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The North Platte River Valley: The Intersectionality between Water Quality and People

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THE NORTH PLATTE RIVER VALLEY: THE INTERSECTIONALITY BETWEEN WATER QUALITY AND PEOPLE

by

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A THESIS

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THE NORTH PLATTE RIVER VALLEY: THE INTERSECTIONALITY BETWEEN WATER QUALITY AND PEOPLE

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The North Platte River (NPR) Valley of western Nebraska is a semi-arid watershed with row crop production, livestock production, and urban land use activity and has a population of diverse stakeholders. These land use activities contribute to the enrichment of surface waters, such as streams, which can affect human and ecosystem health, as well as economic development and recreational activities. The project objectives are to: (1) quantify the movement of dissolved inorganic nutrients from the land within the NPR Valley to the NPR via tributaries and canals, (2) identify spatiotemporal variability of nutrient limitation of periphyton growth within the NPR, and (3) explore the factors that are associated with the adoption of a web-based water quality monitoring tool. To address the first two objectives, I collected water samples and discharge measurements from canals, tributaries (streams leading back into the NPR), and the NPR from the Wyoming–Nebraska border every three weeks from June–September 2021; and I performed repeated nutrient limitation bioassays every three weeks at nine sites. I found that land use within the NPR Valley contributes to nutrient enrichment of the NPR and the subsequent export of nutrients downstream. Based on the lack of response of periphyton to the nutrient bioassays, it is likely that the nutrients coming from the watershed meet periphyton growth demands, except, perhaps, during the end of the growing season when some nutrient limitation of growth was detected. To meet the third objective, I created a survey tool to understand how attitudes, norms, and beliefs (latent variables) affect the use of a web-based water quality monitoring tool. Performance expectancy was the only significant predictor of behavioral intention for water users to use a web-based water quality monitoring tool. From a management perspective, these studies emphasize the need for better management of nutrient exports from the NPR Valley, but the incorporation of functional goals into the deployment of potential water quality tools to ensure high behavioral intention to use the tool.

Dedication

I would like to dedicate this thesis to the community members of the North Platte River Valley, and to everyone who has helped with this project.

Author's Acknowledgements

First and foremost, I would like to thank my advisor, Jess Corman, and my committee members - Chris Chizinski, Steve Thomas, and Mark Burbach - for challenging me to be a better critical thinker and giving me the opportunity to hone my skills as a scientist. Your insight into project formation, experimental design, data analysis, and project completion has helped form me into a better scientist - one who is ready to take on life's challenges and discoveries. You have each left an indelible mark on my life and I will carry that forward into my future endeavors.

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CHAPTER ONE: THE QUANTIFICATION OF DISSOLVED INORGANIC NUTRIENTS INTO AND OUT OF THE NORTH PLATTE RIVER VALLEY AND ASSESSMENT OF NUTRIENT LIMITATION WITHIN THE NORTH PLATTE RIVER

Introduction

Nitrogen (N) and phosphorus (P) are two nutrients that have socioecological importance. Their quantity and relative amounts in an ecosystem affect human health, economic prosperity, food production, primary production, and species community composition, yet, the total and relative abundance of these nutrients have changed globally (Salk *et al.*, 2020; Carmichael, 2001; Ward *et al.*, 2005; Cordell *et al.*, 2009; Penuelas et al, 2020). On a global scale, anthropogenic inputs of N and P have shifted the N:P ratio from 16:1 to ~27-28:1 due to anthropogenic activities that increase the amount of biologically-available (bioavailable) N synthetically derived from the Haber-Bosch process relative to the amount of mined P (Penuelas *et al.*, 2020). Anthropogenic activities that increase bioavailable N include nitrogenous-fertilizer input to agricultural land, fossil fuel burning, and N-fixation from leguminous crops and rice which outweigh the amount of P input from mineral P fertilizers (Penuelas *et al.*, 2013; Liu *et al.* 2008). In addition to changes on a global scale, this imbalance in N and P inputs varies on smaller scales too, such as a watershed or other management scales, that contain multiple human activities on a heterogenous landscape. Watersheds are important scales to manage nutrient inputs as they are areas that drain to a common point via surface flow or subsurface flow, and connect the land use to the stream through the hydrological connectivity (Kerr *et al.*, 2007).

At a watershed scale, the quantity and proportion of N and P differ with row crop production, livestock production, and urban development. For example, in areas with diffuse livestock production, such as concentrated animal feeding operations (CAFOs), leachates are high in P and the resulting N:P input to receiving waters is low (Humer *et al.*, 2015; Waller *et al.*, 2021). Run-off from CAFOs were also characterized by high levels of heavy metals like zinc and copper; pharmaceuticals; and pathogens (Waller *et al.*, 2021). Conversely, in pastures with low density livestock and row crop fields, N inputs are greater than P due to application of nitrogenous-based fertilizer and production of leguminous crops, which leads to high N:P inputs (Howarth *et al.*, 1996; Kemp and Dodds, 2001). Dissolved inorganic N:P ratios are more closely linked to land-use activities, whereas particulate N:P ratios were more closely related to interannual climatic and discharge variability at downstream sites from hog and crop production (Rattan & Chambers, 2017). Lastly, sites downstream of urban centers generally have less bioavailable N compared to agricultural sites, yet urban sites still release high N:P inputs despite the reduction of overall N and P as P is more efficiently reduced in treated water (Lenat & Crawford, 1994; Tong *et al.*, 2020). During high flow events caused by stormwater run-off in urban sites with dense areas of impervious surfaces and roads, P was mobilized into streams more relative to N (Hobbie *et al.*, 2017). Untreated human waste tends to have higher inputs of P relative to N (low N:P ratios) and can also contribute to urban nutrient loads from leaking sewage pipes, as well as urban pet waste (Hobbie *et al*., 2017).

To better understand how anthropogenic activity within a watershed is affecting nutrient exports into a system, nutrient budgets are used to quantify nutrient loads from nutrient surpluses on the landscape and determine if the watersheds are sinks or sources of nutrients (Zhang *et al.*, 2020; Sabo *et al.*, 2021). The basis of nutrient budgets recognizes the connectivity between surface water and run-off, groundwater, and upstream-downstream water movement. In the N budget performed by Lowrance *et al.* (1985), watersheds with high agricultural activity had higher loads of NO_3-N, and overall N, potassium (K), calcium (Ca), magnesium (Mg), and chloride (Cl) than watersheds with less agricultural activity. When assessing N inputs and fluxes throughout the United States, Sabo *et al.* (2019) identified high N fluxes derived from high fertilizer inputs in the Midwestern sub-basins. For a P budget comparing agricultural and urban areas, the magnitude of P loadings was similar between both areas, as large areas of non-riparian, agriculturally derived P is loaded from a greater area in the watershed (Soranno *et al.*, 1996). However, P loads from urban areas were not attenuated as they directly connect to waterways through storm sewers (Soranno *et al.*, 1996). The resulting nutrient budget for a given system can elucidate areas of intense loading activity, unknown sources or sinks within a system if a budget is not balanced, and areas of management priority (Sabo *et al.*, 2021).

The North Platte River (NPR) Valley of western Nebraska is an ideal system to quantify surface water imports and exports as it is a semi-arid, single watershed with multiple uses, including row crop production, livestock production, and urban activity. Precipitation is exceeded by evapotranspiration in the NPR Valley and increased water demand for agricultural activity is met through water diverted upstream of the system in a series of canal networks that are used throughout the growing season in the valley (Acharya *et al.*, 2012; Szilagyi, 2013). Two main canals run parallel to the river, and the water between the canal and the rivers drains toward the river via tributaries. Thus, the canal water serves as a reference for water concentrations with no anthropogenic effects from the NPR Valley in comparison to the tributaries that drain the landscape and the subcatchments within the valley. Consequently, this system affords us the opportunity to quantify the nutrient inputs drained from the land itself within the NPR Valley.

Excess, land-derived nutrients can have measurable effects on biological components within local surface waters and downstream systems. Ambient water column concentrations of nitrogen (N) and phosphorus (P) can limit growth in periphyton, or primary producers that grow on stream beds, through single nutrient limitation (N or P), simultaneous co-limitation (N and P act as a single limiting resource), or independent co-limitation (the limitation of one nutrient and, once met, results in the limitation of another nutrient and is order-dependent) (Harpole *et al.*, 2011). The increased algal biomass can result in the stimulation of other biological processes, such as increased decomposition and shifts in community structure as the basal level of the food web becomes more abundant or shifts due to competition of available resources in the aqueous environment (Smith *et al.*, 1999). Ratios of N:P can also promote algal growth as algal species require different relative amounts of N and P to grow, and the ratios can indicate whether areas experience nutrient limitation based on their relative abundance (>16 N: 1P, P-limited; <16 N: 1P, N-limited; Stelzer & Lamberti, 2001). For example, when testing whether variable N:P ratios and nutrient inputs affected algal community abundance and structure, Stelzer and Lamberti (2001) found that ratios and concentrations impacted the types of algal species within a community and the amount of biomass accrued by the algae. Riseng *et al.* (2004) confirmed these findings when studying the effects of hydrologic disturbance and nutrient inputs on benthic community structure in midwestern U.S. streams, and emphasized that nutrient inputs significantly affected algal growth under conditions of high hydrological flows that scour algae from the streambeds. By determining nutrient limitation within river systems, the effects of nutrient inputs on biological functions are better understood

The purpose of our study is to quantify the movement of dissolved inorganic nitrogen (DIN, as the sum of ammonium (NH_4-N) and nitrate (NO_3-N)) and dissolved inorganic phosphorus (as soluble reactive phosphorus, SRP) as inputs into and output from the North Platte River in western Nebraska, and to assess whether there is nutrient limitation due to variable amounts of nutrients derived from irrigation run-off.

Materials and Methods

Study Area Description

The headwaters of the North Platte River of western Nebraska begin as snowmelt on the Rocky Mountains of Colorado before flowing through Wyoming (WY) and entering Nebraska (NE). Prior to the development of dams, reservoirs, and irrigation canal systems, the NPR had only ephemeral tributaries in the NPR Valley between the

WY-NE border to Bridgeport, NE. To supplement precipitation in the area, the Sweetwater Project was funded by the Bureau of Reclamation to support agricultural producers in the area and build over 2000 miles of canals and laterals that irrigate 220,000 acres within the valley (Brookshire *et al.*, 2004; North Platte Natural Resources District, *n.d.*) A combination of increased surface flows from the canal networks and higher water tables due to seepage resulted in a few perennial tributaries (Petersen *et al.*, 2015).

Within the valley of our system, agriculture (32%), rangeland/pastureland (61%), urban (4%), and other (3%; barren, natural, and water) are the land use types represented in the system (USGS, 2018). Crop techniques include irrigated and dryland farming.

The study system is bounded geographically by canals to the north and south, the WY-NE border to the west, and Bridgeport, Nebraska, to the east. The system and the sample collection sites (n=38) are within this semi-arid region (Shulski 2015).

The outermost north and south canals (NC and SC, respectively) were diverted from the North Platte River (NPR) upstream of our system and are treated as distinct waterways in this study (Figure 1.2). The canal water ultimately drains back into the NPR through a series of extensive canals, creeks, and agricultural returns, known collectively as north tributaries (NT) and south tributaries (ST). When the outermost north canals were dry, I sampled from the north canals that make up the Farmer's Irrigation District (NC-FID; Figure 1.1). The distance of the NPR, NT, and ST sites along the river (km) has also been provided in Table 1.1 for reference.

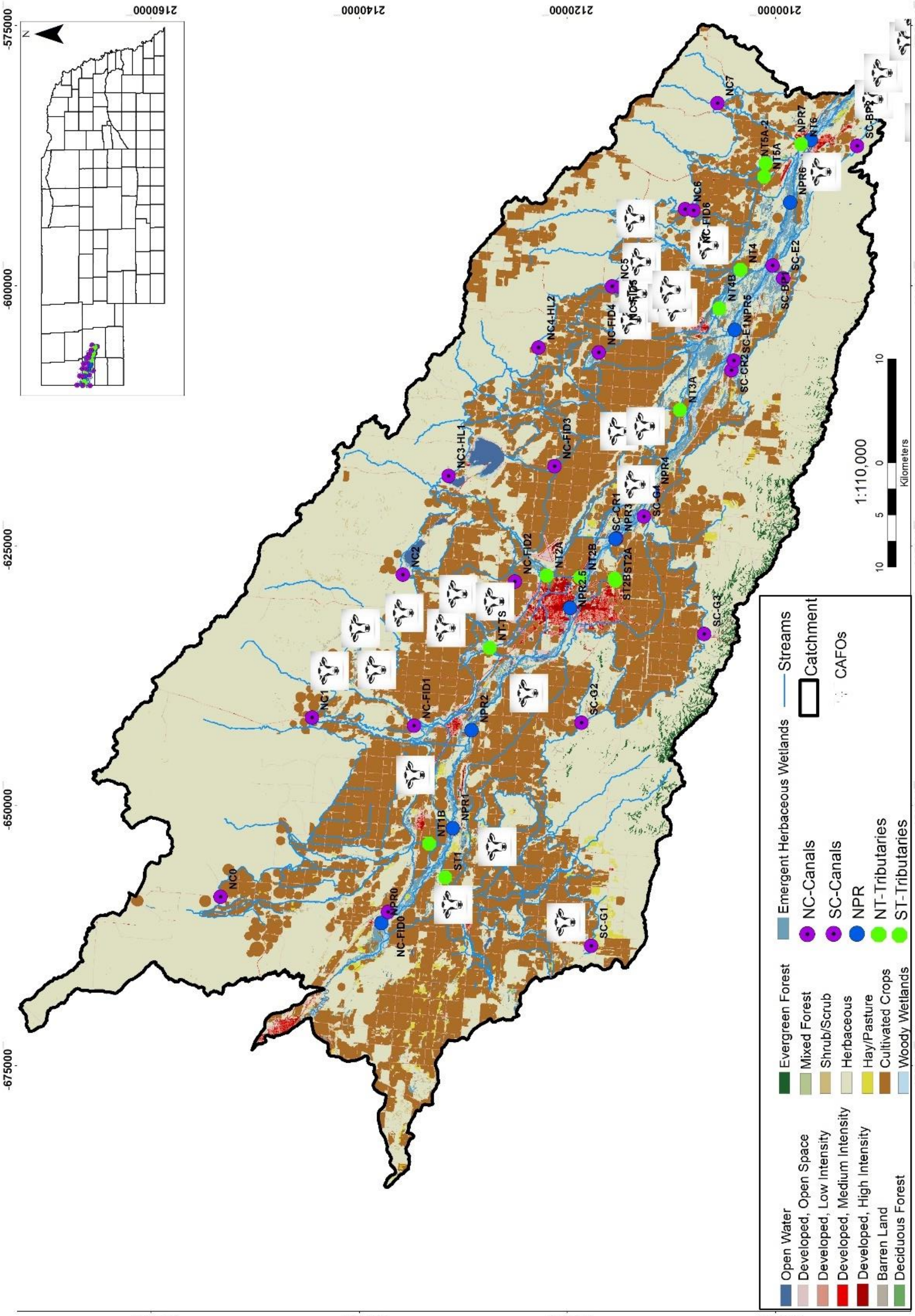

Figure 1.1 Map of the North Platte River Valley Watershed from the Wyoming - Nebraska border in the west to Bridgeport, Nebraska, in the east. River flow of the North Platte River in the center of the system flows west to east.

The system inputs and outputs were defined relative to the NPR outlet, NPR7. Inputs were defined as all tributaries and agricultural returns that flow into the NPR Valley prior to NPR7. Outputs were defined as canals, NC-FID0 and SC-BP1, that were diverted from the NPR into the valley for irrigation prior to NPR7.

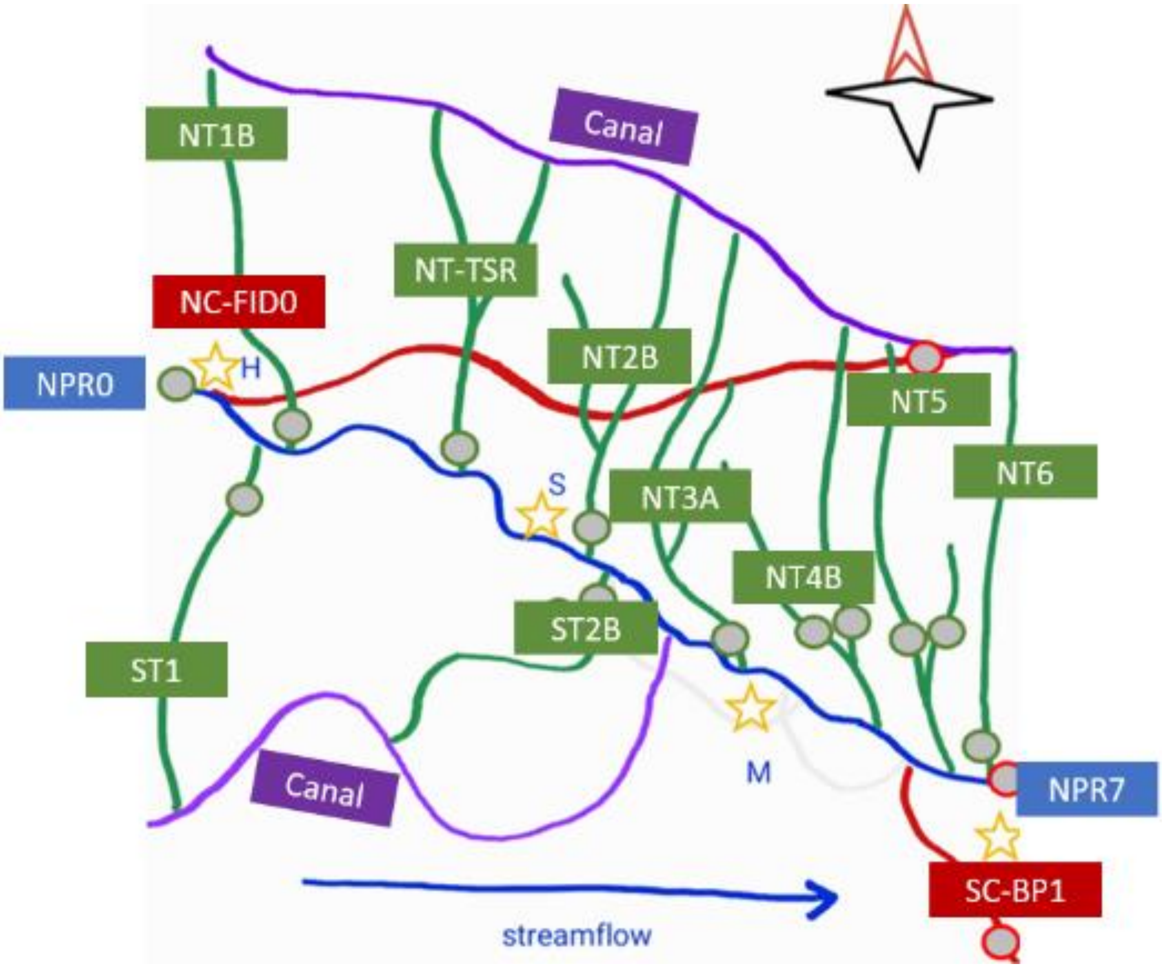

Figure 1.2 A conceptual model of the NPR Valley system with the north and south canals used for reference (purple), the tributaries (green), the diverting canals (red), the NPR (blue), major towns (Henry, Scottsbluff, Morrill, and Bridgeport; stars), and collection sites (circles).

