Exploratory Spatial Data Analysis of Phosphorus in the Magic Valley, Idaho using Food-Energy-Water Systems (FEWs)

A Thesis

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Abstract

The effects of phosphorus in the Snake River Water Basin are under-studied and there is risk for future issues in water quality. In part, this is due to a lack of a framework to study water quality from publicly available sources. This thesis used an Exploratory Spatial Data Analysis (ESDA) framework to explore the relationship between impaired stream locations and various point and non-point sources of phosphorus. ESDA tools utilized are histograms to highlight distributions, Global Moran's I to understand spatial autocorrelation, and principal component-based clustering to highlight patterns in data. Based on the findings of the analysis, spatial econometric modeling will establish if there is a need for further investigations into water quality, what questions the data might produce, and who needs to answer these questions. More specifically, hydric soils, waste holding capacity, aquaculture, manure application, hydroelectric dams, confined animal feeding operations (CAFOs), food processors, crop type, septic systems, synthetic fertilizer, and surface flow accumulation were tested for spatial correlation against EPA designated stream impairments of phosphorus. My analysis shows the strongest support for a Spatial Durbin Model (SDM) regression to appropriately visualize spillover effects of phosphorus sources. Insights gained by this study discover previously unknown associations and form hypotheses that can provide future policy makers a starting point for further investigation into managing phosphorus in southern Idaho.

Acknowledgments

Thanks to Olivia, Leah, Maribel, Sarah, and fellow students who added insight and helped with data wrangling for my research. Paula Williams Ph.D. who was instrumental in getting my research to a written thesis. My committee for giving all the academic input to make this a memorable experience. And to any professor who offered me research opportunities to expand my learning.

Dedication

"Maps are engines that convert social energy to social work.

… Maps convert energy to work by linking things in space."

Denis Wood, Rethinking the Power of Maps

To friends who fed and clothed me during some unbearable times.

Family who gave me so much opportunity to go out into the world to make a difference.

My cat, Zara, who was the most consistent person in my life, truly a vessel of irrevocable love.

To anyone out there fighting the good fight for environmental justice. I see you, hear you, and hope one day to rejoice with you.

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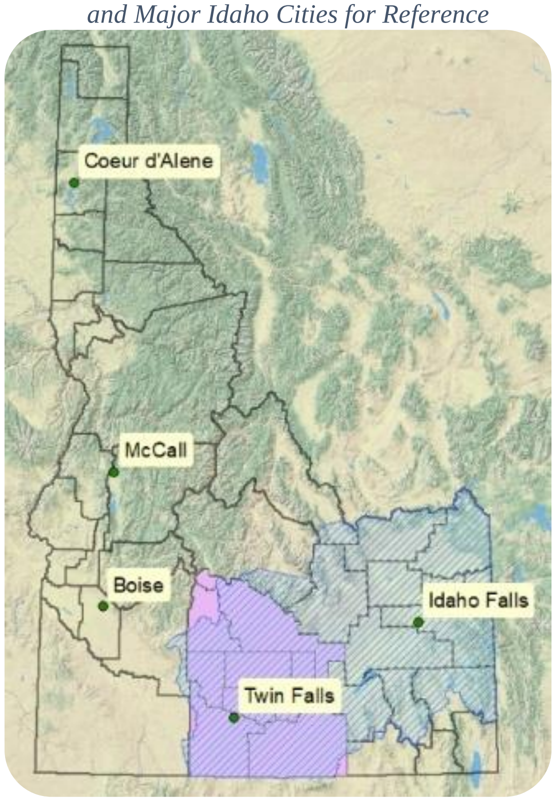
Chapter 1: Introduction

Study Area

The Snake River Water Basin (SRWB) (Figure 1 - colored with blue stripes) is the most productive aquifer in the country (The Nature Conservancy, 2014). The SRWB covers more than 40% of the state of Idaho and supplies water to more than 500,000 people (IWRB, 1998; Konikow, 2013; Van Kirk, 2008). The productivity of an aquifer is its potential to sustain groundwater flow. Transmissivity is a measure of this, referring specifically to the acceleration of groundwater transit throughout its entire saturated thickness. The SRWB has a transmissivity anywhere from 100,000 to 1,000,000 ft2 per day (Lindholm, 1996). The fast recharge of water has allowed for the expansion of many human industries which in turn increased populations. The first record of irrigated lands was in 1902 with 569,286 acres (U.S. Bureau of the Census, 1921), then increased in 1960 to more than 2 million acres irrigated (Mundorff et al., 1964), and most recent estimates find the SRWB supports 2.1 million irrigated acres (IDWR, 2009). Respectively in the early 1900s, the SRWB had a population of 111,500 people. In the early 1960s, the population increased to 521,000, and nearly 60 years after that 1,440,000 people reside in the area (Mahler, 2019)

Figure 1: Study Area Comprised of the State of Idaho Boundary with the Magic Valley Counties and SRWB and Major Idaho Cities for Reference

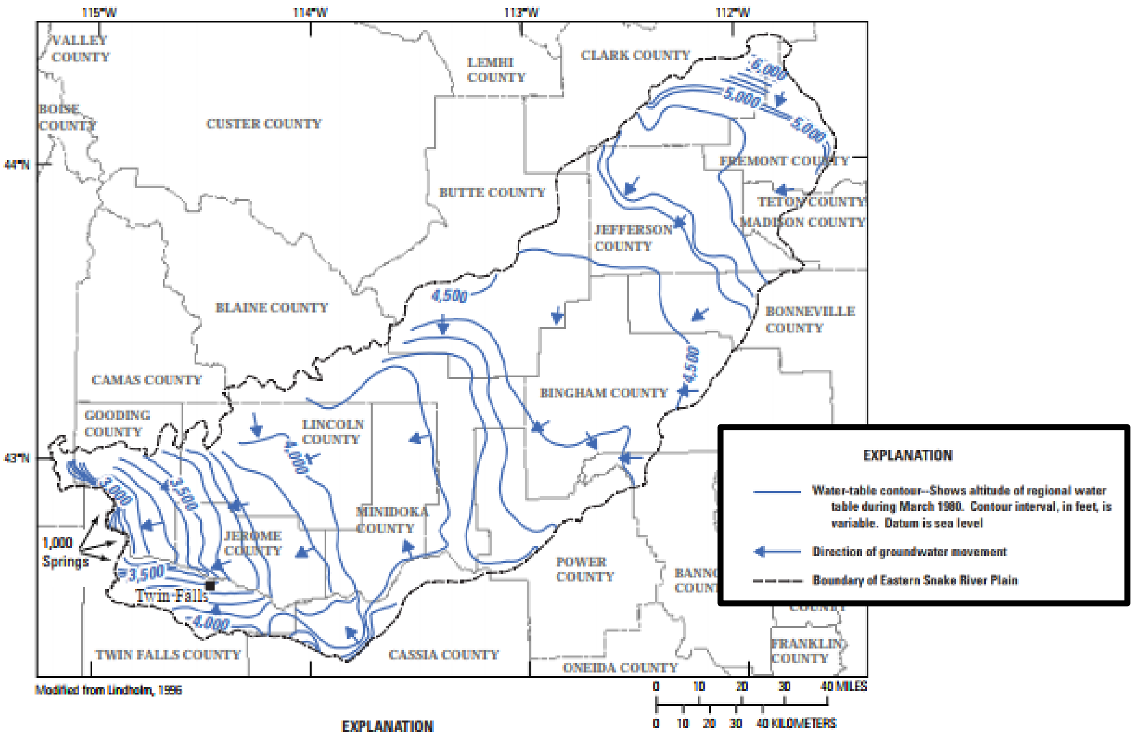


This study focused on the Magic Valley (highlighted with purple in Figure 1) which was selected in part for its potential to bring meaningful science to a large citizen population and for its data availability within an important ecoregion. The Magic Valley includes the counties of Blaine, Camas, Cassia, Gooding, Jerome, Lincoln, Minidoka, and Twin Falls. The Magic Valley is characterized as a semiarid region that experiences a mean annual precipitation of 280 mm (Tasumi & Allen, 2007); and is classified as a North American cold desert ecoregion III (Omernik & U.S. Environmental Protection Agency, 2003) which is characterized by a dry climate, warm summers, and cold winters. The mean annual temperature is approximately 10°C in the western portion and 6°C in the eastern portion. Precipitation during the growing season is negligible with the system largely dependent on winter and early spring precipitation in tributary watersheds (Bjorneberg et al., 2008). Vegetation in the region is characterized by a sagebrush steppe; sagebrush, bluebunch wheatgrass, Idaho fescue, Indian ricegrass, rabbitbrush, fourwing saltbush. Interesting geology includes inactive lava fields and plains. Ancient volcanic activity created basalt formations in the majority of this area. The landscape has plains and gently sloping hills which have an elevation ranging from 640 to about 1,980 meters above sea level (masl) and provide habitat for far-ranging mammals like mountain elk, mule deer, pronghorn antelope, black bear, coyote, cougar, and bobcat.

Hydrology of SRWB

Due to the aquifer's volcanic rock properties, there is a strong connection between the surface water and groundwater. Basalt and sedimentary aquifers such as the Snake River Basin are highly vulnerable to water contamination as mobility of water from surface water to groundwater can concentrate contaminants to problematic amounts (Lentz et al., 2018). Additionally, the direction and magnitude of these interchanges are often dependent upon streamflow volumes and water table elevations. Figure 2 shows one theorized view of groundwater flow direction.

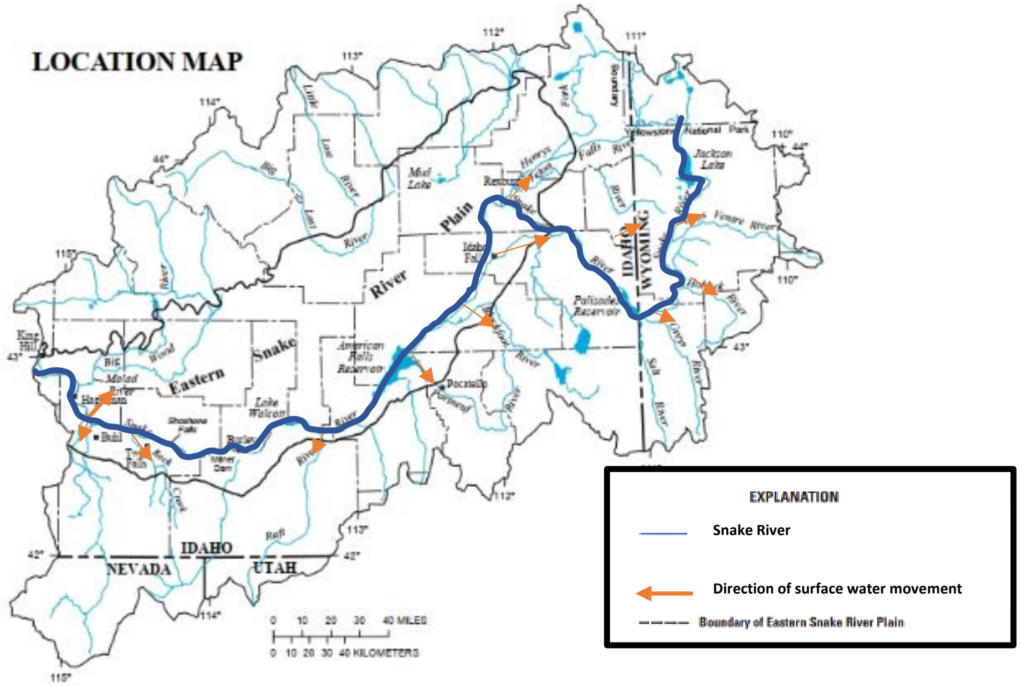
Figure 2: Groundwater Flow of the SRWB (Frans et al., 2012)



These patterns of surface and groundwater interaction have been well described (IWRB, 1998). While the general patterns of connectivity are understood, the complex interactions of location, streamflow, and groundwater levels mean that predicting the impacts of water management activities is highly context-specific (The Nature Conservancy, 2014). For example, groundwater recharge activities may augment streamflow rather than contribute to aquifer storage.

The exchange between surface and groundwater is a unique feature of the study area and was an important consideration when researching water quantity and quality. The surface hydrology is centered around the Snake River and waters streaming from that are lower gradient, warmer, and sparser than surrounding ecoregions as shown in Figure 3.

Figure 3: Surface Water Areas of the SWRB (Clark et al., 1998) with Orange Arrows Showing Downgradient Streams



Within the basin, surface water processes have been highly modified from the base or natural flow conditions. Natural streamflow conditions that were once driven primarily by snowmelt have become carefully managed through diversions and reservoir operations to satisfy water user rights (Van Kirk, 2008). Approximately 40% of the total water that entered the watershed as irrigation and precipitation is returned to the Snake River via the irrigation return flow system (IWRB, 1998).

SES Approach

Coupled with the ecology are the human interactions that influence the Magic Valley. Settlement within the Snake River area began in the nineteenth century and irrigation structures were needed to turn the sagebrush landscape into agricultural lands (Kjelstrom, 1995). The Reclamation Act of 1902 funded the construction of dams, reservoirs, and canals (Stene, 1997). The landscape was changed by water diversions creating productive lands which led to even more settlement. This became a feedback loop; as more lands were placed into agricultural production, more people moved to the area to be a part of the gainful employment. Over time this meant more water resources needed to be diverted.

Creating management plans for communities and for natural resources has become a complex task. First one must understand the ecological processes and natural resources, but an understanding of how humans, the social system, interact with the ecological system is also needed. Recent use of the Social-Ecological-System (SES) framework has started to make this process easier. When using SES, we are attempting to create a model that acknowledges the complexity of a landscape's dynamics by having both a social and ecological system that is interconnected with feedback loops. The proposed framework helps organize findings and allows for the interdisciplinary identification of different drivers that lead to achieving optimum sustainability (Ostrom, 2009).

The social system of the Magic Valley has changed much of the ecological system from sagebrush steppe to cultivable land and population increase trends are fueled by the successful agricultural sector. Cropland increased 0.3% annually from 2002 to 2012 and productivity within the lands increased (Villamor et al., 2020). The region is ranked as one of the top 12 U.S. manufacturing communities (IDWR, 2015), due to the many food processors. This has brought many jobs to the area which are reflected in the last census taken. In the 2020 census, there was an average population increase of 6.4% throughout the Magic Valley. In Twin Falls County, there was a 16.1% increase (Idaho Department of Labor, 2021), well over the national average.

This social system has altered not just water resources, but also nutrient cycles. To sustain crops, the nutrient systems have required increased flows. Synthetic fertilizer use in the Snake River Plain rose sharply after 1950 and continues to increase. Applied synthetic fertilizer is efficiently taken up by crops but if it is poorly-timed or over-applied, a fraction of it can leach with rain and excess irrigation water (Frans et al., 2012).

Crops are processed for human consumption but many of the crops are also used to feed the dairy industry. Idaho was the 3rd largest milk producer of the United States in 2020 (USDA - National Agricultural Statistics Service, 2021). To accommodate the high production, cows are often kept in a Concentrated Animal Feeding Operation (CAFO) defined by the EPA as a facility holding more than 700 animals held and raised with no cropping sustained over any portion of the facility (U.S. Environmental Protection Agency - OW, 2015). As expected with high milk production, there is also high production of dairy cow manure. Nutrients from animal agriculture can be lost to the outer environment from leaching and runoff (Hooda et al., 2000). In 2019 The Magic Valley had 580,000+ cows, located on approximately 490 dairy farms (Naerebout, 2019). Nutrients from the manure can be offset by applying to croplands, but manure cannot yet be as efficiently used as synthetic fertilizer. Modeling of manure use indicated that 70% of farms would have a deficit of nitrogen and 80% would have a surplus of phosphorus, not correctly meeting crop growing needs (Leytem et al., 2021).

Here we finally reach the apex of the situation. In the current SES, there is a rapid increase in the nutrient flows to the system. By finding ways to reduce inefficiencies, we bring the system closer to an equilibrium in which nutrient inputs do not exceed the proper agricultural sinks. My master's thesis was funded by an INFEWS project (Innovations at the Nexus of Food Energy and water systems). We used an SES framework of the food, energy, water, and waste systems to find drivers and connections between the agricultural system and water systems of our study area. To measure the sustainability and success of an SES, the typologies of food-energy-water systems (FEWs) can be used. Impacts within these individual systems have been well-characterized, we can easily see disputes over water, energy, and food access. Their connections drive demographic, regulatory, economic, and climatic factors, just to name a few (Calder et al., 2021). Only one ecological factor, phosphorus in surface water, was investigated to see how FEWs contributed to that system. By researching what stresses may occur over time and space with FEWs, we made suggestions on how to improve the overall SES.

My study of the SES in the Magic Valley looks specifically at the drivers of surface water quality as it pertains to phosphorus (P), human and non-human interactions, and implications of social policies which have influenced the study area. The research parsed the components of the landscapes that contribute, and those that do not, to the interactions among phosphorus and surface water in this area.

Water Quality

Originally enacted in 1948, the Federal Water Pollution Control Act offered broad national objectives to restore and maintain the chemical, physical, and biological integrity of the Nation's waters but there was no regulation or structure for integrity. In 1972, The Clean Water Act (CWA) of 1972 (revised version of the 1948 act) established that all waters need to support conditions that allow for aquatic life and recreation (U.S. Fish and Wildlife

Service, 2000). This led to the framework we have today for the standard of water integrity and how it should be enforced. In Idaho numerous state agencies are involved in administering water quality policies: The Idaho Department of Environmental Quality (IDEQ), the Idaho Soil and Water Conservation Commission (ISWCC), the Department of Fish and Game (IDFG), and the Idaho State Department of Agriculture (ISDA). The IDEQ has administrative authority to regulate and enforce water quality standards. The primary role of the IDEQ is to issue National Pollutant Discharge Elimination System (NPDES) permits, a regulation under the CWA. These permits regulate the volume of pollutants a point source is allowed to discharge into "waters of the United States". This protects surface waters from point source pollution (an identifiable polluter) but not nonpoint source pollution (collective contributions) and does not protect groundwater from pollution (U.S. Environmental Protection Agency - OW, 2017).

NPDES DEFINITIONS:

i. Pollutant: "Dredged spoil, solid waste, incinerator residue, sewage, garbage, sewage sludge, munitions, chemical waste, biological materials, radioactive materials, heat, wrecked or discarded equipment, rock, sand, cellar dirt and industrial, municipal, and agricultural waste discharged into water".

ii. Point Source: "Any discernible, confined and discrete conveyance, including, but not limited to, any pipe, ditch, channel, tunnel, conduit, well, discrete fissure, container, rolling stock, concentrated animal feeding or vessel or other floating craft, from which pollutants are, or may be, discharged."

iii. Nonpoint Source: discharges without an identifiable point of discharge. Not required to have an NPDES permit.

National Pollutant Discharge Elimination System permits specify the type and concentrations of contaminants allowed in streams. The EPA has created federal limitations imposed on such discharges. Dischargers must monitor and report their compliance or non-compliance with their discharge allowances (Bell, et al., 2017).

Previous Research on Water Quality

Attention was drawn to nitrogen as a source of pollution in 2000 when a policy memorandum titled "Policy for Addressing Degraded Ground Water Quality Areas" was published by the IDEQ to list areas degraded by nitrates that were the top priority for management. At that time, it became public knowledge that nitrate was the most common and widespread contaminant in Idaho (Keene, 2015). It can be caused by human activities like confined animal feeding operations (CAFO), food processing, fertilizers, septic systems, and abandoned wells (Keene, 2015; Mitchell, 2011). Due to nitrates' very visible effects on human health, including blue baby syndrome, there was a push to create Nitrate Priority Areas (NPAs) (Thomas, 2006).

Research specific to the Magic Valley has been focused on nitrogen for this reason. In addition, nitrogen transport pathways bind to water, resulting in increased concentration in groundwater making it easy to test. Well testing was already prominent at the time and with plentiful data, understanding problematic areas and trends was straightforward. A thesis written by Baumgarten looked at whether the current best management practices (BMPs) that the USDA recommended for farmers resulted in significant changes in groundwater nitrate levels. Testing was conducted in two fields in Minidoka County. Its findings suggested that there was a statistical difference between fields that implemented BMPs and those that didn't. It also noted a curious relationship between crop type and nitrate concentration in the well. In some well locations, crop type had a greater influence on nitrate concentration than the implemented irrigation BMPs but not at other well locations. The author concluded that there was a relationship between nitrate and groundwater (spatial relationship was not studied specifically) and recommended that the magnitude and variability should be studied further to see the effects of BMP implementation (Baumgarten, 1999).

In conjunction with this study, Carlson, (1999) explored the geostatistical relationship that Baumgarten hinted at. Carlson created a time series comparison based on groundwater nitrate concentrations. The results of the net time series were then compared with sequential Gaussian simulations (SGS). The SGS mapping in the study had consistent results with monthly sample collections. His study was one indication that geostatistical analysis methods were a valid way to study groundwater nitrate concentrations.

Lastly Wolf, 1995 assessed nitrogen and phosphorus loads in surface water to determine the effectiveness of BMPs. A regression model was used to assess if loads decreased over a 6-year period. The type of regression model was not divulged, only that it was from an ESTIMATOR program on which information is now lost and obsolete. This study also included only two sites. Progress with nutrient research has been slow due to the difficulty of establishing routine water testing in which access and money become a constraint (Idaho Office of Performance Evaluations, 2014). Following infrequent well testing for nutrients starting in the 1960s, the National Water-Quality Assessment Program (NWQAP) was adopted in 1991 (Gilliom et al., 2006). This created a baseline assessment of water-quality conditions in 51 of the nation's river basins. It was largely up to "those interested" to request a summary report for use (USGS, 2014). There is no enforcement or follow-up written for the program. All of this is to say that there are methods and indicators used for testing nitrogen, that can potentially be used for phosphorus with modifications to account for sparse and inconsistent data.

Phosphorus

Phosphorus is necessary for all biological processes (Filippelli, 2008) as phosphorus is needed for the body to make DNA, proteins, cells, tissues, and ATP. While essential for life on earth, it is in limited supply, as it is an immobile nutrient, and the availability of "new" phosphorus through natural means is restricted to weathering of rocks. The main way synthetic phosphorus is introduced is through mining. Phosphorus content is low in mineralized form and comes at a large environmental cost to process it for agricultural uses (Smil, 2000). Phosphorus interacts with mineral and organic matter surfaces through diffusion, so it does not readily move through the root zone as other nutrients. In simpler terms, phosphorus mostly binds to sediment particulates as opposed to water particles (USGS, 2021). To read more about phosphorus forms and their abbreviations, refer to Appendix A.

In agricultural ecosystems, soil total nitrogen and soil total phosphorus are the major determinants and indicators of soil fertility and quality (Wang et al., 2009). Using animal manure to supply a crop's nitrogen requirements tends to result in applying more phosphorus than the plant needs. When over-applied, phosphorus becomes a problem because it causes eutrophication, which is the overgrowth of plant life and the decline of the biological community in aquatic systems. Chronic over-enrichment causes the growth of algal blooms which can lead to the following consequences: low dissolved oxygen, fish kills, an overabundance of macrophytes, likely increased sediment accumulation rates and species shifts of both flora and fauna. EPA's 1996 National Water Quality Inventory report identifies excessive nutrients as the leading cause of impairment in lakes and the second leading cause of impairment in rivers (U.S. Environmental Protection Agency, 2000).

To meet crop yield goals, fertilizers and/or animal manure applications are used but the continued applications of phosphorus to agricultural land causes phosphorus to accumulate and accelerate eutrophication. In agricultural systems, the phosphorus content of surface layers is greater than that of subsoil layers because of direct agricultural application and greater biological activity. Plant available phosphorus can decrease after 6 months if soil binding factors such as clay, organic C, Fe, Al, and $CaCO_3$ increase (Sharpley, 1995a). For agriculture, manure applications have been N-based. This leads to a soil increase of phosphorus because of the lower N:P ratios in plant uptake. Phosphorus losses are influenced by the rate, time, and method of fertilizer application. Fertilizer application influences the rate of loss depending on the form of phosphorus applied, the amount and time of rainfall after phosphorus application, and vegetative cover (Sharpley et al., 2003). Studies had been conducted to understand and control this within agricultural lands (Sharpley & U.S. Agricultural Research Service, 1999)

In 1996, the Environmental Quality Incentive Program was established in the cycle update of the U.S. Farm Bill. It was administered by the NRCS and states were asked to adopt the federal policies which created technical and financial assistance to farmers and ranchers that could help improve environmental quality (Federal Agriculture Improvement and Reform Act of 1996, 1996). Idaho produced their state compliance plan in 1999. It started the groundwork for creating nutrient management plans that would minimize non-point pollution, but it pertains only to farms that have land application of animal wastes (NRCS Idaho, 1999). At the time, a phosphorus threshold (TH) was used to develop a Nutrient Management Plan (NMP) to keep farms on track for phosphorus compliance. The

Figure 4: Threshold Concentration by Resource (Leytem et al., 2017)

Primary Resource Concern	**P Threshold Concentration**	
	Olsen	**Bray 1**
Surface Water Runoff	40 ppm	60 ppm
Ground Water, fractured bedrock, cobbles or gravel		
< 5 feet	20 ppm	25 ppm
> 5 feet	30 ppm	45 ppm

threshold used a phosphorus soil concentration, and the threshold number was dependent on the resource of concern (Figure 4). If the amount were more than the threshold, the NM planner and producer would need to design a plan that would reduce soil test results.

In 2017, NMPs were updated to utilize a Phosphorus Site Index (PSI) instead and this is the currently used standard. The PSI grades the applicator with two parts; part A characterizes the risk of phosphorus loss based on soil properties and hydrologic considerations. Part B characterizes past and current nutrient management practices that lead to increases in phosphorus concentrations in soil and potential for loss. The index ranks risk so that when resources are limited, sites with higher scores can be targeted for management. TH only measures the amount of phosphorus land applied but has no mechanism for rating risk or ranking management priorities. Under the PSI, a producer could apply as much phosphorus as they wanted to the land if the index was within an acceptable range. This was helpful for some producers as they could offload their lagoon and manure pile that normally would not be usable. (Chen & Vermeer, 2020; Leytem et al., 2017). In 2021, some producers have challenged the use of the PSI because they are no longer able to apply phosphorus. Under the threshold rule, they were in compliance, but with the PSI the site characteristics of their land increased the risk for transport which created higher PSI values. Currently, the Idaho Dairyman’s Association (IDA) is proposing a HB51 bill to allow farm operators the option between the two tests (Idaho Farm Bureau, 2021).

