively acquire ammonium-N rather than nitrate-N, potentially leading to runoff of excess nitrate (Hart et al. 2006, Bryla and Vargas 2012). Despite the potential for these changes in management and land cover to influence nutrient cycling and export, no previous studies have determined their net effect on nutrient fluxes through local waterways.

A pertinent management shift in WRIA1 is that irrigation water is increasingly sourced from groundwater rather than surface streams. Due to high nitrate concentrations in the Sumas-Blaine Aquifer underlying much of the Nooksack Basin (Morgan 1999, Mitchell et al. 2003, Carey 2013), increased groundwater use is likely to raise surface water nitrate levels (Chuck Timblin, WCD, personal communication, 2017). Additionally, upper Kamm Creek is partially spring-fed, allowing nutrients dissolved in the groundwater to flow directly to the stream. The Sumas-Blaine Aquifer acts as a long-term sink for leached nitrate, not only from past agricultural practices in Whatcom County, but, because the aquifer flows from north to south, also from sources in British Columbia, Canada (Mitchell et al. 2003). This complicates determining the effectiveness of local and current BMP's in reducing surface water nitrate enrichment.

A further challenge in identifying the effect of management shifts on nutrient fluxes is that fluxes depend not only on nutrient concentrations, but also the flowrate of the waterway in question (Vanni et al. 2001). Practices that increase streamflow, particularly peak streamflow (Banner et al. 2009), can potentially lead to increased nutrient fluxes, even if average nutrient concentrations decrease (Blann et al. 2009, Hatfield et al. 2009). Increased streamflow can be beneficial to biota in an individual stream or river, but the overall flux of nutrients may also be of concern for downstream ecosystems such as estuaries (Pinckney et al. 2001). Conversely, reduced streamflow may lead to environmentally damaging levels of nutrients or other pollutants, even if the overall flux decreases. Determining the relative contributions of nutrient concentrations and streamflow to nutrient flux is necessary to assess their impact on specific waterways and downstream ecosystems, and to untangle the impacts of changing management.

This study investigated the net effect of local changes in crop type, fertilization practices, and groundwater use on nutrient fluxes in upper Kamm Creek, a small tributary of the Nooksack River (Figure 1). This watershed encompasses agricultural lands representative of the broader Nooksack Basin, and the creek has been monitored periodically for water quality since at least 1985, displaying persistently high nutrient levels and other signs of environmental degradation (Matthews and Vandersypen 1998). Most recently, the stream (Assessment Unit 17110004000436) was on the 2012 Washington Department of Ecology 303D list of impaired water bodies for both pH and dissolved oxygen levels. The Institute for Watershed Studies (IWS; Huxley College of the Environment, Western Washington University) collected extensive data on streamflow and nutrient fluxes on this waterway from 1993 -1998 (hereafter referred to as ‘historical data’ or ‘historical study period’), but monitoring was discontinued (Matthews and Vandersypen 1998). These data showed high levels (median 7.3 mg L^{-1}, maximum 10.3 mg L^{-1}) of nitrate in upper Kamm Creek, as well as elevated levels of phosphorous compared to pristine watersheds. Matthews and Vandersypen (1998) attributed these levels primarily to local agricultural practices, but numerous studies cite the Sumas-Blaine Aquifer as another potential source of surface water nitrate contamination (Matthews and Vandersypen 1998, Morgan 1999,

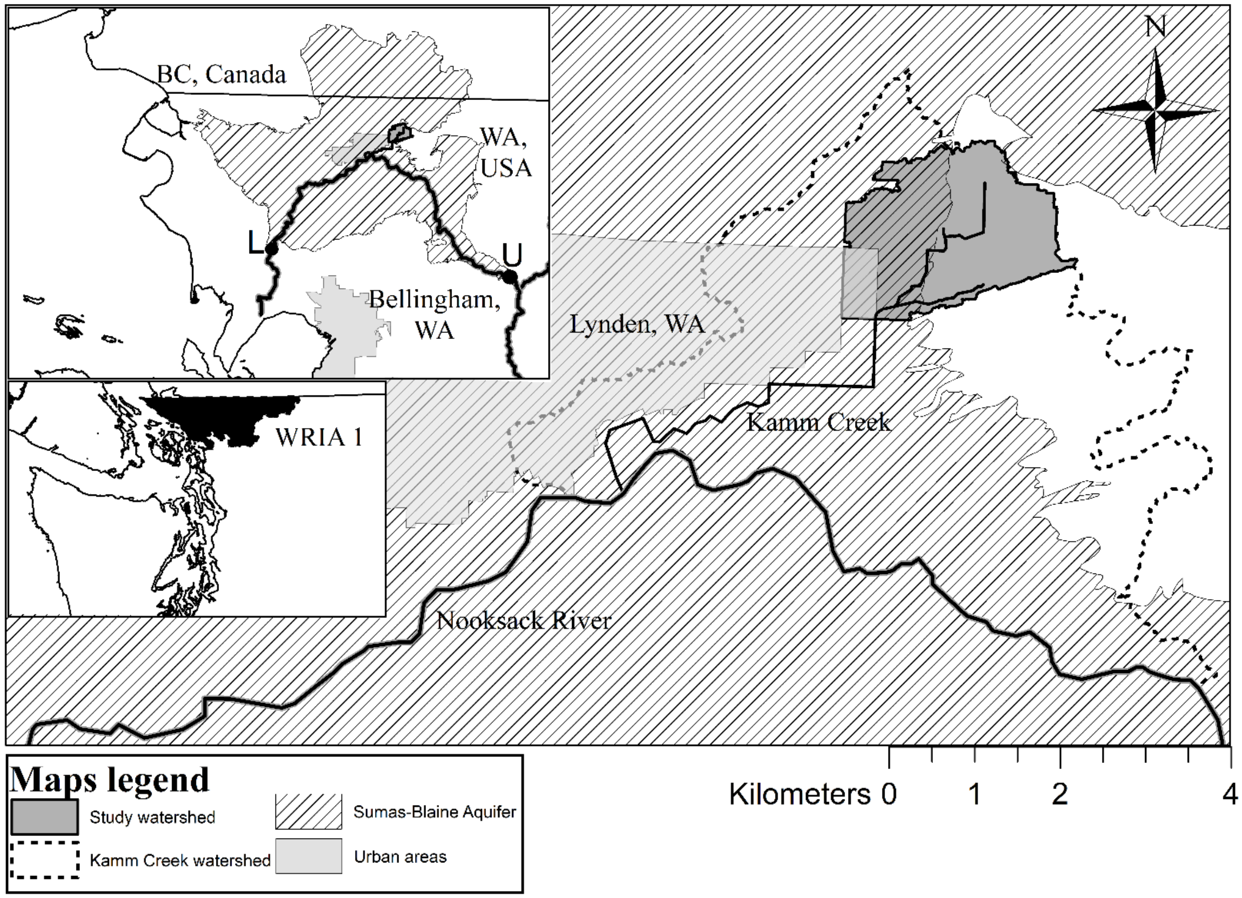

Figure 1. Study watershed of upper Kamm Creek in the context of the full Kamm Creek watershed, the Nooksack River, and the Sumas-Blaine Aquifer. The urban area surrounding Lynden, WA is shown in gray for reference. Insets depict study watershed location relative to the Canadian border and Bellingham, WA, and WRIA 1 location relative to NW Washington State. 'U' and 'L' denote approximate locations of upper and lower Nooksack River reference data collection sites.

Carey 2013). However, data from wells within the watershed boundaries are scarce, do not cover the entire time period since the IWS study, and are restricted to the portion of the Kamm Basin underlain by the Sumas-Blaine Aquifer. It is therefore difficult to directly quantify changes in nutrient contributions from specific activities or sources. Kamm Creek nevertheless provides an opportunity to explore how overall nutrient fluxes respond to a complex combination of land management shifts.

To determine the direction and magnitude of any shifts in nutrient flux, I measured streamflow and nutrient concentrations in upper Kamm Creek (Oct. 2015 - Oct. 2016; hereafter referred to as ‘current data’ or ‘current study period’), using comparable methods to the historical IWS survey. I then calculated the net annual flux for each nutrient in the historical (1993-98), and current (2015-16) data and analyzed changes in these fluxes, and their component concentrations and streamflow measurements, between the two sampling periods. Anticipating the impact of environmental legislation and reduced manure use in more recent cropping systems, I hypothesized decreased annual fluxes of all nutrients in the current data. I further hypothesized that annual streamflow in upper Kamm Creek would not differ significantly between the historical and current sampling periods, and that nutrient concentrations would follow the same general correlations with streamflow in both datasets. Therefore, any annual nutrient flux reductions would derive from lower concentrations of nutrients for a given level of streamflow.

Methods

Study Site

The location for this project was upper Kamm Creek, just east of Lynden, WA (Figure 1). From Oct. 2015 - Oct. 2016, I sampled for nutrients and streamflow immediately upstream from Kamm Road, where the creek enters a culvert. A second, similar culvert, parallel to the original pipe, was discovered in March of 2016 and was included in testing after that point. However, the streamflow through the second culvert was never more than 4% of the total flow, and frequently had no detectable flow. As a result, pre-March 2016 streamflow values were retained without amendment. The watershed above my sampling site included dairy cattle pasture, hay, blueberry and caneberry (raspberry) fields and natural woodlots, with small areas of residential and light commercial development. The sampling point itself is surrounded by pasture, with a dense but narrow band of shrubs, Himalayan blackberry (*Rubus armeniacus*) and reed canarygrass (*Phalaris arundinacea*) bordering the creek. My sampling site was approximately 33 meters upstream from the sampling site used by the IWS for their historical data collection (Matthews and Vandersypen 1998) and captures a similar watershed area.

Measurements

Water Chemistry – I collected stream water for nutrient analyses as triplicate 1000 ml samples taken from Kamm Creek twice monthly for a full year, from October 2015 through October 2016. Collections were at least five days apart, to limit the possibility of correlation between time points. In addition to the twice monthly samplings, I collected additional samples in April, May and October 2016 to provide more detail on spring and fall nutrient pulses, for a total of 27 dates used for comparative analyses (‘current data’).

Using a SmartChem 200 autoanalyzer (Unity Scientific LLC, Milford, MA), I ran five nutrient chemistry tests per water sample: ammonia (NH_3), nitrate (NO_3^-), phosphate (PO_4^{-3}), total nitrogen and total phosphorous. Nitrate measurements included any nitrite present; however, nitrite was an extremely minor (<1%) portion of the total in the historical data, and therefore I made no attempt to evaluate these components separately. Nutrient analyses followed standard, EPA-certified SmartChem protocols (Table A2) and used both internal and external lab standards for quality assurance and quality control; external standards were obtained from IWS, to facilitate direct comparison with historical Kamm Creek data (Matthews and Vandersypen 1998). Samples were vacuum-filtered through acid-washed 0.45μm mixed cellulose ester membrane filters (HAWP04700 – MilliporeSigma, Darmstadt, Germany) prior to analyses for ammonia, nitrate, and phosphate. Unfiltered samples for total phosphorous and total nitrogen were digested with an alkaline potassium persulfate solution in an autoclave at 121° C and 117.2 kPa (EPA methods 353.2/365.1). Analyses of filtered samples for NH_3 took place immediately following collection, NO_3^- within 24 hours and PO_4^{-3} within 48 hours. Digestion of unfiltered samples for total N and P took place within 48 hours, after which digested samples were stored at 4° C prior to analysis. Concentrations below the limit of detection (five samples for PO_4^{-3}, two for TP) were retained for analysis, but negative readings (five samples for PO_4^{-3}, one for TP) were zeroed for calculating monthly averages of concentration and flux.

Streamflow and Fluxes – I calculated streamflow as the product of the stream cross-sectional area and velocity on each sampling date, with measurements taken immediately inside the culvert entrance. Velocity was measured using a Flo-Mate Model 2000 electromagnetic flowmeter (Hach Company, Loveland, CO), resting at 60% of the water depth at the mouth of the culvert. Cross sectional area was calculated using the culvert radius, water depth and sediment depth according to the equations described in (Beschta 1981). For post-March 2016 data, I calculated streamflow using the sum of the primary and secondary culverts.

Daily nutrient fluxes were calculated from streamflow and nutrient concentration data using the equation:

$$\text{nutrient flux (kg day}^{-1}\text{)} = \frac{\text{nutrient concentration (mg L}^{-1}\text{) * streamflow (m}^{3}\text{ s}^{-1}\text{) *86400 s day}^{-1}}{10000}$$

Post-March 2016, I calculated nutrient concentration data as a weighted average using streamflow and concentration data from both culverts. For water and nutrient flux calculations, I assumed streamflow and nutrient concentrations remained constant throughout the day.

Annual fluxes of nutrients and water were calculated as the sum of monthly fluxes for each year, which were in turn derived from daily fluxes averaged for each month of a particular year and then multiplied by the number of days in that month (leap years considered, missing data points not considered). Streamflow and nutrient concentration data for the upper and lower stretches of the mainstem Nooksack River, used for reference, were obtained from the Washington Department of Ecology River and Stream Water Quality Monitoring Network (https://fortress.wa.gov/ecy/eap/riverwq/regions/state.asp) and the USGS National Water Information System (https://waterdata.usgs.gov/nwis/rt). Nutrient fluxes were calculated using the previously described methodology, with upper river nutrient concentrations measured at North Cedarville, WA (WA DoE site 01A120) and flow rates measured at Deming, WA (USGS site 12210500), approximately 7 km SE. Lower river nutrient concentrations were measured at Slater Road Bridge, WA (USGS site 12213140), with flow rates measured at Ferndale, WA (USGS site 12213100), approximately 3 km NW. Upper Nooksack historical data cover from 11/1994 – 10/1997, lower Nooksack flux data cover the full historical time period.

Statistical Analyses

All statistical analyses were performed using R software (R Core Team 2015), with a critical α value of 0.05. To determine whether there had been significant changes over time in Kamm Creek's water and nutrient contributions to the Nooksack River, I generated standard parametric 95% confidence intervals for the historical means of annual and seasonal fluxes of water and nutrients, then plotted the current fluxes against these. I also examined monthly distributions of nutrient concentrations, streamflow, and rainfall within and between sampling periods using notched box plots and described relationships between streamflow and nutrient concentrations using linear regression. Nitrate concentrations showed a negative exponential relationship to streamflow and were $\log_{10}$-transformed for linear regression analysis.

Complete nutrient concentration data from the full year of the current dataset did not meet assumptions of normality and homoscedasticity, regardless of transformations. I therefore used the rank-based 'nonparametric ANCOVA' function in the 'sm' package of R (Bowman 2014) to determine the probability that the slopes and intercepts of concentration vs. streamflow linear regressions for each nutrient were different between the two sampling periods. To check the nonparametric ANCOVA results against those from a parametric analysis, I also compared generalized linear models (GLMs) for each nutrient's concentration, using Akaike Information Criterion corrected for small sample sizes ($AIC_{c,}$ 'MuMin' package of R) to indicate relative parsimony (Barto 2017). Each GLM predicted nutrient concentration as a function of streamflow and/or sampling period with and without interactions. Results of AICc analysis did not conflict with nonparametric ANCOVA results and are included in Table A3.

Results

Nitrogen

The current annual flux of nitrate increased significantly compared to the historical flux (Figure 2). Fluxes of nitrate were significantly higher in the winter than in the summer months for the historical nitrate, but roughly equal in the current data (Figure 2). The current winter flux of nitrate was higher than the historical mean but within the historical 95% confidence interval; the current summer flux was almost double the historical mean and far outside the historical 95% confidence interval (Figure 2). Concentrations of nitrate were significantly higher than the historical range in all months of the current study (Figure 3). Nitrate concentrations in Kamm Creek displayed a negative exponential correlation with streamflow in both current and historic sampling periods, but with higher levels for a given flowrate in the current data (Figure 4).

Current annual nitrate fluxes on the upper and lower Nooksack River were significantly lower than the historical data, and current winter fluxes were also both lower, but just within the historical 95% confidence interval (Figure 5). Current summer nitrate fluxes were lower on both reaches of the Nooksack River, but only significantly so in the upper river. Annual nitrate fluxes on the lower Nooksack River were roughly 169% and 202% of upper river fluxes, for the historical and current sampling periods, respectively (Figure 5).

Poor data quality from the current sampling period precluded extensive statistical comparisons for ammonia. In both datasets, NH_3 represented <2% of the total nitrogen flux through upper Kamm Creek, so I do not address it further. No total or organic nitrogen data exist for the historical dataset, but organically-bound nitrogen made up ~9% of the total nitrogen flux in the current dataset. Organic nitrogen levels ranged from below the detection limit to 2.56

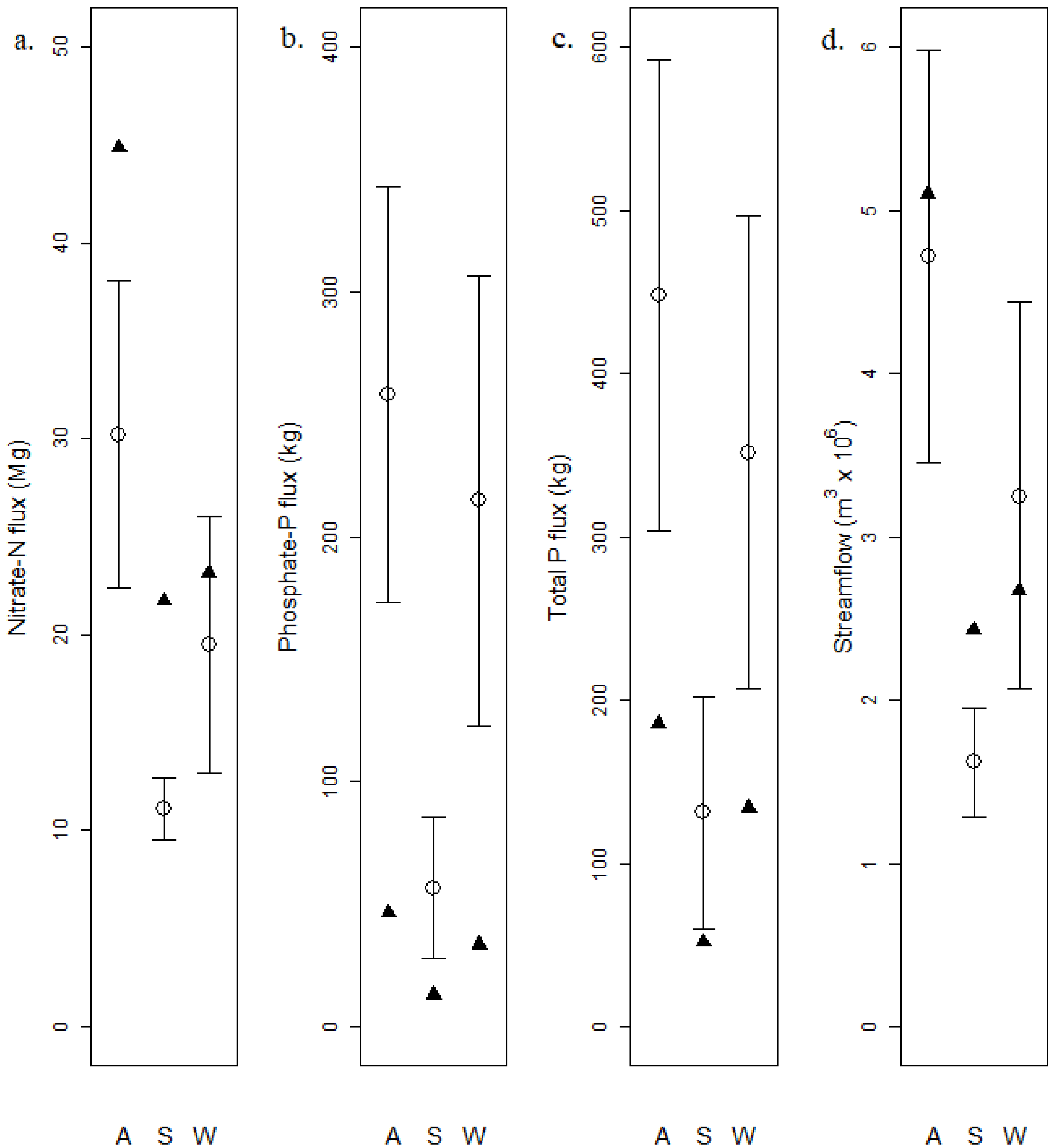

Figure 2. Annual (A), summer (S), and winter (W) total fluxes of nitrate-N (a), phosphate-P (b), and total P (c), and streamflow (d), on upper Kamm Creek. Annual fluxes are calculated from samplings every other week starting in May and extending through the following April. 'Summer' includes all observations from May-October, 'winter' includes all observations from November through April. Unfilled circles indicate the mean from the historical sampling period with 95% confidence intervals displayed. CI's generated from historical data, with N=4 (N=5 for summer data). Solid triangle indicates current annual or seasonal flux.

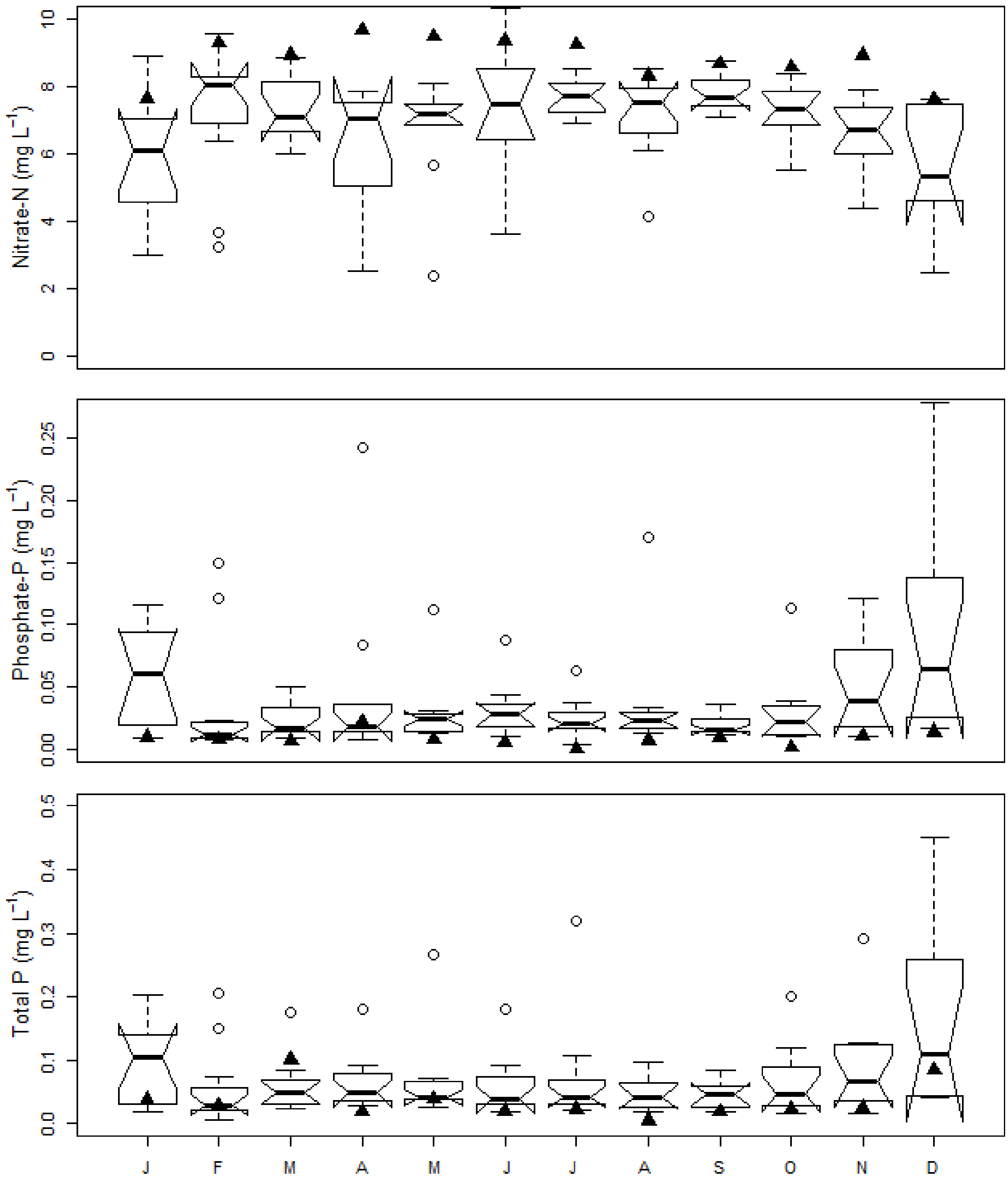

Figure 3. Distributions of (a) nitrate-N, (b) phosphate-P, and (c) total P concentrations on upper Kamm Creek during the historical study (2/1993 - 2/1998, N = 11-12/mo), grouped by month. Notched box plots of historical data show medians (line), and 95% confidence intervals of the median between notches. Mean of current data (10/2015 - 10/2016, N = 2-3/mo) represented by solid triangles. Current mean displayed rather than median due to small sample size.

