Central Coast Watershed Studies

CCoWS

Evaluation of agricultural management practices and water quality in the lower Salinas and Pajaro Valleys

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Gilbert Mak
Jessie Doyle
Savannah J. Peña
John R. Olson

The Watershed Institute

Department of Applied Environmental Science
California State University Monterey Bay
www.watershed.csumb.edu

100 Campus Center, Seaside, CA, 93955-8001
831 582 3873

Corresponding author contact details:
joolson@csumb.edu

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Executive Summary

The Central Coast Regional Water Quality Board (CCRWQCB) is developing policies to prevent avoidable water pollution from agricultural runoff. Two Agricultural Orders (2012 and 2017) currently require farms that pose the greatest risk to water quality to implement Best Management Practices (BMPs), monitor water quality and report their actions to the CCRWQCB's Irrigated Lands Regulatory Program (ILRP).

Policy makers and stakeholders are interested in how currently applied BMPs are affecting water quality outcomes to inform further management and policy to improve surface water quality. A study completed by CSUMB's ENVS660 Fall 2017 class examined how reported on-farm management practices related to water quality monitoring data. The BMP with the strongest correlation to increased nitrogen concentration was classifying practices as trade secret, while the strongest correlations to decreased nutrient concentration association were evaluating fertilizer need and timing, scheduling fertilizer to match crop requirements, and measuring nitrogen and phosphorus content of applied organics.

This study expands upon previous work by CSUMB's ENV 660 class. Specifically, we had four main objectives:

1. Obtain and format the most recently published Irrigated Lands Regulatory Program (ILRP) farm management practice data.
2. Revise the hydrologic framework to better link farming intensity and practices to water quality observations. In coordination with Central Coast Cooperative Monitoring Program, develop a refined set of watersheds for each of the Cooperative Monitoring Program (CMP) stations used in the original analysis.
3. Characterize the farming practices (e.g., nutrient management practices, nitrogen applied, irrigation) and environmental factors (e.g., geology, weather, groundwater quality) of each watershed.
4. Develop empirical models relating water quality to both farming practices and environmental factors (e.g., soils, climate, geology), and determine which farming practices are related to changes in water quality and how natural factors interact with these relationships.

We met these objectives by evaluating the relationship between measured chemical

analytes, farming practices, and environmental variables in the watersheds upstream of 53 CMP monitoring stations across the Central Coast. The analytes considered were total ammonia as N, nitrate + nitrite as N, total nitrogen as N, and total phosphorus as P. We evaluated relationships by developing random forest models – a non-parametric empirical modeling technique. These models then were used to determine which variables have the strongest correlation with variation in chemical concentration and load across all sites.

We produced 32 models, one for each of the concentrations and loads of four analytes across four temporal scales. Our most robust models predicted annual nitrate + nitrite and total nitrogen concentrations ($R^2 \geq 0.70$). Models of summer concentrations or loads explained > 40% of the variation for all four analytes. Analysis of the models suggest that the groundwater quality has the greatest influence on surface water quality. Our models further suggest that several BMPs, most notably the lack of reporting, to be positively correlated with surface water quality. Reported total nitrogen applied and in soils was not significantly correlated with surface water quality though.

Contents

1 Introduction

1.1 Background

Agricultural Order 3.0, approved by the Central Coast Regional Water Quality Control Board (CCRWQCB) in March 2017, required growers whose farms pose the greatest risk to water quality in the Central Coast Region of California to implement Best Management Practices (BMPs) and to monitor the quality of water discharged from irrigated land they own or operate in order to prevent avoidable water pollution (CCRWQCB 2012). Ag Order 3.0 added a groundwater monitoring component and an expanded Total Nitrogen Applied reporting obligation to the requirements of Ag Order 2.0 (CCRWQCB 2017). Complying with these regulations can require a substantial amount of effort and fiscal expenditures on the part of the growers. While growers have been tasked with rethinking and altering many of their on-farm practices, they have yet to be presented with concrete evidence that their efforts over the last few years have improved regional water quality. Our client, the Water Quality Protection Program administrators at Monterey Bay National Marine Sanctuary (MBNMS), have therefore requested an analysis of how the water quality monitoring data of the lower Salinas and Pajaro Valleys relates to reported on-farm practices to help guide the development of future agricultural orders.

The Central Coast Region extends approximately 250 miles from San Mateo County to Santa Barbara County and contains roughly 435,000 acres of irrigated land, over 3,000 agricultural operations, more than 17,000 miles of surface waters, and approximately 4,000 square miles of groundwater basins (CCRWQCB 2012). Although the State of California has some of the most stringent water pollution control regulations in the country under the Porter-Cologne Water Quality Control Act, the highest rates of nutrient loading and toxicity in California are routinely detected in the Central Coast Region largely due to years of unchecked nonpoint source pollution from agricultural runoff (Starner et al. 2006, CCRWQCB 2011).

Ag Order 1.0, implemented in 2004 and revised several times since, created a new regulatory framework to ensure grower compliance and a means to monitor regional changes in water quality. The Irrigated Lands Regulatory Program (ILRP) is administered by the CCRWQCB and serves as the means through which the board regulates discharges from irrigated agricultural lands used for commercial crop production through issuing Conditional Waivers of Waste Discharge Requirements. Depending on the size of a grower's operation, the type of crops being grown and a ranch's proximity to impaired waterways, an agricultural operation will be placed into one of three tiers through the ILRP: Tier 1, 2, or 3. Tier 3 growers potentially pose a larger risk to water quality and are thus subjected to more extensive regulations, while Tier 1 and Tier 2 growers have fewer obligations under the most recent Ag Orders. The Cooperative Monitoring Program (CMP) evolved in accordance with Ag Order 3.0 to reduce the burden of monitoring requirements on growers. Over 99% of all farms participating in the ILRP have elected to take part in the CMP and thus pay Preservation Inc., a local nonprofit, an annual fee to perform mandatory surface water quality monitoring on their behalf. Preservation Inc. monitors over 50 sites throughout the Central Coast Region.

1.2 Objectives

Our study objectives were to:

- In coordination with Monterey Bay National Marine Sanctuary (MBNMS), obtain and format the most recently published Irrigated Lands Regulatory Program (ILRP) farm management practice data (2015 – 2018).
- Revise the hydrologic framework to better link farming intensity and practices to water quality observations. In coordination with Central Coast Cooperative Monitoring Program, develop a refined set of watersheds for each of the CMP stations used in the original analysis.
- Characterize the farming practices (e.g., nutrient management practices, nitrogen applied, irrigation) and environment (e.g., geology, weather, groundwater quality) of each watershed.
- Develop empirical models relating water quality to both farming practices and environmental factors (e.g., soils, climate, geology), and determine which farming practices are related to changes in water quality and how natural factors interact with these relationships.

1.3 Study area

The Salinas and Pajaro watersheds, in California's Central Coast, span parts of Monterey, Santa Cruz, San Benito, San Luis Obispo and Santa Clara counties and share boundaries with a handful of small watersheds (Elkhorn Slough, Moro Cojo and Alisal/Gabilan) on the coast (Figure 1). All drain into the Monterey Bay National Marine Sanctuary, comprising most the bay's freshwater inputs (Fig 1). Land use across the upper watersheds varies while the lower watersheds are heavily used for agricultural production where a mild, Mediterranean climate makes year-round cultivation possible. Primary crops in the lower Salinas Valley include leaf and head lettuces, strawberries and various other vegetable row crops (MCAC 2016) while the majority of crops in the Pajaro Valley include caneberries (raspberries and blackberries), strawberries, apples and vegetable row crops (SCCAC 2016). The fertile soil in the flat valley bottoms of these two regions makes growing conditions ideal and agricultural operations highly profitable. The agriculture industry contributes billions of dollars to the local economies on an annual basis.

Due to decades of intensive agricultural production, groundwater and surface waters in the lower regions of the Salinas and Pajaro Watersheds are affected by a variety of nonpoint source pollutants, especially by nitrate. Harter and Lund with UC Davis (2012) found that nitrogen fertilizer and animal wastes are the primary sources of nitrate pollution in the Salinas Valley and that over one third of domestic and irrigation wells in the Salinas Valley exceed the drinking water standard for nitrate (10 mg/L as N) deemed acceptable by the California Department of Public Health. Comparable agricultural practices and histories of the Pajaro Valley make similar findings likely.

The 2010 List of Impaired Waterbodies, pursuant to Section 303(d) of the federal Clean Water Act, designated fifteen waterbodies in the Lower Salinas watershed and five water bodies in the Pajaro River watershed as impaired by nitrate pollution (CCRWQCB 2011) while others were listed for a variety of other pollutants including, but not limited to: un-ionized ammonia, low dissolved oxygen, orthophosphate and chlorophyll a (CCRWQCB 2013).

Few deny that water pollution on the Central Coast is a negative externality of local agricultural production. However, developing a region-wide solution to mitigating the problem is and will be a long, arduous task. As more stringent water quality policy changes begin to take effect, growers will have to adapt to new requirements. It is essential that throughout this process growers and regulators, alike, understand the true outcome of their efforts to best use limited time and resources.

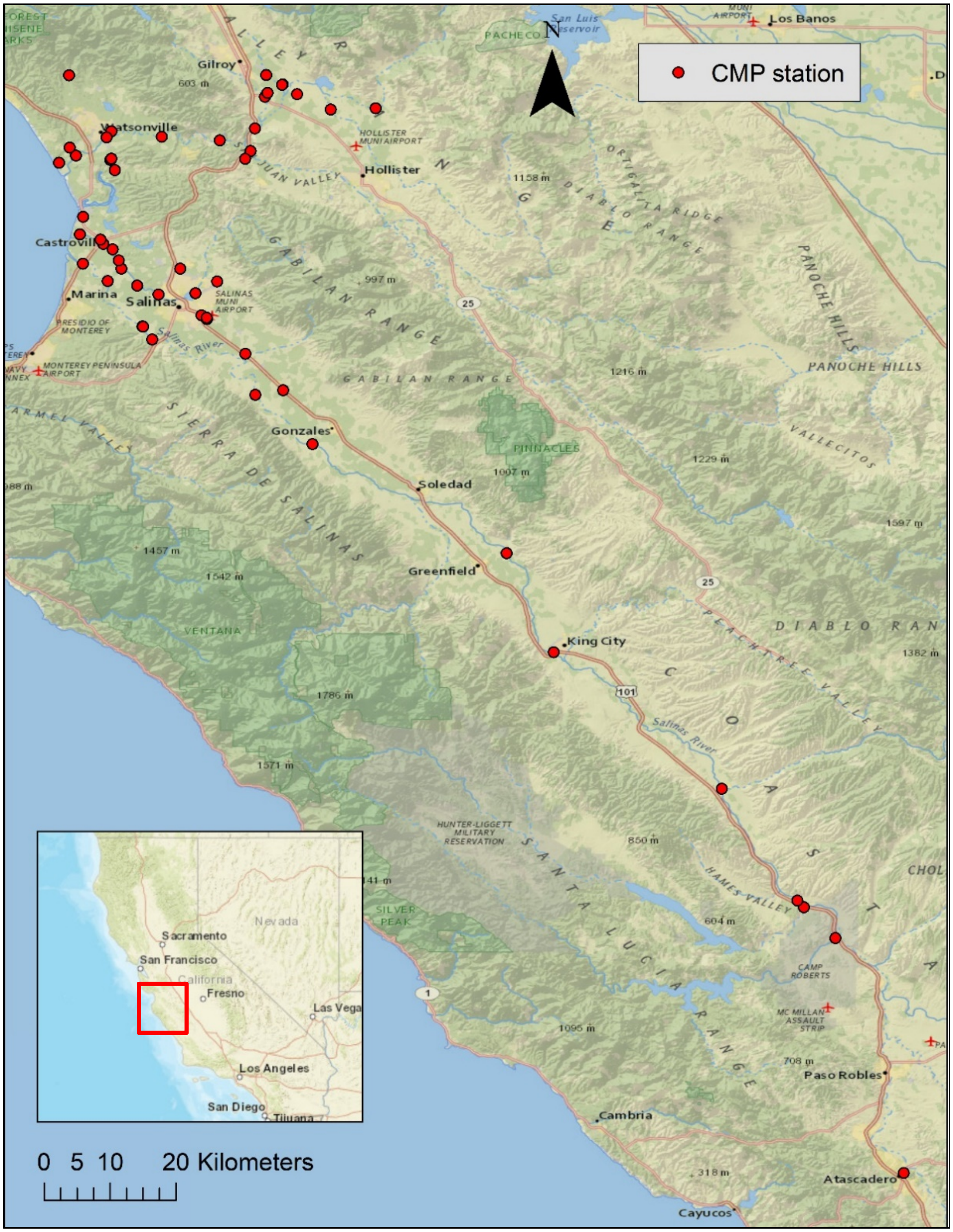

Figure 1. Cooperative Monitoring Program water quality monitoring sites assessed in this study.

2 Methods

2.1 Overview

We based our analysis on CMP chemical data and ILRP data collected from 2016 through 2018. We delineated watersheds for each CMP site using ArcGIS. We then summarized ILRP and publicly available environmental data to characterize each watershed and identify correlations with water quality. We assessed all correlations between predictors and response variables at a watershed scale by developing random forest (RF) models – a non-parametric empirical modeling technique. These models can determine the relative importance of predictors in a model and show the effects of each predictor on the response variable after controlling for the effects of all other variables.

2.2 Watershed Delineation

Watersheds were delineated using CMP sampling site coordinates and a digital elevation model (DEM). We used ArcMap to plot each CMP sampling site. A DEM was downloaded from USGS National Map service at a resolution of 30 meters and used to produce two rasters representing flow direction and flow accumulation. The spatial points were snapped to the nearest, highest flow accumulation. Watersheds were produced at each spatial point using the flow direction raster.

Each watershed raster and shapefile produced was quality control checked by hand against aerial or satellite photographs in Google Earth and with local experts from the CMP. Incorrect watersheds boundaries were then re-run with additional stream burns or walls as needed to create the correct flow pattern. Stream burns were created by decreasing the pixel value along a hand drawn line or NHD flowlines to "burn" a deeper value and force flow accumulation to flow through the lines. This technique was often used in very flat areas. Barrier walls were created by increasing pixel value along a hand drawn line or TIGER road lines to build up a "wall" that the flow direction and accumulation would see as a barrier. This technique was often used in areas where roads were observed blocking flow.

Final quality check required manual matching of vertices between watershed polygons (especially along ridgelines) and merging upstream watersheds together where watersheds overlapped.

2.3 Data Clean-up & Composition

We obtained analyte and environmental data from publicly available sources (Table 1 and Appendix A). CMP chemical data was downloaded from the California Environmental Data

Exchange Network (CEDEN). We obtained farming data from the Central Coast Water Board through a request for public information. Environmental data on soils and precipitation were obtained from publicly available gridded datasets.

Table 1. Forty-five predictors, across 7 categories, were used for model development. A full list and description of all predictors are in Appendix A.

Predictor category	No. of predictors	Source
Nutrient management	15	Water Board
Drainage	5	Water Board
Ranch characteristics	6	Water Board
Irrigation	3	Water Board
Nitrogen applied	2	Water Board
Groundwater	3	GAMA groundwater
Geologic and environmental	11	USGS & PRISM

We extracted analyte concentration data for ammonia, nitrate + nitrite, total nitrogen, and phosphorus at 53 CMP monitoring sites and calculated average concentration across four temporal scales at each site (Figure 2). We used one half the minimum detectable level (MDL) for records with no analyte concentrations. We next calculated load for each analyte at each of the four temporal scales by multiplying the mean concentration by the mean stream flow. Temporal scales were chosen to assess if water quality was more predictable during certain times of the year. We calculated the mean concentrations and loads based on the following time scales: October to March (winter), April to September (summer), October to September (annual water year), and October (first flush).

A Ammonia as N total		Annual (Oct – Sep)
N2 Nitrate + Nitrite as N, Total	Concentration	First Flush (Oct)
N Nitrogen, Total	Load	Winter (Oct – Mar)
P Phosphorus as P, Total		Summer (Apr – Sep)

Figure 2. Response variable data flow chart. Mean concentration and load were calculated for each analyte across each of four temporal scales.

We used a combination of Access, Excel, and R to clean drainage type, ranch characteristic, irrigation, and nitrogen applied data from the ILRP dataset. Drainage and irrigation data are calculated as proportions of total irrigated acres. Using the coordinates reported for each ranch in the IRLP data, we plotted each ranch using ArcMap to determine which watershed(s) they resided in. Ranches near watershed boundaries likely lie in multiple adjacent watersheds, so ranch boundaries would provide a more accurate association of farming practices and watersheds. But this data is not available, and would have negligible impact on watershed summaries of farming practices. We used a one to many spatial join in ArcMap to account for upstream to downstream effects whereby farms may reside in multiple nested watersheds.

We extracted nutrient management practices from the ILRP dataset (Table 2). Similar to the other ILRP data, we used a one to many join in ArcMap to account for ranches that may reside in multiple watersheds. We then used Python programming language to parse out and calculate the number of irrigated acres within each watershed where each practice was implemented. We used Excel to determine which ranches that did not submit an Annual Compliance Form (ACF).

Table 2. ILRP nutrient management practice implementation codes.

Abbreviation	Definition
IA1	Evaluated fertilizer needs and timing of application
IA2	Scheduled fertilizer applications to match crop requirements
IA3	Measured nitrogen concentration in irrigation water
IA4	Measured soil nitrate or soil solution nitrate
IA5	Used precision techniques to place fertilizer in the root zone
IA6	Measured nitrogen in plant tissues
IA7	Measured phosphorus in soil
IA8	Measured nitrogen and phosphorous content of organic amendments
IA9	Mixed and loaded fertilizers on low runoff hazard sites
IA10	Used urease inhibitors and/or nitrification inhibitors
IA11	Modified crop rotation
IA12	Used treatment systems (eg wood chip bioreactor)
IA13	Other
IA14	None
IA15	Answer left blank or No ACF

Groundwater quality data was downloaded from the Groundwater Ambient Monitoring and Assessment (GAMA) Program's Groundwater Information System using the most recent record for each well from between 2015 and 2019. We created three separate rasters for nitrate, nitrite, and nitrate + nitrite by interpolating the downloaded data using Inverse Distance Weighting in ArcMap (Figure 3). We then calculated the watershed average for each raster for each of the CMP watersheds.

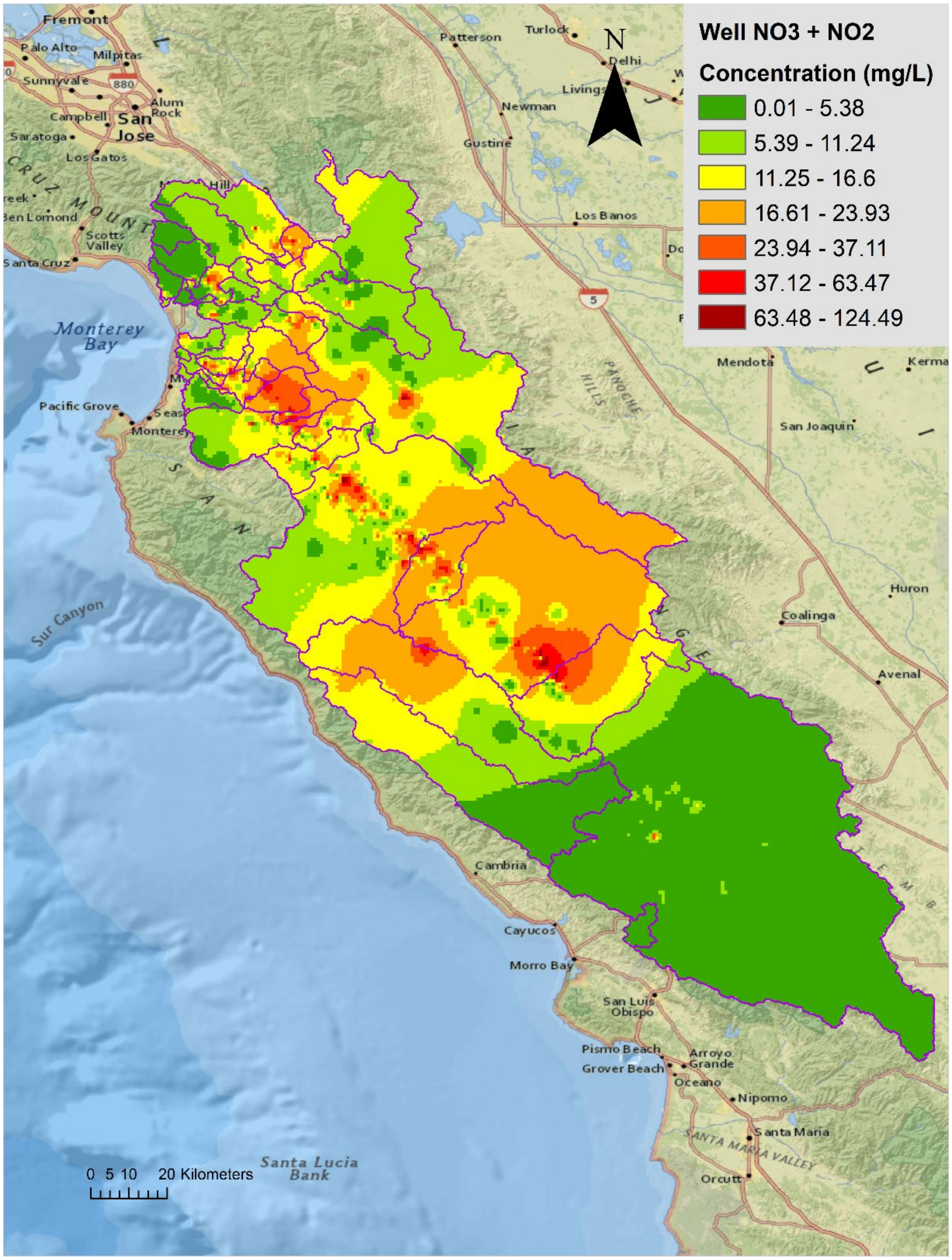

Figure 3. Interpolated raster of nitrate + nitrite concentrations in wells (groundwater).