Table 1.1 Distances of the North Platte, tributary, and canal sites along the river

Site	Distance from the WY-NE border (km)	Site Type
NPR0	0.00	River
NC-FID0	1.83	Canal
ST1	11.01	South Tributary
NT1B	13.17	North Tributary
NPR1	14.55	River
NPR2	27.93	River
NT-TSR	38.76	South Tributary
NPR2.5	47.26	River
NT2B	51.52	North Tributary
ST2B	48.61	North Tributary
NPR3	56.07	River
NPR4	64.03	River
NT3A	74.83	North Tributary
NPR5	84.19	River
SC-BP1	92.21	Canal
NT4B	93.61	North Tributary
NPR6	99.22	River
NT5	104.35	North Tributary
NT6	105.74	North Tributary
NPR7	106.40	River

Land Use Type of Natural Subcatchments

To identify the percentage of land use type for each of the tributaries, land use land cover data from the National Land Cover Database (USGS, 2018) was used to fit the natural subcatchment boundary layers in ArcGIS (Esri, Redlands, California) over the study area, download the affiliated land use land cover data affiliated with the delineated watershed, and the calculated the percentage of land use types within each natural watershed. Since tributaries drain multiple subcatchment within the NPR Valley, the area for each land use was added together for each respective tributary, and then percentages were calculated.

Water Chemistry

To describe the physiochemical characteristics of the North Platte River Valley, I established sampling sites in the NPR (n=9), SC (n=10), NC (n=7), NT (n=9), and ST (n=3). Sites were sampled every three weeks from Early June to Mid September 2021 for a total of six experimental runs. Due to canals running dry or water levels being too high to safely collect discharge measurements from, not every site was sampled at every sampling event.

At each site, I sampled for basic physicochemical parameters, nutrient concentrations, sediment load, and discharge. Water was sampled from the shoreline using a painter pole with a 1L bottle attached to the end. Temperature, specific conductivity, pH, and dissolved oxygen (%, mg L^{-1}) were collected using a handheld YSI Multimeter ProPlus (YSI Incorporated, Yellow Springs, OH). Water was collected in acid-washed, HDPE bottles for chemical analysis. Water for dissolved constituents – nitrate (NO_3-N µg L^{-1}), soluble reactive phosphorus (SRP µg L^{-1}), and ammonium (NH_4-N µg L^{-1}), cations (iron, Fe mg L^{-1}; potassium, K mg L^{-1}; magnesium, Mg mg L^{-1}; sodium, Na mg L^{-1}; silicon Si, mg L^{-1}), and anions (fluoride, F mg L^{-1}; chloride, Cl mg L^{-1}; and sulfate, SO_4^- mg L^{-1}) were filtered in field using an EZFlow Glass Fiber Syringe Filter (Foxx Life Sciences, Salem, NH; 0.45 µm pore size). All water was frozen for further analysis, except samples for cations, which were preserved to pH <2 using concentrated nitric acid. To determine the sediment load, water was filtered on pre-weighed, combusted filters (Whatman GF/C Microfiber Glass Filters, 1.2 µm pore size) for determination of total suspended solids (TSS). Field blanks and daily duplicates were also collected at the start of each day of collection.

Water chemistry was run in the Ecosystem Stoichiometry Lab at the University of Nebraska, Lincoln, with the exception of the cation samples which were run at the Metals, Environmental and Terrestrial Analytical Laboratory at Arizona State University, Tempe. To process samples, I used an Astoria 2 Autoanalyzer (Astoria Pacific, Clackamas, Oregon) following the protocol within its operator manual for NO_3-N and SRP samples; a handheld fluorometer AquaFluor (Turner Designs, San Jose, California) with an adapted Taylor *et al.* (2007) protocol for NH_4-N samples; an Agilent 9000 (Agilent Technologies, Santa Clara, California) for cations; a Dionex ICS-1100 Ion Chromatography System (ThermoScientific, Waltham, Massachusetts) following the protocol within its operator manual for anions; a Genesys 150 spectrophpotometer (ThermoScientific, Waltham, Massachusetts) using a modified Steinman *et al.* (2017) protocol for chlorophyll-α analysis.

Discharge Measurements

Discharge measurements were derived using the USGS streamflow Midsection Method for the experimental runs (Turnipseed & Sauer, 2010), except for the run that occurred in mid-August when discharge measurements was determined using the “Dry Injection” method with a known amount of salt mixed within a water solution prior to releasing it in the river (Hudson & Fraser, 2005). For the NPR sites, stream gages by the USGS (No. 06684498) and the Nebraska Department of Natural Resources (NE-DNR; No. 06684500) supplied the mean daily discharges (ft^3 s^{-1}) for each of the experimental runs (Nebraska Department of Natural Resources, 2022). Discharge data for tributary sites and canals were not collected due to water depth and compromised accessibility. Instead, I used mean daily discharges for each of the experimental runs using the NE-DNR stream gages: 0009000 (SC-BP1), 00145100 (NC-FID0), 06679000 (NT-DST), 06683000 (NT-BC), 6680970 (ST2B), and 6681000 (NT2B).

To calculate the mean experimental run discharge, I downloaded the sub-hourly streamflow data for the entire experimental run and took the average discharge of those values. For NC-FID0 and SC-BP1, I added an additional step since I did not regularly collect concentration measurements at these sites. Instead I used the concentration of these canals at the sites that were regularly collected from sites furthermost downstream, NC6 and SC-BP2, respectively. For example, NC-FID0 starts at the river but diverges off into the valley until it reaches NC6. I used the concentrations at NC6 multiplied by the average daily discharge procured from the NE-DNR website. Similarly, any missing discharge data was supplemented using the same method for averaged discharge data by the NE-DNR stream gages.

Calculations for quantifying nutrient inputs and exports

Water balance calculations

To understand the amount of water accounted for by the identified surface waterways within the study system, I completed the water balance for each experimental run using the following equation:

$$Q_{\text{River-out}} - (Q_{\text{River-in}} + \Sigma Q_{\text{Tributaries-in}} + \Sigma Q_{\text{Canals-out}}) = \text{Balance}$$

(Equation 1),

where Q signifies discharge (m s^{-1}) and the subscripts “River-out,” “River-in,” “Tributaries-in,” and “Canals-out” denote from which sources I have calculated the discharge. More specifically, “River-out,” “River-in,” “Tributaries-in,” and “Canals-out” refer to the NPR outlet (NPR7), the NPR inlet (NPR0), all the tributaries (NT/ST), and the canals that are fed directly from the river within the NPR Valley (NC-FID0 and SC-BP1), respectively.

A positive, negative, or net zero water balance elucidates the amount of water being accounted for within a system of interest. If the balance is positive, more water is leaving the system than what is being accounted for solely in the surface water pathways. Therefore, water is being added into the system from processes like surface water – groundwater interaction. Conversely, if the balance is negative, more water is coming into the system than what is leaving. In this scenario, water is leaving the system from processes like evapotranspiration and volatilization. Lastly, if the balance is net zero, then all water is being accounted for and other processes are not acting on the system. For this study, surface water is the only source being studied due to time and budget constraints.

Nutrient export calculations

To calculate the fluxes of dissolved inorganic nutrients (NO_3-N kg day^{-1}, NH_4-N kg day^{-1}, SRP kg day^{-1}) of each tributary coming into the system and canal leaving the system prior to the outlet of our system, NPR7, I multiplied the discharge of the site by the concentration of each nutrient measured at each site.

$$\text{Flux}_{\text{Day, Nutrient}} = Q_{\text{Site}} * \text{Concentration}_{\text{Site, Nutrient}} \quad \text{(Equation 2)}$$

where Flux$_{\text{Day, Nutrient}}$ measured in the units NO_3-N kg day^{-1}, NH_4-N kg day^{-1}, and SRP kg day^{-1} depending on the nutrient measured for an experimental run. DIN and SRP were the only nutrients quantified.

For the two canals (NC-FID0 and SC-BP1) that diverge from the river prior to the NPR outlet, NPR7, I use Equation 2, but I use the discharge measurements procured from the NE-DNR website and the concentrations from the sites as they leave our study system.

To quantify the amount of nutrients drained from the land between the canals and the North Platte River, I then used the following equation for each tributary and its respective canal site upstream:

$$\text{Flux}_{\text{Land use -in, Nutrient}} = Q_{\text{Tributary}} * (\text{Concentration}_{\text{Tributary, Nutrient}} - \text{Concentration}_{\text{Canal, Nutrient}}) \quad \text{(Equation 3)}$$

Nutrient yields derived from natural subcatchments

Next, I determined the nutrient yield associated with different subcatchments in the watershed. For each sub-catchment, I calculated the natural watershed boundary and area within each of the subcatchments using the National Land Cover Database (USGS, 2018). I also used this database to determine the classification of each land use type within the natural watershed boundaries.

$$\text{Flux}_{\text{Normalized, Nutrient}} = \text{Flux}_{\text{Land use -in, Nutrient}} / \text{Area}_{\text{Natural Sub-catchment}} \qquad \text{(Equation 4)}$$

Net flux from the North Platte River Valley

To determine whether the NPR Valley within the study system results in nutrient exports, I used the following equation:

$$\text{Flux}_{\text{River-out, Nutrient}} - \text{Flux}_{\text{River-in, Nutrient}} = \text{Net flux}_{\text{NPR Valley}} \qquad \text{(Equation 5).}$$

If the difference between what is leaving the NPR (at NPR7) and what is initially coming into the NPR (at NPR0) is a positive net flux, then more nutrients are leaving the NPR Valley than what originally came into the system, whereas a negative value would mean nutrients are being retained within the NPR Valley or lost in a gaseous form, which is not quantified in this study design.

To compare our results to other findings, the yield was calculated by multiplying the resulting difference and dividing it by the area of the system drainage area in square kilometers, 4211.02 km^2 (USGS, 2018). I took the quotient from Equation 4 and multiplied it by 365 to scale our findings to kg km^{-2} year^{-1}.

Assumptions and limitations of the surface water nutrient imports and exports

For our nutrient imports and exports of the North Platte River, these are the assumptions I made, as well as limitations:

(1) the northern-most and southern-most canals are representative of water that is not affected by anthropogenic land use activities within the NPR Valley

(2) the tributaries represent the only pathway of surface water drainage from the canals to the river.

(3) other possible sources for nutrient inputs and exports to the system are unaccounted for, such as groundwater, atmospheric deposition, sewage pipeline seepage, evapotranspiration/volatilization, etc.

(4) precipitation is not a major source of water entering the system

(5) biogeochemical processes within the river that transform nutrients from one species to another are unaccounted for

Nutrient bioassay amendments and algal biomass accrual

To determine the primary limiting nutrient(s) to periphyton growth within localized stretches of the North Platte River, I deployed nutrient diffusing substrata (NDS) at each of the nine sites for 21-day incubation periods starting early June 2021 to mid-September 2021 (total experiments = 54). To make the NDS, I followed the protocol by Tank *et al.* (2006) and included four treatments - control (Ctrl), nitrogen (N), phosphorus (P), and nitrogen and phosphorus (N+P). I used ammonium chloride (NH_4Cl) and potassium dihydrogen phosphate (KH_2PO4) for N and P treatments, respectively. Additions were made at 0.33 M N and 0.5 M P. Each agar-based treatment was poured into 60mL cups, where the agar solidified and was covered with a glass frit. The NDS were made the day before deployment, refrigerated, and placed on ice when in transit to the site.

In the field, NDS cups (four replicates per treatment) were fastened to a steel L-bar that was secured using stakes to the bank of the river site. After the incubation period, I analyzed the accumulation of chlorophyll-α (Chl-α) on each glass frit as a proxy to periphyton growth. As the North Platte River is a sediment-laden river, sand would occasionally accumulate on the NDS in the course of the incubation period. If sand on the glass frit could be removed by gentle agitation, it was assumed that the sand did not compromise the results of the periphyton growth, and, therefore, the sample was collected per normal. However, if agitation did not dislodge the coating of sand or mud, the glass frit was still collected, but the replicate was recorded as covered in either sand or mud. Upon retrieval, glass frits were stored in the dark, on ice, until transported to the field lab, where they were frozen until analysis. The experiment was repeated every three weeks, starting with early June 2021 and ending in Mid September. The entirety of the July run was lost during the transportation from the NPR Valley to the laboratory, so, although I ran the experiment six times, five data collection points are represented in the data.

To assess whether a site was limited by N, P, or N+P relative to the Ctrl, I transformed the Chl-α data using a natural log transformation and then analyzed the data using a one-way ANOVAs for each site during each experimental run using R statistical program (R Core Team, Vienna, Austria, 2022). The function aov() was used to run the following code: Chl- α ~ Treatment, where Chl- α is the natural log of the algal biomass accrued for each treatment as chlorophyll-α as a function of the different treatments. This was done for each site and experimental run individually.

Results

Land Use Type of Natural Subcatchments

Throughout the NPR Valley, each tributary has variable percentages of land use types (Figure 1.3). The site with the highest percentage of urban land is ST2B, which drains Gering and Terrytown. NT2B and NT3A also have higher percentages of urban land use as they drain Scottsbluff and McGrew, respectively. ST1, ST2B, and NT3A have high percentages of rowcrop within their natural subcatchments, while NT1B, NT6, NT-TSR, and NT2B have high percentages of pastureland.

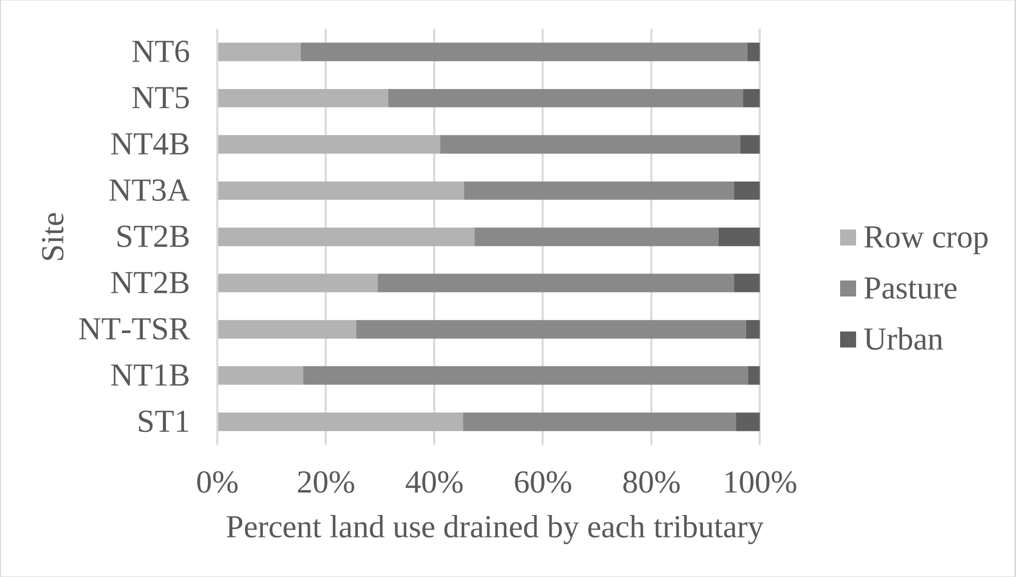

Figure 1.3 The percent land use area - row crop, pasture, and urban - drained by each tributary based on natural subcatchment areas.

Water Chemistry

The mean DIN and SRP concentrations were 2371.91 +/- 1094.69 ug L^{-1} and 52.63 +/- 17.10 ug L^{-1} in the NPR for Summer 2021, respectively (+/- SD). The NPR sites with the highest concentrations of DIN and SRP were NPR3 (4679.68 DIN ug L^{-1}) during Mid September and NPR7 (102.99 SRP ug L^{-1}) during Late August.

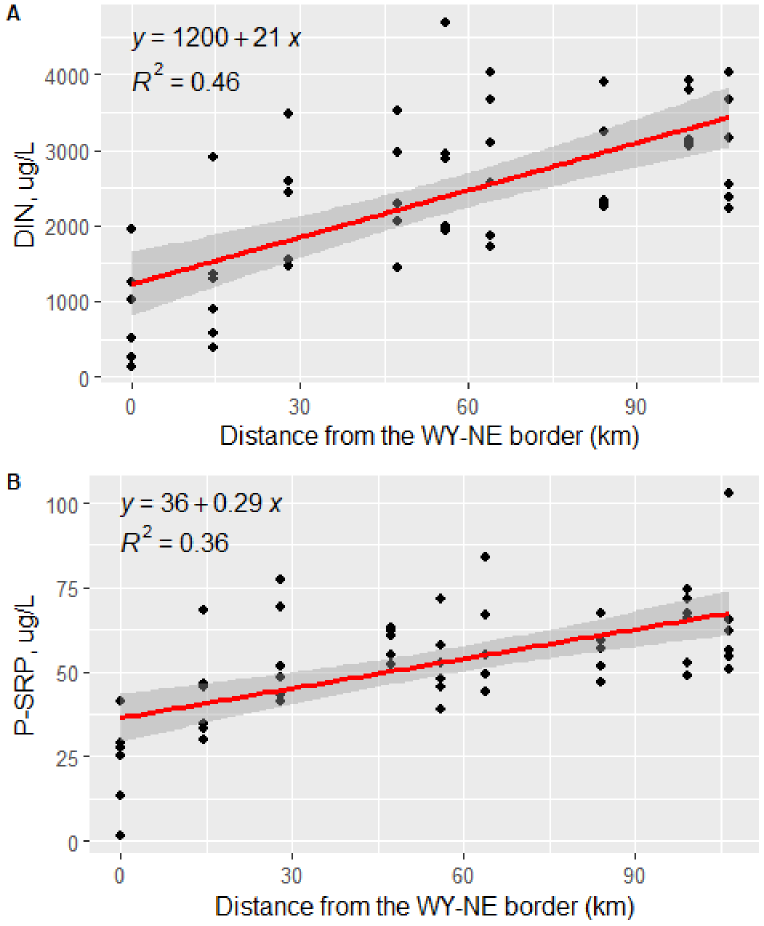

Figure 1.4 The relationship between DIN (Panel A) and SRP (Panel B) concentrations with distance from the WY-NE border. Both p-values for the linear regression models are <0.001.