The study area has unique factors which contribute to the transport of phosphorus. It is challenging to study phosphorus as a water quality issue due to the lack of routine water testing. Even if elevated levels of phosphorus are found in water, those results do not result in enforcement. Those standards that are enforceable are specific to soil testing and only apply to animal agriculture, not to crop farmers. Drawing from previous research that implied regression modeling can be used to make inferences about a spatial relationship, the next chapter discusses a methodology that included all potential contributors of phosphorus to the system, and how to measure phosphorus vulnerability despite having a lack of unified data on concentrations.

Importance of this Research

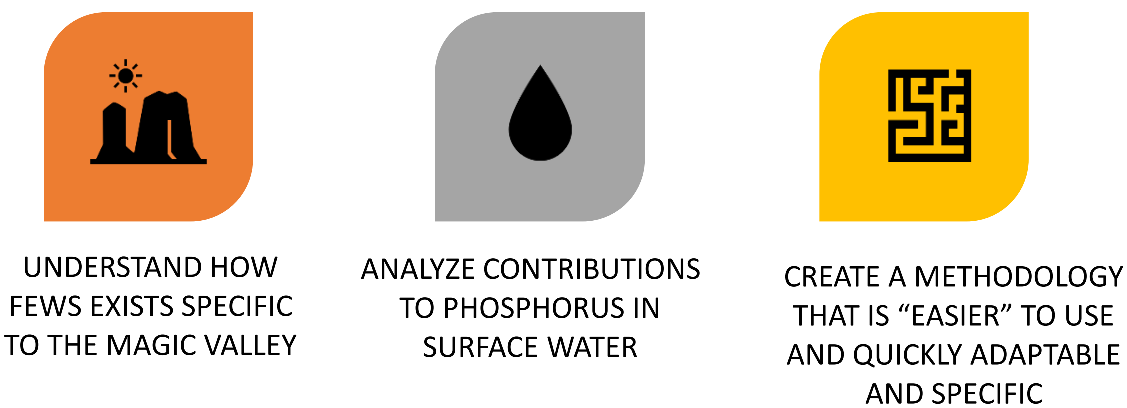
With this body of research, my proposal was to update geostatistical models, as these studies are widely outdated. Geostatistical modeling has been greatly improved by modern programming, but it has not yet been applied to study nutrient movement in southern Idaho. Phosphorus, especially in surface waters, has not been researched to the extent that nitrogen has. Studying phosphorus in surface water can help us understand more immediate changes to runoff nutrients. Groundwater testing requires expensive permitting and well infrastructure for every new point. Surface waters can be tested anywhere to help bridge spatial gaps in data and could theoretically be done by citizens' science groups. Therefore, it was important to use an Exploratory Spatial Data Analysis (ESDA) approach to guide the choice of appropriate modeling for surface water. If it is used in the future, we can increase our knowledge base of how phosphorus is affecting our communities.

Chapter 2: Methodology

In this chapter, the steps and associated frameworks are presented to meet the research aims. A suite of ESDA techniques were used for the primary analysis to investigate how a variable interacts within the spatial neighborhood. Using a regular non-spatial analysis, such as correlation statistical methods, neglects the relationship that the variable has in surrounding space and only considers the direct relationship with another variable (Abdishakur, 2019). Independent variables were selected from the literature review of nitrogen studies and the review of how the landscape contributes to the biogeochemical pathways of phosphorus. As mentioned earlier, human activities such as confined animal feeding operations (CAFO), food processing, synthetic and animal fertilizers, and septic systems can influence nitrogen nutrient systems. The literature review notes different environmental indicators that can influence how phosphorus moves through the system. Chapters 3 and 4 will further explain how these variables could cause major impacts on phosphorus in water systems based on the FEWs. Using impairments in surface water by phosphorus, as opposed to those in groundwater as a response variable is under-researched but, in the future, data availability could increase.

The research aims are described below in Figure 5. To achieve these aims, several frameworks were utilized to meet these objectives as described below.

Figure 5: Research Aims



Exploratory Spatial Data Analysis

For the research conducted for this thesis, data was collected to best represent the SES components in the Magic Valley relevant to phosphorus in surface water. The data was first analyzed for its distribution by using Moran's I statistic on each variable to see the association between values and location (otherwise known as spatial autocorrelation). This helps understand if variables are random, dispersed or spatially clustered (Dall'erba, 2009). If a variable were clustered, we would infer that a high value means similarly high values will be nearby. A dispersed variable would mean that higher values repel each other. A hypothetical case of this relationship would be that manure application values are dispersed as farmers drive away from the site of production, since there is no need for manure at the main CAFO site and application would be farther away from each other. A spatially random variable would be uniformly distributed over space. In this case, the events do not interact with each other. A study with multiple spatial autocorrelative variables violate the assumptions for certain sets of regression models. If one of these independent variables ended up being a spatial contributor, there could be ways to condense, or disperse the values across the landscape to decrease the phosphorus loss. Lastly, multiple types of regression models were tested for the best-of-fit. Using statistical tools like R^2 value and AIC can validate the model's ability to predict HUC areas with phosphorus. Likelihood and heteroskedasticity tests were used to decide on a model that did not overfit the data.

Framework for Characterizing Phosphorus Contributions

SPARROW (SPAtially Related Regressions On Watershed attributes) is a watershed modeling technique that relates water quality measurements to attributes of a watershed. The framework is unique in that it uses a watershed delineation to objectively evaluate hypotheses about contaminant transport. Individual watersheds in SPARROW are delineated using stream network properties, such as discharge, depth, area, and slope that impact long-distance nutrient transport (Schwarz et al., 2006). The SPARROW framework allows environmental managers and other stakeholders to identify sources that contribute nutrients to waters and to evaluate reduction scenarios (Wise & Johnson, 2013). This thesis adopted the general framework of SPARROW but modified the model to accommodate data that was available at our study area resolution.

Framework for Creating a Methodology for Future Iterations

To visually show the modeling process, a Unified Modeling Language (UML) is used and has been provided in Appendix B. UML is a visual language using shapes and arrows to represent objects and the association between them to portray system relationships in a standardized way. The diagram used in this manuscript is loosely based on an activity diagram, a specific type of UML that captures the dynamics of methods, operations, and functions of a software (Jain, 2017). In this case, the integrated development environment (IDE) used is R Studio.

Chapter 3: Data Collection

Data were selected to represent both the FEWS specific to the Magic Valley SES and to accommodate the USGS SPARROW used for general nationwide use. Reference for the sources, units, and definitions are provided in Table 1. Data representing soil hydrology, surface flow accumulation, and waste holding capacity were used to model important drivers in the ecosystem for phosphorus loading. Hydroelectric dams represent the linkage of energy and water in a FEWS, and crop type and CAFOs represent food and water in the Magic Valley context. Nutrient sources in SPARROW modeling were organized as nonpoint sources: the number of people not living in municipal sewage districts (and thus using septic systems), synthetic farm fertilizer, and livestock applications. Point source data such as aquaculture and industrial waste inputs (Wise & Johnson, 2013) were also included. The variables section of the UML diagram below (Figure 6) shows the data and spatial format of the datasets. The data included in “data creation node” was produced with a variety of sources and filtered or manipulated to correctly represent the variable. Variables outside the creation node had one source that required little to no editing from how it was originally downloaded.

Figure 6: Diagram of Selected Variables, a Segment of the UML

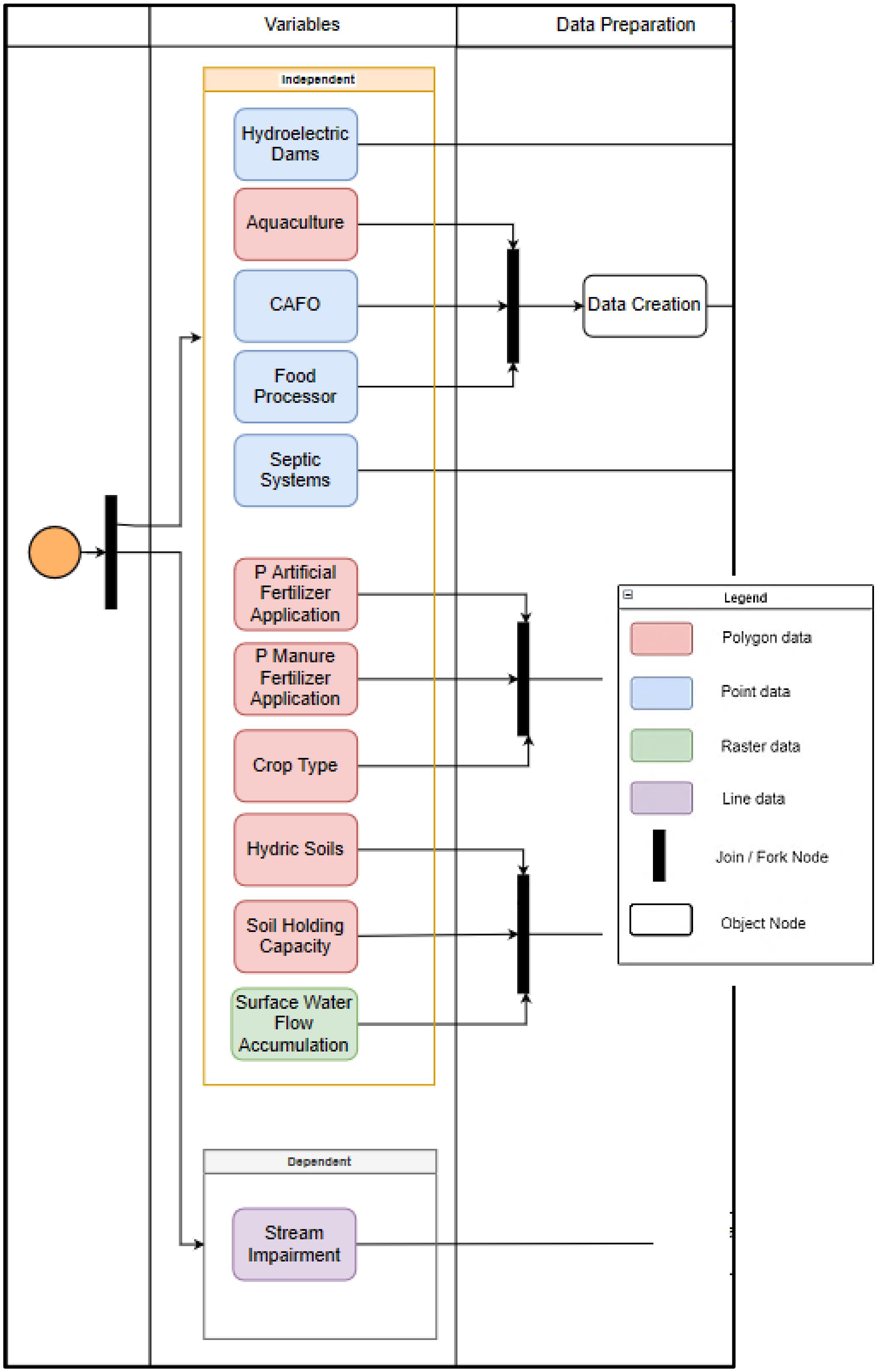


Table 1: Variable Selection Information and Supporting Frameworks

Spatial Data	Definition	Reported Units	Source
Hydric Soils	Soils under saturation flooding	% of hydric soil within USDA soil delineation	(Natural Resources Conservation Service & Soil Survey Staff, 2019)
Waste Holding Capacity	Soil properties that affect the absorption of manure and food-processing waste applications	3 Point Likert scale	(Natural Resources Conservation Service & Soil Survey Staff, 2019)
Aquaculture	Fish farm	Number of sites / Acres	(IDWR, 2017)
Manure Application	EPA estimation manure application	Manure kg P/yr. per HUC	(U.S. Environmental Protection Agency, 2014)
Hydroelectric Dam	Dams that create energy by water	Number of sites	(EIA, 2019)
CAFO Density	Concentrated Animal Feeding Operation	Number of animals	(Idaho Power, 2019; ISDA 2019; IDWR 2019)
Food Processors	Refine food into a product (creameries, cheese factories)	Number of sites	(Idaho Potato Commission, 2019; Naerebout, 2019; Self-made)
Crop Type	Potato, corn, barley, wheat, sugar beet, alfalfa, other	Lbs. P fertilizer applied/acre	(USDA, 2020, Leytem, unpublished)
Septic	Systems that manage human wastes	Number of sites	(USGS, 2011)
Artificial Fertilizer	Manufactured fertilizer which can be wet or dry	kg P/ha/yr.	(USGS, 2013)
Surface Flow Accumulation	Areas that water bodies flow into	Pixel Value	Self-made
Phosphorus Impair Streams	Streams with problematic phosphorus concentrations	Phosphorus and Total Phosphorus	(U.S. Environmental Protection Agency - OW, 2015)

Nonpoint Source Data

CAFO

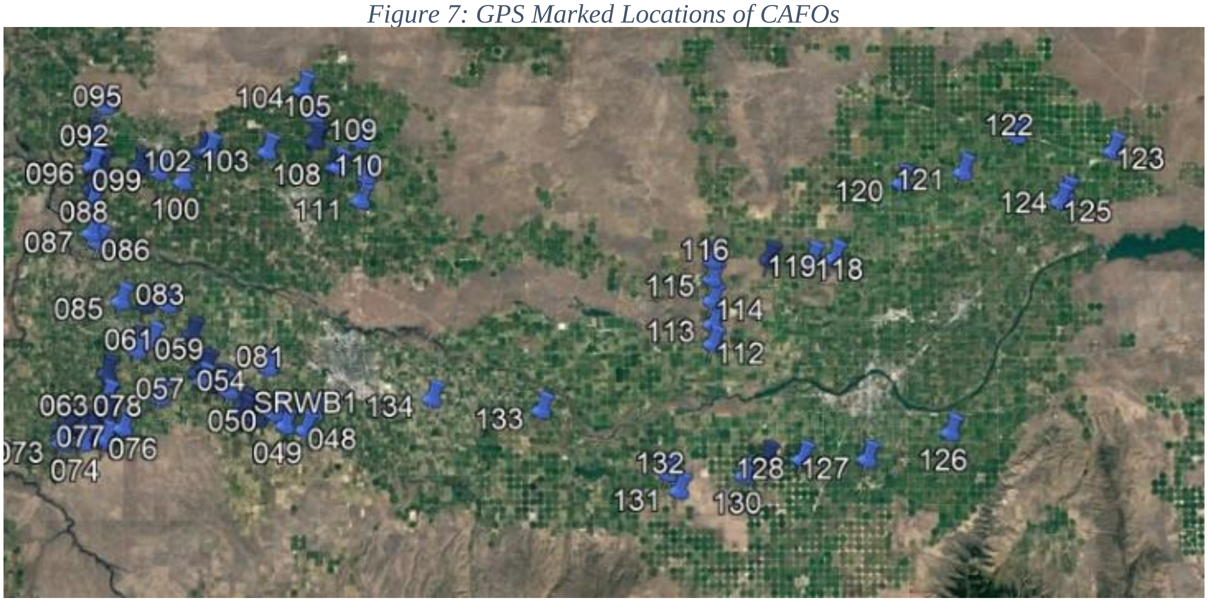
Despite the EPA classifying CAFOs as a point source, the agency does not have facility-specific information for all CAFOs. For the EPA it is classified as "low enforcement priority" as it largely leaves states to regulate (Miller & Muren, 2019). The EPA suggests using NPDES for CAFOs but in Idaho, the Department of Environmental Quality (DEQ), issues §401 water quality certifications. These certificates state that a facility discharge will comply with the Clean Water Act and will not cause an exceedance of state water quality standards (Idaho DEQ, 2011). Thus, CAFOs do not have formal, publicly accessible, NPDES. For this reason, CAFOs in this study were classified as nonpoint sources since the storage and concentration of manure were unidentifiable. CAFO locations were constructed by combining a variety of sources that had indirect information about names or coordinates. The sources synthesized included the data shown in Table 2 below:

Table 2: Descriptions of Sources Used for CAFO Locations and Densities

Source	Items	File type	Cow amounts	Location	Details
Idaho Power	322	Point shapefile	N	Y	Locations of CAFOs for research in biodigesters. Points were censored with large buffers and locations averaging multiple farms
ISDA	644	Point shapefile	N	Y	Point locations outdated by more than a decade.
Unknown Online Google Map	122	KML	Y	Y	Appears to be civilian made; no state agencies took credit
IDWR Water Rights for Animals	16,707	Polygon shapefile	Y	N	Water rights and claims for animal/farm use. Shapefile contained links to PDFs permits which occasionally contained dairy animal headcount.
ISDA milking permits	475	Spreadsheet	Y	N	Contained dairy licenses with names of dairies but no locations
Ground-truthing	54	GPS coordinates	Y	Y	2 trip visits to confirm questionable sites. A Garmin GPSMAP 62s navigator was used to mark positive feedlot points
Visual inspection	All	DigitalGlobe Quickbird	N	Y	Google Earth inspection at 300ft resolution to KML

To perform ground-truthing of these points, a handful of trips were taken to Twin Falls county. Positive feedlot points were marked using a Garmin GPSMAP 62s navigator. These coordinates were exported using the BaseCamp ™ program into a KML file which was then opened with Google Earth. The points were marked from the road and not directly in the field, so Google Earth was used, shown in Figure 7 below, to edit each point and tag it

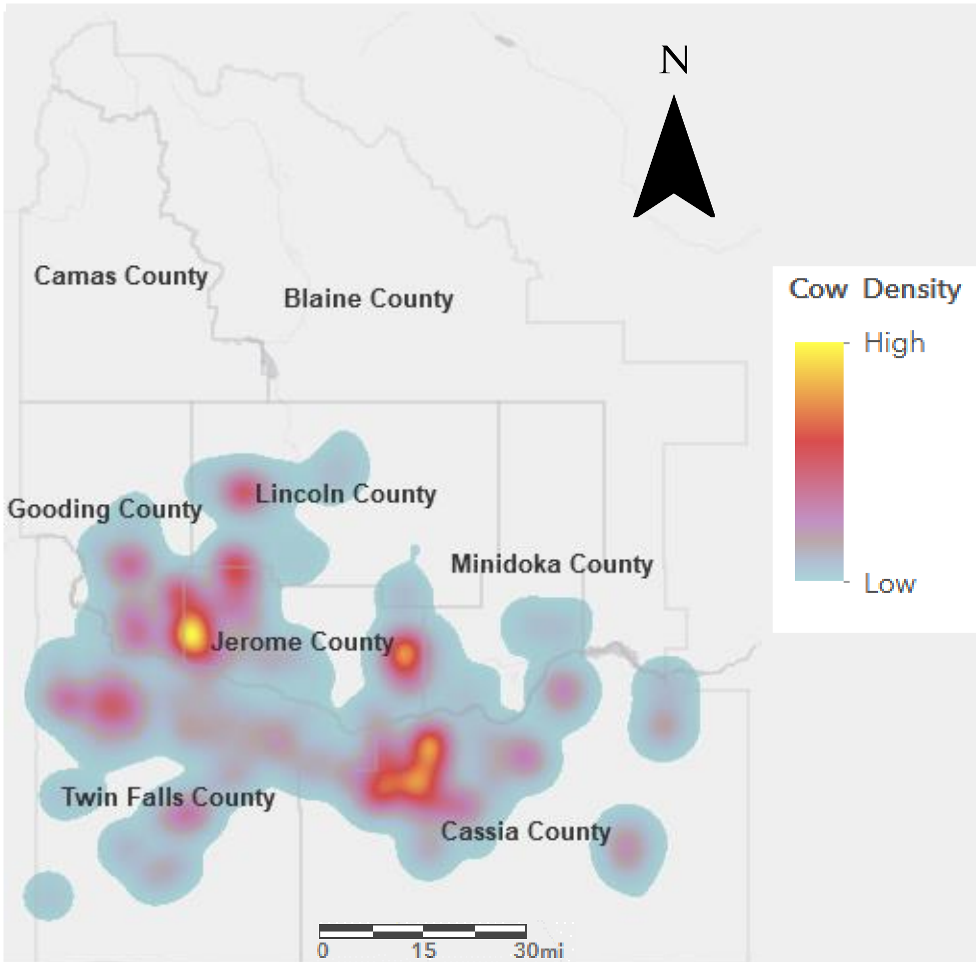
Figure 7: GPS Marked Locations of CAFOs



to the adjacent feedlot location. After this was finished, the points were converted to a point shapefile for use in ArcGIS ®.

All sources were combined into one shapefile, with each attribute referring to a different source for estimated dairy cows. Duplicates were removed using '*Delete Identical'* as well as the '*Dissolve' t*ools within ArcGIS 10.7.1. The *Editor* toolbar was used to create and modify the polygons of the feedlot area. It was only necessary to include the areas where cows were held and not buildings used for milk processing or other non-animal holding areas that sometimes were contained in the water right polygon. This shapefile shown below in Figure 8 represents CAFO density with the assumption that denser CAFOs generated more phosphorus. However, it was also important to consider how much manure was applied as fertilizer to nearby farms.

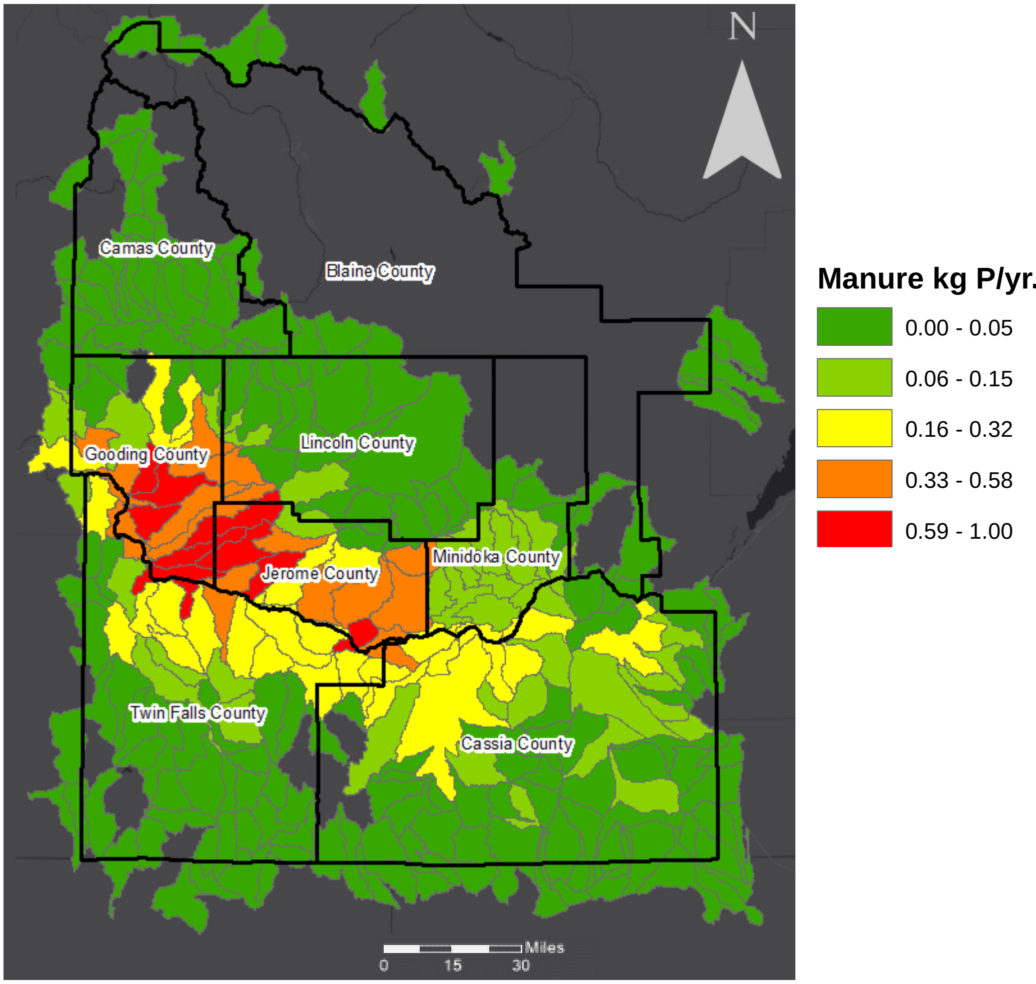
Figure 8: CAFO Map as a Heat Density Using the Synthesized CAFO Dataset Described Above.



Manure Application

Dairy manure is a slurry comprising 90%-96% liquid content with the other portion consisting of solid components (Lorimor et al., 2004). Due to the high liquid content, raw manure is dense and expensive to move long distances either for field-application as fertilizer, or to be processed into compost. It is often applied in its raw form directly on nearby agricultural lands. The EPA hosts the EnviroAtlas which has geospatial indicators for a variety of ecosystem services (U.S. Environmental Protection Agency, 2015). This dataset estimates the application rate of phosphorus (P) as manure on croplands in kilograms phosphorus per hectare per year within each subwatershed (12-digit HUC) for 2012 shown in Figure 9 below (U.S. Environmental Protection Agency, 2014). This source represents good estimates of concentration but utilizes old feedlot data. Both datasets, the CAFO density mentioned earlier, and the manure application discussed here, were used to adequately represent the use of manure as fertilizer in the Magic Valley.