2.4 Building random forest models

Random forest is a non-parametric empirical modeling technique that is based on an ensemble of decision trees fitted to a dataset (Breiman 2001). Fitting a single classification tree to one dataset may lead to models that are overfit (Cutler et al. 2007). Random forest avoids overfitting by fitting thousands of classification trees using different random subsets of the original data. Random forest then averages predictions across all trees within the "forest" of classification trees to produce ensemble predictions that are robust when applied to many ecological datasets (Fox et al. 2017).

We developed 32 separate RF models, one for each of the four analyte responses, for both concentrations and loads at four temporal scales (Figure 2). Each initial model was fitted to the 45 predictors which were used to predict analyte concentrations and loads across each of our four temporal scales (response).

We used the R package VSURF to refine which predictors were retained in our models. VSURF uses a step-wise variable selection algorithm that first eliminates irrelevant variables and then selects all variables related to the response for interpretation purpose (Genuer et al. 2015). From each model we extracted the importance of each variable in predicting the response data. RF estimates importance by calculating the percent increase of mean squared error (%incMSE) of a prediction when the model is built with the predictor of interest randomized. A positive %incMSE value indicates the model performance is decreased when the predictor in question is randomized, suggesting it is important to the model. We summarized the top predictors for all models by ranking each predictor based on their %incMSE for each model. To determine the most important predictors across models, we calculated average predictor ranking for each predictor.

We also evaluated the direction of effect of each predictor in each model. This was done by evaluating partial dependence plots for each predictor, which graph how the average response changes in relation to an individual predictor, while holding all other predictors at their mean value. We summarized this data as either showing a positive or negative correlation between predictors and response variables.

3 Results

3.1 Watershed Delineations

A total of 53 watersheds were delineated in the Pajaro and Salinas Valleys (Figure 4). The combined watershed area covered 14,782 sq km, spanning five counties. Over 2700 ranch operations were reported each year. The majority were Tier 1 and Tier 2 operations, with a near even split. As many as 18 ranches were still under review to determine ranking and

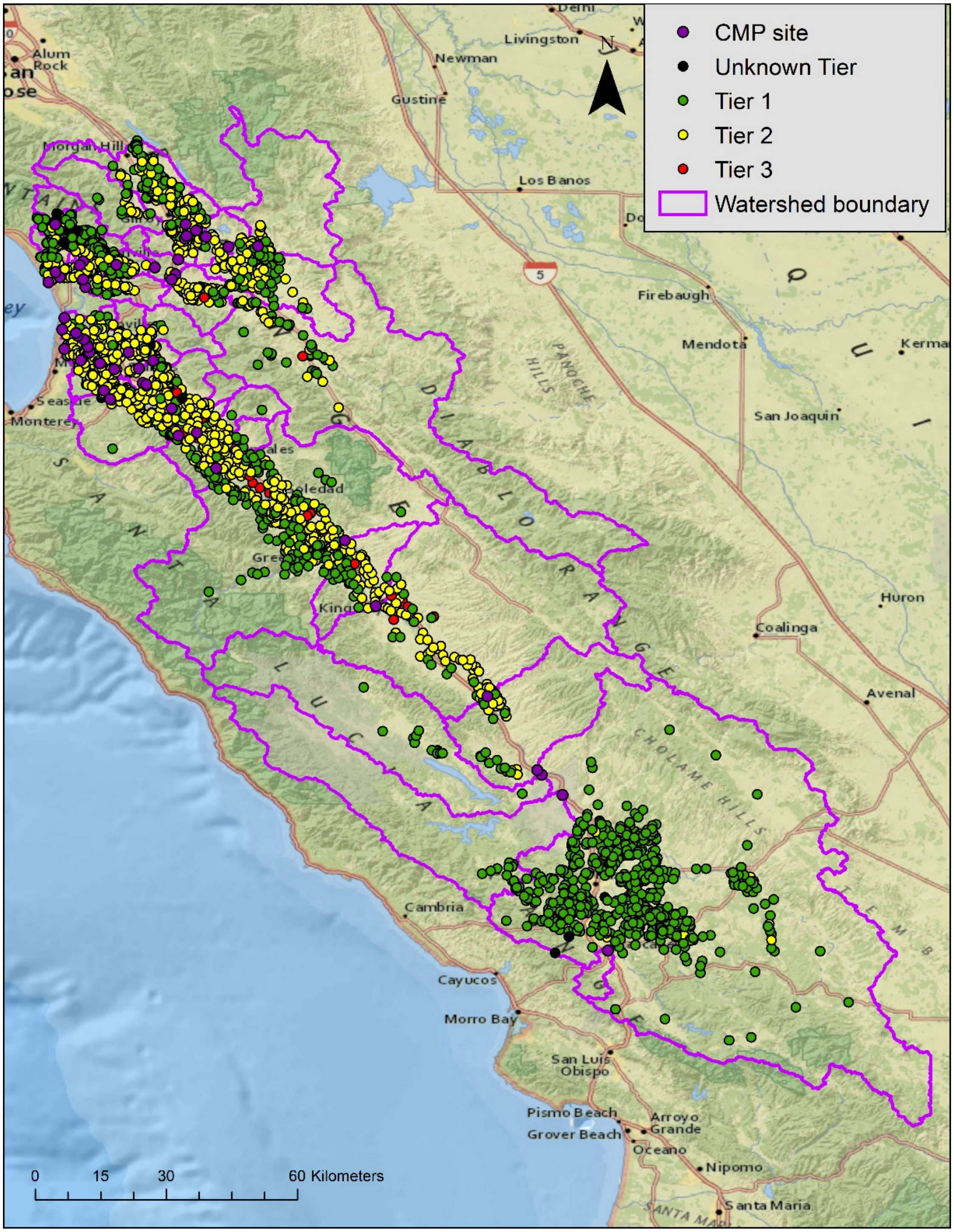

Figure 4. Map of watershed delineations and 2018 ranch locations by tier.

were listed as Tier 0.

3.2 Analyte concentrations within watersheds

Water quality monitoring indicated the greatest surface water nutrient concentrations occurred in the lower Salinas watershed. Ammonia concentrations were generally lower in the Pajaro and mid to upper Salinas watersheds across all temporal scales (Figure 5). The greatest concentrations of ammonia were elevated during the first flush and summer months (1.1 – 5.0 mg/L). Nitrate + nitrite and total nitrogen analytes exhibited similar patterns, both spatially and temporally, where higher concentrations were observed during summer (14.1 – 70.0 mg/L; Figures 6 and 7). Phosphorus concentrations were assessed to be low throughout the study area with the highest annual concentrations in the lower Salinas watershed and lower to mid Salinas watersheds during the first flush events (2.1 – 10.0 mg/L; Figure 8).

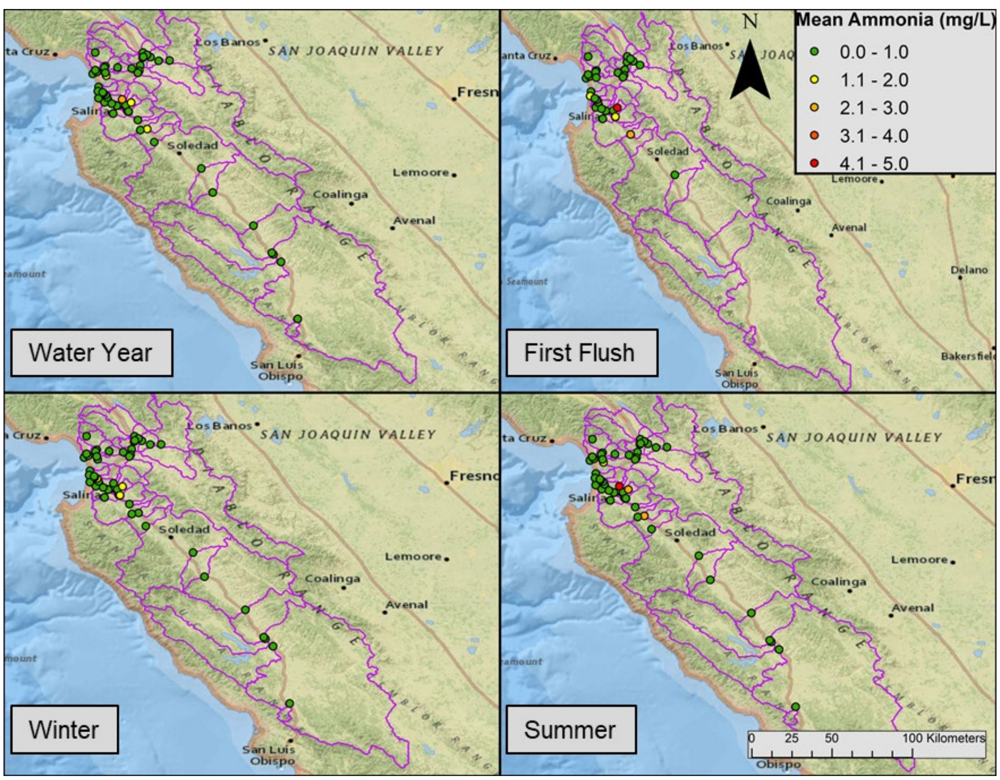

Figure 5. Average ammonia concentrations at 53 CMP monitoring sites over four temporal scales.

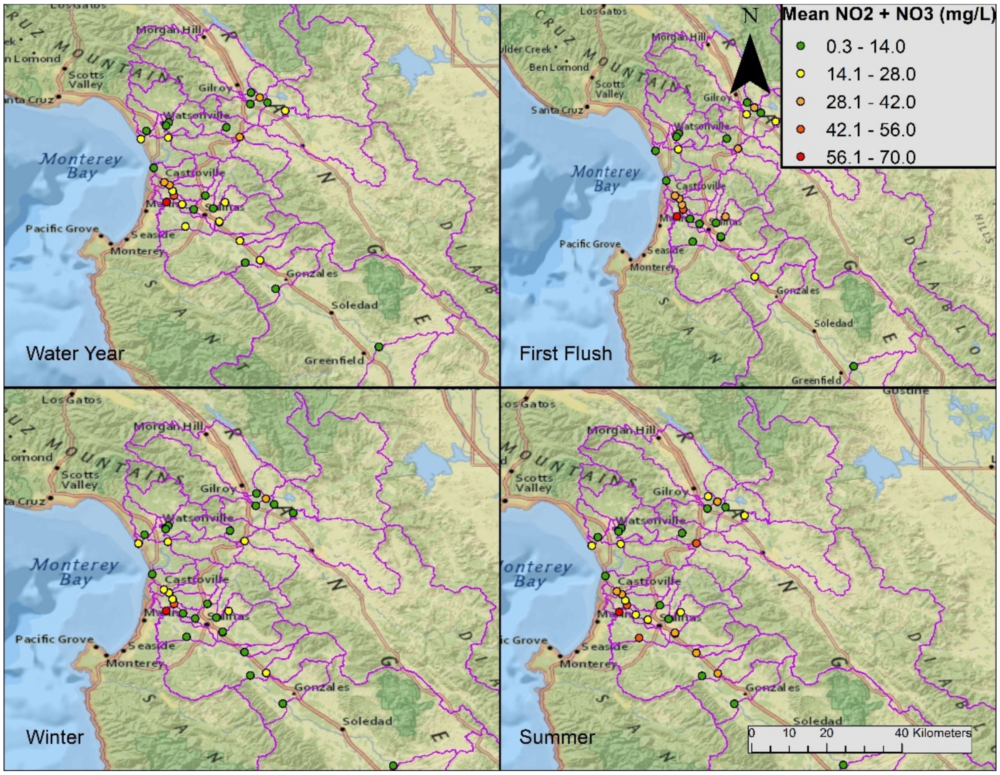

Figure 6. Average nitrate + nitrite concentrations at 53 CMP monitoring sites over four temporal scales.

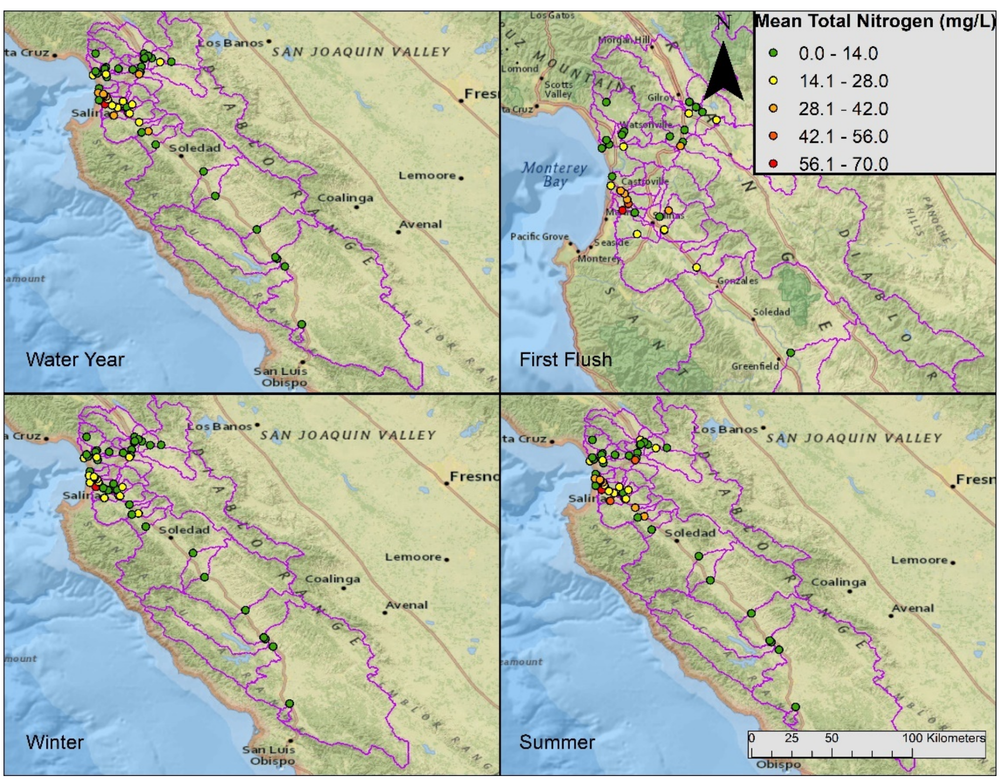

Figure 7. Average total nitrogen concentrations at 53 CMP monitoring sites over four temporal scales.

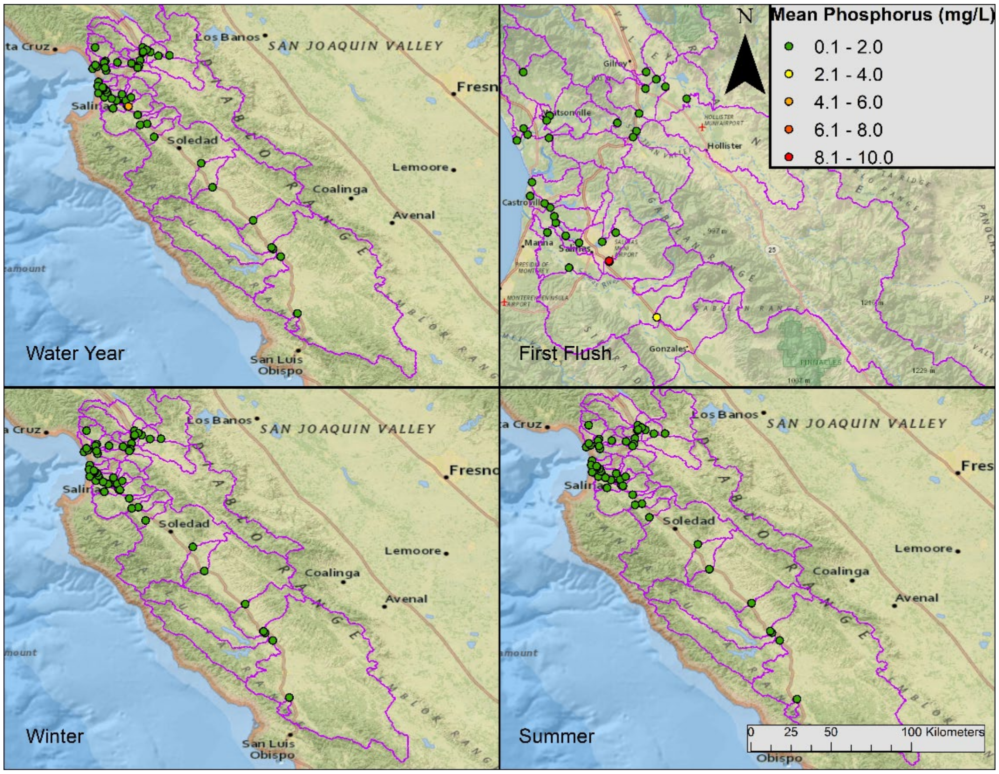

Figure 8. Average total phosphorus concentrations at 53 CMP monitoring sites over four temporal scales.

3.3 Model results

The RF analysis produced 19 models that explained greater than 30 percent of the variability in the response data ($R^2 \geq 0.30$) (Table 3). Our most robust models predicted Nitrate + Nitrite and Total Nitrogen concentrations, explaining more than 60% of the variability over annual and summer time periods.

3.3.1 Top models for each analyte

Our most robust concentration models predicted first flush ammonia, summer nitrate + nitrite and phosphorus, and annual total nitrogen (Table 4). Groundwater quality was among the top predictors for each of these models.

Our most robust load models predicted summer load for each analyte (Tables 3 and 5). Groundwater quality were among the top predictors in the ammonia and phosphorus load models. Nutrient management practices were among the top predictors for Nitrate + Nitrite and Total Nitrogen Summer models.

Table 1. Percent of the variation in response explained by the predictor data. Highlighted values indicate models with less than 30% of the variation explained ($R^2 < 0.30$).

Analyte		Annual	First Flush	Summer	Winter
Ammonia	Concentration	30.8	35.27	0.63	10.84
	Load	10.01	-4.58	42.23	5.94
Nitrate +Nitrite	Concentration	71.38	38.18	72.49	55.73
	Load	11.45	41.2	71.02	-0.8
Total Nitrogen	Concentration	72.31	46.31	61.72	68.19
	Load	13.62	40.76	72.23	6.81
Phosphorus	Concentration	26.71	30.6	63.43	20.03
	Load	23.67	41.53	48.4	5.58

Table 2. Summary of the top performing analyte concentration models and the top predictors based on percent increase in mean square error (%incMSE). Correlations were inferred from partial dependence plots.

Model	R^2	Metric	Correlation	%incMSE
Ammonia First Flush	0.35	Water table depth	Positive	15.57
		Ground water – Nitrate + Nitrite	Positive	14.50
		Tier 1 ranches	Negative	12.19
		Ground water – Nitrate	Positive	6.33
Nitrate + Nitrite Summer	0.72	Ground water – Nitrate + Nitrite	Positive	27.25
		Ground water – Nitrate	Positive	23.90
		Irrigated acres reporting measuring nitrogen and phosphorus in organic amendments	Positive	23.18
		Irrigated ares with no reporting	Positive	22.56
		Irrigated acres measuring N in irrigation wa	Positive	22.38
Total Nitrogen Annual	0.72	Ground water – Nitrate	Positive	73.85
		Rock deposition	Positive	67.45
Phosphorus Summer	0.63	Proportion tailwateracres/irigated acres	Positive	47.85
		Ground water – Nitrate	Positive	33.32
		Proportion ditch drain acres/irrigated acre	Positive	28.90

Table 5. Summary for the top performing analyte load models and their top predictors based on percent increase in mean squared error (%incMSE). Correlations were inferred from partial dependence plots.

Model	R^2	Metric	Correlation	%incMSE
Ammonia Summer	0.42	Total crop acres	Positive	23.36
		Ground water – Nitrite	Negative	23.05
Nitrate + Nitrite Summer	0.71	Irrigated acres scheduling fertilizer application to match crop requirements	Positive	45.42
		Irrigated acres measuring phosphorus in sc	Positive	39.93
Total Nitrogen Summer	0.72	Tier 2 ranches	Positive	25.01
		Irrigated acres scheduling fertilizer application to match crop requirements	Negative	24.32
		Irrigated acres using precision techniques to place fertilizer in root zone	Positive	14.69
		Total crop acres	Positive	14.53
		Total irrigated acres	Positive	14.18
Phosphorus Summer	0.48	Ground water – Nitrite	Negative	54.11

Ammonia Concentration – First Flush

The top three predictors in this model are water table depth, irrigated acres where management practices were not disclosed, and Tier 1 ranches. All predictors were positively correlated with increased ammonia concentration except for Tier 1 ranches (Figure 9).

Nitrate + Nitrite – Summer

Eleven predictors were used in this model. The top predictors included groundwater quality, measurement of nitrogen and phosphorus in organic amendments, no reported management practice, and measuring nitrogen concentration in irrigation water (Figure 10). All the predictors in this model have positive correlations with increasing analyte concentration.

