DISSERTATION

A META-ANALYSIS OF MEASURED ANNUAL NUTRIENT RUNOFF FROM AGRICULTURAL LAND IN NORTH AMERICA

Submitted by

Austin P. Hopkins

Department of Soil and Crop Sciences

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Doctoral Committee:

Advisor: Jim Ippolito

Daren Harmel
Nathan Mueller
Matthew Ross

ABSTRACT

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Nitrogen (N) and phosphorus (P) are significant agricultural inputs and drivers of water quality. It is the focus of producers and government agencies to keep soil and nutrients in productive agricultural land and out of waterways. Field-scale runoff and water quality data are critical to understanding the fate of agricultural nutrients and mitigating their off-site transport; it is at the field-scale that agricultural management decisions are typically made. However, regional influences such as precipitation, temperature, and prevailing cropping and management practices also impact nutrient runoff. The goal of this dissertation was to quantify the effects agricultural practices have on nutrient loss from agricultural lands. The Measured Annual Nutrient load from Agricultural Environments (MANAGE) database was updated with 27 additional studies focused on N and P loss to bring the total number of site years to over 3,300. EPA level II ecoregions were assigned to each entry, and it was observed that the database covered much of the North American humid/semi humid agricultural landscape.

In the early 1980's, the first compilation of nutrient export coefficients for specific land uses in the U.S. was completed. Building off that initial effort, the "Measured Annual Nutrient loads from AGricultural Environments" (MANAGE) database was developed in 2006 to make annual nutrient runoff data from agricultural land uses publicly available. MANAGE presents annual field-scale N and P runoff data, along with descriptive data such as land use, tillage, conservation practices, soil type, soil test P, slope, and fertilizer formulation, rate, and application method along with runoff, precipitation, and soil erosion data. Subsequent MANAGE updates added more studies and additional data fields (e.g., crop yield, nutrient uptake, fertilizer application timing) as well as runoff N and P data from forests and drainage studies from the Midwestern and Eastern U.S. Here, we update MANAGE to facilitate its use in regional analyses, expanding the database to 3326 site years of data, including 27 additional studies along with Level II ecoregion delineations for each of the 94 studies. Annual N and P runoff data are now available from 11 of the 50 North American Level II ecoregions, which represent the major U.S. agricultural regions. Surprisingly, many of the studies did not report information such as fertilizer application timing or crop yields, thus we strongly encourage future nutrient loss studies to collect important descriptive data along with response data. This contemporary data repository is freely available from the USDA Ag Data Commons (https://data.nal.usda.gov/dataset/measured-annual-nutrient-loads-agricultural-environments-manage-database) to support future scientific analyses, model evaluations, and management and policy decisions.

In the present study, we used the recently updated MANAGE database to conduct meta-type analyses of N and P in runoff from cropland and grasslands for North American Level II ecoregions. Specifically, we analyzed annual N and P loads and the impact of land use, tillage, fertilizer timing, and fertilizer placement. We compared nutrient loads across ecoregions and found that Temperate Prairies had significantly greater median total N loads (11.7 kg/ha/yr) than all other ecoregions. We found that there was considerable variability between ecoregions and management practices making one size fits all best management practice recommendations difficult. When management practices were compared across all ecoregions, consistent trends were evident. Conventional tillage, incorporating fertilizer, preplant fertilizer application timing,

and corn land use all had significantly higher median total N loads compared to other practices, at 19.5, 23.6, 12.3, and 33.0 kg/ha/yr respectively.

We observed several notable differences between ecoregions, for example: 1) the Temperate Prairies, dominated by highly erodible cultivated land, had significantly higher median annual total N loads (11.7 kg/ha/yr) than the South Central Semi-Arid Prairies (2.4 kg/ha/yr) dominated by grasslands; 2) corn production tended to produce higher N and P loads than other land uses in the Mixed Wood Plains, Southeastern USA Plains, and Ozark-Ouachita/Appalachian Forests; and 3) no-till had the highest dissolved P loads in the Southeastern USA Plains and Temperate Prairies, but conventional tillage had the highest dissolved P loads in the Ozark-Ouachita/Appalachian Forests. These data – that have never before been compiled and analyzed by ecoregion - should prove valuable for improving regional understanding of nutrient fate and transport, informing field-scale agricultural management decisions, and launching more in-depth, multi-factor analyses.

Common agricultural land management practices, as present in MANAGE, were also quantified based on the effect they had on N and P loads. Consistent trends were defined across ecoregions. Conventional tillage led to significantly greater total N load (19 kg/ha/yr) than conservation or no-tillage practices (5.9 and 6.8 kg/ha/yr respectively). Incorporating N and P fertilizers typically led to significantly higher total N loads than injection or surface applications. Total N (23 kg/ha/yr), for example, was greater than injection or surface applications (5.4 and 3.2 kg/ha/yr respectively). Fertilizer application timings associated with preplant or out of season applications also led to typically greater loads, with preplant and split (preplant and out of season) producing 12.33 and 16.0 kg/ha/yr. Lastly, corn production and to a lesser extent wheat

and small grains were the most significant drivers of N and P load loss. Corn and wheat produced 33.0 and 5.9 kg/ha/yr of total N.

The interaction of management decisions on one another was examined and quantified using a generalized linear model. We found that there were significant pairwise interactions between agricultural management practices. For example, conventional tillage generally increased nutrient loads when combined with surface fertilizer placement. We were able to produce a model aimed at predicting nutrient loads based upon fertilizer timing and placement, ecoregions, tillage, and land use that produced an R^2 value of 0.92 and a mean absolute error (MAE) and root mean square error (RMSE) of 0.30 and 0.50 for annual dissolved N loads in runoff. Our results should lead to improved policy and management decisions and are of importance across a wide scale of management size from small scale farms to large scale farms, to governmental agencies managing soil and water resources across the continent.

Based on results of this research, a proposed ecoregion nutrient load target was suggested, along with practices that could be implemented within those ecoregions to reduce the possibility of excess nutrient loads. The load target was set as the 90th percentile of the annual nutrient load produced under conservation tillage. Under these guidelines, the ecoregions that had the greatest volume of exceedances were the Southeastern USA Plains, Temperate Prairies, and the Mississippi Alluvial/Southeastern USA Plains, which are ecoregions in which conservation tillage and split application of fertilizer timing were shown to be effective in reducing nutrient loads.

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DEDICATION

I dedicate this work to Karenna, my wife, as well as Penelope and Marilla, my daughters. Thank you for always pushing me and being my shining sun, moon, and stars.

"How can I stand on the ground every day and not feel its power? How can I live my life stepping on this stuff and not wonder at it?"- William Bryant Logan

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Chapter 1: Introduction

1.1: The 4th Revolution: Smart Farming

The advent of the 21st century has brought technological innovation which has wrought significant change in agriculture. Commonly referred to as the 4th revolution (Virk et al., 2020) or “smart farming”, this new data and technology driven era of crop production and resource management allows producers to more finely tune agricultural systems. The three largest drivers behind the advent of smart farming are ecological necessity, technological innovation, and resource use efficiency or conservation. Natural resources such as fresh water and fertilizer minerals are considered finite. Fresh water is a small percentage of the overall global water supply (Gleick, 2000), and reduction in the levels of freshwater aquifers such as the Ogallala in the western US is cause for alarm (Terrell and Johnson, 1999). Smart farming is increasingly important in arid areas such as the western United States where irrigated agriculture is essential for most crops and rainfall is not a sufficient source of water for crop growth. Growers seek to increase their “Crop Per Drop” (Luquet et al., 2005). Smart farming can be used to support and supplement technological decision support systems in crop growth. Innovations allow for fine tuning of fertilizer application, crop yield estimation, weed and pest management, variable rate irrigation management, and many other aspects of crop production (Radočaj et al., 2022; Chlingaryan et al., 2018; Alam et al., 2020; Mendes et al., 2019). Smart farming has ecological benefits in terms of potential reduced water usage and nutrient runoff; however, there are many additional benefits that directly influence the producer and not only the global ecosystem. Variable rate irrigation systems have been shown to reduce water usage, smart controlled fertilizer and pest applications reduces quantities of material needed and applied, and crop yield estimation allows farmers to plan more appropriately (Yari et al., 2017; Hedley, 2014; Sishodia et al., 2020). In the future, as greater food supplies are needed to feed a growing population, undoubtedly smart farming will expand accordingly.

This influx of smart farming is supported by technological advances assisting decision support systems. Proximal soil sensors allow spatially and temporally variable measurements of soil water, chemical, and physical characteristics. Improvements in localized weather stations aid more accurate water balance modeling. Remote sensors such as near-infrared (NIR) spectrometers allow crop canopy temperature to be accurately measured. Unmanned aerial vehicle and satellite imagery allows a wide range of metrics to be evaluated based on visible, multi, and hyper-spectral imagery data (Cao et al., 2013; de Lara et al., 2019). Remote imagery from UAVs or satellites, proximal soil sensors, local weather stations, near infrared radiometers, NDVI sensors, crop yield monitors, and many other data collection techniques can combine to form the Internet of Things (IoT). IoT is a technology paradigm contemplated as a vast network of digitally connected devices and machines or “things” which can connect over the internet. Machine learning and artificial intelligence has also added value and insights to the smart farming era and has allowed users to have sharper, faster, and more informed insights into technology that they would otherwise not been able to utilize to its fullest extent. For example, machine learning systems have been implemented in applications of precision weed management, early detection of animal disease, and crop yield prediction to name just a few. The combination of technological innovation and ecological necessity has ushered in the current period of agriculture which can be directed by “big data”. The aim of big data in agriculture and smart farming is to minimize the gap between the technological potential of smart farming and our ability to utilize data resources efficiently.

1.2: Big Data in Agriculture

The term "big data" refers not only to the quantity of data, but also the many different sources from which we gather data. To understand big data, we need to detail the characteristics of big data. Big data is commonly broken into four characteristics referred to as the 4 V's, or Volume, Velocity, Variety, and Value (Katal et al., 2013).

Volume refers to the staggering quantity of the generated, stored, and processed data. Prior to the era of big data, data was commonly measured in megabytes or gigabytes, yet now we work in terabytes and petabytes. *Velocity* refers to the unprecedented speed of data transmission and the rates at which they are transmitted, which also must be processed and analyzed in an expeditious manner. *Variety* represents diverse data types, and this diversity includes both structured and unstructured data. There are many different formats and structures of data resulting from the varied methods by which data are produced and collected (e.g., spatial GIS data, weather station data, soil sensor data, yield data, economic data). *Value*, or density, is inversely proportional to total data size. The greater the big data scale, the less overall valuable the data becomes due to difficulty in analysis, interpretability, and application. Value also refers to the value that is derived by data analysis to detect patterns, trends, and knowledge models using algorithms and smart data analysis techniques. Machine learning and artificial intelligence have and will continue to lend value to datasets. The task of deriving value in a timely manner from big datasets is too computationally intensive for humans, and thus requires finely tuned models and machines. Naturally, precision agriculture systems still allow farmers to 'logic check' the system manually when needed. The future of agricultural machine learning and artificial intelligence will be centered on developing and improving these systems, increasing knowledge of data patterns and behaviors, and making the most of processes and thus discoveries.

Additionally, there has been proposed a fifth V, *Veracity*, or how much can the data be trusted. Veracity relates to the accuracy and trustworthiness of the data. In agriculture, data can come from multiple sources with varying degrees of accuracy and precision. Ensuring data quality is crucial for making reliable decisions and drawing meaningful insights. I would mention the potential sixth V of big data, *Variability*, different from variety. This refers to the inconsistency or fluctuations in data over time, and is about understanding the changes and fluctuations within data. Variability acknowledges that data is not always constant, it can change, fluctuate, or exhibit different patterns over time. For instance, crop yields might vary from season to season due to weather conditions, disease outbreaks, or other factors. Similarly, sensor data can show fluctuations in soil moisture levels, temperature, and other metrics based on changing environmental conditions. Overall, the main difference between variety and variability is that variety focuses on the different types, formats, and sources of data that exist, while variability focuses on the changes and fluctuations that data can exhibit over time. Both concepts, variety and variability, are vital to consider when working with big data, especially in complex fields like agriculture, where diverse data types and dynamic conditions are common.