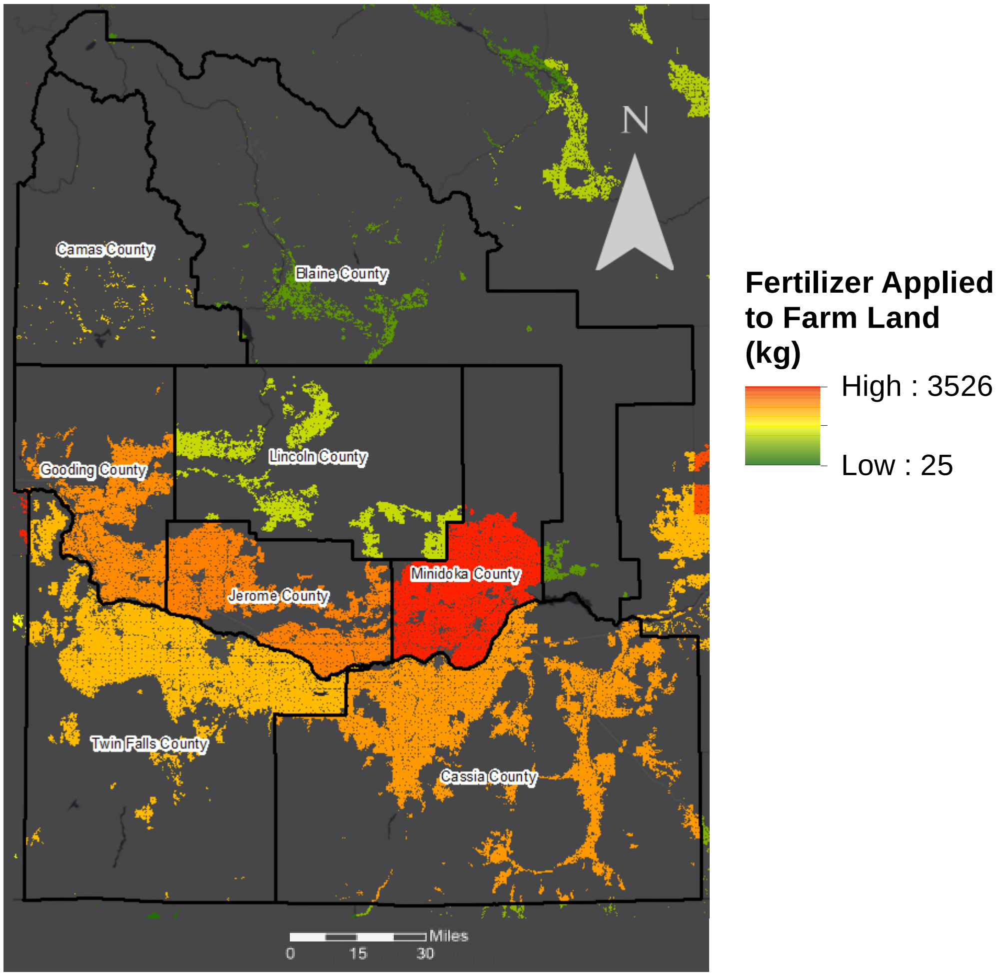
Figure 9: Manure Application Rate of P in HUC 12 According to EPA EnviroAtlas (U.S. Environmental Protection Agency, 2015)



Artificial (Synthetic) Fertilizer

Idaho Administrative Code (IDAPA) does not currently regulate nutrient application for crops (State of Idaho, 2020). As there is no reporting regulation, synthetic fertilizer application rates can only be extrapolated from fertilizer sales at the county level. To help address this gap, the USGS SPARROW model used land cover to assign the fertilizer application rate to the farmland areas (USGS, 2013; Wise & Johnson, 2013) - see Figure 10. Synthetic fertilizer refers to the manufactured form of fertilizers. There is a distinction between this and manure wastes, as the ratio of NPK is specified in synthetic fertilizers, yet manure nutrients vary based on the animal's diet. Fertilizer is applied according to crop nutrient requirements, but soil properties, topology, and vegetation can influence how fertilizer is retained.

Figure 10: Fertilizer Rates kilograms per Year Inferred from Landscape Nutrient Loadings of Farmlands Using Data from (USGS, 2013)

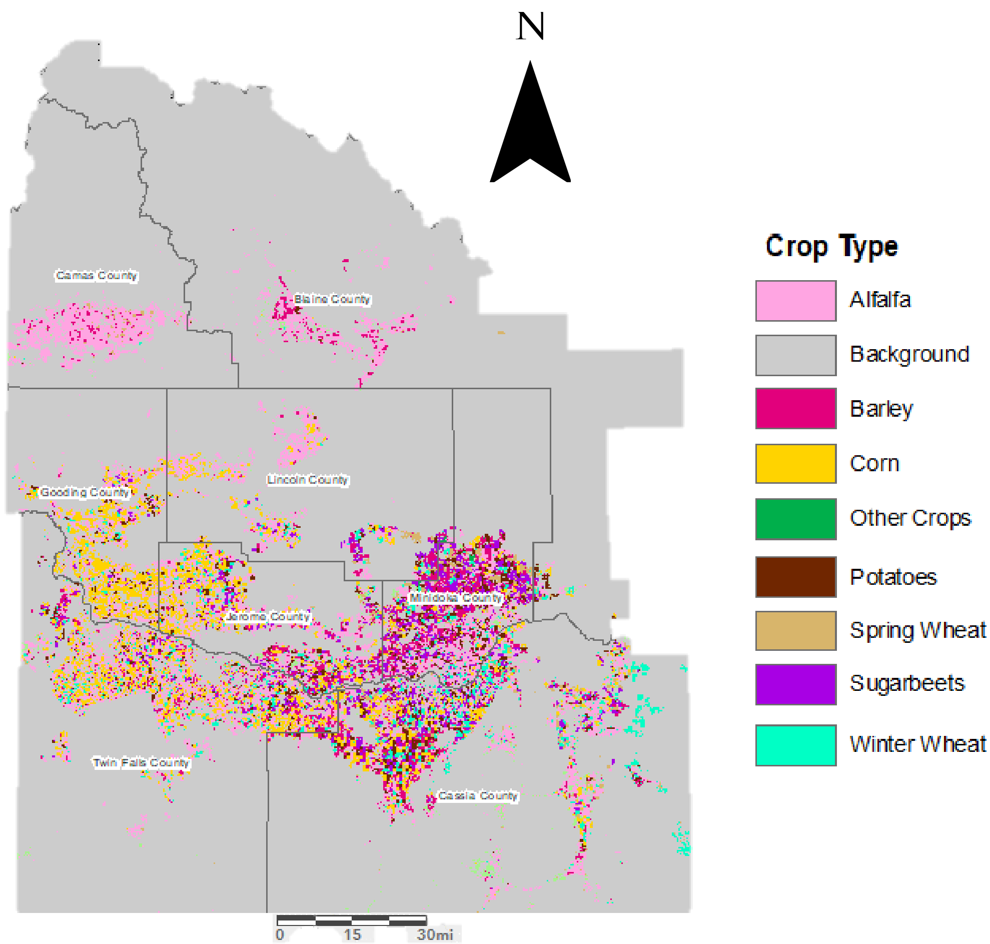


Crop Type

Crops are highly dependent on phosphates and consequently uptake phosphorus with great efficiency. Unfortunately, food production accounts for 50-60% of the global phosphorus supply, so even small losses from crops are magnified by the scale of crop production (Smil, 2000). The eight primary crops produced in the Magic Valley are alfalfa, barley, corn, sugar beets, potatoes, triticale, wheat, and dry beans (USDA NASS, 2018). The CropScape dataset includes the Cropland Data Layer (CDL) which identifies specific crop acreage. The National Land Cover Dataset (NLCD) assembled by the USGS was another option that is commonly used for land use. The CDL is a superior dataset as it is updated yearly compared to the NLCD which is updated only every 5 years. The categories in the

NLCD are also limited, and specific crops are not identified as they are in CropScape. The year 2019 was selected as it was the most recent year that had been corrected and verified at the time of research. The data utilizes Landsat 8 imagery with a 30m resolution. The data ranges from mid-80% to mid-90% in accuracy depending on the specific crop (USDA, 2020). The CDL data is shown in Figure 11.

Figure 11: Crop Land Cover Data Taken from the CDL Filtered for Relevant Crops (USDA, 2020)



Crop type could indicate phosphorus loadings as nutrients for growth vary with the crop needs and uptake. The values used for crop phosphorus needs were gathered from unpublished data produced by Dr. April Leytem, a USDA soil scientist in Idaho (see Table 3 below). The CDL was *'clipped'* to the Magic Valley extent then filtered using '*extract by attributes'* in which the bands for potato, corn, barley, wheat, sugar beet, and alfalfa were extracted. Those values of phosphorus were available through Dr. Leytem's data whereas triticale, wheat, and dry beans were not. The "other" application rate was used for crops that did not have a specified amount.

Table 3: April Leytem's Survey Data from Magic Valley Farmers, Unpublished Data

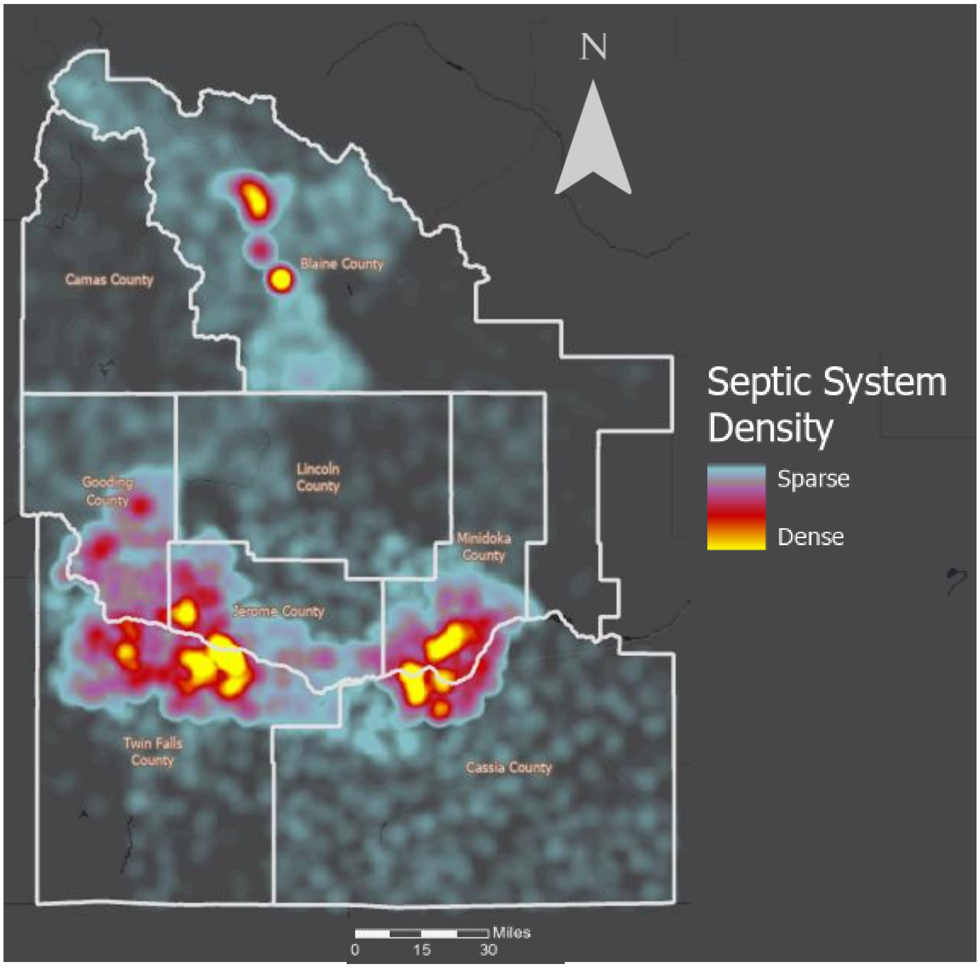
Crop Type	Total P Lbs. applied
Potato	121.67
Corn	183.67
Barley planted	68.67
Spring wheat	68.67
Winter wheat	68.67
Sugar beet	50.33
Other	50.00
Alfalfa harvested	34.33

Point Source Data

Septic

Septic systems manage human wastes by removing and processing the waste before being released back into the environment. If the system is compliant with code, it can be a safe and effective way to protect surface and groundwater quality in communities. However, if not properly maintained, septic tanks can leak wastes and nutrients into water sources which can cause contamination of nearby streams (USGS, 2011). Septic systems can be in active use for those who do not have access to municipal wastewater treatment plants. There are also inactive or "legacy" septic tanks that were built before municipal water treatment was available (Wise & Johnson, 2013). Both are considered since each can pose leakage issues.

Figure 12: Shapefile of Position Septic Sewer Systems, 22,038 Points Available from the USGS (2011)



Data for septic systems are available as an extrapolation of the 1990 Census tract block group and encompasses possible currently-in-use septic systems and those no longer in use (USGS, 2011) as shown in Figure 12 above. SPARROW modeling indicated that septic wastes could contribute phosphorus loading to surface water and therefore were included in this study.

Food Processing

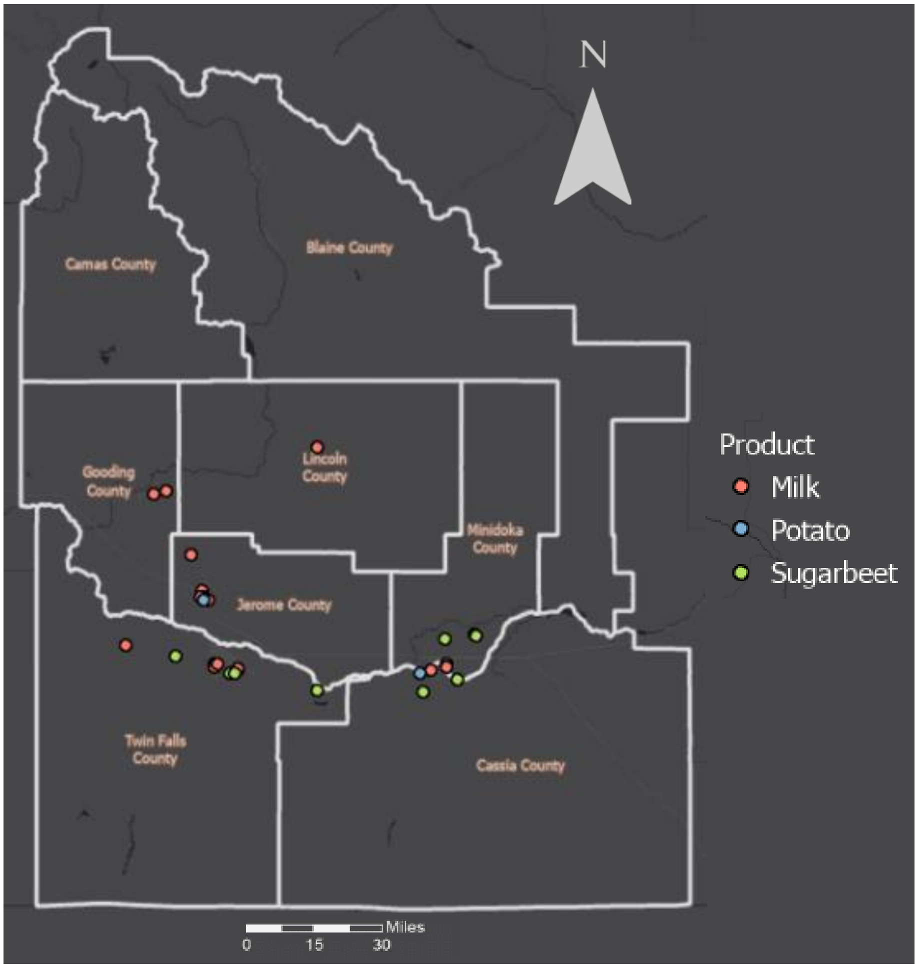
Dairy foods, meat, and cereals are the largest dietary sources of phosphorus for humans (Smil, 2000). Food processors are required to have an NPDES permit because they are defined as point source discharges. Food processing facilities have a wide variety of discharges, commonly reported in complex formulas, and performing the stoichiometry on individual forms in all the factories to produce isolated phosphorus amounts is beyond the scope of this thesis. The count of processors was used instead. The ready availability of agriculture has attracted a high density of food processors that refine various crops into foods for human consumption. According to The Office of the U.S. Trade Representative, Idaho's top three food exports were plant products, dairy products, and processed vegetables (United States Trade Representative, 2019). Two of the top ten planted crops in the Magic Valley are sugar beets and potatoes (USDA, 2020) which both are processed within the valley. The number one animal product is milk which is also processed. Thus, the shapefile included data on milk, potato, and sugar beet food processors. Table 4 shows the number of processors in the Magic Valley in 2019 for milk, potatoes, and sugar beets.

Table 4: Mapped Food Processors by Agricultural Products in 2019

Input Food Labels	Count of Processors
Milk	16
Potato	21
Sugar beet	15
Grand Total	52

Processor point locations were collected by searching through Google Earth for the company name while zoomed out to the southern state extent. The company names were collected by various directories. First was from the Idaho Potato Commission (IPC), a state agency, that publishes a yearly shipping and processor directory for potato products. An example of a large processor in southern Idaho included in the directory is McCain Foods which produces powdered potatoes that can be made into mash (Idaho Potato Commission, 2019). Milk processors include creameries, cheese factories, yogurt, and even protein bars which utilize milk whey protein. The Idaho Department of Agriculture has a list of processors and co-ops that are formally recognized by the association as being prominent businesses (IDA, 2019). These processors were included in a point shapefile. Amalgamated Sugar Company is also an important food processor, that was added to the shapefile. The locations of all these food processors are shown in Figure 13 below.

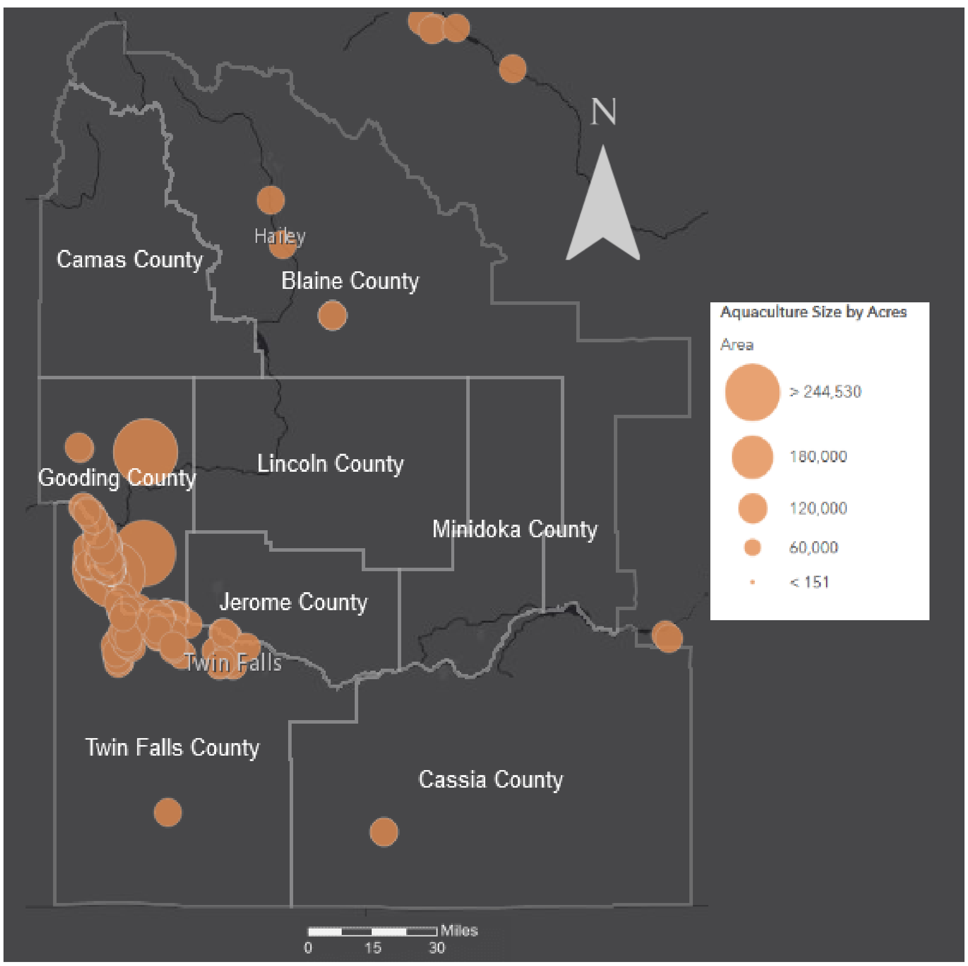
Figure 13: Point Shapefile of Food Processing Locations, 52 Points Using the Synthesized Dataset Described Above



Aquaculture

Idaho uses more water to support aquaculture than any other state (Dieter et al., 2018) making it important to include for water quality contributions. As mentioned earlier, farming of fish was considered a point source for total nitrogen and total phosphorus, and this data is also used in SPARROW. Idaho aquaculture farms are required by the Clean Water Act to have NPDES permits. These permits are issued by the Idaho DEQ and require water that is released from the farm to match the standards of the natural water body it is being released into. Water quantity and water quality are important to aquaculture farms because the water they take in must be as clean as possible for the fish to thrive, but those waters cycle from springs, through the farms, and back into the Snake River system. The SPARROW method calculates the inputs and outputs of each aquaculture farm, but this was beyond the scope of this thesis. Aquaculture farms were not mapped directly; so, a water rights shapefile was used instead. A shapefile produced by the IDWR, accessed in 2017, contained polygons depicting point of use (POUs). Water rights in Idaho are represented as areas where water can be used from a POU. Defined POUs have assigned beneficial use(s) under a water right which describes for what activity the water is needed and used (IDWR, 2017). In this case, the beneficial use attribute was filtered selecting 'FISH PROPAGATION' and 'FISH PROPAGATION STORAGE'. The shapefile was then *'clipped'* to the Magic Valley extent. There is no source for the locations of these farms. Sites were checked using Google Earth to visually determine if they were still active and to determine accurate boundaries. Two-Hundred Forty-Seven (247) farms were confirmed with this method. The shapefile included acreage attached to the water right and in Figure 14 the phosphorus impact operated under the assumption that the larger the farm, the larger the phosphorus inputs.

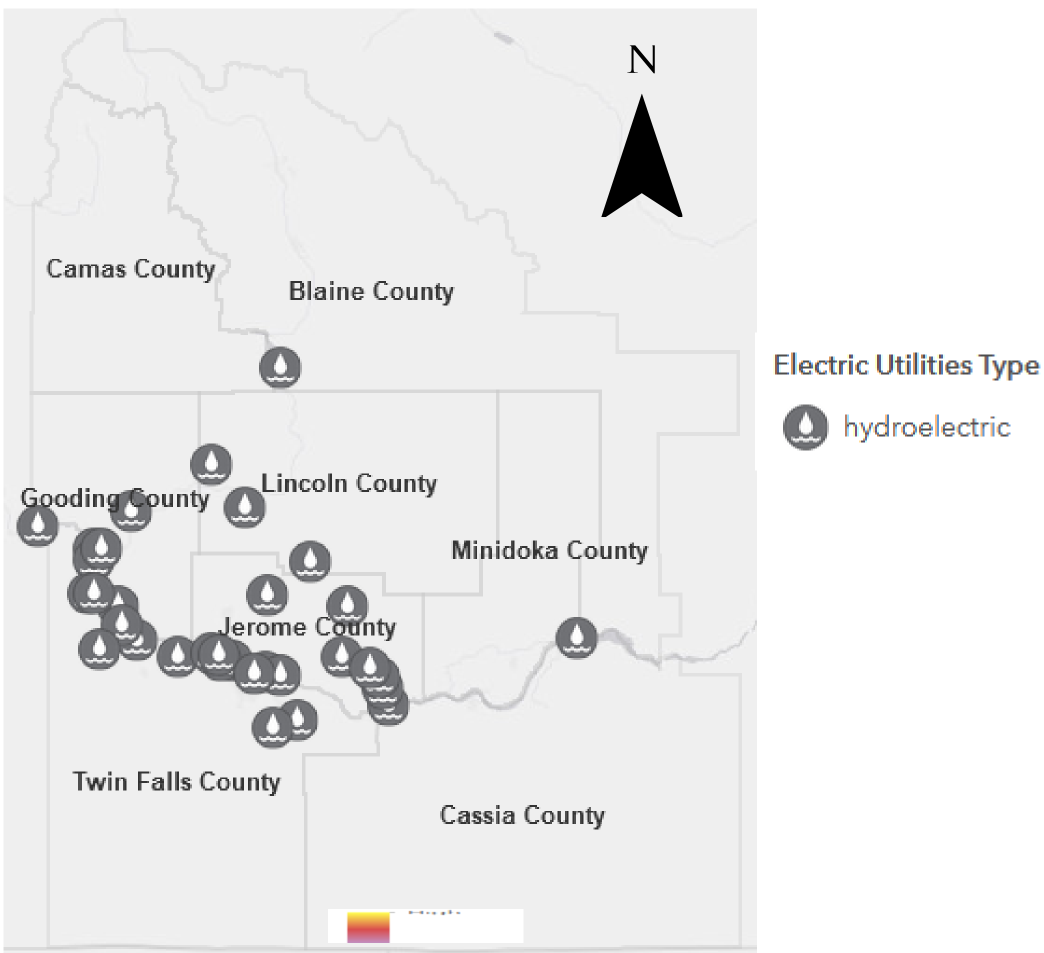
Figure 14: Dot Density Map of Aquaculture Locations with Dot Sizes Representing Relative Size



Hydroelectric Dams

In the Magic Valley, hydropower is dependent primarily on reservoir operations, and spring or early summer runoff. Additional hydropower facilities further downstream on the Snake River are also dependent on hydrologic flow out of the basin (Clark et al., 1998). There is evidence to suggest hydropower can affect water quality. While the facility itself does not pollute; the dam can affect the surrounding natural habitat. The dam constructs a reservoir area that can change water temperature and flow. This can cause water quality issues as the concentration of nutrients increases in the dammed reservoir (USGS, 2018). The presumption was more dams would provide more areas for phosphorus to become bioavailable. It is important to include energy contributions in a FEW system, thus hydroelectric dams were used as an indicator.