Total Nitrogen Concentration – Annual

Two predictors were used in this model and were found to be positively correlated with total nitrogen concentration (Figure 11). The top predictor for this model was groundwater nitrate concentrations.

Phosphorus Concentration – Summer

Three predictors were used for this model (Figure 12). All predictors were found to be positively correlated with summer phosphorus concentrations.

Partial dependence plots for predictors in all models are presented in Appendix C.

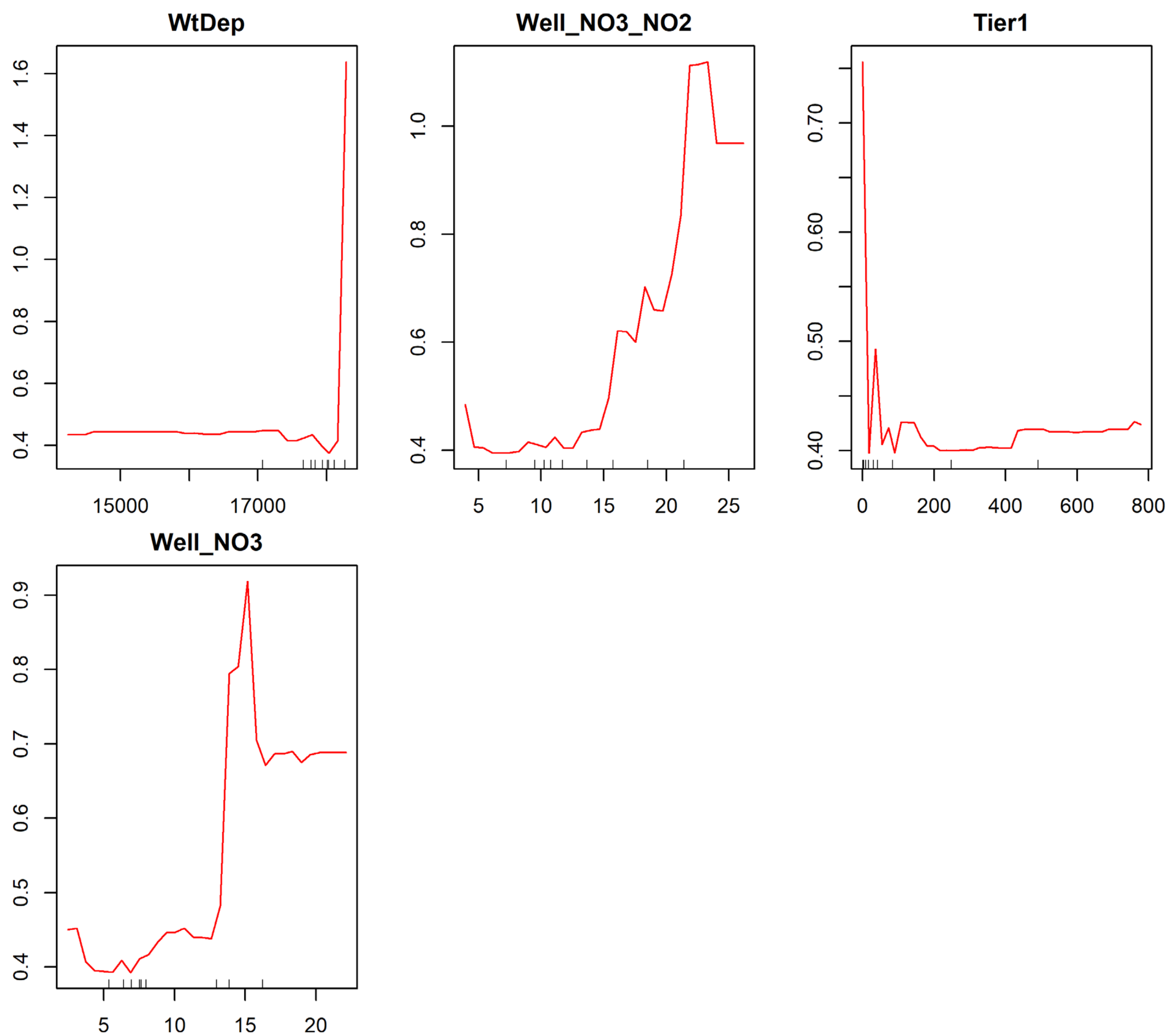

Figure 9. Partial dependence plots of the predictors in the ammonia concentration – first flush model. Y axis shows change in ammonia concentration vs. each variable, holding all other variables in the model at their mean. Variables listed in order of importance from top, left to right. WtDep = water table depth, other variables described in Appendix A. Tier 1 ranch was the only predictor that was negatively correlated with ammonia concentration.

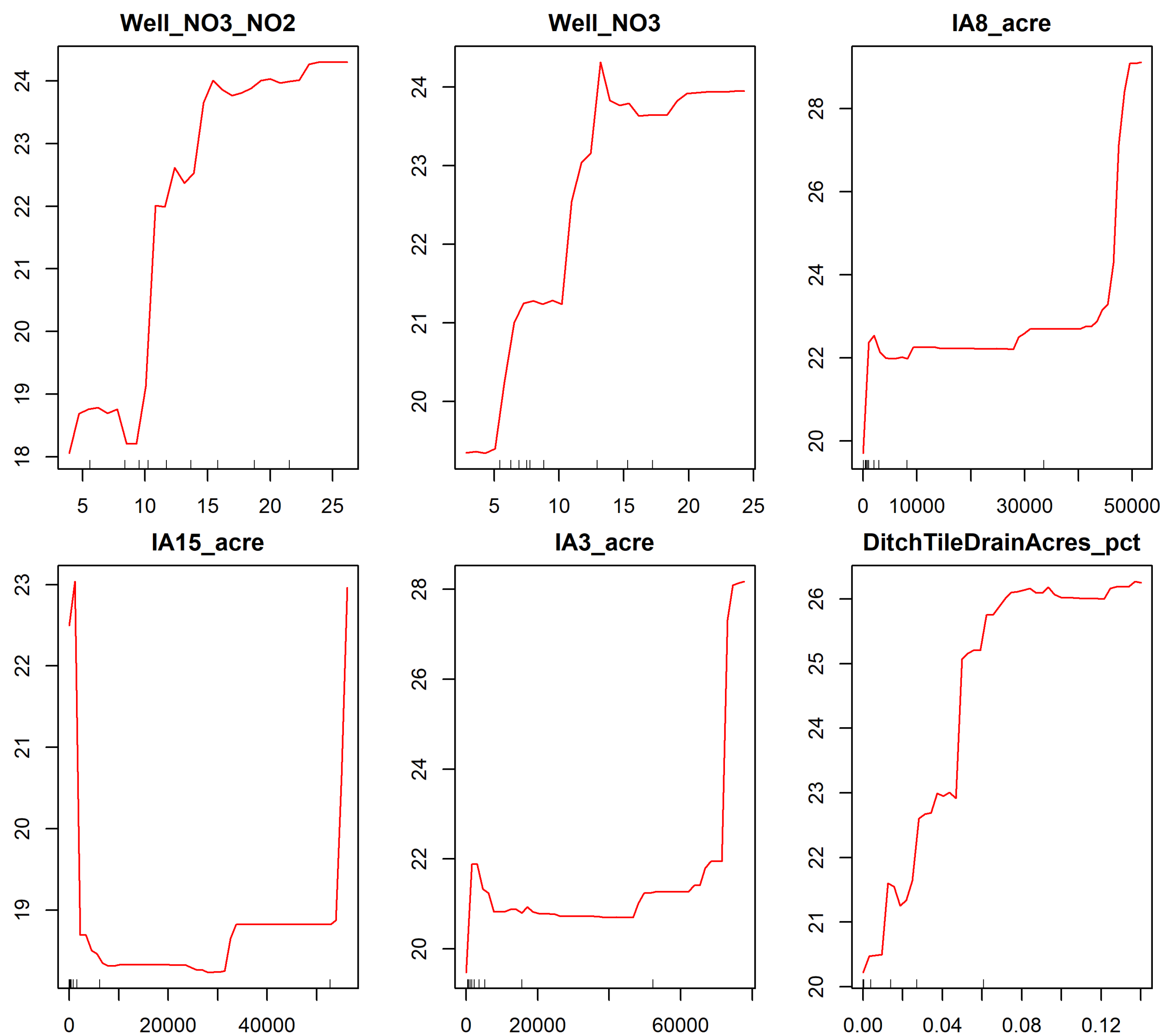

Figure 10. Partial dependence plots of the top six predictors in the Nitrate + Nitrite concentration – summer model. Y axis shows change in Nitrate + Nitrite concentration vs. each variable, holding all other variables in the model at their mean. Variables listed in order of importance from top, left to right. IA8=Measured nitrogen and phosphorous content of organic amendments, IA15=Answer left blank or No ACF, and IA3=Measured nitrogen concentration in irrigation water. Other variables described in Appendix A.

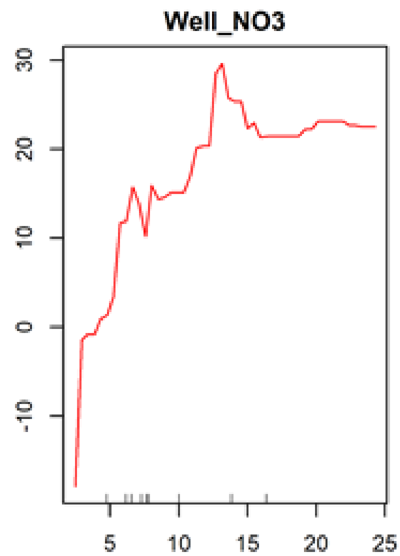

Figure 11. Partial dependence plots of the top two predictors in the Total Nitrogen – annual model. Y axis shows change in Total Nitrogen concentration vs. each variable, holding all other variables in the model at their mean. Variables listed in order of importance from left to right. RckDep=Rock Depth. Other variables described in Appendix A.

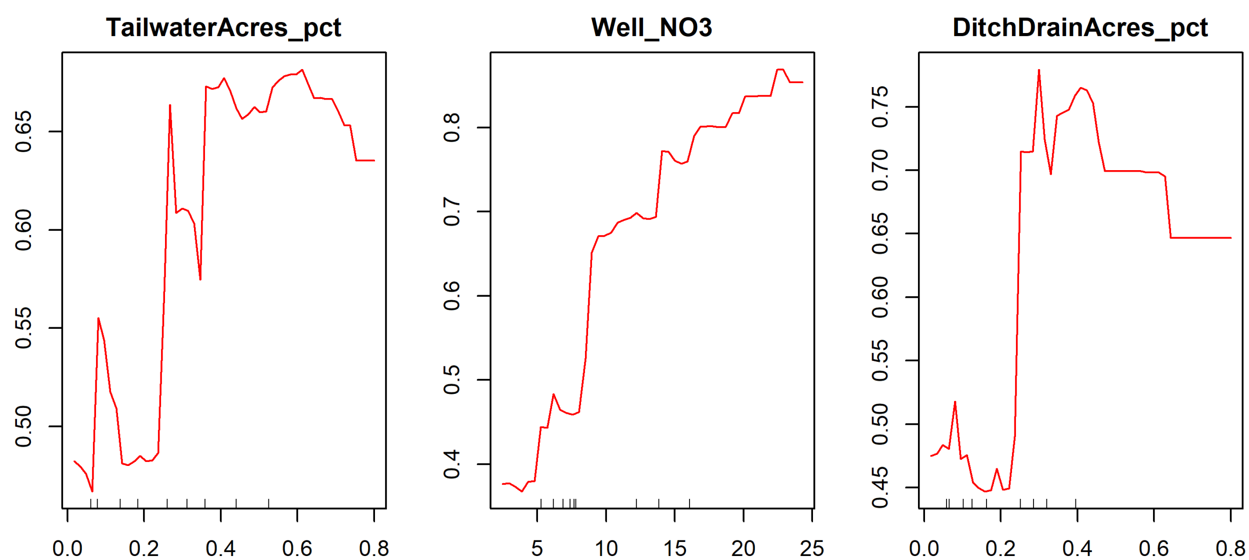

Figure 12. Partial dependence plots of the top three predictors in the summer phosphorus concentration model. Y axis shows change in phosphorus concentration vs. each variable, holding all other variables in the model at their mean. Variables listed in order of importance from left to right. Other variables described in Appendix A.

3.3.2 Top predictors for all models

The predictors that had the greatest average importance across all models included three measures of groundwater quality (section 3.3.4), three nutrient management practices (section 3.3.3), proportion of tailwater to irrigated acres, and water table depth (section 3.3.5). Groundwater nitrate concentration was found to be among the top predictors in 11 models. Importance of all predictors for each model are listed in Appendix B.

3.3.3 Nutrient management practices

We examined the nutrient management practices that were assessed to be the most important in our models – scheduling fertilizer application to match crop needs (IA2), use of urease and/or nitrification inhibitors (IA10), and no reported nutrient management practice (IA15). Scheduling fertilizer application to match crop requirements (IA2) was found to be the most important nutrient management practice in our models on average (Table 6). IA2 was included in seven load models, with four being positively correlated with water quality. IA2 was also found to be negatively correlated with summer total nitrogen load and annual phosphorus load. IA2 was not assessed to be an important predictor in any of the winter models. The use of urease and/or nitrogen inhibitors (IA10) was positively correlated with each of our first flush load models (Table 7).

Non-reporting of management practices (IA15) was included as a predictor in nine models. Increases in non-reporting were found to be positively correlated with water quality for all for analytes – three concentration and six load models (Table 8). Non-reporting was also a predictor across annual, summer, and winter temporal scales.

Measuring nitrogen and phosphorous content of organic amendments (IA8) was the most important nutrient management practice among just concentration models, occurring in 5 models. Like IA10, IA8 was also always positively correlated with nutrient concentrations.

Table 6. Scheduling fertilizer application to match crop requirements (IA2) was assessed to be the most important management practice for predicting loads.

Analyte – (Concentration/Load)	Temporal scale	%incMSE	Correlation
Ammonia – Load	First flush	7.58	Positive
Nitrate + Nitrite – Load	First flush	25.84	Positive
	Summer	45.42	
Total Nitrogen – Load	First flush	23.56	Positive
	Summer	24.32	Negative
Phosphorus – Load	Annual	12.71	Negative
	Summer	15.58	Positive

Table 7. The use of urease and/or nitrification inhibitors (IA10) are positively correlated with higher analyte loads during first flush.

Analyte – (Concentration/Load)	Temporal scale	%incMSE	Correlation
Ammonia – Load	First flush	14.50	Positive
Nitrate + Nitrite Load	First flush	20.30	Positive
Total Nitrogen – Load	First flush	21.34	Positive
Phosphorus – Load	First flush	10.53	Positive

Table 8. Non-reporting of management practices (IA15) was positively correlated with increases in ammonia and nitrate + nitrite concentrations and load of four all four analytes.

Analyte – (Concentration/Load)	Temporal scale	%incMSE	Correlation
Ammonia – Concentration	Annual	15.82	Positive
	Summer	12.11	
Ammonia – Load	Annual	14.07	Positive
	Winter	7.70	
Nitrate + Nitrite – Concentration	Summer	22.56	Positive
Nitrate + Nitrite – Load	Annual	11.78	Positive
	Winter	10.24	
Total Nitrogen – Load	Winter	8.75	Positive

3.3.4 Groundwater quality

Groundwater quality was assessed to be the most important predictor for across all models on average. Nitrate, nitrite, and nitrate + nitrite concentrations in municipal wells were used in 25 models, across all analytes and temporal scales. Groundwater nitrate concentration was included in 12 concentration models. Increases in nitrate concentration in groundwater was positively correlated with increases in total nitrogen concentrations across all temporal scales (Table 9).

Groundwater nitrate + nitrite concentration was used in nine concentration models. Increases in nitrate + nitrite concentration in groundwater were positively correlated with increases in total nitrogen concentrations across all temporal scales.

Groundwater nitrite concentration was a predictor in four models. Increases in nitrite concentration was positively correlated with summer ammonia load, first flush nitrate + nitrite and total nitrogen concentrations. However, there was a negative correlation with annual phosphorus concentration.

3.3.5 Water table depth and tailwater

Increasing water table depth was positively correlated with ammonia concentrations across all temporal scales. First flush phosphorus concentration was also positively correlated with water table depth (Table 10). Higher proportion of tailwater to irrigated acres was positively correlated with increased winter total nitrogen concentration and annual and summer phosphorus concentration.

3.3.6 Predictor interactions

Several of our models suggest interactions between predictors. The annual nitrate + nitrite concentration model ($R^2 = 0.714$) was found to increase with increases in groundwater nitrate + nitrite concentrations and the total irrigated acres that were reported to have measured nitrogen concentrations in irrigation water (IA3) (Figure 13). Summer total nitrogen load ($R^2 = 0.722$) was found to have an interaction between total irrigated acres and the total irrigated acres that implemented the practice of scheduling fertilizer applications to match crop requirements (IA2). In this model the management practice was shown to be effective in limiting total nitrogen load regardless of the total irrigated acres (Figure 14).

Table 9. Summary of models with groundwater quality as a predictor.

Metric	Analyte – (Concentration/Load)	Temporal scale	%incMSE	Correlation
Nitrate	Ammonia – Concentration	Annual	13.86	Positive
		First flush	6.33	
		Summer	6.33	
	Nitrate + Nitrite – Concentration	Annual	25.71	Positive
		Summer	23.90	
	Total Nitrogen – Concentration	Annual	50.54	Positive
		First flush	22.37	
		Summer	54.97	
		Winter	29.29	
	Phosphorus – Concentration	Annual	12.96	Positive
		Summer	33.32	
		Winter	77.99	
Nitrite	Ammonia – Load	Summer	23.05	Positive
	Nitrate + Nitrite – Concentration	First flush	23.94	Positive
	Total Nitrogen – Concentration	First flush	19.67	Positive
	Phosphorus – Load	Summer	54.11	Negative
Nitrate + Nitrite	Ammonia – Concentration	First flush	14.50	Positive
		Winter	7.57	
	Nitrate + Nitrite – Concentration	Annual	29.31	Positive
		Summer	27.25	
	Total Nitrogen – Concentration	Annual	58.55	Positive
		First flush	19.16	
		Summer	57.20	
		Winter	27.28	
	Phosphorus – Concentration	Annual	7.94	Positive

Table 10. Summary of models with water table depth and tailwater as predictors.

Metric	Analyte – (Concentration/Load)	Temporal scale	%incMSE	Correlation
Water table depth	Ammonia – Concentration	Annual	25.21	Positive
		First flush	15.57	
		Summer	6.31	
		Winter	10.87	
	Phosphorus – Concentration	First flush	15.89	Positive
Tailwater	Total nitrogen – Concentration	Winter	33.06	Positive
	Phosphorus – Concentration	Annual	13.16	Positive
		Summer	47.85	

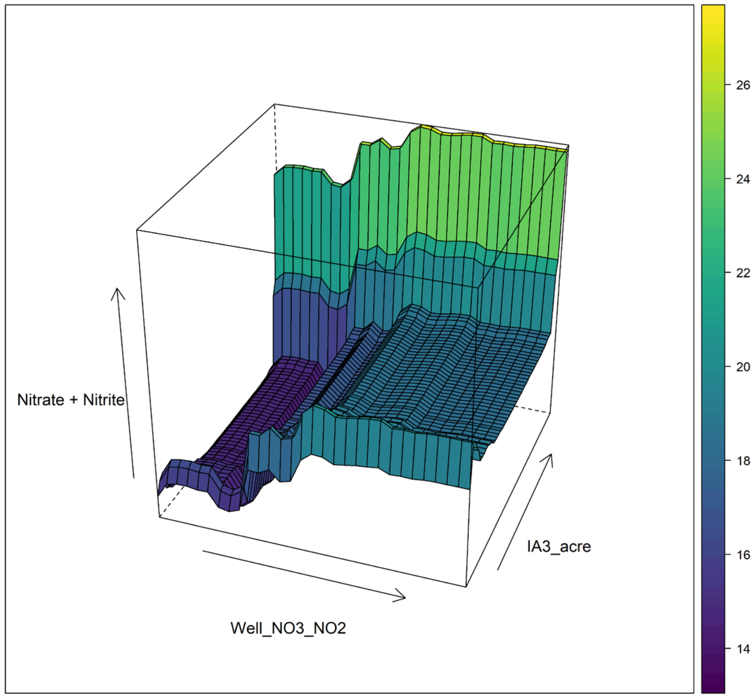

Figure 13. Partial dependence plot shows an interaction between groundwater NO^{3-} + NO^{2-} concentration and the management practice assessing N concentrations in irrigation water.