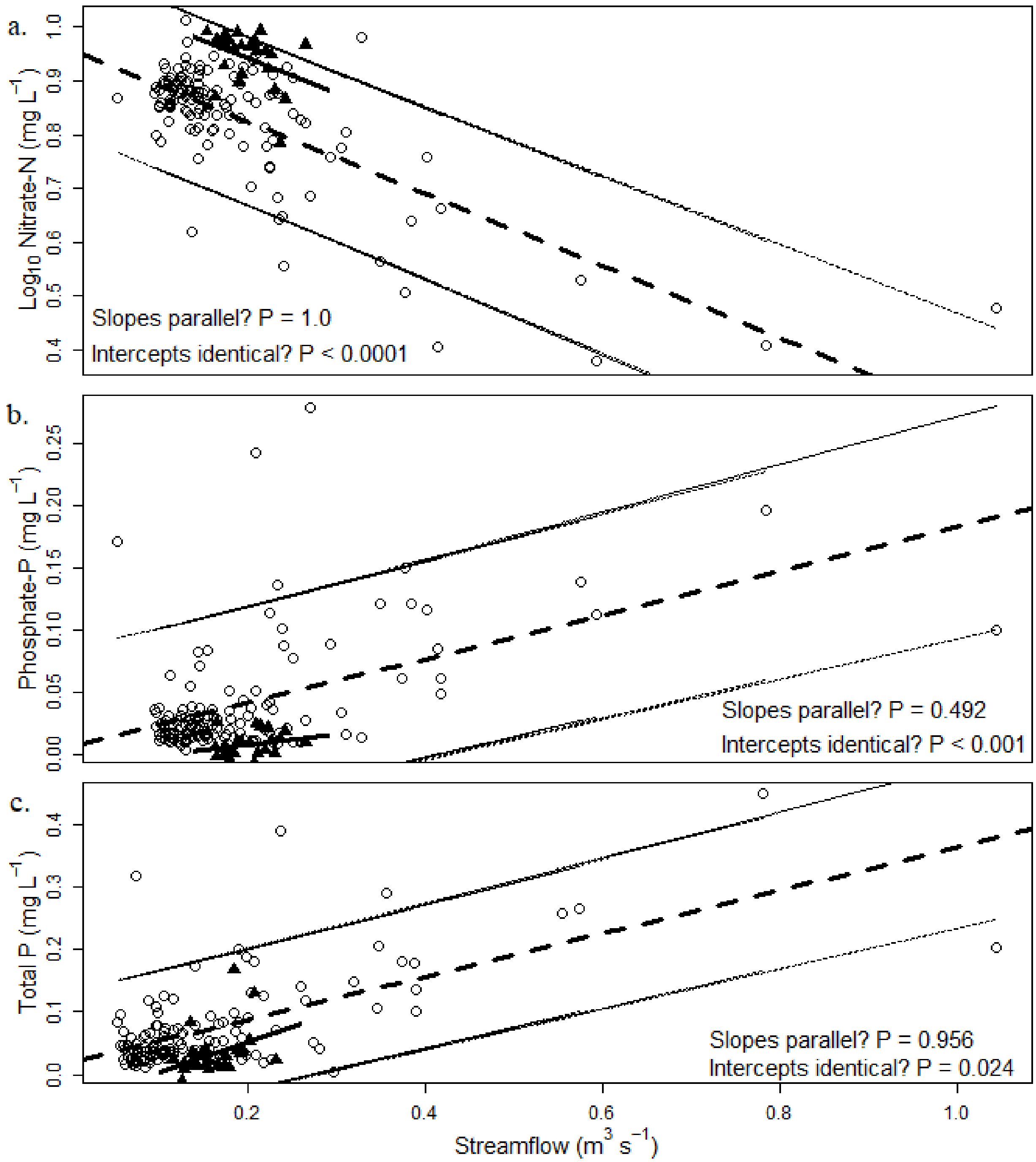

Figure 4. Concentrations of nitrate-N (a), phosphate-P (b), and total P (c), plotted against streamflow. Historical data (N = 133) represented by unfilled circles, with dashed linear regression best fit-line; 95% prediction intervals displayed as dotted lines. Current data (N = 27) are represented by solid triangles with a solid linear regression best-fit line. P-values represent the results of a nonparametric ANCOVA test, which compared the regression lines for both sampling periods against a null model with parallel regression lines having identical intercepts. See Table A4 for regression equations and coefficients of determination.

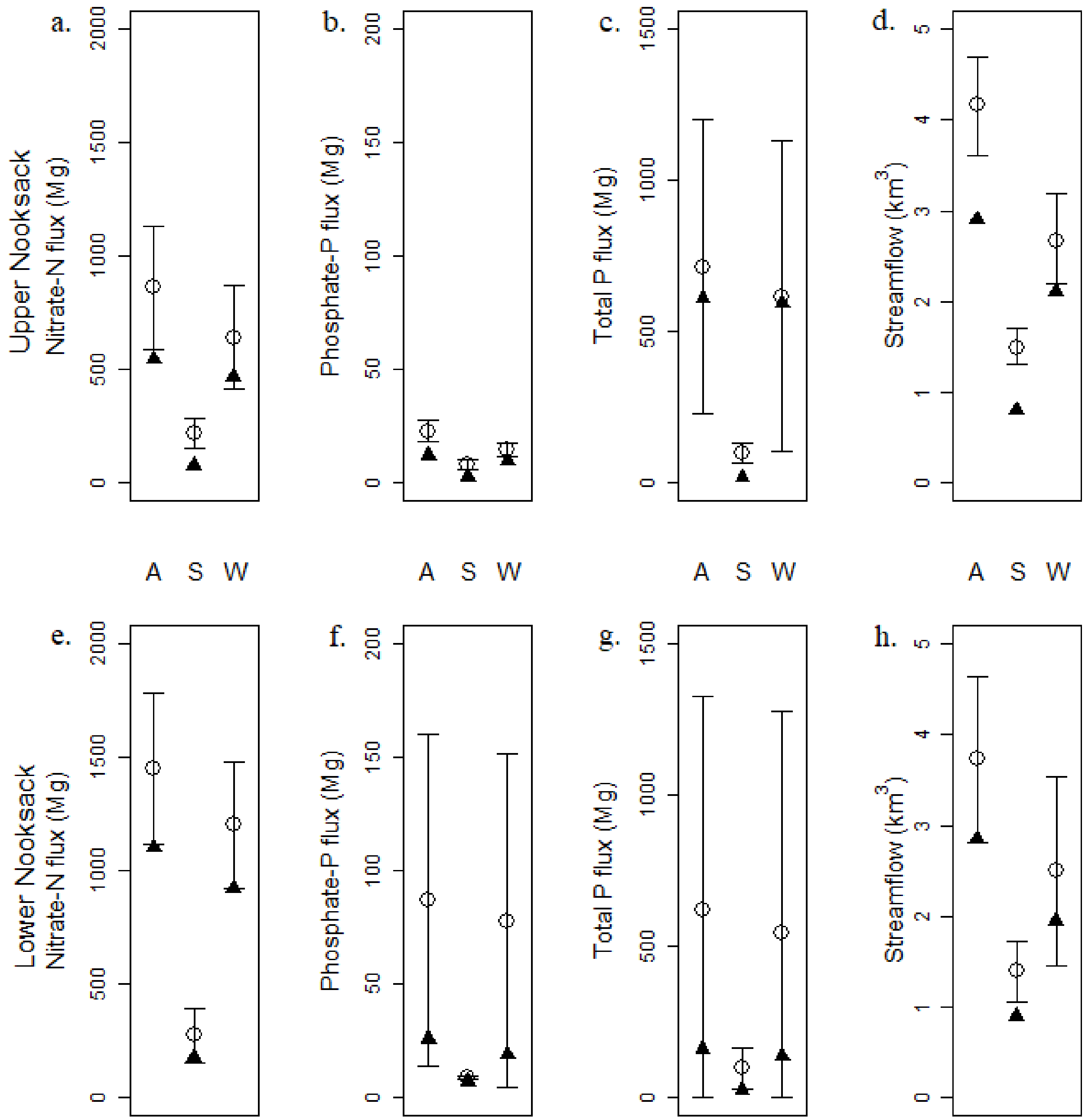

Figure 5. Annual (A), summer (S), and winter (W) total fluxes of nitrate-N (a, e), phosphate-P (b, f) and total P (c, g), and streamflow (d, h), on the upper and lower Nooksack River. Annual fluxes are calculated from samplings every other week starting in May and extending through the following April. 'Summer' includes all observations from May-October, 'winter' includes all observations from November through April. Unfilled circles indicate the mean from the historical sampling period with 95% confidence intervals displayed. CI's generated from historical data, with N=3. Solid triangle indicates current annual or seasonal flux.

mg L^{-1}, but did not correlate with streamflow, sampling date, or nitrate levels, either as a concentration, or as a percentage of total nitrogen.

Phosphorous

The current annual fluxes of phosphate and total phosphorous were lower than in any year from the historical sampling period, and significantly lower than the historical mean (Figure 2). Both summer and winter phosphate and TP fluxes in the current data were significantly lower than historical fluxes, with the difference relatively greater in winter (Figure 2). Winter fluxes of both phosphorous forms accounted for the majority of their annual fluxes in both datasets, though with a relatively more balanced distribution in the current than the historical data (Figure 2). Phosphate-P contributed 57.5% of the mean annual TP flux during the historical sampling period, but only 25% during the current sampling period. Current mean concentrations of phosphate were significantly lower than historical medians in all months except April (Figure 3), with TP concentrations significantly lower in all months except February, March, and December. Concentrations of both mineral and total phosphorous showed similar positive linear correlations with streamflow in both sampling periods, but with significantly lower concentrations for a given flow rate in the current data (Figure 4).

Current fluxes of phosphate on the upper Nooksack River were significantly lower than historical fluxes for all seasons, while TP fluxes were only lower in summer (Figure 5). On the lower Nooksack River, summer fluxes of both phosphate and TP were significantly decreased compared to the historical data, but current annual and winter fluxes of both nutrient species were within the historical 95% confidence interval (Figure 5). Annual fluxes of phosphate from the upper river constituted only a 26% of the lower river's phosphate flux in the historic data, but 47% in the current data. Total annual phosphorous flux through the upper Nooksack was higher than through the lower Nooksack during both sampling periods, but the difference was minor in the historical data (+15%) compared to the current data (+282%) (Figure 5). However, the extremely high current TP flux on the upper Nooksack is largely due to the influence of an extreme flood event during sampling on 12/8/2015, which had 100x the average daily flux and 20x the second highest daily flux in the dataset. With the flux for this sampling date replaced with the median December value (from 2010-2015), the current upper Nooksack River TP flux was only 22% higher than current lower river TP flux.

Streamflow

The total yearly streamflow passing through upper Kamm Creek was similar between the current and historical sampling periods (Figure 2), as was winter flow. However, summer flow rates were significantly higher in the current data, and current streamflow appeared more evenly distributed throughout the year (Figs. 2, 6). Differences in monthly precipitation totals between sampling periods did not closely match differences in streamflow for those months, particularly in summer, suggesting that differences in rainfall were not the primary driver of differences in streamflow in that season (Figure 6).

Current annual, winter, and summer flows on the upper Nooksack River were all significantly lower than the historical mean (Figure 5). The current lower Nooksack summer flow was also significantly lower than the historical mean; current winter flows and annual flows were lower, but not significantly (Figure 5). Annual, winter and summer stream flows on the upper Nooksack were slightly higher than on the lower Nooksack in both sampling periods, except for summer streamflow in the current sampling period (Figure 5).

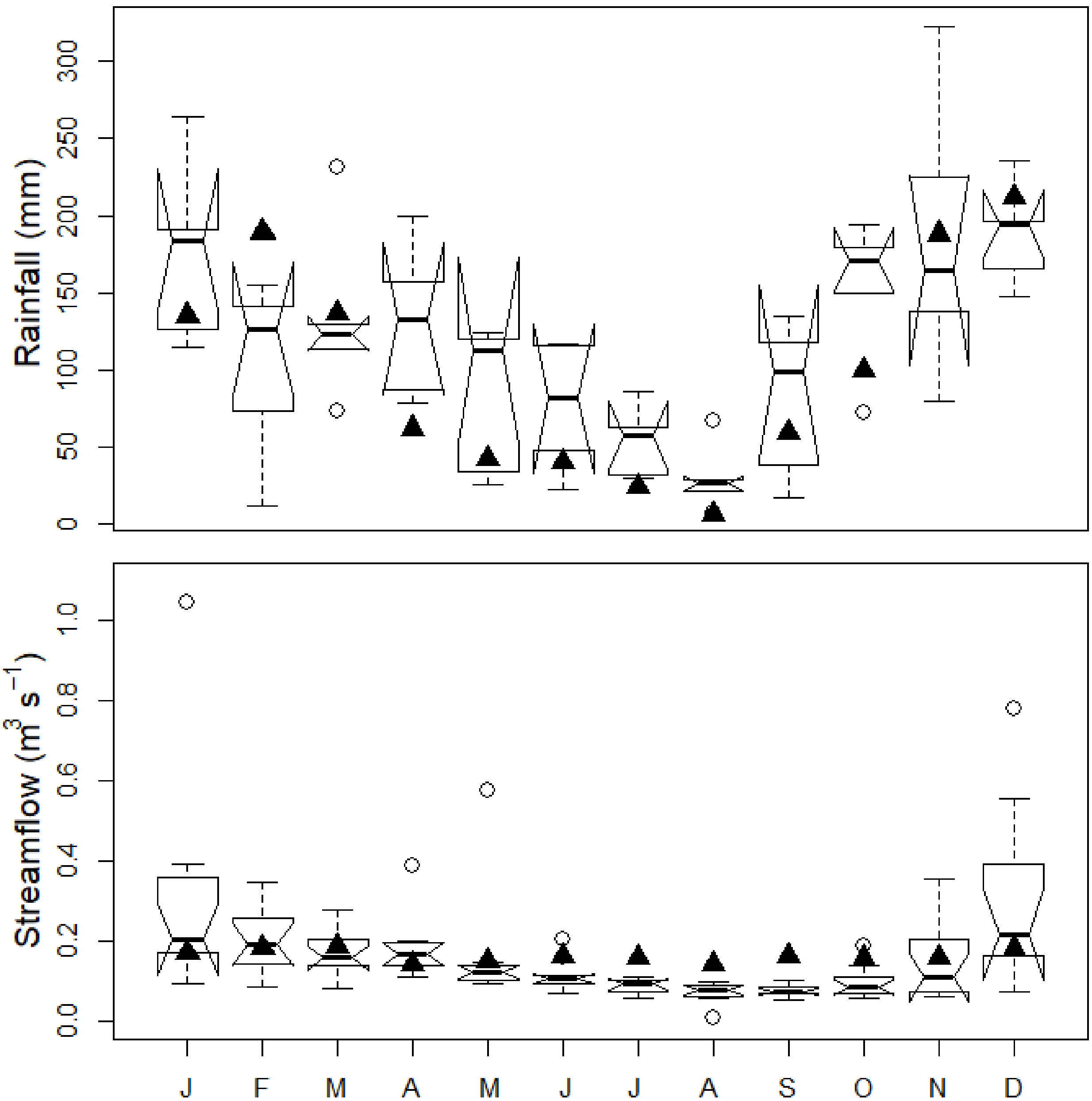

Figure 6. Distributions of monthly rainfall (a) and streamflow (b) in upper Kamm Creek's watershed during the historical study (2/1993 - 2/1998, N=5/mo for rainfall, N = 11-12/mo for streamflow). Notched box plots of historical data show medians (line) and 95% confidence intervals of the median between notches. Mean monthly values for each month of the current study (10/2015 - 10/2016, N=1/mo for rainfall, N = 2-3/mo for streamflow) shown as solid triangles. Current mean displayed rather than median, due to small sample size. Rainfall data are PRISM projections for the geographic center of the upper Kamm Creek study area (48.97°, -122.39°); acquired from the Oregon State University NW Alliance for Computational Science & Engineering, Corvallis, OR (http://prism.oregonstate.edu/explorer/). Data accessed 11/2017.

Discussion

Summary

This study found strong changes in nutrient fluxes through upper Kamm Creek between 1998 and 2015, likely resulting from the net impact of shifts in local land cover, agricultural management practices, and groundwater inputs. Annual phosphate and total phosphorous fluxes decreased significantly between the sampling periods, supporting my hypothesis for these nutrient species, and potentially validating the effects of improved nutrient management strategies. However, annual nitrate flux displayed a large and significant increase over this same time period, counter to the trends observed for phosphorous, and rejecting my initial hypothesis for nitrate. These disparate trends in nitrate and phosphorous fluxes are not inherently contradictory, as responses of the two nutrients to reduction attempts can be independent (Carpenter et al. 1998, Sims et al. 1998, Heathwaite et al. 2000). Compared to nitrate, phosphorous is more strongly retained by soils via adsorption to sediment or immobilized within organic molecules (Chapin et al. 2011), so inputs to agricultural streams such as upper Kamm Creek are determined largely by particulate inputs from sediment and manure runoff (Matthews and Vandersypen 1998, Haygarth et al. 1999, Roberts et al. 2012). Reducing manure inputs to streams was a key rationale for the introduction of The Washington State Dairy Nutrient Act (1998) and the Whatcom County Manure Nutrient Management Act (1998); to the extent that these acts are primarily responsible for the 3-5-fold reductions in soluble phosphate and total phosphorous fluxes seen between the historical and current sampling periods, they functioned as intended on upper Kamm Creek. In contrast, the increases in nitrate concentrations and fluxes suggest that this legislation was not effective in reducing nitrate inputs to upper Kamm Creek, or that their impact was overwhelmed by the effects of other changes within the watershed.

Shifts in nutrient fluxes, particularly of nitrate, through Kamm Creek were not reflected in the Nooksack River. Previous research (Inkpen and Embrey 1998, Freimund et al. 2015) and the data examined in this study suggest that nutrient inputs from sources in the lower watershed are important determinants of nutrient export from the Nooksack River to Portage Bay. However, nutrient fluxes in the mainstem Nooksack River remained stable or decreased between the sampling periods. Both the upper and lower reaches of the Nooksack River showed significant decreases in annual nitrate flux between the sampling periods, as opposed to the increase seen in Kamm Creek. This finding indicates that local mechanisms such as cropping practices or nitrate-enriched groundwater inputs likely exercise considerable control over nitrate fluxes in small waterways such as Kamm Creek. However, the lower basin's contributions of nitrate to the Nooksack River did not increase substantially between the sampling periods, failing to support the assumption that other tributaries of the lower Nooksack River experienced similar changes in local nitrogen cycling mechanisms. Total phosphate and TP fluxes through both reaches of the Nooksack decreased in patterns similar to those through Kamm Creek, but the Nooksack's decreases were not as extreme, nor always significant. Mean annual TP fluxes were higher through the upper Nooksack River than through the lower Nooksack River during both sampling periods, likely due to sediment-bound phosphorous settling out between the sampling locations (Stone 2000), but also reflecting a lack of substantial inputs from tributaries in the lower basin. Annual and summer streamflow on the Nooksack River decreased, rather than increased as on Kamm Creek. These data suggest that Kamm Creek is not fully representative of other tributaries of the lower Nooksack River, but may share similarly low phosphorous fluxes.

Potential Explanatory Factors

Several major factors influence N and P fluxes in upper Kamm Creek, particularly land-management practices and inputs of nitrate-enriched groundwater. The data presented here do not allow for attribution of increased or decreased nutrient fluxes to a particular source or sources; however, by assessing potential driving factors in the watershed, this study helps evaluate the extent to which they may or may not contribute to nutrient loading.

Changes in crop type and management, whether due to economic or regulatory pressures, might have influenced nutrient fluxes through Kamm Creek between the study periods. Between 1998 and 2015 large areas of Upper Kamm Creek's watershed were converted from hay fields, corn silage and dairy cattle pasture to raspberry and blueberry crops (Table 1). These fruit crops require less manure, but larger additions of chemical fertilizer than do dairy cattle pastures (Table A1). Increasing raspberry acreage in the region was suspected as possible source of additional nitrate as early as 1998, with raspberries associated with high nitrate levels in well-water (Erickson 1998, Matthews and Vandersypen 1998, Morgan 1999). Higher percentages of berry crops in upper Kamm Creek's cropping regime increase estimated nitrogen application rates overall (+42.7%), while decreasing estimated total phosphorous applications rates (-12.3%), based on the nutrient management recommendations listed in Table A1. Additionally, improved fertilization and manure management strategies, such as injecting rather than broadcasting manure, can reduce nutrient inputs to waterways, even if the total volume of applied nutrients remains constant (Sharpley et al. 1994, Withers and Jarvis 1998, Hernandez and Schmitt 2012).

Higher fertilization rates, particularly via fertigation (dissolved fertilizers applied via irrigation), can lead to buildup of nitrates in the soil and eventual leaching into surface or ground waters (Messiga et al. 2017). This might have contributed to the increased current nitrate flux through Kamm Creek. Blueberries present a pertinent local example of this process. Blueberries are adapted to low-pH soils and ammonium-based sources of nitrogen, as they lack sufficient enzymes to process nitrate effectively (Claussen and Lenz 1999). In Whatcom County, they are typically fertilized with urea and ammonium sulfate through a combination of granular applications and fertigation (Hart et al. 2006, Wasko DeVetter 2017)). However, unabsorbed ammonium is readily nitrified during the growing season, even in the low-pH soils typical of blueberry cultivation (Ehret et al. 2014, Zebarth et al. 2015); application of nitrification inhibitors is uncommon in the region (Lisa DeVetter-Wasko, WSU NWREC, personal communication, 2017). Subsequent leaching during fall rain events can increase nitrate inputs to groundwater or neighboring streams.