Figure 15: Point Shapefile of Hydroelectric Dam Locations (EIA, 2019)



The U.S. Energy Information Administration (EIA) provides a shapefile of power plants across the US (EIA, 2019). The shapefile was 'clipped' to the Magic Valley extent then the PrimSource attribute was filtered using ‘select by attributes’ in which only ‘hydroelectric’ was selected. This resulted in 34 hydroelectric plants mapped as shown in Figure 15.

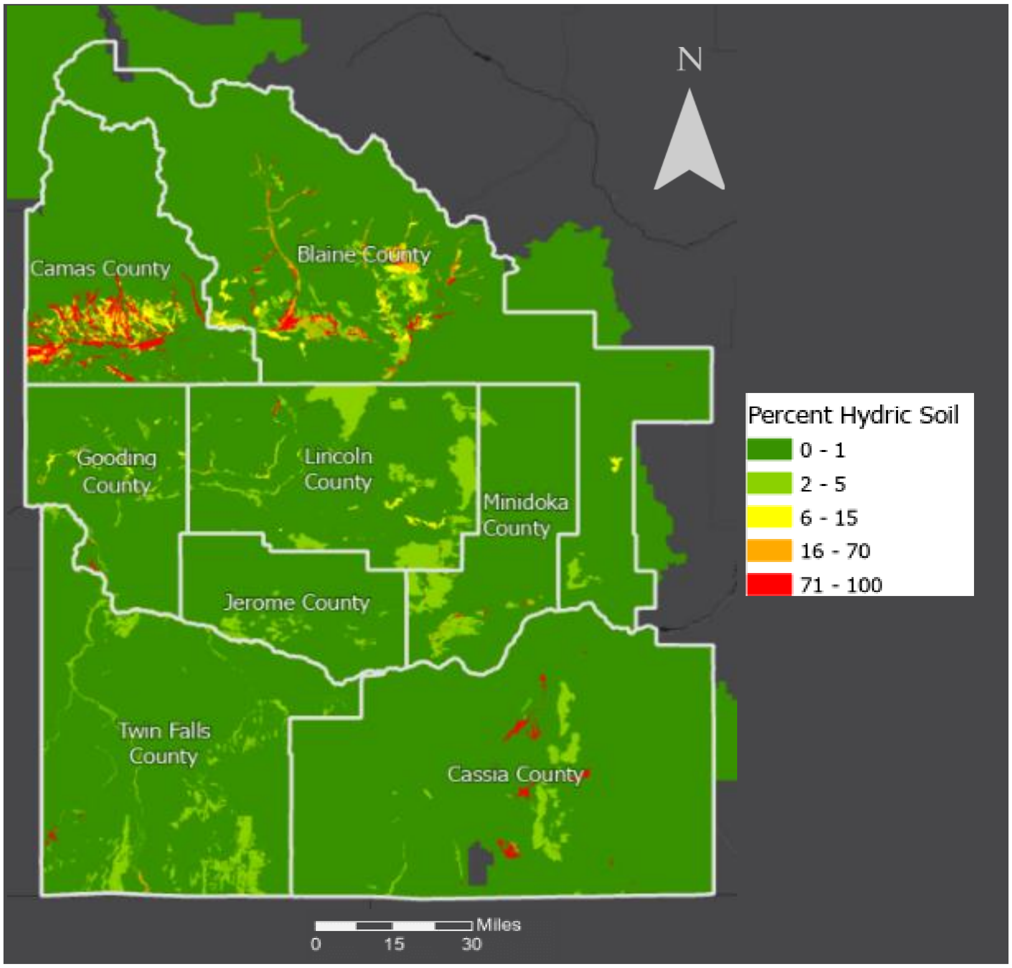
Natural

Hydric Soils

Hydric soils are also important in phosphorus movement since wetland soils can function as sinks and sources of phosphorus depending on water residence times and the biophysical properties of the soils (Seltzer & Wang, 2004). Phosphorus has a greater potential of movement for runoff and drainage in wetland soils than it does in dryland soils. The anaerobic conditions of wetlands speciate Fe which then functions as a sink in dissolved phosphorus concentrations. Phosphorus associates with Fe complexes which act to retain phosphorus within the wetland system. This can decrease phosphorus downstream but increases the retention of phosphorus in the upstream hydric areas (Reddy et al., 1999). There is also the niche in which shallow waters allow phosphates to circulate more freely from soils. The shallowness of water provides more sunlight through the water column promoting photosynthesis and exacerbating eutrophication (Smil, 2000) making some hydric soils a high contamination risk.

Web Soil Survey (WSS) houses the most comprehensive soil data for the United States. It was created by scientists from USDA and can be used for farm or urban planning. Spatial resolution is set by soil delineation. Soil delineations are a map unit that has a boundary drawn wherever there is a significant change in the type of soil. These can vary in size and change as new survey data is added. A layer provided by WSS has a hydric soil rating based upon the idea that soils under saturation flooding or ponding during the growing season develop anaerobic conditions. The criteria to determine whether soils were in hydric conditions included soil and field indicators that can cause frequent ponding for long durations. The shapefile used a rating system of soil delineation with percent of hydric components within the delineation and is shown in Figure 16 (Natural Resources Conservation Service & Soil Survey Staff, 2019).

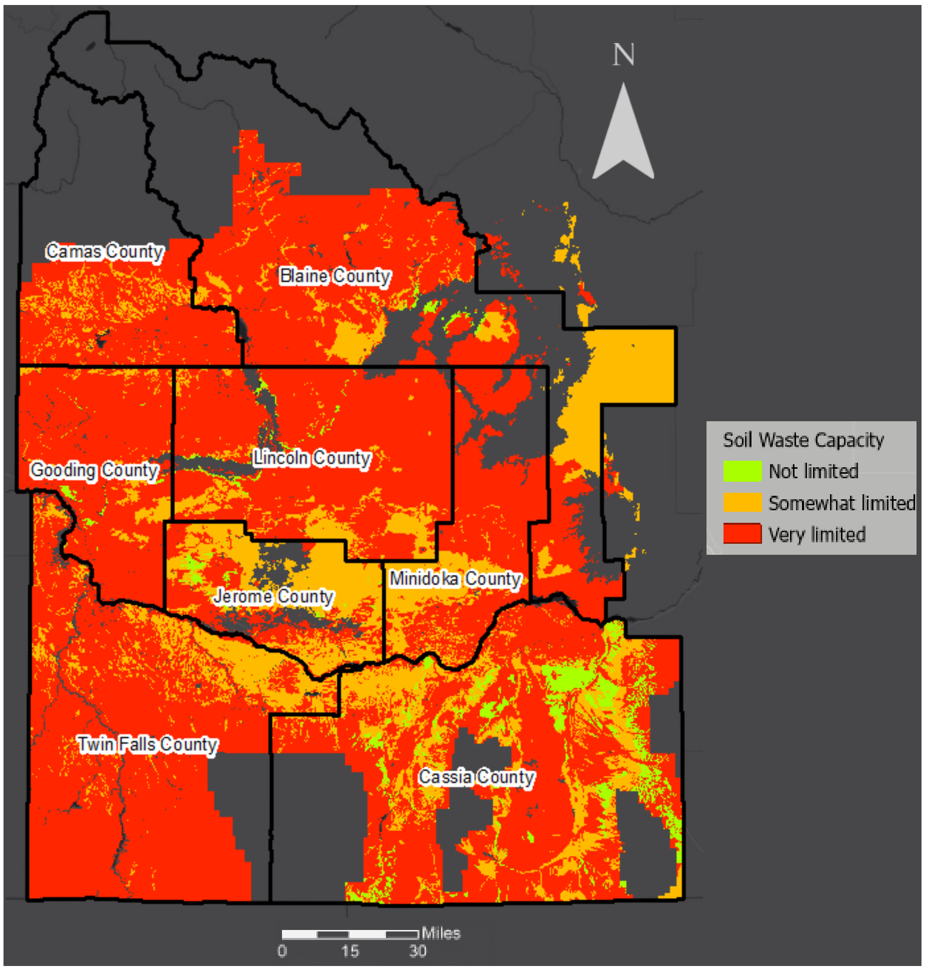
Figure 16: Hydric Soil Ratings (Natural Resources Conservation Service & Soil Survey Staff, 2019)



Waste Holding Capacity

Soil properties influence both which human activities can be supported and to what extent those activities influence nutrient leaching into waters. The waste holding capacity layer from WSS rates soils to determine how agricultural wastes are likely to be absorbed. Manure and food-processing wastes in both solid, slurry, or liquid form are included in the layer. These waste materials can improve crop production if applied as fertilizer as it increases the supply of nutrients in the soils. Manure is the excrement of livestock and poultry, and food-processing waste is damaged fruit and vegetables and the peelings, stems, leaves, pits, and soil particles removed in food preparation. The soil's holding capacity was evaluated using absorption properties, plant growth, microbial activity, and erodibility. The shapefile rates the soil classes in qualitative terms: "Not limited", "Somewhat limited", and "Very limited". Not limited soils would have good performance for retaining and utilizing wastes whereas very limited soil would not be able to sustainably hold wastes without major soil reclamation, design, or installation procedures first being implemented. (Natural Resources Conservation Service & Soil Survey Staff, 2019). Figure 17 illustrates soil ratings. Agricultural wastes do not include toxic or otherwise dangerous wastes in the definition so ratings will not account for extreme events.

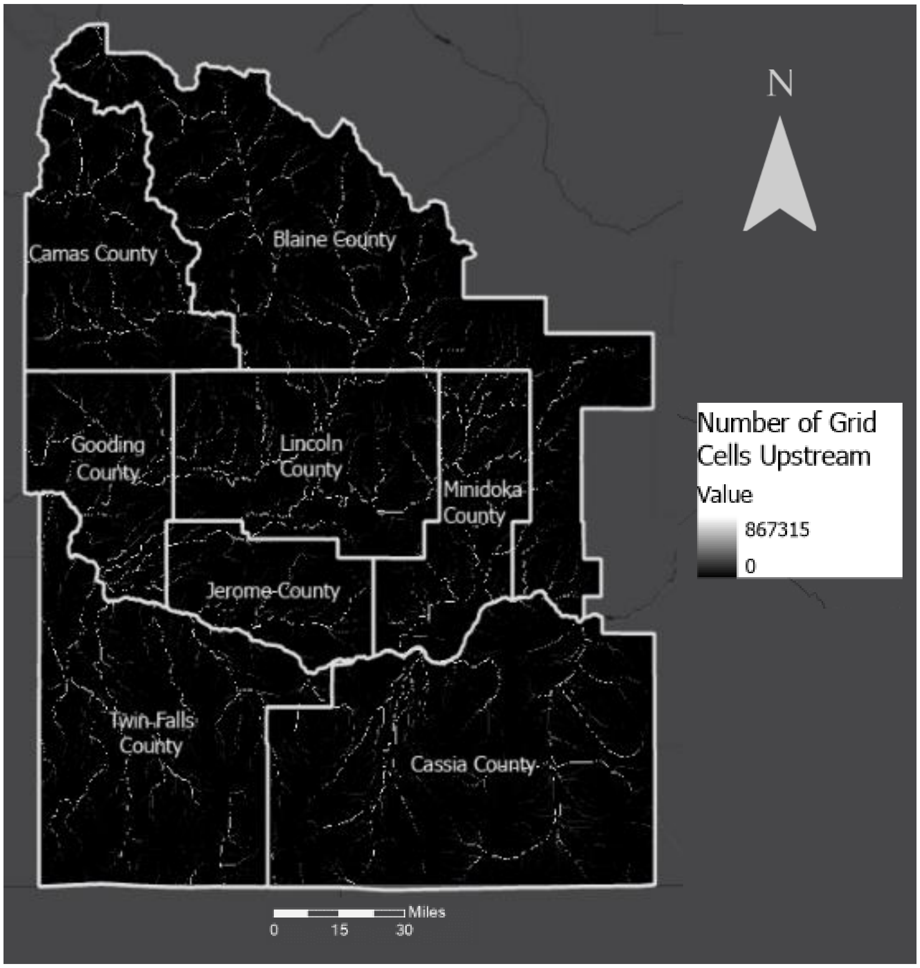
Figure 17: Soil Rating for Waste Holding Capacity (Natural Resources Conservation Service & Soil Survey Staff, 2019)



Surface Flow Accumulation

Phosphorus collects in the surface soil and concentration decreases as the depth of the horizon zone increases. The result is phosphorus movement occurring from erosion and surface runoff toward downslope areas (Sharpley, 1995b). A surface accumulation flow creates a raster with channels that represent the flow of sediments and water (ESRI, 2019b), in other words, the downslope cell areas of the raster. The raster was created by using a Digital Elevation Model (DEM) which was downloaded from the Idaho Enterprise Open Data Portal. The Idaho DEM tile resolution was at the 1/3 arc-second scale. Next, the '*Fill*' tool was executed to remove any sinks; areas that had an undefined drainage direction. Finally, the '*Flow Accumulation'* tool was run on the filled DEM. The shapefile is shown in Figure 18.

Figure 18: Flow Accumulation Areas



Impaired Streams

A concentration of phosphorus does not directly positively correlate with higher environmental harm. As mentioned in the introduction, phosphorus comes in multiple forms, bioavailable and not, and can be bound or unbound to soils. To determine locations at which accumulation of phosphorus would be detrimental, the EPA 303(d) Listed Impaired Waters dataset was used. Per the Clean Water Act, states are required to analyze whether its waters are meeting water quality standards to support its beneficial uses, or if management needs to be implemented. The Idaho Integrated Report authored in 2016 by the Idaho DEQ addresses this regulatory need. The report was a summary of the monitoring and restoration effort to restore the chemical, physical, and biological integrity of Idaho's waters (Steimke, 2018).

The waters contained in the EPA shapefile were only EPA approved Category 5 waters of a state's Integrated Report (see Table 5 for the categories).

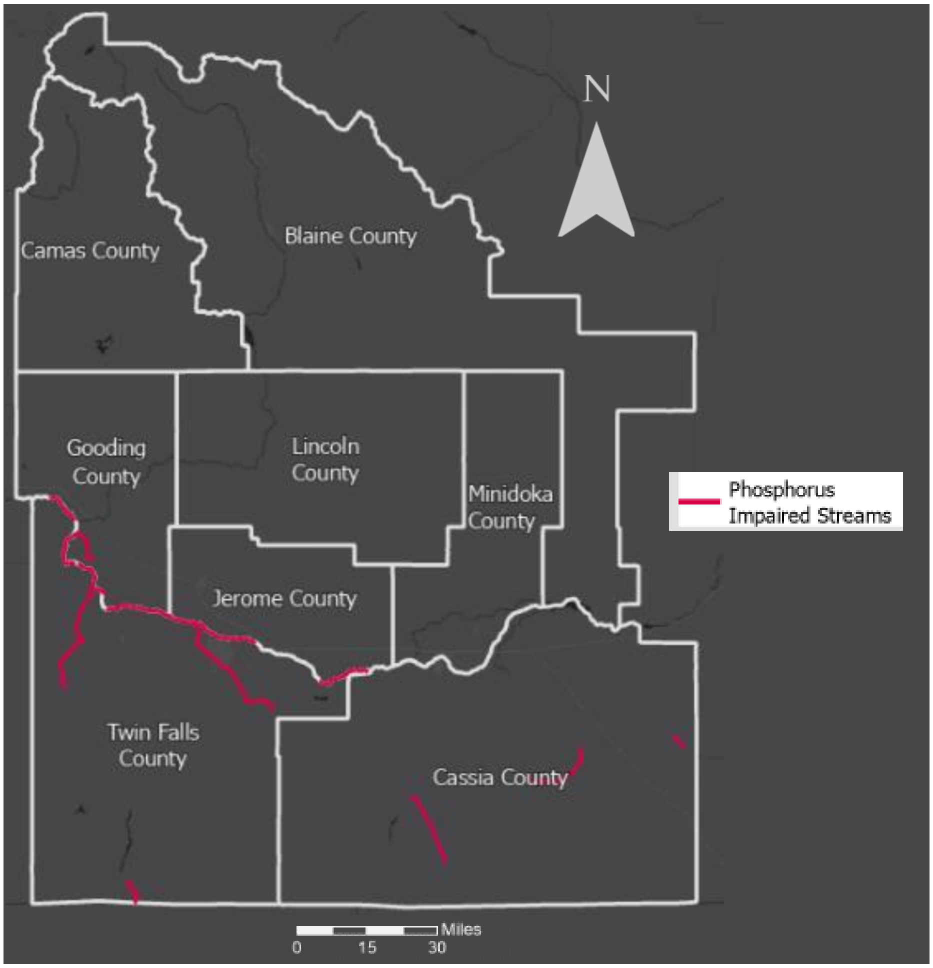
The EPA categorizes waters 1-5 which are described in Table 5 below.

Table 5:Five Assessment Categories as Defined by the EPA for Use in State Integrated Reports (U.S. Environmental Protection Agency - OW, 2010)

Category 1:	All designated uses are met
Category 2:	Some of the designated uses are met but there is insufficient data to determine if remaining designated uses are met
Category 3:	Insufficient data to determine whether any designated uses are met
Category 4:	Water is impaired or threatened but a TMDL is not needed
Category 5:	Water is impaired or threatened and a TMDL is needed

Idaho may have had other bodies of water that are impaired by phosphorus but might not have supporting data nor a total daily maximum limit (TMDL) requirement. Only category 5 streams were used as there was enough data to make a determination of contamination and the contamination was enough to cause a TMDL requirement (U.S. Environmental Protection Agency - OW, 2010). Those streams are shown in Figure 19.

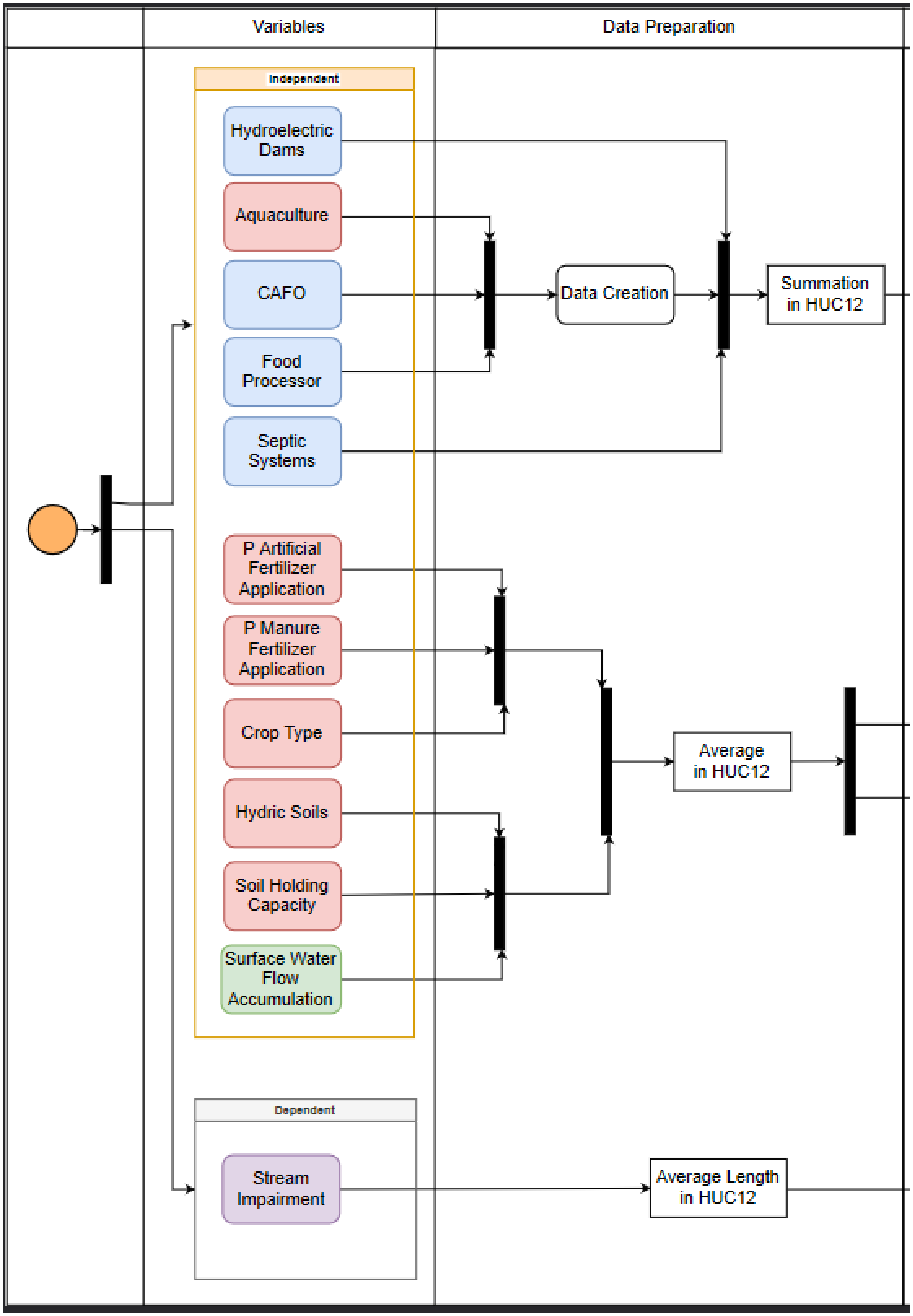
Figure 19: Streams Impaired by TP and P (U.S. Environmental Protection Agency - OW, 2010)



Chapter 4: Data Distribution and Correlations

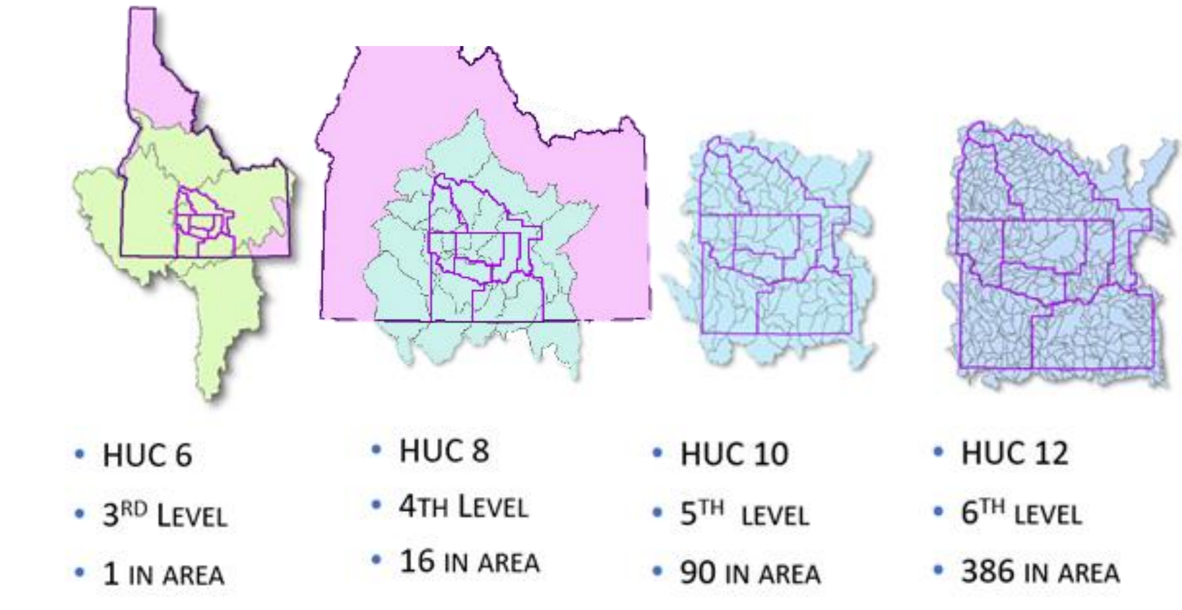
Having characterized the data that were collected, this section describes how the data were prepared for use in a regression model. Data needs to have consistent spatial resolution and the values must be normalized to meet assumptions for statistical analysis and validate that analysis. Figure 21 shows the spatial resolution of the data; most data were either summarized or averaged within a HUC 12 aggregation.

Figure 20: Diagram of Variable Aggregation, a Segment of the UML



HUC Usage

Figure 21: HUC Classifications for the Magic Valley Area.



The United States Geological Survey has divided the United States into increasingly smaller hydrologic units which are classified into four levels: regions, subregions, accounting units, and cataloging units. The units are nested within each other. Each hydrologic unit is identified by a unique hydrologic unit code (HUC). This study used the HUC 12 which is a sub-watershed level for local areas that captures tributary systems (U.S. Geological Survey, 2020). More information about HUCs is located in Appendix C.

HUC Aggregation

In this chapter all data were appended at the HUC level then a new column was created as a phosphorus vulnerability index. As mentioned in chapter 3, some of the phosphorus values are based on actual phosphorus amounts while others were developed based on assumptions of how much phosphorus was created and others on environmental indicators for phosphorus vulnerability.

Table 6: ArcMap Stats Summary Phosphorus Vulnerabilities within HUC Region

Aggregation Layer	Min:	Max:	Sum:	Mean:	Standard Deviation:	Nulls:
Manure Application Rate	0.0	17.8	490.6	1.33	2.8	116
Aquacultures Acres	0.0	1,502,740.0	4,606,061.0	12,516.47	109,212.5	
Hydroelectric Dams	0.0	4.0	34.0	0.09	0.4	
CAFO Density	0.0	57,120.0	584,044.0	1,587.08	5,562.0	
Food Processors	0.0	4.0	28.0	0.08	0.4	
Septic Systems	0.0	1,366.0	22,038.0	59.89	145.4	
Phosphorus Response	0.0	36,618.7	306,419.8	832.66	3,890.7	
Hydric Soil	0.0	24.3	845.7	2.30	4.4	
Waste Holding Capacity	2.0	5.0	940.3	3.05	1.0	60
Crop Type	0.0	143.1	12123.92	32.95	21.32	
Artificial Fertilizer	0.0	3526	465049.42	1263.72	942.86	
Accumulation Flow	0.0	9.68	326.74	0.89	1.54	

Table 6 shows the summarized statistics from ArcGIS of each shapefile layer. For each layer: minimum value, maximum value, sum, mean, standard deviation, and the number of missing values (nulls) were reported. These values were then normalized between 0-1 to make it comparable to the other layers as shown in Table 7. Explanations of what data was included in these values and how they were calculated are within this chapter.