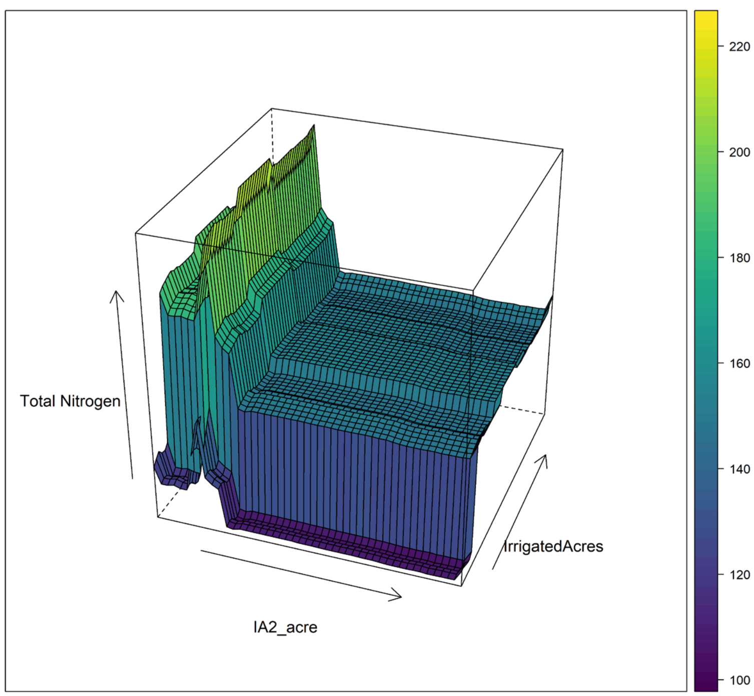

Figure 14. Partial dependence plot indicating the number of irrigated acres where fertilizer application was scheduled to match crop needs is effective in limiting total summer N load.

4 Discussion

Our models suggest that surface water quality is influenced by groundwater quality. This is a legacy effect of unregulated farming practices prior to the implementation of California's stringent water quality regulations. Nutrient enriched groundwater discharge to rivers (either through runoff of pumped water or natural discharge) appears to be one of the major drivers of current river nutrient concentrations. However, we do not have an understanding of why groundwater nitrate and nitrite concentrations effect phosphorus concentrations and load as some of our models suggest.

Correlations between management practices and nutrient concentrations in this analysis do not provide explicit explanations of causation, but do indicate which practices are most closely related to lower nutrient concentrations and loads. While most of the practices evaluated here (e.g., the timing of fertilizer application to match crop requirements or the use of urease or nitrification inhibitors) are expected to improve water quality in agricultural runoff, many of the practices had no effect or positive effects. Given that this is just a correlation, the actual cause of this relationship could be that areas with higher nitrogen loadings have greater adoption or reporting of these practices. But given the lack of a negative relationship, the practice not yet effective at reducing nutrient runoff. An example of this is the widely adopted practice of adjusting fertilizer application in response to nitrogen concentrations in irrigation water which was reported by over 80% of farms. The lack of effect could be due to uneven or sporadic use of the practice over time or across crop types within a given farm. Practices are reported annually by March, but the actual adoption dates are not reported or validated. Or, given that this analysis only used three years of data, the practice may need to be used for a longer period of time before improvements are seen. Other practices may be quite effective but are not currently applied at a scale large enough to effect water quality at watershed scales, like the practice of using treatment systems to remove nutrients from irrigation runoff or drainage water.

4.1 Water quality and drainage

The poorest surface water quality within the study area was in the lower Salinas watershed. The lower Salinas watershed also hosts the greatest concentration of irrigated acres in the Central Coast. These waterways generally transport agricultural runoff from the fields with tile drain systems.

While our models did not investigate the effect of individual drainage system types, increase in tailwater (proportion of acreage using ditch, tile or ditch and tile drainage) was positively correlated with winter total nitrogen concentrations and annual and summer phosphorus and nitrate concentrations. Installation of tile drains may reduce surface runoff by providing a storage capacity in the soil above the tiles. Tile drains have been noted to be effective in reducing runoff associated with sediment and phosphorus, but additional mitigation strategies maybe needed for soluble pollutants such as nitrates (Christianson and Harmel 2015). Tile drains have the advantage of diverting nutrient enriched waters from groundwater, preventing the current problem with nitrogen enriched groundwater from being exacerbated. However, nutrient loads are then deposited into surface waters instead.

Water from tile drains has the advantage of placing much of the nutrient load in one central location where it can be treated instead of being dispersed across an entire farm. Research by Brauer et al. (2015) in the San Joaquin River, showed that wetlands have an estimated 75 percent efficiency in removing nitrates from tailwaters. Bioreactors are an additional treatment method that removes nitrates by promoting denitrification of agricultural tailwaters. However, the Pajaro and Salinas watersheds have been largely denuded of wetlands and the reported us of bioreactors is very limited. There was no reported use of bioreactors in the Pajaro and upper Salinas watersheds. In 2018, only 48 ranch operations reported using a bioreactor across the 2700 farming operations.

4.2 Limitations

Our analysis was largely limited by the quality and availability of data. Our annual and first flush load models were not as robust as the concentration models. This may be the result of having limited flow data to calculate load for each analyte. We did not use crop types as a predictor, but certain crops may be associated with increased fertilizer and water use. While crop types were available in the ILRP dataset, it would be difficult to parse out how long each crop type was cultivated. This makes attributing crop type to individual farms problematic. We also did not account for distances between individual ranches and CMP monitoring sites. Ranches that were located closer to rivers and to the CMP sites may have more influence on water quality at the site, whereas waters from further away would be subject to denitrification during transport.

Applied nitrogen was expected to be an important predictor in some models. However, in

2018, there were 60–100% of ranches that failed to report or were tier 1 ranches and not required to report the amount of total nitrogen applied to the fields. This minimal data did not support a strong enough correlation with the analytes and was not a predictor in any of the models. As this reporting becomes better established, this factor may be a better predictor of nutrient levels in surface waters and help us understand how much current application rates influence water quality.

Another limitation of this study is the fact that we assessed the effectiveness of farming practices by comparing them to temporally coincident nutrient concentrations and loads. A better comparison may be between reductions in load or trends in concentrations over time with trends in management practices. However, this would require more than 3 years of data currently available but could be undertaken in the future.

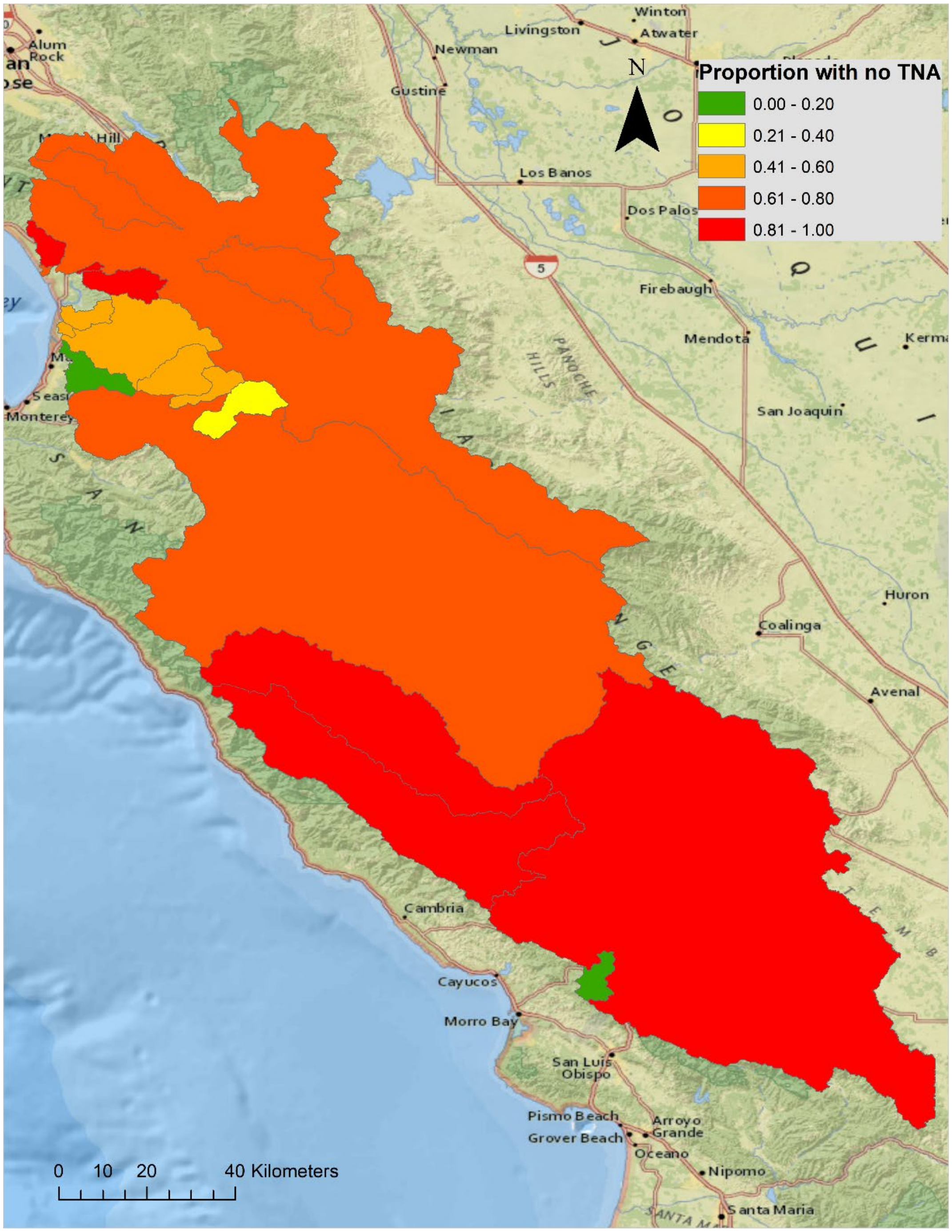

Figure 15. Map of the proportion of 2018 ranches with no total nitrogen applied (TNA) data.

5 Conclusion

We found that surface water quality was correlated with groundwater quality and some management practices. The lack of reporting was positively correlated with increased nutrient concentrations. Scheduling fertilizer applications and the use of urease and/or nitrogen inhibitors were also positively correlated with increased loading. These two management practices should reduce concentrations and loading, so the correlations we observed may not be causal, but rather the result of high adoption rates of these practices in areas with high nutrient loadings. Other management practices, including the amount of nitrogen applied to fields, showed little to no correlation with water quality. However, these practices may not be widely enough implemented or reported to produce any measurable effects in our models.

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Appendix A

Table 11. Data dictionary

Abbreviation	Definition	Source
IA1-IA15	Total irrigated acres within water shed using A# nutrient management practice (see table 2)	
CropAcre	Total Crop Acres	
DitchDrainAcres	A). Acres Discharging to ONLY Ditches or Any Other Type of Surface Discharge / IrrigatedAcres	
TileDrainAcres	B). Acres Discharging to ONLY Tile Drains or Any Other Type of Sub-Surface Drainage System / IrrigatedAcres	
DitchTileDrainAcres	C). Acres Discharging to BOTH Ditches and Tile Drains / IrrigatedAcres	
PondDrainAcres	D). Acres Discharging to Pond(s) / IrrigatedAcres	
TailwaterAcres	Total Tailwater Acres (Equals A + B + C and cannot exceed Total Irrigated Acres) / IrrigatedAcres	
IrrigatedAcres	Total Irrigated Acres	
N_app	Nitrogen applied in fertilizers and other materials (lbs/crop-acre)	ILRP
N_soil	Total nitrogen present in soil (lbs/crop-acre)	
NonSurfaceIrrigatin_only_pct	Percent of irrigated acres with nonsurface irrigation only	
Surface_NonSurface_irrigation_pct	Percent of irrigated acres with a combination of surface and nonsurface irrigation (does not include surface only or nonsurface only)	
SurfaceIrrigation_only_pct	Percent of irrigated acres with surface irrigation only	
Tier0	Count of unknown Tier ranches in WS	
Tier1	Count of Tier 1 ranches in WS	
Tier2	Count of Tier 2 ranches in WS	
Tier3	Count of Tier 3 ranches in WS	
BulkDensity	Mean bulk density in WS	
Clay	Mean clay content of soils in WS	
Om	Mean organic matter content in WS	
Perm	Mean permeability in WS	USGS
RckDep	Mean depth to bedrock of soils in WS	
Sand	Mean sand content of soils in WS	
WtDep	Mean seasonal water table depth of soils WS	
Well_NO2	Mean NO2 in well	GAMA well data interpolated into a raster
Well_NO3	Mean NO3 in well	
Well_NO3_NO2	Mean NO3 and in NO2 in well	
Precip	Total precip from PRISM monthly totals	PRISM Climate Group
Channel_slope	Channel slope - rise over run (250m upstream from CMP station)	
WS_acres	WS area (acres)	Derived from ArcMap
WS_slope	Mean WS slope	

Appendix B

Table 12a. Summary of concentration models with the %incMSE for each of their predictors. Only predictors used in the models are included. Symbol in parenthesis indicates positive or negative correlation with each analyte.

	Nitrate + Nitrite				Total Nitrogen			
Metric	Annual	First Flush	Summer	Winter	Annual	First Flush	Summer	Winter
WS_acres	24.397 (+)	29.516 (+)	20.155 (+)					30.063 (+)
Well_NO2		23.942 (+)				19.670 (+)		
Well_NO3	25.708 (+)		23.896 (+)		50.537 (+)	22.367 (+)	54.975 (+)	29.294 (+)
Well_NO3_NO2	29.305 (+)		27.253 (+)		58.550 (+)	19.161 (+)	57.197 (+)	27.279 (+)
IA3_acre	20.725 (+)		22.383 (+)					
IA5_acre	18.554 (+)							
IA7_acre	17.373 (+)							
IA8_acre	20.849 (+)		23.177 (+)	62.418 (+)				29.169 (+)
IA9_acre	19.312 (+)							
IA14_acre			18.204 (+)					
IA15_acre			22.558 (+)					
Tier1			18.578 (+)					
TailwaterAcres_pct								33.062 (+)
TileDrainAcres_pct	28.575 (+)		21.057 (+)					28.601 (+)
DitchTileDrainAcres_pct	23.132 (+)	31.553 (+)	21.206 (+)			21.093 (+)		
NonSurfaceIrrigation_only_pct						19.929 (–)		
WtDep								
RckDep			18.385 (+)		53.211 (+)		50.368 (+)	
Clay								
BulkDensity								
Precip						14.258 (+)		

Table 12b. Summary of concentration models with the %incMSE for each of their predictors. Only predictors used in the models are included. Symbol in parenthesis indicates positive or negative correlation with each analyte.

	Ammonia				Phosphorus			
Metric	Annual	First Flush	Summer	Winter	Annual	First Flush	Summer	Winter
WS_acres								
Well_NO2								
Well_NO3	13.858 (+)	6.335 (+)	6.975 ()		12.964 (+)		33.319 (+)	77.993 (+)
Well_NO3_NO2		14.497 (+)		7.574 (+)	7.941 (+)			
IA3_acre								
IA5_acre								
IA7_acre								
IA8_acre				11.092 (+)				
IA9_acre								
IA14_acre								
IA15_acre	15.821 (+)		12.113 (+)					
Tier1	14.531 (–)	12.192 (–)	8.027 (–)					
TailwaterAcres_pct					13.165 (+)		47.846 (+)	
TileDrainAcres_pct								
DitchTileDrainAcres_pct				9.671 (+)				
NonSurfaceIrrigation_only_pct								
WtDep	25.207 (+)	15.575 (+)	6.310 (+)	10.868 (+)		15.888 (+)		
RckDep								
Clay					9.459 (–)			
BulkDensity				3.928 (+)				
Precip				12.870 (–)				

Table 13a. Summary of load models with the %incMSE for each of their predictors. Only predictors used in the models are included. Symbol in parenthesis indicates positive or negative correlation with each analyte.

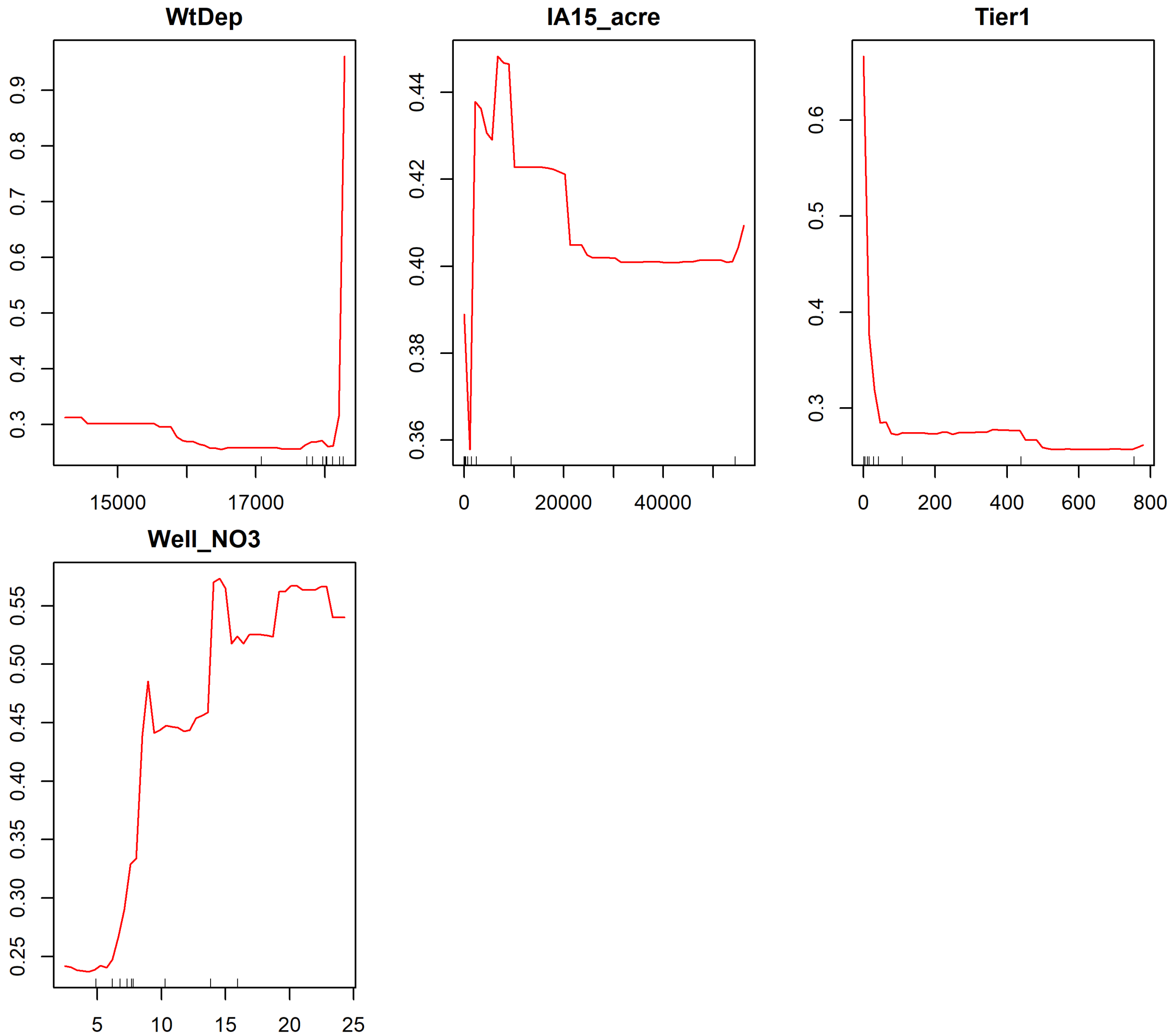
	Ammonia				Nitrate + Nitrite			
Metric	Annual	First Flush	Summer	Winter	Annual	First Flush	Summer	Winter
Well_NO2			23.047 (–)					
IA1_acre								9.782 (+)
IA2_acre		7.582 (+)				25.837 (+)	45.420 (+)	
IA3_acre		14.966 (+)						
IA4_acre								
IA5_acre								
IA6_acre								
IA7_acre							39.931 (+)	
IA8_acre								
IA9_acre								
IA10_acre		14.500 (+)				20.303 (+)		
IA11_acre	11.420 (+)			6.361 (+)	7.607 (+)			7.980 (+)
IA12_acre		7.921 (+)						
IA13_acre								
IA14_acre	15.295 (+)				11.302 (+)			
IA15_acre	14.071 (+)			7.698 (+)	11.781 (+)			10.241 (+)
Tier1								
Tier2								
Tier3								
IrrigatedAcres								9.359 (+)
SurfaceIrrigation_only_pct								
Surface_NonSurface_irrigation_pct	12.971 (–)							
NonSurfaceIrrigation_only_pct	11.925 (+)			7.222 (+)	11.150 (+)			
Crop_acres		11.617 (+)	23.358 (+)					
Channel_slope								
Precip	16.239 (+)	11.866 (+)		12.592 (+)	11.496 (+)			14.021

Table 13b. Summary of load models with the %incMSE for each of their predictors. Only predictors used in the models are included. Symbol in parenthesis indicates positive or negative correlation with each analyte.