These same changes in agricultural management, in concert with legislation aimed at reducing manure use, can help explain the observed reductions in phosphorous fluxes. Nutrient management guidelines for hay and pasture crops recommend higher average rates of phosphorous fertilizer, whether in manure or mineral form, than berry crop guidelines (Table A1). As hayfields and pasture are converted to berry crops, their different fertilization regimes may reduce inputs to the waterway from both overland flow and subsurface leaching. An additional consideration is that the high rates of nitrogen fertilizers (or applications of elemental sulfur) used in berry crops may lead to decreases in soil pH, particularly in blueberries, where a low soil pH is desirable (Hart et al. 2006). Low soil pH encourages soluble phosphate to sorb to iron and aluminum oxides in soil particles, immobilizing it and preventing leaching (Chapin et al. 2011). This effect may partially explain the lower relative contribution of phosphate to TP flux through upper Kamm Creek in the current data, as well as the reductions seen in both.

Groundwater nitrate contributions are the second potential factor underlying the increased nitrate flux through upper Kamm Creek. The groundwater in the western half of the upper Kamm Creek Basin comes from the Sumas-Blaine Aquifer, which had nitrate concentrations greater than 10 mg L^{-1} in many portions during both the historical and current sampling periods (Carey 2013, Carey et al. 2017). This groundwater feeds the stream directly via several springs above my sampling point. It is possible that these springs contributed a larger volume of water, or more heavily nitrate-laden water, during the current sampling period. Groundwater is also increasingly used for irrigation in Kamm Creek's watershed (Chuck Timblin, WCD, personal communication, 2017), providing another avenue for nitrate inputs. Irrigation strictly with groundwater could add up to 9.2 kg N $hectare^{-1}$ $year^{-1}$ to fields planted in blueberry (which cannot effectively absorb nitrate) at average irrigation rates (38 cm $year^{-1}$), given the high levels of nitrate (mean 10.73 mg L^{-1}) found at test wells in the study watershed (Carey 2013). But, nitrate deposited on berry fields may be immobilized or denitrified rather than flowing into surface waters, and maximum annual theoretical contributions (~520 kg N) from groundwater-irrigated blueberry fields cannot account for the observed increase in annual nitrate flux (~25,000 kg N). Models of two neighboring creeks predicted that a shift in irrigation sources from surface to groundwater could boost summer streamflow, and therefore summer nutrient fluxes (Pruneda et al. 2010), similar to what I observed for streamflow and nitrate on upper Kamm Creek. The shift towards groundwater irrigation and higher summer stream flows could have diluted phosphate and total phosphorous concentrations in upper Kamm Creek, as levels in the Sumas-Blaine Aquifer are generally extremely low (Cox and Khale 1999). However, these effects should not have impacted other inputs, and therefore fluxes.

Data and Analysis Limitations

Neither conversion to berry fields nor increases in groundwater nitrate inputs offer a clear and complete explanation for the increased nitrate fluxes in upper Kamm Creek. Blueberry acreage in the lower Nooksack Basin increased roughly four-fold between the sampling periods, but the lower Nooksack River has not experienced a similar increase in nitrate flux. Local differences in crop nutrient management may help partially explain these distinct responses, as cropping practices varied widely among Nooksack tributary watersheds during both the current and historic sampling periods. Unfortunately, data on cropping practices at the scale of individual fields are incomplete in the historic period; for current crops, the details of total nutrient additions, the ratio of mineral to organic forms, timing, and application method are typically confidential 'trade secrets' not shared among individual growers, or between growers and researchers (Lisa DeVetter-Wasko, WSU Extension, personal communication, 2016). Nutrient losses from different crops are not thoroughly documented in our region; edge-of-field monitoring within upper Kamm Creek's watershed is non-existent. Further complicating comparative evaluations, recommended nutrient management strategies for particular crops have evolved between the study periods. These changes have likely reduced average nutrient inputs to some crops such as hay and silage corn crops, and modestly increased average nutrient inputs to others such as berry crops, based on advances in knowledge leading to increased yields and improved crop management. Due to concurrent improvements in fertilization timing and method, higher total nutrient application rates for a crop may not lead to increased nutrient inputs to waterways (Nichole Embertson, WCD, personal communication, 2018).

Understanding groundwater inputs to upper Kamm Creek is crucial because they have the potential to decouple nitrate fluxes through the creek in both space (Mitchell et al. 2003) and time (Meals et al. 2010) from the impacts of local conservation measures. Unfortunately, groundwater inputs were not measured during either the current or historical study, so thorough analysis of their nitrate contributions is impossible. The total volume or proportion of irrigation water sourced from the Sumas-Blaine aquifer for the study watershed is also poorly documented. Integrated sampling of surface water, groundwater, and stable isotopes offers a plausible way to differentiate among potential sources and transformations of nitrogen in Kamm Creek (Xue et al. 2009, Jankowski et al. 2012, Wells et al. 2016, Ji et al. 2017). However, such studies are complicated by Kamm Creek's multiple nitrate sources and by local anomalies in flows and concentrations of nitrate in the Sumas-Blaine Aquifer (Mitchell et al. 2003, Xue et al. 2009).

Comparative analyses between current and historical datasets, particularly those for streamflow, have inherent limitations. In this study, a lack of high streamflow events (above 0.4 $m^3 s^{-1}$) in the current, single-year, dataset limited correlations of current nutrient levels to streamflow, compared to the historical dataset. Collections were made fairly regularly every two weeks in both datasets, but the historic dataset also includes one sampling date from each of three additional high-water sampling periods (Matthews and Vandersypen 1998). Current samplings were also intended to capture winter high-water events, but sampling dates were chosen based on weather forecasts and did not ultimately capture streamflow levels as high as those found in the historical dataset.

With almost two decades between the current and historical sampling periods, the current sampling year could have occurred in a different climatic context from any of the historical years. Global climate change and long-term cycles such as the Pacific Decadal Oscillation (PDO), can influence rainfall and temperature and therefore streamflow, crop growth, and nutrient utilization (Mantua et al. 1997, Fuhrer 2003, Mantua et al. 2010). However, current minimum and maximum temperatures were within the range of historic data for most months. While current summer rainfall was often below the historic range, annual rainfall was extremely similar between the study periods (Table A5, Fig. 5). Current nitrate deposition levels in western Washington were below the range of historical data, the opposite of trends in upper Kamm Creek's nitrate flux data (Table A6). Ammonia/ammonium deposition appears to be rising in both absolute and relative terms, which could impact nitrogen supply and cycling within the watershed in the future (Li et al. 2016). However, as of the current study period, increased ammonia/ammonium deposition would account for <1% of the observed increase in nitrate flux, even if all deposited ammonium-N was exported as nitrate-N.

Conclusions and Ecological Significance

My findings present evidence for higher concentrations and fluxes of nitrate and much lower concentrations and fluxes of phosphate and total phosphorous on upper Kamm Creek in 2015-16 compared to 1993-1998. While these data suggest a potential victory for BMP's in reducing P loading, the divergent responses of N and P in upper Kamm Creek suggest that separate factors are increasing nitrate export from, and likely therefore inputs to, the watershed. Mechanisms underlying these changes are difficult to determine with the data presently available. These connections are worth further investigation, because management changes in the watershed of Kamm Creek are comparable to those for other agricultural tributaries of the Nooksack River, which is an economically, socially and environmentally key resource for local communities. The study area provides spawning grounds for ESA-listed runs of Pacific salmon, and the WRIA1 Salmonid Recovery Plan specifically mentions reducing agricultural nutrient inputs as a way to improve salmon habitat on Kamm Creek (Nooksack Indian Tribe 2004).

Fluxes of both phosphorous species through the upper and lower Nooksack River followed broadly similar trends to those on upper Kamm Creek, decreasing somewhat between the sampling periods, though not always significantly, or by the same percentage. Both sections of the Nooksack River also displayed significant decreases in annual nitrate flux, counter to what was observed on Kamm Creek. Ecological effects on the health of Portage Bay and other downstream ecosystems will depend on the complex relationships between nutrient enrichment and algal ecology (Biggs 2000, Anderson et al. 2002). Existing research suggests that increased overall nutrient fluxes could harm shellfish and salmon through the promotion of harmful algal blooms (Anderson et al. 2002, Rabalais 2002, Trainer et al. 2003, Rabotyagov et al. 2014). But, issues with fecal coliform levels in Portage Bay remain, despite reduced nutrient inputs from the Nooksack River. Aquatic ecosystems regionally and worldwide are of immense conservation and economic concern, while the potential for rapid future shifts in agriculture due to economic, technological or climatic changes is increasing (Schneider et al. 2011, Kurukulasuriya and Rosenthal 2013). Research into how specific agricultural practices and environmental factors affect water quality can help farmers feed a growing population while maintaining clean water and healthy stream ecosystems.

Literature Cited

Anderson, D. M., P. M. Glibert, and J. M. Burkholder. 2002. Harmful algal blooms and eutrophication: nutrient sources, composition, and consequences. Estuaries **25**:704-726.

Banner, E. B., A. J. Stahl, and W. K. Dodds. 2009. Stream discharge and riparian land use influence in-stream concentrations and loads of phosphorus from central plains watersheds. Environmental Management **44**:552-565.

Barney, D. L., P. Bristow, C. G. Cogger, S. M. Fitzpatrick, J. M. Hart, D. Kaufman, C. Miles, T. Miller, P. P. Moore, and T. Murray. 2007. Commercial red raspberry production in the Pacific Northwest. Oregon State University Extension Service, Corvallis, OR.

Barto, K. 2017. R package 'MuMIn': multi-model inference (version 1.40.0).

Beaulac, M. N. and K. H. Reckhow. 1982. An examination of land use - nutrient export relationships. Water Resources Bulletin **18**.

Beeler, K. R. and R. J. Mitchell. 2017. Sediment and Phosphorus Inputs from Perennial Streams to Lake Whatcom, Washington State. Environmental and Engineering Geoscience **23**:153-164.

Beschta, R. L. 1981. Streamflow estimates in culverts. Oregon State University, School of Forestry, Corvallis, OR.

Biggs, B. J. 2000. Eutrophication of streams and rivers: dissolved nutrient-chlorophyll relationships for benthic algae. Journal of the North American Benthological Society **19**:17-31.

Blann, K. L., J. L. Anderson, G. R. Sands, and B. Vondracek. 2009. Effects of agricultural drainage on aquatic ecosystems: A review. Critical Reviews in Environmental Science and Technology **39**:909-1001.

Borah, D. K. and M. Bera. 2004. Watershed-scale hydrologic and nonpoint-source pollution models: Review of applications. Transactions of the American Society of Agricultural Engineers **47**:789.

Bowman, A. W. a. A., A. . 2014. R package 'sm': nonparametric smoothing methods (version 2.2-5.4).

Braden, J. B. and K. Segerson. 1993. Information problems in the design of nonpoint-source pollution policy. Pages 1-36 *in* C. S. Russell and J. F. Shogren, editors. Theory, Modeling and Experience in the Management of Nonpoint-source Pollution. Springer, Boston, MA.

Bryla, D. R. and O. Vargas. 2012. Nitrogen fertilizer practices for rapid establishment of highbush blueberry: A review of six years of research. Pages 415-421 *in* X International Symposium on Vaccinium and Other Superfruits 1017, Maastricht, The Netherlands

Burrows, C. and D. Bretz. 2011. Whatcom County community food assessment. Washington State University-Whatcom County Extension, Bellingham.

Butler, D. M., N. N. Ranells, D. H. Franklin, M. H. Poore, and J. T. Green. 2007. Ground cover impacts on nitrogen export from manured riparian pasture. Journal of environmental quality **36**:155-162.

Carey, B. C., R. 2013. Sumas-Blaine Aquifer nitrate contamination summary. Washington State Department of Ecology Olympia, WA.

Carey, B. M., C. F. Pitz, and J. H. Harrison. 2017. Field nitrogen budgets and post-harvest soil nitrate as indicators of N leaching to groundwater in a Pacific Northwest dairy grass field. Nutrient Cycling in Agroecosystems:1-17.

Carpenter, S. R., N. F. Caraco, D. L. Correll, R. W. Howarth, A. N. Sharpley, and V. H. Smith. 1998. Nonpoint pollution of surface waters with phosphorous and nitrogen. Ecological Applications **8**:559-568.

Cavero, J., R. Barros, F. Sellam, S. Topcu, D. Isidoro, T. Hartani, A. Lounis, H. Ibrikci, M. Cetin, and J. Williams. 2012. APEX simulation of best irrigation and N management strategies for off-site N pollution control in three Mediterranean irrigated watersheds. Agricultural Water Management **103**:88-99.

Chapin, F. S., P. A. Matson, and P. Vitousek. 2011. Principles of terrestrial ecosystem ecology. Springer Science & Business Media.

Chaubey, I., L. Chiang, M. W. Gitau, and S. Mohamed. 2010. Effectiveness of best management practices in improving water quality in a pasture-dominated watershed. Journal of Soil and Water Conservation **65**:424-437.

Chen, W., B. He, D. Nover, W. Duan, C. Luo, K. Zhao, and W. Chen. 2018. Spatiotemporal patterns and source attribution of nitrogen pollution in a typical headwater agricultural watershed in Southeastern China. Environmental Science and Pollution Research **25**:2756-2773.

Cherry, K., S. J. Mooney, S. Ramsden, and M. A. Shepherd. 2012. Using field and farm nitrogen budgets to assess the effectiveness of actions mitigating N loss to water. Agriculture, Ecosystems & Environment **147**:82-88.

Chislock, M. F., E. Doster, R. A. Zitomer, and A. E. Wilson. 2013. Eutrophication: Causes, consequences, and controls in aquatic ecosystems. Nature Education Knowledge **4**:10.

Claussen, W. and F. Lenz. 1999. Effect of ammonium or nitrate nutrition on net photosynthesis, growth, and activity of the enzymes nitrate reductase and glutamine synthetase in blueberry, raspberry and strawberry. Plant and Soil **208**:95-102.

Cooper, R. J., Z. Hama-Aziz, K. M. Hiscock, A. A. Lovett, S. J. Dugdale, G. Sünnenberg, L. Noble, J. Beamish, and P. Hovesen. 2017. Assessing the farm-scale impacts of cover crops and non-inversion tillage regimes on nutrient losses from an arable catchment. Agriculture, Ecosystems & Environment **237**:181-193.

Cox, S. E. and S. C. Kahle. 1999. Hydrogeology, ground-water quality, and sources of nitrate in lowland glacial aquifers of Whatcom County, Washington, and British Columbia, Canada. US Geological Survey, Tacoma, WA.

Daggupati, P., N. Pai, S. Ale, K. R. Douglas-Mankin, R. W. Zeckoski, J. Jeong, P. B. Parajuli, D. Saraswat, and M. A. Youssef. 2015. A recommended calibration and validation strategy for hydrologic and water quality models. Transactions of the American Society of Agricultural and Biological Engineers **58**:1705-1719.

Diaz, R. J. and R. Rosenberg. 2008. Spreading dead zones and consequences for marine ecosystems. Science **321**:926-929.

Dodds, W. K., W. W. Bouska, J. L. Eitzmann, T. J. Pilger, K. L. Pitts, A. J. Riley, J. T. Schloesser, and D. J. Thornbrugh. 2008. Eutrophication of US freshwaters: Analysis of Potential Economic Damages. Environmental Science & Technology **43**:12-19.

Dowd, B. M., D. Press, and M. Los Huertos. 2008. Agricultural nonpoint source water pollution policy: The case of California's Central Coast. Agriculture, Ecosystems & Environment **128**:151-161.

Ehret, D. L., B. Frey, T. Forge, T. Helmer, D. R. Bryla, and B. J. Zebarth. 2014. Effects of nitrogen rate and application method on early production and fruit quality in highbush blueberry. Canadian Journal of Plant Science **94**:1165-1179.

Erickson, D. 1998. Sumas-Blaine surficial aquifer nitrate characterization. Washington State Department of Ecology, Olympia, WA.

Fageria, N., V. Baligar, and Y. Li. 2008. The role of nutrient efficient plants in improving crop yields in the twenty first century. Journal of Plant Nutrition **31**:1121-1157.

Freimund, J., S. Fawell, J. Snyder, and G. Gabrisch. 2015. Lummi Nation nonpoint source pollution management plan: 2015-2020. Water Resources Division, Lummi Natural Resources Department

Fuhrer, J. 2003. Agroecosystem responses to combinations of elevated CO 2, ozone, and global climate change. Agriculture, Ecosystems & Environment **97**:1-20.

Giri, S., Z. Qiu, T. Prato, and B. Luo. 2016. An integrated approach for targeting critical source areas to control nonpoint source pollution in watersheds. Water Resources Management **30**:5087-5100.

Hart, J. M., B. Strik, L. White, and W. Yang. 2006. Nutrient management for blueberries in Oregon. Extension Service, Oregon State University, Corvallis, OR.

Hart, J. M., D. Sullivan, M. Gamroth, T. Downing, and A. Peters. 2009. Silage corn: western Oregon. Oregon State University Extension Service, Corvallis, OR.

Hatfield, J. L., L. D. McMullen, and C. S. Jones. 2009. Nitrate-nitrogen patterns in the Raccoon River Basin related to agricultural practices. Journal of Soil and Water Conservation **64**:190-199.

Haygarth, P., A. Heathwaite, S. Jarvis, and T. Harrod. 1999. Hydrological factors for phosphorus transfer from agricultural soils. Advances in Agronomy **69**:153-178.

Heathwaite, L., A. Sharpley, and W. Gburek. 2000. A conceptual approach for integrating phosphorous and nitrogen management at watershed scales. Journal of Environmental Quality **29**:158-166.

Hernandez, J. A. and M. A. Schmitt. 2012. Manure management in Minnesota. University of Minnesota Extension, St. Paul, MN.

Hopkins, B. G., C. J. Rosen, A. K. Shiffler, and T. W. Taysom. 2008. Enhanced efficiency fertilizers for improved nutrient management: Potato. Crop Management **7**:0-0.

Inkpen, E. L. and S. S. Embrey. 1998. Nutrient transport in the major rivers and streams of the Puget Sound Basin, Washington. US Department of the Interior, US Geological Survey, Tacoma, WA.

Jankowski, K., D. E. Schindler, and G. W. Holtgrieve. 2012. Assessing nonpoint-source nitrogen loading and nitrogen fixation in lakes using $\delta15N$ and nutrient stoichiometry. Limnology and Oceanography **57**:671-683.

Ji, X., R. Xie, Y. Hao, and J. Lu. 2017. Quantitative identification of nitrate pollution sources and uncertainty analysis based on dual isotope approach in an agricultural watershed. Environmental Pollution **229**:586-594.

Kaushal, S. S., P. M. Mayer, P. G. Vidon, R. M. Smith, M. J. Pennino, T. A. Newcomer, S. Duan, C. Welty, and K. T. Belt. 2014. Land use and climate variability amplify carbon, nutrient, and contaminant pulses: a review with management implications. Journal of the American Water Resources Association **50**:585-614.

Kugler, J. L. 2006. Orchardgrass hay production guide for the Columbia Basin of Washington. WSU Grant/Adams County Extension, Moses Lake, WA.

Kurukulasuriya, P. and S. Rosenthal. 2013. Climate change and agriculture: A review of impacts and adaptations. The International Bank for Reconstruction and Development, Washington, D.C.

Lewis, W. M., W. A. Wurtsbaugh, and H. W. Paerl. 2011. Rationale for control of anthropogenic nitrogen and phosphorus to reduce eutrophication of inland waters. Environmental Science & Technology **45**:10300-10305.

Li, Y., B. A. Schichtel, J. T. Walker, D. B. Schwede, X. Chen, C. M. B. Lehmann, M. A. Puchalski, D. A. Gay, and J. L. Collett. 2016. Increasing importance of deposition of reduced nitrogen in the United States. Proceedings of the National Academy of Sciences **113**:5874-5879.

Makarewicz, J. C., T. W. Lewis, I. Bosch, M. R. Noll, N. Herendeen, R. D. Simon, J. Zollweg, and A. Vodacek. 2009. The impact of agricultural best management practices on downstream systems: Soil loss and nutrient chemistry and flux to Conesus Lake, New York, USA. Journal of Great Lakes Research **35**:23-26.

Mantua, N., I. Tohver, and A. Hamlet. 2010. Climate change impacts on streamflow extremes and summertime stream temperature and their possible consequences for freshwater salmon habitat in Washington State. Climatic Change **102**:187-223.

Mantua, N. J., S. R. Hare, Y. Zhang, J. M. Wallace, and R. C. Francis. 1997. A Pacific interdecadal climate oscillation with impacts on salmon production. Bulletin of the American Meteorological Society **78**:1069-1079.

Matthews, R. A. and J. P. Vandersypen. 1998. Kamm Creek watershed monitoring final report. Western Washington University Bellingham.

Meals, D. W., S. A. Dressing, and T. E. Davenport. 2010. Lag time in water quality response to best management practices: A review. Journal of Environmental Quality **39**:85.

Messiga, A. J., M. Dorais, and D. Haak. 2017. Blueberry yield and soil properties in response to long-term fertigation and broadcast nitrogen. Agassiz Research and Development Centre, Agassiz, BC.

Mitchell, R. J., R. S. Babcock, S. Gelinas, L. Nanus, and D. E. Stasney. 2003. Nitrate distributions and source identification in the Abbotsford–Sumas aquifer, northwestern Washington State. Journal of Environmental Quality **32**:789-800.

Morgan, L. 1999. The aquifer vulnerability project: Nooksack pilot study report. Washington State Department of Ecology, Water Quality Program, Watershed Management Section, Olympia, WA.

Mulla, D. J., A. S. Birr, N. R. Kitchen, and M. B. David. 2008. Limitations of evaluating the effectiveness of agricultural management practices at reducing nutrient losses to surface waters. Pages 189-212 *in* Gulf hypoxia and local water quality concerns workshop. American Society of Agricultural and Biological Engineers, St. Joseph, MI.

Niraula, R., L. Kalin, P. Srivastava, and C. J. Anderson. 2013. Identifying critical source areas of nonpoint source pollution with SWAT and GWLF. Ecological Modelling **268**:123-133.

Pinckney, J. L., H. W. Paerl, P. Tester, and T. L. Richardson. 2001. The role of nutrient loading and eutrophication in estuarine ecology. Environmental Health Perspectives **109**:699.

R Core Team. 2015. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Rabalais, N. N. 2002. Nitrogen in aquatic ecosystems. AMBIO: A Journal of the Human Environment **31**:102-112.

Rabotyagov, S., C. Kling, P. Gassman, N. Rabalais, and R. Turner. 2014. The economics of dead zones: causes, impacts, policy challenges, and a model of the Gulf of Mexico Hypoxic Zone. Review of Environmental Economics and Policy **8**:58-79.