Table 7: Summary of Normalized Phosphorus Vulnerabilities within HUC Regions

Normalized Aggregation Layer	Min:	Max:	Sum:	Mean:	Standard Deviation:	Nulls
Manure Application Rate	0.00	1.00	27.57	0.07	0.16	116.00
Aquacultures Acres	0.00	1.00	3.07	0.01	0.07	
Hydroelectric Dams	0.00	1.00	8.50	0.02	0.11	
CAFO Density	0.00	1.00	10.22	0.03	0.10	
Food Processors	0.00	1.00	7.00	0.02	0.11	
Septic Systems	0.00	1.00	16.13	0.04	0.11	
Phosphorus Response	0.00	1.00	8.37	0.02	0.11	
Hydric Soil	0.00	1.00	34.75	0.09	0.18	
Waste Holding Capacity	0.00	1.00	247.64	0.80	0.15	
Crop Type	0.00	1.00	93.37	0.25	0.15	
Synthetic Fertilizer	0.00	1.00	131.89	0.36	0.27	
Accumulation Flow	0.00	1.00	33.77	0.09	0.16	

The following sections show the basic statistics and distribution of data, Moran’s I, a visual of the data in its HUC form, and comments pertaining to the data. Global Moran’s I tests the null hypothesis that the spatial layer being evaluated was randomly distributed. It can help find patterns in complicated data sets and is measured from -1 to 1 (ESRI, 2019a). A value of 0 represents perfect randomness, a positive value indicates clustering, and a negative value indicates dispersion of values. Originally it was commonly used for disease cases but now is considered a standard for any geostatistical analysis (Jackson et al., 2010). When Moran's I is significant, it indicates that the value being assessed is clustered (see Chapter 2 for a more detailed discussion) and has directional trends. This is important with phosphorus because it suggests that the nutrient will be concentrated in areas that are highly clustered.

Manure Application

Manure application, determined by Moran's I, was clustered with $p = < .001$, or less than 1% likelihood that this clustered pattern could be the result of random chance. Because manure is heavy and expensive to transport, manure applications are not transported far from CAFOs. Figure 22 has a large skew to the left demonstrating there is not a mix between small and large application amounts.

Figure 22: Manure Application Frequency Distribution of the HUCs Containing Values Greater than 0

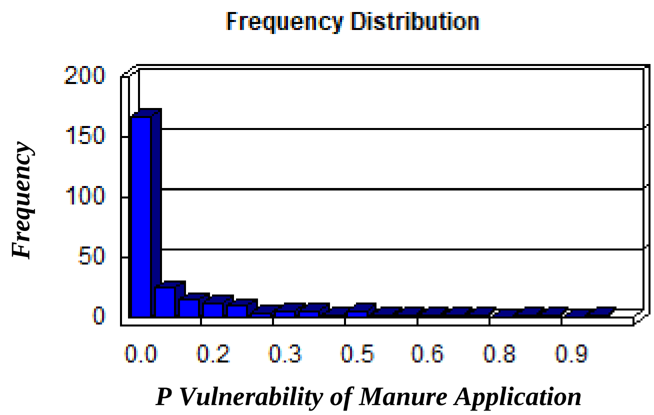
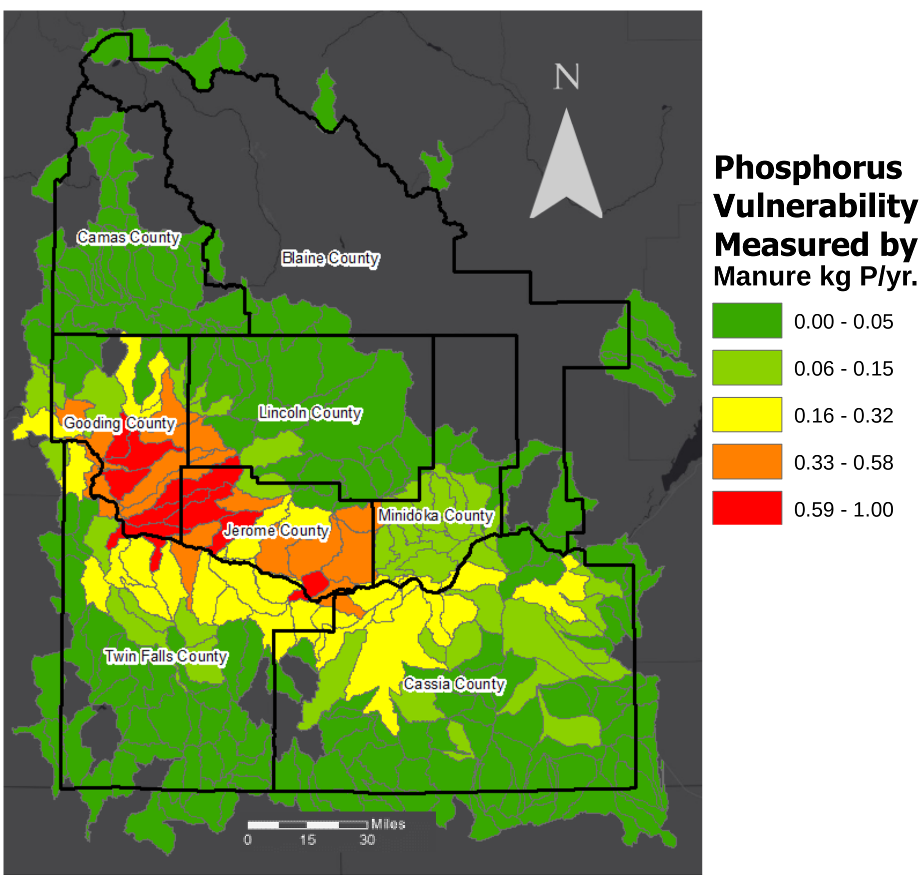


Figure 23: HUC 12 with Phosphorus Vulnerability of Manure Application



116 HUCs had no data available for manure distribution resulting in null values (Figure 23). No spatial aggregation was needed as the data was already provided in the HUC 12 areas by the EPA. The only changes to the data were the normalization adjustments.

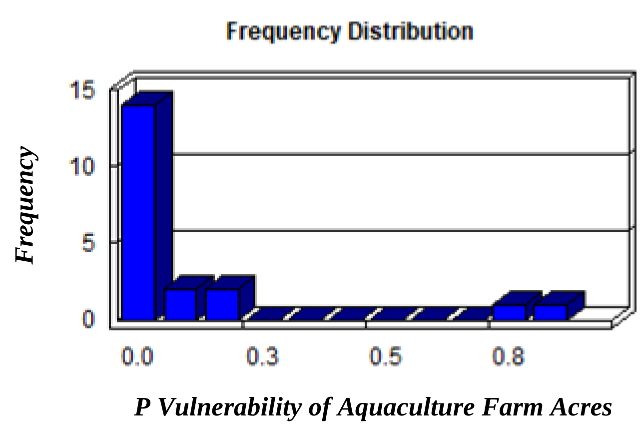
Sum Spatial Join

Spatial joins affix data from one feature layer's attribute table to another from a spatial perspective. Essentially it takes the attribute data of the join feature and associates it with the spatial area of the target feature. In this case, all variable data needed to be aggregated into the HUC watershed units to meet the regression assumption that predictor variables are spatially consistent across all layers. Potential sources of phosphorus were summed within a HUC area to form a phosphorus vulnerability index. When working with unknown phosphorus amounts, the assumption is that an increased occurrence of a source will lead to more phosphorus accumulation.

Aquaculture

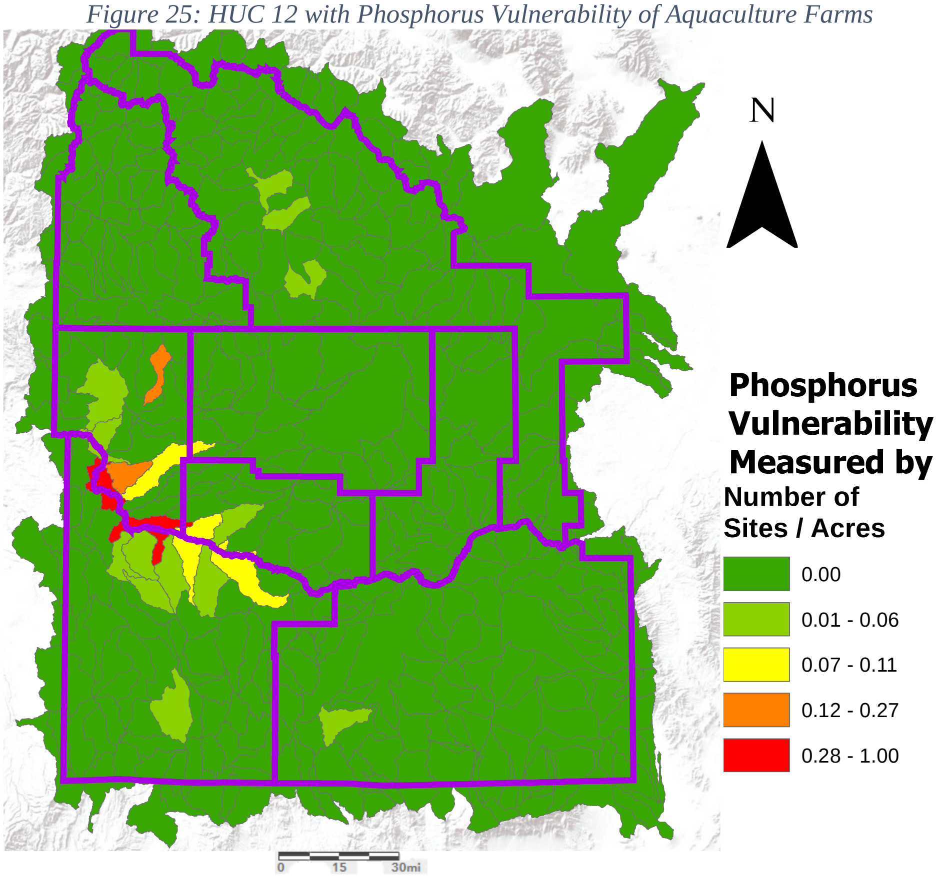
The aquaculture farm area was estimated by drawing polygons around each facility. It was assumed that the larger the aquaculture operation, the larger the potential phosphorus output. Thus 1 was assigned to the largest summed areas and 0 to areas with no aquaculture. 20 HUCs had aquacultural acreage (Figure 25) most of which were in the western part of the Snake River. The data distribution Moran's I statistic indicated that the layer was significantly clustered with $p < .001$.

Figure 24: Aquaculture Frequency Distribution of the HUCs Containing P Ranking Values Greater than 0



The majority of HUCs have smaller aquaculture farms but there is a bimodal distribution in which there are some large-scale aquaculture farms but none that are medium-sized (Figure 24).

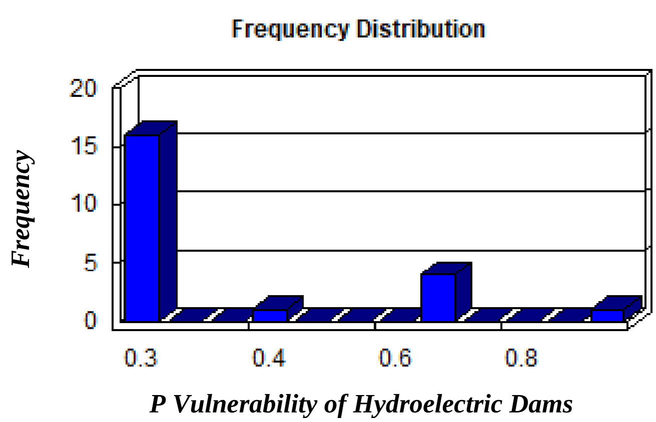
Figure 25: HUC 12 with Phosphorus Vulnerability of Aquaculture Farms



Hydroelectric Dams

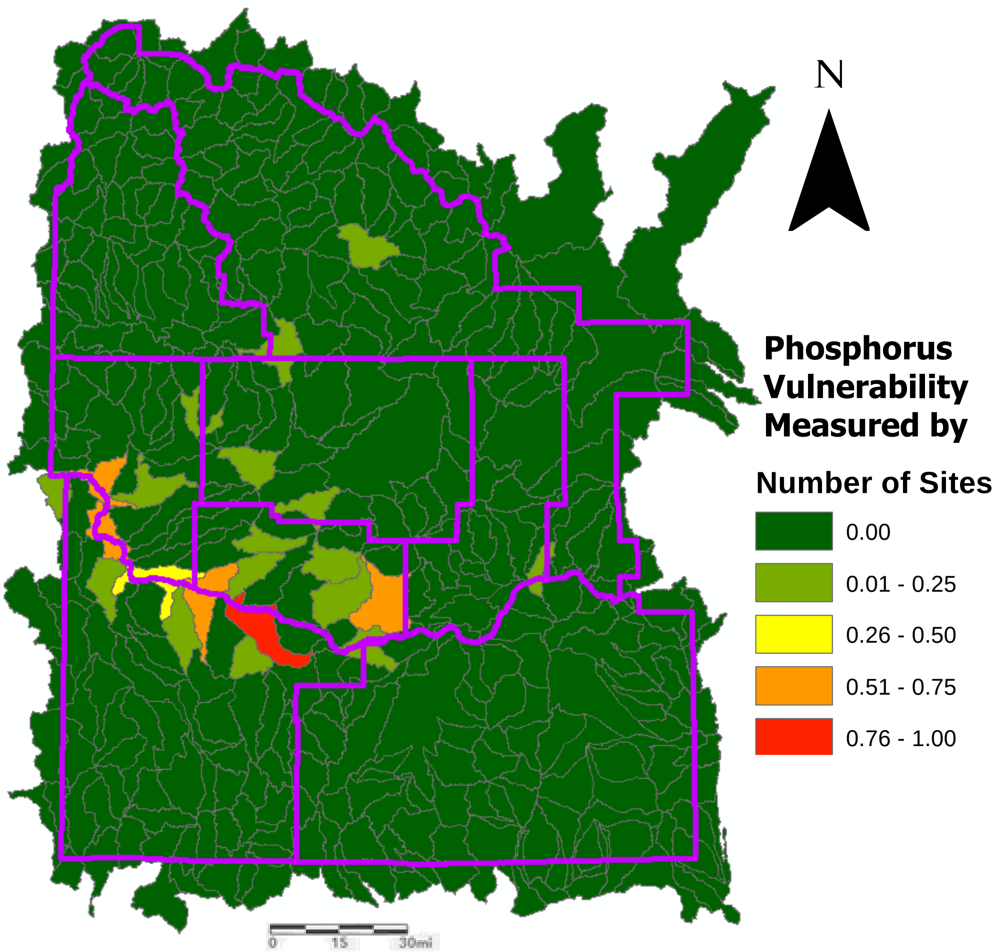
The number of hydroelectric dams were summed within the HUC. This produced 22 HUCs with the majority of hydroelectric dams along the Twin Falls Snake River area (Figures 26 and 27).

Figure 26: Dam Frequency Distribution of the HUCs Containing Values Greater than 0



The Moran's I statistic suggested that the pattern of hydroelectric dam placement did not appear to be significantly different than random as $p = .18$ and the null hypothesis (of no difference from random distribution) cannot be rejected.

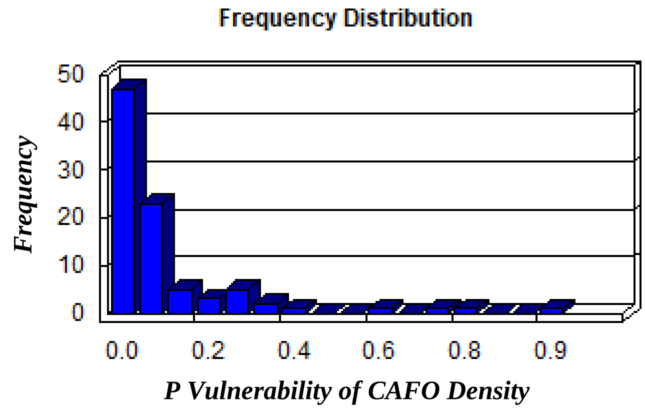
Figure 27: HUC 12 with Phosphorus Vulnerability of Hydroelectric Dams



CAFO

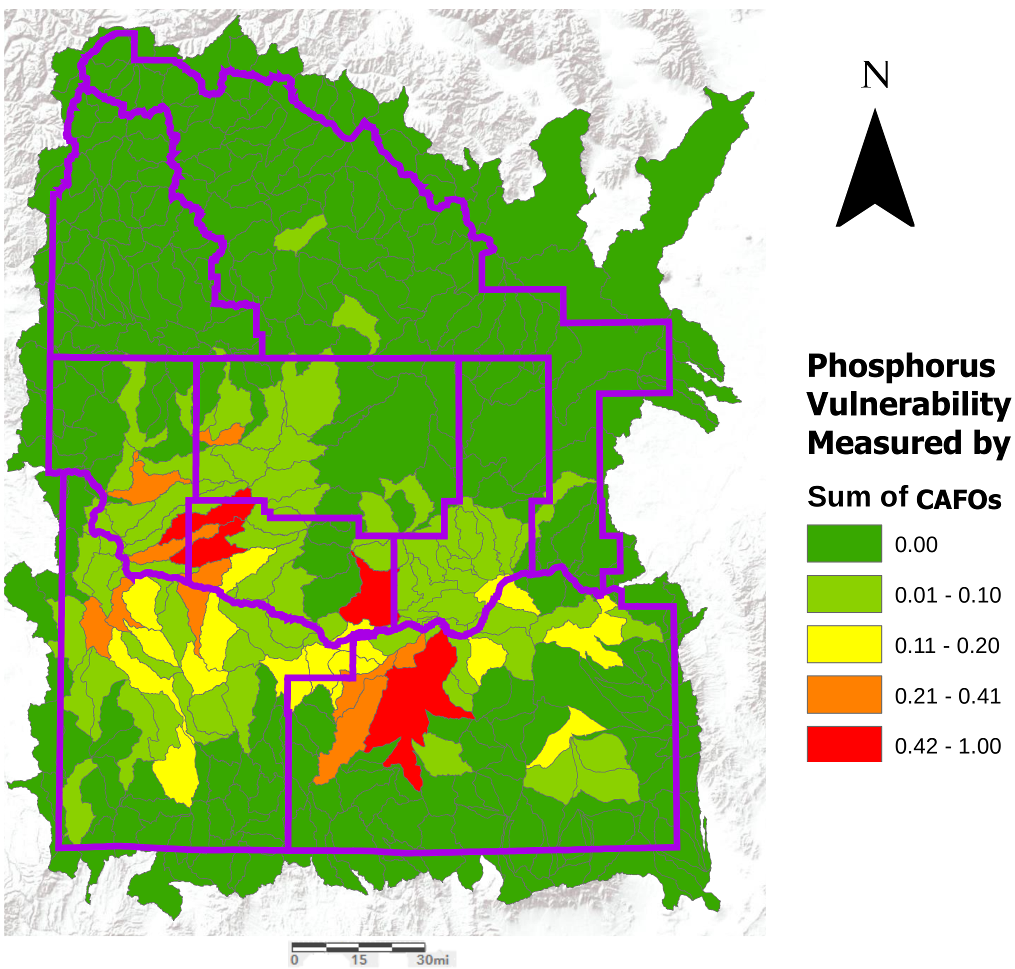
The count of dairy cows was summed within each HUC. Active milking cows were selected as this produces the highest amount of excreted phosphorus in the life cycle of dairy cattle (Lorimor et al., 2004). The 1 rating, or the highest output of expected phosphorus, refers to HUCs with the greatest number of cows. HUCs containing no cows were rated 0 Figure 28. In Figure 29 the largest sum of CAFOs were located in Jerome and Cassia counties.

Figure 28: CAFO Frequency Distribution of the HUCs Containing Values Greater than 0



The Moran's I statistic denoted that the layer was significantly clustered $p < .001$.

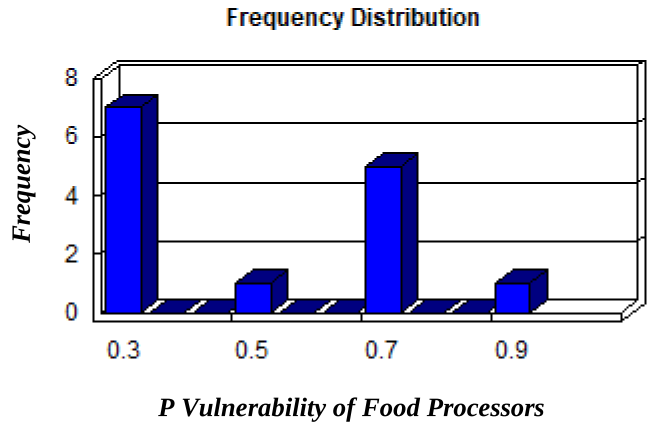
Figure 29 HUC 12 with Phosphorus Vulnerability of CAFO Count



Food Processors

Similar to the hydroelectric dam layer, food processor instances with a 1 rating contained the most facilities, and a 0 contained none (Table 7, Figures 30 and 31).

Figure 30: Food Processor Frequency Distribution of the HUCs Containing Values Greater than 0



Moran's I statistic concluded the layer was significantly clustered with p = .013

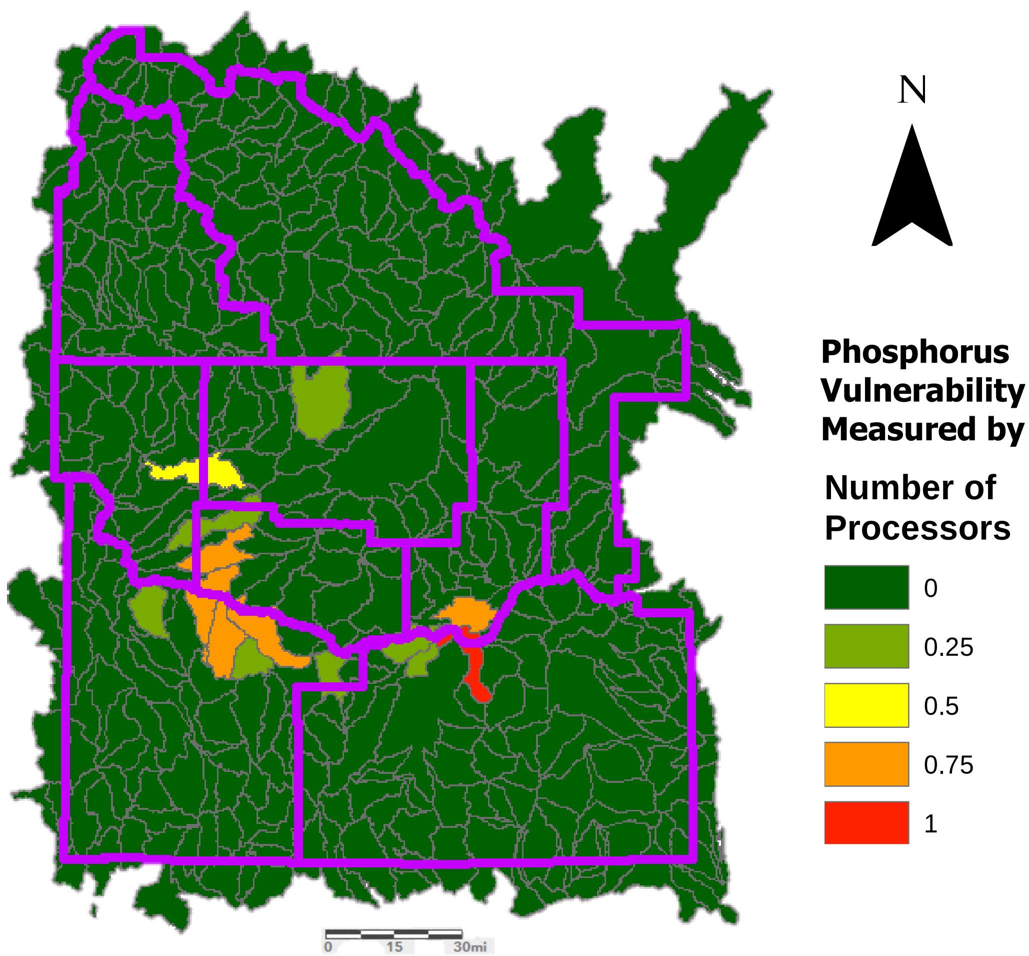
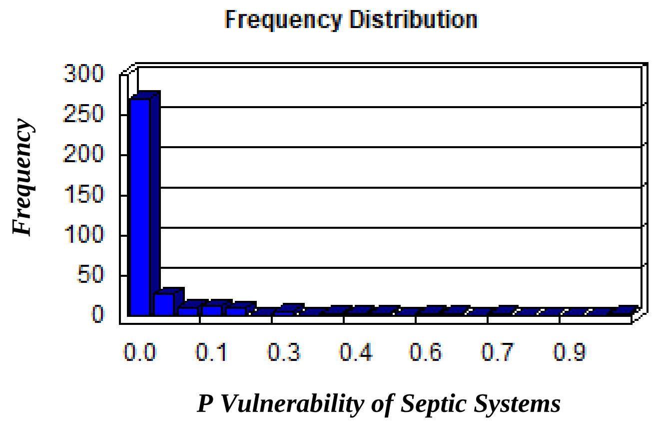


Figure 31: HUC 12 with Phosphorus Vulnerability of Food Processors

Septic System

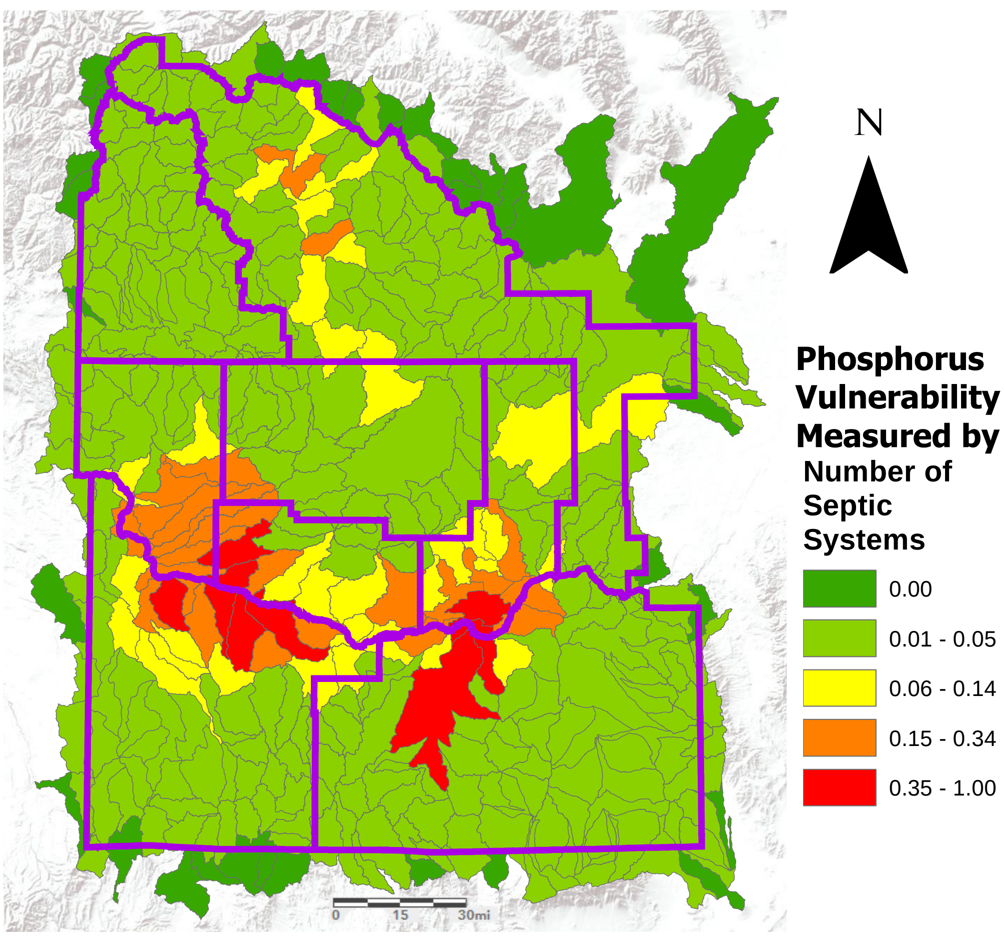
There were a range of numbers of septic systems in HUCs with a 1 rating containing the most facilities and 0 containing none (Table 7, Figures 32 and 33).