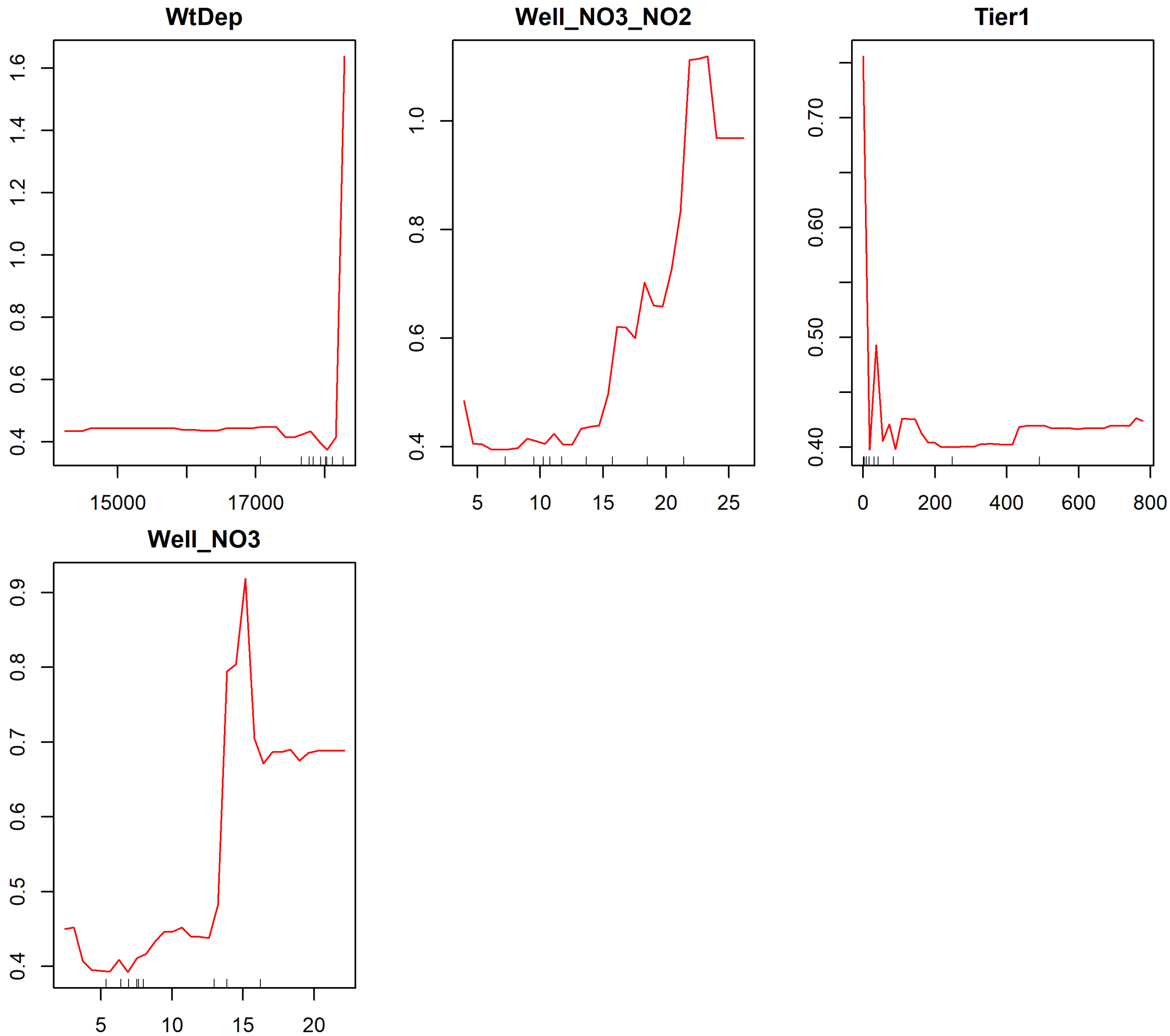
	Total Nitrogen				Phosphorus			
Metric	Annual	First Flush	Summer	Winter	Annual	First Flush	Summer	Winter
							54.108 (–)	
Well_NO2								
IA1_acre			13.084 (+)			9.08 (+)		7.271 (+)
IA2_acre		23.558 (+)	24.322 (–)		12.708 (–)	15.578 (+)		
IA3_acre			12.893 (+)			7.308 (+)		
IA4_acre						6.421 (+)		
IA5_acre			14.688 (+)			7.992 (+)		
IA6_acre			12.653 (+)			6.019 (+)		
IA7_acre						7.857 (+)		
IA8_acre						8.266 (+)		
IA9_acre			12.987 (+)			10.751 (+)		
IA10_acre		21.337 (+)				10.528 (+)		
IA11_acre	10.190 (+)			5.739 (+)	12.501 (+)			7.538 (+)
IA12_acre								
IA13_acre								
IA14_acre	11.520 (+)				15.040 (+)			
IA15_acre				8.754 (+)				8.704 (+)
Tier1						6.324 (–/+)		
Tier2			25.010 (+)			4.152 (+)		
Tier3								
IrrigatedAcres			14.188 (+)	7.083 (+)		7.733 (–)		9.034 (+)
SurfaceIrrigation_only_pct						8.146 (+)		
Surface_NonSurface_irrigation_pct	12.521 (–)							
NonSurfaceIrrigation_only_pct	11.910 (+)							
Crop_acres			14.528 (–)			10.400 (+)		
Channel_slope						7.376 (+)		
Precip	13.491 (+)			9.202 (+)	14.112 (+)	6.600 (+)		8.651 (+)

Appendix C

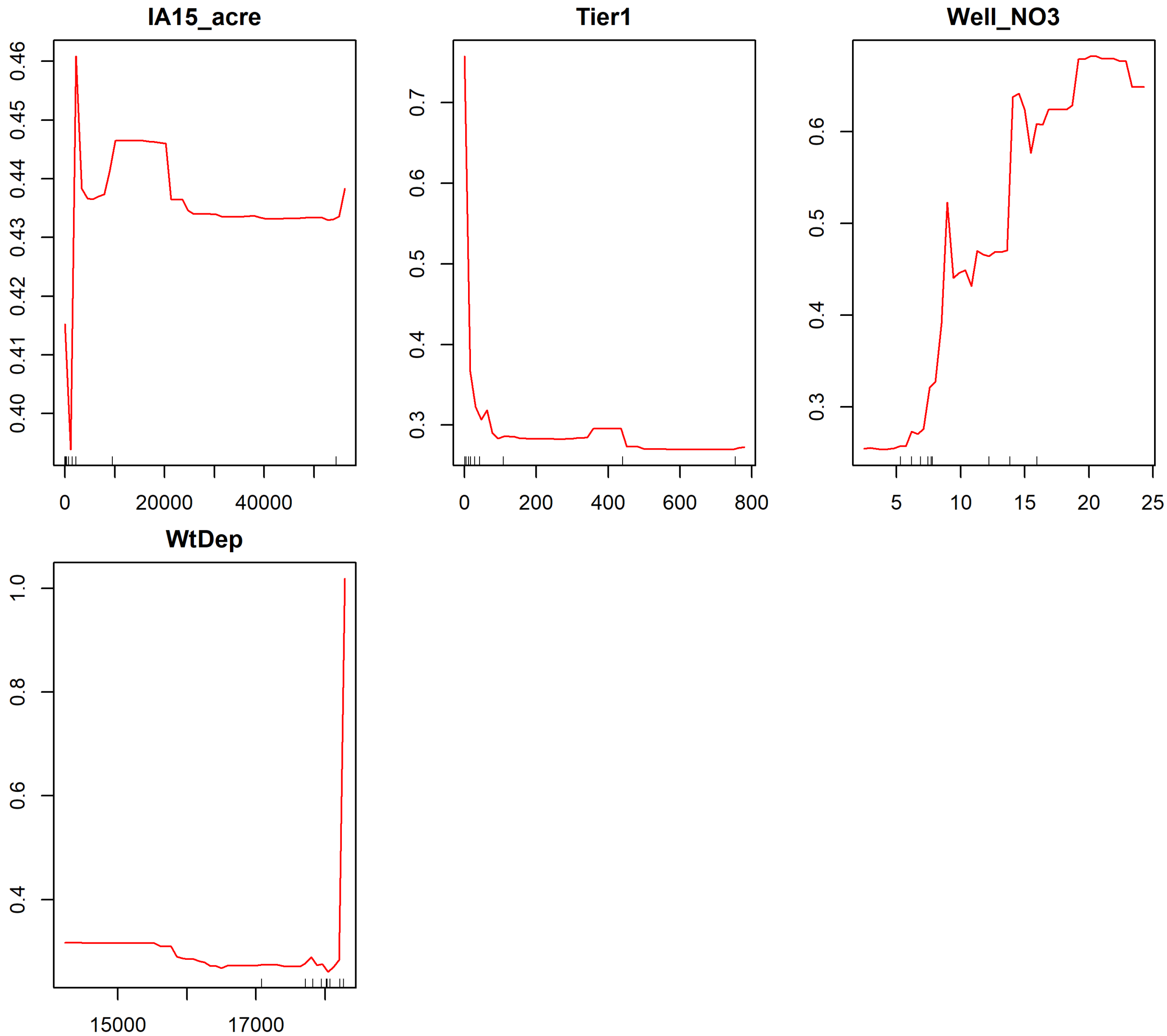
Ammonia as N total – Annual Concentration



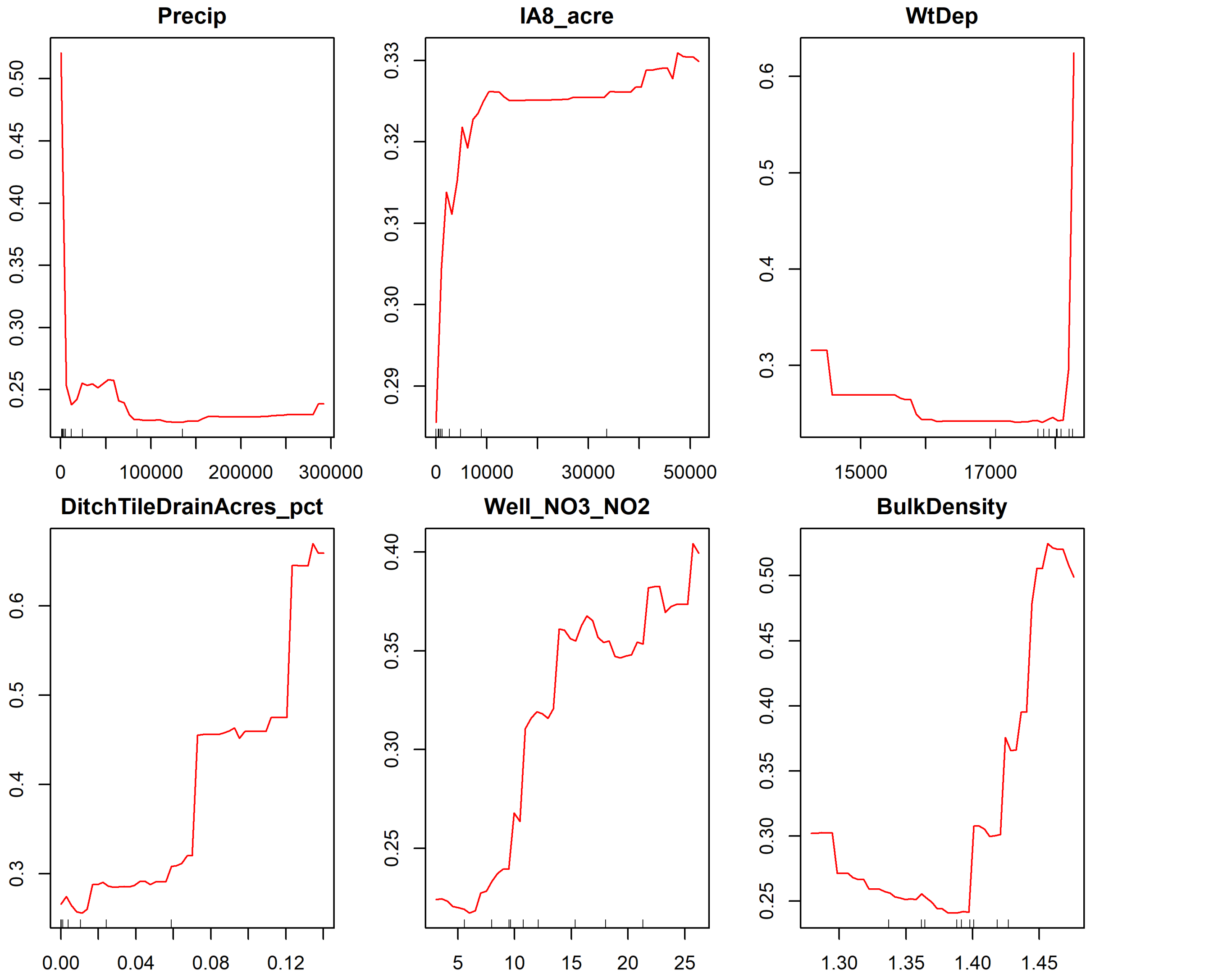
Ammonia as N total – First Flush Concentration



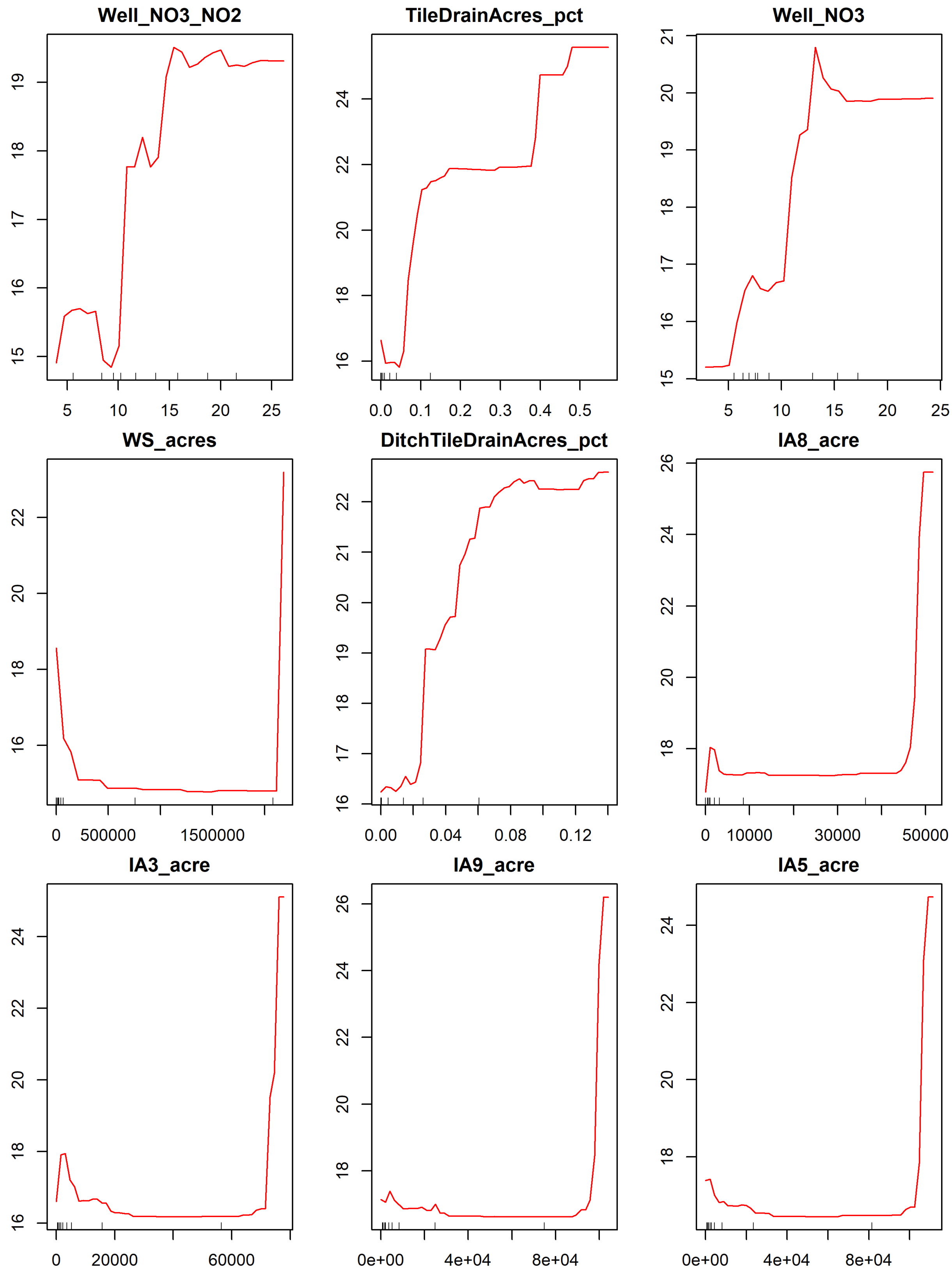
Ammonia as N total – Summer Concentration



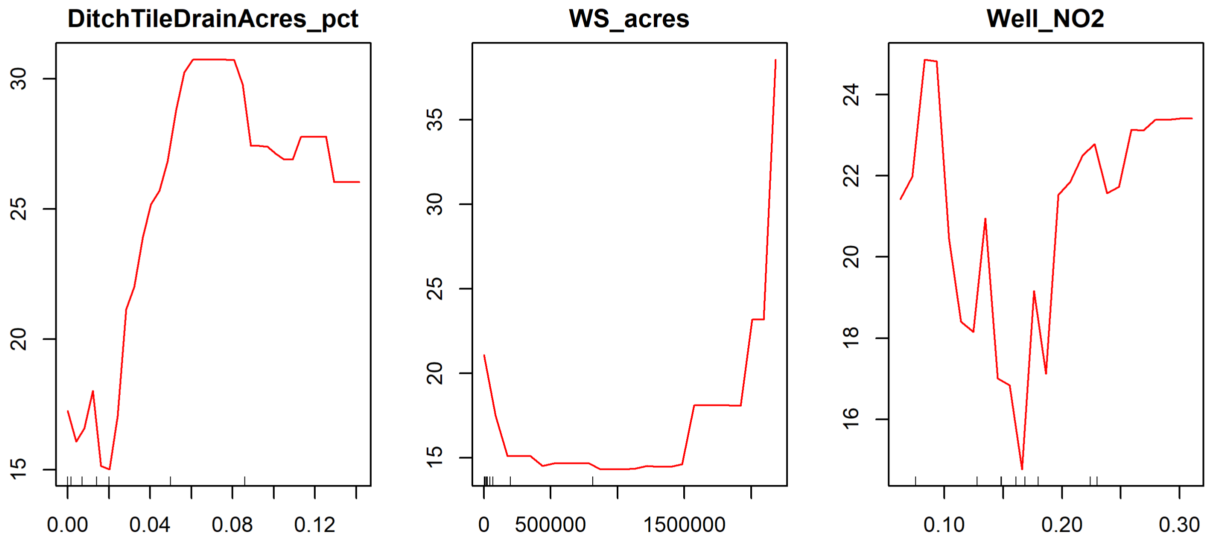
Ammonia as N total – Winter Concentration



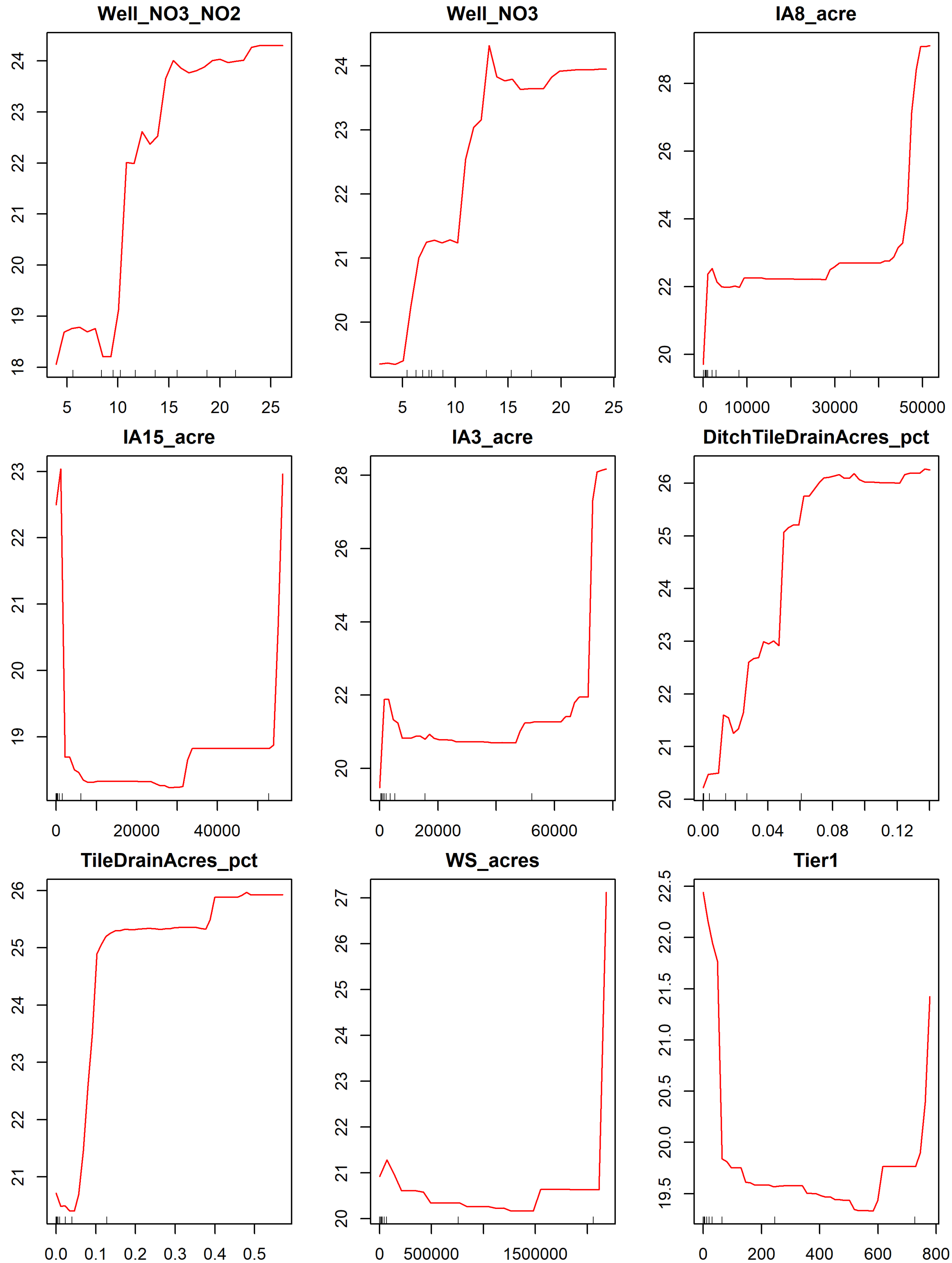
Nitrate + Nitrite as N total – Annual Concentration