1.3: The Ethics of Big Data and Data Ownership

Big data and its associated manipulation and analysis is not a uniformly accessible resource for a wide range of agricultural producers. Small-scale producers typically do not have the resources to take advantage of existing decision support systems based upon big data and machine learning inputs. Corporations like Climate Corp, John Deere, Bayer, Trimble, IBM, and others offer data collection and analysis as a service to producers. Large-scale production farms often have increased margins to be able to afford such services, unlike small-scale producers. Several open-source decision support systems exist that utilize big data in agriculture. Resources such as AgStack, CGIAR, GeoFIS, Ag-Analytics, Agricultural Data Coalition, and SSURGO among others are examples of open-source big data resources that are more accessible than traditional resources. Furthermore, these are often more accessible by large-scale producers. These platforms are often also not simply useful or realistic to utilize for the small scale producer. SSURGO and many other platforms operate with many inputs or a larger spatial scale requirement than a small hold farmer operating on a single acre may have.

There are also concerns in the world of agricultural big data about data ownership and privacy. A significant portion of modern-day farmers are wary of sharing their data with big data platforms and services. There is concern that competitors will be able to have access to and take advantage of sensitive data of competing farms. Similarly, there is concern that sharing data to the overall big data pool will have disadvantageous ramifications in the selling price of crops and even insurance and operational costs. Limited open-source big data resources, along with data privacy and ownership concerns are some challenges and difficulties of the growth and application of big data in agriculture. Carbonell (2016) described a “big data divide” between most producers and their data. Big data as a tool for illustrating larger patterns requires a complicated array of technology, infrastructure, and expertise, most of which is unattainable for the average grower. Exceptionally sized agribusinesses lack a responsibility or obligation to make their data available and they also control who has data access. Corporations such as John Deere prevent farmers from modifying, accessing, or repairing software on their equipment. Climate Corp additionally dictates that producers cannot “modify, edit, adapt, disassemble, scrape… decompile, reverse engineer or create derivative works from any Climate Corp products" (Carbonell, 2016).

Lee Manovich wrote about three classes of people within the realm of big data: data creators, data collectors, and expert data analyzers (Manovich, 2012). Farmers make up the first group. The second group holds the informational power and are essentially "data brokers" (Cukier and Mayer- Schönberger, 2014). Data trade is so profitable that some companies such as Acxiom and Experian deal only in collecting and trading data. The analysts in the third group hold the key to expert power, dictating how the data will be utilized, who gets access, and who is allowed to participate. Producers are not often granted access to their own data, and lack the tools or context to analyze it. Therefore, it is the corporations and not the individuals holding the power of big data in the context of agriculture.

A 2016 Farm Bureau survey found that nearly all farmers want "to control the information their equipment collects every time it passes through a field" (Precision Farming Dealer, 2016). Farmers also firmly believe that creating a cooperative style central repository for their data is the best way to enhance its security and maximize its value. The Farm Bureau survey also found that 77% of farmers are concerned about which entities can access their farm data and whether it could be used for regulatory purposes. Additionally, 61% of farmers are worried that companies could use their data to influence market decisions. Similar to the big data gap between producer and data, there seems to be a "big trust" gap between farmers and the data collectors and analysts. An additional survey by the American Farm Bureau (Hopkins, 2019) in October 2014 found that "Fully 77.5% of farmers surveyed said they feared that regulators and other government officials might gain access to their private information without their knowledge or permission. Nearly 76% of respondents said they were concerned others could use their information for commodity speculation without their consent. While more than 81% of farmers believe they retain ownership of their farm data, more than 82% of farmers said they had no idea what companies were going to do with their data”. Carbonell (2016) suggested two solutions to some of the unique challenges in making big data more equitable to farmers regardless of their size. First, the collection of multiple large databases to form big datasets should be open-sourced and in the public domain, as advocated by the GODAN initiative (Musker and Schaap, 2018), under the condition of anonymizing contributions from specific individuals. Second, big data analytics can be costly, complex, and necessitate large teams to assemble and develop. For these tools to enter the public domain, work for the common good and not just for corporate interests needs to be funded and developed by public organizations. Further work is needed to illustrate the differences in value, ease of use, and features of privately owned and public/open-source big data decision support systems.

1.4: Challenges of Big Data in Agriculture

Cravero and Sepúlveda (2021) conducted a systematic literature review in which they analyzed 34 real cases focused on machine learning within big data in agriculture. Their results found that manipulating large volumes of data is no longer a challenge because of the versatility and strength of cloud computing technologies. However, the authors suggested that specific pitfalls need to be addressed by future research and development: 1) processing speed due to little control of the data in its various stages such as raw, semi-processed, and processed data (aka value data); and 2) information visualization systems, which support technical data little understood by many farmers (Cravero and Sepúlveda, 2021). The technological knowledge gap is beginning to shorten, yet challenges will continue to exist.

One significant challenge, especially for small-scale farmers, is availability (Coble et al., 2018). In the world we live and grow in today, “data is the new oil”, with this phrase becoming the motto of AgTech providers and big data companies. Big data resources and decision support systems are not easily accessible or a viable economic option for smaller-scale farmers. With the advent of the 21st century, there is a new species of farmer, the data driven farmer. These modern growers base their decisions on big data and intelligent decision support systems. Those with resources and connections to be able to more than adequately participate in the big data revolution gain more power by becoming an isolated data island. Larger scale farms and organizations can hoard and hide their own data to prevent smaller, less data wealthy farmers from gaining a foothold in data applications on the farm. Unfortunately, farmers that are unable to “pay to play” in the big data playground (e.g., small-scale farmers) are forced down the more traditional route of manual data collection and processing.

Another challenge is the massive power gap between the major resources of businesses like Climate Corp and John Deere compared to those of the open-source ag tools. This power imbalance is a threat for the operating capacity of today’s farming systems. On one side, there is a mistrust between competing growers, especially of drastically different scales, leading to uncertainty. On the other side, this power imbalance generates new forms of economic and technological dependency. The latter can arguably and eventually turn into a “learned dependency”, locking farmers into the current support systems and providers (Lioutas and Charatsari, 2020), which could be viewed as mutualistic or parasitic depending on who you ask. If there is mutual trust and respect between farmers and support systems, then these systems can be beneficial for both sides. However, farmers ought to be wary of too much of a good thing, especially if that good thing monopolizes their options to choose.

1.5: Big Data Analysis and Application

There are two main divisions of big data analysis and application in agriculture. The first is active data collection and analytics. These situations occur when a farmer has incoming real-time field and crop data and needs to make precision agriculture decisions based on data driven models. For example, irrigation is required, and a field has a variable rate irrigation system. That grower needs to know, based on current incoming data, when, how much, and where to water within that specific field. Another example would be that a farmer pays to have aerial visual monitoring of his fields, detecting outbreaks of disease or pests or other attention worthy anomalies. Daily aerial imagery data will be collected and must be processed to give the grower the necessary feedback to manage disease or pests. A patch of diseased crops is detected using machine learning processing of the captured imagery and a notification is sent to the manager letting them know the extent and location of the issue. All this real-time data collection and analytics assists the grower in making management decisions.

Active real-time big data processing provides tremendous detail and value to the growers that can utilize the information, but this approach has two major limitations. The first limitation applies directly to that grower, namely resources. To be a real-time big data smart farming operation, remote and proximal sensors, aerial imagery, and others all must be collected through some means as well as enlisting the services of a data analysis as a service provider. Converting farmland into ‘smart farmland’ is often costly and has a steep learning curve. The second limitation applies only to other growers in which they derive no value from the active real-time data collection occurring on regional farms around them or elsewhere. Smart farms and research stations can often become ‘data silos’ with a wealth of data that could potentially be of regional or global value, but are not readily accessible due to concerns about data privacy or logistical roadblocks. The benefit therefore of historic big data in agriculture is that the collected and stored data and data products derived from them can be applied to farms and current research with little to no installation of ‘smart farming’ equipment. Data driven models can be utilized by growers without meeting the equipment installation requirement of smart farms. Decision support systems for growers based on historical data can run on relatively little data collection within farm compared to real-time data analysis.

The second field of big data analytics in agriculture, with perhaps a broader audience, is historic big data or less common, outside concurrent data. In contrast with active real-time big data analytics, which is concerned only with the here and now, this branch of big data focuses on the past. Many modern growers have decades worth of historic data. It can consist of almost anything in the agricultural world such as spatially or temporally variable soil water conditions, canopy temperature, soil nutrient test results, topography, irrigation requirements and applications, as well as yield to list a few. These varied data can be combined with big data machine learning techniques and management software to produce value for the current and future cropping years. Past data can be used to create estimation models based on relatively easily obtained data like soil electrical conductivity (EC), topography, or normalized difference vegetative index (NDVI) and can be aimed at estimating required agricultural inputs or controls like fertilizers, yield, or irrigation. Another contrast and potential benefit that historical big data has is its broad application to other growers.

The benefit and utility of big data analysis is well established; however, this practice is not an agricultural cure-all. In a recent review on the practice of big data analysis in agriculture, Kamilaris et al. (2017) reviewed 34 papers that examined specific related problems, and proposed solutions, tools, algorithms, and data to overcome big data challenges. The authors detailed some of the open problems and barriers to wider adoption of big data techniques. Several of the problems with big data have been the creation of large monopolies in agri-food, privacy issues, access disparities between developed vs. developing countries, and limited access to ground truth information. Additionally, barriers to wider adoption are an issue, such as lack of human resources and expertise, limited availability of reliable infrastructures to collect and analyze big data, and a general lack of structure and governance related to agricultural big data. In the Kamilaris et al. (2017) publication, the authors also list another common barrier involving the absence of data itself and its limited reliability, variety, or time relevance. At the time of this dissertation, these barriers are still valid; however, big data has proliferated significantly in the last five years and this barrier is now not as acute.

The approach to analysis can be extremely varied due to big data depth and breadth. To make big data analyses more consumable, a systematic and logical approach is needed. Majumdar et al. (2017) addressed the usage of data mining techniques and their application in big data. The authors followed a detailed, intentional approach that an essential issue for agriculture is the accurate yield estimation for numerous crops within a region. The authors went on to use data mining, finding optimal parameters to maximize crop production using techniques such as partitioning around medoids (PAM), clustering large applications (CLARA), density-based spatial clustering of applications with noise (DBSCAN), and multiple linear regression. These methods are various data clustering methods that group units together via similar characteristics. Majumdar et al. (2017) determined that multiple linear regression was the optimum method to fit significant regional attributes and eventually form a yield prediction equation. According to their analysis of clustering quality metrics, DBSCAN provided better clustering quality than PAM and CLARA, but CLARA provided better clustering quality than

PAM. These data mining techniques can easily be expanded to analyze soil and other within field factors to increase crop production under spatially variable climates. This type of big data analysis can assist with not only crop yield prediction, but selecting the most optimum crop based on regional climates.

1.6: Big Data: From Inception to Consumption

Underlying big data use in agriculture are outside factors such as requirements to meet local, state, federal, or other entity standards. However, big data in agriculture likely starts from the ground up, with the producer trying to increase their yield, resource use efficiency, profitability, and/or sustainability. The process of utilizing big data in agriculture starts with producer questions, such as When should I plant? What should I grow? When should I irrigate? When should I fertilize and what fertilizer source should I use? Who should I sell to?

The next step is determining what method of data collection is most suitable for growers. Providers exist that offer various soil sensors (e.g., temperature, moisture, electrical conductivity), satellite data, and UAV imagery. Producers are also free to gather this information themselves. At this point, some of the challenges of big data in agriculture begin to present themselves.

As mentioned previously, the 4 V’s play an important role in big data challenges. A large and varied amount of data is being collected from a single field. A lone field can have weather, soil sensor, canopy temperature and NDVI, remote imagery, yield, and additional data sources. In addition to the large array of data types and formats being collected, data collection velocity can also be practically instantaneous and thus potentially be overwhelming compared to traditional agricultural data monitoring.