Ribaudo, M. O., R. Heimlich, R. Claassen, and M. Peters. 2001. Least-cost management of nonpoint source pollution: source reduction versus interception strategies for controlling nitrogen loss in the Mississippi Basin. Ecological Economics **37**:183-197.
Roberts, W. M., M. I. Stutter, and P. M. Haygarth. 2012. Phosphorus retention and remobilization in vegetated buffer strips: a review. Journal of Environmental Quality **41**:389-399.
Schaffner, M., H.-P. Bader, and R. Scheidegger. 2009. Modeling the contribution of point sources and non-point sources to Thachin River water pollution. Science of the Total Environment **407**:4902-4915.
Schlegel, B. and J. L. Domagalski. 2015. Riverine nutrient trends in the Sacramento and San Joaquin Basins, California: A comparison to state and regional water quality policies. San Francisco Estuary and Watershed Science **13**.
Schneider, U. A., P. Havlík, E. Schmid, H. Valin, A. Mosnier, M. Obersteiner, H. Böttcher, R. Skalský, J. Balkovič, and T. Sauer. 2011. Impacts of Population Growth, Economic Development, and Technical Change on Global Food Production and Consumption. Agricultural Systems **104**:204-215.
Sharpley, A. N., S. Chapra, R. Wedepohl, J. Sims, T. C. Daniel, and K. Reddy. 1994. Managing agricultural phosphorus for protection of surface waters: Issues and options. Journal of Environmental Quality **23**:437-451.
Sims, J., R. Simard, and B. Joern. 1998. Phosphorus loss in agricultural drainage: Historical perspective and current research. Journal of Environmental Quality **27**:277-293.
Stone, M. 2000. The role of erosion and sediment transport in nutrient and contaminant transfer. International Association of Hydrological Sciences, Wallingford, UK.
Trainer, V. L., B.-T. L. Eberhart, J. C. Wekell, N. G. Adams, L. Hanson, F. Cox, and J. Dowell. 2003. Paralytic shellfish toxins in Puget Sound, Washington State. Journal of Shellfish Research **22**:213-223.
Van Es, H., R. Schindelbeck, and W. Jokela. 2004. Effect of manure application timing, crop, and soil type on phosphorus leaching. Journal of Environmental Quality **33**:1070-1080.
Van Es, H. M., J. M. Sogbedji, and R. R. Schindelbeck. 2006. Effect of manure application timing, crop, and soil type on nitrate leaching. Journal of Environmental Quality **35**:670-679.
Vanni, M. J., W. H. Renwick, J. L. Headworth, J. D. Auch, and M. H. Schaus. 2001. Dissolved and particulate nutrient flux from three adjacent agricultural watersheds: A five-year study. Biogeochemistry **54**:85-114.
Vitousek, P. M., J. D. Aber, R. W. Howarth, G. E. Likens, P. A. Matson, D. W. Schindler, W. H. Schlesinger, and D. G. Tilman. 1997. Human alteration of the global nitrogen cycle: sources and consequences. Ecological Applications **7**:737-750.
Wang, J., G. Lü, X. Guo, Y. Wang, S. Ding, and D. Wang. 2015. Conservation tillage and optimized fertilization reduce winter runoff losses of nitrogen and phosphorus from farmland in the Chaohu Lake region, China. Nutrient cycling in Agroecosystems **101**:93-106.
Wang, X. 2006. Management of agricultural nonpoint source pollution in China: current status and challenges. Water Science and Technology **53**:1-9.
Wasko DeVetter, L. 2017. Nutrient management update for blueberry and raspberry. Presentation, Washinton State University NWREC, Mt. Vernon, WA.

Wells, N. S., W. T. Baisden, T. Horton, and T. J. Clough. 2016. Spatial and temporal variations in nitrogen export from a New Zealand pastoral catchment revealed by stream water nitrate isotopic composition. Water Resources Research **52**:2840-2854.

Whatcom County Ag Watershed Project. 2014. Whatcom County Ag-Watershed Pilot Project. Bellingham.

Withers, P. and S. Jarvis. 1998. Mitigation options for diffuse phosphorus loss to water. Soil Use and Management **14**:186-192.

Withers, P. J., C. Neal, H. P. Jarvie, and D. G. Doody. 2014. Agriculture and eutrophication: Where do we go from here? Sustainability **6**:5853-5875.

Xue, D., J. Botte, B. De Baets, F. Accoe, A. Nestler, P. Taylor, O. Van Cleemput, M. Berglund, and P. Boeckx. 2009. Present limitations and future prospects of stable isotope methods for nitrate source identification in surface-and groundwater. Water Research **43**:1159-1170.

Zebarth, B. J., T. A. Forge, C. Goyer, and L. D. Brin. 2015. Effect of soil acidification on nitrification in soil. Canadian Journal of Soil Science **95**:359-363.

Zebarth, B. J., B. Hii, H. Liebscher, K. Chipperfield, J. W. Paul, G. Grove, and S. Szeto. 1998. Agricultural land use practices and nitrate contamination in the Abbotsford Aquifer, British Columbia, Canada. Agriculture Ecosystems & Environment **69**:99-112.

Appendix A: Supplementary Tables and Figures

TABLE A1. Nutrient management guidelines for common crops grown Whatcom County (Hart et al. 2006, Kugler 2006, Barney et al. 2007, Hart et al. 2009). Application rates are annual averages over the course of the full crop rotation period, grown in soils with typical nutrient content. Actual nutrient applications typically occur in multiple additions over the course of the year, and the management of individual fields may differ substantially due to local conditions and grower preferences.

	N App. rate (kg ha^{-1})	**P_2O_5 App. rate (kg ha^{-1})**	**Application methods**
Blueberry	106	*	Urea (fertigation)
Caneberry (Raspberry)	62	*	Ammonium nitrate
Hay (Orchardgrass)	336	106.4	Manure
Pasture (Orchardgrass, etc.)	34	11.2	Manure (via grazing)
Corn Silage	84	78.4**	Manure, amm. nitrate

*Typical soils in northern Whatcom County contain ample phosphorous for blueberry and raspberry production. Additional P_2O_5 (up to 80 kg ha^{-1}) may be added if Bray-Kurtz P1 soil test indicate low extractable P (<40 mg L^{-1}).
** Silage corn fertilized with manure typically does not need applications of mineral phosphate. Bray-Kurtz P1 soil tests indicating low extractable P may require the addition of up to 100 kg ha^{-1} additional P_2O_5.

TABLE A2. Analytical methods for determining stream water nutrient concentrations using a Unity Scientific Instruments, Inc. SmartChem 200 Discrete Analyzer. The ammonia method was switched in May 2016 to limit hazardous waste generation.

Nutrient	**Method**	**Detection limit**	**Upper bound**
Orthophosphate	EPA 365.1	0.0041 mg L^{-1}	1 mg L^{-1}
Total Phosphorous	EPA 365.1 with alkaline persulfate digestion	0.0095 mg L^{-1}	1 mg L^{-1}
Nitrate-Nitrite	EPA 353.2	0.0531 mg L^{-1}	20 mg L^{-1}
Total Nitrogen	EPA 353.2 with alkaline persulfate digestion	0.0473 mg L^{-1}	20 mg L^{-1}
Ammonia (Before 5/20/2016)	EPA 350.1	0.0734 mg L^{-1}	2 mg L^{-1}
Ammonia (After 5/21/2016)	SmartChem AMM-003-A	0.0601 mg L^{-1}	2 mg L^{-1}

TABLE A3. Generalized linear models for Log_{10} nitrate-N, phosphate-P, and total P concentrations, and for streamflow based on combinations of sampling time period (current vs. historical; T) and streamflow (continuous; S), with and without interaction. Models are listed in order of decreasing relative parsimony, with increases in Akaike Information Criterion corrected for small sample sizes (AICc) scores denoted. P-values for individual predictive variables and intercept are listed, with statistical significance indicated as: * = [0.05, 0.01], ** = [0.001, 0.0001], *** = [0.0001, 0.0]. N = 159 for NO_3^-, N = 160 for PO_4, N = 157 for TP, and N = 161 for streamflow.

Δ AICc	**Nitrate**	**T**	**S**	**T x S**	**Intercept**
	[NO3] ~ Period + Streamflow (No interaction)	***	***		***
2.1	*[NO3] ~ Period * Streamflow (Interaction)*	0.16	0.19	0.968	***
45.5	*[NO3] ~ Streamflow*		***		***
71.2	*[NO3] ~ Period*	***			***
Δ AICc	**Phosphate**	**T**	**S**	**T x S**	**Intercept**
	[PO4] ~ Period + Streamflow (No interaction)	***	***		***
2.0	*[PO4] ~ Period * Streamflow (Interaction)*	0.627	0.317	0.732	0.415
13.9	*[PO4] ~ Streamflow*		***		***
25.5	*[PO4] ~ Period*	**			0.078
Δ AICc	**Total Phosphorous**	**T**	**S**	**T x S**	**Intercept**
	[TP] ~ Period + Streamflow (No interaction)	**	***		**
2.0	*[TP] ~ Period * Streamflow (Interaction)*	0.286	0.585	0.696	0.178
8.6	*[TP] ~ Streamflow*		***		0.122
64.2	*[TP] ~ Period*	**			***
Δ AICc	**Streamflow**	**T**			
	Streamflow ~ Period	0.884			

TABLE A4. Equations and coefficients of determination for the linear regression best fit lines for nitrate-N, phosphate-P, and total P, as a function of streamflow (S) on upper Kamm Creek. Equations and R^2 values shown for regressions in Fig. 4 of both historical (N = 133) and current (N=27) data.

		Historic	**Current**
Nitrate-N	Best fit line:	$Log_{10}[N] = -0.65 \times S + 0.93$	$Log_{10}[N] = -0.62 \times S + 1.05$
	R^2 =	0.628	0.106
Phosphate-P	Best fit line:	[P] = 0.19 x S + 0.009	[P] = 0.08 x S - 0.006
	R^2 =	0.357	0.017
Total P	Best fit line:	[TP] = 0.477 x S - 0.0001	[TP] = 0.488 x S - 0.046
	R^2 =	0.5	0.11

TABLE A5 Ranges for 1993-1998 monthly average minimum and maximum temperature data (current monthly averages in parentheses) for the geographic center of the upper Kamm Creek study area (48.97°, -122.39°). Data are PRISM projections acquired from the Oregon State University NW Alliance for Computational Science & Engineering, Corvallis, OR (http://prism.oregonstate.edu/explorer/). Data accessed 11/2017.

	Min. Temp. (°C)		**Max. Temp. (°C)**	
January	-0.1 - 3.6	(0.8)	5.1 - 9.5	(7.4)
February	0.0 - 3.9	(3.8)	6.8 - 10.8	(11.1)
March	2.5 - 3.4	(4.7)	10.1 - 13.1	(12.9)
April	4.8 - 6.8	(6.5)	14.7 - 15.6	(18.2)
May	7.8 - 10.2	(8.4)	16.0 - 20.6	(20.0)
June	10.1 - 11.8	(10.5)	20.0 - 22.1	(21.8)
July	12.0 - 13.3	(12.4)	20.9 - 25.1	(23.7)
August	11.3 - 13.1	(11.5)	22.2 - 26.0	(26.2)
September	8.1 - 10.9	(9.0)	19.3 - 23.5	(20.7)
October	5.9 - 6.8	(10.0)	14.2 - 16.5	(21.2)
November	-0.3 - 4.3	(1.7)	7.7 - 12.2	(9.4)
December	-1.5 - 1.3	(1.9)	4.1 - 7.9	(7.3)

TABLE A6 Nitrate deposition data acquired from the US EPA Clean Air Status and Trends Network (CASTNET) (https://java.epa.gov/castnet/clearsession.do). Data are for the North Cascade National Park, WA monitoring station. Data accessed 11/2017.

Year	NH_4-N (kg ha^{-1})	NO_3-N (kg ha^{-1})
1993	0.6	1.2
1994	0.6	1.4
1995	0.6	1.2
1996	0.9	1.6
1997	0.6	1.8
1998	0.3	1.1
2015	0.6	0.9
2016	1.4	1.0

Appendix B: Watershed nutrient modeling using APEX

APEX introduction

This appendix documents the process of modeling the upper Kamm Creek watershed, using the Agricultural Policy/Environmental eXtender (APEX) model[1] (Williams et al. 2006). The APEX model presents an opportunity to predict the water quality outcomes of both general land management changes in a basin, and specific restoration measures such as riparian buffers. The end goal is to develop a fully parameterized and well-calibrated version of the model for our region, which can accurately predict hydrologic and nutrient fluxes in small watersheds across WRIA 1. APEX could then help target riparian restoration efforts by simulating the relative effectiveness of potential sites for riparian buffers or other BMP's.

APEX is suited for prioritizing and targeting riparian restoration and other management actions, as it can simulate complete watersheds composed of multiple heterogeneous subareas, while remaining sensitive to field-scale actions such as buffer strip installation (Gassman et al. 2010, Williams et al. 2010). APEX has been used in the Mediterranean region of Europe, as well as in the Eastern and Southern U.S., to determine the best management regimes for reducing nutrient pollution, to estimate the effect of buffer strip widths and soil types on nutrient losses, and to determine which locations will provide the largest reduction in nutrient flux for a given management action (Williams et al. 2006, Tuppad et al. 2010, Cavero et al. 2012, Plotkin et al. 2012, Francesconi et al. 2014, Van Liew et al. 2017). APEX's flexibility regarding spatial scale and management inputs make it ideal for predicting the impact of BMP implementation or other land management shifts on the farm-to-small-watershed scale.

[1] Developed by the US Department of Agriculture – Agricultural Research Service (USDA-ARS) in Temple, Texas

While APEX is generally successful in predicting nutrient fluxes, sediment yield and streamflow for regions with established environmental and management parameters, these parameters must be updated before APEX can be applied in new regions, including northwest Washington (Moriasi et al. 2014). Suites of parameters relating to crop growth and agricultural management may require substantial new research before they can be accurately input into APEX, and existing data sources (e.g., soil properties) require careful evaluation to achieve optimal model results (Monks 2016). Additionally, the characteristics of each individual watershed modeled by APEX must be entered carefully in order for APEX to accurately represent streamflow and nutrient cycling dynamics within that system. The following guide is designed to help researchers successfully apply APEX and its supporting tools to more effectively delineate, parameterize, and calibrate new watersheds, using the example watershed of upper Kamm Creek. Its ultimate goal is to support APEX's use in guiding local environmental policy and prioritizing riparian restoration projects throughout Whatcom County and northwest Washington. However, using the data currently available for upper Kamm Creek, streamflow and nutrient flux calibrations did not produced satisfactory fits to measured data, and neither model validation nor its use for prioritization were attempted in the study described below. This guide should therefore be treated as a living document, and updated to reflect improved parameterization or calibration techniques, new supporting tools, and updates to the model itself.

Overview of APEX Modeling and Data Requirements

Watersheds in APEX are represented by one to many subareas, each with its own associated data describing soil type, specific geography, vegetation and land management (Gassman et al. 2010, Wang et al. 2011). By definition, each subarea must be homogenous for these variables, but the watershed overall can have many different soils, crops, etc. Weather data is generally used for the entire watershed but can be specified for individual subareas if necessary (e.g., for a very large watershed). Water accumulates in subareas via precipitation and irrigation, and water and associated nutrient fluxes move through the watershed based on user-defined routing information. Each watershed has an outlet, which represents movement of water and nutrients out of the watershed area. The model simulates biological and physical processes within each subarea, and eventually the watershed overall, based on a set of manually controlled settings ('control files'), such as CO_2 concentration and number of years under cultivation. The actual model processes relate component data to each other using a series of equations, most with adjustable coefficient or limit parameters ('PARM files'). Accurate modeling in APEX therefore requires three general steps, each requiring separate data:

Delineation – Establishes watershed boundaries and divides the whole watershed into subareas based on hydrology, soil type, vegetation, and management. This step also routes water and nutrient fluxes between subareas, through the watershed to the outlet. Delineation requires accurate, fine-scale data describing elevation, notable waterways, soil types, vegetation or crop type, and agricultural management within the watershed.

Parameterization – Populates subarea and control file variables with meaningful data. For soils, each soil type requires data on the number of layers, and the depth, hydraulic conductivity and sand/silt/clay percentages, etc. for each. Crops and other vegetation types require both data on biological characteristics such as maximum height and rooting depth, radiation use efficiency, etc., but also management data describing irrigation, fertilization, harvest and plowing techniques, etc. Many of these processes may require their own parameterization step (e.g., percentage of certain nutrients in cattle manure). APEX also requires accurate weather, nitrate deposition, CO_2 concentration, and other data describing the entire watershed.

Calibration – Model outputs, e.g., nitrate flux through the watershed outlet, are compared against equivalent field data, to determine the optimal PARM values for the modeled watershed (Wang et al. 2011, Moriasi et al. 2012, Wang et al. 2012)[2]. Calibration is an iterative process where one or more model parameters are repeatedly tweaked, and the fits of the resultant output data compared to deduce which values produce the most accurate predictions. Calibration is also iterative in the sense that different categories of model outputs are best calibrated sequentially, to reduce the possibility of getting good results for one output variable (e.g., nutrient flux) due to synergistic errors in other outputs (e.g., crop growth and streamflow). Each stage of calibration requires accurate field data for comparison with model outputs, including crop yields per unit area, and measurements or estimates of runoff, streamflow, transpiration, and N and P flux on a consistent timestep. A different subset of these field data should be used for a final validation to assess the predictive capabilities of the model, but validation is not discussed in this appendix.

APEX Mechanistic Overview and Description of Supporting Tools

The basic APEX model consists of a series of text-based files containing the previously described data, which are related to each other using an executable file coded in FORTRAN (Gassman et al. 2010, Williams et al. 2006). Depending on which outputs are desired, the model can be set to generate several other text files representing annual, monthly or daily outputs of water, nutrients, crop yields, etc. Different files have different extensions, but all files are located within the same folder, and are generally adjustable manually using a standard text editor such as Notepad. For a complete description see official APEX documentation and user guides.

[2] APEX can, in theory, model a delineated watershed without extensive calibration, using best professional judgment to parameterize the model inputs and set PARM values. However, a thorough calibration for all output variables of interest is recommended for best results, as supported by a recent study (Van Liew et al. 2017).

Due to the difficulties involved in manually manipulating the hundreds of relevant variables in the APEX model using a text-based format, multiple supporting tools were developed to simplify the delineation, parameterization, and calibration processes for users. These include a windows-based graphic interface (WinAPEX - Magre et al. 2006), a tool for converting spreadsheet datasets to APEX subareas format (SUB_Builder), a program for converting weather data to APEX's .DLY format (Weather Converter Tool), a GIS-based interface (ArcAPEX - Tuppad et al. 2009), an Excel spreadsheet-based data editor (APPX) and an automated sensitivity analysis and calibration/validation tool (APEX-CUTE - Wang et al. 2014). These tools are used to modify the input data files used by APEX, and typically install to their own folder with their own input files and executables. While version compatibility can be an issue, the different interfaces used to modify parameter values ultimately do not change input data format, or the nature of the model itself; files generated or modified using any supporting tool can be transferred between all supporting tools and the base model.

Methods and Results

The following section details a protocol for using APEX to model crop growth, streamflow and nutrient fluxes within the watershed of upper Kamm Creek, in Whatcom County, WA. The delineation, parameterization, and calibration steps listed in the previous section are explored in detail below, along with preliminary calibration results and a brief treatment of errors and difficulties encountered during each step. These methods are described in the context of Kamm Creek but are applicable to other small agricultural watersheds in western Washington State.

Delineation

To delineate the upper Kamm Creek watershed, I first compiled GIS data as outlined in Table B1. After enabling both Spatial Analyst and ArcAPEX in ArcGIS, I located the general area of my watershed using the imagery data and created a polygon shapefile that covered approximately twice the height and width of my anticipated basin ('mask' in ArcAPEX). I also used hydrology and imagery layers to create a basic polyline shapefile tracing the main path of the creek ('burn-in' in ArcAPEX). To establish a base digital elevation map (DEM) layer, I combined LiDAR data (high resolution, but incomplete coverage) with a traditional 3m DEM. First, I reduced the grid cell size of the 3m DEM to the LIDAR cell size (typically 2m x 2m) using bilinear interpolation. I then mosaiced the LIDAR and interpolated 3m DEM, with both layers as input rasters (using the 'last' rule and with LIDAR the second input), and the destination raster as a copy of the LIDAR data.

I used my combined DEM, watershed area mask layer and upper Kamm Creek burn-in layer as inputs to the ArcAPEX interface. The process of creating an accurate steam network was iterative and required extensive edits, since ArcAPEX only delineates on the basis of topography and often ignored ditches and other forms of stream rerouting. I used my initial stream burn-in

TABLE B1: Watershed delineation GIS data for APEX, with data type, source and download information. Specific data sources or links may be out of date or otherwise unsuitable for future delineations, however the general categories and data types will still apply. Point source and dairy data were acquired successfully, but not used in this particular watershed modeling project. Select UTM, instead of Lat./Long when downloading DEM's and other data from NRCS or similar data clearinghouses.

Data category	**Database type**	**Specific source**	**External Link (**https://)
Topography (3m DEM)	Raster	USDA/NRCS Geospatial Data Gateway	gdg.sc.egov.usda.gov/GDGOrder.aspx
Topography (LiDAR)	Raster	WA DNR Washington Lidar Portal	http://lidarportal.dnr.wa.gov/
Aerial Photography	NAIP mosaic raster	USDA/NRCS Geospatial Data Gateway	gdg.sc.egov.usda.gov/GDGOrder.aspx
Soils	SSURGO raster layer	USDA/NRCS Web Soil Survey	websoilsurvey.sc.egov.usda.gov/App/HomePage.htm
Field Boundary/Crop Type	Shapefile	WSDA Ag. Land Use web-page	agr.wa.gov/PestFert/natresources/AgLandUse.aspx
Cover Type	Satellite imagery as 30m raster	USDA/NRCS Geospatial Data Gateway	gdg.sc.egov.usda.gov/GDGOrder.aspx
Waterways	Shapefile	Obtained from Andrew Phay at WCD	
Drainage Districts	Shapefile	Obtained from Andrew Phay at WCD	
Point Sources	Online data viewer	EPA N & P Pollution Data Access Tool	gispub2.epa.gov/npdat/
Dairies	Pointfile w/ stocking numbers	WA Geospatial Portal	geography.wa.gov/data-products-services/data

shapefile to generate a watershed (Figure B1), deleting all the potential outlet points generated by ArcAPEX, and instead creating and selecting a custom outlet at the location of my sampling point. I then exported the generated reach network to a new shapefile, and edited it to reflect visual stream pathing, drainage district boundaries, and other hydrographic data. I repeated this process multiple times, using the most recent edited shapefile as the new burn-in stream path each time, and adjusting the drainage field size to produce the most accurate stream network (Figure B1). For the upper Kamm Creek watershed, a drainage field size of 3-10 hectares performed best. Eventually, I produced a stream reach network that resembled the real upper Kamm Creek watershed, with separate hydrologic sub-basins (Figure B1), and longest paths of water flow for each, automatically generated by ArcAPEX.

The sub-basins generated using ArcAPEX were not homogenous for soil type and cropping system, requiring further manipulation outside of ArcAPEX's scope. After exporting and saving my final reach, longest path, basin and sub-basin layers as separate shapefiles, I manually divided the original, hydrologically-based sub-basins into true subareas based on their intersection with soil and cropping layers (Figure B2). In the delineation process, I attempted to maximize subarea homogeneity while minimizing the number of final subareas. In some cases where adjacent soil types had extremely similar parameter values, I did not create separate subareas for each, but rather retained the original subarea boundary and defined its soil type as whichever was most dominant. As APEX subareas contain a variable for the fraction of impermeable urban area (*URBF*)[3], I also did not create separate subareas for small areas of development within larger homogenous areas of a single crop. Small inclusions of one crop or soil in a subarea dominated by another were generally ignored, particularly if there was a

[3] Specific parameter names used in APEX are italicized.