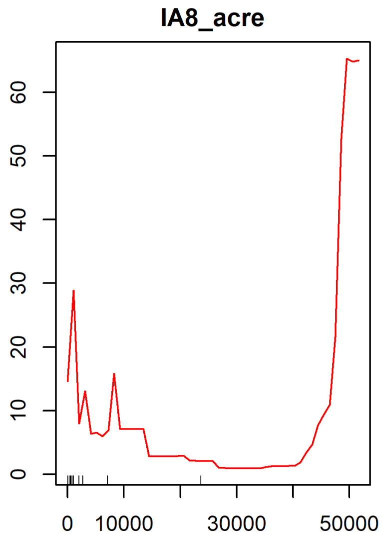
Nitrate + Nitrite as N total – First Flush Concentration



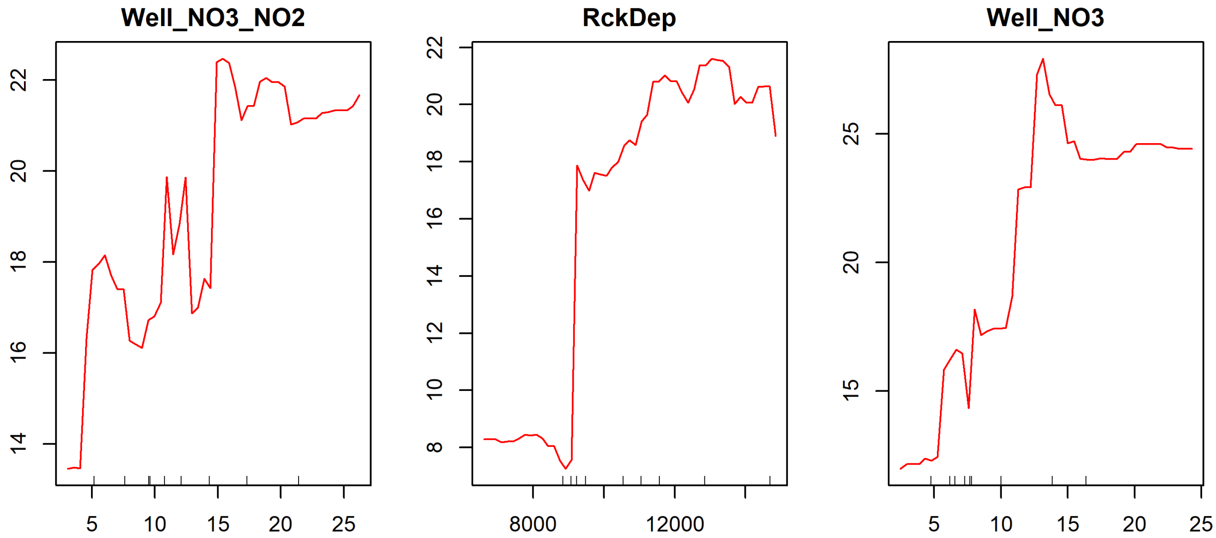
Nitrate + Nitrite as N total – Summer Concentration



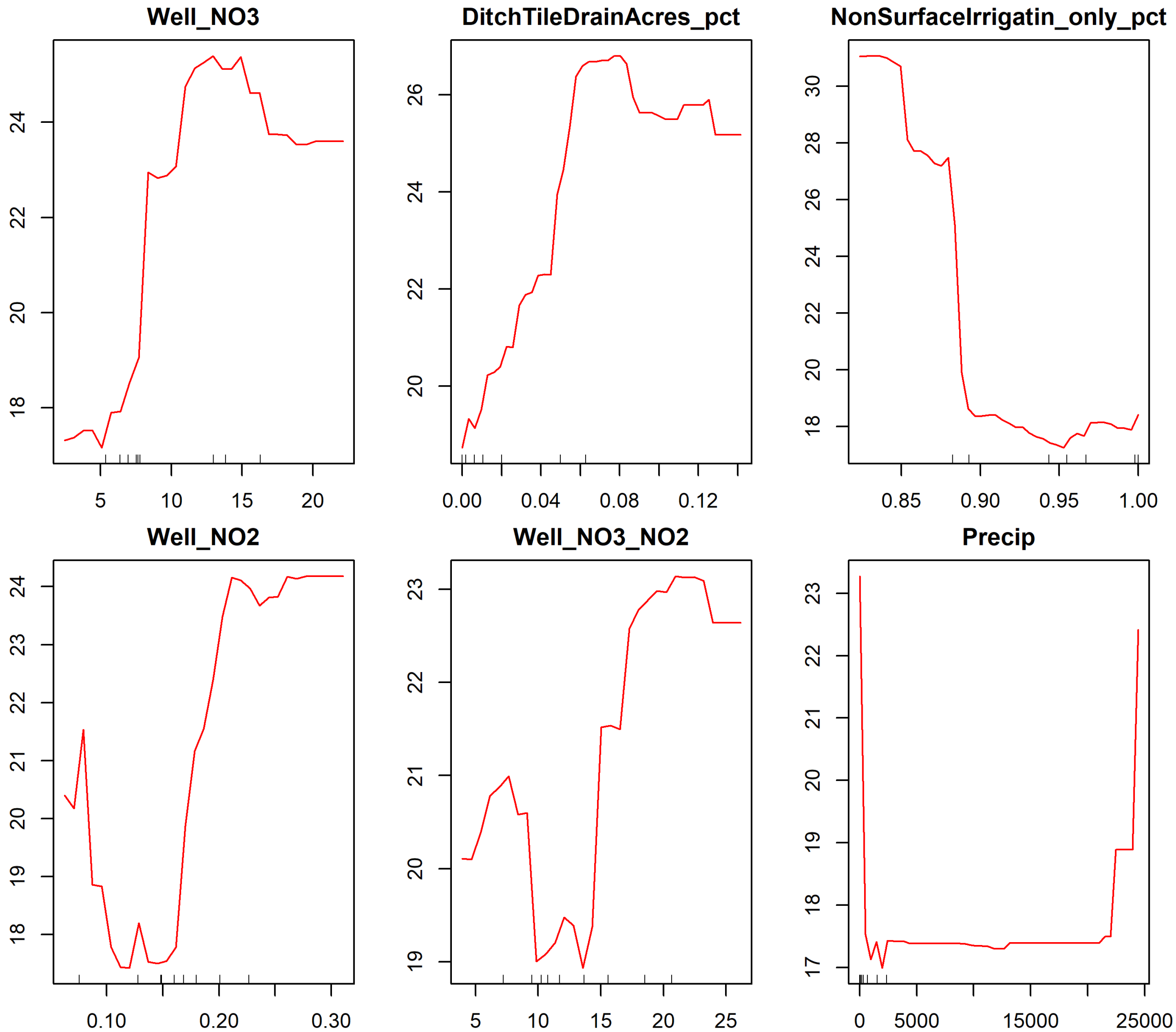
Nitrate + Nitrite as N total - Winter Concentration



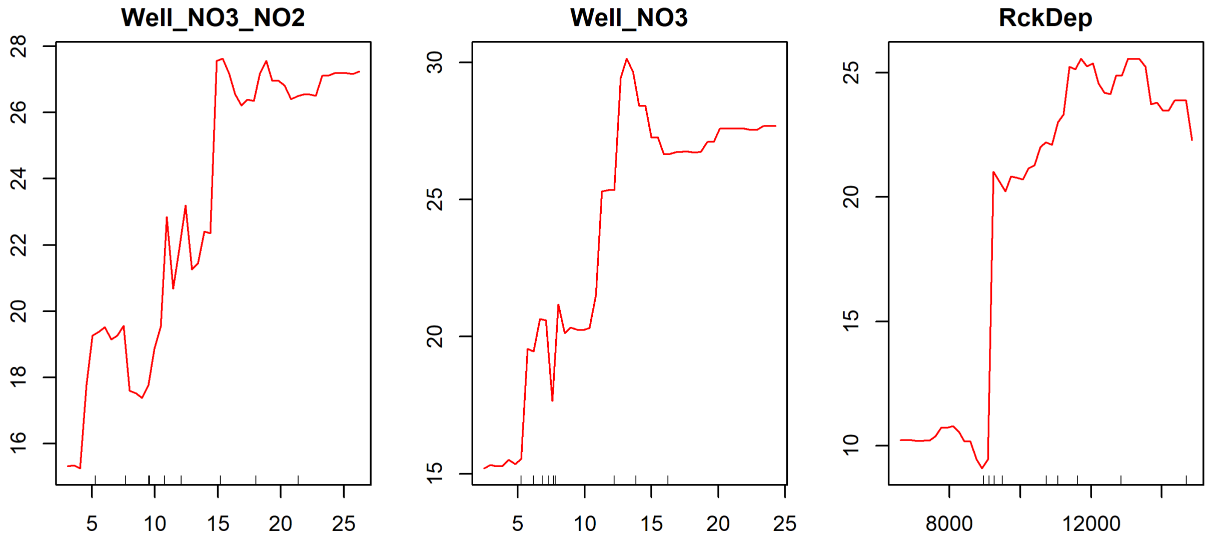
Total Nitrogen as N total – Annual Concentration



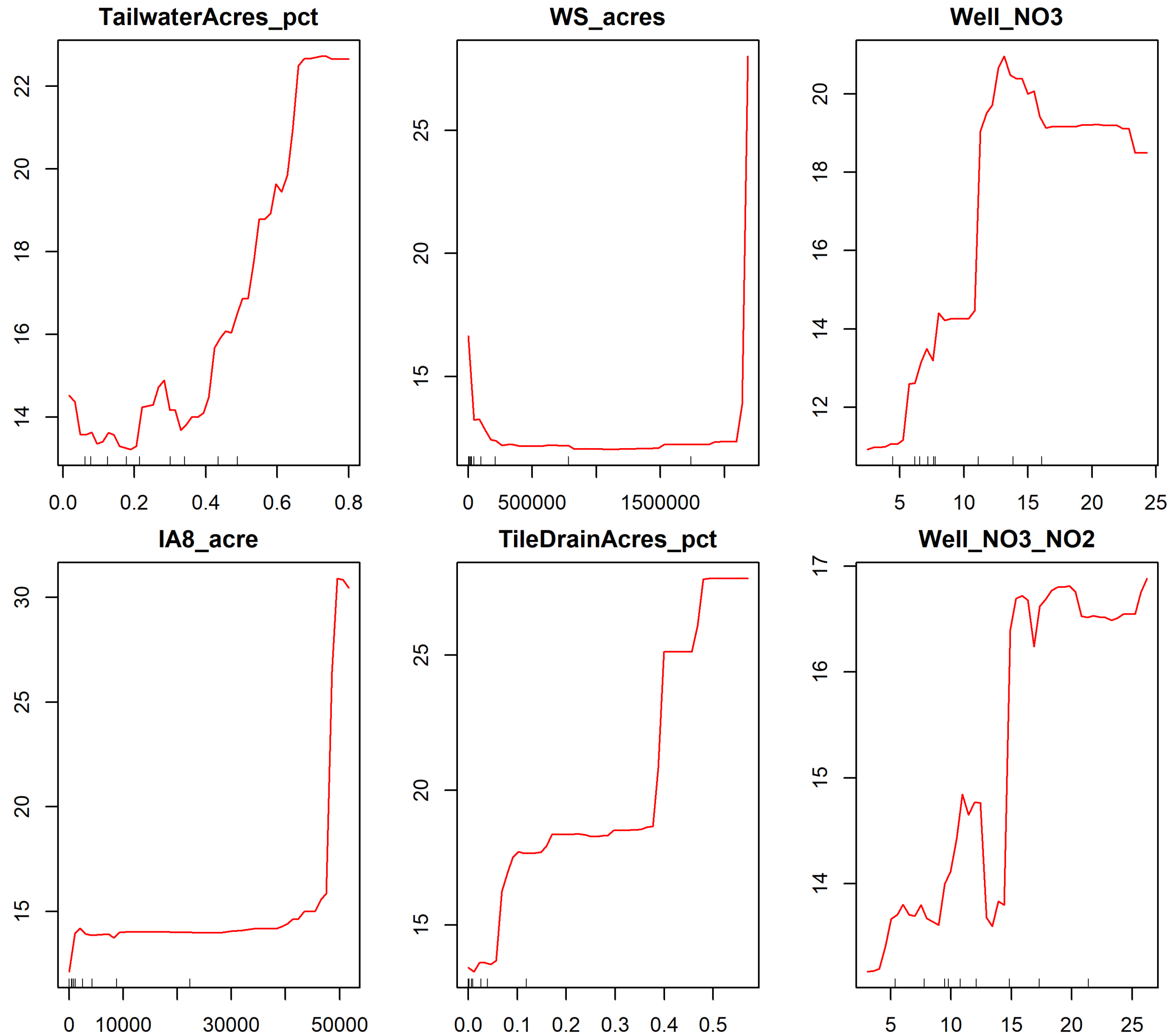
Total Nitrogen as N total – First Flush Concentration



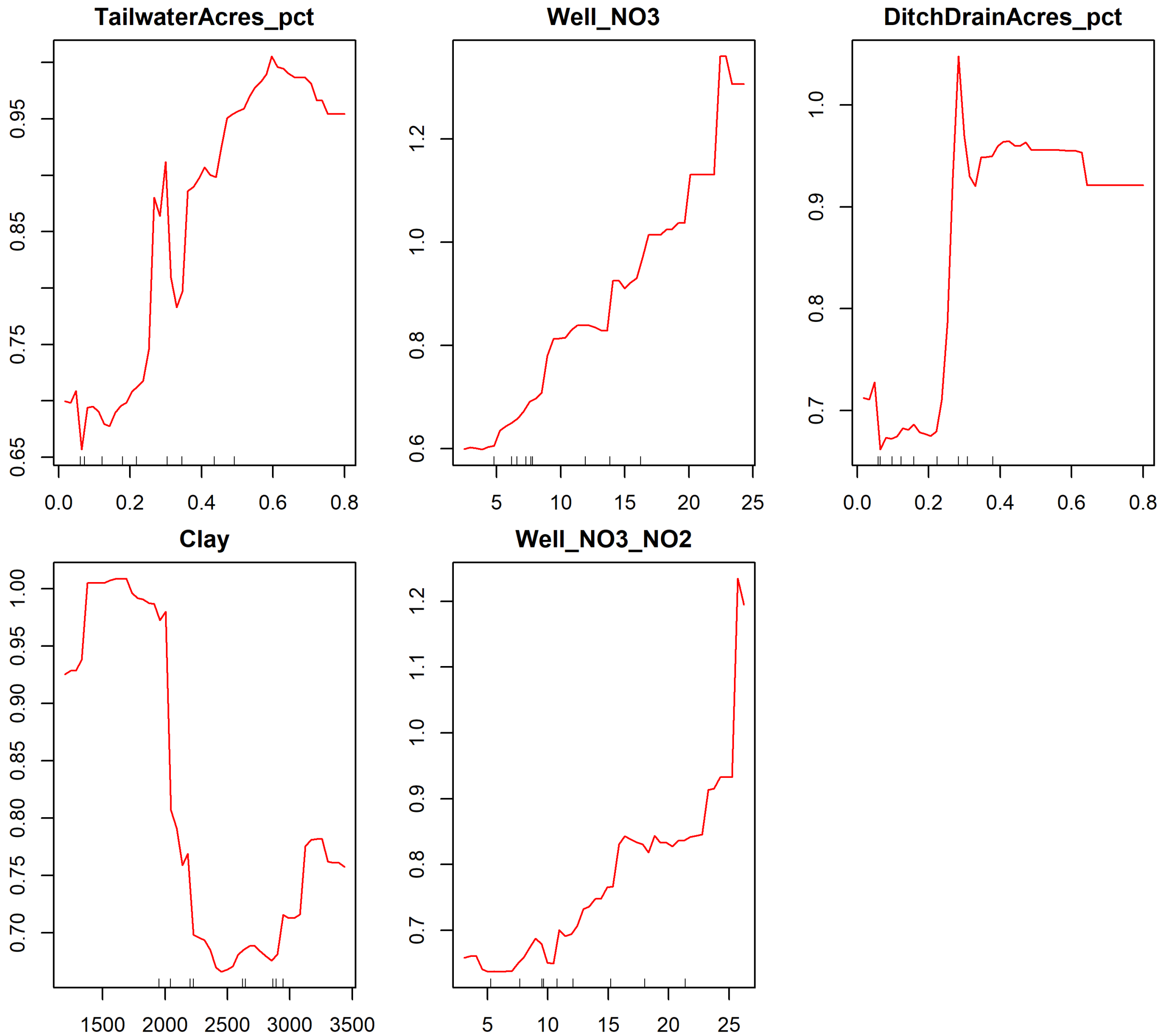
Total Nitrogen as N total – Summer Concentration



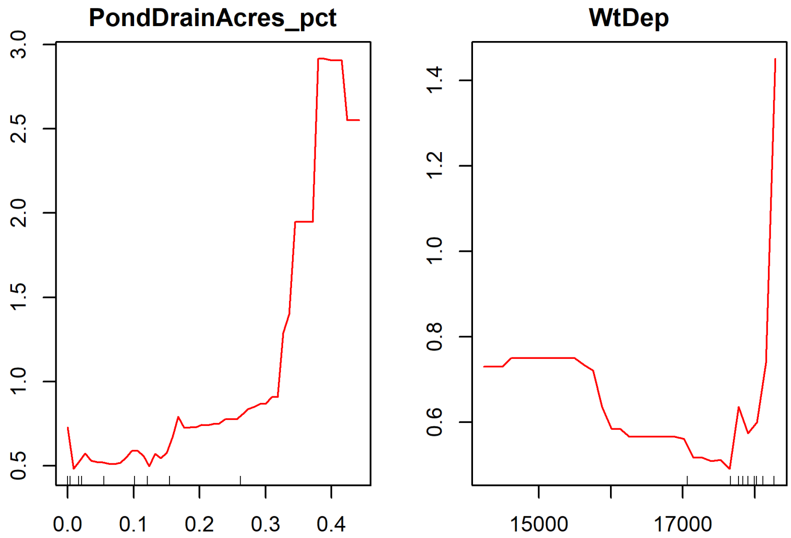
Total Nitrogen as N total – Winter Concentration



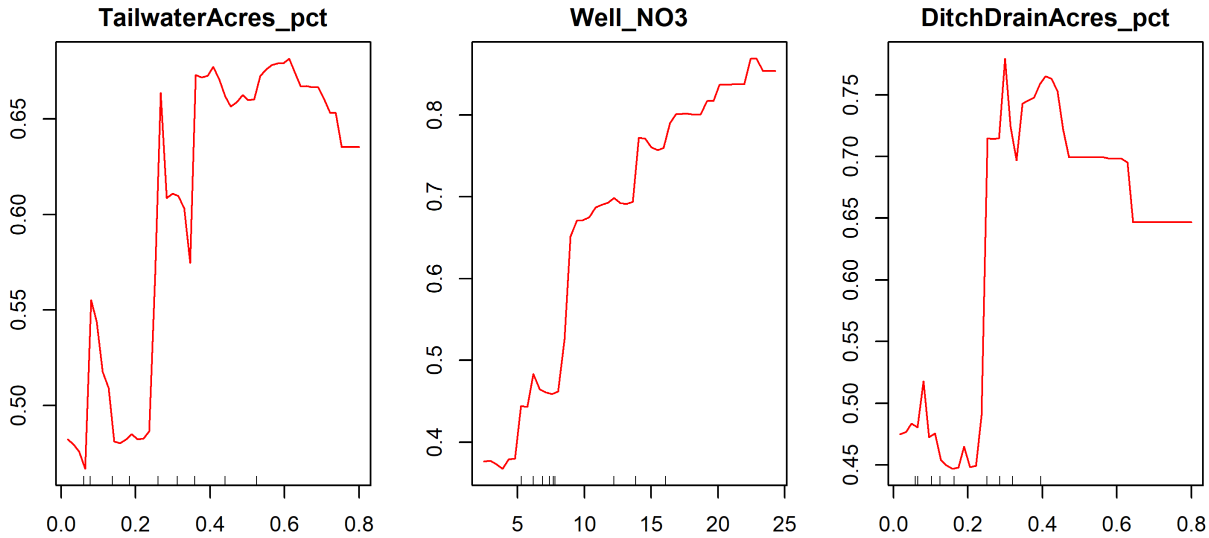
Phosphorus as P total – Annual Concentration



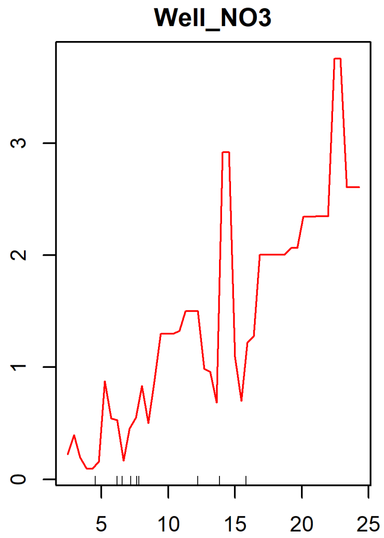
Phosphorus as P total – First Flush Concentration