Figure 32: Septic System Frequency Distribution of the HUCs Containing Values Greater than 0



The Moran I statistic indicated that the layer was significantly clustered with $p < .001$

Figure 33: HUC 12 with Phosphorus Vulnerability of Septic Systems



Phosphorus Response

Idaho DEQ reports Category 5 waters, those that are impaired or threatened and for which a TMDL is needed. For creating a dependent variable, the length of the impaired stream indicates the HUC is showing a stronger response to unknown explanatory variables.

The Category 5 stream length of total phosphorus (TP) and phosphorus (P) were overlapped, then the length of the stream was summed into total kilometers. HUCs with the longest impaired streams, or the higher km, were rated with a 1 rating, and no known impairments rated 0 (Figures 34 and 35). The Moran's I statistic indicated that the layer was significantly clustered with $p < .001$

Figure 34: Phosphorus Response Frequency Distribution of the HUCs Containing Values Greater than 0

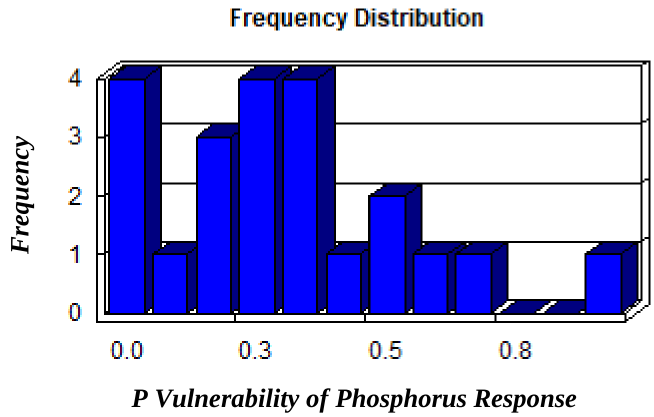
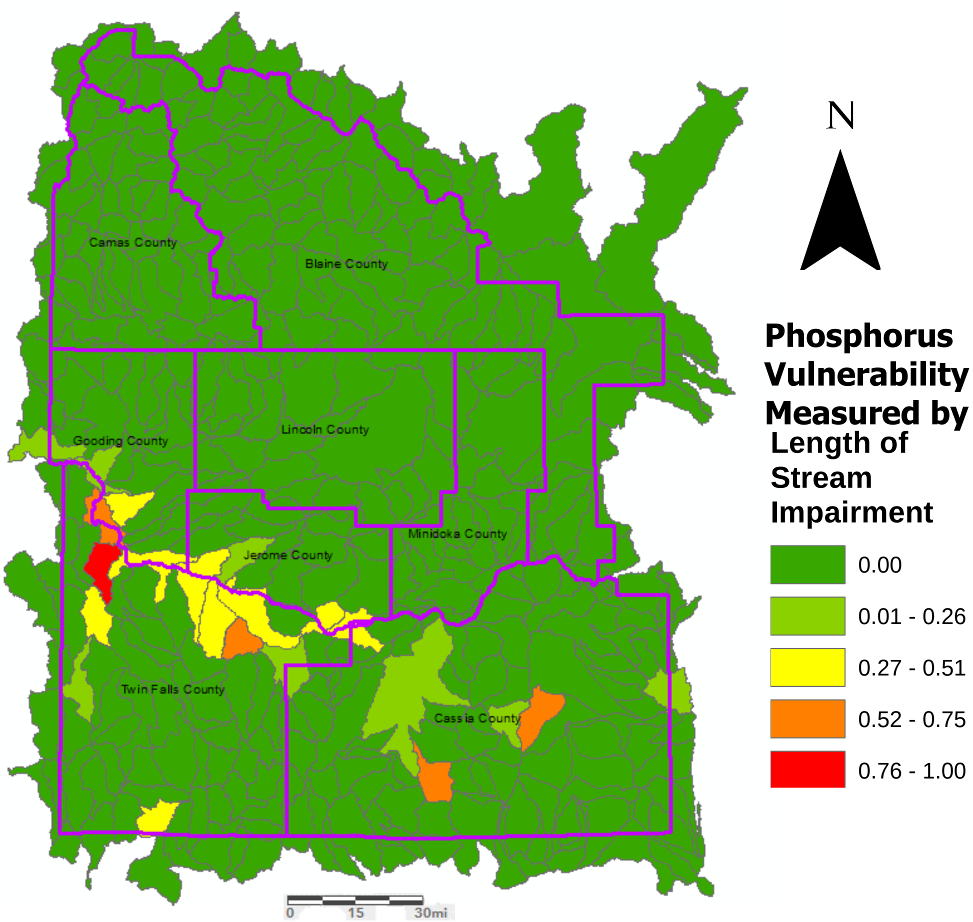


Figure 35: Phosphorus Response Stream Length Summed among HUC 12 Aggregation



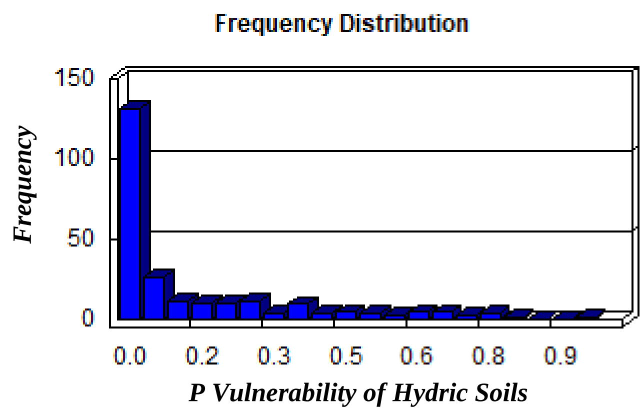
Average Spatial Join

This section explains the variables that were used to compute the "average" summarization within the HUC 12 boundary. Data layers that had known phosphorous amounts, or that were environmental indicators were averaged within a HUC to accommodate the variance between values. For best display purposes, 0 was placed in a category level then *Natural Breaks* were used for the rest of the symbology level classification.

Hydric Soils

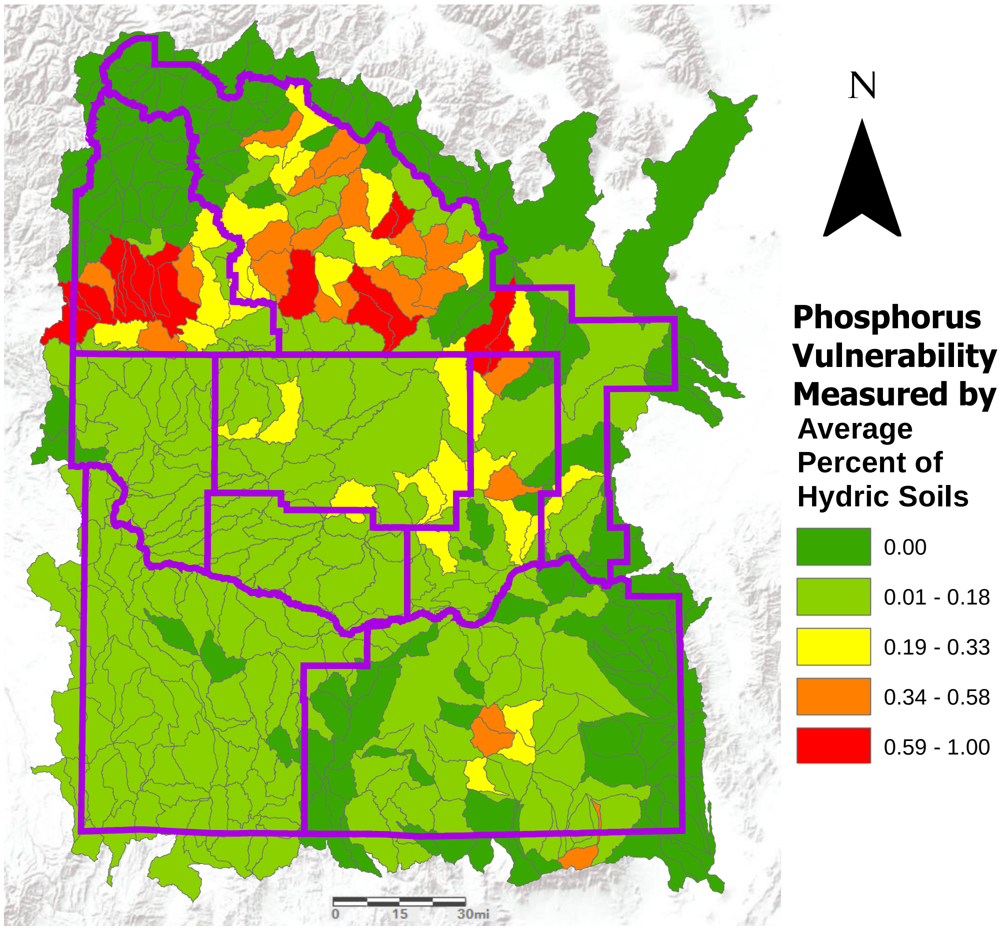
Soils were rated by percent of components containing hydric soils. The mean soil percentage was used to aggregate the HUCs. A higher percentage of hydric components were rated 1 for more phosphorus potential and 0 for HUCs containing no hydric properties (Table 7). The Moran's I statistic indicated that the layer was significantly clustered, with $p = 0.00$

Figure 36: Hydric Soils Frequency Distribution of the HUCs Containing Values Greater than 0



The northern areas of the Magic Valley had larger percentages of hydric soils but more than half of HUCs rated low on this measure of phosphorus vulnerability (Figures 36 & 37).

Figure 37: HUC 12 with Phosphorus Vulnerability of Hydric Soils



Waste Holding Capacity

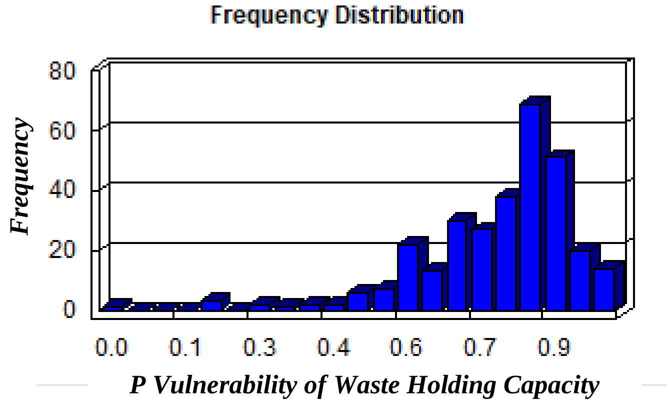
The WSS designed this layer as a shapefile with three qualitative rankings of how well the soil can hold wastes (Figure 39). A soil ranking of "not limited" denotes that the soil would reasonably hold waste applications without releases to the environment. This was rated numerically as 0.33. HUCs that were "very limited" would be prone to runoff of waste and were rated with 1 being a high risk for phosphorus release potential (Table 7).

Table 8: Waste Holding Capacity Ranking

WSS Qualitative Rating	Quantitative Assignment
Not Rated	0
Not Limited	0.33
Somewhat Limited	0.66
Very Limited	1

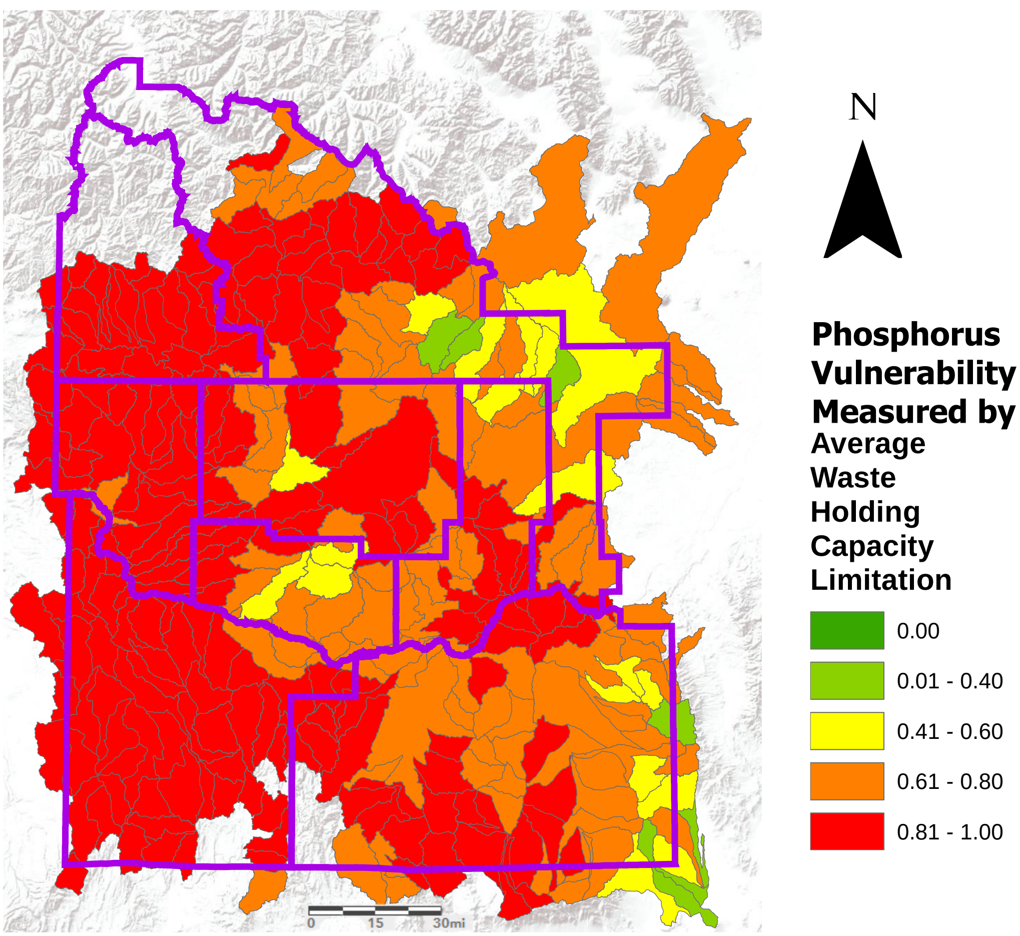
There were 60 areas that had no available data resulting in null values (Table 6). The Moran's I statistic suggested that the layer was significantly clustered with $p = < .001$

Figure 38: Waste Holding Capacity Frequency Distribution of the HUCs Containing Values Greater than 0



The frequency distribution is skewed to the right and indicates that the majority of HUC soils are not good for holding wastes in the Magic Valley Area (Figure 38). Jerome and Blaine counties have a few areas with lower phosphorus vulnerability (Figure 39).

Figure 39: HUC 12 with Phosphorus Vulnerability of Waste Holding Capacity



Crop Type

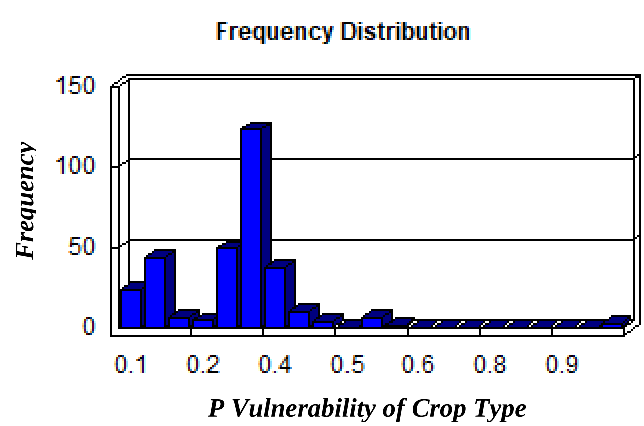
Synthetic phosphorus fertilizer applied, and crop uptake was estimated by unpublished data produced by Dr. April Leytem in 2020 and used for HUC boundaries. County level data for phosphorus balance is available in the (Leytem et al., 2021) publication. Crop uptake was subtracted from the average phosphorus applied to measure excess phosphorus. The excess phosphorus was then normalized to produce the phosphorus ranking for this layer (Table 9).

Table 9: Crop Type Ranking

	Total P lbs. applied	Average P uptake (lbs./acre)	Excess P lbs.	P Ranking
Sugar Beet	50.33	56.00	-5.67	0.00
Alfalfa	34.33	26.70	7.63	0.09
Other	50.00	36.76	13.24	0.13
Spring Wheat	68.67	44.90	23.77	0.20
Winter Wheat	68.67	44.90	23.77	0.20
Barley	68.67	44.60	24.07	0.20
Potato	121.67	34.80	86.87	0.62
Corn	183.67	40.60	143.07	1.00

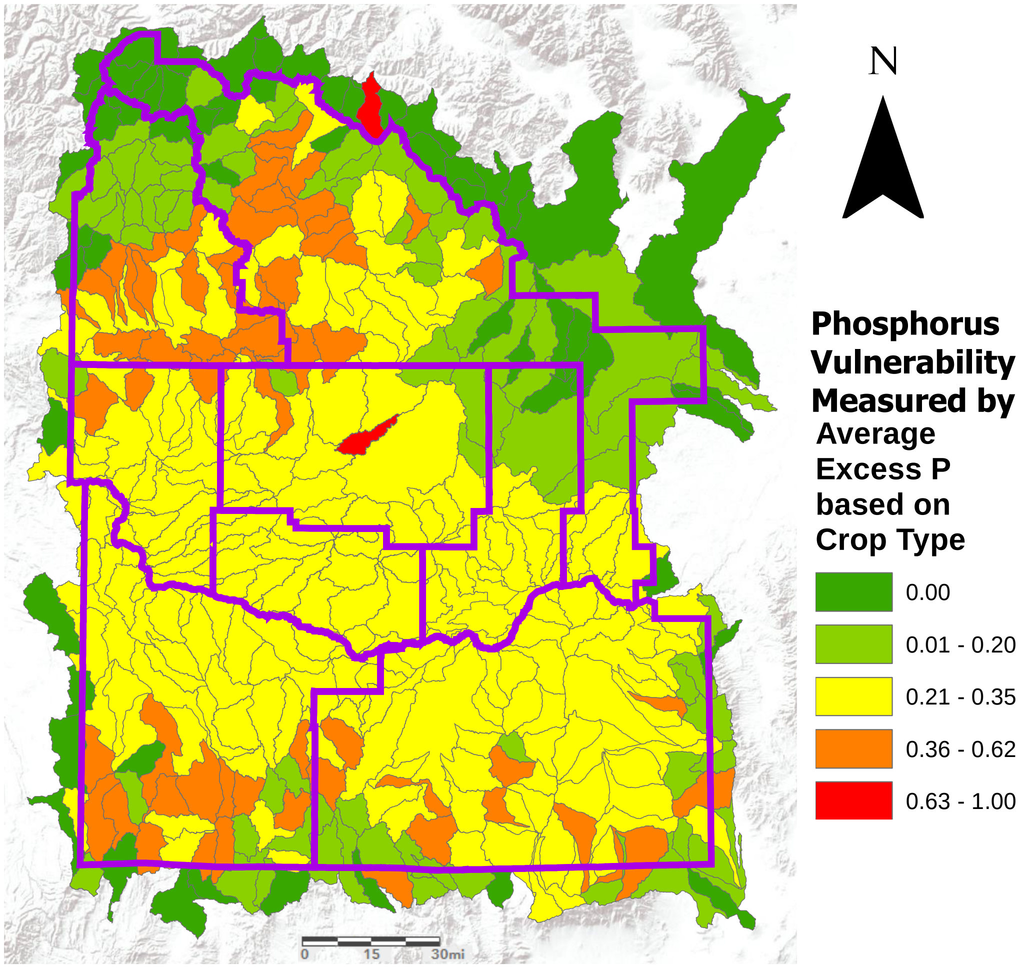
The normalized value of excess P was then spatially joined with each HUC unit. Sugar beets were ranked as the least vulnerable and corn as the most vulnerable for P losses. Moran's I concluded the layer was significantly clustered with $p < .001$

Figure 40: Crop Type Frequency Distribution of the HUCs Containing Values Greater than 0



When all excess phosphorus from crops were averaged into a HUC unit, the vulnerability distribution was lower (Figure 40). There is a ring effect where HUCS farther away from the Snake River increased in vulnerability but decreased at the Magic Valley boundary (Figure 41).

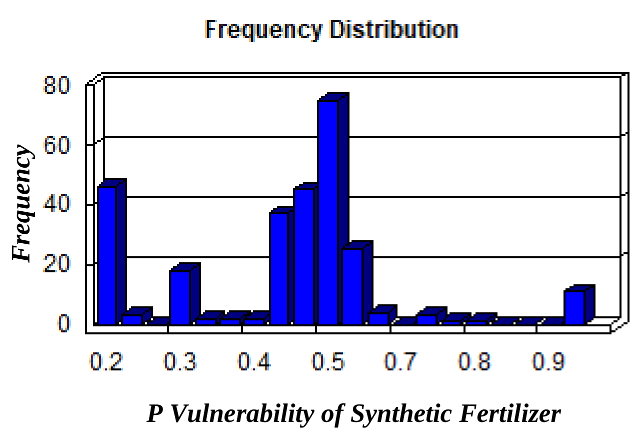
Figure 41: HUC 12 with Phosphorus Vulnerability of Crop Type



Artificial (Synthetic) Fertilizer

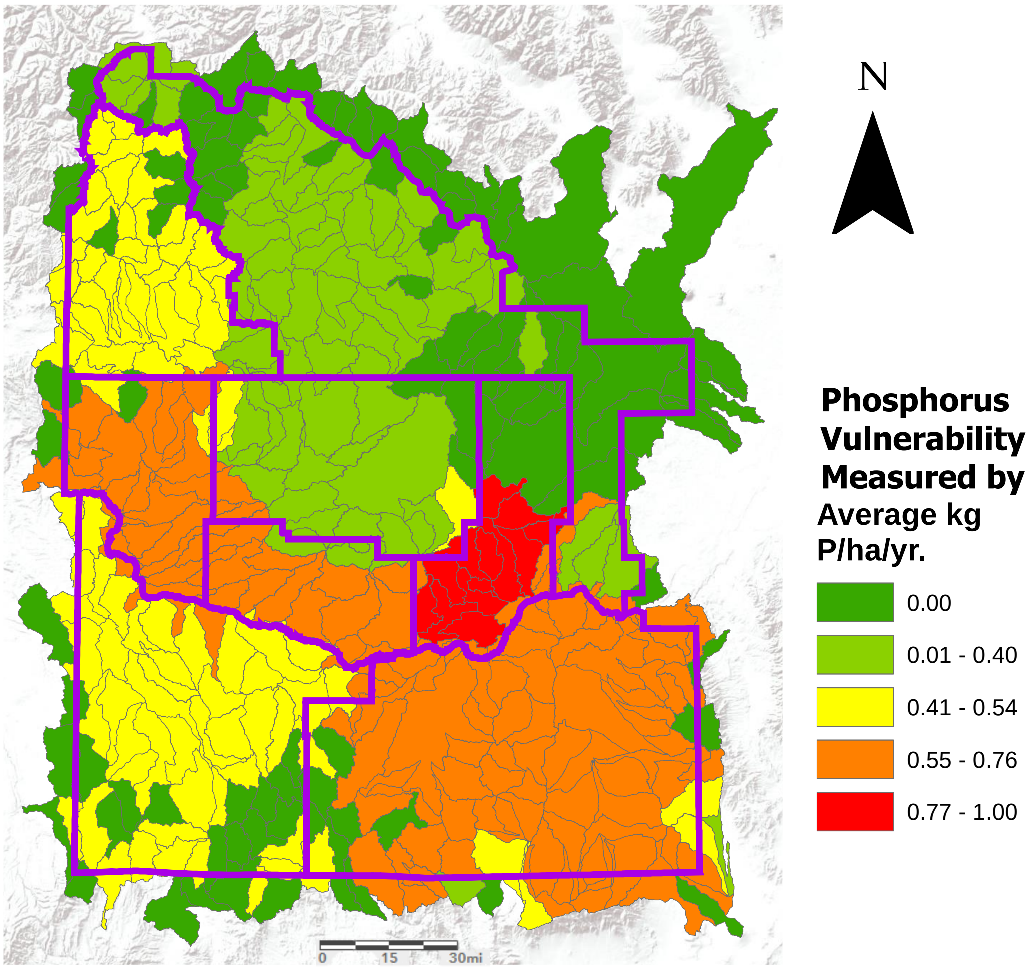
HUCs, where a greater mass (kg) of fertilizer was applied, were ranked higher, and no use of phosphorus fertilizer application was ranked 0 (Table 7). Moran's I statistic suggested that this layer was significantly clustered with p = <.001

Figure 42: Synthetic Fertilizer Frequency Distribution of the HUCs Containing Values Greater than 0



Based on the frequency distributions (Figure 42) most HUC are moderately vulnerable (0.45-0.70) with the highest synthetic phosphorus likely being applied in south Minidoka County.