DIN and SRP concentrations increased as a function of distance from the WY-NE border, or as they moved downstream (Figure 1.4). With each kilometer downstream, DIN would increase by 21 ug N L^{-1} and SRP would increase by 0.29 ug P L^{-1}. DIN increased from starting concentrations of 0 - <1500 ug N L^{-1} at the WY-NE border (NPR0) to 2000 - >3000 ug N L^{-1} 106.4km downstream at NPR7 during all experimental runs except for Mid September. During this run, the DIN concentrations was 2000 ug N L^{-1} at NPR0 and 4000 ug N L^{-1} at NPR7. SRP followed similar trends as DIN through

Summer 2021 (Figure 1.4). SRP concentrations were between 0 - 50 P ug L^{-1} at NPR0 and concentrations rose to 50 - 100 P ug L^{-1} at NPR7.

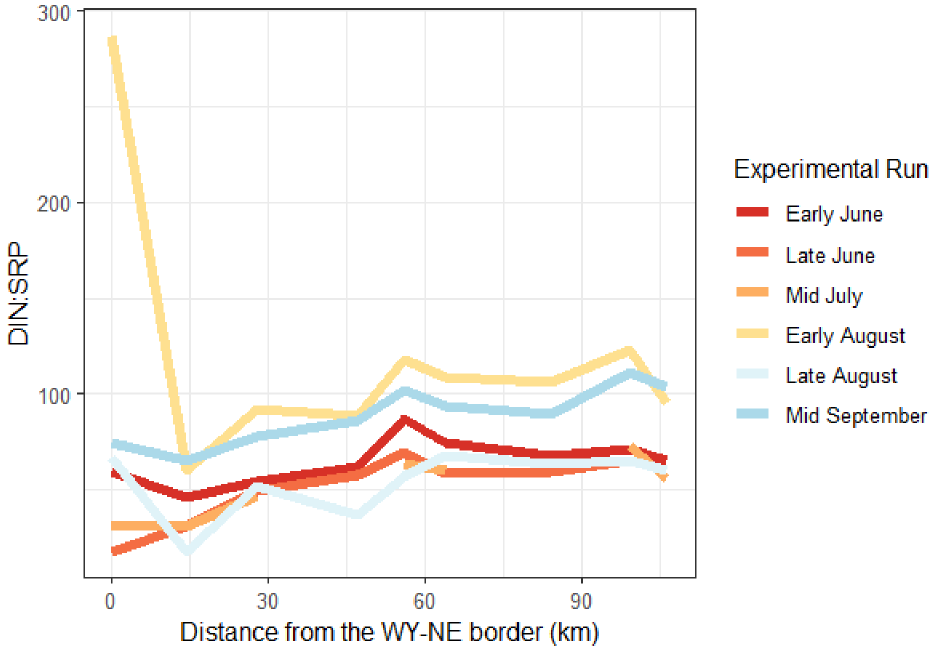

Figure 1.5 The Summer 2021 trend of DIN:SRP.

The DIN:SRP is relatively high at the WY-NE border except for Late June (Figure 1.5). When DIN:SRP was regressed on the distance from the WY-NE border, the model fit was not significant. The changes in DIN:SRP are likely to be driven by higher N inputs to P given downstream increases in DIN and SRP.

The other cation and anion concentrations within the NPR generally increased in concentration in their relationship to downstream movement from the WY-NE border (Figure 1.6). Si^{+4}, K^{+}, Cl^{-}, and Na^{+} increased their concentrations from the beginning to end of the NPR Valley system, sometimes by double their starting values. Neither SO_4^{-2} nor total Fe (Fe^{+2} + Fe^{+3}) had apparent trends. See Appendix 1 for tables regarding sites and their average values for physicochemical parameters.

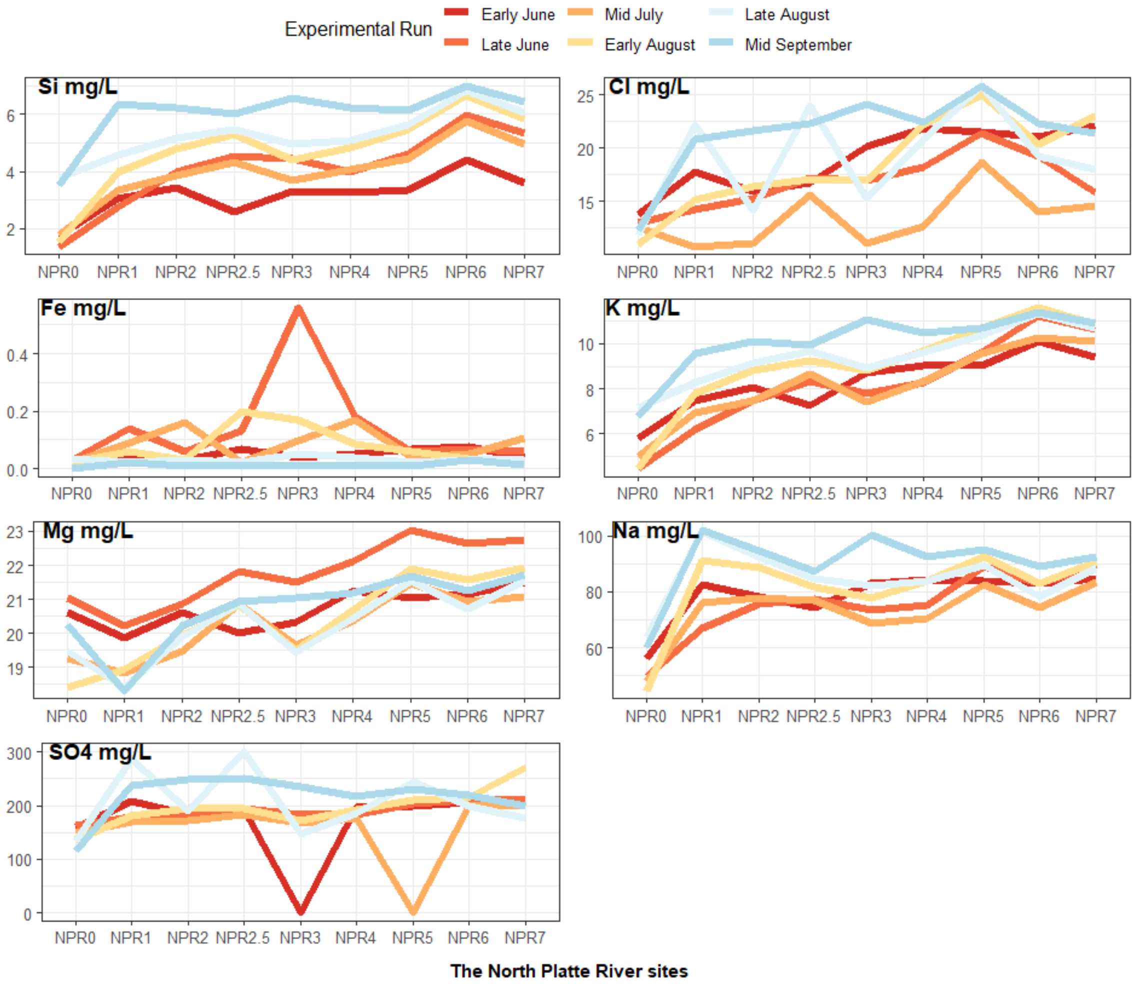

Figure 1.6 The trends of ion concentrations moving from the WY-NE border (NPR0) to Bridgeport, NE (NPR7). Note the y-axes are on different scales.

None of the NPR sites reached levels of public health concern (EPA drinking water guideline, 10 NO_3-N mg L^{-1}), yet one tributary site that flows into the NPR 49 km downstream of the WY-NE border, ST2B, had one collection point in which the N-NO3 concentration was 12,555 NO_3-N ug L^{-1}, or 12.6 mg L^{-1}. The averages for all north tributaries were 3597.87 +/- 1429.38 DIN ug L^{-1} and 95.71 +/- 89.83 SRP ug L^{-1}, while the averages for all south tributaries were 3310.79 +/- 3675.39 DIN ug L^{-1} and 59.91 +/-

25.91 SRP ug L^{-1}. The north tributaries had higher concentrations on average for both DIN and SRP, but the south tributaries had higher variability in DIN concentrations.

Water balance

During Summer 2021, more water came into the system from upstream compared to what left the system at NPR7. At the WY-NE border (site NPR0), water flowed into the NPR Valley at 25.06 m^3 s^{-1}, on average, while the mean tributary input was 12.08 m^3 s^{-1}. The canals NC-FID0 and SC-BP1 that were diverted from the river decreased the amount of water in the system by 12.29 m^3 s^{-1} on average. At NPR7, water leaves the system at an average rate of 12.95 m^3 s^{-1}. The tributary discharges exhibited variable flow throughout the summer, and discharges for Early June were the lowest compared to other run dates (Table 1.2).

Table 1.2 The discharge measurements in cubic meters per second for all inputs and outputs measured in the North Platte River Valley.

Site	M	SD	Early June	Late June	Mid July	Early August	Late August	Mid September
NPR0	25.06	13.36	9.19	37.66	32.64	31.01	32.9	6.95
ST1	2.17	1.67	0.16	4.37	4.04	1.66	1.65	1.15
NT1B	1.14	1.32	0.12	0.49	0.46	0.44	3.58	1.74
NT-TSR	0.93	0.48	1.3	0.33	1.01	0.79	1.61	0.52
NT2B	2.27	3.42	9.19	0.07	1.14	1.06	1.5	0.68
ST2B	1.76	1.28	0.06	3.03	2.83	2.67	1.47	0.5
NT3A	2.27	1.23	0.08	2.18	2.92	2.86	3.62	1.94
NT4B	2.11	0.59	1.08	2.38	2.59	2.36	2.53	1.73
NT5	0.16	0.09	0.01	0.215	0.16	0.12	0.16	0.27
NT6	0.65	0.35	0.04	1.13	0.65	0.73	0.62	0.72
NPR7	12.95	3.63	10.45	10.35	13.08	10.46	13.61	19.74
SC-BP1	2.47	0.28	2.46	2.53	2.5	2.83	2.53	1.96
NC-FID0	22.10	12.32	4.89	31.61	28.69	28.39	31.25	7.78

During my sampling period, the water balance in the NPR was unbalanced. The unaccounted-for discharge by percent for each sampling event was +54.45% (Early June), -81.50% (Late June), -31.23% (Mid July), -18.10% (Early August), -15.53% (Late August), and -32.73% (Mid September) (Figure 1.7). Negative values of the unknown discharge percentages reflect water that stayed within the system, as the total discharge at the end of the system (NPR7 Q) was less than the total amount of water that flowed into the system (NPR0 Q + $\text{Tributaries}_{\text{in}}$ – $\text{Tributaries}_{\text{out}}$). Conversely, the positive value reflects when water left the system at NPR7.

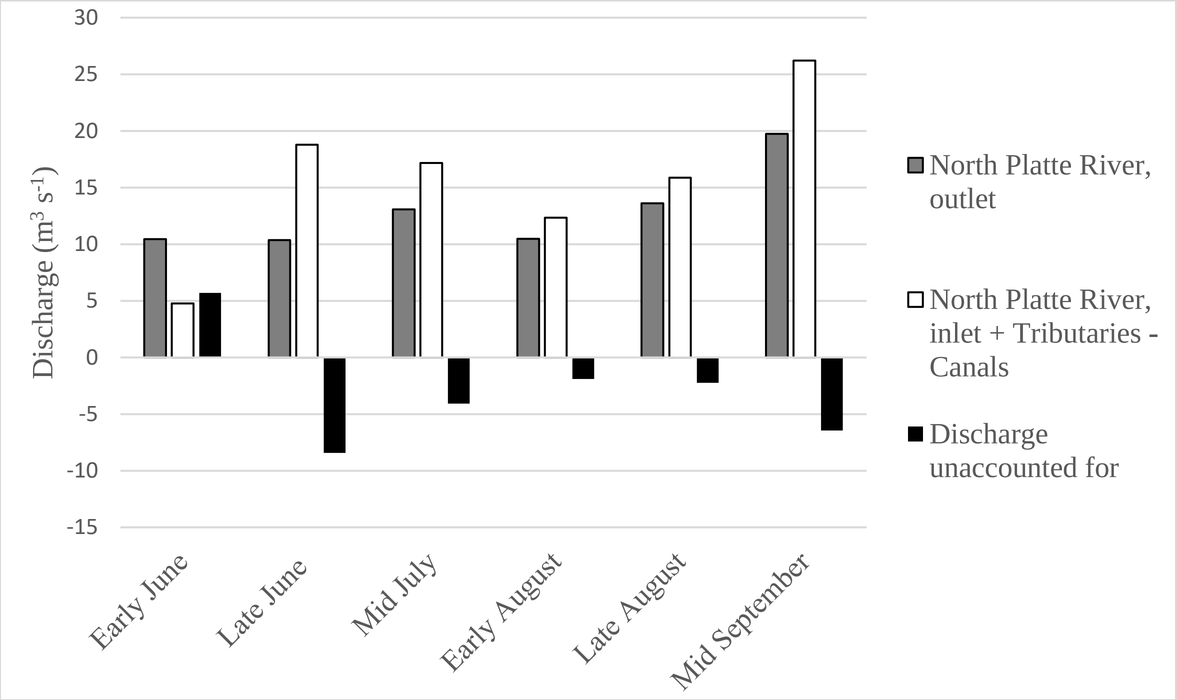

Figure 1.7 The Summer 2021 water balance for the NPR Valley.

Nutrient fluxes

In general, DIN and SRP fluxes out of the NPR Valley at NPR7 were greater than the fluxes coming into the system at NPR0. Fluxes out of the system were about 2.5 times higher than those into the system during Summer 2021, on average. In total, 12,717 kg DIN and 192.1 kg SRP exited the system each day. These values were 1.6X higher than what cumulatively went into the system for DIN and 0.7X less than what cumulatively came into the system throughout the summer.

To quantify the nutrient fluxes derived from the land, the DIN and SRP fluxes were calculated using Equation 3 and nutrient input into the NPR was determined by the sign of the resulting flux. Positive values signified when nutrients were greater in the tributaries relative to their respective canal concentration.

For DIN, the North Tributary and South Tributary sites exported the most land-derived nutrients in Early August and Mid September based on their average fluxes, whereas the highest fluxes of SRP occurred in Late August (Table 1.3). North tributaries, in general, input more DIN (M = 320 kg day^{-1}, SD = 322 kg day^{-1}) to the river compared to the south tributaries (M = 266 kg day^{-1}, SD = 298 kg day^{-1}). For SRP, the north tributaries had generally higher inputs of SRP yet were more variable (M = 9.11 kg day^{-1}, SD = 23.1 kg day^{-1}) compared to the south tributary sites (M = 6.17 kg day^{-1}, SD = 6.35 kg day^{-1}).

Table 1.3 The average, land-derived nutrient fluxes with their respective standard deviations for the experimental runs.

	DIN kg day^{-1}		SRP kg day^{-1}	
Experimental Run	M	SD	M	SD
Early June	132	217	2.81	4.53
Late June	258	225	5.29	7.02
Mid July	334	323	6.19	4.89
Early August	385	358	9.84	14.4
Late August	296	397	20.8	47.5
Mid September	440	320	5.86	4.20

Within each experimental run timeframe, sites were compared to understand what sites contributed the most nutrients via fluxes (Figure 1.8). With exception of Early June and Mid September, NT3A (75 km downstream of the WY-NE border) consistently had the highest flux values. Even in Mid September, NT3A had the second highest amount. For South Tributary sites, ST2B (50 km downstream of the WY-NE border) consistently released the highest fluxes of DIN. Like our results for DIN fluxes, NT3A tended release the highest amount of SRP into the river with exception of Early June. ST1 (11.04 km downstream of the WY-NE border) had higher contributions of SRP fluxes compared to ST2B, except during Early and Late August.