Combine all these data sources that are rapidly collecting and storing data and you arrive at the third challenge with big data, volume. In a single year, a grower can easily accumulate enormous quantities of data for a single field. Given that most small-scale producers will not be the early adopters of big data, most farmers that are using precision agriculture technologies and methods have many fields over hundreds or thousands of acres. Thus, being able to analyze the terabytes or larger amounts of data is a challenge in and of itself. This exceeds the capabilities of traditional data analysis tools, computers, and users, leading to the next big data challenge.

The fourth challenge in agricultural big data is value. How are decision makers going to find and create value out of the enormous datasets they collect? Value can be derived and created two ways. First is utilizing cloud computing, processing, and storage. Services like Azure Data Manager for Agriculture, formerly FarmBeats, can handle the sheer volume, velocity and variety of precision agriculture and big data more efficiently than by users and their desktops or laptops (Malvar et al., 2022). Cloud computing can be combined with machine learning programs and models to completely remove hands-on data analytics. Azure Data Manager for Agriculture is a paid data analytics service based on the Azure cloud (Microsoft, 2022). In addition to meeting the 6 V challenges of big data, FarmBeats also overcomes a serious logistical challenge in connectivity. For practical, real-world decisions based on real-time collected field data, the process of manually uploading data to the cloud every day is impractical. For Internet of Things technology to be integrated into farmer operations, connectivity is a prerequisite. Wi-Fi connectivity is an option but severely limited as many farmers do not have Wi-Fi coverage extending far enough from their homes or businesses. In certain regions, 5G coverage can be utilized, and additionally LoRa or LoRaWan can be used (Zourmand et al., 2019). LoRa is a physical proprietary radio communication technique derived from chirp spread spectrum technology. Where cloud connectivity for data upload or program download cannot be achieved, Azure and others are able to license and use TV White Spaces from empty cable broadcast channels (Fatemieh et al., 2010). This process essentially allows increased cloud connectivity to data collection devices within the field. For some agricultural operators, they simply do not have the bandwidth to upload (with any reasonable speed or reliability) such vast quantities of data to the cloud. To combat this challenge, the Azure Gateway instead is downloaded locally to a farmer's own server. Using local computation, Azure is then able to provide cloud style ag services from data from sensors, drones, and cameras, using EdgeCNN, Panorama Generators, and HeatMap Generators. These locally computed insights can be directed at precision irrigation, precision pH maps, yield prediction, pest infestation, and precision fertilization (Microsoft, 2022).

The second addition of value to this system, and where 'big data' becomes "really big", is via collaboration. Sometimes growers covet their operation's data, aware that someone could take advantage of them if their field data falls into the wrong hands. However, if growers could be assured of security and anonymity, as well as having demonstrated for them the value and utility that large agricultural databases would have, they might be more likely and willing to collaborate with others. Without willing collaboration, many decision makers in big data and precision agriculture will re-trod work and insights that have already been accomplished by others but be unaware of those data and insights. By contributing to shared databases, growers will be able to add to the growing body of knowledge and observation. Scientists and analysts will have a stronger base from which to make assertions and inferences about agriculture and how it can be best supported and utilized with the resources at hand. Local through global data pooling collaborations should be where the big data "rubber" meets the agricultural "road". It becomes a system of thousands of farms, large and small, pooling their data resources to create deeper value and meaning from the plethora of collected data.

Big data collection and storage is relatively well understood, and many services offer themselves as data collectors, providers, or intermediaries. However, nationwide or global big data databases often provide data, yet no consumption in the form of data analysis or interpretation. Even global soil databases such as Varda (a subsidiary of Yara) offer themselves as a source of data, but as of 2022 they do not provide insights to what the data means for the data user. Many publicly available agricultural databases exist such as that USDA-National Agricultural Statistics Service "Quick-Stats", but the data without tools to interpret them are not of tremendous value to the data consumer. There are, of course, data analytics as a service business; however, these can be costly and out of reach for small hold farmers.

1.7: Big Data and Reducing Nitrogen and Phosphorus Runoff on a Nationwide Scale - MANAGE

As previously detailed, big data can be split into active or historical categories. The focus of the research within this dissertation will pivot around historical big data, specifically the MANAGE database which spans decades and ecoregions summarizing annual nutrient loads from agricultural lands in North America. With the aforementioned challenges and divisions within big data, the objectives of this dissertation are to: 1) review, update, and prepare the MANAGE database (Harmel et al., 2022) for regional analysis and include contemporary nutrient runoff research; 2) quantify, analyze, and detail how agricultural land management practices vary in their effect on field-scale nutrient loss within EPA level II ecoregions; and 3) examine and identify the interactions that management practices and other field scale characteristics have on the impact of nutrient loss across all ecoregions.

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Chapter 2: Updates To The Manage Database To Facilitate Regional Analyses Of Nutrient Runoff

2.1: Introduction

The first effort to compile annual nutrient losses or “nutrient export coefficients” for various land uses in the U.S. was made in the early 1980’s (Beaulac, 1980; Reckhow et al., 1980; Beaulac and Reckhow, 1982). Then building off that initial effort, Harmel et al. (2006) developed the “Measured Annual Nutrient loads from AGricultural Environments” (MANAGE) database to make up-to-date data publicly available. MANAGE presents annual field-scale dissolved, particulate, and total nitrogen (N) and phosphorus (P) runoff data from published studies of agricultural land uses (cultivated and grassland including improved pasture and rangeland). For each study, the database contains land use information, including crop rotations, grazing management, and artificial drainage; tillage category (no-till, conservation, conventional, pasture); conservation practice category (waterway, terrace, filter strip, riparian buffer, contour farming); soil series and hydrologic soil group; soil test P and extractant; land slope, watershed size; and fertilizer formulation, rate, and application method (surface applied, incorporated, injected). Annual runoff volume, precipitation, and soil erosion data are also included when available. Subsequent updates to MANAGE included additional published studies, data fields (e.g., crop yield, nutrient uptake, timing of fertilizer application), N and P runoff concentration data, and forest land uses (Harmel et al., 2008, 2016; Table 1). More recent updates added 79 studies of drainage N and P concentrations and loads mainly from the Midwestern and Eastern U.S. (Christianson and Harmel, 2015a, b; Christianson et al., 2016; Hertzberger et al., 2019a, b).

A variety of studies have used the MANAGE database for meta-type analysis of management impacts on drainage nutrient losses (Zhao et al., 2016; Liu et al., 2021; Flores et al.,

2021) and on the impact of agricultural conservation practices on nutrient losses in surface runoff (Reckhow et al., 2009; Qian and Harmel, 2016; Nummer et al., 2018). The database has also been used to evaluate modeling tool predictions of best management practices effectiveness, regional water balances, and regional ranges of runoff, sediment, and nutrient loss (e.g., Merriman et al., 2009; White et al., 2010, 2015a, b). The objective of the present work was to publish this contemporary data repository with up-to-date data from North American studies on N and P runoff from agricultural lands to assist with future analyses.

Table 2.1. Summary statistics for annual N and P runoff data from cultivated lands and grasslands in the original and updated MANAGE database versions.

	Harmel et al. (2006)	**Harmel et al. (2008)**	**Harmel et al. (2016)**	**Present work**
Site Years[a]	1103	1677	1980	3326
Publications (studies)[b]	40	55	67	94
Database Records[b]	163	274	330	507
Nutrient Export Data	Loads	Loads and Concentrations	Loads and Concentrations	Loads and Concentrations
Major additions	-	15 additional studies	12 additional studies; crop yield, N and P uptake, fertilizer timing	27 additional studies; Level II ecoregion

[a] Product of the number of sites and number of years.

[b] In some instances, data/information from paired publications are grouped and listed together as a single record.

2.2: Materials and Methods

In this update we added 27 studies and 1346 additional site years to the MANAGE database. Specifically, we entered annual dissolved, particulate (sediment bound), total N and P runoff loads, precipitation, runoff, and erosion data along with descriptive data related to land use, land management, and site conditions for each treatment. We also included dissolved, particulate, and total N and P concentration data when available, but the present discussion focuses on annual N and P runoff loads.

In addition, we determined the Level II ecoregion (Omernik, 1987; Omernik and Griffith, 2014) for each study (Table 2). The 50 Level II ecoregions delineated in North America provide national and subcontinental overviews of ecological patterns (EPA, 2021), and we felt they were the most appropriate representation of the spatial distribution of N and P runoff. Level I was too coarse (15 ecoregions) and Level III too fine (182 ecoregions), and alternatives such as U.S. states or Canadian provinces do not adequately represent differences in soils, physiography, potential natural vegetation, and land uses.

2.3: Results and Discussion

Of the 50 Level II ecoregions in the U.S. and Canada, annual dissolved, particulate, or total N and P runoff load data are available for 11 ecoregions (Table 2; Figure 1, 2). Level II ecoregions such as Cold Deserts (10.1) are not represented in MANAGE because of arid conditions and limited runoff. Similarly, no data are available from the Upper Gila Mountains (13.1) or the Boreal Cordillera (6.1), which have few agricultural land uses. The database is publicly available on the USDA Ag Data Commons website (https://data.nal.usda.gov/dataset/measured-annual-nutrient-loads-agricultural-environments-manage-database).

The present analyses revealed considerable variability in the descriptive information/metadata reported by studies included in MANAGE. All 94 studies presented land use information for each treatment (and all 3326 site years of data), and a vast majority included tillage information (99% of site years), watershed area (98% of site years), land slope (87% of site years), and P application rate (80% of site years). In contrast, fewer site years of data had associated fertilizer application timing (62%), fertilizer placement (66%), N application rate (50%), or crop yield (13%) information. While these lower percentages may be partially attributed to factors such as references to corresponding studies with this information and to treatments that did not apply fertilizer and thus would not report fertilizer timing or placement, these instances do not account for all the cases of data omission. It is also interesting that data on precipitation, which is the driver of nutrient runoff, were reported for only 60% of site years. Data on other "response" variables such as runoff and erosion were reported for 86% and 73% of the site years. Eagle et al. (2017) classified these descriptive and response data as "highly recommended (minimum requirements)" for nutrient management research and stressed their importance for future research, review studies, and meta-analyses, in which the focus may or may not be the same as in the original study. We also strongly encourage that the descriptive and response data types as described in Eagle et al. (2017) be collected and reported in future nutrient loss studies to support research, policy, and management of nonpoint source nutrient runoff.

Table 2.2. Median annual dissolved, particulate, and total N and P runoff loads (kg/ha/yr, weighted by site years) for Level II ecoregions.