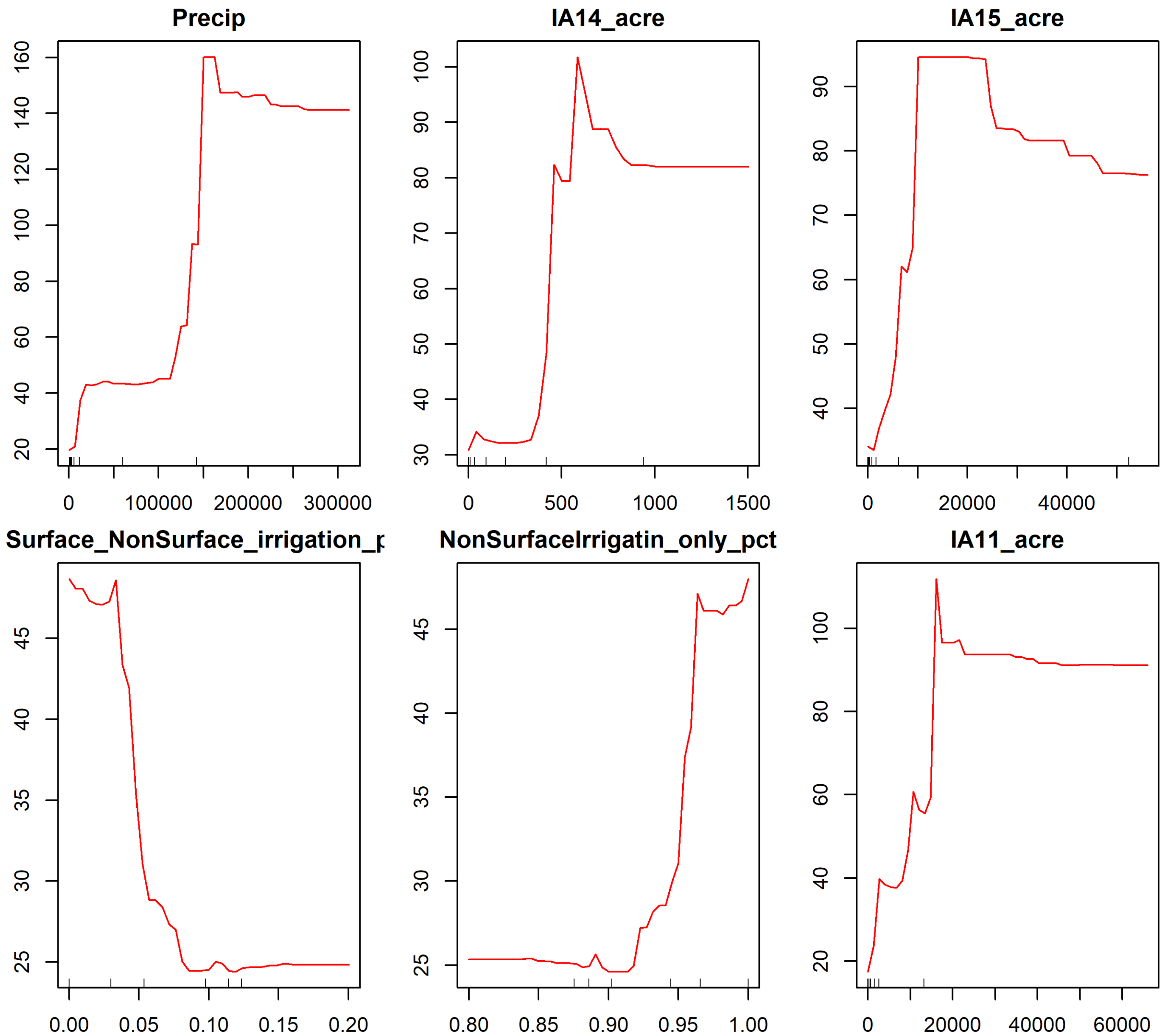
Phosphorus as P total – Summer Concentration



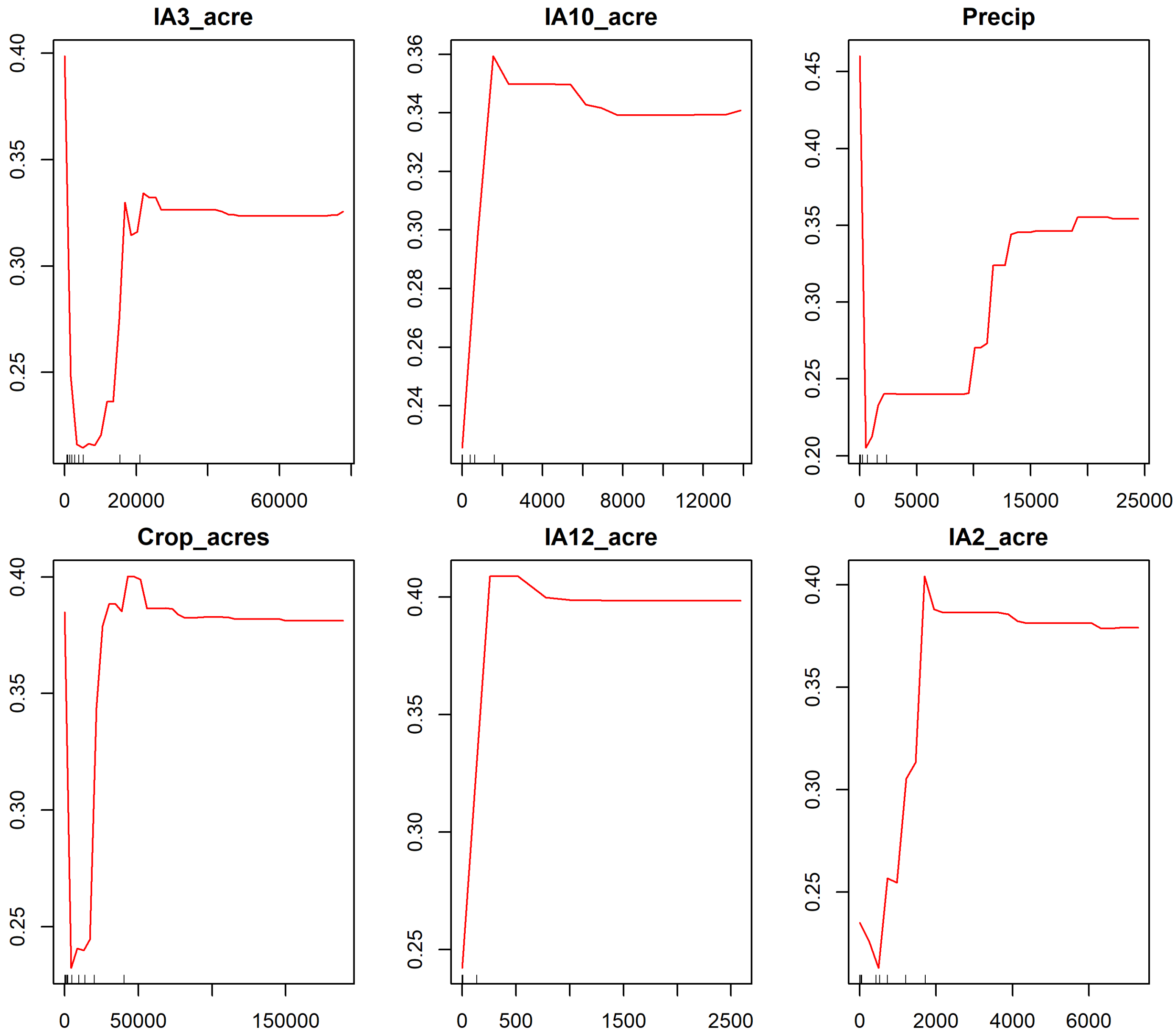
Phosphorus as P total – Winter Concentration



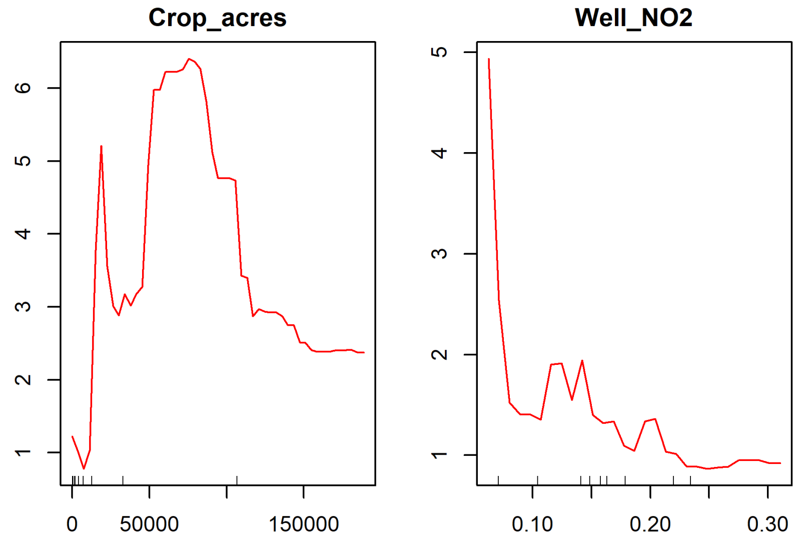
Ammonia as N total - Annual Load



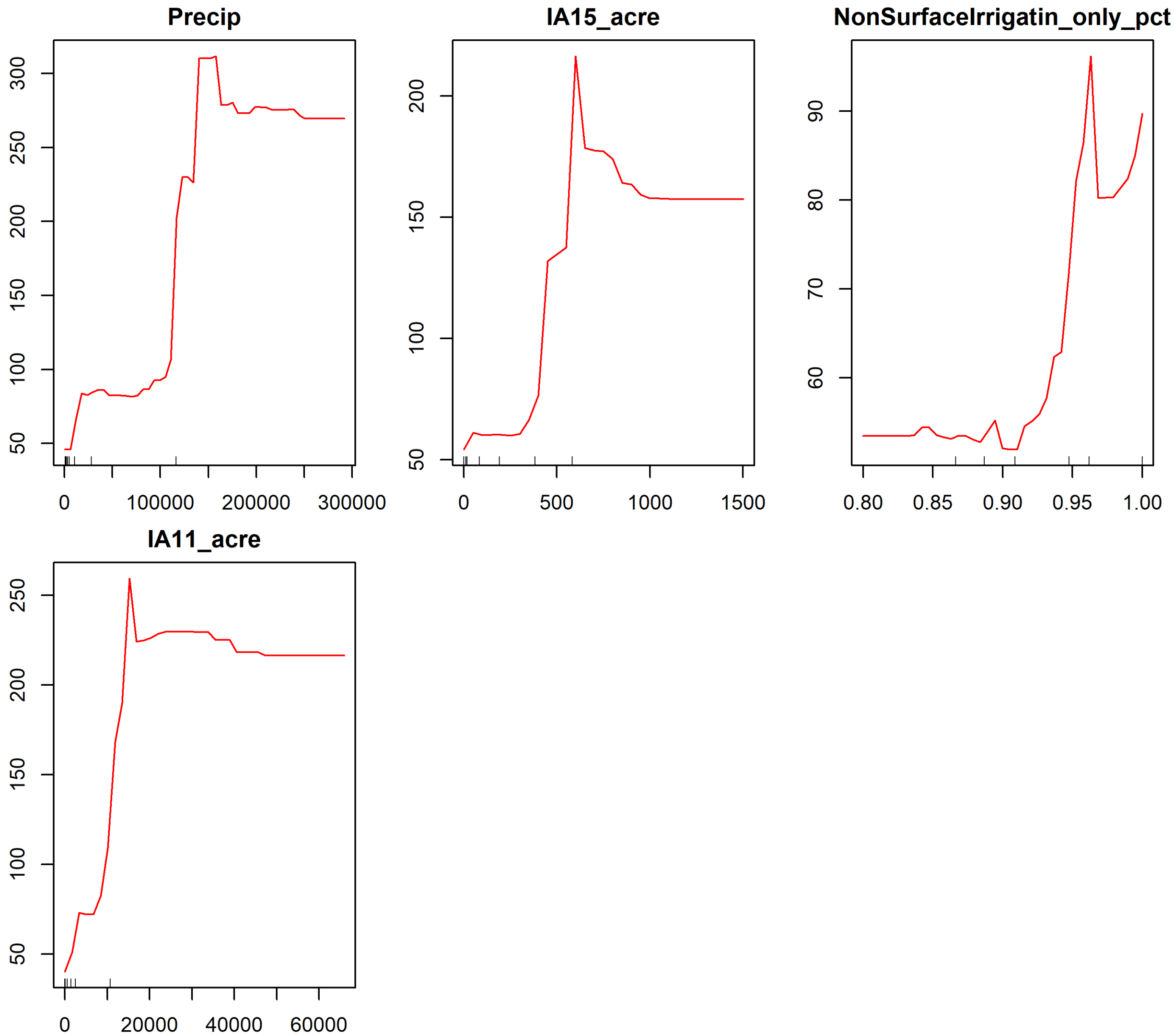
Ammonia as N total – First Flush Load



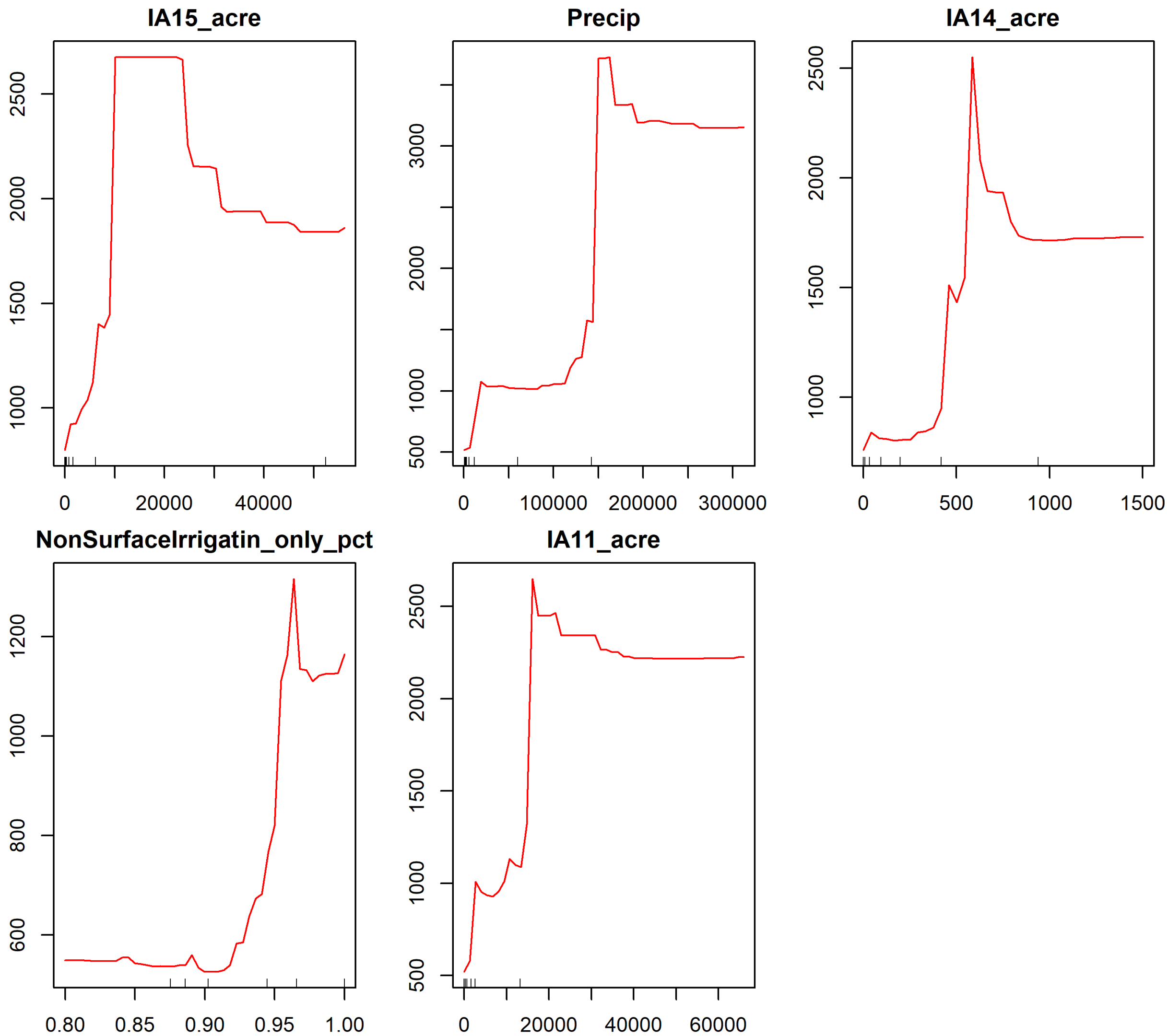
Ammonia as N total – Summer Load



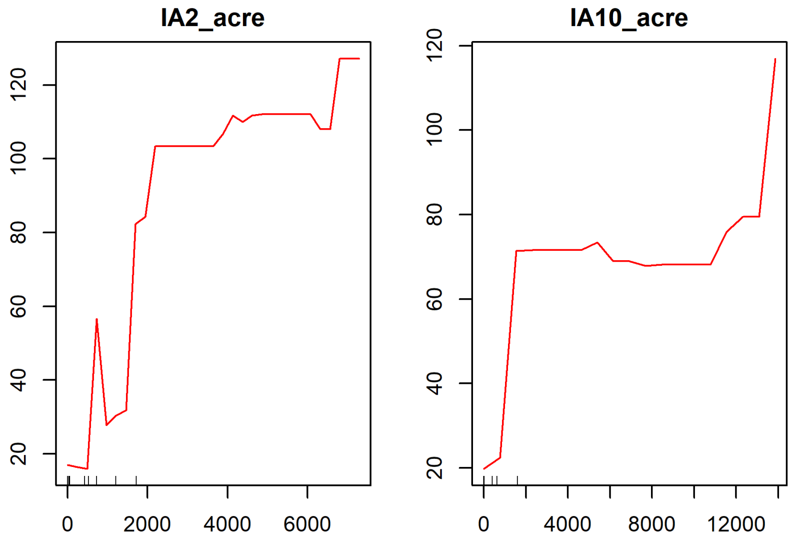
Ammonia as N total – Winter Load



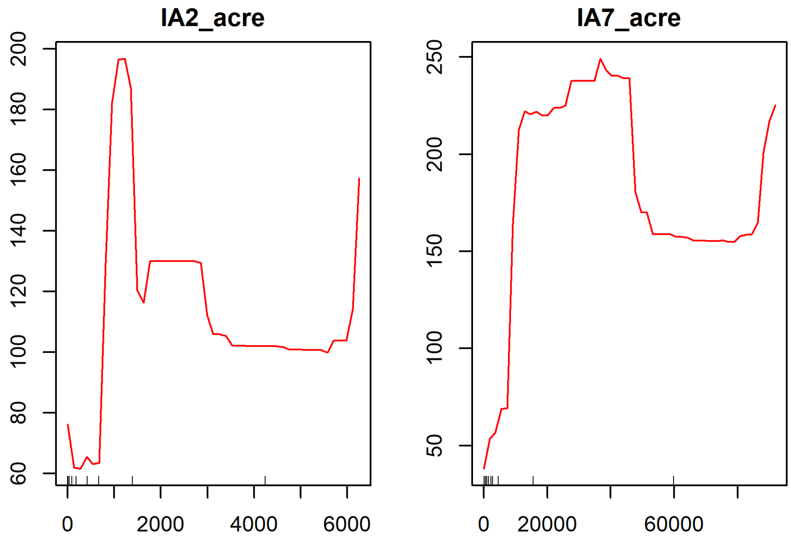
Nitrate + Nitrite as N total - Annual Load