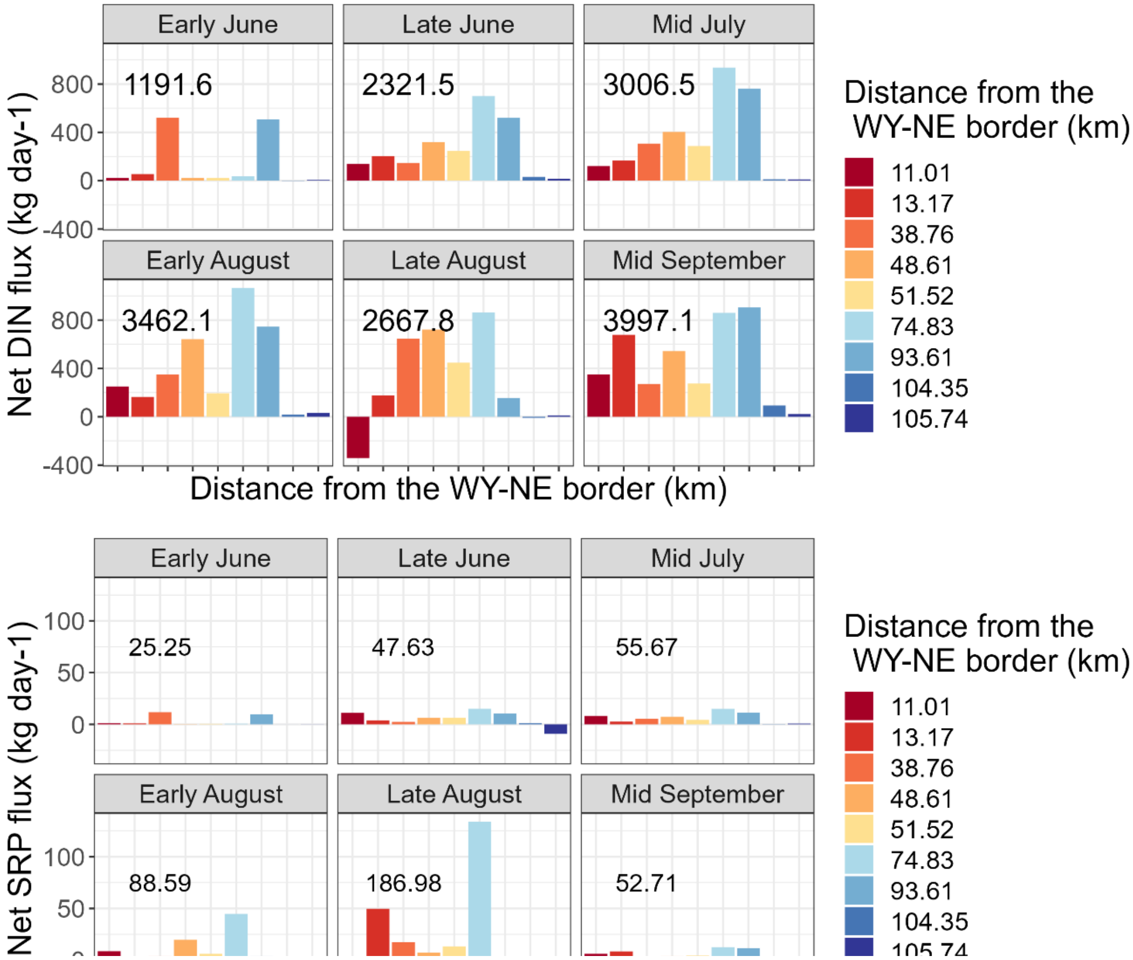

Figure 1.8 The land-derived nutrient fluxes for DIN (top panel) and SRP (bottom panel) in kg day^{-1} *for each experimental run. Each tributary site is plotted at the distance along the North Platte River where it flows into the river.*

Figure 1.0.9 The average land-derived DIN yield for each tributary site, +/- standard error (SE), for all experimental runs during Summer 2021.Figure 1.0.10 The land-derived nutrient fluxes for DIN (top panel) and SRP (bottom panel) in kg day^{-1} *for each experimental run. Each tributary site is plotted at the distance along the North Platte River where it flows into the river.*

Nutrient yield

When the nutrient yield for DIN and SRP, the relative contribution of each north tributary site (M = 0.02 g SRP km^{-2} day^{-1}, SD = 0.04 g SRP km^{-2} day^{-1}; M = 1.12 DIN km^{-2} day^{-1}, SD = 1.08 DIN km^{-2} day^{-1}) and south tributary site (g SRP km^{-2} day^{-1}, M = 0.07 g SRP km^{-2} day^{-1}, SD = 0.17 g SRP km^{-2} day^{-1}; M = 1.05 DIN km^{-2} day^{-1}, SD = 1.34 DIN km^{-2} day^{-1}) became more salient.

The overall temporal trends reflect the flux trends in terms of Early August and Mid September releasing the most DIN from the landscape (1.34-1.49 g N km^{-2} day^{-1}), and Late August releasing the most SRP compared to the other runs (0.09 g N km^{-2} day^{-1}; Table 1.4). Late August had the most variable DIN yields (SD=1.84 g N km^{-2} day^{-1}) followed by Early August (SD=1.16 g N km^{-2} day^{-1}), and Late August also had the most variable SRP yields (SD=0.21 g P km^{-2} day^{-1}).

Table 1.4 The average, land-derived nutrient yields with their respective standard deviations for the experimental runs.

	DIN, g N km^{-2} day $^{-1}$		SRP, g P km^{-2} day $^{-1}$	
Experimental Run	M	SD	M	SD
Early June	0.48	0.82	0.01	0.02
Late June	0.91	0.70	0.01	0.04
Mid July	1.17	1.01	0.02	0.01
Early August	1.34	1.16	0.03	0.05
Late August	1.25	1.84	0.09	0.21
Mid September	1.49	0.86	0.02	0.01

When looking at the spatial trends, NT-TSR (39 km from the WY-NE border) and NT2B (49 km from the WY-NE border) had the highest DIN yields into the system relative to the other tributary sites (Figure 1.9). The tributaries near the midsection of the river, including NT-TSR and NT2B, have higher DIN yields than tributaries at the start and end of the system. NT2B had the highest and most variable average SRP yield during Summer 2021 (Figure 1.10), while NT-TSR, ST2B, and NT3A also yielded large amounts of SRP.

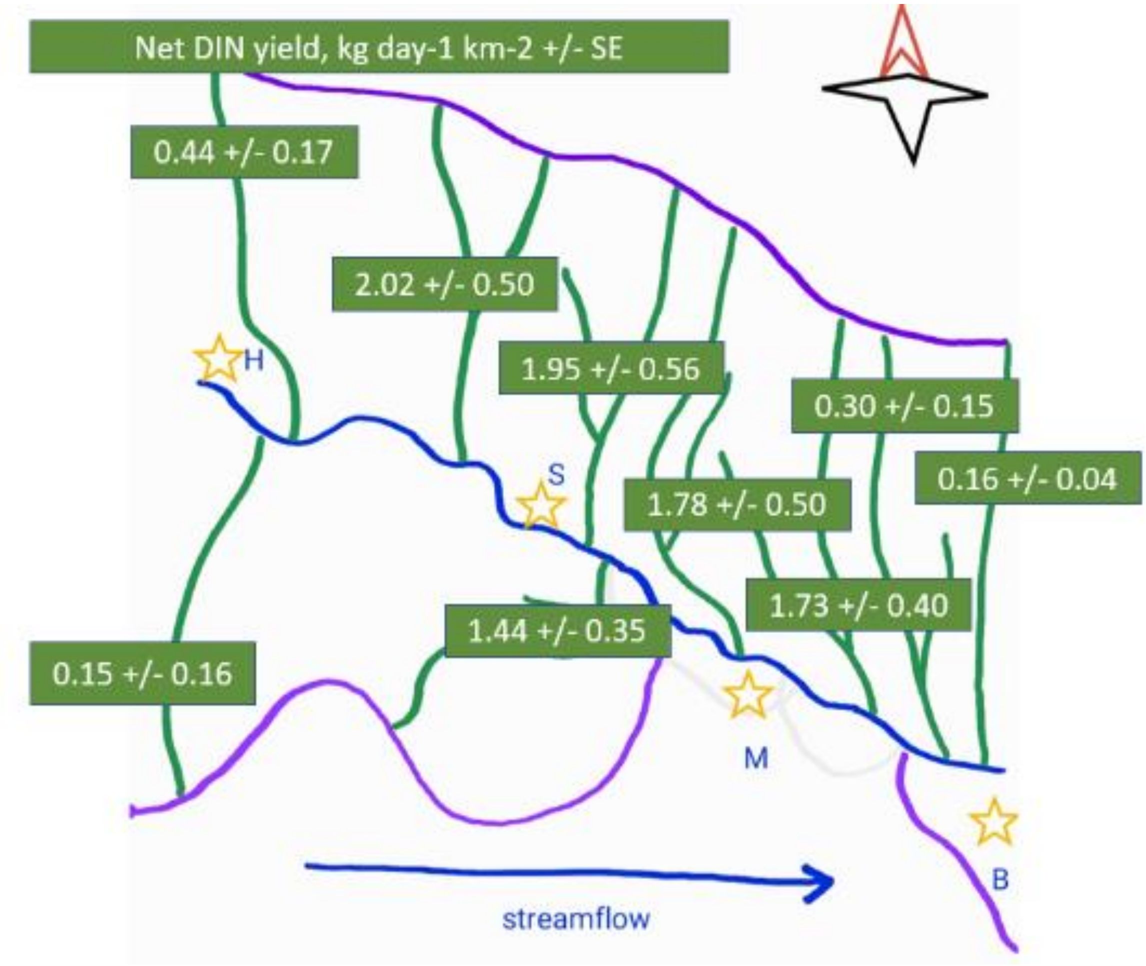

Figure 1.11 The average land-derived DIN yield for each tributary site, +/- standard error (SE), for all experimental runs during Summer 2021.

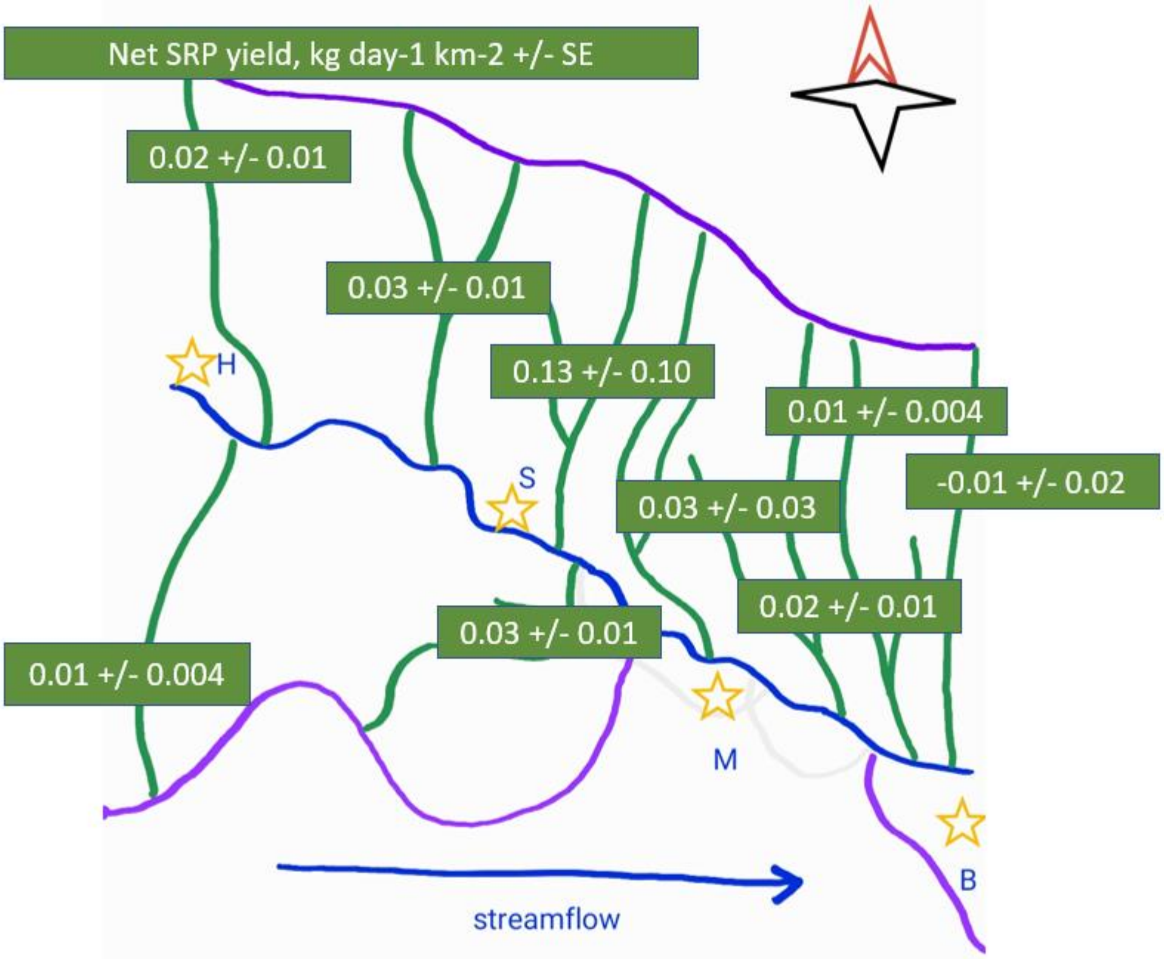

Figure 1.12 The average land-derived SRP yield for each tributary site, +/- standard error (SE), for all experimental runs during Summer 2021.

Net Fluxes from the NPR Valley

During each of the experimental runs, the net fluxes from the NPR Valley were positive values except for the SRP flux during Mid July (Table 1.5). The DIN:SRP column in Table 1.5 has positive values, signifying that the DIN:SRP ratio increased (NPR7 ratio > NPR0 ratio). Conversely, the negative values signify the DIN:SRP decreased from where it entered the system to where it left the system.

Table 1.5 The derived fluxes (kg day^{-1}) of dissolved inorganic nutrients from the land within the NPR for every experimental run date, and the resulting difference of DIN:SRP.

Experimental Run	DIN (NO_3-N + NH_4-N), kg day^{-1}	NO_3-N , kg/ day^{-1}	NH_4-N, kg day^{-1}	SRP, kg day^{-1}	DIN:SRP
Early June	1338.71	1345.49	-6.79	29.02	0.10
Late June	1816.51	1833.59	-17.08	14.87	-27.31
Mid July	1102.07	1104.77	-1.49	-1.49	-19.56
Early August	2178.89	2197.41	-18.52	42.09	-20.55
Late August	1184.01	1191.98	-7.97	39.12	-19.29
Mid September	5097.01	5102.16	-5.15	68.47	12.79

Nutrient Limitation

For Summer 2021, the mean chlorophyll growth for the control treatment was 1.23 ug cm^{-2} +/- 0.81. For each treatment during Summer 2021, the mean values for Ctrl (M = 1.22 ug cm^{-2}, SD = 0.69 ug cm^{-2}), N (M = 1.11 ug cm^{-2}, SD = 0.70 ug cm^{-2}), N+P (M = 1.33 ug cm^{-2}, SD = 0.94 ug cm^{-2}), and P (M = 1.26 ug cm^{-2}, SD = 0.90 ug cm^{-2}) were like the Ctrl treatment.

The one-way ANOVA results were significant for river sites during our Late August and mid-September experimental runs (Table 1.6; Figure 1.11). More specifically, P was the main limiting nutrient and sometimes N + P. The July run was dropped from analyses due to missing data. The overall lack of nutrient limitation in our system shows that another driver is most likely limiting algal growth within the NPR Valley.

Table 1.6 The one-way ANOVA results with the natural log of chlorophyll-a as a function of treatment, p<0.05. The following symbols are used to denote nonsignificant ANOVA results (~) or no data (.)

River sites	**Early June**	**Late June**	**Early August**	**Late August**	**Mid September**
NPR0	~	~	.	~	~
NPR1	~	~	C > P; C > NP; C > N	~	~
NPR2	~	.	~	NP > C; P > C	~
NPR2.5	~	.	.	~	.
NPR3	~	.	.	~	~
NPR4	~	.	~	~	~
NPR5	~	~	.	NP > C	C > NP
NPR6	~	.	.	~	NP > C; NP > N
NPR7	~	.	~	~	NP > C; NP > N

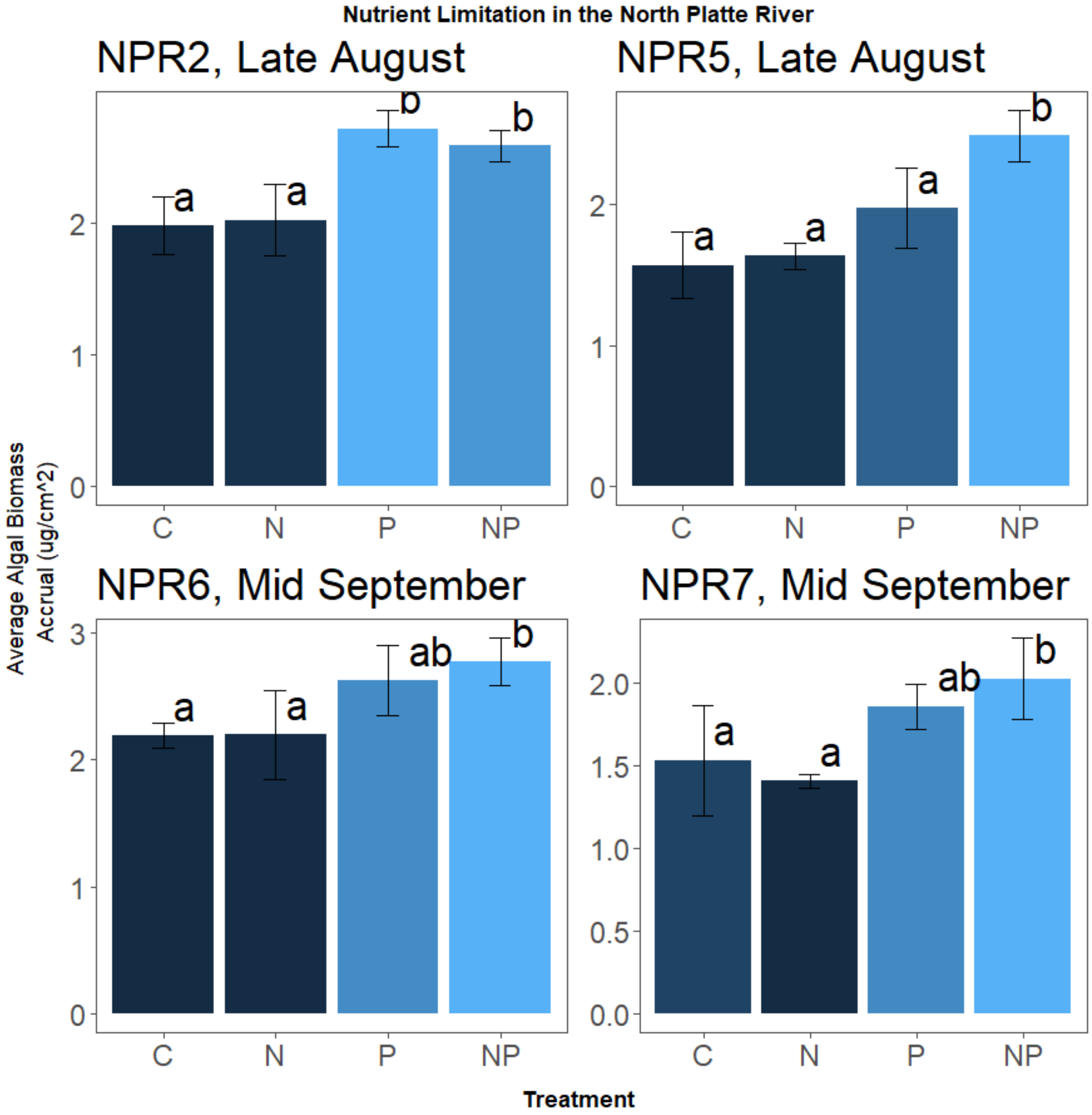

Figure 1.13 The post-hoc Tukey test results for nutrient amendments.