			Diss. N	**Part. N**	**Total N**	**Diss. P**	**Part. P**	**Total P**
Level II ecoregion	**Dominant land uses**	**Major data sources**	**-------------------------- kg/ha/yr ---------------------------**					
7.1 Marine West Coast Forest	Corn for silage	British Columbia, Canada	5.4 (n=12)	-	43.5 (n=12)	-	-	12.3 (n=12)
8.1 Mixed Wood Plains	Corn, grassland (grazed), and various rotations	WI, NY, and Canada	3.0 (n=97)	-	24.2 (n=8)	0.17 (n=159)	1.0 (n=40)	0.86 (n=152)
8.2 Central USA Plains	Corn and corn/soybean rotations	On-farm studies in OH	1.6 (n=76)	-	3.0 (n=76)	0.12 (n=110)	0.13 (n=4)	0.25 (n=82)
8.3 Southeastern USA Plains	Corn, grassland (hayed), and cotton/peanut rotations	USDA-ARS watersheds (Tifton, GA, Watkinsville, GA)	3.1 (n=170)	0.32 (n=80)	11.1 (n=46)	0.17 (n=196)	1.7 (n=67)	1.5 (n=69)
8.4 Ozark-Ouachita, App. Forests	Corn and grassland (grazed)	USDA-ARS watersheds (Booneville, AR, Coshocton, OH)	1.0 (n=366)	1.2 (n=188)	4.9 (n=442)	0.80 (n=664)	0.15 (n=308)	0.97 (n=552)
8.5 Mississippi Alluvial and Southeast USA Coastal Plains	Corn, cotton, citrus, and sugar cane	Louisiana State Univ., Univ. Ark, on-farm study in FL	3.3 (n=44)	1.5 (n=7)	4.9 (n=28)	0.48 (n=40)	0.92 (n=7)	3.0 (n=49)
9.2 Temperate Prairies	Corn, corn/soybean, and small grain rotations	Manitoba, Canada, and Univ. Nebraska-Lincoln	1.7 (n=362)	21.0 (n=193)	11.7 (n=262)	0.23 (n=566)	1.9 (n=199)	0.73 (n=599)
9.3 West-Central Semi-Arid Prairies	Wheat and wheat rotations	Saskatchewan, Canada	0.40 (n=24)	-	0.05 (n=24)	0.03 (n=75)	-	0.00 (n=24)
9.4 South-Central Semi-Arid Prairies	Grassland (hayed and/or grazed), wheat, and wheat rotations	USDA-ARS watersheds (Riesel, TX, Woodward, OK, El Reno, OK)	0.78 (n=527)	2.2 (n=212)	2.4 (n=527)	0.19 (n=565)	0.56 (n=187)	0.60 (n=874)
9.5 Texas-Louisiana Coastal Plain	Sugar cane	Univ. Louisiana-Lafayette	-	-	-	0.38 (n=15)	-	1.5 (n=15)
11.1 Mediterranean California	Grassland (grazed)	Univ. California	5.1 (n=1)	-	1.6 (n=18)	0.00 (n=1)	-	0.03 (n=18)
		Total site years by constituent	n=1679	n=680	n=1443	n=2391	n=812	n=2446

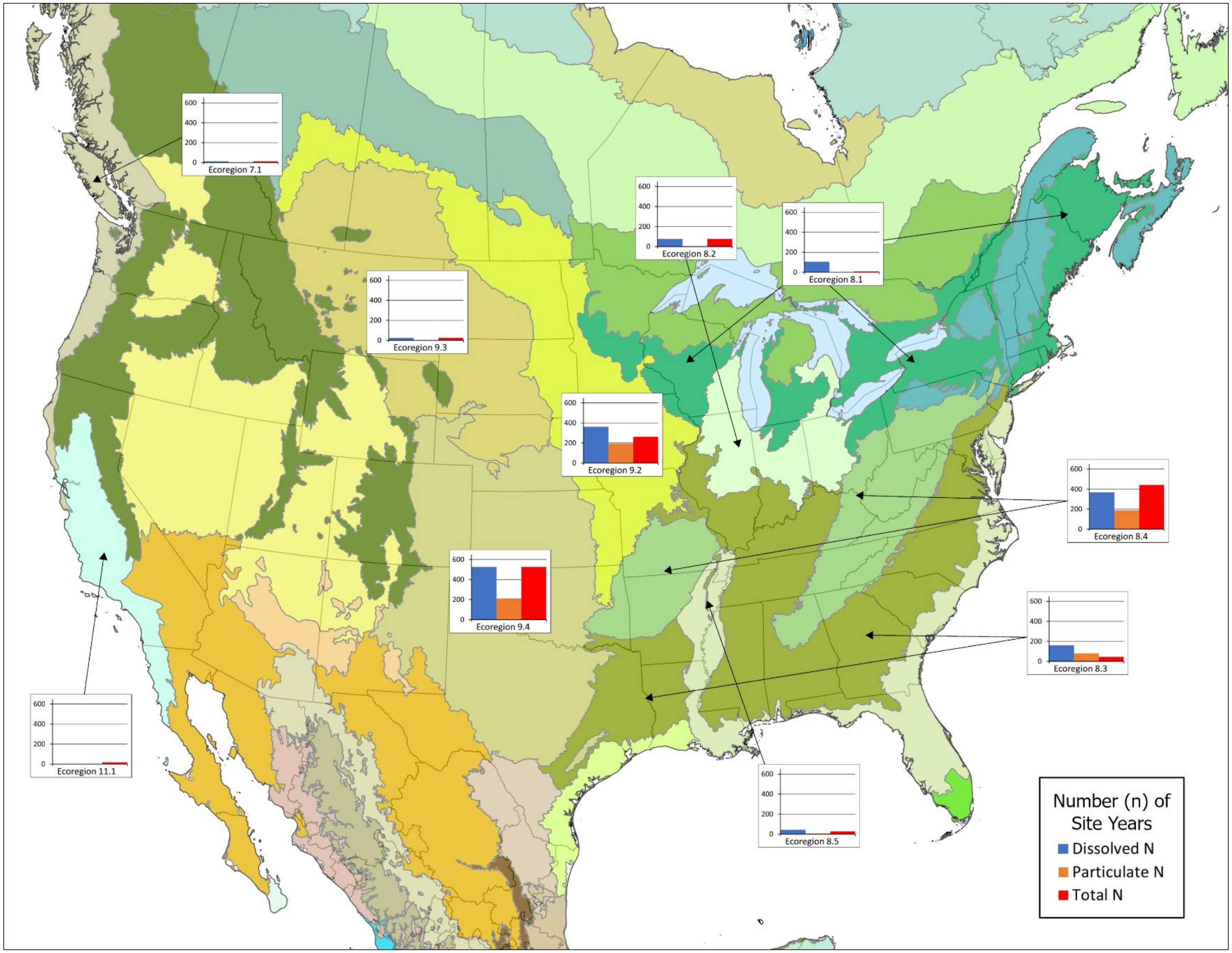

Figure 2.1. The number of site years of annual N runoff load data (dissolved, particulate, and total) in Level II ecoregions in North America.

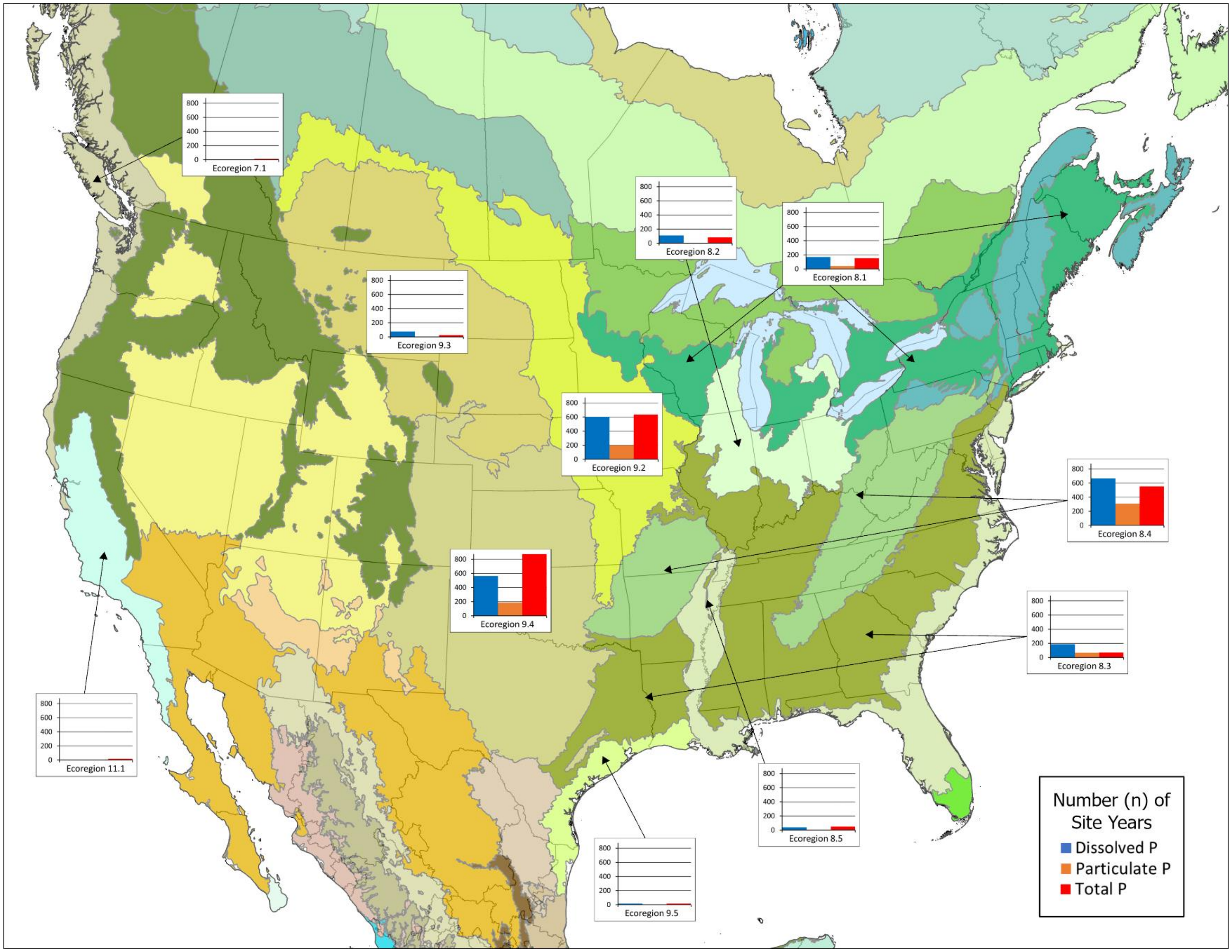

Figure 2.2. The number of site years of annual P runoff load data (dissolved, particulate, and total) in Level II ecoregions in North America.

2.4: Conclusions

With summary data from the vast majority of relevant North American studies, MANAGE contains more than 3000 site years of published annual N and P runoff data and corresponding metadata (e.g., land use and management, soil type, runoff, precipitation). Our team is currently working with data compiled in MANAGE to evaluate regional differences in N and P loss and the impacts of land use and management. It is hoped the MANAGE database proves valuable for additional scientific analyses, model evaluations, and management and policy decisions related to nutrient management and conservation planning.

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Chapter 3: Nutrient Runoff From Agricultural Lands In North American Ecoregions

3.1: Introduction

Liebig's law of the minimum states that "if one growth factor or nutrient is deficient, plant growth is limited, even if all other vital factors and nutrients are adequate… plant growth is improved by increasing the supply of the deficient factor or nutrient" (de Baar, 1994). Nitrogen (N) and phosphorus (P) are often the limiting nutrients in algal growth in North American waterbodies, and offsite transport from agricultural watersheds is often a substantial contributor to accelerated eutrophication (Beman et al., 2005; White et al., 2014). The land humans occupy is vastly different across time and space. Many people work and live on the land to produce food, fiber, and fuel, and these stewards make choices on how to utilize and care for holdings. On a small scale, their actions may seem inconsequential, but they in fact affect global nutrient cycling and their associated ecosystems (Kleinman and Harmel, 2023). Resource mismanagement can become a negative reinforcement loop. For example, poor soil management increases water runoff, nutrient, and soil loss and then increases the perceived need for increased fertilizer application, which can exacerbate agriculture's contribution to accelerated eutrophication of aquatic ecosystems (e.g., streams, lakes, ponds). Thus, reducing off-site nutrient losses is intimately linked to sound agroecosystem management.

Agricultural management decisions are typically made at the field-scale, thus runoff and water quality data at that scale are critical to improve the understanding of the fate and transport of nutrients applied to agricultural lands (Reba et al., 2013; Daniels et al., 2018; Klausner et al., 1974). Specifically, runoff and water quality data are vital for understanding and designing effective regional agricultural non-point source pollution reduction strategies considering farm-level hydrologic, soil, weather, and management factors.

The present research compiles and analyzes regional nutrient runoff data from agricultural land in North America to better inform and improve these on-farm management decisions. The "Measured Annual Nutrient loads from AGricultural Environments" (MANAGE) database was created to provide up-to-date field-scale N and P load data from published studies of agricultural land uses in North America, including cultivated and grassland (i.e., improved pasture and rangeland) (Harmel et al., 2006). The initial version of MANAGE was built off an effort in the early 1980s to gather and compile "nutrient export coefficients" or annual nutrient losses for a variety of land uses (Beaulac, 1980; Reckhow et al., 1980; Beaulac and Reckhow, 1982). Subsequent revisions added additional runoff studies including those from forest lands, as well as N and P concentration, crop yield, nutrient uptake, and timing of fertilizer application (Harmel et al., 2008, 2016, 2022). White et al. (2015) developed a national database of localized export coefficients for Level III U.S. ecoregions (Omernik, 1987) using Soil and Water Assessment Tool (SWAT) modeling, applying land use, topography, climate, management, conservation practice, and soil data to stochastically represent annual N and P load distributions and utilized MANAGE data for validation. The present study was designed to: 1) evaluate potential differences in measured annual N and P runoff loads across North American Level II ecoregions, and 2) evaluate the impact of agricultural management factors such as land use, tillage, and fertilizer timing and placement on N and P runoff.