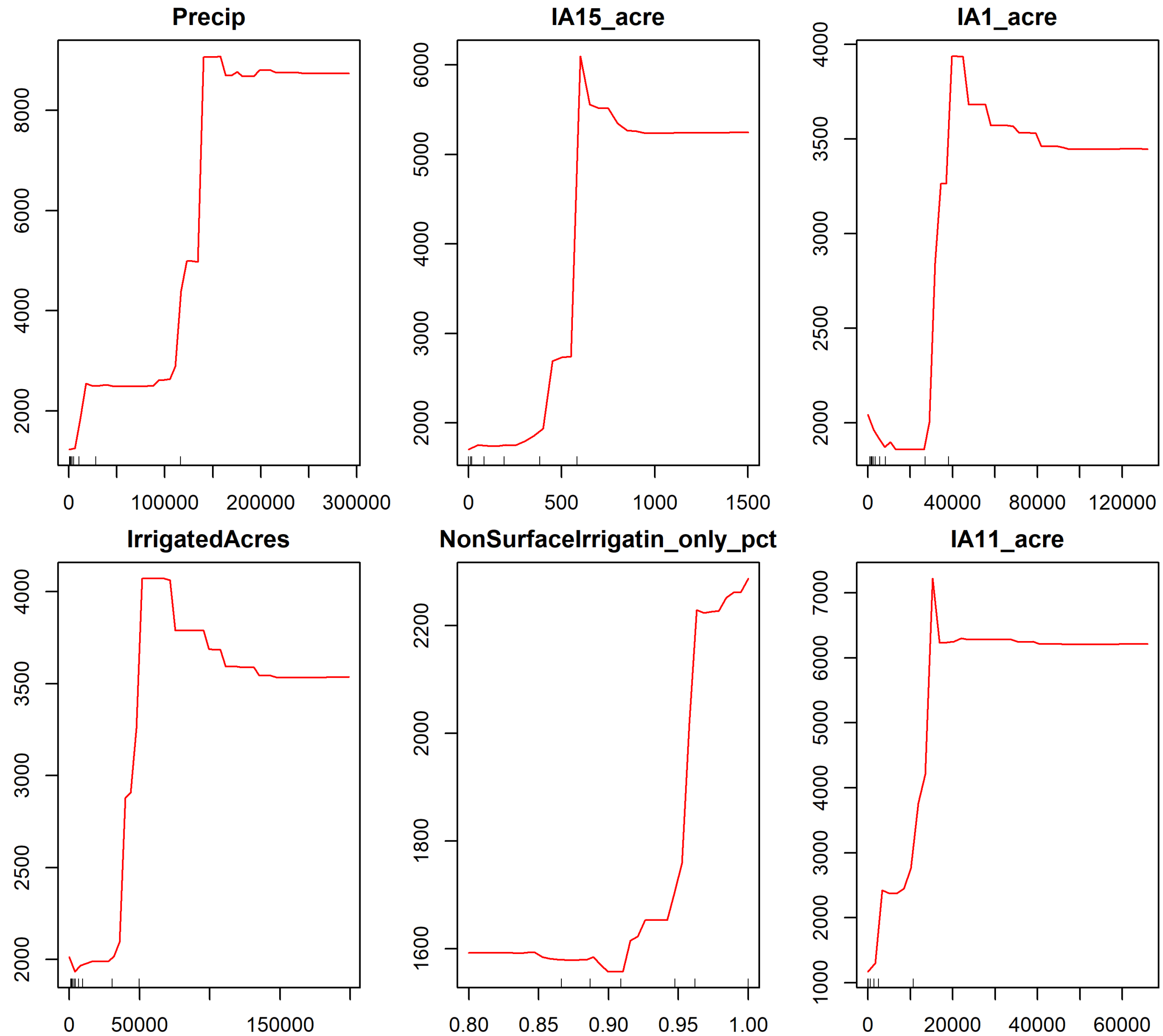
Nitrate + Nitrite as N total – First Flush Load



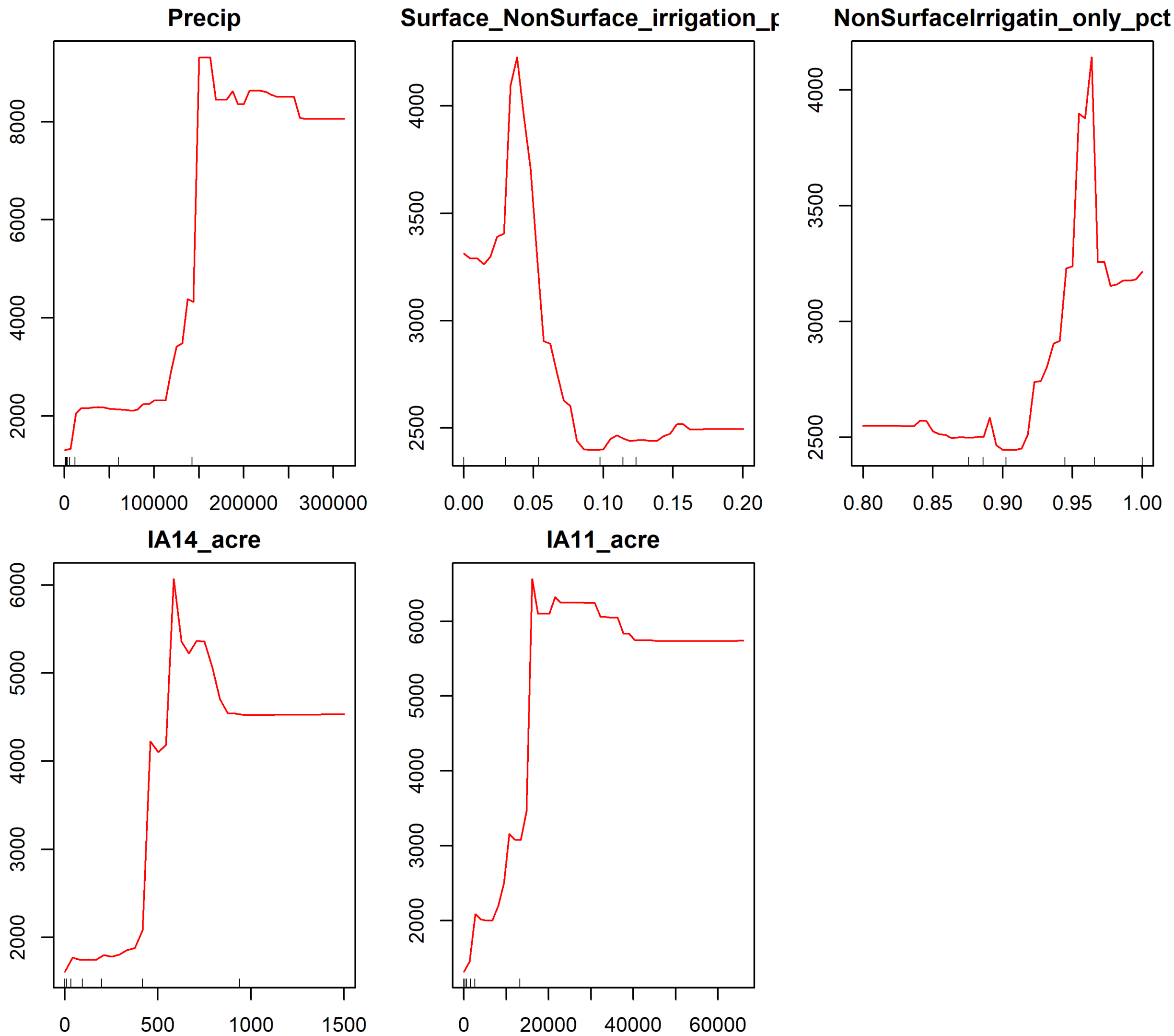
Nitrate + Nitrite as N total – Summer Load



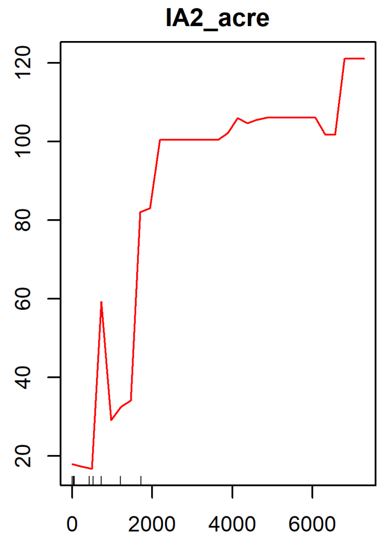
Nitrate + Nitrite as N total – Winter Load

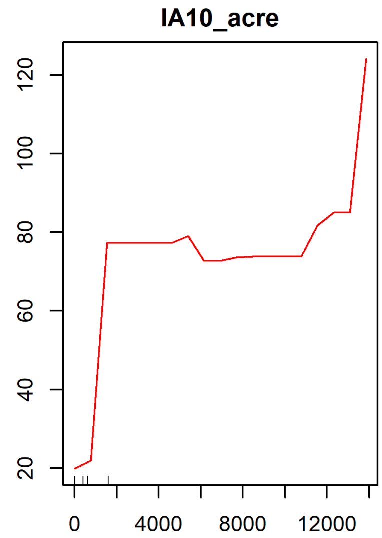


Total Nitrogen as N total - Annual Load

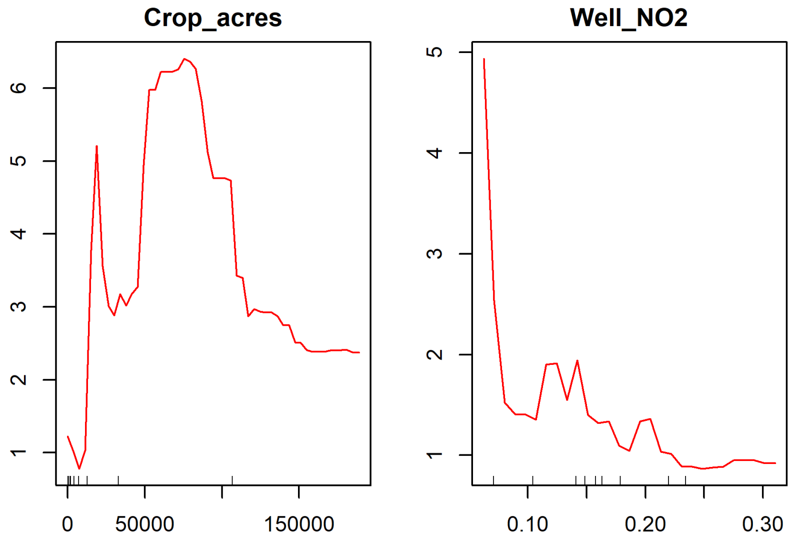


Total Nitrogen as N total – First Flush Load

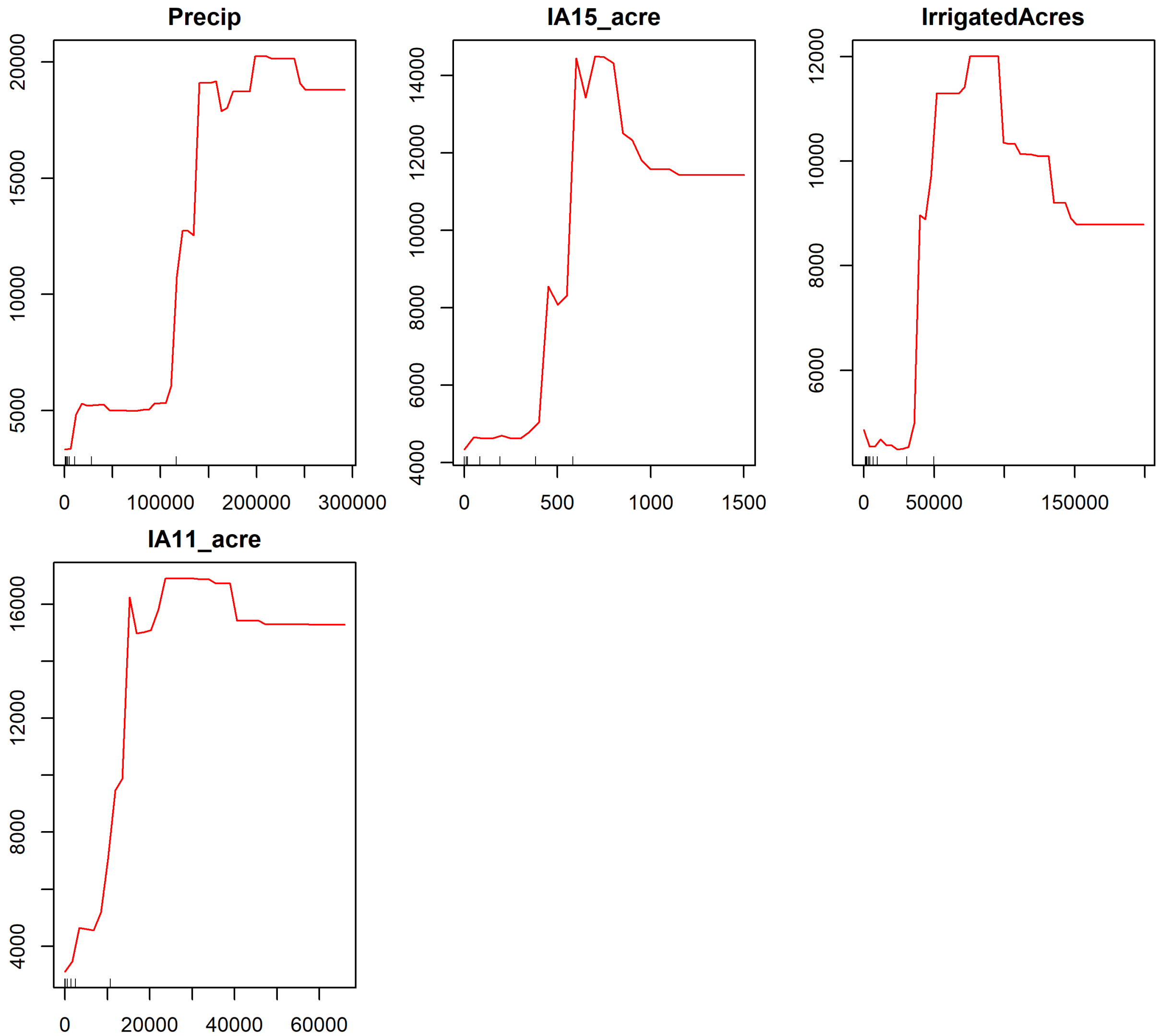




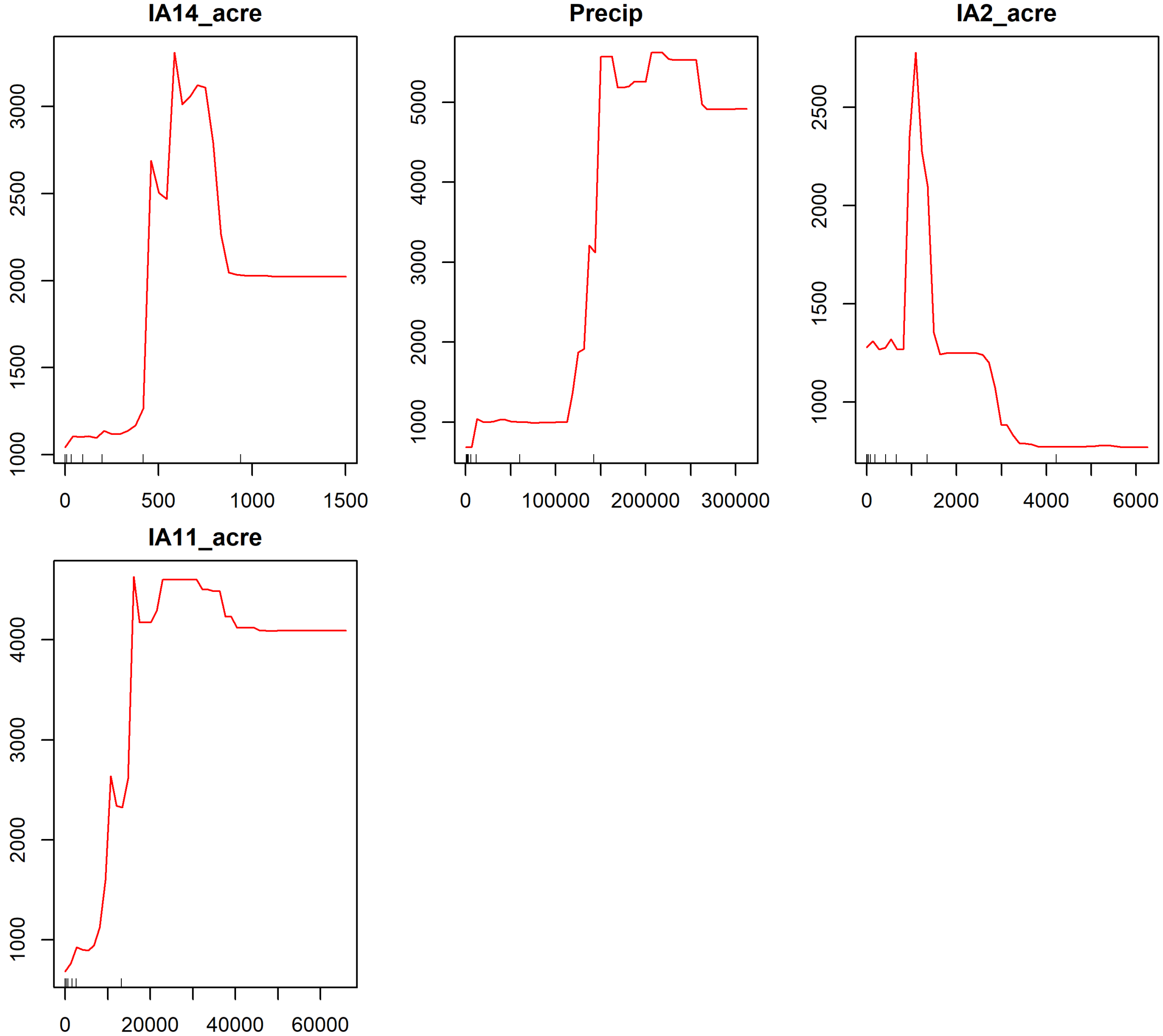
Total Nitrogen as N total – Summer Load



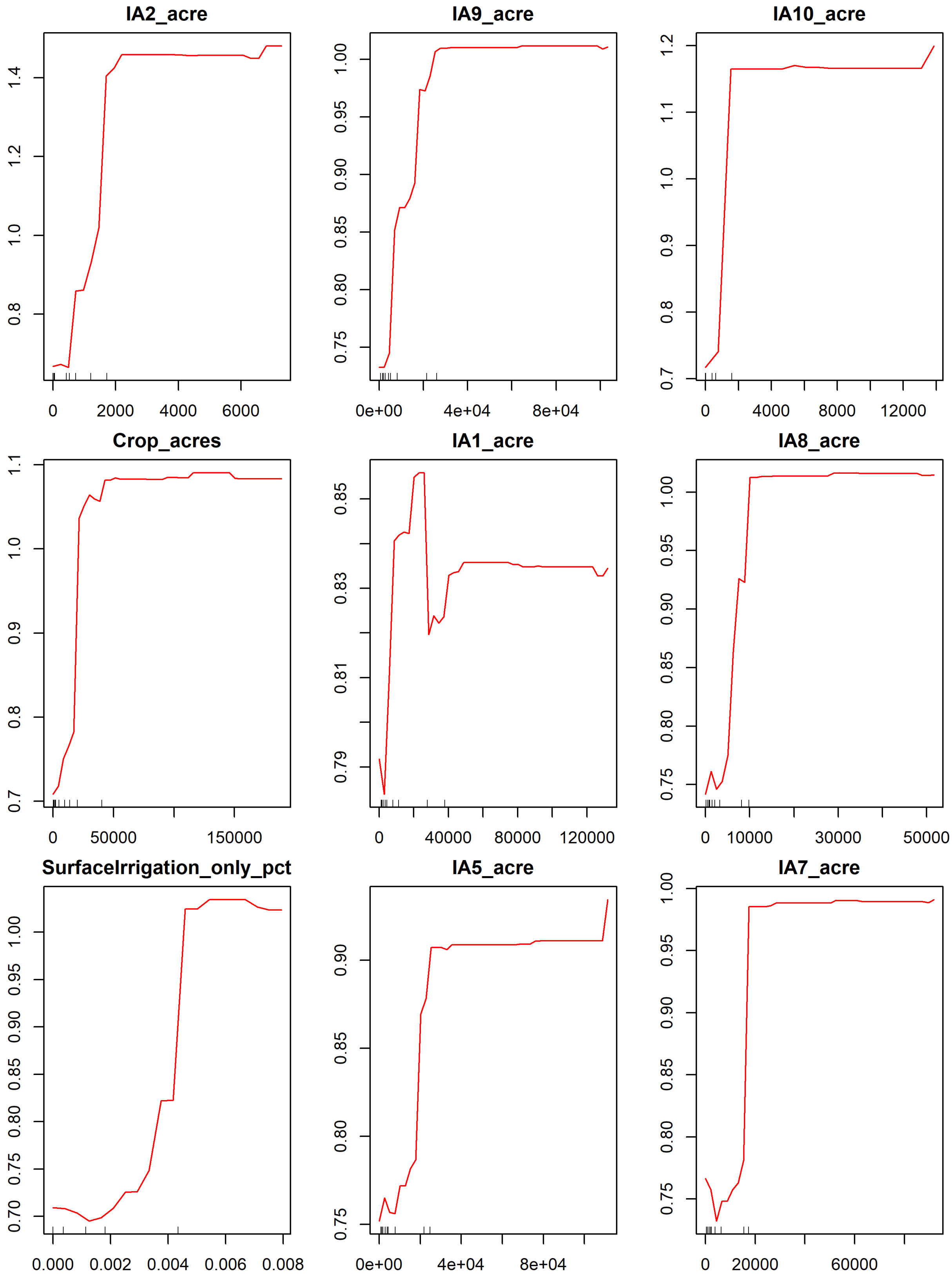
Total Nitrogen as N total – Winter Load



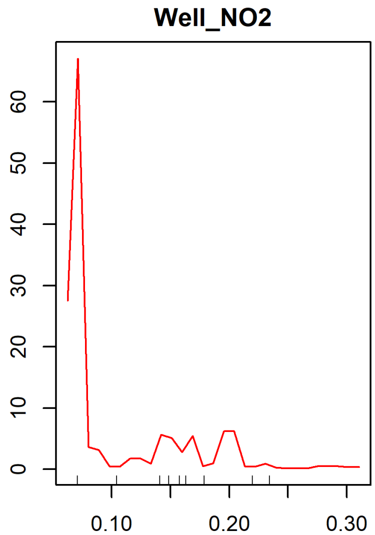
Phosphorus as P total – Annual Load



Phosphorus as P total – First Flush Load



Phosphorus as P total - Summer Load



Phosphorus as P total – Winter Load