Discussion

The system within the North Platte River Valley is a source of dissolved inorganic nutrients: nitrate, ammonium, and phosphorus. The nutrient exports from our system confirm findings by Goolsby *et al.* (2000), David *et al.* (2010), and Jacobson *et al.* (2011) where the section of the western Nebraska North Platte River system contributes 183.72

kg DIN km^{-2} $year^{-1}$ and 2.7 kg SRP km^{-2} $year^{-1}$. However, the heterogenous landscape made it difficult to correlate loads with a specific land use type. Future studies should take soil samples, measure atmospheric deposition, and erosion rates to better link land use to nutrient loads. The measured loads are a small fraction of the amount of nutrient loads from other tributaries within the Mississippi River Basin being exported into the Gulf of Mexico (Alexander *et al.*, 2017). I also found that despite having high DIN:SRP ratios, phosphorus limitation was not prevalent throughout Summer 2021 within the NPR Valley. Instead, I found that the mid-section of the river that represented all four land use types and included higher occurrences of CAFOS tended to input the most DIN, whereas NT2B, a site that had the second highest percentage of urban land use resulted in the highest SRP yields relative to the other sites.

Land Use Type of Natural Subcatchments

The mid-section of the river has higher percentages of urban development and includes cropland and pastureland. Furthermore, this area within the NPR Valley has the bulk of CAFOs. Therefore, it is difficult to attribute any specific land use as contributing more to land-derived nutrient fluxes of DIN and SRP into the system, as no one land use type dominates a subcatchment.

Water balance

The unbalanced water balance indicates that other hydrological processes are occurring in the system that either add water to the system as is the case for Early June or lose water to the system. Possible losses of water within the system include evapotranspiration and groundwater seepage. Petersen *et al.* (2015) simulated the groundwater budget for this study system and found that groundwater recharge was largely in part due to canal seepage and a smaller part due to precipitation. They also found that groundwater outflows were due primarily due to discharge into streams, and a small component due to evapotranspiration.

The results of the water balance for Late June through Mid September show that more water enters the system than leaves, which offers two main explanatory pathways: groundwater seepage or evapotranspiration. This indicates that I am accounting for most of the water within the system and that land-derived nutrient loads can be seeping into groundwater or leaving the system through evapotranspiration.

Nutrient flux

NT3A, also known as Nine-Mile Creek, has two concentrated animal feeding operations that are just upstream and close to the river. Although NT3A drains a heterogenous landscape, the proximity and potential size of the CAFOs could be driving the amount of DIN and SRP coming into these sites. ST2B, Gering Valley Drain, has the highest urban percentage of land use relative to the other sites and also has a CAFO upstream of our sampling point which could be driving its fluxes of DIN and SRP. Interestingly, ST1, by the WY-NE border, drains SRP from its sub catchment, which could be indicative of high erosion due to lands use activity or natural causes, legacy phosphorus within the soil, or the CAFO upstream of the sampling point.

Nutrient yield

The natural subcatchments drained by the tributaries within the mid-section of the NPR Valley yielded the highest amount of DIN and SRP. NT-TSR had the highest DIN yield while NT2B yielded the most land-derived SRP (g km^{-2} day^{-1}) on average throughout Summer 2021 (Figure 1.9). It also had the most variable compared to the other sites as its SE was higher than the other sites. This site is immediately downstream of the largest town of the area within the NPR Valley study system, Scottsbluff.

Net nutrient flux of the NPR Valley

In comparison to other studies of DIN fluxes from major tributaries in the Mississippi River basin, our results support work by Goolsby *et al.* (2000) who found that the North Platte River Valley exported between 14 and 300 kg km^{-2} $year^{-1}$ using historical data on discharge and nutrient concentrations. In the Goolsby *et al.* (2000) study, our average, scaled yearly export from the NPR Valley of 183.72 kg DIN km^{-2} $year^{-1}$ was only one-fifth to one-tenth of the total yield coming from other Upper Mississippi Basin tributaries, especially those with tile-drainage such as the Skunk River basins (Iowa), the Illinois River basin (Illinois), and the Great Miami basin (Ohio). A more recent study by David *et al.* (2010) quantified the relative contributions of each county within the Mississippi River Basin and predicted that the counties comprising of our study system, Scotts Bluff County and Morrill County, contributed 0.00-3.00 kg NO_3-N ha^{-1} $year^{-1}$ (0-300 kg NO_3-N km $^{-2}$ year $^{-1}$) from 1997 to 2006. After scaling our net nutrient export from the NPR to the watershed area (4211.02 km^2) and scaling it to a year, our nutrient export from Scotts Bluff County and Morrill County was 183.72 kg NO_3-N km^{-2} $year^{-1}$, fitting within the range observed by David *et al*. (2010).

P yields of the NPR Valley were also estimated by Jacobson *et al.* (2011). From 1997 to 2006. The average annual yield was 0.01-0.27 ha^{-1} $year^{-1}$, or 1-27 kg DIP km^{-2}

year^{-1}. Our study includes only SRP, a subset of dissolved inorganic phosphorus (DIP), yet our estimated value of 2.7 kg SRP km^{-2} year^{-1} is consistent with the lower end of the findings by Jacobson *et al.*

Nutrient limitation

Ambient nutrient concentrations, N:P molar ratios, and land use can impact biomass accrual. Most ratios were above 16:1 which is associated with P limitation. I would have expected to see much more P limitation throughout the system, yet there were only a few sites the showed P limitation. Similarly, nutrient concentrations within the river for DIN and SRP are relatively constant which would suggest that neither DIN nor SRP are the main forms of nutrient limitation. In a nutrient saturated system, Wagenhoff *et al.* (2013) found that algal growth is no longer driven by a limited nutrient. Due to the heterogenous land use for each natural watershed, I was unable to distinguish effects from different land use types.

The limitations to using NDS as an experimental unit include that results are variable and include multiple environmental or experimental factors. A few factors could explain our results or lack thereof, including herbivory, light availability, and increased flow. We did not control for herbivory within our experiment, yet herbivory from grazers can affect the amount of biomass accrued on the glass frits of each treatment replicate (Feminella & Hawkins, 1995). In addition to herbivory, periods of high flow can scour benthic algal mats, as well as the added scouring effect of suspended solids and decreased levels of light availability due to shade or high turbidity in waters (Riseng *et al.*, 2004; Francoeur & Biggs, 2006; Hill *et al.*, 1995).

Conclusion

By understanding the spatiotemporal input of nutrients into local, heterogenous watersheds, as well as the subsequent effect on functional processes of biota, managers, decision makers, and water users can better understand areas to manage of high priority, identify unknown pathways in nutrient fluxes, and create an environment that benefits human and ecological health. For future work, I would like to better understand some questions pertaining to unclear results. Namely, I would like to set up an experiment that could better understand the impact and relative contribution of nutrient loading by each land use type. This would include more aspects of the ecosystem, such as soil sampling and quantifying atmospheric deposition, and result in an accurate nutrient budget of the system. Secondly, I would like to explore the internal processing of nutrient species and their effect on nutrient loads.

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CHAPTER TWO EXPLORING THE DRIVERS OF ADOPTION OF A WEB-BASED WATER QUALITY MONITORING TOOL WITH AN ADAPTED UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY MODEL

Introduction

Water management is necessary to ensure sustainable water use for water users and their diverse needs. A key aspect of water management is access to reliable water quality data that accurately reflects the changing conditions of water systems, as well as stakeholder engagement in water governance, or water management policymaking and practices (Restrepo-Osorio *et al.*, 2022; Sato *et al.*, 2013; When *et al.*, 2018). Water quality data increases knowledge about local systems for water users and identifies areas of concern within a management area, thus maximizing available resources to address the concerns (i.e., time, professionals, monitoring tools) and minimizing costs that would otherwise be induced if implementing management practices on a broad scale without insight to the relevancy of water quality parameters (Burroughs, 2010). Technological advancements, such as web-based water quality monitoring tools that are comprised of in-situ sensor networks and provide near real-time water quality data, can enhance the understanding of changing water systems by collecting data at high spatial and temporal resolutions (Arndt *et al.*, 2022). However, it can be difficult to get water users to use these tools, although their participation in water management decision-making and water conservation behaviors are crucial to sustainably using water resources (Ostrom, 2007).

Water quality monitoring methodologies such as grab sampling, or sampling that involves a field technician collecting water samples at a discrete moment in time and processing the sample in a laboratory, have been complemented by web-based water quality monitoring tools that collect, analyze, and disperse water quality data in near-real time (i.e., sub-hourly). The high-frequency data derived from these tools and their sensor networks can better portray the nutrient dynamics, physicochemical parameters (i.e., pH, dissolved oxygen, and temperature), and flow regimes of riverine systems relative to data derived from grab sampling (Cassidy & Jordan, 2011; Demetillo *et al.*, 2019). More specifically, the data collected from these sensors can be accessed by decision makers and water users to understand local water quality characteristics and apply the knowledge to decision making and their respective interests (Arndt *et al.*, 2022; Altenburger *et al.*, 2019).

Fostering use behavior of web-based water quality monitoring tools by water users begins with an understanding of the antecedents, or indicators, of water use behavior. Although knowledge and information build awareness about water scarcity issues, information-intensive programs do not successfully lead to the adoption of more sustainable behaviors (i.e., the promotion of a tool and its capabilities; McKenzie-Mohr, 2000). This is due to the complexity of human behavior. For example, Azjen (1991) found that one’s attitude toward a behavior, the subjective norms surrounding the behavior, and one’s perceived behavioral control regarding a behavior is correlated with behavioral intention which predicts human behavior.

Antecedents have been extensively studied under multiple theories such as the Theory of Planned Behavior (Azjen, 1991) and the Unified Theory of Acceptance and Use of Technology (UTAUT, Venkatesh *et al.*, 2003). Compared to eight other prominent theories on intention and behavior, the UTAUT model explains the most variance accounted for in intention, or the intention to usurp a behavior of interest like using a web-based water quality monitoring tool (Venkatesh *et al.*, 2003).

In the present study, an extended UTAUT model was applied to understand landowners' intentions to use a web-based water quality monitoring tool. The UTAUT postulates that use behavior is determined by the intention one has to do the behavior of interest and the conditions that are in place to facilitate the use behavior, such as technological use of a web-based water quality monitoring tool. The behavioral intention to do a use behavior, such as technologically use a web-based water quality monitoring tool, is argued to directly predict usage of the tool, yet intention is influenced by social influence, performance expectancy, and effort expectancy as postulated in the theoretical UTAUT model. The specific relationships postulated in the theoretical UTAUT model are:

H_1: Performance expectancy is positively associated with the intention of an individual. Both gender and age will moderate the effect of performance expectancy on intention, with a stronger effect displayed in younger men.

H_2: Effort expectancy is negatively associated with the intention of an individual to use a web-based water quality monitoring tool. Gender and age moderate the degree of influence on effort expectancy on intention so that the effect will be stronger for younger women.

H$_3$: Social influence is positively associated with the intention to use a web-based water quality monitoring tool, and its effect is stronger when moderated by age and gender.

H$_4$: Facilitating conditions are not associated with behavioral intention but has positive association with use behavior when the relationship is moderated by age.

In addition to the determinants of intention and behavior posited by the UTAUT model, the present study extends the model to include trust and personal norms as determinants of intention as well as a moderator, producer versus non producer.

Trust is the foundation for interactions between diverse stakeholders, natural resource managers, and agencies. Coleman and Stern (2018) defined trust as “a psychological state in which an entity (a trustor) accepts some level of vulnerability (i.e., a risk) based on a positive expectation of another entity (a trustee).” With high levels of trust, stakeholders are more willing as trustors to respond positively to compliance with water use regulations (Hamm *et al.*, 2016; Hamm *et al.*, 2013). Moreover, stakeholders identified higher levels of trust in resource managers and agencies based on perceptions of past support and cooperation, as well as reputation (Ford *et al.*, 2020). The presence of trust has many benefits as it facilitates goal attainment, regulation compliance, conflict resolution, and collaboration (Coleman & Stern, 2018; Davenport *et al.*, 2007). In regard to emergent technologies where the public has little exposure to the technology and its capabilities, acceptance of the technology mostly depends on trust in the actors that are responsible for the technology (Huijits *et al*., 2012). Based on the literature on trust, I hypothesize the following:

H_5: Trust in the agency responsible for the creation and administration of a technology has a positive influence on intention to voluntarily use a web-based water quality monitoring tool.

Personal norms are also an antecedent to intention that I will include in the model. The norm activation theory (Schwartz 1977) assumes that the activation of a personal norm, which is based on one's feeling of moral and personal obligation toward a specific behavior, depends on the awareness of the issue the behavior is intended to rectify, a perceived sense of responsibility, and the means to address the issue the behavior is intended to rectify. When looking at landowner personal norms on water conservation and their antecedents, Pradananga *et al.* (2016) found that ascription of responsibility [to relevant persons to proactively prevent adversities from occurring] and awareness of consequences [to valued entities or situations], the activators of personal norm, were predicted by the collectivistic values and the "biospheric, altruistic" values of landowners. In some studies, personal norms have been shown to moderate the relationship between social norm and intention (de Groot *et al.*, 2021), while other studies include personal norm as a main effect predicting intention in altruistic as opposed to prosocial behavior (Norm Activation Model, Schwartz 1977). Following the conceptualization by Schwatrz (1977), I hypothesize that:

H_6: Personal norm will have a positive influence on intention to voluntarily use a web-based water quality monitoring tool.

The type of community member, producer versus nonproducer, is imperative to understanding the various indicators and how they are associated with behavioral intention to use a web-based water quality monitoring tool. Diffuse pollution from agricultural activity is attributed to nutrient enrichment of water ways which necessitates an understanding of producer behavior (Blackstock *et al.*, 2010). Similarly, behavior from densely populated urban centers can also impact local water quality, such as behaviors regarding pet waste removal and home gardening (Hobbie *et al.*, 2017). Berenguer *et al.* (2005) found that, although pro-environmental attitudes tended to be more salient in urban residents, producers tended to have higher levels of moral obligation and conservation behaviors as pro-environmental behaviors are more relevant to their livelihoods.

The purpose of this study is to identify the factors associated with the use of a free, web-based water quality monitoring tool among landowners. The relationships between each factor are quantified using both multiple linear regressions and structural equation models (SEMs) to capture the effect of the factors independently from one another and the effect of the factors when considering the covariance structure, measurement error, and latent variables in a more holistic approach, respectively.

Materials and Methods

To explore the potential factors associated with the use of a web-based, water quality monitoring tool, I conducted a cross-sectional study of producers and nonproducers within the North Platte watershed of Nebraska using a mail survey. I identified a geographically-representative, stratified sample of landowners within Scotts Bluff, Morrill, Garden, and Banner Counties, and purchased their addresses directly from two marketing companies, Dynata (Shelton, Connecticut) for nonproducers and DTN

(Burnsville, Minnesota) for producers. I sampled 1100 community members total, 550 from both producers and nonproducers, to run our UTAUT model using structural equation modeling. The survey participants were selected from the North Platte Watershed of Nebraska as these communities in western Nebraska face water scarcity, rely heavily on agriculture, and dwell in a semi-arid climate.

Sampling Strategy

A geographically representative, stratified sample of 1100 addresses was identified within the counties of Scotts Bluff, Morrill, Garden, and Banner (Figure 2.1). To participate in the survey, the participant had to be: 1) a landowner or make managerial decisions for the land, 2) at least 19 years of age or older, and 3) a producer or non-producer within the geographic parameters of the study area. Additionally, producers had to own at least 25 acres of land.

Producers, albeit a small proportion of the population within the counties, are proportionally represented more in the survey than they are in the population. This was to ensure that producer viewpoints were being heard, as agricultural activities are constantly identified as primary sources of nonpoint pollution and the behaviors of producers directly impact pollution (Blackstock *et al.*, 2010).

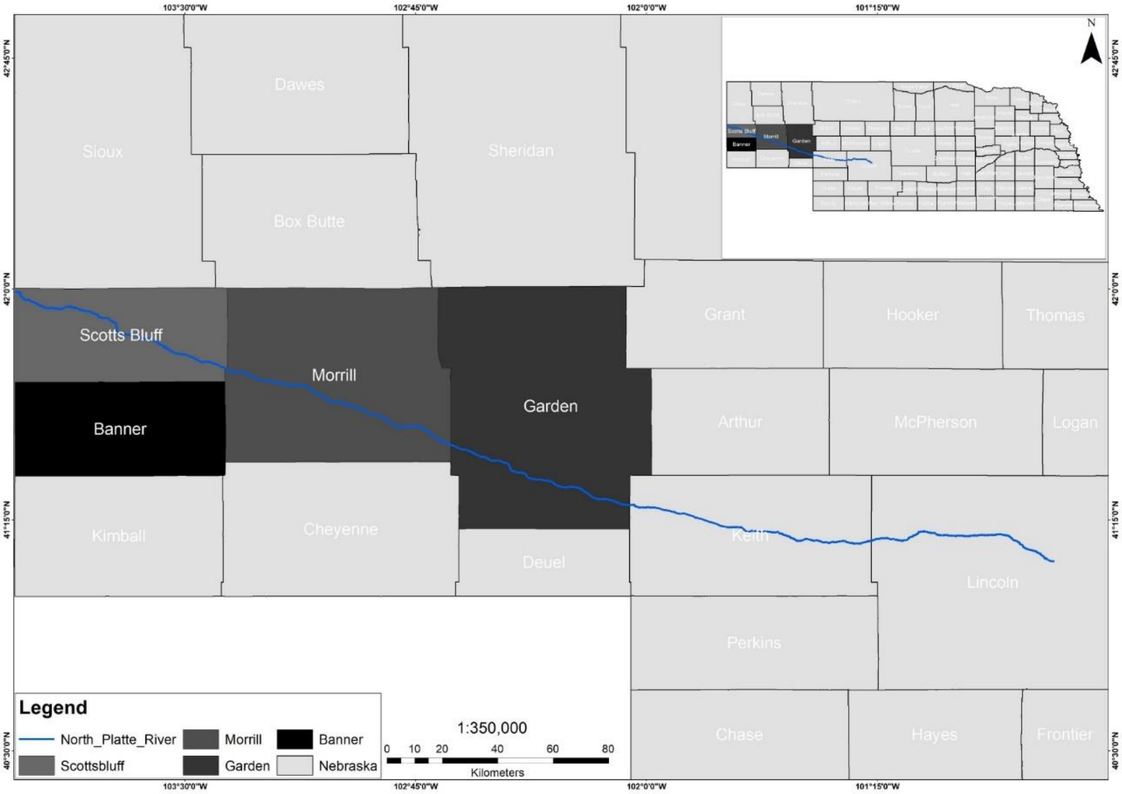

Figure 2.1 A map of the NPR Valley study system which includes Scotts Bluff County, Morrill County, Banner County, and Garden County.