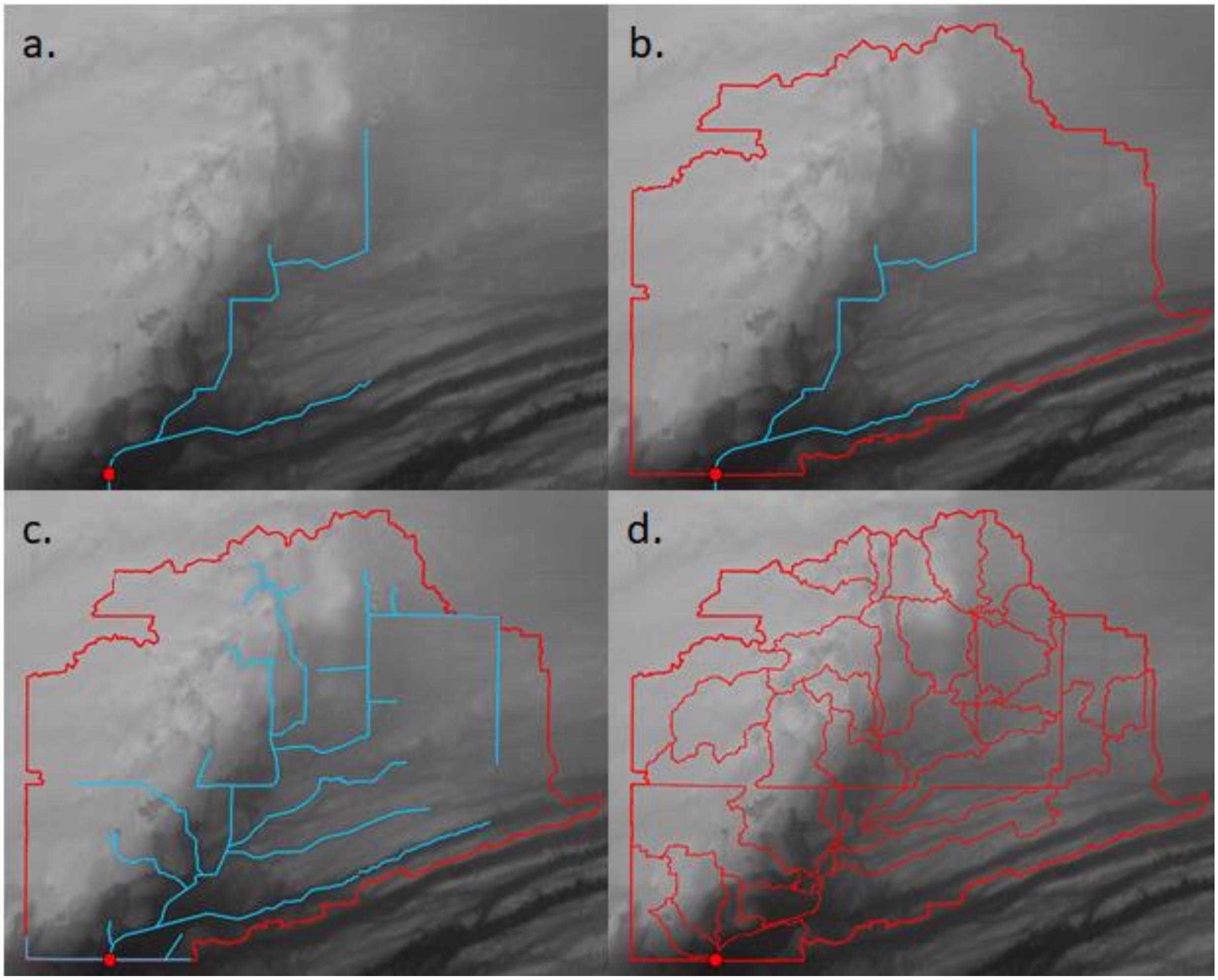

Figure B1. Watershed setup using ArcGIS and ArcAPEX. Panel ‘a’ shows the initial ‘burn-in’ stream path and the location of my sampling point. Panel ‘b’ shows the generated watershed boundary (in this case identical to the final boundary, which will not typically be the case) and the selected watershed outlet. Panel ‘c’ shows the updated stream network shapefile used to generate the final watershed. Panel ‘d’ shows the final watershed with generated sub-basins.

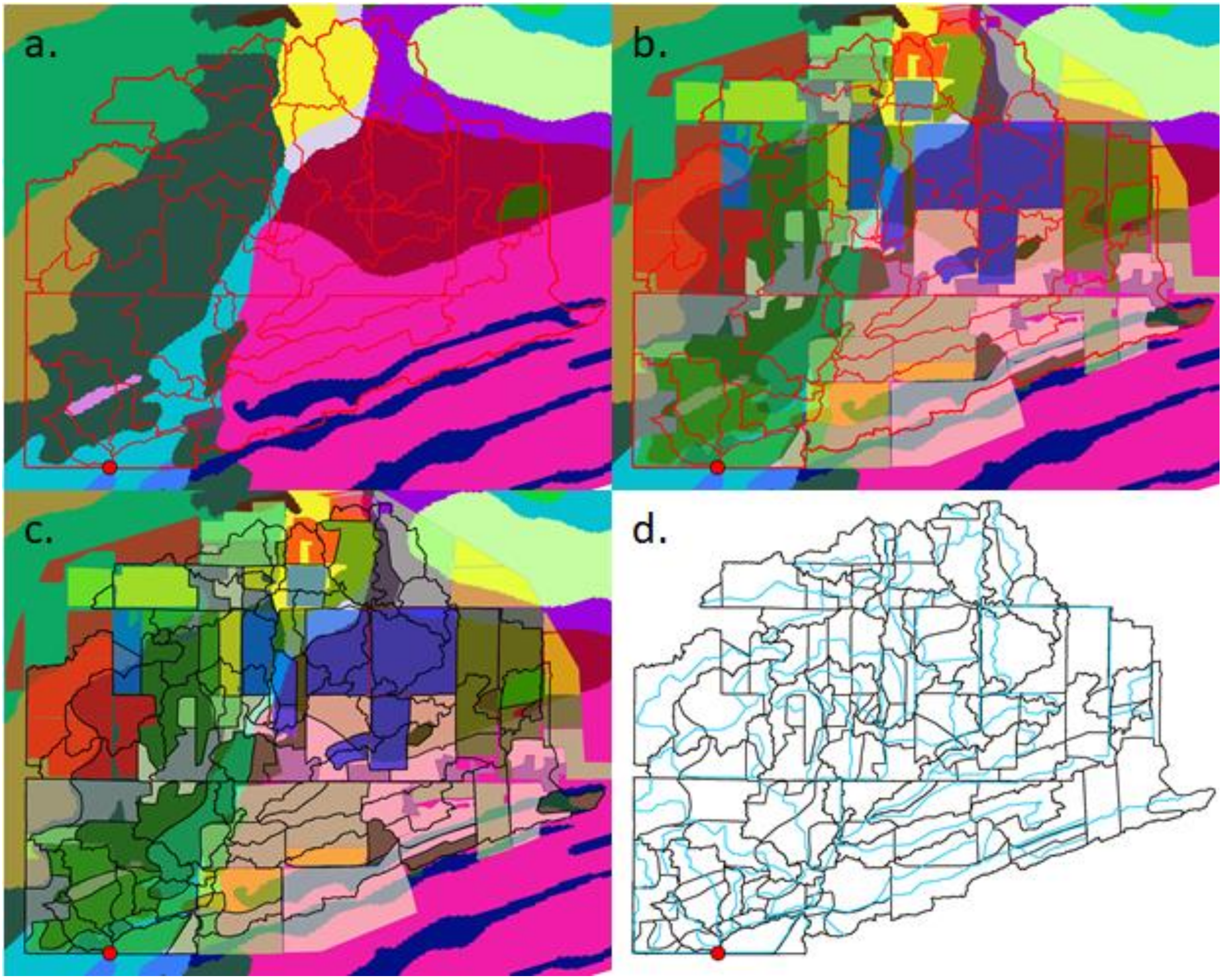

Figure B2. Subarea setup using ArcGIS. Panel 'a' shows the generated watershed and sub-basins, underlain by a soil-type layer. Panel 'b' shows the same but with an additional underlay of a crop-type layer. Panel 'c' shows sub-basins divided into true subareas which contain (to the extent possible) a single combination of soil and crop type. Panel 'd' shows the final watershed and subareas, with stream routing reaches and connecting reaches displayed.

reciprocal pattern in an adjacent subarea. The final number of subareas (162) was much higher than for a previous delineation of a Kamm Creek watershed by Monks (2016), which resulted in 36 subareas, albeit for a 41% smaller watershed than the current study area. Previous studies in other regions (Tuppad et al. 2009, Wang et al. 2009, Tuppad et al. 2010) have used similar or larger numbers of subareas to describe modeled watersheds, but with much larger subarea sizes (mean 12.3 – 2800 Ha) compared to those delineated in this study (mean 2.4 Ha).

After establishing subareas, I split and edited the routing reaches and longest paths so that there was one, and only one, of each per subarea (Figure B2). Longest path and reach segments were added where necessary and adjusted to make sense for the new subareas. Each segment was constructed completely and exactly within its subarea, to comply with APEX routing requirements. In extreme subareas (those that generate stream reaches, but do not receive water from any, i.e., headwater subareas), the reach and longest path segments were identical. Reach and longest path routing was also somewhat subjective, as my DEM did not clearly display all possible channels. In these situations, I relied on imagery data and my best judgment to establish routing, generally trying to maintain an even distance from each neighboring stream reach. Additionally, some subareas contained two or more stream routing reach sections, an issue I skirted by creating a new layer, ‘connecting reaches,’ containing the shorter or less significant (those derived from fewer subareas) reaches.

Once routing is established for the watershed in GIS, the attributes of each subarea’s reach and longest flow path must be described in terms of the relevant APEX parameters. I first calculated the length of all reach and longest path segments (*RCHL* and *CHL*, respectively), and the coordinates for their start and end points. I exported these start and end points as a new shapefile and used the ‘zonal statistics to table’ tool to find their elevations, after making sure that they were in the proper positions. The elevations of some start and end points (e.g., those underneath an elevated road) required manual adjustment. I also assumed an artificial drop of 0.01m to preserve routing in the case of drainage ditches and other unnatural features. I then divided the difference in elevation by the segment length to get routing reach slope and channel slope (*RCHS* and *CHS*) for each. For the other channel variables, reach top and bottom widths (*RCTW* and *RCBW*), and reach and longest path segment depths (*RCHD* and *CHD*), I used the ArcAPEX-generated subbasin values, copied for each subarea that was part of the original subbasin. Because subareas were small, I assumed equal top and bottom widths for each reach.

I also transferred values for parameters describing the subareas themselves to APEX. Using the field calculator function of ArcGIS, I extracted the area of each subarea in hectares (*WSA*[4]), and also its centroid coordinates (*YCT* and *XCT*). After numbering (*SUB* or *IE*, depending on interface) and labeling the subareas according to their latitude[5], I manually recorded whether each subarea was a source (received no water other from subareas) or downstream subarea, and the other subarea into which each flowed (*IO*)[6]. With routing established, I used ArcGIS's 'join data from another layer based on spatial location' ability in 'joins and relates' to match each routing reach and longest path with the proper subarea, after editing those shapefiles to ensure they were fully within subarea borders. To extract values for soil type (*ISOL*) and the combination of crop and management type (*IOPS*)[7] within each subarea,

[4] WSA in the subarea file is NOT the same as *WSAha* listed in the .RCH file output used for calibration and analysis. *WSAha* in the .RCH file is the sum area of all subareas feeding into a reach, plus the subarea containing the reach. For extreme subareas *WSA* and *WSAha* are the same, and the *WSAha* value for the outlet should equal the total watershed area.
[5] The primary axis of upper Kamm Creek is North-South, but another numbering system may make more sense in other watersheds where the primary axis is East-West, etc.
[6] The subarea that drains to the watershed outlet has an *IO* value of 0.
[7] Note that the values extracted are based on the attribute tables of these layers, and must be translated to the relevant APEX parameters prior to conversion to the .SUB file used in APEX.

I converted the crop type shapefile to raster format, and used the ‘zonal statistics as table’ extraction method to get the ‘majority’ soil cover and ‘median’ crop type.

I extracted or estimated values for additional subarea variables (Table B2) and organized all variable values according to *SUB* in spreadsheet format for input to the APEX model. I also formatted spreadsheet cells to reflect the inability of the text based .DAT and .SUB files to allow more than four decimal places for any parameter value. The resulting ‘SUB BUILDER’ spreadsheet was organized in the same format as the example .DAT file provided with the ‘SUB_Builder.exe’ program. After preliminary error checking, a copy of the ‘SUB BUILDER’ spreadsheet was saved as a Unicode text file (.txt) and copied into a blank copy of an existing .DAT file. I then used the resulting Kamm.DAT file to generate a new .SUB file for the upper Kamm Creek watershed, via the method described by the included ‘ReadMe.txt’ file.

Difficulties – Delineation proceeded with relatively few issues after obtaining the necessary data and establishing a proper protocol. Most problems encountered related to flow routing through the watershed, which required manual inputs that were not always obvious due to the area’s limited topographic relief and the presence of a several constructed drainage channels. This delineation process also resulted in a large number of subareas, which contributed to model errors during calibration due to the large size of output files. But, the number of final subareas is more a function of the actual landscape, and user tolerance for soil and crop heterogeneity in subareas, than it is of this delineation protocol. Finally, a number of the component processes described above, particularly establishing subarea boundaries and modifying routing and longest reaches to reflect these, were highly tedious, and as such, prone to human error. Future users should investigate automating such processes.

TABLE B2: Subarea variables used in the upper Kamm Creek watershed APEX delineation. 'Column' references the organization of the 'SUB BUILDER' spreadsheet and .DAT file. Other subarea variables were left at default values during this delineation, but should be considered for future efforts.

Column	Abbreviation	Definition	Method
1	SUB or IE	Subarea/entering subarea	Extracted from GIS
2	IO	Receiving subarea	Manually input based on routing
3	ISOL	Soil # from the SOIL.DAT file	Extracted from GIS
4	IOPS	OPSC # from OPSC.DAT	Extracted from GIS
10	WITH	Daily weather station #	Identical for all subareas, value from WPM.DAT
17	YCT	Latitude	Extracted from GIS
18	XCT	Longitude	Extracted from GIS
19	AZM	Azimuth of land slope	Extracted from GIS
20	SAEL	Elevation	Extracted from GIS
24	WSA	Subarea area in Ha	Extracted from GIS
25	CHL	Channel length (km)	Extracted from GIS
26	CHD	Channel depth (m)	ArcAPEX generated
27	CHS	Channel slope (m/m)	Extracted from GIS
28	CHN	Manning's N for channel	Estimated based on APEX guidelines
29	STP	Average upland slope	Extracted from GIS
30	SLPG	Ave. upland slope length (m)	Estimated from GIS
31	UPN	Manning's N for upland	Estimated based on APEX guidelines
33	URBF	Urban fraction of subarea	Extracted from GIS
34	RCHL	Length of routing reach (km)	Extracted from GIS
35	RCHD	Routing reach depth (m)	ArcAPEX generated
36	RCBW	Bottom width of routing reach (m)	Extracted from GIS
37	RCTW	Top width of routing reach (m)	Extracted from GIS
38	RCHS	Routing reach slope (m/m)	Extracted from GIS
69	IRR	Irrigation code	Manually input based on crop type
84	EFI	Runoff Vol / Vol. of irrigation water applied	Estimated based on APEX guidelines

Parameterization

Unlike delineation, which ultimately created and adjusted only one .SUB file, parameterization involved modifying many different APEX input files, which are outlined in Table B3. I used the WinAPEX 'APEXprog' folder as the location for my APEX input files, using both the WinAPEX graphic interface and the APPX spreadsheet to modify parameter values. Working on the different categories of parameters in the order listed below, I tested whether each modification or addition would run successfully in APEX (using default settings, crops, etc. where necessary) before moving on. This streamlined my file organization and prevented avoidable errors.

Soils – Settings for soils in the upper Kamm Creek watershed were based off of parameter values previously established for APEX (version .0806) by Monks (2016), using the SSURGO dataset. These values were translated to the proper format for the current APEX version .1501, and two soils, Tromp loam and Shalcar drained muck, were modified slightly (increased clay content and bulk density, respectively) based on suggestions from a model developer (Jaehak Jeong, Texas A&M University, personal communication, 2018); otherwise soil attributes were unchanged. See Table B3 for further information.

Weather – APEX uses 'weather stations' to group data on wind speed, precipitation, and minimum and maximum temperatures for an area. Weather station and associated files were constructed using the APEX Weather Converter Tool. Daily precipitation and temperature data for the upper Kamm Creek watershed from 1981-2017 were obtained from PRISM projections (Oregon State University NW Alliance for Computational Science & Engineering, Corvallis, OR). I formatted these data as a comma-delimited spreadsheet file and combined it with similar data from 1970-1980, sourced from a previous model build by Monks (2016). I used the weather

TABLE B3: Categories of data used in the APEX model, and file types and general sources for each. File extensions preceded by “ ” indicate the file can be renamed as necessary, or there can be many separate files for each category. For example, each soil type is represented by its own .SOL file, which are listed and organized using the SOLC.LIST file.

Data Category	Associated Files	Comments
Soils/Soil List	" ".SOL/SOLC.LIST	Based on SSURGO values, generally unmodified
Weather/Wind	WDLST.DAT & WPM1.LIST/WIND.LIST	Weather data (.DLY) are from PRISM projections[8], wind data (.WND) are from Anacortes, WA
Crop Growth	CROP.DAT	Heavily modified based on literature and field studies
Land Management/Rotations	" ".OPC/OPSC.LIST	Heavily modified based on literature and advice from various individuals
Fertilizers	FERT.DAT	Unmodified
Tillage & Harvest Operations	TILL.DAT	Generally unmodified, but two operations added for blueberry and raspberry pruning by Monks (2016).
Pesticides	PEST.DAT	Unmodified, not used in watershed simulation
Subareas	" ".SUB	See previous section on delineation
General Watershed	" ".SIT	General watershed values derived via methods similar to those for individual subareas
Control File	APEXCONT.DAT	Modified for increased atmospheric CO_2 concentration (390ppm) and irrigation water nitrate concentration (8ppm)
Dimensions File	APEXDIM.DAT	Increased maximum number of subareas (to 250) and maximum number of years in crop rotation to 80 years)

[8] Data acquired from the Oregon State University NW Alliance for Computational Science & Engineering, Corvallis, OR (http://prism.oregonstate.edu/explorer/). Data accessed 11/2017, for the center of the upper Kamm Creek study area (48.97°, -122.39°).

tool to convert this .CSV to APEX's .DLY format, and then generated a new weather station with the '26.WND' file (describing monthly average wind speed for Anacortes, WA[9], the closest previously-formatted wind dataset available) selected as the wind station.

Crop Growth – Crop growth is described by a large number of parameters in APEX, and accurate parameterization is critical for generating proper crop yields, water uptake, and nutrient uptake; APEX technical documentation describes these variables in detail. Initial crop parameter values were imported from the APEX database, but were replaced where possible by parameter values selected from academic publications, or extension agency guides (Table B4). Crop parameter values were entered, and later edited, via the APPX spreadsheet editor.

Land Management – I input and modified management schedules for crops using the WinAPEX interface, which was more user-friendly than text- or spreadsheet-based editing methods, given the highly complicated management plans for most crops in the watershed. Planting, tillage, harvest, fertilization, irrigation, and other management actions were all considered, except the application of pesticides, which are not the focus of this project. Management plans for each crop were based on a combination of sources, including published scientific literature, presentations, extension agency nutrient management guidelines, and advice from local experts (Table B4). All aspects of crop management can and do vary among fields and years, so final settings were approximations of an 'average' management plan for a crop in the upper Kamm Creek watershed. I worked within the WinAPEX graphic user interface to establish basic management settings, as it provided an easy way to select specific operations. Later, modifying large numbers of operations (e.g., the volumes of irrigation applied on different days) was quicker using the WinAPEX Access database directly, or via APPX. I established all rotations using the

[9] Future researchers should consider using wind data from a closer source (.e.g., Bellingham airport) to create a new .WND file, updating the 'WND.DAT' file accordingly to reflect the addition of a new wind station.

TABLE B4: Sources for crop and management data used to parameterize and calibrate the APEX model for Northwest Washington. All parameters were initially copied from either model defaults or values established by Monks (2016). Values for harvest index (*HI*) and Leaf Area Index (LAI) (*DMLA*, *DLAI*, *DLAP1*, and *DLAP2*) for blueberry and raspberry crops were based on unpublished data collected by Monks and Bridger Cohan (2015). Local estimated crop yields (*YLDG* and *YLDF*) and biomass (*BIOM*) used for calibration were based on data from the United States Department of Agriculture - National Agricultural Statistics Service (USDA-NASS), in addition to the other sources listed below.

Raspberry:
Carew et al. 2000, Rempel et al. 2004, Strik 2005, Hart et al. 2006a, Strik and Bryla 2015
Blueberry:
Strik and Buller 2005, Hart et al. 2006b, Bryla et al. 2011, Bryla et al. 2012, Bryla and Vargas 2012, Chuck Timblin, WCD, personal communication, 2015, Lisa Wasko-DeVetter, WSU Extension, personal communication, 2016
Pasture, Hay and Fallow (Orchardgrass):
Hannaway et al. 1999, Chaney and Fransen 2002, Kugler 2006, Bush et al. 2012, Steven Fransen, WSA IAREC, personal communication, 2015, Chris Benedict, WSU Extension, personal communication, 2016, Chuck Timblin, WCD, personal communication, 2017
Corn silage:
Hart et al. 2009, Chris Benedict, WSU Extension, personal communication, 2016
Forest:
Grier et al. 1981, Ares et al. 2007, Hudiburg et al. 2009, Devine et al. 2013, Raymond and McKenzie 2013, Belart 2016

WinAPEX interface, with rotations for each species representing the most common cropping cycles found in the watershed, as determined using the sources in Table B4. As I did not have continuous cropping type data, I set up rotations to run for the full 48-year model length, so that the crop of interest was present (and, in the case of blueberry and raspberry, at full maturity) during the growing seasons of my calibration period, 2016-2017.

Difficulties – The primary difficulty associated with parameterization was in locating suitable, regionally-specific resources on which to base parameter values. Translating information from available literature (e.g., a grower's guide describing desired leaf N-content) into specific APEX parameters (e.g., *BN2* – N content of a particular crop at 50% maturity) was frequently convoluted as well. Even complete, standardized datasets such as the SSURGO soils database required substantial effort to properly import to APEX (Monks 2016). Management practices for particular crops are not standardized among growers, and specific management practices are generally regarded as 'trade secrets' by individual growers, and as such are treated as confidential information. Entering complicated management schedules into APEX is also highly tedious, which increases the potential for human error. To simplify both parameterization and analysis of results, I set the APEX management files for a particular crop as an initial estimate for our region, which can be updated when and where more specific data is available. A more technical issue was that APEX program executable files within each supporting tool were not always identical, and it proved important to check version compatibility. Thorough review of all parameters, of which there are hundreds, is essential to avoiding model errors, as described in the 'Streamflow and Nutrient Flux Calibration' section of this appendix.

Crop Calibration

After establishing baseline values for all model input parameters, I proceeded with crop calibration by manually adjusting crop and management parameters to produce crop yield or biomass values that fell within the expected range for the watershed. Field-specific crop and management parameters were all uncertain to varying degrees and were therefore subject to modification during the calibration process. Stable and well-documented parameters were modified only slightly, if at all, from the values set during parameterization, while poorly-researched or unparameterized variables were modified more extensively. I paid special attention to the output variables of grain or forage yield (*YLDG* or *YLDF*), crop biomass (*BIOM*) and water, nitrogen, phosphorus, and temperature stress days (*WS*, *NS*, *PS*, *TS*) in the annual subarea crop yield tab of the WinApexOut.MDB Access database (" ".ACY file). The stress variables were particularly important for informing crop calibration, as heavily stressed crops would not produce adequate yields. Even a small number of phosphorous stress days would cause large decreases in biomass and yield, while most crops were much less sensitive to nitrogen stress days, and moderately sensitive to temperature and water stress days. Other difficulties were crop-specific and are described below as part of individual calibration procedures for each crop type.