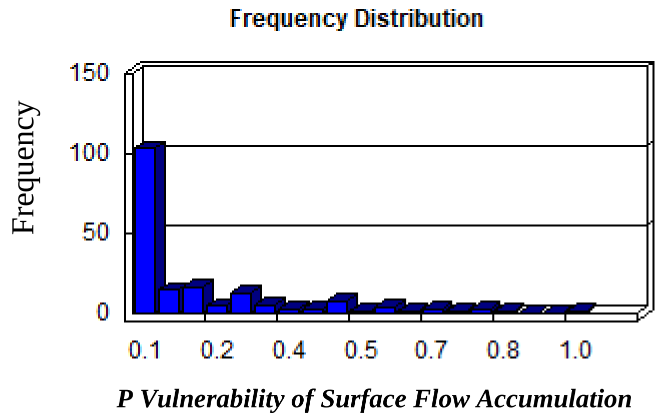
Figure 43: HUC 12 with Phosphorus Vulnerability of Synthetic Fertilizer



Surface Flow Accumulation

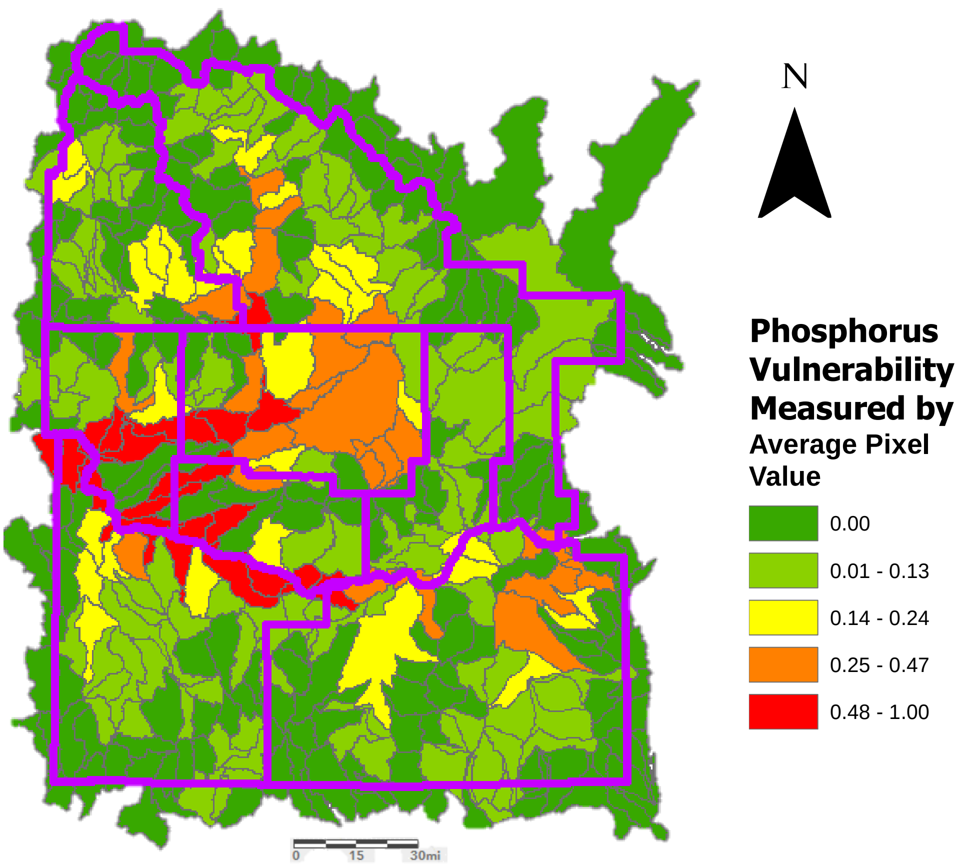
Surface flow accumulation had a pixel value that represents areas of greater water accumulation. Pixel values were averaged within a HUC, and the highest average pixel value was given a 1 whereas 0 represented areas with no surface water accumulation (Figures 44 and 45). Moran's I statistic suggested that the layer was significantly clustered with $p < .001$.

Figure 44: Surface Flow Accumulation Frequency Distribution of the HUCs *Containing Values Greater than 0*



The vulnerable areas are west of the Snake River and the Malad River (See Figure 45 for vulnerability and Figure 3 for river locations).

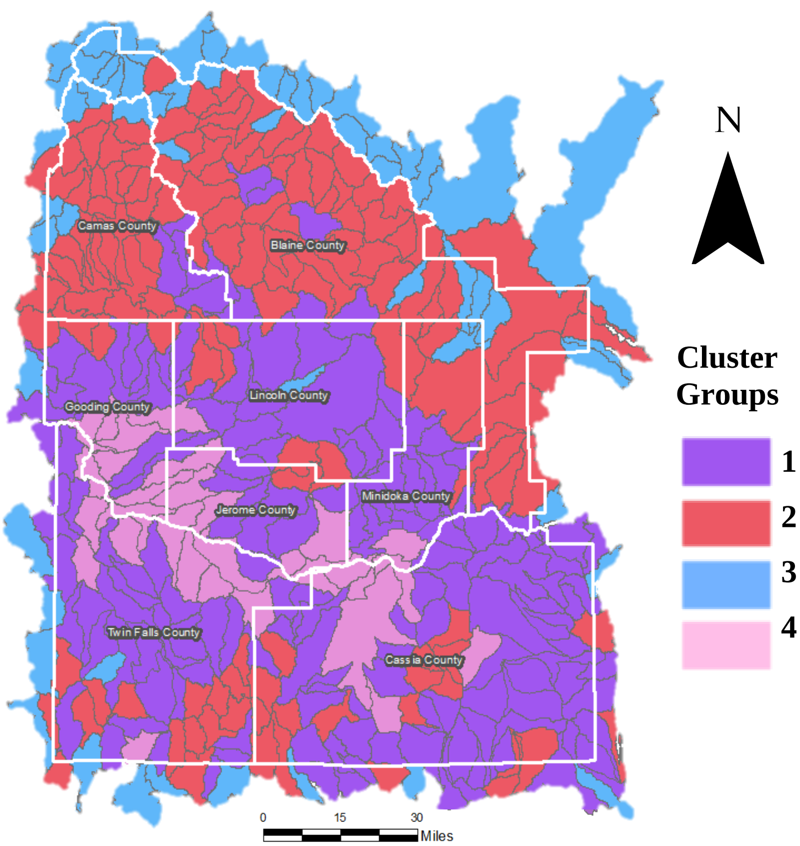
Figure 45: HUC 12 with Phosphorus Vulnerability of Surface Flow Accumulation



Aggregation Properties

To visualize how the variables interact with each other, a k-mean clustering visualization was used (Figure 46). Clustering, under the definition of traditional statistics, are a variety of techniques that find similar subgroups of observations within a dataset. It is a statistical tool that does not use spatial information, only the attributes of the data. The **factoextra** package for R (Kassambara & Mundt, 2020) has a K-Means type of clustering function called *fviz_cluster* which uses an unsupervised learning algorithm, and the user defines K; the number of clusters the computer needs to assign data to. K is selected by considering values on scree plots and what visually creates the most useful interpretations.

Figure 46: Magic Valley HUCs Groups by Similar Attributes per R Clustering



The observations are assigned to a cluster group based on the first two principal components of the dataset which account for 46% of the variance. Creating cluster groups based on all 12 variables would be difficult due to the variation of each variable from all observations. But a principal component analysis reduces the number of variables by removing unnecessary explanatory information from the dataset and creating new variables that successively maximize the percentage of variance explained. Most of the information is still retained but it is simpler for the algorithm to identify similarities. For these principal components, the first dimension is mostly comprised of manure application rate, septic systems, accumulation flow, hydroelectric dams, and the second dimension: crop type and waste holding capacity. Four k-means were selected based on the distinguishable cluster groups. Increasing past four caused overlapping of clusters making it difficult for analysis.

Only cluster group 4, seen in the legend on Figure 46, incorporates all known HUCs with phosphorus impairments (see Figure 35 for comparison). It also includes other HUC units with no known phosphorus impairments. If we are to assume that the similarities of the regions are due to being in the same cluster group, we could make a reasonable argument that the other HUCs may also have phosphorus impairments if they were tested. This can be thought of as a phosphorus priority area.

During the process of aggregation, strong clustering patterns were visible and confirmed with Moran’s I. All variables were significantly clustered other than hydroelectric dams which were shown to be random. The majority of variables had a left skew distribution. Notable deviations were waste holding capacity had a right skew distribution, synthetic fertilizer had closer to a normal distribution. Both food processors and phosphorous response variables had multimodal distributions. Due to the spatial autocorrelation and distribution skews, a regression model needed to be selected that could resolve the spatial properties of the data. The spatial econometric regression family was selected as it accounts for spatial effects in regression analysis.

Chapter 5: Regression Modeling

The first section of this chapter covers the model selection process including the key decisions based on an understanding of the available data and how it might be represented in space. Relevant questions include:

a. How is our data distributed?
b. Do the data parameters meet the assumptions of the regression model selected?
c. How well does a regression model explain the variance?

Answers to these questions will come from the analysis of spatial statistics that integrate mathematics directly into space. This integration can be created by introducing spatial weights (W) coefficient within modeling. Choices must not merely apply traditional statistical methods to data that just happens to be spatial. In this study, regression modeling was used to find a mathematical model that best fit the existing data (the independent variables) to the response variable. Among all the choices of regression models, spatial econometric models have a unique ability to incorporate simultaneous feedback between regions located in space. This fits well with the SES theory that humans and nature have a dynamic relationship (Virapongse et al., 2016). After identifying the family of regression models best suited to the data and our objectives, we then start a "specification search" that involves selecting a statistical model based on its ability to pass validation tests. Fitness tests are run to determine if the model's predicted values are close to the observed data points and the models found to perform well can be called "best of fit". In this regression, the predicted or response variable is impaired phosphorus streams. The final modeling step involves validating regression results. In addition, the Breusch-Pagan test was applied, which parses out if the model is predicting properly across all areas. This chapter is divided into two sections discussing decisions that were made for modeling the data. First the analysis of appropriate regression parameters and then the validation of the selected model.

Analysis

Much of the preliminary work described in earlier chapters provides a comprehensive understanding of the data and what it is expected to show so that an accurate model selection and refinements to the model can be made. Many regression models exist, and it is a common mistake to mis-specify data by using the wrong regression. There are rules and assumptions for different types of regression, occasionally there is disagreement about models based on disciplines (traditional statistics vs. spatial statistics). Both disciplines agree, however, that a mis-specified model is an incomplete model.

Ordinary Least Squares (OLS) is the starting point for all spatial regression analyses and its representation is shown in the equation below:

$$\mathbf{y} = \mathbf{X}\,\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

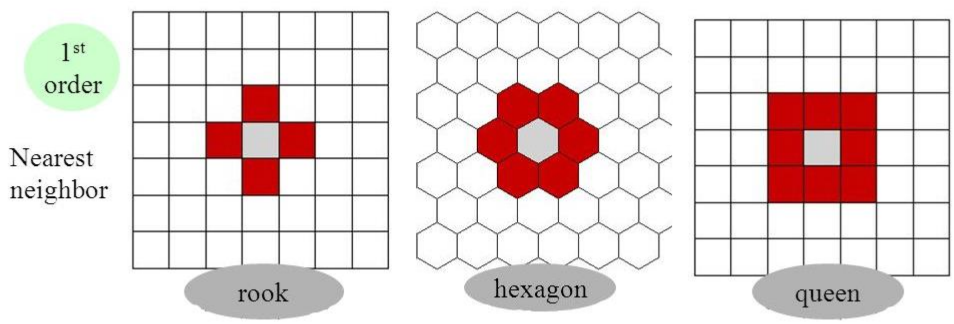
OLS creates a single equation for a global model where the Y response can be explained by X variable(s), **β** is the vector of X variable slope plus ε the error term (Scott & Pratt, 2009). The data from the Magic Valley poses two problems for the proper use of OLS. The first problem is that OLS assumes the data is normally distributed. OLS gives the most accurate *p*-values with normally distributed variables, otherwise, *p*-values and coefficients are unreliable for correct interpretation. Most of the explored explanatory variables in the Magic Valley had a left skew distribution. The second problem of OLS is autocorrelated variables. Notice there is no W coefficient in the OLS equation because it is not an inherently spatial model. Therefore, spatial clustering can introduce an over-counting type of bias, known as autocorrelation, which also renders model interpretation unreliable. Similarly, most independent variables were spatially clustered. Traditional statisticians would correct for autocorrelation but when using spatial statistics, clustering and skewness is an important story of human and environmental behavior and removing that will impair the ability to make recommendations (ESRI, 2020). OLS is within the umbrella of spatial econometric models, but a more advanced model that handles spatial autocorrelation and skewness well is available and would suit the data better (LeSage & Pace, 2009; Scott & Pratt, 2009). To create an equation that manages the complexity of spatial data, a spatial weight must be added.

As stated above, spatial weights appear as a matrix *W* in a written regression equation. To integrate spatial relationships, a spatial weights matrix type must be selected. The construction of spatial weights determines how spatial dependence (degree of spatial autocorrelation) is expressed between regions. In other words, you set parameters in a computational program for how closely to relate regions, if they are close, they are defined as neighbors. It is important to choose a matrix structure that best represents how spatial variables are thought to interact with each other. Then to conclude the analysis section, a specification search is conducted to find a regression model that best interprets neighbor interactions.

Spatial Weights

Defining how regions select neighbors in R can be done in two ways, contiguity, or distance. In the simplest categorization, neighboring units can be those that include common vertices (contiguous) which are then assigned a binary weight 1 (touching) or 0 (non-touching). The other case has neighbors defined by a distance buffer and the spatial weight may not be binary but based on a distance. When there are defined regions with neighbors such as states, counties, or HUC 12 boundaries, we use contiguous nearness because neighbor units are not uniform. Nonuniform areas cannot be defined using only one distance therefore it wasn't useful to use a distance weight. The two most common contiguity weights are queen and rook which assign neighbors shown in Figure 47.

Figure 47:Visual of Spatial Weight in a Matrix (Briggs Henan University, 2010)



Rook will result in fewer neighbors which is helpful in instances of uniform polygon units to get finer resolution of neighboring regions. It is customary practice for irregular polygons to use a queen weight as it can better deal with potential inaccuracies due to it having broader neighboring assignments (Anselin, 2020). HUC units vary in area and shape, so a queen configuration was used to give spatial weight to the data using the *poly2nb* function in **spdep** package for R (Bivand et al., 2013).

Model Selection

Spatial econometric models rely on the dependence between observations incorporating spatial autocorrelation to make theoretical assumptions about how phosphorus pollution migrates (or doesn't) between regions. Figure 48 shows the full family of spatial econometric models. When we believe neighbor relationships exist between regions then there are 3 ways in which the regression model can reflect this:

- Lag x: values of explanatory variables in one region predict the dependent values in another region (**$W X \theta$**)
- Lag y: the value of the dependent variable spills across regions (**$\rho W y$**)
- ε: when residuals are related to each other across space (**$\lambda W u$**) (Burkey, 2018)

To incorporate all these relationships the most complex econometric model is the Manski Model.

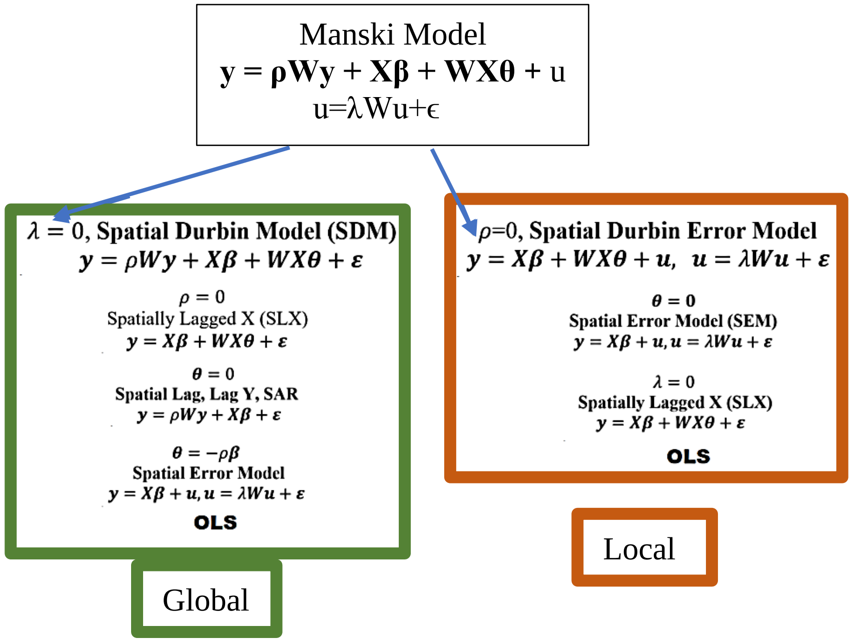
$$\mathbf{y = \rho W y + X\beta + W X \theta + \lambda W u + \epsilon}$$

This regression equation includes the most terms; lagged dependent (**$\rho W y$**), lagged explanatory (**$W X \theta$**), lag error (**$\lambda W u$**) and the basic explanatory (**$X\beta$**) and error (**ε**) variables. Notice the inclusion of the W coefficient, which creates the neighbor relationship between spatial regions which we call lag.

Lag effects support the SES idea that our landscape has complex interactions that cause feedback loops within the systems (Virapongse et al., 2016). Both social and ecological variables can be evaluated on the indirect, direct, or total effects in changing the system's entropy as discussed in Chapter 1. When we include one or more of these regional terms into a more advanced econometric model, we can then make inferences on what neighborhood effects "spillover" into other regions. Spatial econometric models are mostly used for economics modeling, but they have also been used for pollution studies as you can quantify direct and indirect effects from pollution sources using empirical analysis (Feng et al., 2018; LeSage, 2014).

The Manski model is rarely used as it is extremely difficult to solve for all the terms, and interpreting the neighbor effects is too complex and not useful for making scientific recommendations (Elhorst, 2014). A better place to start is one of the branches from the Manski model as seen in Figure 48.

Figure 48: Spatial Econometric Model and its Decompositions, Adapted from (Burkey, 2018)

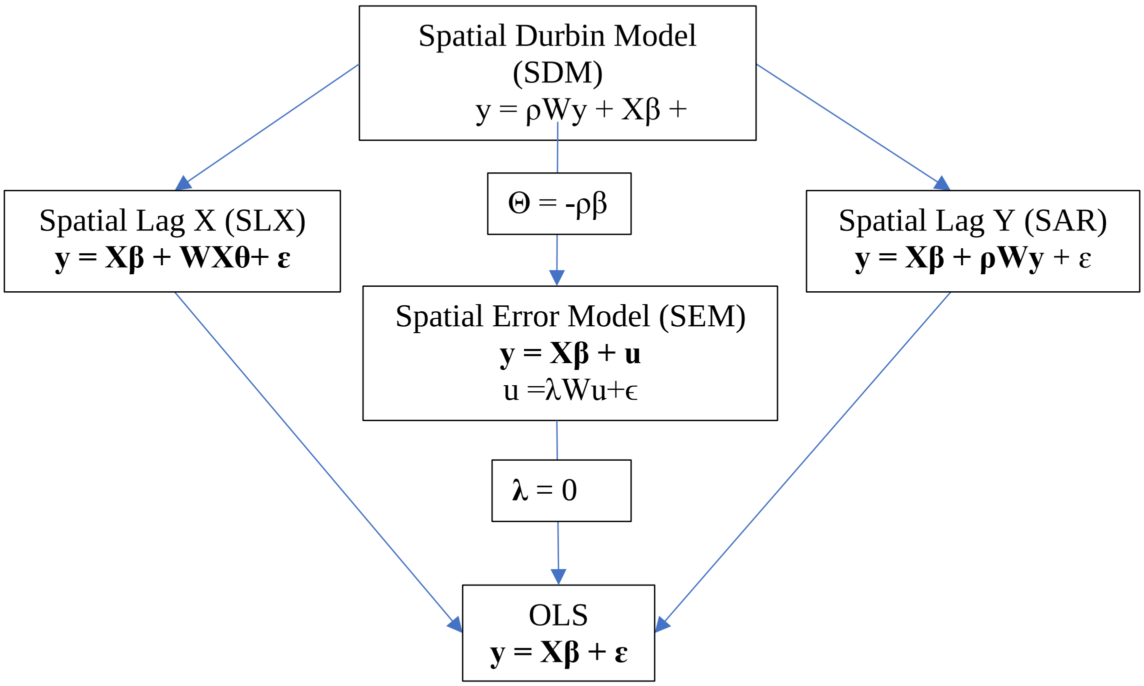


If we assume a term is not spatially explicit, we set the W to 0 thus restricting a term creating a "smaller" equation. Figure 48 shows the restricted forms of the Manski model which allow the research to explore the spatial relationship between terms deemed important using a simpler equation form. However, a problem can result if it is unknown which terms have a spatial relationship. In that case, one would first decide if the model needed to be local or global. A global model contains a spatially lagged y meaning one region's impact will cause a ripple effect into all other regions even if they aren't specified as neighbors. A local model has regions only affecting their neighbor regions and will have no feedback effects. What we know about our response variable y, is that it is a shared resource that passes through multiple regions in a connected way. Because of our y variable, surface water phosphorus contamination, we know it has endogenous interactions so a global model will better represent the SES (LeSage, 2014).

To select the best model within the global branch, there are a few methods but the most common is the top-down approach suggested by Lesage and Pace (2009). Since OLS doesn't seem to be sufficiently complex for spatial interactions, it is suggested a spatial Durbin model is a good starting place with a top-down global model. Figure 49 shows the nested models of the spatial Durbin. It's a hierarchy, SDM is nested within Manski, and SLX, SEM, and SAR are nested within SDM. The spatial terms (W) are set to zero to reduce to a "smaller" equation. It is easy to test whether to restrict the model to give a better fit.

Another possibility would be to restrict down to an OLS and be confident that the *p*-value is not overinflated.

Figure 49: Global Spatial Econometric Model Search and their Decompositions, Adapted from (Burkey, 2018; LeSage & Pace, 2009)



The Spatial Durbin Model (SDM) excludes the lag error term but considers Lag X and Lag Y. This model is most informative as both types of neighbor effects can be evaluated. The cost of ignoring the spatial dependencies in the error is relatively low as compared to omitting the other terms (Elhorst, 2014). The other models nested within spatial Durbin only look at spatial interactions of one term. For more clarity, Table 10 provides the models and terms in which spatial neighbors are evaluated.

Table 10: Models and the Spatial Terms Considered

Model	Spatial Term Evaluated
Manski Model	ρWy, $X\beta$, $WX\theta$, λWu
Durbin (SDM)	ρWy, $WX\theta$
Lag Error (SEM)	λWu
Lag Y (SAR)	ρWy
Lag X (SLX)	$WX\theta$
OLS	

Using a validation process we can evaluate whether these neighbors' relationships exist and restrict the model for those. We can then test each term individually to see if it performs better than the larger model.

Validation

Validation of the spatial econometric model starts with a likelihood ratio test to see if the model needs to be restricted to a smaller form. Other fitness tests: R^2, Akaike information criterion (AIC), and Bayesian information criterion (BIC) are used to view the regression's performance. Then a final regression assumption of homoskedasticity is tested to understand how confidently we can interpret the results of the final selected model.

Fitness Tests

The likelihood ratio test assesses the goodness of fit of two nested statistical models, a smaller model versus a more complex model. The test calculates the likelihood function at maximum probability for the two different models; then, the two scalars are compared to see which is a better fit to the sample data (LeSage, 2014). The null hypothesis is to restrict the model to a simpler form. Rejecting the null hypothesis means the model should not be restricted but should use the larger more complex model. To perform this test in R the *LR.Sarlm* function in **spatialreg** package can be used (Bivand et al., 2013).

Table 11: R Output of Likelihood Tests between Models

	Log-Likelihood		
Model	Small Model	SDM	ρ-value
OLS	374.25	408.62	0.000
SLX	404.61	408.62	0.005
SAR	388.67	408.62	0.000
SEM	380.51	408.62	0.000

All values predict that a spatial Durbin model is a significant improvement over a small model and so a restriction was not performed (Table 11). For completeness, other common goodness of fit verifications are included.