Survey Development and Distribution

The survey was developed with three major sections: (1) general surface water quality information, (2) UTAUT related-section, and (3) demographic information.

UTAUT-derived construct items were adapted from the Venkatesh *et al.* (2003) paper and trust items were adapted from the rational and affinitive definitions of trust (Stern & Coleman, 2015). Lastly personal norm items were derived from conceptualizations within the Norm Activation Theory by Schwartz (1977).

To maximize the response rate, I utilized the Tailored Design Method (Dillman, 2000). The initial survey booklet was sent out with a consent form and a standardized handwritten note thanking prospective participants for participating in our study. A week after the first mailing, a reminder postcard was sent out. Lastly, a second booklet was sent out two weeks after the postcard reminder. The methods for this project were approved by the Institutional Review Board at the University of Nebraska-Lincoln (IRB# 20211221243EX).

Data Preparation

Upon receival of the surveys, all responses were entered into Qualtrics (Provo, Utah). Then, the responses of all participants were transferred from Qualtrics to R (version 4.2.1) for coding. Once in R, the responses were coded so that 0 = “Not at all” responses and 4 = “Extremely” while -2 = “Strongly Disagree” and 2 = “Strongly agree.” The coded responses were exported to Microsoft Excel (Redmond, Washingston) to calculate the composite construct means, their standard deviations, as well as to calculate the population variance of the items used to make the composite variable and the residual variance (Table 2.1). Prior to mean-centering the data, the reliability (Cronbach’s alpha, α) and the residual variance for each of the items contributing to the composite factors were calculated. To determine the residual variance of each composite construct I used the formula: (1- α) * population variance (σ^2). The construct items were then consolidated into a composite form by averaging the response items and mean-centering them.

To better understand which dataset was more appropriate for our analyses, a qualitative comparison was made between pairwise and listwise deletion data and linear regression results. After observing the trends were similar in both pairwise (n = 151) and listwise datasets (n = 62), the listwise dataset was chosen for the analyses. While listwise reduced the dataset, it minimized the potential bias from partially missing data.

The packages used in R were tidyverse (Wickham *et al*., 2019), dplyr (Wickham *et al*., 2022), lm.beta (for standardized regression coefficients, B; Behrendt, 2022), and psych (for the internal reliability measure; Revelle, 2022).

Table 2.1 The composite factors, their acronyms, and their associated values - their means used for mean centering (μ), their standard deviation (s), their internal consistency (Cronbach's alpha, α), and number of items averaged together to form the composite factors.

Composite Factor	Abbreviation	μ	s	A	σ^2	Items (n)
Behavioral Intention	BI	1.54	0.88	0.76	0.77	2
Performance Expectancy	PE	2.31	1.11	0	1.21	1
Social Influence	SI	-0.31	0.92	0.12	0.84	2
Facilitating Conditions	FC	-0.30	1.01	0.74	1.00	2
Effort Expectancy	EE	-0.28	1.10	0.85	1.18	2
Personal Norm	PN	0.60	1.16	0.71	1.32	2
Community Trust	TC	2.72	0.88	0.92	0.76	4
Organizational Trust	TO	2.94	0.78	0.91	0.61	12

Multiple Linear Regressions

The data was analyzed using multiple linear regressions. The theoretical model was run as a multiple linear regression model with main effects, and subsequently with each interaction term iteratively for each of the proposed moderators measured in the survey - gender, age, and producer. Similarly, the adapted model was also run as a multiple linear regression with just the main effects initially, and then subsequently with each of the interaction moderator terms. By repeating this process, the significant interactions (or lack thereof) were identified to include in the model with the main effects. This approach was taken due to our small sample size and large number of possible interactions to attenuate any effect on the aggregate contribution of R^2, which is likely to be small under datasets that are small with many interactions (Cohen *et al.*, 2003).

Structural Equation Modelling

To include measurement error in our models and the quantification of the underlying, abstract drivers of behavioral intention, I used MPlus8 software (Muthen and Muthen, 2017) to conduct two-step structural equation models as proposed by Bollen (1989). Before assessing the fit of the model, the models were identified. Both models were initially just-identified but, because I had two composite manifest variables for the latent trust (LT), OT and CT, their error measurements were constrained to be equal. The reason being that they were both measurements of the same latent variables, had similar alphas, as well as attenuation correction values. The arrows pointing from latent variables (in ovals) to manifest variables (in squares) indicate that the latent variables are reflective of the manifest variables. PE was the only single indicator in the models, which was set to “0” indicating that it measured LPE without error. For the other composite indicator variables, the reliability was determined using Cronbach’s alpha, then fixed their residual variance to the unreliability value (1 – Cronbach's alpha) multiplied by the variance of the sample. The loadings of PE, EE, SI, FC, and PN were fixed onto their respective latent variables to one as they are single-indicator manifest variables. The residual variances were set to the attenuation correction values and the estimated relationships of interest were marked with asterisks (Figure 2.2). The factor loadings for every manifest indicator variable was fixed at 1.0 to elucidate the pathways between the underlying latent variables in our model to latent BI (LBI).

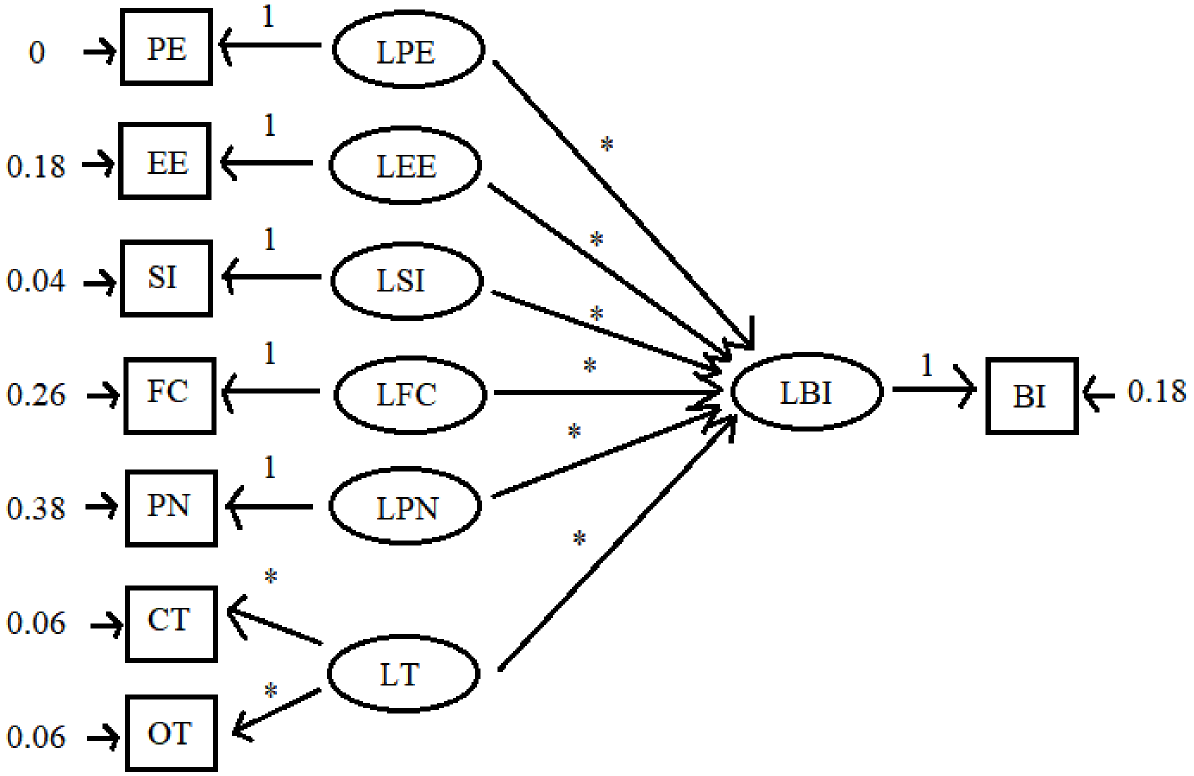

Figure 2.2 The structural model of the extended UTAUT model. Latent Behavioral Intention (LBI), Latent Performance Expectancy (LPE), Latent Effort Expectancy (LEE), Latent Social Influence (LSI), Latent Facilitating Conditions (LFC), Latent Personal Norm (LPN), and Latent Trust (LT) reflect the values of their respective measured, manifest variables in the square while considering the residual variance for each measured, manifest variable. LBI was regressed on the other latents to understand the contribution of each in predicting LBI, and thus BI.

Results

The response rate for our surveys was 172 out of 1,100, or 15.6%. After completing a listwise deletion on the data, only 62 survey responses, or 5.64% of the sampled population, were used for the analyses of the data.

Of those 62 responses, 39 were from Scotts Bluff County, 18 from Morrill County, three from Banner County, and ten from Garden County. Participants who self-identified as male (n = 45) and female (n=17) were also represented within the data set. The 62 participants could also be divided into nonproducers (n= 25) and producers (n=37).

From this cross-section of the NPR Valley community, 83% did not seek out water quality information and 22% were familiar with local water quality. More than 80% of respondents identified tributary and river water quality as either average or good. When shown a list of potential parameters used to determine water quality and prompted to selected how important each was from “Not at all important” to “Extremely important,” agricultural chemicals (38%), fecal matter (38%), and algal growth (29%) were the top identified indicators labelled as “extremely important” indicators of water quality.

Multiple Linear Regression

For the linear regression model of the theoretical UTAUT model, performance expectancy ($\beta = 0.559$, $p < 0.001$) is the only variable that significantly predicts behavioral intention (adjusted $R^2 = 0.46$, $F(4,57) = 13.8$, $p = < 0.001$; Table 2.2). This means for every one unit increase from the mean in performance expectancy, behavioral intention is expected to increase by 0.559 units from the mean, holding all other variables constant. The results from our regression did not support the hypotheses within the theoretical foundational UTAUT model. No interactions with gender were significant, and one of the main effects - performance expectancy (PE) - was significant for the sampled population.

Table 2.2 The linear regression results of the variables within the theoretical UTAUT model - performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and social influence (SI) - predicting behavioral intention.

	B	β	S.E.	Estimate/S.E.	p-value
Intercept	<0.001	NA	0.083	0.000	1.000
Performance Expectancy	0.444	0.559	0.085	5.258	<0.001***
Effort Expectancy	0.026	0.032	0.101	0.253	0.801
Facilitating Conditions	0.137	0.156	0.115	1.193	0.238
Social Influence	0.113	0.118	0.105	1.081	0.284

In the adapted model, performance expectancy ($\beta = 0.566$, $p < 0.001$) was the only factor to significantly impact behavioral intention, adjusted $R^2 = 0.44$, $F(7,54) = 7.712$, $p = <0.001$ (Table 2.3). When holding all other independent variables constant, an increase of performance expectancy by one unit results in an average unit increase of 0.451 for behavioral intention.

*Table 2.3 The linear regression results of the variables within the adapted UTAUT model. "***" denotes a significant effect (p<0.001).*

	B	β	S.E.	Estimate/S.E.	p-value
Intercept	<0.001	NA	0.084	0.000	1.000
Performance Expectancy	0.451	0.566	0.087	5.203	<0.001***
Effort Expectancy	0.023	0.029	0.110	0.224	0.824
Personal Norm	-0.068	0.090	0.090	0.760	0.451
Facilitating conditions	0.140	0.160	0.119	1.175	0.245
Social Influence	0.081	0.085	0.117	0.694	0.491
Community Trust	0.024	0.024	0.110	0.220	0.827
Organizational Trust	-0.035	-0.031	0.120	-0.289	0.773

Structural Equation Modelling

The theoretical UTAUT models were just-identified, which meant the model could not be fit using the chi-square test of exact fit, nor tests used for approximate fit like the RMSEA, CFI, and SRMR. Due to this outcome, I interpreted qualitatively, looking at the relationships between variables. For a standard deviation increase in LPE, there is a $\beta = 0.424$ increase in latent behavioral intention (Table 2.4). The path coefficient suggests that the higher an individual believes a tool will assist with a specific job, the more inclined they are to use the tool.

*Table 2.4 The theoretical UTAUT structural equation model results with main effects, n = 62. "***" denotes a significant variable at p<0.001.*

Effect	Est.	SE	Est./SE	Stand. Est.	P-value
LBI ON LFC	0.295	0.244	1.208	0.343	0.227
LBI ON LEE	-0.073	0.166	-0.438	-0.099	0.661
LBI ON LPE	0.424	0.079	5.378	0.631	<0.001***
LBI ON LSI	0.098	0.111	0.883	0.119	0.377

In the adapted UTAUT model, the main effect of LPE on LBI was significant (p<0.001). Under our adapted model, the results suggest that, as in the theoretical UTAUT SEM results, a positive relationship exists between LPE and LBI, where a unit increase from the mean of LPE will result in an associated increase of 0.428 from the mean in LBI on a latent scale (Table 2.5). This model did have model fit indices which all indicated that this model has good fit ($X^2(7)$= 3.98, p=0.7819; CFI = 1.00; TFI = 1.00; RMSEA = 0.00; SRMR = 0.039)

*Table 2.5 The adapted UTAUT structural equation model results with main effects, n = 62. "***" denotes a significant variable at p<0.05.*

Effect	Est.	SE	Est./SE	Stand. Est.	P-value
LBI ON LPN	0.532	1.701	0.313	0.695	0.754
LBI ON LFC	0.716	1.669	0.429	0.834	0.668
LBI ON LEE	-0.405	1.307	-0.310	-0.550	0.757
LBI ON LPE	0.428	0.126	3.392	0.636	0.001***
LBI ON LSI	-0.095	0.593	-0.160	-0.114	0.873
LBI ON LT	-0.975	3.809	-0.256	-0.579	0.798

Discussion

Access to reliable water quality data from a web-based water quality monitoring tool and active engagement of stakeholders in water management lead to improved decision-making that reflects the community interests and needs. In this study, the objectives were to explore the drivers associated with the intention to use a web-based water quality monitoring tool, and to extend the UTAUT model with the drivers trust and personal norm, and the moderator producer versus nonproducer. The results from the study are limited by our adjusted sample size and a lack of representation from diverse groups (i.e., youth, ethnic groups).

Within the NPR Valley, adoption of a web-based water quality monitoring tool was significantly correlated with performance expectancy. Thus, community members are interested foremost in the practicality of the tool to their own goals whether for work, health, or pastime.

Effort expectancy (M = -0.28, SE = 1.10) has been identified as a dynamic factor with varying degrees of significance depending on whether the use of the technology is intrinsic or extrinsic. In the study by Gefen *et al.* (2000), effort expectancy was operationalized as the ease of use, ease of learning, flexibility, and intuitive interface when using a tool for intrinsic tasks primarily processed by the tool itself (i.e., using the tool and its features to inquire about a product). In this context, effort expectancy significantly predicted behavioral intention. However, Davis (1989) identified "ease of use," synonymous with effort expectancy, as not significantly associated with the intention to use a tool. A technology can have varying degrees of ease of use, but users may continue to use it if it meets a specific task or goal.

Social influence (M = -0.31, SE = 0.92), or social norms, can also vary in their significance to behavioral intention. Social norms can be divided into two forms, descriptive (how often persons of reference do a specific behavior) and injunctive (how persons of reference feel one ought to act). Gockeritz *et al.* (2010) found that descriptive social norms had a positive correlation with intention, but they also recognized that norm beliefs can misalign so that (1) people care about conservation behavior but do not participate in it or (2) participate in conservation behavior but do not approve of it. In addition to injunctive social norm as a moderator, personal involvement (one cares about the entity [i.e., surface water quality] and perceives it as important). Farrow *et al.* (2017) found similar effects while also using descriptive social norms. Similarly, Callery *et al.* (2021) identified when targeted, aspirational behaviors that aligned near one's baseline behavior, social norms were significant. Yet still, nonconforming behavior could occur because the social norm is seen as irrelevant, the social norm is too low to the individuals' belief, or the goal is overly ambitious (Callery *et al.*, 2021). In our current study, I did not account for descriptive social norms but rather injunctive as the main effect. Due to the perceived high quality of surface waters and the lack of interest for the tool, the perceived importance and concern may not be immediately present for the community and thus is not significant for our sample.

Personal norms in our study were operationalized using personal and moral obligation as defined by the Norm Activation Theory (Schwartz 1977). In this theory, personal norms must first be activated by the awareness of the consequences of a behavior as well as the level of responsibility one feels for the behavior. In situations where farmers did not ascribe personal responsibility to water conservation behaviors, they were less likely to have strong personal norms for the intention to participate in the specific water conservation behavior (Valizedeh *et al.*, 2020). Neutral feelings or moral and personal obligation as quantified by the composite factor, personal norm (M = 0.60; SE = 1.16) reiterates this argument that neutral feelings may lead to ambivalence in certain water conservation behaviors.

Both organizational and community trust were also predictors within our model. In our analyses, both forms of trust lacked significance in their association with behavioral intention. For organizational trust, when there were high levels of trust in natural resource management organizations and high perceptions of shared values among the trustor and trustee, low levels of participation in conservation behaviors have been reported (Smith *et al.*, 2013). Organizational trust in our survey (M = 2.94; SE = 0.78) had the second highest mean of all the factors. Its insignificance to behavioral intention could be a result of high levels of trust in natural resource decision makers such as the North Platte - Natural Resources District, local government officials, and university or college scientists inversely leading to complacency to act. Community trust (M = 2.72; SE = 0.88) can increase group cohesiveness yet, when coupled with our results on social and personal norms, local surface water quality monitoring is not a personal or social concern (Bodin *et al.*, 2005).