I modeled each crop as part of a locally common rotation, using the different soil types on which it was grown in the upper Kamm Creek watershed. I calibrated crops using a two to seven subarea trial watershed, with each subarea differing in soil type but otherwise identical. These subareas were all one hectare in size, with good infiltration. To limit potential transfers of water or nutrients among subareas, I set routing so that the subareas containing the crop of interest all drained into one subarea set to fallow management, which then drained to the outlet. I then compared the mean and range of modeled yield or biomass values to values derived from grower’s guides and estimates by local experts (Table B4). I averaged yields over multiple years during or close to the calibration period depending on the particular species, and the maturity of perennial crops. Successfully calibrated crops produced suitable yields for all soil types. Specific processes for the eight management categories in the Kamm Creek model are described below.

Raspberry – Basic parameter settings for raspberry, specifically the ‘Meeker’ variety commonly grown in Whatcom County, were previously established by Monks (2016). Raspberry was grown as a perennial crop in APEX (*IDC* = 6), with a seven-year planting cycle. A tillage operation was also entered in November of year ‘0’. Yields for calibration were averaged from the final five years of the planting cycle, when the plants were fully mature. Parameters for raspberry required relatively minor adjustments, however rotations involving more than one cycle of raspberry were prone to errors, the cause of which was not determined. A locally common rotation that modeled successfully was one year of fallow, followed by seven years each of raspberry, pasture, and raspberry. Raspberry was extremely sensitive to phosphorous deficiencies and required small additions to grow and produce normally on some soils, which was in line with literature recommendations. As with several other crops, modeled yields for raspberry were typically low for the first several rotations, but stabilized several rotation cycles prior to the calibration period.

Blueberry – The ‘Duke’ variety of highbush blueberry was selected for modeling, as it is the most popular variety grown in Whatcom County. Monks (2016) previously simulated blueberry as a deciduous tree cop (*IDC* = 8), however in the current version of APEX, blueberries grown as tree crops did not regenerate well after harvest, leading to continually decreasing biomass and yield during the 15-year planting cycle. I therefore chose to model blueberry as three different perennial (*IDC* = 6) crop types in APEX, with slightly modified parameters and management settings to represent newly-planted, establishing, and mature blueberry plants. I simulated these in succession (two years of new, three years of immature, and 10 years of mature plants), following one year of fallow. Yields for calibration were averaged from the final seven years of the most current planting cycle, when plants were fully mature. Calibration produced a suitable growth curve, with minimal jumps in modeled yield and biomass among blueberry crop types.

Forest – I simulated forested subareas in the model using a combination of three crops grown concurrently: An evergreen tree (*IDC* = 7, *HMX* = 60m), a deciduous shrub (*IDC* = 8, *HMX* = 1.5m), and the 'fallow' variant of orchardgrass (described below). For all soil types modeled, the evergreen tree accounted for virtually all of the final biomass. For calibration, I used the total biomass from all species from only the last year of the model run, which represented the maximum modeled biomass. The forest 'crop' type was not subject to any management actions, and was allowed to grow indefinitely. No rotation was constructed, and 'seed' weight for the evergreen species was set at APEX maximum limit (*SDW* = 99999 kg ha^{-1}) to 'jump-start' biomass to simulate older trees than the 48-year model run time allowed. Even with high *SDW*, the simulated evergreen tree crop had difficulty attaining target biomass values. To achieve these biomass values, I set N- and P-content parameters for mature plants (*BN3*, *BP3*) very low (0.001 and 0.0002, respectively), and values for radiation use efficiency (*WA*) and maximum LAI (*DMLA*) extremely high (74 and 10, respectively).

Corn Silage – I based corn silage crop parameters on APEX defaults, with only small modifications. Corn silage was fertilized modestly to reproduce local management conditions and produce the low yields typical of the upper Kamm Creek Watershed (Chuck Timblin, WCD, personal communication, 2015). Two sequential corn crops were rotated with one year of fallow and one cycle of pasture. I averaged corn yields from the six most current harvest years to compare to target values during the calibration process.

Hay – I simulated hay fields as highly managed perennial orchard grass (*Dactylis glomerata*), as it is a common agricultural grass species (perennial, *IDC* = 6) in the watershed, and was previously modeled in APEX by Monks (2016). However, hay mixes in the area can include other species of graminoids, and sometimes legumes. APEX can theoretically simulate hay or forage mixes with multiple species, but initial experimentation showed orchardgrass typically dominating other modeled species within three years. As a result, for simplicity of management setup and calibration, I modeled hay as just one species. I set field rotation length to seven years, following one year of fallow. Calibration yields were averaged from the final five years of hay growth in the most current rotation, to represent mature fields. Simulated yields varied substantially among different soil types. Hay crops in our region can be intensely managed (e.g., fertilized) to maximize productivity, or more minimally managed to lower input costs. APEX parameters for 'hay' were set to mimic the former strategy, with 'pasture' settings (below) meant to mimic the latter. Future calibration efforts should investigate the specific cropping practices used in their watershed and readjust crop rotations and management settings as necessary.

Pasture – I used the pasture crop type to simulate grass fields with low levels of management. Pasture crop settings were identical to those of orchardgrass hay. Management settings were also generally similar, but with a 56% decrease in fertilizer application per advice from Chuck Timblin (WCD, personal communication, 2015). I decreased target pasture forage yields for calibration by the same percentage, compared to hay yields. In the actual watershed, land classified as pasture may be grazed or mechanically harvested. For APEX simulation, grazing harvest was not considered due to the difficulty of implementation. However, pasture was fertilized almost exclusively with dairy cattle manure to represent that aspect of cattle use, and was also harvested mechanically throughout the growing season to simulate the removal of biomass and nutrients from the field that would occur during grazing and milking. Pasture was simulated as a seven-year cropping system, rotated with two years of silage corn.

Fallow – As fertile soils in the northwest Washington typically support at least some vegetation, I simulated fallow land cover as another variant of orchardgrass with considerably lower values for radiation use efficiency (*WA*), maximum LAI (*DMLA*) and other parameters relating to growth. These changes, combined with a lack of any management actions, greatly decreased maximum potential biomass. Fallow orchardgrass was not calibrated in the same manner as other crops, since fields are left fallow as part of rotations with several other crops, each of which impacted fallow biomass differently. I simulated fields classified as fallow during the calibration year as three year-long cycles of fallow with one six-year cycle of pasture, if no other data on rotation crop types was available. Different rotation crops and soil types impacted fallow biomass, but it was always extremely low compared to other crop types.

Developed – Only 12 of the 162 modeled subareas in the watershed were categorized as developed, as APEX includes a parameter to account for small percentages of developed (impervious) surfaces within majority-cropped subareas. APEX defaults include an 'impervious' crop option[10] for entire subareas, but the 12 subareas categorized as developed in this study were not completely paved or otherwise impervious, but rather represented areas without notable plant growth, typically graveled or barren soil. I simulated them using a highly-modified version of the orchardgrass crop with extremely low values for radiation use efficiency (*WA*) and other parameters necessary for growth. I did not plant other crops in rotation for developed subareas, nor apply any management actions. I did not calibrate this crop type, but did ensure that developed subareas maintained extremely low biomass throughout the calibration period.

[10] Every subareas must have a land cover type, which is simulated by APEX in the form of a 'crop'. However, crop parameters can be modified extensively so that the resulting crop type functions as a bare or impervious surface.

Crop Calibration Results – Annual yield calibration was successful for crops in the upper Kamm Creek watershed, with modeled yields falling well inside the target range for all soil types (Fig B3). The only exception was corn silage, in which mean modeled yield exceeded the mean target yield by 25.6%. However, because of infertile soils and limited nutrient applications in the study watershed, target yields for this crop were set very low, approximately 35% of typical corn silage yields in Whatcom County (Chuck Timblin, WCD, personal communication, 2015). Therefore, modeled corn silage yields were actually closer than the target yields to USDA-NASS values for Whatcom County (~16 Mg ha^{-1} dry weight), though actual yields of silage corn within the specific study watershed are unknown. Soil type had a moderate impact on yields of silage corn, hay, and pasture, but a very limited impact on berry crop yields (see error bars in Fig. B3).

I used biomass to calibrate forested, fallow, and developed subareas, as these lacked yields to calibrate against. I also compared modeled and estimated nitrogen content of forested subareas to investigate potential impacts on watershed nutrient cycling. But, I did not calibrate forest or any other crop type for nitrogen content. Forested subareas had an average biomass within the target range, though somewhat lower than the target mean (Fig. B4). Soil type had a relatively large impact on forest biomass, leading to higher variation in modeled values than other crops. Mean modeled forest N-content was 46% lower than the target mean, but both values had large, overlapping ranges of uncertainty. Fallow subarea biomass varied substantially based on soil type and other cropping systems in rotation but was almost always <1 Mg Ha^{-1}. This was assumed to be an accurate representation of fallow areas in the watershed, which are typically sparsely covered with grasses and weedy annuals. Developed subareas had zero, or nearly zero biomass regardless of soil type; developed subareas did not rotate with any other crop or management schedule.

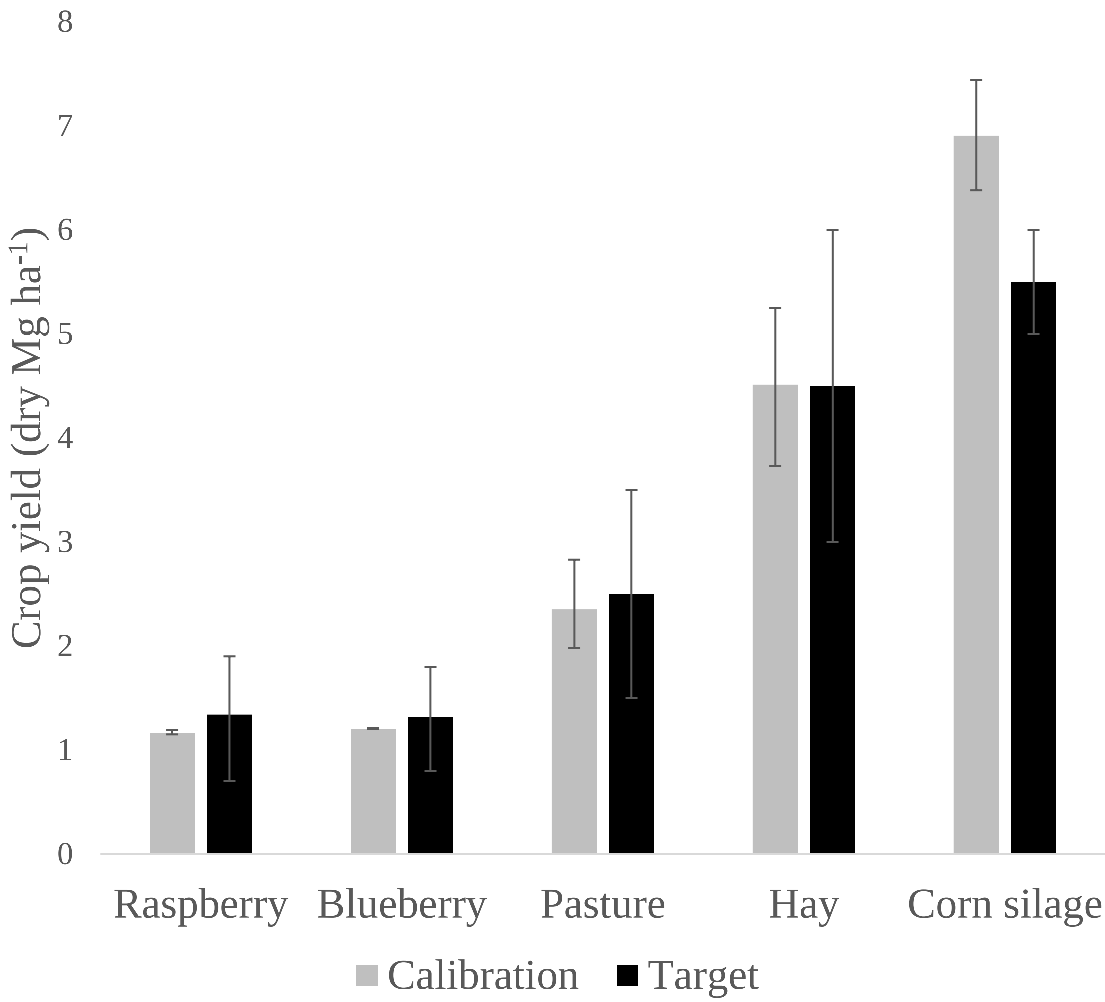

Figure B3. APEX simulated and target annual yields of crops grown in the upper Kamm Creek watershed. Error bars for APEX-generated calibration yields represent the full range of yields from different soil types (N=2-6) on which the crop was simulated. Error bars for target data represent the full historical yield range or the degree of uncertainty in yield estimates.

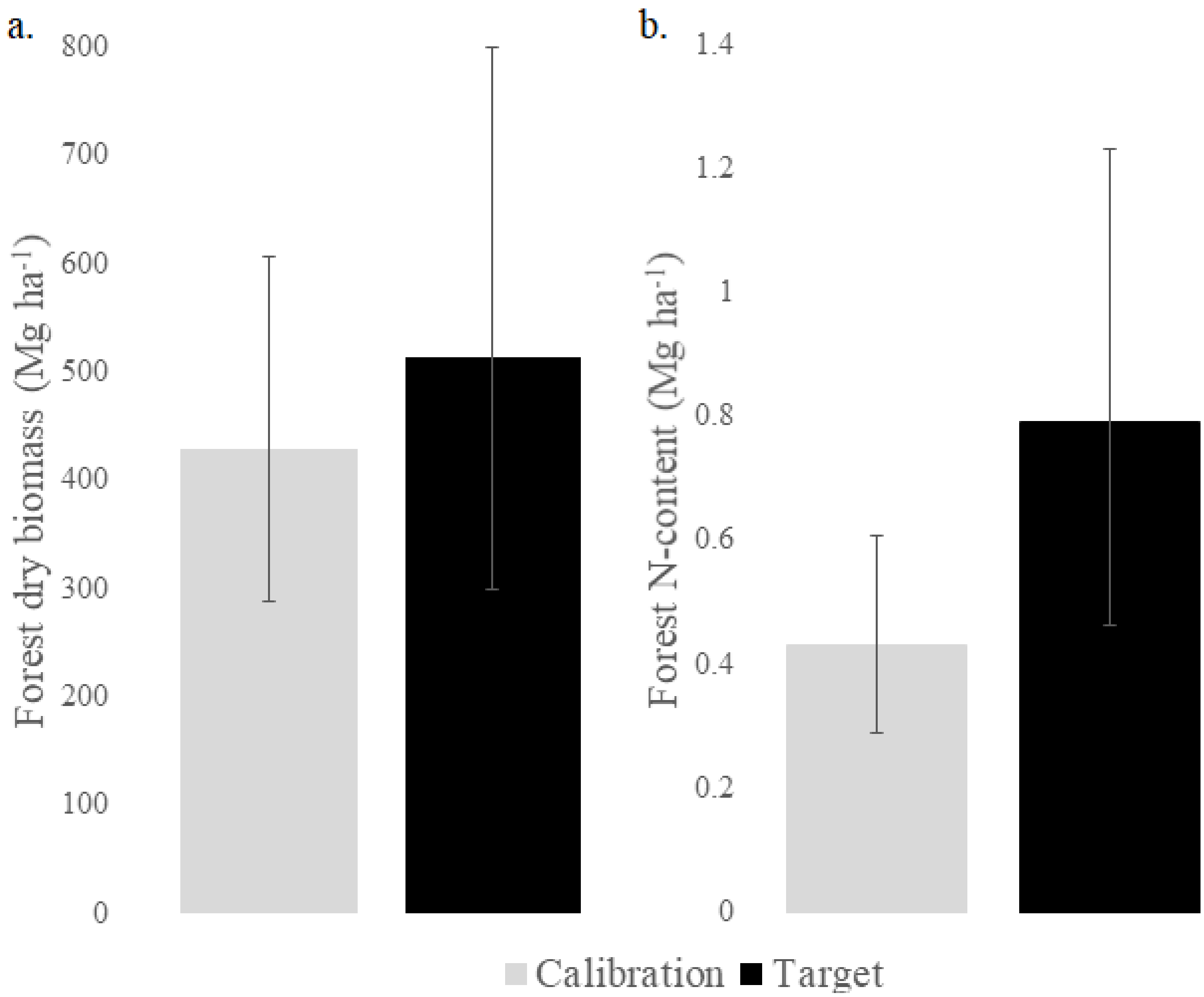

Figure B4. APEX simulated and target biomass (a) and nitrogen content (b) for mixed coniferous and broadleaf forest in the upper Kamm Creek watershed. Error bars for APEX-generated calibration data represent the full range of final biomasses and N-content from forest simulated on different soil types (N=2). Error bars for target biomass and N-content represent uncertainty due to the range of forest maturity and species composition in the watershed.

Streamflow and Nutrient Flux Calibration

I calibrated streamflow and nutrient fluxes through the watershed outlet using the APEX-CUTE autocalibration tool[11] (Wang et al. 2014). APEX-CUTE is built around a dynamically dimensioned search algorithm, which simultaneously adjusts a large number of potentially influential parameters during the early stages of calibration, but converges towards adjustment of only a few key parameters as results improve. Calibration is an iterative process, with parameter values perturbed randomly, run results assessed, and those perturbations either increased or scaled back depending on the outcome. I selected the control file variables and PARMs subjected to calibration based on user-guides and previous studies, with different suites of parameters modified for the streamflow and nutrient flux calibration processes (Table B5). All initial control file parameter settings were set based on values from the previous study by Monks (2016) or left at default values. Parameter values and calibration statistics from the most successful iteration or iterations of each run were recorded in separate spreadsheets for comparison.

Streamflow – I calibrated streamflow first, using 48 daily streamflow records (in $m^3 s^{-1}$) collected from 10/2015 to 11/2017 on upper Kamm Creek. These data constituted the entire available dataset at the time of the first successful calibration and were approximately evenly distributed among months. I modeled the upper Kamm Creek watershed in APEX from 1970-2017, setting 2015-2017 as the calibration period in APEX-CUTE. I selected the 'Channel Flow' APEX output variable (corresponding with 'Flow $m^3 s^{-1}$' in the calibration 'wq_daily.CSV' file) as the calibration variable with a weight of 100% and set the output file set to 'RCH'. I selected the watershed outlet (Subarea 162) as the 'Reach ID' for comparison with measured data, and used

[11] APEX-CUTE can also automatically adjust crop parameters (but not management settings) to calibrate for biomass and yield, but this feature was not tested during this calibration effort.

TABLE B5: Parameters in the APEX control and PARM files modified during calibration for streamflow and nutrient fluxes. Parameters were selected based on recommendations from the following sources: a - Yen et al. 2016, b - Monks 2016, c - Wang et al. 2014, d - Francesconi et al. 2014, e - Nelson et al. 2016.

PARM (control file variable)	**Explanation**	**Sources**
Streamflow		
RFPK (RFPO)	Return flow ratio	a, b
RFTT (RFTO)	Groundwater residence day	a, b
QCF	Watershed flow rate exponent	a
12	Soil evaporation coefficient	a
17	Evaporation plant cover factor	a, b
20	Runoff curve number initial abstraction	a, b
34	Equation exponent	b, c, d
40	Groundwater storage threshold	a, b, c
42	Curve Number index coefficient	b, c, d
90	Regulates lateral subsurface flow	a
Nutrient fluxes		
7	Nitrogen fixation	a, d
8	Soluble P runoff coefficient	a, c, d
14	Nitrate leaching ratio	a, d
29	Biological mixing efficiency	a, d
36	Upper limit of daily denitrification rate	a, d
46	RUSLE C factor coefficient	a, c
59	Phosphorus upward movement by evaporation	d
70	Microbial decay rate	a, d, e
72	Volatilization/nitrification partitioning coefficient	a, d, e
86	Nitrogen upward movement by evaporation	a, d
92	Curve number retention parameter coefficient	a, c

the 'F' statistical metric, combining Nashe-Sutcliffe efficiency (NSE) and percent bias (PBIAS), to assess results during the calibration procedure (Wang et al. 2014). NSE (Nash and Sutcliffe 1970) is used to describe the goodness of fit between observed and modeled data, with values ranging between one (perfect model fit) and negative infinity (no model fit). Model performance for all monthly outputs is generally considered satisfactory if NSE > 0.5 (Moriasi et al. 2007). Percent bias describes the tendency of the model to over- (negative PBIAS) or underestimate (positive PBIAS) measured values, with smaller PBIAS absolute values indicating closer fit between modeled and measured data (Aouissi et al. 2014, Wang et al. 2014). Satisfactory model performance guidelines for monthly nutrient fluxes (PBIAS < |70%| are considerably less strict than for monthly streamflow (PBIAS < |25%|, reflecting the greater difficulty of modeling nutrient cycling (Moriasi et al. 2007). I initially set the number of model iterations in each calibration run to 500, but APEX-CUTE completed only 388 before an unexplained 'Memory Error' stopped the process. However, as the output and performance analysis files from those 388 iterations were not corrupted in any way, it was possible to extract the best-performing combination of parameter values and then update the model for another attempt. I set subsequent streamflow calibration runs for 380 iterations, followed by an additional 120 iterations, with the 'Continuing from previous run' option selected. I completed several combined 500-iteration runs, with the starting parameter values for each set to the best-performing iteration from the all previous runs[12]. Parameter value high and low limits were initially left at APEX-CUTE defaults, but were adjusted to a narrower range of values, representing the range observed in the five most successful runs, as calibration progressed. Model performance did not always increase for every run, due to the randomized nature of the calibration process. Following daily calibration, I used

[12] Starting values and limits for parameters to be modified during calibration must be entered manually in APEX-CUTE, rather than relying on the values entered into 'PARMS.DAT' file.

estimates of monthly streamflow (derived from the mean of available daily values for each month of calibration data) to calibrate the model on a monthly timestep. Due to time constraints and lack of promising results, I conducted only one initial 500-iteration monthly calibration run.

Streamflow Calibration Results – APEX did not model daily streamflow through upper Kamm Creek satisfactorily (Moriasi et al. 2007, Moriasi et al. 2014), underestimating streamflow volume and exhibiting a weak fit to measured data (Fig. B5). The median flow projected by the model during the calibration period was only 0.05 m^3 s^{-1}, while the measured median streamflow was 0.17 m^3 s^{-1}. Mean modeled streamflow was similarly lower than measured data, but modeled minimum streamflow (0.033 m^3 s^{-1}) and maximum streamflow (0.43 m^3 s^{-1}) were closer to the equivalent measured values (0.047 m^3 s^{-1}, 0.58 m^3 s^{-1}). In general, the model matched general high and low streamflow trends, but severely underestimated low flows, particularly in summer (Fig. B5). Linear regression analysis showed a modest but significant correlation between modeled and measured streamflow, but this analysis was heavily influenced by the presence of two high flow samples (Fig. B6). With outliers removed, measured streamflow was not a significant predictor of modeled streamflow, and the coefficient of determination was only 0.12. Monthly calibration did not improve model performance compared to daily calibration, based on model NSE and PBIAS (Fig. B7).