3.2: Materials and Methods

We used the recent MANAGE update (Harmel et al., 2022), which added 27 studies representing an additional 1,346 site years of data, to complete the present analysis ensuring the most comprehensive data set possible. This update also delineated the Level II EPA ecoregion (Omernik, 1987; Omernik and Griffith, 2014) for each study, presenting annual N and P runoff load data for 11 of the 50 Level II ecoregions in the US and Canada (Figure 1, 2, Table 1).

Specifically, we compiled annual N and P runoff load data for each ecoregion (i.e., dissolved, particulate, and total N and P, kg/ha/yr – as generally categorized, although MANAGE also presents the specific form and/or laboratory analysis technique), along with various agricultural management practices (i.e., land use, tillage, fertilizer timing, fertilizer placement) within each ecoregion to showcase the analyses possible using data within MANAGE. We evaluated potential differences in N and P runoff loads between and within ecoregions with statistical and graphical approaches. We conducted non-parametric Dunn tests with an *a priori* $\alpha = 0.05$ significance level on median values weighted by the site years of data (R Core Team, 2022) because the data were not normally distributed. Box-and-whisker plots were created to visually evaluate potential differences as recommended by Helsel and Hirsch (1993), as presented in Figures 3 through 6.

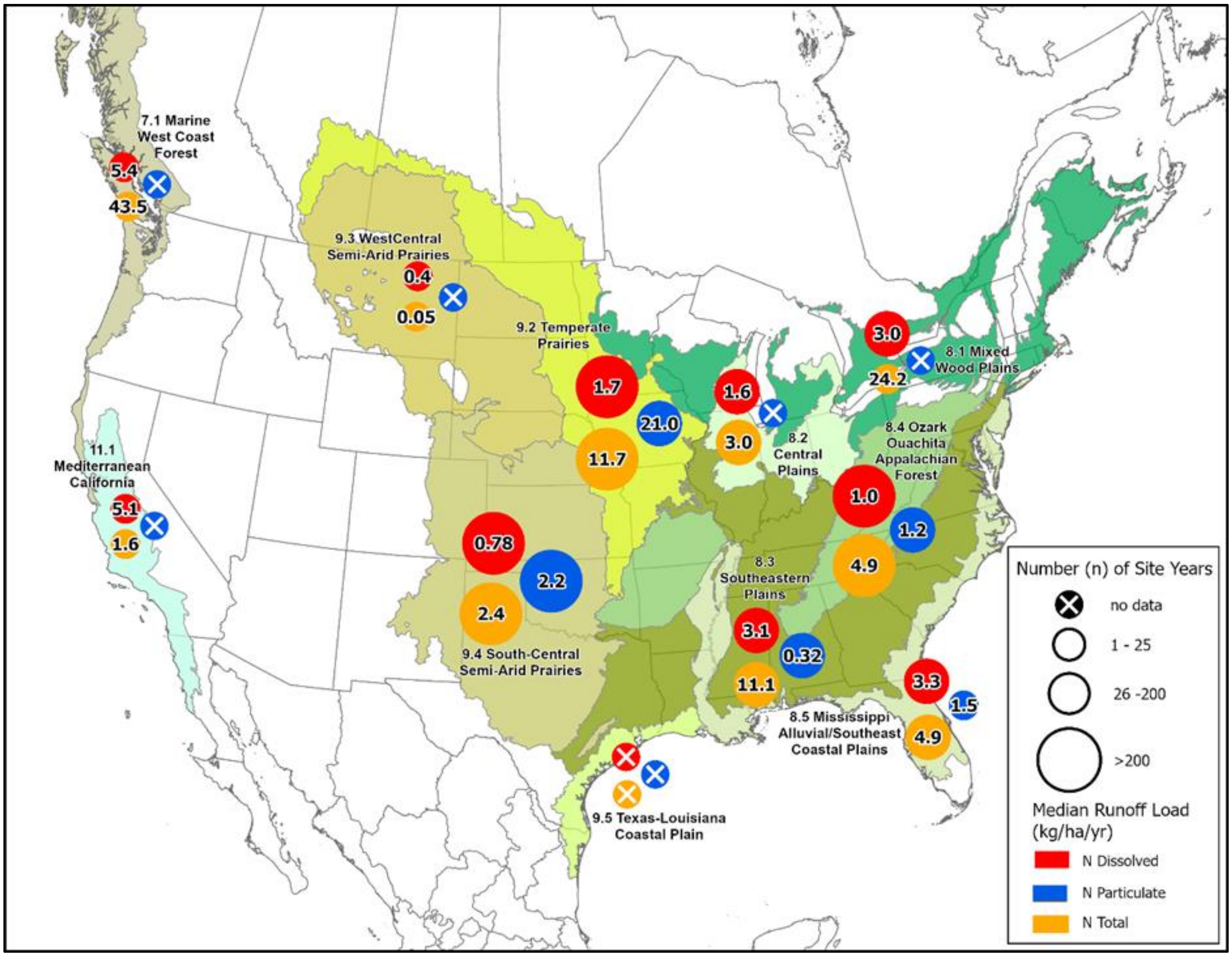

Figure 3.1. Annual N runoff load data (dissolved, particulate, and total) in Nort American Level II ecoregions.

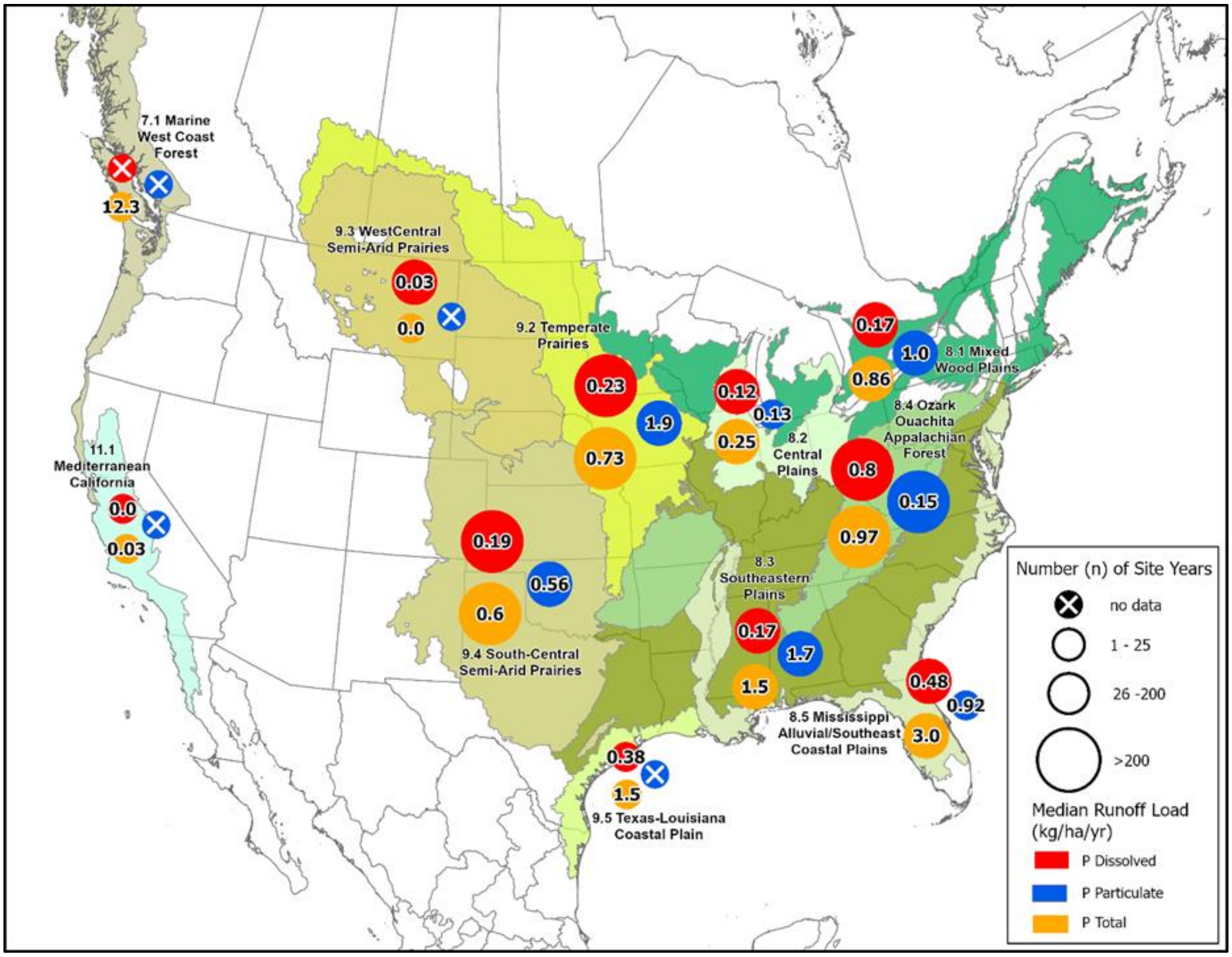

Figure 3.2. Annual P runoff load data (dissolved, particulate, and total) in North American Level II ecoregions.

Table 3.1. Median annual dissolved, particulate, and total N and P runoff loads (kg/ha/yr), weighted by site years) for Level II ecoregions.

			Diss. N	**Part. N**	**Total N**	**Diss. P**	**Part. P**	**Total P**
Level II Ecoregion[a] (site years, number and % of total)	**Dominant land uses**	**Mean annual precipitation and temperature[b]**	**------------------------------ kg/ha/yr ------------------------------**					
7.1 Marine West Coast Forest (n=12, < 1%)	Corn for silage	2291 mm 4.1 °C	5.4 (n=12)	-	43.5 (n=12)	-	-	12.3 (n=12)
8.1 Mixed Wood Plains (n=218, 7%)	Corn, grassland (grazed), and various rotations	1045 mm 7.3 °C	3.0a (n=97)	-	24.2 (n=8)	0.17a (n=159)	1.0ab (n=40)	0.86ac (n=152)
8.2 Central USA Plains (n=110, 3%)	Corn and corn/soybean rotations	1042 mm 10.2 °C	1.6ab (n=76)	-	3.0ab (n=76)	0.12a (n=110)	0.13ab (n=4)	0.25c (n=82)
8.3 Southeastern USA Plains (n=289, 9%)	Corn, grassland (hayed), and cotton/peanut rotation	1342 mm 16.4 °C	3.1a (n=170)	0.32ab (n=80)	11.1ab (n=46)	0.17abc (n=196)	1.7a (n=67)	1.5abc (n=69)
8.4 Ozark-Ouachita/Appalachian Forests (n=964, 29%)	Corn and grassland (grazed)	1287 mm 13.0 °C	1.0ab (n=366)	1.2a (n=188)	4.9ab (n=442)	0.80bc (n=664)	0.15b (n=308)	0.97ac (n=552)
8.5 Mississippi Alluvial/Southeast USA Coastal Plains (n=65, 2%)	Corn, cotton, citrus, sugar cane	1403 mm 18.7 °C	3.3a (n=44)	1.5 (n=7)	4.9ab (n=28)	0.48b (n=40)	0.92 (n=7)	3.0b (n=49)
9.2 Temperate Prairies (n=675, 20%)	Corn, corn/soybean, and small grain rotations	748 mm 6.7 °C	1.7ab (n=362)	21.0b (n=193)	11.7a (n=262)	0.23ac (n=566)	1.9a (n=199)	0.73ac (n=599)
9.3 West-Central Semi-Arid Prairies (n=75, 2%)	Wheat and wheat rotations	462 mm 6.3 °C	0.40 (n=24)	-	0.05 (n=24)	0.03ac (n=75)	-	0.00 (n=24)
9.4 South-Central Semi-Arid Prairies (n=884, 27%)	Grassland (hayed and/or grazed) and wheat and wheat rotations	684 mm 14.2 °C	0.78b (n=527)	2.2b (n=212)	2.4b (n=527)	0.19ac (n=565)	0.56a (n=187)	0.60ac (n=874)
9.5 Texas-Louisiana Coastal Plain (n=15, <1%)	Sugar cane	1091 mm 22.0 °C	-	-	-	0.38 (n=15)	-	1.5 (n=15)
11.1 Mediterranean California (n=19, < 1%)	Grassland (grazed)	489 mm 16.4 °C	5.1 (n=1)	-	1.6 (n=18)	0.00 (n=1)	-	0.03 (n=18)
		Total site years by constituent	n=1679	n=680	n=1443	n=2391	n=812	n=2446

[a] For each constituent, median values followed by the same letter are not significantly different ($\alpha = 0.05$). Results of statistical analysis presented only for ecoregions with more than 25 site years of data.