Table 12: R Output of Fitness Tests Between Models

Model	R^2	AIC	BIC
OLS	0.32	-722.49	-671.69
SLX	0.42	-761.22	-667.43
SAR	0.39	-749.34	-694.63
SEM	0.36	-733.03	-678.31
SDM	0.44	-767.23	-669.53

Traditional R^2 is a test for use on linear models only but a pseudo R^2 can be used in nonlinear cases. The pseudo R^2 is the ratio of 1 minus the sum of squared residuals divided by the total sums of squares. This test indicated the SDM was a better fit for the data. R^2

works to find a model that minimizes error but the downside is that in minimizing error you maximize complexity and create an overfit model (Aragones et al., 2002). AIC and BIC are both penalized-likelihood criteria tests, in that they penalize for complexity in addition to error. It is good to run multiple types of fitness tests to find the balance between complexity and error. Both criteria are often used for non-nested models and choose the optimal predictor subsets in the regression. The AIC is a frequentist approach to estimate the difference between the true likelihood function for the data and the fitted likelihood function of the model. BIC is based on the probability of a model being true under a Bayesian setup. Bayesian, unlike a frequentist approach, incorporates the number of observations with the number of parameters (complexity) against the goodness of fit. For both scores, a lower value indicates better fit or a higher likelihood with fewer parameters (Penn State University, 2020). BIC indicated that SLX and SDM were the best model choices with a negligible difference. AIC indicated that an OLS model was the best fit. It is unusual for AIC to pick a less complex model than BIC as BIC penalizes more heavily for complexity due to the added penalty working with larger data. As a Bayesian model the BIC increases the probability of selecting a true model the larger a training data set is. AIC does not depend directly on sample size so perhaps that accounts for the differences in selection. While most scores point to SDM (Table 12), we have one last test we can perform

Heteroskedasticity

Another regression assumption to consider is that the error (residual) is homoskedastic. In essence, homoskedasticity means the predicted value of the dependent variable from the regression model is consistent across all the known values. Breaking the assumption indicates that residuals are heteroskedastic, which might predict areas with high values accurately but low dependent variable areas inaccurately, as one example (Floch & Saout, 2018). The usual test for heteroskedasticity is the Breusch-Pagan test which sets the null hypothesis as the error variance is homoskedastic but the alternative hypothesis is heteroskedasticity is present (Floch & Saout, 2018). The R package used for the Breusch-Pagan test is **lmtest** with the function *bptest* (Zeileis & Hothorn, 2002) which fits a linear regression model to the residuals of the model and calculates how much variance there is between errors and the explanatory variables.

Figure 50: R Terminal Output for Breusch-Pagan Test

```
        studentized Breusch-Pagan test

data:
BP = 68.416, df = 16, p-value = 1.887e-08
```

The results (Figure 50) support the alternative hypothesis that there is heteroskedasticity. While the result is unfortunate it's not uncommon. SDM models exhibit a great deal of heterogeneity arising from the presence of the additional W terms; lagged dependent (**ρWy**), and lagged explanatory (**WXθ**), (LeSage & Pace, 2009). When interpreting regression results, because the model's parameters are variable, heteroskedasticity is going to affect errors and *p*-values. It will not affect or bias coefficients which can still be interpreted. There is variability in how serious to take this violation and how to distinguish heterogeneity and correlations (Floch & Saout, 2018). In spatial econometrics, experts recommend that for values of *p* close to alpha 0.05, one might be more skeptical but values of several magnitudes can still be confidently viewed as highly probable of rejecting the null hypothesis (Burkey, 2018). There are ways a statistician could alter the data to create a more homoskedastic model, but it requires diagnosis and multiple methods may be employed. This is ultimately beyond the scope of this thesis so regression coefficients will only be interpreted with certainty and correlations with caution.

Chapter 6: Conclusion

The spatial Durbin regression model was determined to be the regression that best fit the data while minimizing overfitting. The results of the model are shown below (Tables 13-16).

Results

In the spatial Durbin model, the spatially lagged Y term **ρWy** has output results from the R terminal that show Rho (**ρ**) is 0.239. Rho explains the impact that the spatially lagged Y multiplier has on neighboring Y values. In other words, how the change of phosphorus impairments in one HUC impacts the neighboring HUC impairment. The first set of reported X values are **Xβ**, beta (**β**) is the vector of X variables individually in Table 13.

Table 13: Beta X coeffects of Spatial Durbin showing the direct impacts

Variables	Coefficient (β)	Std. Error	Z-Score	ρ-values
(Intercept)	-0.01	0.01	-0.80	0.42
Waste Holding Capacity	-0.004	0.03	-0.15	0.88
Manure Application Rate	0.001	0.07	0.27	0.78
Crop Type	0.005	0.04	0.09	0.93
Septic Systems	-0.014	0.08	-0.20	0.84
Synthetic Fertilizer	0.009	0.03	0.28	0.78
Hydroelectric Dams	0.342	0.05	5.98	< .001
Accumulation Flow	0.009	0.04	0.33	0.74
Food Processors	0.119	0.06	1.89	0.06
Hydric Soil	-0.013	0.04	-0.33	0.74
Aquaculture Farms	0.291	0.07	3.93	< .001
CAFO Density	-0.059	0.06	-1.07	0.28

These beta coefficients are the direct impacts; how the change of a particular phosphorus vulnerability indicator changes the impairment of surface water due to phosphorus. For the spatially lagged X terms **WXθ**, the R terminal reports the theta (**θ** - labeled as lag coefficients) which are the neighboring X vector values as seen in Table 14.

Table 14: Beta X coeffects of Spatial Durbin showing the indirect impacts

Variables	Lag Coefficients (θ)	Std. Error	Z-Score	ρ-values
Waste Holding Capacity	0.01	0.04	0.32	0.75
Manure Application Rate	-0.47	0.11	-3.42	<.001
Crop Type	0.04	0.07	0.47	0.64
Septic Systems	0.08	0.15	0.42	0.68
Synthetic Fertilizer	0.05	0.04	0.99	0.32
Hydroelectric Dams	0.71	0.12	4.01	< .001
Accumulation Flow	-0.10	0.08	-1.09	0.28
Food Processors	0.10	0.14	0.39	0.70
Hydric Soil	-0.03	0.05	-0.48	0.63
Aquaculture Farms	0.60	0.14	2.99	< .001
CAFO Density	0.15	0.12	1.17	0.24

For a HUC's measure of phosphorus vulnerability, indirect impacts are those that affect the regions neighboring the immediate area. The coefficients with a positive sign in Tables 13 and 14 can be interpreted as having an increase in explanatory value when surface water phosphorus increases nearby. Negative coefficients indicate increasing the response variable will decrease the value of the explanatory variable.

The sum of direct impacts coefficient (**DI**) and indirect impacts coefficient (**II**) create the value of total impacts coefficient (**TI**) or **DI+II = TI**.

Table 15: Columns marked with a black dot are the contributing most to total impacts

	Total Impacts Breakdown			
Variable	Direct	Indirect	Total Impacts	Indirect Contribution to Total Impacts
Waste Holding Capacity		●	0.010	78%
Manure Application Rate		●	-0.472	99.89%
Crop Type		●	0.047	90%
Septic Systems		●	0.062	85%
Synthetic Fertilizer		●	0.056	84%
Hydroelectric Dams		●	1.048	67%
Accumulation Flow		●	-0.096	92%
Food Processors	●		0.224	47%
Hydric Soil		●	-0.048	73%
Aquacultures Farms		●	0.891	67%
CAFO Density		●	0.095	72%

A change in 1 unit of X, will lead to the increase or decrease of phosphorous vulnerability by the total impact's amount throughout the whole region. In Table 15, the total impacts coefficient was divided by the indirect coefficient to show the percent contribution to the total impacts. While coefficient values are interesting, they might not be meaningful to the model. The *p*-value of the coefficient tests whether the coefficient influences the predictor. The null hypothesis states that changes in the coefficient are not associated with changes in the response variable. Below in Table 16, the *p*-values from both direct, indirect, and total impacts coefficients are condensed for better viewing and interpretation.

Table 16: P values of the direct and indirect impacts of the Spatial Durbin

	Simulated ρ-values		
Variables	**Direct**	**Indirect**	**Total**
Waste Holding Capacity	0.87	0.73	0.76
Manure Application Rate	0.96	< .001	< .001
Crop Type	0.94	0.59	0.60
Septic Systems	0.85	0.65	0.72
Synthetic Fertilizer	0.69	0.24	0.14
Hydroelectric Dams	< .001	< .001	< .001
Accumulation Flow	0.85	0.31	0.35
Food Processors	0.05	0.59	0.28
Hydric Soil	0.71	0.54	0.33
Aquacultures Farms	< .001	< .001	< .001
CAFO Density	0.29	0.32	0.58

The econometric framework recommended using simulated ρ-values for interpretation (Burkey, 2018) has the advantage that it picks the *p* with the highest frequency. This is useful for data that isn't normally distributed or a complex model that has multiple interacting variables. One thousand (1000) simulation repetitions were used to generate probable *p*-values. Significant results suggest that hydroelectric dams and aquaculture may have direct, indirect, and total impacts on water quality pertaining to phosphorous as their usage increases. Direct neighbors could be affected by an increase of food processors to a less confident extent. Manure application was significant with negative indirect and total impacts. As phosphorus in surface water increases manure application in its neighboring regions will decrease phosphorus vulnerability.

Discussion

Explaining the significance of aquaculture and dams could be due to the spatial dependence that both activities have with surface water and not necessarily representing a phosphorus impairment in the model. Dams and aquaculture are built right on top of streams or are nearby diversions from streams that might be unfairly biasing the model. A more optimistic view could be that there is an underlying process in these anthropomorphic activities that change the stream resulting in a higher value of phosphorus. Both aquaculture and dams change the geomorphology of stream networks by straightening natural bends and increasing temperatures which increase the amount of erosion and sediment, in the water. In addition, the hold times of water that these activities create also increase residency times which would allow phosphorus concentrations to accumulate and speciate from the soil before being released into the environment. Neither hydric soils nor surface flow accumulation was identified as significant. A possible explanation could be that it is less about where phosphorus settles, and more about the capture, hold, and release process that makes phosphorus more available in surface waters (Bol et al., 2018). Both activities pond water for a period of time then release it, which stirs up settled sediments in the water column. A third postulation could be that NPDES permits are required from both activities, so water testing is more routine, which created an abundance of data for the model, versus areas where surface water testing is rare, and issues may not be reflected in the data.

Food processors were also shown as significant but to a lesser extent (in the 5% range) and only for direct impacts. Food processing has some similarities to hydroelectric dams and aquacultures. It had somewhat of a spatial dependence on surface streams as water is needed to cool down machinery and effluents after treatment need to be released. It also utilizes NPDES permitting which makes data more abundant and publicly available.

The last significant variable identified by the spatial Durbin was the manure application rate that showed a negative relationship for the total impacts. Initially, this was puzzling, but when viewing what contributed to the total impacts, indirect impacts contributed overwhelmingly (99.8%); which was abnormally high compared to the other variables. Manure application had 116 HUCs with no data available, meaning a third of the HUC dataset for the Magic Valley did not have data. To have indirect impacts contributed almost exclusively to the total impacts yet be underrepresented in data, contributed to an oversensitive response.

Table 17 lists a summary of impact results. This ESDA findings provided more questions than solutions. Moving forward, in future iterations, there are steps we can take to further improve our understanding of phosphorus in surface water.

Table 17: A Summary of all SDM Results Including Both Significant and Insignificant Variables with Possible Explanations of Results

Variable	Direct	Indirect	Total	Explanation
Hydroelectric Dam & Aquacultures Acres	+ +	+ +	+ +	● Strong spatial dependence on surface streams ● Change the geomorphology of stream networks ● Residency times ● NPDES permitting
Food Processors	+	+	+	● Strong spatial dependence on surface streams ● NPDES permitting
Crop Type & Synthetic Fertilizer	+ +	+ +	+ +	● Nonpoint sources may diffuse through the watersheds ● Release rates of phosphorous could be constant as it moves through the watersheds
Hydric Soil	-	-	-	● Hydric Soils function as a sink rather than a source as its indirect and total impact also have a negative relationship
Accumulation Flow	+	-	-	● Accumulation of phosphorus stays in the region hence the positive direct relationship. Because phosphorus is contained in the low surface areas as a catchment, there is little spillover effect, and the surrounding areas benefit.
Manure Application Rate	+	-	-	● Missing data ● Release rates of phosphorus ebbs as it moves through the watersheds
Waste Holding Capacity	-	+	+	● Soil properties are conducive to phosphorus leaving the regions and settling in a neighboring region as seen by the positive indirect and total impacts
CAFO Density	-	+	+	● On the farm nutrient loss is minimal, but outside the farmgate, we see a phosphorus impact by the positive indirect and total impacts. ● County boundaries influence CAFO density
Septic Systems	-	+	+	● The number of septic systems that are leaking is negligible ● Many systems could have been updated to municipal treatments ● Areas with large clustering of septic systems (urban areas) may have more funding for treatment. Neighboring regions

Limitations

Widely accepted frameworks were followed when selecting ESDA techniques, but other analysis frameworks might be better suited for this data. While the best-known practices were utilized and empirical knowledge guided the exploratory analysis, this approach to data collection and modeling may still not be the best method possible. The following are limitations that came about through this process. Fitness tests were run to confirm the best regression modeling for the set of data. Ultimately there is always the possibility of misspecification due to lack of data, data quality, and heteroskedasticity. Writing statistical programs make validation faster and more efficient, but it also poses problems as the more tests that are run, the more likely you are to find confirming results. Choices in using HUC 12 as the aggregation units for data and the assumption that feedback loops are bound mostly within HUC 12 regions built into the spatial weighting of neighboring HUCs might not be accurate for all cases. Data quality was variable as some came directly from authoritative sources that had known amounts of phosphorus while others were based on qualitative knowledge of the system that had inferred the existence of phosphorus. Some data were represented by the presence of an event or count data and might not directly imply phosphorus output.

Lack of consistently collected or available data caused a variety of problems. As many variables as possible were researched that pertained to phosphorus in surface waters of the Magic Valley but due to lack of and difficulty obtaining data, some possible explanatory variables were left out. One value not originally included that may need to be in future iterations is beef cattle. It was estimated in the year 2020 that over 495,000 beef cattle and 635,000 dairy cows were raised in Idaho (USDA, 2020b). Only dairy cow manure was included in this model. Originally beef cattle manure wasn’t included because the density of cattle, as opposed to dairy cows, is lower, with more land per cattle unit. Also, cattle are moved from grazing lands to agricultural fields in the winter, and finally to CAFOs for finishing which makes spatial representation difficult. Similar to dairy cows, no source listed locations of farms and headcounts simultaneously. It wasn’t possible to calculate the spatial distribution of both industries so dairy alone was selected. Poultry farms were not included as it isn’t a dominant animal in the state but its N:P ratio is higher than cows so it may be worth researching. Finally, heteroskedasticity was confirmed in the regression which made the interpretation of results more cautionary than confident. This could be due to a lack of phosphorus data in surface water or needed transformations of data. I will make some recommendations on how to improve this model in the future below.

Recommendations

The results of the spatial Durbin model were interesting, but it became apparent that the manure application layer needed to be removed from the next iteration unless missing data can be reduced. Aquaculture and dams should be researched to see whether their significance is due to the spatial dependence that both activities have with surface water as was picked up by the y response, or due to an underlying process in these anthropomorphic activities that changes the stream. Based on the data, I would recommend starting with the transformation of the response variable. There are multiple types of transformations: log, square root, etc. so, more research would need to be done to find the right transformations for the data assumptions (Frost, 2017). The advantage of using a SDM to model phosphorus vulnerability is that its spillover effects are flexible (Eilers, 2019). Using the total impacts, we can change variable X and see how phosphorus may change across the landscape allowing future modeling of scenarios. For these purposes, I think SDM is the best regression model.

Earlier it was mentioned that data fell into four groups based on similar principal components, one of which highlighted all the current impaired HUC in addition to 12 others. I speculate a phosphorus priority area could be created from the cluster group. Taking the 12 HUCs we can delegate which water reaches are likely to be impaired but are not yet listed. Table 18 identifies ten waterways that would fit the criteria for a proposed priority area. The largest water reaches were selected because they are not limited to one property, meaning monitoring will not unfairly fall to one person. These water reaches are named, so there is a defined area and recognition which will help with public opinion as it will be seen as a community resource. I recommend these reaches be tested routinely for phosphorus surface water increases as the attributes are similar to those that have already been placed on the EPA's Listed Impaired Waters 303(d) Category 5.

Table 18: Proposed Phosphorus Priority Reaches to Test

Longest Reaches	Length (m)	Associated HUC 12
J Canal	35,910	170402121003, 170402091305, 170402091306, 170402091307
Little Wood River	33,030	170402190906
Snake River	30,929	170402091306, 170402091307
South Gooding Main Canal	28,750	170402190904, 170402190906
Lateral S-19	23,489	170402121004
S Canal	22,005	170402121003
Main Drain	19,641	170402091207
Mud Creek	19,301	170402121005
Malad River	19,252	170402190905
B Canal	19,186	170402120108

The y response variable is considered weak under the current model as data is based on the known observations of surface phosphorus impairments but not the severity of impairment. It also leaves out waters that are impaired but don't get tested due to a variety of barriers or areas that are only seasonally impaired. In another scenario, incorporation of quantitative phosphorus from soil and groundwater phosphorus might resolve the heteroskedasticity issue without the need for a transformation, which is the current hypothesized reason for the cause of heteroskedasticity in this thesis. If relying solely on surface water, an alternative source of the heteroskedastic readings would have to be determined. A balance should be maintained between more interpretable results and reducing manipulation of the data. Some solutions might include running the Breusch-Pagan test on each explanatory variable individually to find and fix heteroskedasticity to avoid having to transform the dataset. No outliers were removed in this study to preserve the natural distribution of data a decision made prior to the knowledge of its heteroskedastic nature. An alternative option is to remove outliers just from variables flagged for heteroskedasticity (Klein et al., 2016). This is tricky as most datasets have a skew, but it is possible that on the larger datasets outliers could be removed without altering coefficient results significantly. A weighted regression could be implemented so that each data point has a weight based on the variance of its fitted values which would reduce the residuals. This is not an intuitive approach and finding theoretically correct weights can be difficult and time-consuming (Bobbitt, 2020; Frost, 2017).

Summary

Within this study area, water quality has been affected by a growing population and agricultural sector. Due to the natural properties of the aquifer, there is a strong connection between surface and groundwater. Studying phosphorus is complicated as there is no routine water testing or enforcement that creates a solid database of values. Therefore, it was important to study phosphorus in a surface water context. The ESDA approach was conducted to better understand what this would look like and how to improve future modeling of the Magic Valley area. In this spatial analysis, variables were selected based on knowledge of the SES of the Magic Valley. Data was then aggregated into spatial regions based on the SPARROW watershed modeling technique created by USGS. With variables processed for a spatial regression, a queen spatial weights matrix was selected. Global Econometric regression models were considered then validated using the likelihood test, R^2, AIC, and BIC tests. The spatial Durbin model was selected based on those tests and it was then tested for heteroskedastic characteristics.

Hydroelectric dams and aquaculture both showed significant direct, indirect, and total impacts in the Magic Valley. It is unclear whether this is due to an actual phosphorus relationship, or that these variables will always coincide with HUCs waterways as will the response variable. The majority of variables contributed with an indirect impact showing that this is a community issue, and the spillover effects of all potential phosphorus sources are a likely cause of surface water impairments. I would recommend the use of a SDM to simulate phosphorus in surface water in the future, provided there are adequate response variable data. With currently available data, I cannot suggest this as a useful method for surface phosphorus water data without modifications. Future research can include either well and soil data or involve performing a transformation of the Y variable to try and fix the issue with heteroskedasticity. I also made suggestions based on clustering groups where there are likely to be areas of phosphorus impairments, which can help narrow down resources to help with future studies.

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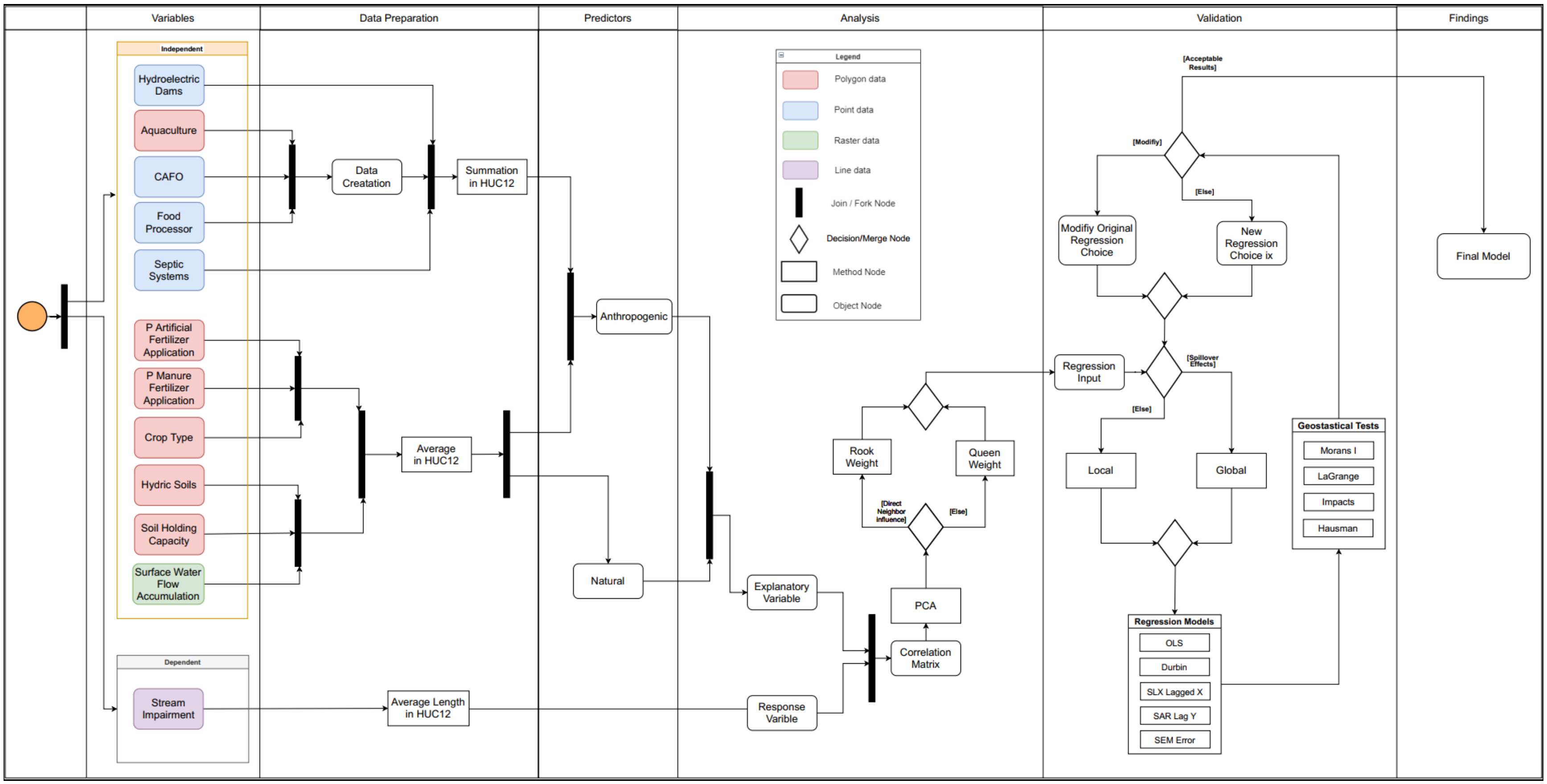
Appendix A

Phosphorus Definitions and Explanations: phosphorus forms especially relevant to the study area (agricultural areas) and where it might be found in the landscape, along with whether it can be absorbed (Dabkowski & White, 2015; Davis, 2008; Kaiser, 2018)

Forms	Formula	Other Names or Forms	Bioavailability	Usual Source	Description
Phosphorus	P	P, elemental phosphorus	Unavailable	Exists as part of a molecule	Rare in nature.
Total Phosphorus	All forms	TP,	NA	Animal waste and food residues	Total amount of phosphorus in the soil. This information has limited agronomic use as it does not indicate bioavailability but all forms of phosphorus.
Organic phosphates	H3PO4	Organophosphates	Not easily broken down	Animal waste and food residues	ATP energy transfer between cells. Are esters of phosphoric acid.
Inorganic Phosphate	[HPO4]2- and [H2PO4]-	Condensed phosphates, Polyphosphates, Orthophosphate	Readily Available	Mined from in rock or ore	Used to produce agricultural and industry products (food additives). Are salts of phosphoric acid.
Orthophosphate	[PO4]3-	Phosphate, Reactive Phosphorus	Very Reactive	Fertilizers used for agriculture and residential purposes	Mammals use for structural material of bone and plants for nutrient uptake.
Condensed Phosphates	(X(H2PO4)2)	Pyrophosphate, Metaphosphate, Polyphosphate	Very Reactive	Naturally occurring in water or can be synthetic	Bonds to a metal cation. Common use in food processing
Dissolved		DP			Filtered in laboratory.
Particulate		PP			Unfiltered in laboratory.

Appendix B

Full UML Diagram showing ESDA Elements and Decisions: Steps are broken down starting with variable creation indicating which format the data was collected in represented by color. Then the steps for data preparation to aggregate the different data formats into the same boundary and file type. Analysis of data utilizing ESDA tools to determine weights matrix. Finally, the validation section included tests that were researched and used for model selection.



Appendix C

HUC Delineations and Definitions from Largest to Smallest: Hydrologic Unit Code (HUC) are the levels of classification in the hydrologic unit system. This is a reference for the area size of units and alternative names in the literature. (NRCS, 2007)

Hydrologic Unit	Hydrology Feature Name	Level	Total in US	Classification	Details
2	REGION	1st	21	Regions	
4	SUBREGION	2nd	222	Subregions	Each Region has from 3 to 30 Subregions
6	BASIN	3rd	352	Accounting Unit	
8	SUBBASIN	4th	2149	Cataloging Unit	The smallest is 448 K Acres (700 mi^2). Most are much larger
10	WATERSHED	5th	Not completed	Watershed 5th Level (Was formerly called HUC-11)	Typically, from 40 to 250 K Acres (62 to 390 mi^2)
12	SUBWATERSHED	6th	Not completed	Watershed 6th Level (Was formerly called HUC-14)	Typically, from 10 to 40 K Acres (15 to 62 mi