Nutrient Fluxes – I calibrated daily fluxes of mineral and total N and P (in 'kg ha^{-1}' – the total daily flux in kg, divided by the area of the upstream watershed in hectares[13]) following a similar process to that for streamflow, using the same calibration dataset. I set calibration runs to 250 iterations to reduce the potential for software error and to quicken individual runs. APEX-CUTE settings were similar to those for streamflow, but I selected 'TN', 'TP', 'Mineral N' and 'Mineral

[13] I converted model outputs and calibration data to kg day^{-1} for analysis and graphing by multiplying values by the watershed area (386.8 ha).

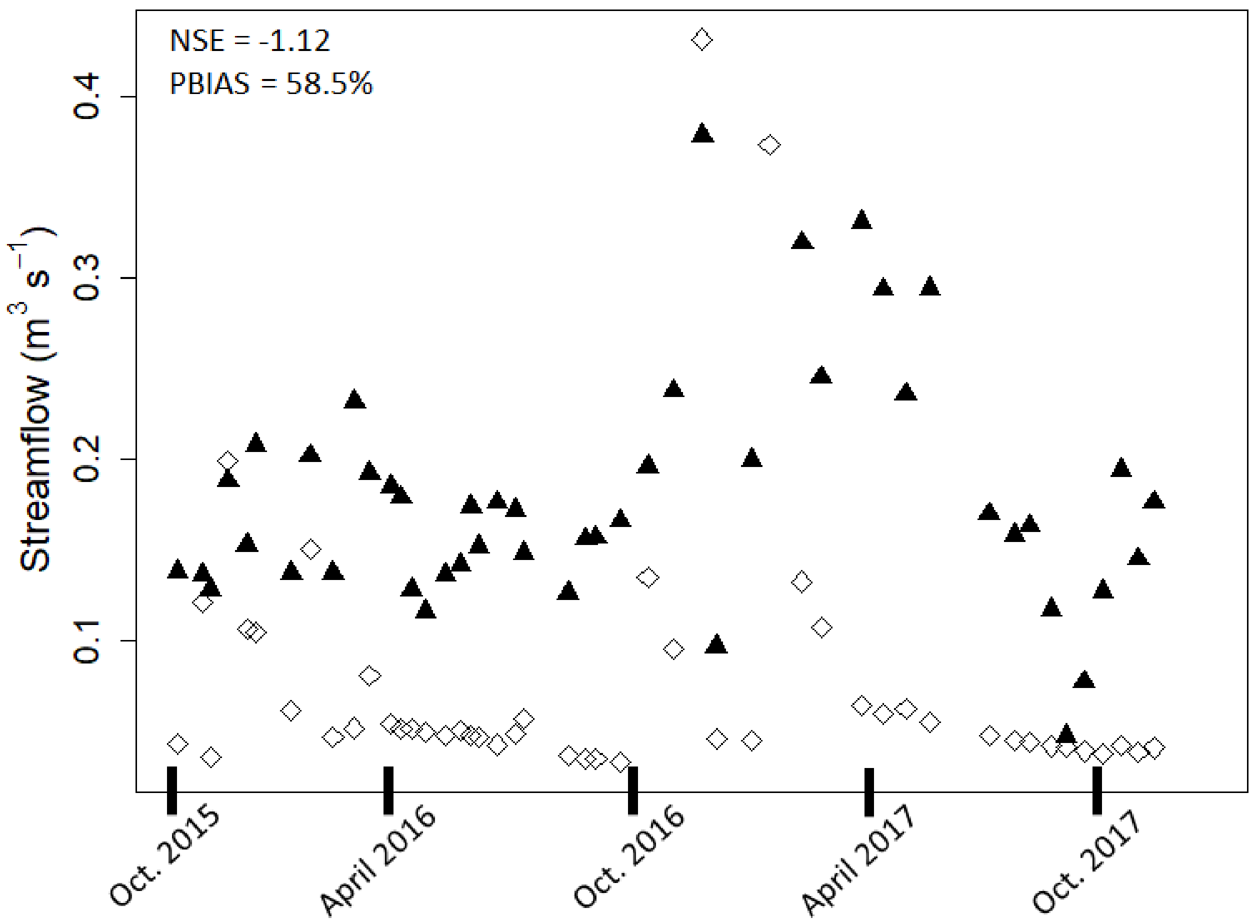

Figure B5. APEX simulation of daily average streamflow through the upper Kamm Creek watershed outlet from October 2015 – November 2017. Unfilled diamonds (N=48) represent APEX predictions, solid triangles (N=48) represent measured data. APEX-CUTE generated values for Nash-Sutcliffe efficiency coefficient and percent bias are displayed.

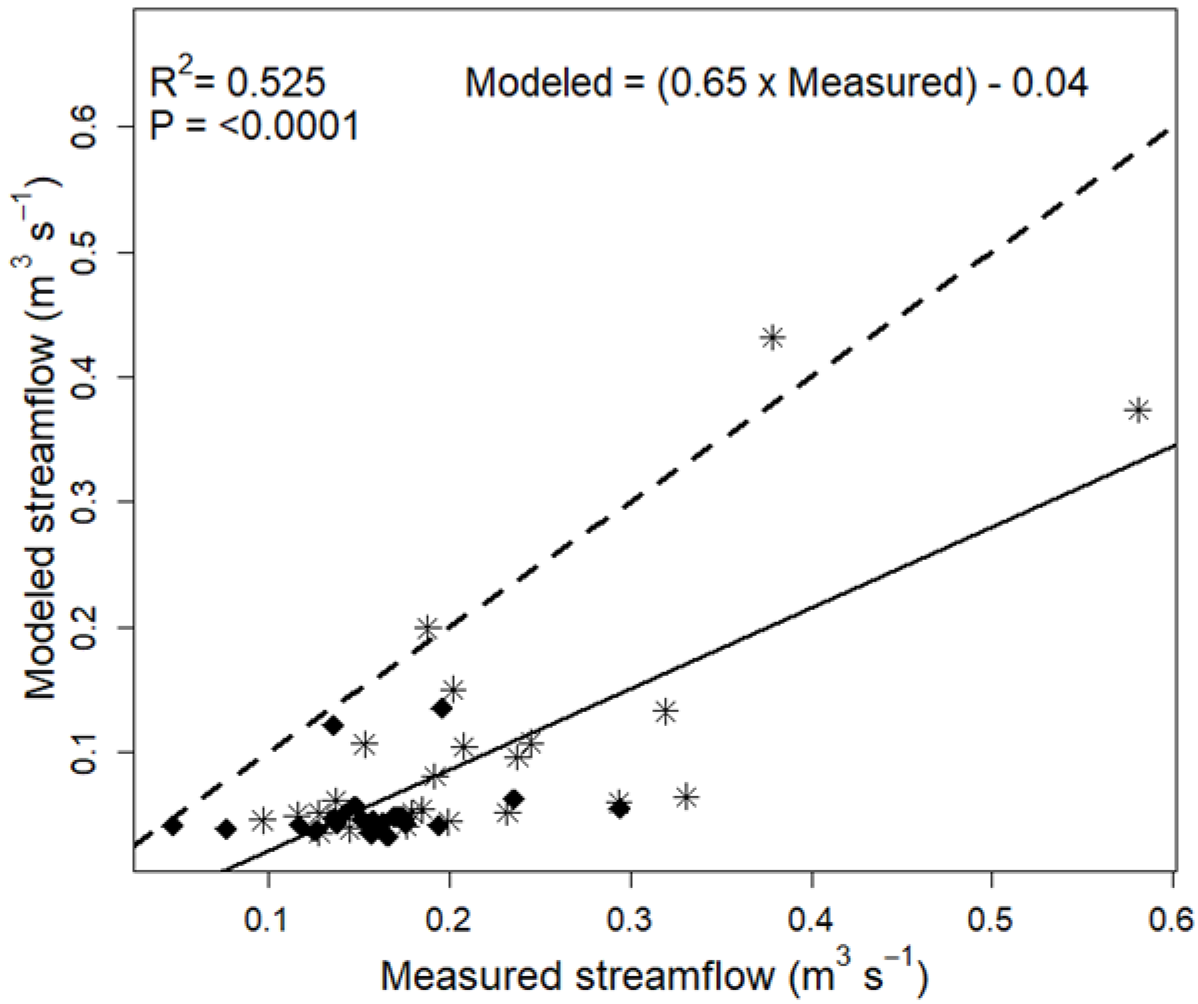

Figure B6. Linear regression of measured vs. modeled daily streamflow (N=48) for upper Kamm Creek, showing best-fit line (solid) and 1:1 line (dashed). Summer (May-October) sampling dates are represented by solid diamonds, winter (November-April) sampling dates are represented by stars. Coefficient of determination, the equation of the best-fit line, and P-value for measured streamflow are also displayed.

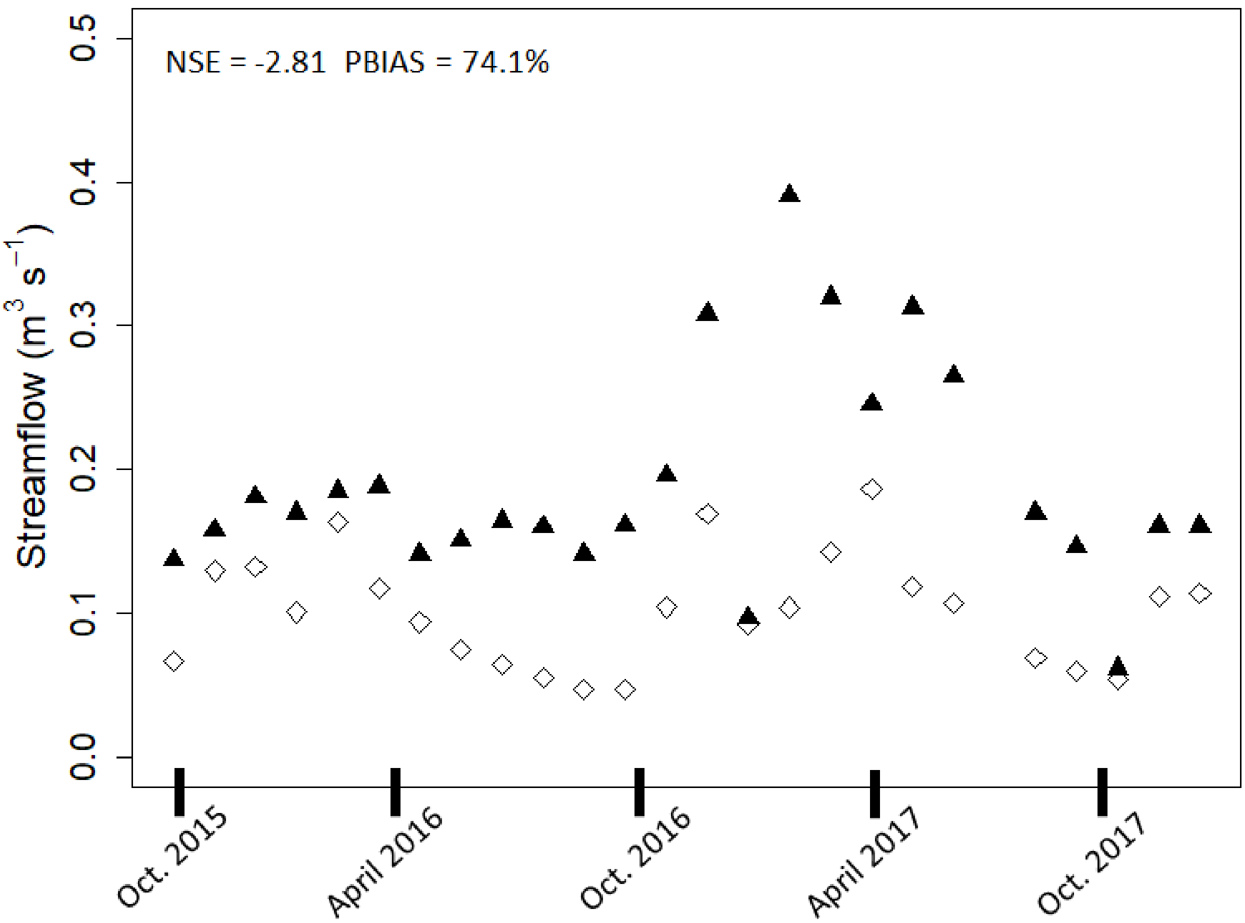

Figure B7. APEX simulation of monthly average streamflow through the upper Kamm Creek watershed outlet from October 2015 – November 2017. Unfilled diamonds (N=25) represent APEX predictions, solid triangles (N=25) represent measured data. APEX-CUTE generated values for Nash-Sutcliffe efficiency coefficient and percent bias are displayed.

P’ as output variables, assigning each a 25% weighting factor. I commenced nutrient flux calibration after three consecutive streamflow calibration runs failed to improve statistical fit. I calibrated nutrient fluxes last because streamflow plays a large role in determining those fluxes. However, modeled streamflow fit to field data was improved by calibrating a second time (three 250-iteration runs) after nutrient flux parameter values were stabilized through the calibration process. The updated PARM values relating to water cycling in turn slightly improved the model fit for nutrient fluxes. I did not repeat this process again during this study, but a more cyclic calibration process should be considered for future efforts. Following completion of daily nutrient flux calibration, I conducted one additional calibration run on a monthly timestep, using the same procedures described for streamflow.

Nutrient Flux Calibration Results – Daily fluxes of mineral and total N and P were not satisfactorily simulated by APEX, despite the less stringent performance guidelines for nutrient fluxes compared to streamflow (Moriasi et al. 2007) (Fig. B8). Median daily fluxes of nitrate and total N projected by the model during the calibration period were 4732 and 4776 kg day^{-1} respectively, a more than 35-fold increase compared to the respective measured median fluxes (both ~127 kg day^{-1}). Mean and maximum values for modeled fluxes of those same nitrogen species exhibited similar increases compared to measured data. Conversely, the median modeled phosphate flux was 0 kg day^{-1}, compared to a median measured flux of 0.14 kg day^{-1}, while the median modeled TP flux ($5x10^{-3}$ kg day^{-1}) was less than 2% of the median measured flux (0.26 kg day^{-1}). However, mean modeled phosphate and total P fluxes were 72 and 319 times greater than mean measured fluxes of those same nutrients, due to the influence of several extremely high daily fluxes; maximum daily flux values for both were two orders of magnitude greater in the modeled data than in the measured data.

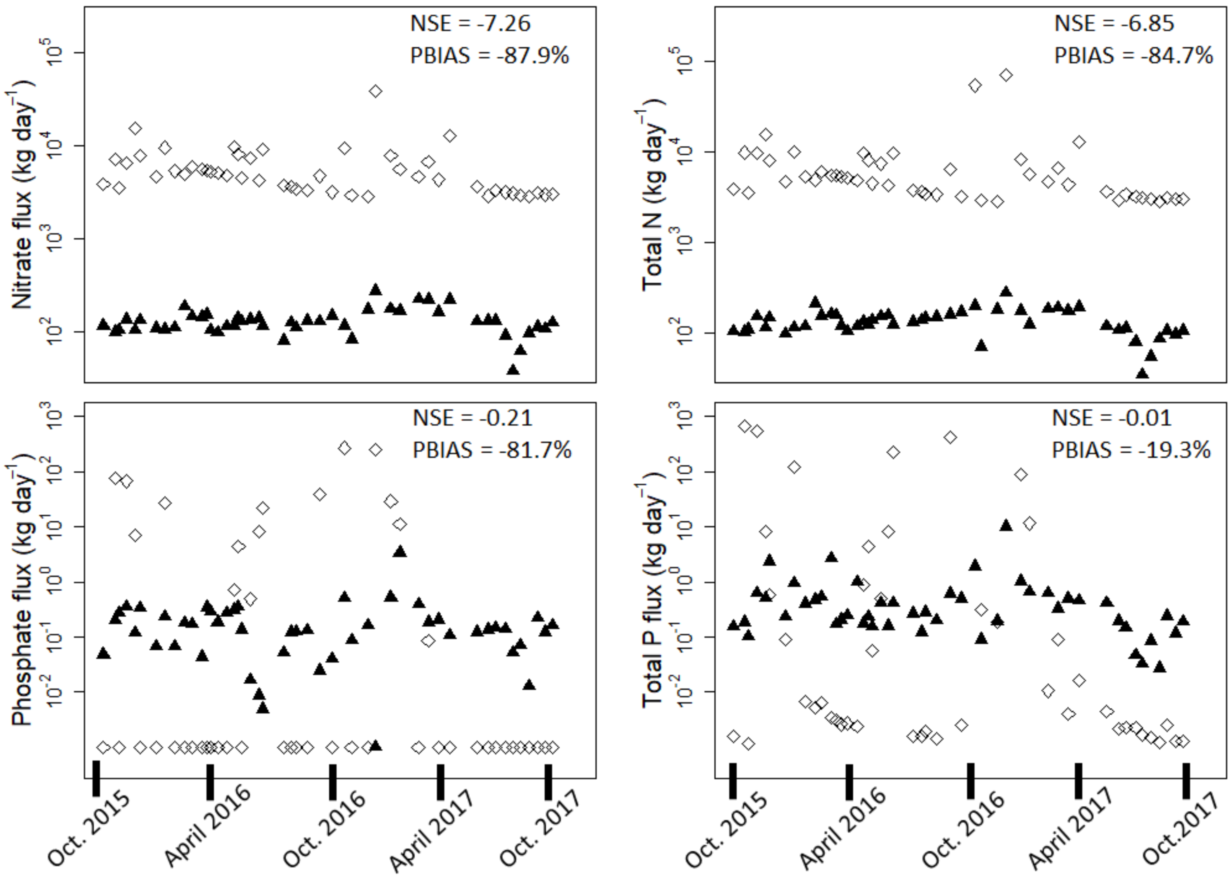

Figure B8. APEX simulation of daily nutrient fluxes through the upper Kamm Creek watershed outlet from October 2015 – November 2017. Unfilled diamonds (N=48) represent APEX predictions, solid triangles (N=48) represent measured data. APEX-CUTE generated values for Nash-Sutcliffe efficiency coefficient and percent bias are displayed. All daily flux values for phosphate were increased by 0.001 kg day^{-1}, so that zero values would display on the log axis.

Modeled nutrient fluxes did not closely track trends in measured fluxes, with extremely poor fit to measured data demonstrated by negative NSE scores for all nutrients (Moriasi et al. 2014) (Fig. B8). Linear regression analysis showed statistically significant correlations between modeled and measured fluxes of nitrate-N, total nitrogen and total phosphorous, but not phosphate-P (Fig. B9). However, these correlations were driven by only one or two points for nitrate-N, total N and total P; with outliers removed, nitrate was the only nutrient species where measured flux values were a significant predictor of modeled values. Coefficients of determination for all nutrient regressions were extremely low ($R^2 < 0.05$) with outliers removed. Calibration results from all best-performing iterations were better for fluxes of phosphate and total P than for nitrate or total N, though no iteration produced satisfactory fit for fluxes of any nutrient. Monthly calibration for all nutrient fluxes did not improve model fit (Fig. B10).

Difficulties – APEX-CUTE experienced several errors during streamflow and nutrient calibration in this study, including the previously described memory error. Most were due to user errors during parameterization, when I input or retained incorrect or zero values for very specific parameters (e.g., a '0.0' value for the bulk density (*BDD*) of one layer of a particular soil type). These produced 'not-a-number' (NAN) outputs in APEX, which caused the model run to abort (Jaehak Jeong, Texas A&M University, personal communication, 2018). Updating the relevant parameter values quickly and simply fixed these issues, though interestingly, these errors did not appear in single runs previously conducted using the WinAPEX interface. One notable software error occurred when the .RCH output file against which I calibrated was logged as 'not found'. Shorter runs of the full 162-subarea watershed and longer runs of smaller watersheds both completed successfully. Therefore, I hypothesized that the error was related to an excessively large .RCH output file size, which resulted in APEX-CUTE being unable to read it. This was

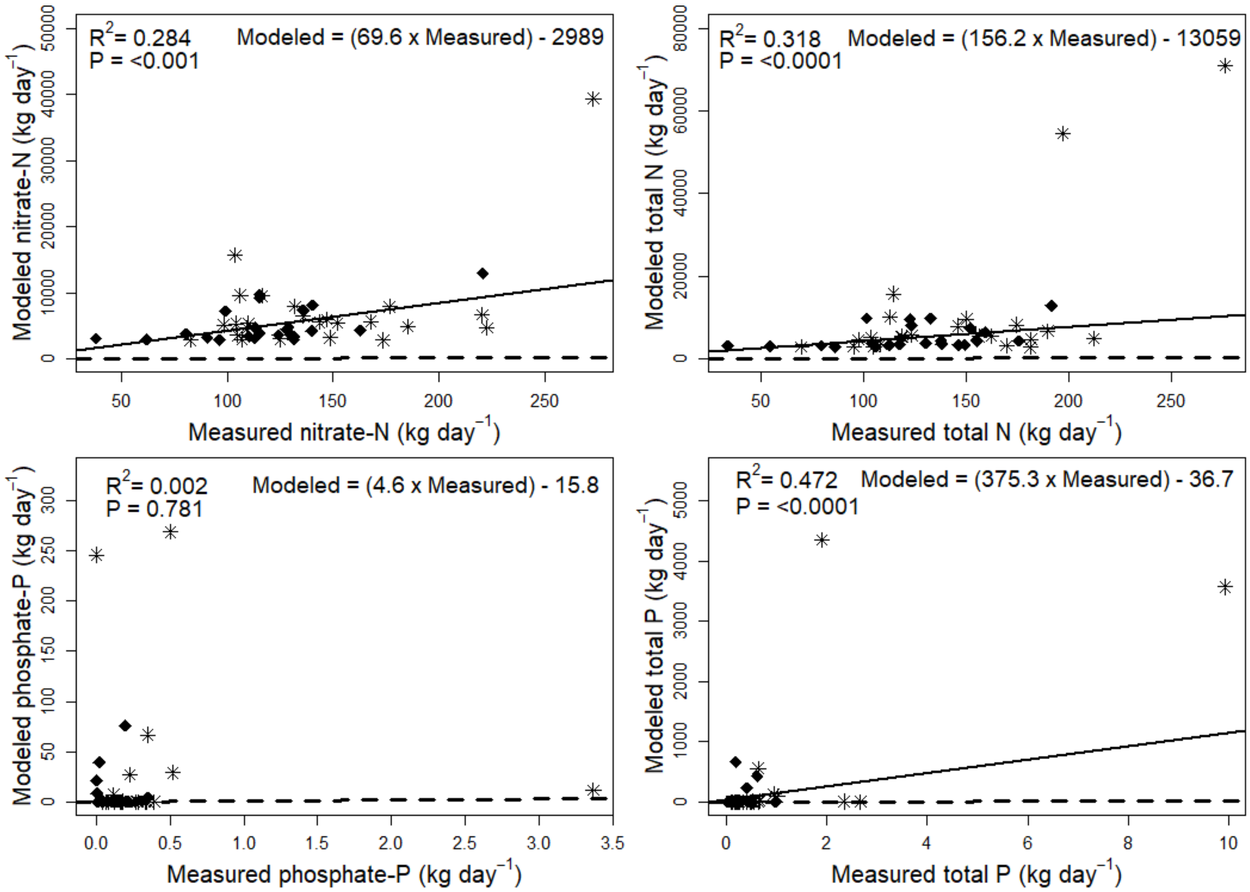

Figure B9. Linear regressions of measured vs. modeled fluxes of nitrate-N, total N, phosphate-P, and total P (N=48 for all nutrients) for upper Kamm Creek, showing best-fit lines (solid) and 1:1 lines (dashed). Summer (May-October) sampling dates are represented by solid diamonds, winter (November-April) sampling dates are represented by stars. Coefficients of determination, the equations of the best-fit lines, and P-values for measured nutrient fluxes are also displayed.