[b] Mean annual precipitation and mean temperature data were obtained from the USGS (2015).

3.3: Results and Discussions

3.3.1 Ecoregion influence on N and P runoff

For annual dissolved N loads, 1679 site years were available from ten ecoregions. For the seven ecoregions with > 25 site years of data (Table 1), notable significant differences in median annual dissolved N loads occurred between the semi-arid South-Central Semi-Arid Prairies (0.78 kg/ha/yr) and the Mixed Wood Plains (3.0 kg/ha/yr), Southeastern USA Plains (3.1 kg/ha/yr), and Mississippi Alluvial/Southeast USA Coastal Plains (3.3 kg/ha/yr). This difference was likely attributed to higher precipitation (684 vs. 1045-1403 mm/yr) and thus higher runoff volume, as well as the dominance of heavily fertilized corn-based systems in the more eastern ecoregions. Note that the Marine West Coast Forest also has high annual dissolved N, total N, and total P loads, which was expected in that high rainfall region; however, these results are based on only 12 site years of data from corn silage production and thus were not used for statistical comparisons.

In contrast, only 680 site years were available for particulate N loads and only from five ecoregions (Table 3.1). For the four ecoregions with > 25 site years of data, notable significant differences in median annual particulate N loads occurred between the Ozark-Ouachita/Appalachian Forests (1.2 kg/ha/yr) and both the Temperate Prairies (21.0 kg/ha/yr) and the South-Central Semi-Arid prairies (2.4 kg/ha/yr). Interestingly, the Ozark-Ouachita/Appalachian Forests have lower loads despite receiving almost double the average rainfall than those ecoregions (1287 vs. 684-748 mm/yr). These counterintuitive differences can be partially attributed to the fact that most of the particulate N load data from the Ozark-Ouachita/Appalachian Forests are from grasslands whereas most of the data from the Temperate

Prairies are from potentially highly erodible cultivated lands in corn or small grain production (Harmel et al., 2022) (Table 3.2).

For total N, 1443 site years were available from ten ecoregions, and six ecoregions had > 25 site years (Table 1). A notable significant difference in median annual total N loads occurred between the South-Central Semi-Arid Prairies (2.4 kg/ha/yr) and the Temperate Prairies (11.7 kg/ha/yr). As with particulate N, this difference may be attributed to the fact that most of the total N load data for the South-Central Semi-Arid Prairies are from grasslands with perennial cover (Harmel et al., 2022). In contrast, data from the Temperate Prairies represent potentially highly erodible cultivated land in corn, corn/soybean, and small grain rotations (Table 3.2).

For dissolved P, 2391 site years of data were available. For the eight ecoregions having > 25 site years of data, several notable significant differences occurred (Table 3.1). The highest annual dissolved P losses occurred in the Mississippi Alluvial/Southeast USA Coastal Plains (0.48 kg/ha/yr) and Ozark-Ouachita/Appalachian Forests (0.80 kg/ha/yr) likely due to high annual precipitation (1403 and 1287 mm/yr). In contrast, the relatively wet Southeastern USA Plains, Mixed Wood Plains, and Central USA Plains (1042-1342 mm/yr) had lower annual dissolved P loads (0.12-0.17 kg/ha/yr).

In contrast, only 812 site years were available for particulate P loads. For the six ecoregions with > 25 site years, several notable significant differences were evident (Table 3.1). Most notably, median annual particulate P loads from the Ozark-Ouachita/Appalachian Forests (0.15 kg/ha/yr) were significantly lower than other ecoregions likely because much of the data were from grassland or corn with winter cover crops (Table 3.2). Research has shown that soil erosion and particulate P losses are lower in corn systems with winter cover crops than in traditional corn production (Kleinman et al., 2005; Jacobs et al., 2022). In contrast, corn production in the Southeastern USA Plains and Temperate Prairies tended to have larger annual particulate P loads (1.9 and 8.1 kg/ha/yr, respectively), which was attributed to major soil disturbances (Panuska et al., 2008) associated with tillage, planting, and fertilizer application (e.g., Burwell et al., 1975).

Total annual P load data (2446 site years) were available from each ecoregion. For the seven ecoregions with > 25 site years, the Mississippi Alluvial/Southeast USA Coastal Plains had the highest annual total P loads (3.0 kg/ha/yr) due to high rainfall (1403 mm/yr) and often tillage-intensive corn, cotton, and sugar cane production (Table 3.1, Fig. 3.3-3.4). The lowest annual total P loads occurred in the driest ecoregions (West-Central Semi-Arid Prairies, Mediterranean California); however, the Central USA Plains also had low total P runoff values are likely due conservation tillage and no-till (King et al., 2018).

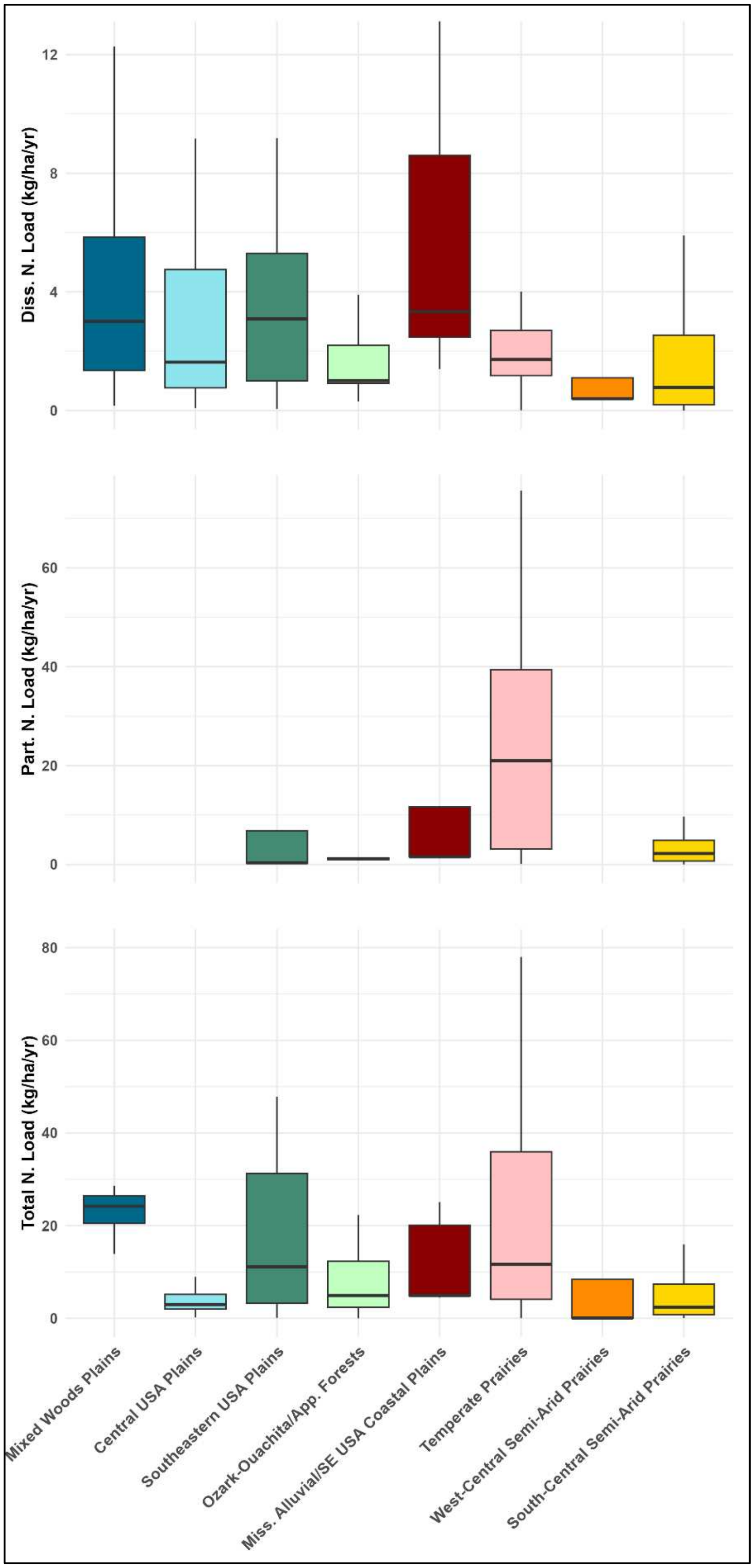

Figure 3.3. Box-and-whisker plots of annual dissolved, particulate, and total N loads (kg/ha).

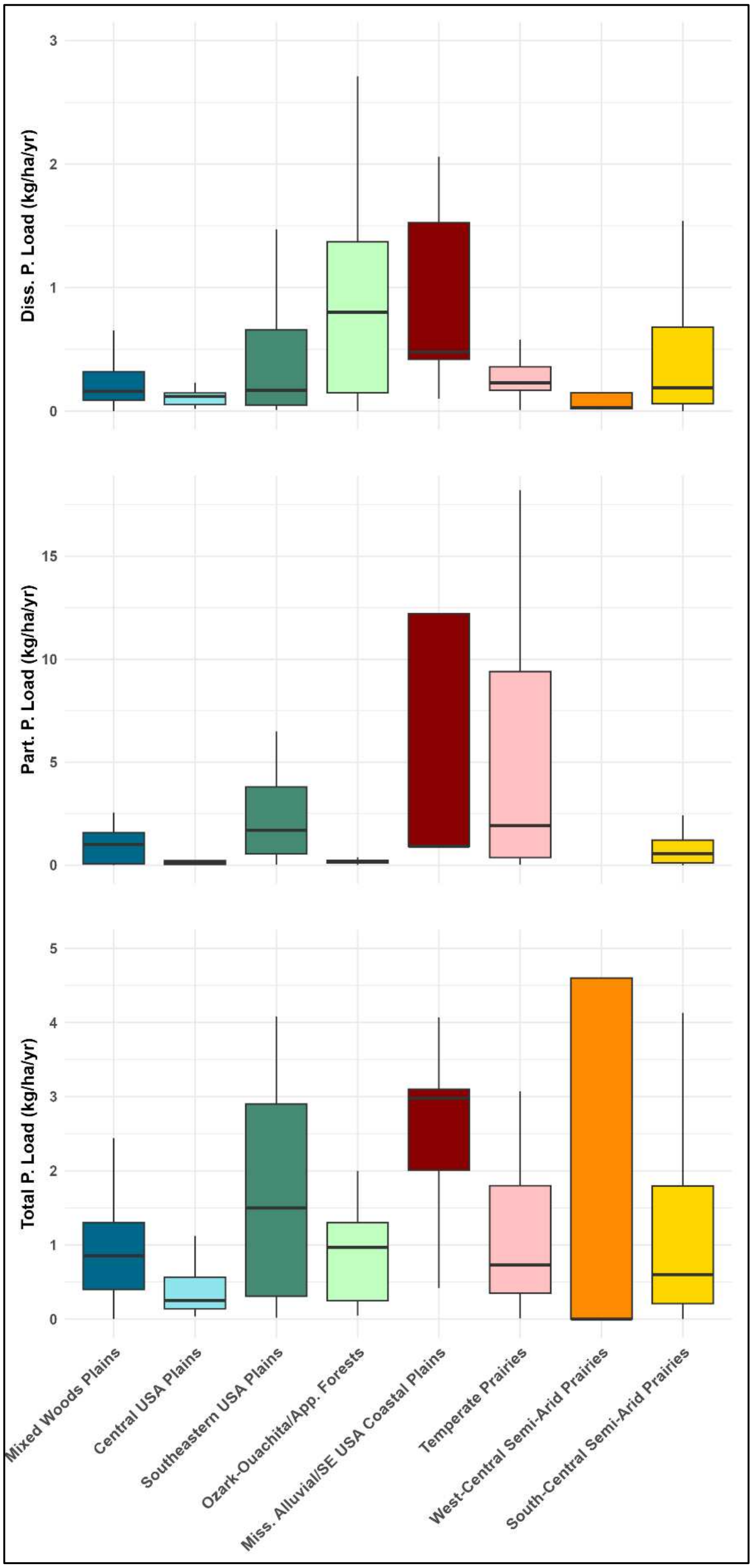

Figure 3.4. Box-and-whisker plots of annual dissolved, particulate, and total P loads (kg/ha).