Facilitating conditions (M = -0.30, SD = 1.01), which was operationalized by “time to learn a web-based water quality monitoring tool” and “ability to interpret information from web-based water quality monitoring tool (i.e., knowledge, reference materials)”, was another factor that did not have a significant association with behavioral intention. Lack of interpretation to understand the information derived from the tool by potential users could results in disinterest in adopting a behavior, as most people rather choose tasks that are familiar and require low levels of self-efficacy (Czaja *et al.*, 2006).

The drivers trust and personal norm did not significantly contributing to the extended UTAUT model, neither were theoretical drivers identified by Venkatesh et al. (2003). For the cross-section of the community members sampled, the conclusions suggest that performance expectancy is a priority when adopting technological tools. However, a more comprehensive study that involved more participants can elucidate if any relationships were not significant due to a small sample size.

Implications

The main implication from this study is that by increasing perceptions of performance expectancy, the intention to use a web-based water quality monitoring tool is strengthened. For our target community, it appears that surface water quality was perceived as good, and the need for the tool to reach a goal of good water quality was not seen as relevant. When presenting a web-based water quality monitoring tool for the community of the NPR Valley, water resource managers should focus on aligning the tool with the practical goals of participants, as performance expectancy was the only significant driver that was positively correlated with the intention to use such a tool.

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APPENDIX A: THE AVERAGE VALUES FOR RIVER, TRIBUTARY, AND CANAL SITES

Table A1. The average physicochemical variables for the northern-most canal sites in the NPR Valley during Summer 2021.

	North Canal Sites								
	NC-FID0	NC0	NC1	NC2	NC3	NC4	NC5	NC6	NC7
SRP	31.56	24.23	11.00	9.87	13.36	101.79	16.50	43.56	54.61
NO_3-N	805.14	326.91	56.59	33.91	70.92	613.70	5.97	1234.10	1031.48
NH_4-N	11.30	8.06	10.53	9.40	7.76	2.85	2.23	12.55	6.41
TSS (mg L^{-1})	11.36	10.82	14.90	9.09	10.53	7.76	7.04	17.77	12.16
Temperature (°C)	25.40	21.52	22.73	23.44	23.06	23.13	23.20	21.77	21.32
Dissolved Oxygen (DO; mg/L)	7.88	8.04	7.83	7.84	8.11	8.74	8.20	8.53	8.23
Specific conductivity (SpC; µS/cm)	767.00	608.80	611.00	630.40	611.00	577.33	613.33	675.66	677.33
pH	8.62	8.31	8.36	8.48	8.42	8.43	8.47	8.45	8.43
Organic Matter (%)	12.77	12.59	12.38	14.73	17.55	18.46	29.91	12.45	14.79
Calcium (Ca, mg L^{-1})	63.12	51.46	50.86	55.02	50.83	49.95	49.96	55.93	54.67
Iron (Fe, mg L^{-1})	0.08	0.10	0.06	0.23	0.14	0.08	0.06	0.06	0.06
Potassium (K, mg L^{-1})	5.91	3.90	3.79	5.08	3.80	3.75	4.44	5.64	5.80
Magnesium (Mg, mg L^{-1})	21.05	19.49	19.24	19.95	19.29	19.00	19.81	19.84	19.69
Sodium (Na, mg L^{-1})	58.92	42.54	42.15	47.69	42.04	41.30	43.28	50.42	50.40
Silica (Si, mg L^{-1})	1.81	1.10	1.07	1.92	1.15	1.18	1.11	2.27	2.34

Fluoride (F, mg L^{-1})	0.22	0.28	0.47	0.24	0.25	0.37	0.58	0.32	0.47
Chloride (Cl, mg L^{-1})	14.90	11.89	10.23	11.31	10.97	13.03	10.99	12.74	12.99
Sulfate (SO_4^-, mg L^{-1})	165.36	145.95	137.45	139.10	137.99	154.65	140.14	120.83	161.77
DIN:SRP	40.96	12.05	6.33	6.68	8.31	5.16	1.11	37.28	37.17

Table A2. The average physicochemical variables for each NPR site in the NPR Valley during Summer 2021.

	North Platte River Sites								
	NPR0	NPR1	NPR2	NPR2.5	NPR3	NPR4	NPR5	NPR6	NPR7
SRP, ug L^{-1}	23.02	43.06	55.12	57.49	52.40	57.24	56.49	63.47	65.41
NO_3-N, ug L^{-1}	840.08	1224.14	2170.54	2377.82	2687.47	2808.34	2660.53	3339.08	2995.46
NH_4-N, ug/L	10.85	8.29	8.39	7.40	44.12	17.48	4.39	6.62	5.23
TSS, mg L^{-1}	12.56	7.82	8.97	13.05	7.68	15.46	9.81	9.45	13.54
Temperature (°C)	21.52	22.20	20.87	21.98	22.00	22.15	22.42	22.30	22.08
Dissolved Oxygen (DO; mg L^{-1})	8.37	7.77	8.24	7.94	8.71	8.59	9.19	8.42	8.36
Specific conductivity (SpC; µS cm^{-1})	683.00	840.83	865.67	880.17	855.00	880.33	933.83	935.17	946.00
pH	8.26	8.24	8.19	8.27	8.21	8.25	8.34	8.27	8.33
Organic Matter (%)	16.87	14.84	13.38	26.64	13.99	12.63	15.30	12.24	14.55
Calcium (Ca, mg L^{-1})	58.04	58.01	63.98	66.65	62.06	65.56	69.54	76.07	72.10
Iron (Fe, mg L^{-1})	0.02	0.06	0.05	0.07	0.15	0.09	0.04	0.05	0.05
Potassium (K, mg L^{-1})	5.62	7.71	8.50	8.84	8.78	9.25	10.00	10.98	10.43
Magnesium (Mg, mg L^{-1})	19.84	19.09	20.17	20.89	20.25	21.01	21.78	21.38	21.75
Sodium (Na, mg L^{-1})	53.70	86.75	84.55	80.37	80.72	81.73	88.67	81.68	88.25
Silica (Si, mg L^{-1})	2.29	4.01	4.57	4.70	4.56	4.57	4.94	6.11	5.38

Fluoride (F, mg L^{-1})	0.26	0.46	0.44	0.26	0.36	0.38	0.20	0.41	0.36
Chloride (Cl, mg L^{-1})	12.40	16.83	15.73	18.82	17.44	19.70	23.05	19.37	19.18
Sulfate (SO_4^-, mg L^{-1})	142.40	210.43	195.63	219.55	150.81	192.28	181.76	207.83	84.54
DIN:SRP	89.32	41.62	61.64	65.86	82.69	77.10	77.08	84.54	73.13

Table A3. The average physicochemical variables for each north tributary site in the NPR Valley during Summer 2021.

	North Tributary Sites						
	NT1B	NT-TSR	NT2B	NT3A	NT4	NT5	NT6
SRP, ug L^{-1}	107.90	91.32	83.69	193.53	68.25	71.48	54.05
NO_3-N, ug L^{-1}	4212.10	4865.45	3207.71	4351.01	4591.58	2677.41	1361.51
NH_4-N, ug/L	6.53	22.96	6.67	6.92	5.7	10.88	20.66
TSS, mg L^{-1}	10.21	7.51	10.95	7.39	4.72	5.39	6.98
Temperature (°C)	18.62	20.95	19.83	20.12	18.63	20.66	20.83
Dissolved Oxygen (DO; mg L^{-1})	10.06	7.54	21.94	28.77	9.92	14.01	8.20
Specific conductivity (SpC; µS cm^{-1})	831.67	846.50	801.17	834.50	841.80	759.58	677.83
pH	8.26	7.85	8.20	8.38	8.19	8.20	8.38
Organic Matter (%)	15.30	23.82	15.08	16.07	14.85	18.19	17.00
Calcium (Ca, mg L^{-1})	74.53	80.27	70.89	74.75	80.15	70.42	58.29
Iron (Fe, mg L^{-1})	0.04	0.28	0.05	0.40	0.04	0.16	0.08
Potassium (K, mg L^{-1})	11.71	11.78	9.03	11.05	11.39	8.88	6.54

Magnesium (Mg, mg L^{-1})	20.97	21.21	18.40	19.83	18.63	19.02	18.81
Sodium (Na, mg L^{-1})	60.74	57.53	63.68	64.09	59.62	53.03	49.22
Silica (Si, mg L^{-1})	8.33	6.90	7.40	7.54	8.28	5.33	3.73
Fluoride (F, mg L^{-1})	0.25	0.47	0.23	0.27	0.38	0.28	0.32
Chloride (Cl, mg L^{-1})	13.86	11.47	13.88	16.46	14.64	13.98	12.63
Sulfate (SO_4^-, mg L^{-1})	176.49	156.29	173.91	146.19	177.72	164.29	126.33
DIN:SRP	78.75	91.10	58.09	59.77	103.44	57.94	34.45

Table A4. The average physicochemical variables for each south tributary and south canal sites in the NPR Valley during Summer 2021.

	South Tributary Sites		South Canal Sites			
	ST1	ST2B	SC-G1	SC-G2	SC-G3	SC-G4
SRP, ug L^{-1}	52.60	66.22	16.98	9.09	6.33	20.81
NO_3-N, ug L^{-1}	1335.81	5015.98	453.12	43.79	12.63	195.76
NH_4-N, ug/L	6.06	5.95	6.35	5.06	10.38	19.29
TSS, mg L^{-1}	7.15	8.51	8.59	10.37	8.42	7.55
Temperature (°C)	20.23	20.16	22.13	23.96	24.84	24.83
Dissolved Oxygen (DO; mg L^{-1})	8.53	8.48	7.57	7.71	7.81	6.73
Specific conductivity (SpC; µS cm^{-1})	967.00	906.36	612.17	497.44	618.60	663.50
pH	8.24	8.08	8.27	8.36	8.47	8.51
Organic Matter (%)	24.03	15.78	19.63	26.95	15.68	13.89
Calcium (Ca, mg L^{-1})	47.20	52.76	48.63	50.11	50.34	53.47
Iron (Fe, mg L^{-1})	0.43	0.29	0.04	0.06	0.07	0.38

Potassium (K, mg L^{-1})	8.80	11.12	3.94	3.84	3.95	5.30
Magnesium (Mg, mg L^{-1})	16.42	17.96	19.14	19.06	19.22	19.84
Sodium (Na, mg L^{-1})	131.77	115.14	42.99	42.34	42.81	51.60
Silica (Si, mg L^{-1})	4.66	6.48	1.15	1.12	1.15	2.16
Fluoride (F, mg L^{-1})	0.59	0.25	0.43	0.45	0.29	0.22
Chloride (Cl, mg L^{-1})	19.26	18.43	10.95	10.34	11.67	11.95
Sulfate (SO_4^-, mg L^{-1})	200.97	194.41	147.48	141.28	144.67	157.80
DIN:SRP	31.93	105.31	17.12	8.67	11.84	20.32

APPENDIX B. THE AVERAGE REFERENCE CANAL, TRIBUTARY, AND NORTH PLATTE RIVER CONCENTRATIONS OF DIN AND SRP AVERAGED FOR THE ENTIRETY OF SUMMER 2021

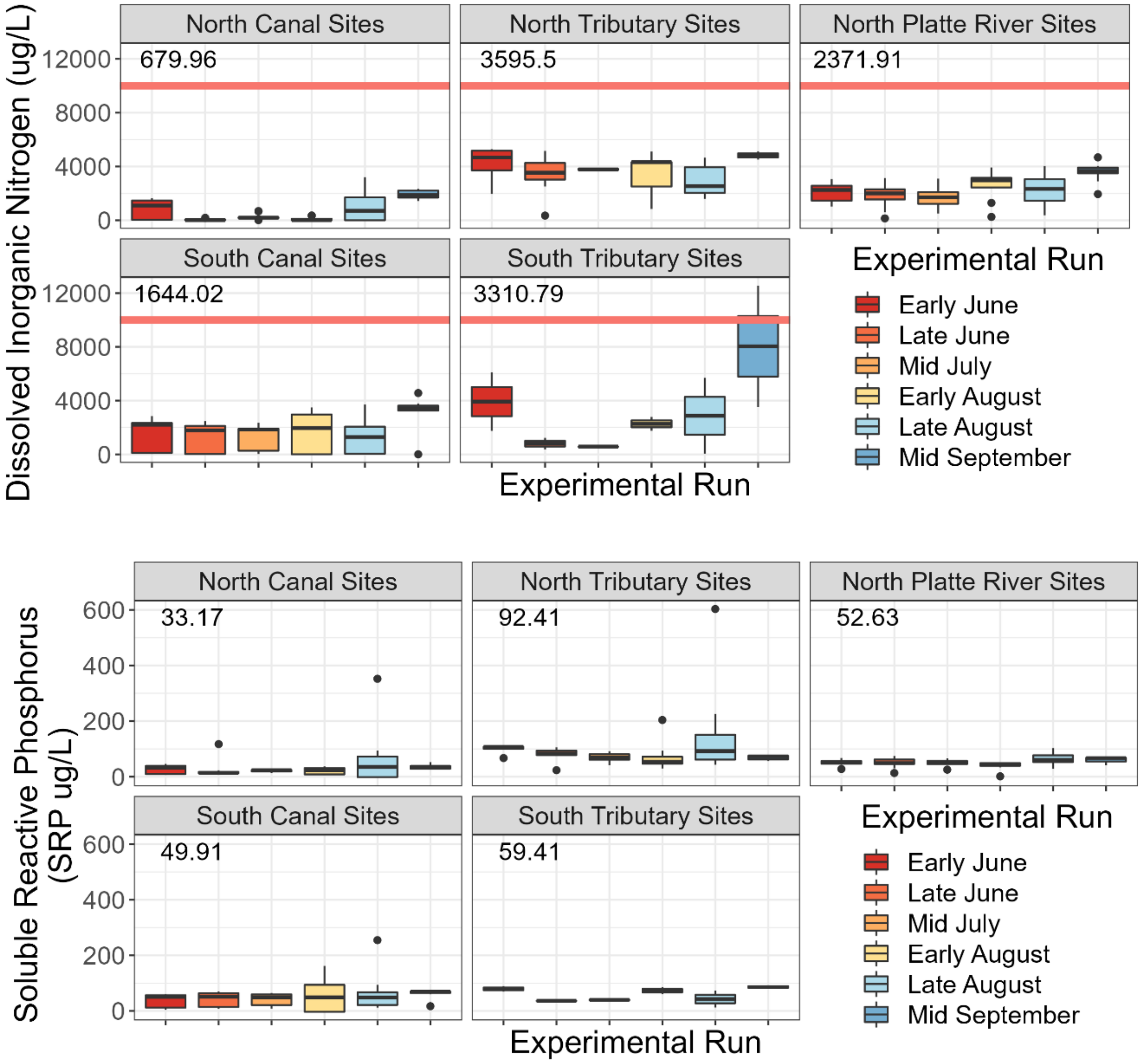

Figure A1. Each panel within the figure represents the DIN (top panel) and SRP (bottom panel) concentrations for the respective site types for each experimental run. The numbers within each box are the average concentrations across all experimental runs for Summer 2021. For the DIN panel, there is a red line that represent the Environmental Protection Agency safety guideline for drinking water at 10000 ug L^{-1}. Water with concentrations above this concentration can cause acute health problems.

APPENDIX C. THE SURVEY ITEMS AND SCALES

Table B. The composite factors, their items, and the scale on which they were analyzed.

Composite Factor	Measurement Variable	Item	Five-Point Likert Scale
Behavioral Intention	BI1	How likely would you: incorporate a free, web-based water quality monitoring tool into your decision-making?	Not at all - 0; Extremely – 4
	BI2	How likely would you rely on this tool solely for water quality data of local waterways?	Not at all - 0; Extremely – 4
Performance Expectancy	PE1	How useful is a free, web-based water quality monitoring tool to your water quality interests?	Not at all - 0; Extremely - 4
Social Influence	SI1	When thinking of the groups of people who are important to you, how strongly do you agree or disagree with: “They would expect me to use a free, web-based water quality monitoring tool.”?	Strongly Disagree - (-2); Strongly agree (2)
	SI2	When thinking of the groups of people who are important to you, how strongly do you agree or disagree with: “They would expect me to stay up-to-date on local surface water quality information.”?	Strongly Disagree - (-2); Strongly agree (2)
Facilitating Conditions	FC1	How strongly do you agree or disagree with: “I have the time to learn and use a free, web-based water quality monitoring tool.”?	Strongly Disagree - (-2); Strongly agree (2)
	FC2	How strongly do you agree or disagree with: “I have the ability to interpret information received from a free, web-based water quality monitoring too.” (i.e., knowledge, access to reference materials)?	Strongly Disagree - (-2); Strongly agree (2)

Effort Expectancy	EE1	How strongly do you agree or disagree with: “I generally find web-based tools easy to use.”?	Strongly Disagree - (-2); Strongly agree (2)
	EE2	How strongly do you agree or disagree with: “I often incorporate information from web-based tools in my decision making.”?	Strongly Disagree - (-2); Strongly agree (2)
Personal Norms	PN1	How strongly do you agree or disagree with: “I feel a moral obligation to protect local surface waters.”?	Strongly Disagree - (-2); Strongly agree (2)
	PN2	How strongly do you agree or disagree with: “I feel a personal obligation to monitor local surface waters.”?	Strongly Disagree - (-2); Strongly agree (2)
Community Trust	CT1	How would you rate the responsiveness of the following groups of people/institutions [community members] to surface water quality concerns in the North Platte Watershed?	Not at all – 0; Extremely -4
	CT2	How similar are your surface water quality goals with the following groups of people/institutions [community members]?	Not at all – 0; Extremely -4
	CT3	How would you rate the competency of the following groups of people/institutions [community members]?	Not at all – 0; Extremely -4
	CT4	How would you rate the past effectiveness of the following groups of people/institutions [community members]?	Not at all – 0; Extremely -4
Organizational Trust	OT1	How would you rate the responsiveness of the following groups of people/institutions [state natural resource agencies (i.e., NRD)] to surface water quality concerns in the North Platte Watershed?	Not at all – 0; Extremely -4