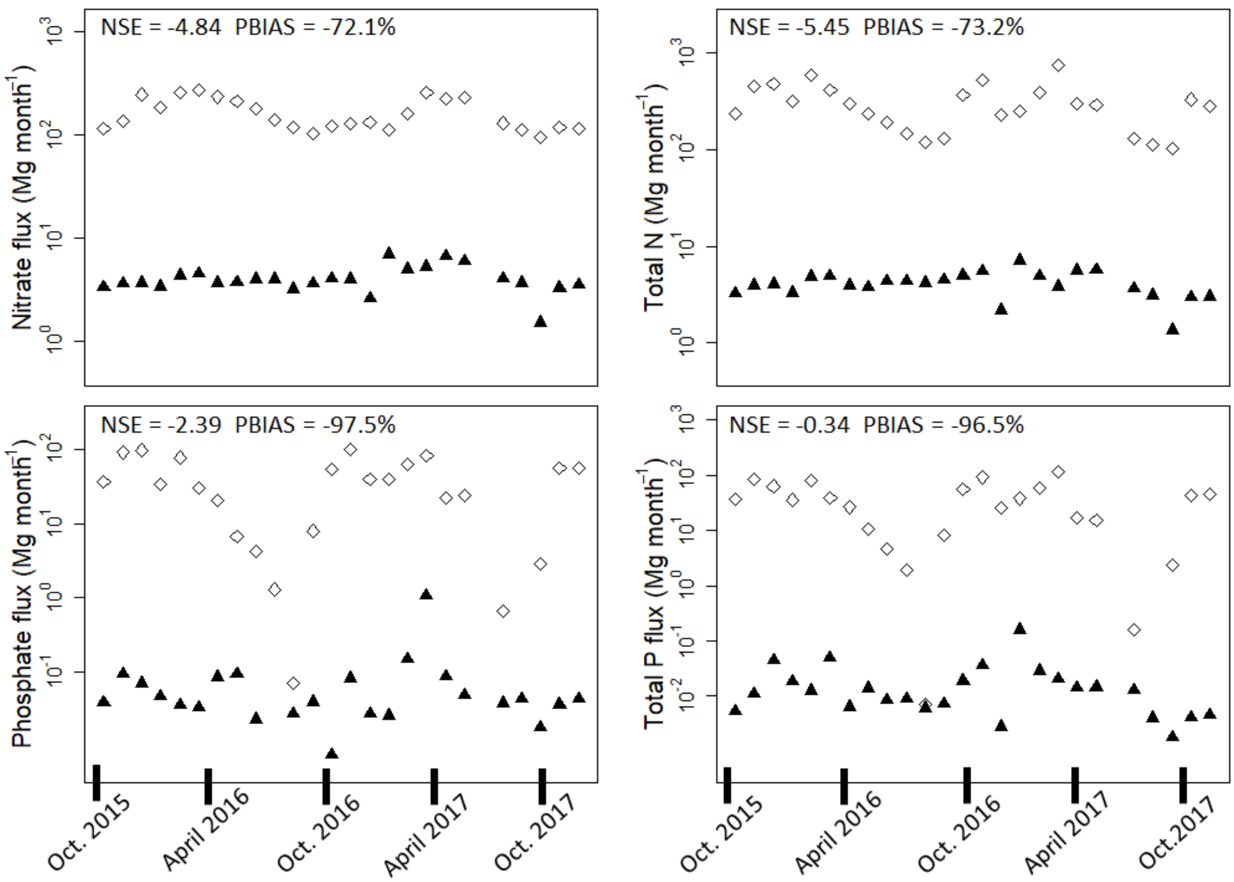

Figure B10. APEX simulation of monthly nutrient fluxes through the upper Kamm Creek watershed outlet from October 2015 – November 2017. Unfilled diamonds (N=25) represent APEX predictions, solid triangles (N=25) represent measured data. APEX-CUTE generated values for Nash-Sutcliffe efficiency coefficient and percent bias are displayed.

confirmed by a model developer (Jaehak Jeong, Texas A&M University, personal communication, 2018), who modified the ‘read’ command in APEX-CUTE’s code to handle the larger file size, completely resolving the issue. However, it is unclear whether this patch has been applied to the publicly downloadable version of APEX-CUTE, or only to the specific .EXE file used in this study. Future researchers should remain alert for the possibility of software errors, in addition to carefully formatting input files and calibration datasets, and verifying parameter values for new soils, crops and management settings.

Discussion

My aim is that the protocol described in this appendix will drastically reduce the length of time required for novice users to model a watershed in APEX, and will produce good calibration results for crop yield and biomass. However, significant challenges remain before APEX is a viable tool for predicting streamflow and nutrient fluxes, and ultimately for prioritizing management actions in northwest Washington. These challenges include the necessity of large, high-quality datasets for calibration, the acquisition of field-specific management information (particularly if crop and management parameters for a watershed have not been previously modeled), and difficulties in accurately modeling local perennial crops and ecosystems (especially forests), possibly due to shortcomings of the model itself.

Previous studies using APEX have typically used long-term datasets collected prior to the modeling effort (Williams et al. 2006, Tuppad et al. 2010, Cavero et al. 2012, Plotkin et al. 2012, Senaviratne et al. 2013, Gautam et al. 2018,). Most also calibrated APEX for nutrient fluxes on a monthly or annual timestep, rather than daily. Longer timesteps moderate the highly stochastic nature of daily fluxes but may not capture the impacts of short-term events such as fertilizer application or storm-induced flooding. Monthly estimates of streamflow and nutrient fluxes, generated from the limited daily data available for this study, did not improve model performance when used to calibrate APEX on a monthly timestep. Accurately approximating monthly or annual nutrient fluxes likely requires a prolonged and intensive sampling effort, which may not be feasible for many potential APEX users. However, the extent of the calibration dataset in large part determines the ultimate success of the calibration effort (Moriasi et al. 2014), and also the degree to which the validated model can predict nutrient fluxes within a large range of climatic variation (Wang et al. 2012).

Another key to successfully modeling agricultural watersheds is detailed knowledge of local management practices (Wang et al. 2012, Bhandari et al. 2017). This level of detail is especially important for watersheds in northwest Washington, which typically grow specialty crops on small fields, as opposed to corn and other commodity crops on more extensive fields, as in the Midwest. While local agricultural experts offered advice on management characteristics for crops within the watershed, obtaining field-specific management details from the growers themselves was not a viable option. Studies comparing the efficacies of watersheds calibrated using field-specific vs. generic management would illuminate the extent to which additional specificity improves model performance, but no such studies have been conducted for APEX.

An additional uncertainty in the modeling process was that, due to limitations of the APEX interface and in available data, I was unable to fully account for groundwater contributions to streamflow and nitrate fluxes in upper Kamm Creek's watershed. However, given the potential magnitude of these inputs, it is highly likely that successful integration of groundwater data would improve calibration results for all output variables for upper Kamm Creek and many other lowland streams in Whatcom County. In particular, the underestimation of summer stream flows by APEX likely resulted from a lack of simulated groundwater inputs. Monks (2016) found a similar pattern of underestimated summer streamflow in APEX outputs for Kamm Creek compared to TOPNET modeled streamflow, which that study used as a calibration dataset. But this pattern was not repeated in other APEX studies using measured calibration data (Francesconi et al. 2014, Wang et al. 2014). Future researchers should prioritize acquisition of suitable groundwater data, including measurements of both hydrologic and nitrogen flux, and exploration of suitable methods for integrating such data with APEX.

The poor fit of modeled streamflow, and in particular modeled nutrient fluxes, to measured data is not adequately explained by the factors previously discussed. Previous studies have used relatively limited daily calibration datasets to successfully predict nutrient fluxes (Francesconi et al. 2014), and modeled crop yields, while not field-specific, closely approximated target values for the watershed. The extremely poor model performance for nutrient fluxes compared to streamflow suggests that additional, unknown factors may be influencing simulation of nutrient cycling and export. Large numbers of model iterations did not seem to benefit nutrient flux calibration, as the best-performing set of parameter values for calibration runs was typically found in the first 25% of iterations. The most successful iteration overall was found in the second calibration run out of five completed, even though the starting parameter values for all additional runs were derived from that same successful iteration. This again suggests that a flaw in either my calibration procedure, the APEX-CUTE calibration interface, or APEX itself may be partially responsible for the poor model fit.

Working with APEX developers and other researchers in the field may clarify the factors responsible for the poor fit of modeled nutrient fluxes to measured fluxes, which needs drastic improvement before APEX can be used for prioritization. If calibration technique is a primary factor, then pending review and adjustments, this study may be replicated quickly with the expectation of greater success. However, another possibility is that APEX in its current form lacks essential equations or inputs necessary to accurately simulate nutrient cycling in our specific region, which features substantially different soil types, crops, management characteristics, and hydrologic conditions than other APEX project areas. Some necessary additions to the model are a) the inclusion of a category for nitrogen-fixing tree species to effectively simulate alders (*Alnus rubra*, an important riparian tree species in our region), and

b) the modification of the shrub vegetation category so that woody vegetations sustains biomass when harvested, to allow APEX to more effectively simulate blueberries and other shrub crops.

APEX's ability to simulate high-biomass forests without a long run-up time also requires improvement, as nitrogen content parameters for the evergreen tree crop type[14] must currently be set approximately 40% lower than measured values (Ares et al. 2007, Devine et al. 2013) to produce biomass in the target range. This discrepancy might be contributing to poor nitrogen flux calibration results, but the difference in forest nitrogen content likely adds < 2 kg N day^{-1} to the watershed, which is inconsequential compared with the ~4500 kg N day^{-1} model overestimates of N flux. The LAI (*DMLA=10*) and radiation use efficiency (*WA=74*) parameters for the evergreen tree crop are set two to three times higher than for other modeled species within the watershed, though a small number of APEX default crops have similar parameter values. The true value of these parameters for local forests is unknown, along with the specific impacts of high *DMLA* and *WA* values on nutrient cycling within forested subareas. Evergreen and mixed deciduous/evergreen forests are common in local woodlots and often planted during riparian restoration efforts, so their accurate representation in the model is critical for both simulating watershed nutrient dynamics and prioritizing management options. Other areas of potential improvement include increasing APEX's efficiency in modeling large numbers of subareas for long timespans, and the inclusion of a subarea variable for the presence or width of shrubby or forested buffer strips (similar variables exist for grass buffer strips).

The upper Kamm Creek watershed contains several subareas that are grazed as seasonal pastures; however, while dairy cattle grazing is an available feature in APEX, I did not

[14] Deciduous trees were not incorporated into modeled forests for this particular watershed, though some local forests commonly contain several deciduous species. Preliminary modeling of deciduous trees in the watershed faced similar problems with low biomass.

implement it for this project beyond the addition of realistic amounts of manure to pasture crops and the periodic harvest of biomass and associated nutrients. Incorporating accurate simulation of grazing in the upper Kamm Creek watershed model seems feasible in the future and may improve calibrations results. This process will require substantial research on cattle stocking rates and management practices, and also modifications to the 'pasture' crop type.

APEX's ability to predict hydrologic and nutrient fluxes in the Pacific Northwest remains unproven. This study agrees with initial work by Monks (2016), demonstrating that APEX can simulate common crops grown in western Washington, though perennial shrub crops such as blueberry are not well-modeled by APEX and currently require work-arounds to achieve target biomass and yield. To improve APEX's ability to model hydrologic fluxes, and in particular nutrient fluxes, in our region, I first recommend an expert review of the streamflow and nutrient flux calibration procedures described previously in this appendix. I also recommend collecting additional, detailed streamflow and nutrient flux data from upper Kamm Creek, and other watersheds, to expand the overall calibration dataset and to provide more accurate monthly estimates. My experience during the modeling process demonstrated that user manuals and basic logic are not sufficient resources to ensure a smooth modeling process; all modeling steps are subject to errors caused by user misinterpretation or by flaws in the code of APEX itself, which is in ongoing development. Supporting tools such as APEX-CUTE are also in relatively early stages of development, and both APEX and supporting tools may require specific changes for successful use in our region. The methods described in this appendix should allow for relatively rapid and accurate delineation and parameterization of new watersheds in our region. But, substantial future work is needed to produce good model fit for hydrologic and nutrient fluxes, so that APEX can be used to prioritize management actions in northwest Washington.

Appendix B Literature Cited

Ares, A., T. A. Terry, K. B. Piatek, o. B. Harrison, R. E. Miller, B. L. Flaming, C. Licata, B. D. Strahm, C. A. Harrington, R. Meade, H. W. Anderson, L. C. Brodie, and J. M. Kraft. 2007. Fall River longterm site productivity study in coastal Washington site characteristics, methods, and biomass and carbon and nitrogen stores before and after harvest. 1422324729, United States Forest Service, Pacific Northwest Research Station, Seattle, WA.

Aouissi, J., S. Benabdallah, Z. L. Chabaane, and C. Cudennec. 2014. Modeling water quality to improve agricultural practices and land management in a Tunisian catchment using the Soil and Water Assessment Tool. Journal of Environmental Quality 43:18-25.

Barney, D. L., P. Bristow, C. G. Cogger, S. M. Fitzpatrick, J. M. Hart, D. Kaufman, C. Miles, T. Miller, P. P. Moore, and T. Murray. 2007. Commercial red raspberry production in the Pacific Northwest. Oregon State University Extension Service, Corvallis, OR.

Bhandari, A. B., N. O. Nelson, D. W. Sweeney, C. Baffaut, J. A. Lory, A. Senaviratne, G. M. Pierzynski, K. A. Janssen, and P. L. Barnes. 2017. Calibration of the APEX model to simulate management practice effects on runoff, sediment, and phosphorus loss. Journal of Environmental Quality **46**:1332-1340.

Bryla, D. R., J. L. Gartung, and B. C. Strik. 2011. Evaluation of irrigation methods for highbush blueberry—I. Growth and water requirements of young plants. HortScience **46**:95-101.

Bryla, D. R., B. C. Strik, M. P. Banados, and T. L. Righetti. 2012. Response of highbush blueberry to nitrogen fertilizer during field establishment—II. plant nutrient requirements in relation to nitrogen fertilizer supply. HortScience **47**:917-926.

Bryla, D. R. and O. Vargas. 2012. Nitrogen fertilizer practices for rapid establishment of highbush blueberry: A review of six years of research. Pages 415-421 *in* X International Symposium on Vaccinium and Other Superfruits 1017, Maastricht, The Netherlands

Bush, T., D. Ogle, L. S. John, M. Stannard, and K. Jensen. 2012. Plant guide for orchardgrass (Dactylis glomerata). USDA-Natural Resources Conservation Service, Aberdeen Plant Materials Center, Aberbeen, ID

Carew, J. G., T. Gillespie, J. White, H. Wainwright, R. Brennan, and N. H. Battey. 2000. The control of the annual growth cycle in raspberry. The Journal of Horticultural Science and Biotechnology **75**:495-503.

Cavero, J., R. Barros, F. Sellam, S. Topcu, D. Isidoro, T. Hartani, A. Lounis, H. Ibrikci, M. Cetin, and J. Williams. 2012. APEX simulation of best irrigation and N management strategies for off-site N pollution control in three Mediterranean irrigated watersheds. Agricultural Water Management 103:88-99.

Chaney, M. and S. C. Fransen. 2002. Pasture and Hayland Renovation for Western Washington and Oregon. Washington State University Extenstion, Puyallup, WA.

Devine, W. D., P. W. Footen, R. B. Harrison, T. A. Terry, C. A. Harrington, S. M. Holub, and P. J. Gould. 2013. Estimating tree biomass, carbon, and nitrogen in two vegetation control treatments in an 11-year-old Douglas-fir plantation on a highly productive site. United States Forest Service, Pacific Northwest Research Station, Seattle, WA.

Fageria, N., V. Baligar, and Y. Li. 2008. The role of nutrient efficient plants in improving crop yields in the twenty first century. Journal of Plant Nutrition **31**:1121-1157.

Francesconi, W., D. Smith, G. Heathman, X. Wang, and C. Williams. 2014. Monitoring and APEX modeling of no-till and reduced-till in tile drained agricultural landscapes for water quality. Transactions of the American Society of Agricultural and Biological Engineers **57**:777-789.

Gassman, P. W., J. R. Williams, X. Wang, A. Saleh, E. Osei, L. M. Hauck, R. C. Izaurralde, and J. D. Flowers. 2010. The Agricultural Policy/Environmental eXtender (APEX) model: An emerging tool for landscape and watershed environmental analyses. Transactions of the American Society of Agricultural and Biological Engineers **53**:711-740.

Gautam, S., E. Mbonimpa, S. Kumar, and J. Bonta. 2018. Simulating runoff from small grazed pasture watersheds located at North Appalachian Experimental Watershed in Ohio. Rangeland Ecology & Management.

Grier, C. C., K. A. Vogt, M. R. Keyes, and R. L. Edmonds. 1981. Biomass distribution and above-and below-ground production in young and mature Abies amabilis zone ecosystems of the Washington Cascades. Canadian Journal of Forest Research 11:155-167.

Hannaway, D., S. Fransen, J. B. Cropper, M. Teel, M. Chaney, T. Griggs, R. R. Halse, J. Hart, P. R. Cheeke, and D. Hansen. 1999. Orchardgrass (dactylis glomerata L.). Pacific Northwest Extension, Corvallis, OR.

Hart, J. M., B. Strik, and H. Rempel. 2006a. Caneberries. Extension Service, Oregon State University, Corvallis, OR.

Hart, J. M., B. Strik, L. White, and W. Yang. 2006b. Nutrient management for blueberries in Oregon. Extension Service, Oregon State University, Corvallis, OR.

Hart, J. M., D. Sullivan, M. Gamroth, T. Downing, and A. Peters. 2009. Silage corn: western Oregon. Oregon State University Extension Service, Corvallis, OR.

Hudiburg, T., B. Law, D. P. Turner, J. Campbell, D. Donato, and M. Duane. 2009. Carbon dynamics of Oregon and Northern California forests and potential land-based carbon storage. Ecological Applications **19**:163-180.

Kugler, J. L. 2006. Orchardgrass hay production guide for the Columbia Basin of Washington. WSU Grant/Adams County Extension, Moses Lake, WA.

Magre, M., J. R. Williams, W. L. Harman, T. Gerik, J. Greiner, L. Francis, E. Steglich, and A. Meinardus. 2006. WinAPEX users guide. Blackland Research and Extension Center., Temple, TX.

Monks, D. 2016. Hydrologic calibration of the APEX model for western Washington. Western Washington University, Bellingham.

Moriasi, D., J. Arnold, M. Van Liew, R. Bingner, R. Harmel, and T. Veith. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Transactions of the American Society of Agricultural and Biological Engineers 50:885-900.

Moriasi, B., D. Bjorneberg, D., and K. King. 2014. A literature review of the current parameterization calibration and validation of APEX to support NTT. USDA Office of Environmental Markets.

Moriasi, D., B. Wilson, K. Douglas-Mankin, J. Arnold, and P. Gowda. 2012. Hydrologic and water quality models: use, calibration, and validation. Transactions of the American Society of Agricultural and Biological Engineers **55**:1241-1247.

Nash, J. and J. V. Sutcliffe. 1970. River flow forecasting through conceptual models part I—A discussion of principles. Journal of Hydrology 10:282-290.

Nelson, A., M. Talebizadeh, D. Moriasi, and S. Teet. 2016. Parameterization and validation of APEX for Willamette study site in Eugene, Oregon. USDA-ARS, El Reno, OK.

Plotkin, S., X. Wang, T. L. Potter, D. D. Bosch, J. R. Williams, E. S. Hesketh, and J. K. Bagdon. 2013. APEX calibration and validation of water and herbicide transport under US southern Atlantic coastal plain conditions. Transactions of the American Society of Agricultural and Biological Engineers 56:43-60.

Raymond, C. L. and D. McKenzie. 2013. Temporal carbon dynamics of forests in Washington, US: implications for ecological theory and carbon management. Forest Ecology and Management 310:796-811.

Rempel, H. G., B. C. Strik, and T. L. Righetti. 2004. Uptake, partitioning, and storage of fertilizer nitrogen in red raspberry as affected by rate and timing of application. Journal of the American Society for Horticultural Science **129**:439-448.

Senaviratne, G. M. M. M. A., R. P. Udawatta, C. Baffaut, and S. H. Anderson. 2013. Agricultural Policy Environmental eXtender simulation of three adjacent row-crop watersheds in the Claypan region. Journal of Environmental Quality **42**:726-736.

Strik, B. and G. Buller. 2005. The impact of early cropping on subsequent growth and yield of highbush blueberry in the establishment years at two planting densities is cultivar dependant. HortScience **40**:1998-2001.

Strik, B. C. 2005. A review of nitrogen nutrition of Rubus. Pages 403-410 *in* IX International Rubus and Ribes Symposium 777. Acta Horticulturae, Pucón, Chile.

Strik, B. C. and D. R. Bryla. 2015. Uptake and partitioning of nutrients in blackberry and raspberry and evaluating plant nutrient status for accurate assessment of fertilizer requirements. HortTechnology **25**:452-459.

Tuppad, P., C. Santhi, X. Wang, J. Williams, R. Srinivasan, and P. Gowda. 2010. Simulation of conservation practices using the APEX model. Applied Engineering in Agriculture **26**:779-794.

Tuppad, P., M. Winchell, X. Wang, R. Srinivasan, and J. Williams. 2009. ArcAPEX: ArcGIS interface for Agricultural Policy Environmental eXtender (APEX) hydrology/water quality model. International Agricultural Engineering Journal **18**:13.

Van Liew, M. W., C. S. Wortmann, D. N. Moriasi, K. W. King, D. C. Flanagan, T. L. Veith, G. W. McCarty, D. D. Bosch, and M. D. Tomer. 2017. Evaluating the APEX Model for Simulating Streamflow and Water Quality on Ten Agricultural Watersheds in the US. Transactions of the American Society of Agricultural and Biological Engineers 60:123-146.

Wang, X., D. Hoffman, J. Wolfe, J. Williams, and W. Fox. 2009. Modeling the effectiveness of conservation practices at Shoal Creek watershed, Texas, using APEX. Transactions of the American Society of Agricultural and Biological Engineers **52**:1181-1192.

Wang, X., A. R. Kemanian, and J. R. Williams. 2011. Special features of the EPIC and APEX modeling package and procedures for parameterization, calibration, validation, and applications. Methods of Introducing System Models into Agricultural Research:177-207.

Wang, X., J. Williams, P. Gassman, C. Baffaut, R. Izaurralde, J. Jeong, and J. Kiniry. 2012. EPIC and APEX: Model use, calibration, and validation. Transactions of the American Society of Agricultural and Biological Engineers **55**:1447-1462.

Wang, X., H. Yen, Q. Liu, and J. Liu. 2014. An auto-calibration tool for the Agricultural Policy/Environmental eXtender (APEX) model. Transactions of the American Society of Agricultural and Biological Engineers **57**:1087-1098.

Williams, J. R., R. Izaurralde, V. Singh, and D. Frevert. 2006. The APEX model. Watershed Models:437-482.

Williams, J., S. Potter, X. Wang, J. Atwood, L. Norfleet, T. Gerik, J. Lemunyon, A. King, E. Steglich, and C. Wang. 2010. APEX model validation for CEAP. Temple, Texas.
Yen, H., A. Sharifi, J. Osorio, L. Doro, and E. Steglich. 2016. APEX-CUTE 4 User Manual. Texas A&M University AgriLife Research, Temple, TX.