3.3.2 Land use influence on N and P runoff

Median annual N and P loads based on land use within and between ecoregions are presented in Table 2. Only results for the dominant land use in each ecoregion (top three based on the number of site years, minimum of 25) are presented as there was a large variety in land uses presented in the MANAGE database. Although these dominant land uses based on studies in MANAGE may differ from actual areal extents, they appear to be reasonable according to prevailing production practices as influenced by topography, soil, temperature, and rainfall.

3.3.2.1 Key results on land use impacts - within ecoregions

For the Mixed Wood Plains, Southeastern USA Plains, Ozark-Ouachita/Appalachian Forests, and Temperate Prairies, corn production tended to produce the highest annual N and P loads; however, a few exceptions occurred (Table 3.2). Grazed grassland tended to produce higher dissolved P loads in the Mixed Wood Plains, due to one study with relatively high median annual loads (0.80 kg/ha/yr). In the Southeastern USA Plains, fertilized grassland and cotton/peanut rotations tended to produce higher dissolved N loads but lower particulate and total N loads than corn production. This may have been attributed to light textured loamy sands and utilization of winter cover crops in the peanut-cotton rotation studies (Bosch et al., 2015; Endale et al., 2017). It is interesting to note the effectiveness of winter cover crops in reducing P loads in corn production in the Ozark-Ouachita/Appalachian Forests (Figure 3.5). In the Temperate Prairies, corn and small grain rotations both produced relatively high N and P loads. While conservation and no-till practices have been applied more frequently in recent years, conventional tillage for corn and grain production is still common within the Temperate Prairies (Mallarino et al., 2019). For the South-Central Semi-Arid Prairies, wheat produced higher N and

P runoff than grasslands likely because of increased erodibility due to tillage (Van Oost et al., 2006) and because not all grasslands are fertilized annually (Harmel et al., 2022).

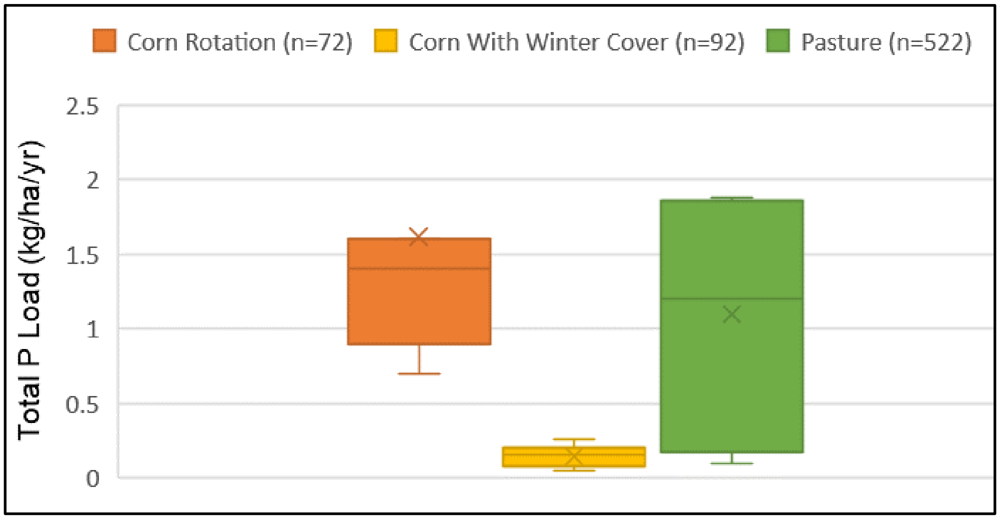

Figure 3.5. Annual total P loads (kg/ha/yr) for the dominant land uses in the Ozark-Ouachita/Appalachian Forests ecoregion.

3.3.2.2. Key results on land use impacts - between ecoregions

For corn production, N and P loads tended to be similar between ecoregions (Table 3.2). For grazed grassland, dissolved and total N and P loads tended to be lower for the South-Central Semi-Arid Prairies with lower precipitation than for the Ozark-Ouachita/Appalachian Forests and Mixed Wood Plains.

For grasslands that are likely hayed instead of grazed, dissolved N loads were lower, but dissolved P loads were higher for the South-Central Semi-Arid Prairies than for the Southeastern USA Plains. The prevalence of organic fertilizer application in studies from the Southeastern USA Plains compared to inorganic fertilizer in the South-Central Semi-Arid Prairies likely contributed to these differences. For wheat and other small grain rotations, total P loads in the South-Central Semi-Arid Prairies were significantly higher than in the Temperate Prairies likely due to the prevalence of rotational cropping and cover crops in wheat systems in the Temperature Prairies, which reduce erosion. It is also noteworthy that N and P loads for wheat and small grain production in the West-Central Semi-Arid Prairies (mostly Saskatchewan, Canada), South-Central Semi-Arid Prairies (mostly Texas and Oklahoma), and Temperate Prairies (mostly Manitoba, Canada) typically increased as rainfall increased across ecoregions from 462 to 748 mm/yr.

Table 3.2. Median annual dissolved, particulate, and total N and P runoff load (kg/ha/yr), weighted by site years) for the top three land uses (minimum of 25 site years) for Level II ecoregions, sorted by ecoregion (left) and by land use (right).

	Diss. N	Part. N	Total N	Diss. P	Part. P	Total P			Diss. N	Part. N	Total N	Diss. P	Part. P	Total P
Level II ecoregion – Land use[a]	----------- kg/ha/yr -----------							**Land use - Level II ecoregion[b]**	----------- kg/ha/yr -----------					
8.1 Mixed Wood Plains								**Corn (and corn years in various rotations)**						
Corn (n=53)	3.0a	-	24.2	0.18a	-	3.1a		8.1 Mixed Wood Plains (n=53)	3.0a	-	24.2a	0.18a	-	3.1a
Various corn/soybean/small grain or alfalfa rotations (n=74)	1.30b	-	-	0.13a	-	0.7b		8.3 Southeastern USA Plains (n=79)	0.78a	6.8a	11.4a	0.10a	1.90a	2.9a
Grassland (grazed) (n=26)	-	-	-	0.80a	-	1.00ab		8.4 Ozark-Ouachita/App. Forests (n=72)	6.9	-	22.1a	0.3	-	1.6
8.2 Central USA Plains								9.2 Temperate Prairies (n=180)	1.89a	20.4a	26.03a	0.17a	8.1a	2.03a
Corn/soybean rotation (n=62)	0.86a	-	2.18a	0.12a	-	0.29a		**Grassland (grazed)**						
Corn/soybean/wheat rotation (n=36)	1.9a	-	2.98a	0.58a	-	0.22a		8.1 Mixed Wood Plains (n=26)	-	-	-	0.80ab	-	1.00a
8.3 Southeastern USA Plains								8.4 Ozark-Ouachita/App. Forests (n=522)	0.95a	1.21a	2.9a	1.0a	0.22a	1.2a
Corn (n=79)	0.78a	6.8a	11.4	0.10a	1.90	2.9a		9.4 South-Central Semi-Arid Prairies (n=197)	0.38b	1.59a	0.8b	0.06b	0.5a	0.2a
Cotton/peanut rotation (n=72)	2.78a	0.27b	-	-	-	-		**Grassland**						
Grassland (n=26)	4.3a	-	-	0.04a	-	0.4b		8.3 Southeastern USA Plains (n=26)	4.3a	-	-	0.04a	-	0.4a
8.4 Ozark-Ouachita/App. Forests								9.4 South-Central Semi-Arid Prairies (n=230)	0.4b	0.66	1.04	0.1b	0.11	0.21a
Corn years in various rotations (n=72)	6.9a	-	22.1a	0.3b	-	1.6b		**Wheat and other small grain rotations**						
Grassland (grazed) (n=522)	0.95a	1.21	2.9b	1.0b	0.22a	1.2b		9.2 Temperate Prairies (n=181)	2.59a	21.0a	23.59a	0.24a	5.01a	0.31a
Corn with winter cover (n=92)	-	-	-	0.07a	0.09b	0.15a		9.3 West-Central Semi-Arid Prairies (n=75)	0.40a	-	0.05a	0.03a	-	0.00ab
9.2 Temperate Prairies								9.4 South-Central Semi-Arid Prairies (n=120)	1.3a	5.9a	5.9a	0.21a	1.90a	2.0b
Corn (n=180)	1.89a	20.4a	26.03a	0.17a	8.1a	2.03a								
Various corn/soybean rotations (n=127)	0.76a	-	0.24b	0.36a	-	0.73ab								
Various small grain rotations (n=181)	2.59a	21.0a	23.59ab	0.24a	5.01a	0.31b								
9.3 West-Central Semi-Arid Prairies														
Wheat and various wheat rotations (n=75)	0.40	-	0.05	0.03	-	0.00								
9.4 South-Central Semi-Arid Prairies														
Grassland (n=230)	0.4a	0.66a	1.04a	0.1ab	0.11a	0.21a								
Grassland (Grazed) (n=197)	0.38a	1.59b	0.8a	0.06a	0.5a	0.2a								
Wheat (n=120)	1.3b	5.9ab	5.9b	0.21b	1.90a	2.0b								

[a] For each ecoregion, median values followed by the same letter are not significantly different (α = 0.05). [b] For each land use category, median values followed by the same letter are not significantly different (α = 0.05).

3.3.3 Impact of tillage on N and P runoff

The median annual runoff loads for the three tillage categories (conventional, conservation, no-till) in each ecoregion (based on the number of site years, minimum of 25) are presented in Table 3.3. All grasslands were excluded from this analysis. The Southeastern USA Plains, Ozark-Ouachita/Appalachian Forests, Temperate Prairies, and South-Central Semi-Arid Prairies ecoregions had adequate data to analyze all three tillage types; however, the Mixed Wood Plains and Central USA Plains ecoregions only had adequate data to compare two tillage types.

3.3.3.1 Key results on tillage impacts - within ecoregions

Tillage differences did not seem to impact annual N and P loads in the Mixed Wood Plains and Central USA Plains (Table 3.3), which was counter to expectations. For the Southeastern USA Plains and Temperate Prairies, no-till had the greatest dissolved P loads and conventional the lowest, which was consistent with prevailing science (e.g., Daryanto et al., 2017). However, the converse was true for the Ozark-Ouachita/Appalachian Forests, even though these ecoregions all have corn as the dominant cultivated land use. This result was largely a product of high average annual dissolved P loads (1.2-31.0 kg/ha/yr) measured from a conventionally tilled corn-wheat-meadow-meadow rotation by Weidner et al. (1969) with very high annual P application rates (188-301 kg/ha). For the Temperate Prairies, conventional tillage sites had higher median annual particulate N, total N, and particulate P loads, and a similar trend with higher particulate and total N and P loads was observed in the South-Central Semi-Arid Prairies.