	OT2	How similar are your surface water quality goals with the following groups of people/institutions [state natural resource agencies (i.e., NRD)]?	Not at all – 0; Extremely -4
	OT3	How would you rate the competency of the following groups of people/institutions [state natural resource agencies (i.e., NRD)]?	Not at all – 0; Extremely -4
	OT4	How would you rate the past effectiveness of the following groups of people/institutions [state natural resource agencies (i.e., NRD)]?	Not at all – 0; Extremely -4
	OT5	How would you rate the responsiveness of the following groups of people/institutions [your government officials] to surface water quality concerns in the North Platte Watershed?	Not at all – 0; Extremely -4
	OT6	How similar are your surface water quality goals with the following groups of people/institutions [state natural resource agencies (i.e., NRD), your government officials, Nebraskan colleges/universities]?	Not at all – 0; Extremely -4
	OT7	How would you rate the competency of the following groups of people/institutions [your government officials]?	Not at all - 0; Extremely - 4
	OT8	How would you rate the past effectiveness of the following groups of people/institutions [your government officials]?	Not at all - 0; Extremely - 4
	OT9	How would you rate the responsiveness of the following groups of people/institutions [your government officials] to	Not at all - 0; Extremely - 4

		surface water quality concerns in the North Platte Watershed?	
	OT10	How similar are your surface water quality goals with the following groups of people/institutions [Nebraskan colleges/universities]?	Not at all - 0; Extremely - 4
	OT11	How would you rate the competency of the following groups of people/institutions [Nebraskan colleges/universities]?	Not at all - 0; Extremely - 4
	OT12	How would you rate the past effectiveness of the following groups of people/institutions [Nebraskan colleges/universities]?	Not at all - 0; Extremely - 4

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APPENDIX D. SURVEY MATERIALS: CONSENT FORM

IRB Project ID #: 21243

StreamNet: Building Capacity to Improve Water Quality

Dear Lanny,

My name is Anni Poetzl and I am a graduate student in the School of Natural Resources at the University of Nebraska–Lincoln. I am conducting this survey with my University of Nebraska–Lincoln colleagues in cooperation with the North Platte Natural Resource District and city officials of Scotts Bluff County to understand what factors influence the adoption (i.e., use) of a web-based water quality monitoring tool by community members. If you are (1) 19 years of age or older, (2) a community member within the North Platte Watershed in Scotts Bluff, Banner, Garden, and Morrill counties, and (3) the primary decisionmaker regarding water and land management for your household/company/ land, you may participate in this research. If you are not the primary decisionmaker, please pass this letter, survey booklet, and its components to the person who is the primary decisionmaker. **I have sent this survey to you once more just in case you would like to participate but misplaced your original survey booklet.**

Purpose of this study

The purpose of this study is to better understand the relationship of facilitators and barriers that affect the behavioral intention to use a novel web-based water quality monitoring tool by community members. A web-based water quality monitoring tool in our study is defined as a tool that allows its users to do the following actions, free of charge:

- Download hourly water quality data from local surface waters
- Access and visualize data of local surface water chemical composition (i.e., nutrient concentrations, temperature, pH) over the Internet
- Monitor local surface water chemistry parameters (i.e., temperature, pH) hourly

Participation in this survey will require approximately 20 minutes. You will be asked to answer the survey items to the best of your ability. Your participation in this survey will help provide a more complete understanding of community attitudes, norms, and behaviors towards local surface water quality and web-based water quality monitoring tools.

Indirect benefits

Although you are not expected to get any direct benefit from being in this study, your responses can better inform future tool development, and help foster more collaboration and knowledge exchange between community members and researchers. There are no known risks to you from being in this research study. We will not pay you to take part in this study or pay for any out-of-pocket expenses related to your participation.

University of Nebraska Lincoln
School of Natural Resources
3310 Holdrege Street | Hardin Hall, Suite 249 | Lincoln, NE 68583

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Protecting your information

Reasonable steps will be taken to protect the privacy and the confidentiality of your study data; however, in some circumstances we cannot guarantee absolute privacy and/or confidentiality.

- If you choose to complete this survey booklet and mail in your response with the pre-paid envelope, your survey packet will be stored in a locked cabinet in the investigator's office and will only be seen by the research team and/or those authorized to view, access, or use the records during and after the study.

Those who will have access to your research records are the study personnel, the Institutional Review Board (IRB), and any other person, agency, or sponsor as required by law or contract or institutional responsibility. The information from this study may be published in scientific journals or presented at scientific meetings and may be reported individually, or as group or summarized data but your identity will be kept strictly confidential.

Your rights as a research subject

You may ask any questions concerning this research and have those questions answered before agreeing to participate in or during the study.

For survey-related questions, please contact the investigators:
(1) Anni Poetzl (402-347-5854; apoetzl2@huskers.unl.edu)
(2) Chris Chizinski (402-472-8123; cchizinski2@unl.edu)

For questions concerning your rights or complaints about the research, contact the Institutional Review Board (IRB):

- Phone: 402-472-6965
- Email: irb@unl.edu

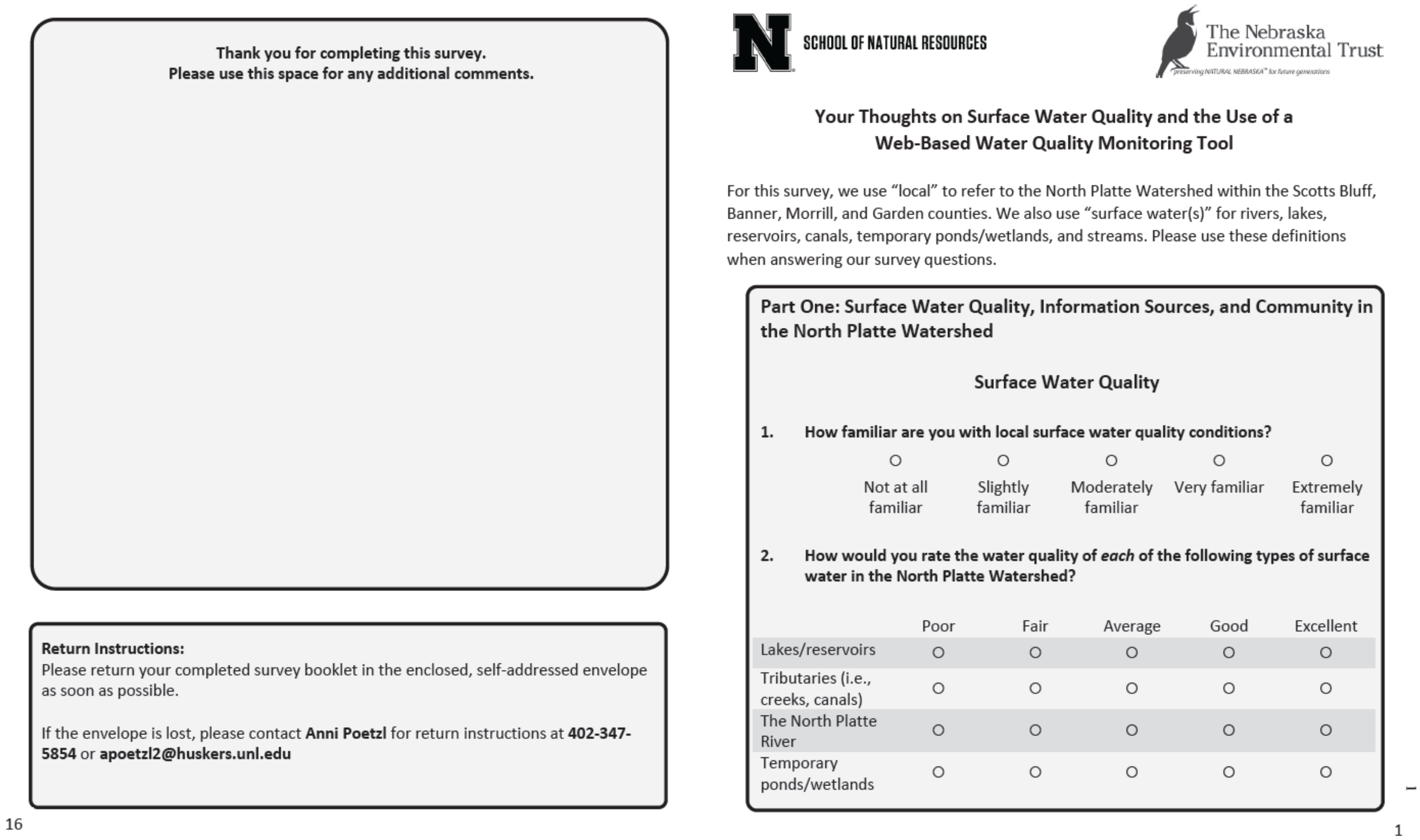
You can decide not to be in this research study, or you can stop being in this research study ("withdraw") at any time before, during, or after the research begins for any reason. Deciding not to be in this research study or deciding to withdraw will not affect your relationship with the investigator, with the University of Nebraska-Lincoln, or your natural resource district. You will not lose any benefits to which you are entitled.

Please mail-in your survey booklet using the enclosed self-addressed envelope by April 11, 2022, so that we can include your responses in our project. This will be the last time we reach out to you.

Thank you,

Anni M Poetzl

Anni Poetzl



Thank you for completing this survey.
Please use this space for any additional comments.

Return Instructions:
Please return your completed survey booklet in the enclosed, self-addressed envelope as soon as possible.

If the envelope is lost, please contact **Anni Poetzl** for return instructions at **402-347-5854** or **apoetzl2@huskers.unl.edu**

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SCHOOL OF NATURAL RESOURCES

The Nebraska Environmental Trust
preserving NATURAL NEBRASKA™ for future generations

Your Thoughts on Surface Water Quality and the Use of a Web-Based Water Quality Monitoring Tool

For this survey, we use "local" to refer to the North Platte Watershed within the Scotts Bluff, Banner, Morrill, and Garden counties. We also use "surface water(s)" for rivers, lakes, reservoirs, canals, temporary ponds/wetlands, and streams. Please use these definitions when answering our survey questions.

Part One: Surface Water Quality, Information Sources, and Community in the North Platte Watershed

Surface Water Quality

1. How familiar are you with local surface water quality conditions?

○	○	○	○	○
Not at all familiar	Slightly familiar	Moderately familiar	Very familiar	Extremely familiar

2. How would you rate the water quality of *each* of the following types of surface water in the North Platte Watershed?

	Poor	Fair	Average	Good	Excellent
Lakes/reservoirs	○	○	○	○	○
Tributaries (i.e., creeks, canals)	○	○	○	○	○
The North Platte River	○	○	○	○	○
Temporary ponds/wetlands	○	○	○	○	○

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3. **How important are the following factors in your ratings of surface water quality in the North Platte Watershed?**

	Not important	Slightly important	Moderately important	Very important	Extremely important
Nutrients (i.e., nitrate, ammonium, phosphate)	○	○	○	○	○
Agricultural chemicals (i.e., atrazine)	○	○	○	○	○
Oxygen level	○	○	○	○	○
Temperature	○	○	○	○	○
pH	○	○	○	○	○
Ion content (specific conductivity)	○	○	○	○	○
Water clarity (turbidity)	○	○	○	○	○
Fecal matter (i.e., urban and livestock run-off)	○	○	○	○	○
Algal growth	○	○	○	○	○

Part Four: Demographic Questions

21. **In what year were you born?** ____________________

22. **What is your gender?**

- ○ Male
- ○ Female
- ○ Non-binary
- ○ Prefer not to say

23. **Which of the following racial/ethnic groups describe you?** Check **all** that apply.

- ☐ Asian or Pacific Islander
- ☐ Black or African American
- ☐ Hispanic, Latino, or of Spanish origin
- ☐ Native American or Alaskan Native
- ☐ White or Caucasian

Part Three: Land Description

20. Do you consider yourself to be an agricultural producer? If you mark "no," please proceed to Question 21.

○ Yes
○ No

If you answered "yes," please answer questions a., b., and c.

a. Does a majority of your agricultural operation income come from crop or livestock production?

○ Crop production
○ Livestock production

b. Considering all the land you farm in the North Platte Watershed, who makes the land management decisions? Check **all** the statements that apply.

☐ I make the decisions.
☐ I leave it up to my renter(s).
☐ I leave it up to the landowner(s).
☐ I work together with the landowner(s)/renter(s) to make decisions.

c. What percentage of each category best describes the land you rent/own in the North Platte Watershed? The total percent should equal 100%.

_____ Rent
_____ Own

Information Sources

4. Do you seek out local surface water quality information?

○ Yes
○ No

a. If "yes," what sources do you use to get your information? Check all that apply.

☐ Natural resource managers/scientists
☐ Websites (i.e., via cell phone, laptop, or computer)
☐ Family/friends
☐ Radio/television/newspaper
☐ Environmental monitoring technology (i.e., sensors)
☐ Community members, excluding neighbors
☐ Neighbors

5. How often do you actively seek out information about local surface water quality?

○ Daily
○ Weekly
○ Monthly
○ Quarterly
○ Seasonally
○ Yearly
○ Never

Community

6. When you think of your community, what primarily comes to mind?

○ Neighbors
○ Township
○ Town/City
○ County
○ Watershed
○ State

Part Two: A Web-Based Water Quality Monitoring Tool

For this part of our survey, we define a **web-based water quality monitoring tool** as **any tool that allows its users to do the following actions, <u>free of charge</u>**.

- **Download hourly water quality data from local surface waters**
- **Access and visualize data of local surface water chemical composition (i.e., nutrient concentrations, temperature, pH) over the Internet**
- **Monitor local surface water chemistry parameters (i.e., temperature, pH) hourly**

As a reminder, we use "local" to refer to the North Platte Watershed within the Scotts Bluff, Banner, Morrill, and Garden counties. Also, the acronym NRD stands for Natural Resource District.

Trust

18. How would you rate the responsiveness of the following groups of people/institutions to surface water quality concerns in the North Platte Watershed?

	Not at all responsive	Slightly responsive	Somewhat responsive	Very responsive	Extremely responsive	NA
State natural resource agencies (i.e., NRD)	○	○	○	○	○	○
Your government officials	○	○	○	○	○	○
Nebraskan colleges/ universities	○	○	○	○	○	○
Community members	○	○	○	○	○	○

19. How similar are your surface water quality goals with the following groups of people/institutions?

	Not at all similar	Slightly similar	Somewhat similar	Very similar	Extremely similar	NA
State natural resource agencies (i.e., NRD)	○	○	○	○	○	○
Your government officials	○	○	○	○	○	○
Nebraskan colleges/ universities	○	○	○	○	○	○
Community members	○	○	○	○	○	○

Trust

16. How would you rate the competency of the following groups of people/institutions in addressing surface water quality issues?

	Not at all competent	Slightly competent	Somewhat competent	Very competent	Extremely competent	NA
State natural resource agencies (i.e., NRD)	○	○	○	○	○	○
Your government officials	○	○	○	○	○	○
Nebraskan colleges/ universities	○	○	○	○	○	○
Community members	○	○	○	○	○	○

17. How would you rate the past effectiveness of the following groups of people/institutions in surface water quality projects?

	Not at all effective	Slightly effective	Somewhat effective	Very effective	Extremely effective	NA
State natural resource agencies (i.e., NRD)	○	○	○	○	○	○
Your government officials	○	○	○	○	○	○
Nebraskan colleges/ universities	○	○	○	○	○	○
Community members	○	○	○	○	○	○

Utility of a Web-Based Water Quality Monitoring Tool

7. How useful is a free, web-based water quality monitoring tool to your water quality interests?

○	○	○	○	○
Not at all useful	Slightly useful	Moderately useful	Very useful	Extremely useful

8. For what reasons, if any, would you be interested in using a free, web-based water quality monitoring tool?
Rank your top three choices - "1" being the top choice and "3" being the lesser of the three choices - by filling in their respective blanks.

___ To ensure waterways are safe for human health
___ To ensure my community members are following regulations
___ To ensure upstream water users are following regulations
___ To maintain waterways for downstream water users
___ To ensure waterways are safe for recreational purposes
___ To be a good steward of our natural environment
___ To keep our environment beautiful
___ To ensure waterways are safe for animal health, wild and domesticated
___ To enhance my water management decisions

Utility of a Web-Based Water Quality Monitoring Tool - Continued

9. **How likely would you do the following actions?**

a. **Incorporate a free, web-based water quality monitoring tool into your decision-making**

○	○	○	○	○
Not at all likely	Slightly likely	Moderately likely	Very likely	Extremely likely

b. **Rely solely on this tool for water quality data of local waterways**

○	○	○	○	○
Not at all likely	Slightly likely	Moderately likely	Very likely	Extremely likely

Social Norms - Continued

15. **When thinking of the groups of people who you listed as important to you in Question 14, how strongly do you agree or disagree with the following statements?**

a. **"They would expect me to use a free, web-based water quality monitoring tool."**

○	○	○	○	○
Strongly Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree

b. **"They would expect me to stay up-to-date on local surface water quality information."**

○	○	○	○	○
Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly Agree

Facilitating Conditions - Continued

13. **How strongly do you agree or disagree with the following statement?**

b. **“I have the ability to interpret information received from a free, web-based water quality monitoring tool.” (i.e., knowledge, access to reference materials)**

○	○	○	○	○
Strongly Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree

Social Norms

14. **When it comes to surface water quality, how important are the expectations of the following groups of people towards your decision-making in monitoring local waterways?**

Rank your top three choices - “1” being the top choice and “3” being the lesser of the three choices - by filling in their respective blanks.

___ Family/friends
___ Neighbors
___ Farmers/ranchers/agricultural producers
___ Natural resource managers/scientists
___ State/local government officials
___ Downstream water users inside of your community
___ Downstream water users outside of your community

Ease of Use

10. **How strongly do you agree or disagree with the following statement?**

a. **“I generally find web-based tools easy to use.”**

○	○	○	○	○
Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree

b. **“I often incorporate information from web-based tools in my decision-making.”**

○	○	○	○	○
Strongly Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree

Personal Norms

11. How strongly do you agree or disagree with the following statements?

a. “I feel a moral obligation to protect local surface waters.”

○	○	○	○	○
Strongly Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree

b. “I feel a personal obligation to monitor local surface waters.”

○	○	○	○	○
Strongly Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree

c. “If I had access to a free, web-based water quality monitoring tool, I would feel an obligation to use the tool.”

○	○	○	○	○
Strongly Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree

Facilitating Conditions

12. Do you have the physical resources to use a free, web-based water quality monitoring tool (i.e., Internet connection, Wi-fi)?

○	○
Yes	No

13. How strongly do you agree or disagree with the following statement?

a. “I have time to learn and use a free, web-based water quality monitoring tool.”

○	○	○	○	○
Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly Agree