3.3.3.2 Key results on tillage impacts - between ecoregions

For no-till, the single significant difference was that particulate N was greater in much wetter Southeastern USA Plains than in the Semi-Arid South-Central Semi-Arid Prairies (Table 3.3). For conservation and conventional tillage, there were several significant differences between ecoregions yet no clear geographic trend except the following. Under conservation tillage, dissolved N and dissolved P loads were significantly greater for the South-Central Semi-Arid Prairies than for the Temperate Prairies, likely due to lower N and P application rates in the studies from Temperate Prairies. The exceptionally high median total N load (24.2 kg/ha/yr) for conservation tillage in the Mixed Wood Plains resulted from one study with corn silage production and application of inorganic fertilizer and liquid dairy manure. Under conventional tillage, the large median value (34.7 kg/ha/yr) for annual total N loads in the Ozark-Ouachita/Appalachian Forests resulted from the Weidner et al. (1969) study. Several significant differences in nutrient loads under conventional tillage between ecoregions. For example, the median total N load from the Temperate Prairies (39.9 kg/ha/yr) was significantly greater than for the South-Central Semi-Arid Prairies (8.84 kg/ha/yr); however, the opposite was true for total P loads (0.69 vs. 2.51 kg/ha/yr).

Table 3.3. Median annual dissolved, particulate, and total N and P runoff load (kg/ha/yr), weighted by site years) based on cropland tillage system (minimum of 25 site years) for Level II ecoregions, sorted by ecoregion (left) and by tillage (right).

	Diss. N	**Part. N**	**Total N**	**Diss. P**	**Part. P**	**Total P**			**Diss. N**	**Part. N**	**Total N**	**Diss. P**	**Part. P**	**Total P**
Level II ecoregion – Tillage [a]	**----------- kg/ha/yr -----------**							**Tillage - Level II ecoregion** [b]	**----------- kg/ha/yr -----------**					
8.1 Mixed Wood Plains								**No-Till**						
Conservation (n=83)	4.29a	-	24.2	0.18a	0.07a	1.3a		8.2 Central USA Plains (n=45)	1.55	-	3.51a	0.12a	-	0.21a
Conventional (n=89)	3.45a	-	-	0.13a	0.89a	0.74a		8.3 Southeastern USA Plains (n=36)	2.07a	10.4a	6.0a	0.71a	1.7a	0.02a
8.2 Central USA Plains								8.4 Ozark-Ouachita/App. Forests (n=88)	4.20a	-	8.9a	0.14a	0.11a	0.25a
No-till (n=45)	1.55a	-	3.51a	0.12a	-	0.21a		9.2 Temperate Prairies (n=88)	3.3a	-	8.89a	0.37a	-	0.97a
Conservation (n=51)	1.07a	-	2.17a	0.06a	-	0.25a		9.4 South-Central Semi-Arid Prairies (n=145)	2.5a	0.3b	2.95a	0.7a	0.10a	1.1a
8.3 Southeastern USA Plains								**Conservation**						
No-till (n=36)	2.07a	10.4a	6.0a	0.71b	1.7a	0.02a		8.1 Mixed Wood Plains (n=83)	4.29ab	-	24.2a	0.18a	0.07ab	1.3ab
Conservation (n=61)	2.23a	0.22a	11.10a	0.22ab	0.34a	0.73a		8.2 Central USA Plains (n=51)	1.07ab	-	2.17b	0.06a	-	0.25a
Conventional (n=142)	3.33a	0.32a	6.38a	0.07a	1.09a	2.42a		8.3 Southeastern USA Plains (n=61)	2.23ab	0.22a	11.10ab	0.22ab	0.34ab	0.73ab
8.4 Ozark-Ouachita/App. Forests								8.4 Ozark-Ouachita/App. Forests (n=127)	3.8ab	-	11.5ab	0.2ab	0.05a	0.9ab
No-till (n=88)	4.20a	-	8.9a	0.14a	0.11a	0.25a		9.2 Temperate Prairies (n=259)	1.46a	3.22a	4.76b	0.21a	1.12b	1.0ab
Conservation (n=127)	3.8a	-	11.5a	0.2a	0.05a	0.9a		9.4 South-Central Semi-Arid Prairies (n=111)	4.72b	2.20a	7.12ab	0.78b	0.58b	1.08b
Conventional (n=67)	3.9a	1.01	34.7a	4.0b	0.24a	0.99a		**Conventional**						
9.2 Temperate Prairies								8.1 Mixed Wood Plains (n=89)	3.45a	-	-	0.13a	0.89a	0.74a
No-till (n=88)	3.3a	-	8.89ab	0.37b	-	0.97a		8.3 Southeastern USA Plains (n=142)	3.33a	0.32a	6.38ab	0.07a	1.09a	2.42ab
Conservation (n=259)	1.46a	3.22a	4.76a	0.21a	1.12a	1.0a		8.4 Ozark-Ouachita/App. Forests (n=67)	3.9a	1.01a	34.7ab	4.0b	0.24a	0.99ab
Conventional (n=277)	1.88a	34.77b	35.95b	0.20a	8.43b	0.69a		9.2 Temperate Prairies (n=277)	1.88a	34.77a	35.95a	0.20a	8.43a	0.69a
9.4 South-Central Semi-Arid Prairies								9.4 South-Central Semi-Arid Prairies (n=200)	1.9a	5.22a	8.84b	0.28ab	1.9a	2.51b
No-till (n=145)	2.5a	0.3b	2.95b	0.7a	0.10b	1.1a								
Conservation (n=111)	4.8a	2.34a	7.12a	0.8a	0.61a	1.08a								
Conventional (n=200)	1.9a	5.22a	8.84a	0.28a	1.9a	2.51b								

[a] For each ecoregion, median values followed by the same letter are not significantly different ($\alpha = 0.05$).

[b] For each tillage category, median values followed by the same letter are not significantly different ($\alpha = 0.05$).

3.3.4 Impact of fertilizer timing on N and P runoff

The median annual runoff loads based on fertilizer timing categories (out-of-season, pre-plant, at planting, side/top dress) on cropland in each ecoregion (based on the number of site years, minimum of 25) is presented in Table 4. Only the Southeastern Plains, Ozark-Ouachita/Appalachian Forests, and South-Central Semi-Arid Prairies had enough data to evaluate potential significant differences based on fertilizer timing. When analyzing fertilizer timing, it became apparent that many of the treatments used split application; therefore, split application with various timing combinations was also included in Table 3.4. For grasslands only fertilization in the growing season had more than 25 site years in any ecoregion (thus no data on grassland fertilization at establishment or in the dormant season are presented).

3.3.4.1 Key results on fertilizer timing impacts - within ecoregions

For the Southeastern USA Plains, split application (at planting and then side/top dress) had significantly higher particulate N, total N, and particulate P loads than pre-plant application, which was counter to prevailing science and recommendations (e.g., Sitthaphanit et al., 2009). This surprising result occurred even though pre-plant application for the studies in the Southeastern USA Plains tended to incorporate fertilizer with tillage (Endale et al., 2017) and thus increased soil disturbance which can increase erosion and particulate N and P losses. In the South-Central Semi-Arid Prairies, however, median annual loads for particulate and total N and P tended to be higher for pre-plant application compared to split application (at planting and then side/top dress). In the South-Central Semi-Arid Prairies, fertilizer application to grass in the growing season produced the lowest N and P loads as expected due to reduced erodibility and to application during the period of active nutrient uptake. In the Ozark-Ouachita/Appalachian Forests, however, all P loads were significantly higher for grass with fertilizer application in the growing season than for crop land with application at planting, which can be partially attributed to most of the cropland sites growing corn with winter cover crops and to higher P application rates on the grasslands (avg = 255 kg/ha/yr) than the cropland (avg. = 40 kg/ha/yr) (Harmel et al., 2022). Fertilizer application timing did not seem to impact N and P loads in the Temperate Prairies (Table 3.4).

3.3.4.2 Key results on fertilizer timing impacts - between ecoregions

For fertilizer application to grass in the growing season, dissolved N and P loads were significantly higher in the Southeastern USA Plains likely due to higher precipitation than in the South-Central Semi-Arid Prairies (1342 vs. 684 mm/yr). Similarly, total N loads were significantly higher in the Ozark-Ouachita/Appalachian Forests than the South-Central Semi-Arid Prairies possibly due to higher precipitation (1287 vs. 684 mm/yr), higher fertilizer rates, and higher slopes. No significant ecoregion differences were observed for pre-plant fertilizer application. For split application (pre-plant and out-of-season), total N, dissolved P, and total P loads were higher for the Temperate Prairies than for the Central USA Plains even though the Temperate Prairies are more arid (748 vs. 1042 mm/yr). Both of these areas are dominated by corn/soybean rotations with land management; thus, this counterintuitive result may be attributed to differences in soil N and P test concentrations, fertilizer application rates, or another confounding factors. For split application (at plant and side/top dress), particulate N and P loads were notably higher for the Southeastern USA Plains than the South-Central Semi-Arid Prairies likely due to higher precipitation (1342 vs. 684 mm/yr).

Table 3.4. Median annual dissolved, particulate, and total N and P runoff load (kg/ha/yr), weighted by site years) based on fertilizer application timing (minimum of 25 site years) for Level II ecoregions, sorted by ecoregion (left) and by fertilizer timing (right).

	Diss. N	Part. N	Total N	Diss. P	Part. P	Total P		Diss. N	Part. N	Total N	Diss. P	Part. P	Total P
Level II ecoregion – Fertilizer Timing [a]	**----------- kg/ha/yr -----------**						**Fertilizer Timing – Level II ecoregion[b]**	**----------- kg/ha/yr -----------**					
8.1 Mixed Wood Plains							**Grass in growing season**						
Split (includes At Plant) (n=89)	3.45	-	24.2	0.17	0.89	1.72	8.3 Southeastern USA Plains (n=42)	4.3a	-	-	6.35a	-	0.4a
8.2 Central USA Plains							8.4 Ozark-Ouachita/App. Forests (n=640)	1.07ab	1.16a	2.90a	0.93ab	0.2a	0.97a
Split (Pre-Plant and Out of Season) (n=49)	2.70	-	2.67	0.06	-	0.36	9.4 South-Central Semi-Arid Prairies (n=60)	1.15b	0.2a	1.76b	0.18b	0.1a	0.22a
8.3 Southeastern USA Plains							**Pre-Plant**						
Grass in Growing Season (n=42)	4.3a	-	-	6.35a	-	0.4a	8.3 Southeastern USA Plains (n=91)	3.33a	0.27a	3.23a	0.3a	0.59a	0.99a
Pre-Plant (n=91)	3.33a	0.27a	3.23a	0.3a	0.59a	0.99a	9.2 Temperate Prairies (n=116)	1.9a	34.77a	23.59a	0.23a	8.43a	2.03a
Split (At Plant and Side/Top Dress) (n=37)	3.4a	6.8b	11.1b	0.3a	1.9b	2.9a	9.4 South-Central Semi-Arid Prairies (n=79)	3.12a	5.51a	9.43a	0.44a	4.46a	4.30a
8.4 Ozark-Ouachita/App. Forests							**Split (Pre-Plant and Out of Season)**						
At Plant (n=130)	6.2a	-	12.5a	0.12a	0.1a	0.25a	8.2 Central USA Plains (n=49)	2.70a	-	2.67a	0.06a	-	0.36a
Grass in Growing Season (n=640)	1.07a	1.16	2.9b	0.93b	0.2b	0.97b	9.2 Temperate Prairies (n=81)	1.88a	20.5	22.4b	0.11b	0.59	0.70b
8.5 Mississippi Alluvial/Southeast USA Coastal Plains							**Split (At Plant and Side/Top Dress)**						
Split (At Plant and Side/Top Dress) (n=29)	3.13	-	4.93	0.32	-	3.1	8.3 Southeastern USA Plains (n=37)	3.4a	6.8a	11.1a	0.3a	1.9a	2.9a
9.2 Temperate Prairies							8.5 Mississippi Alluvial/Southeast USA Coastal Plains (n=29)	3.13a	-	4.93a	0.32a	-	3.1a
Out of Season (n=64)	1.46a	146.85a	150.28a	0.17a	33.15a	2.03a	9.4 South-Central Semi-Arid Prairies (n=82)	2.77a	0.71b	5.90a	0.41a	0.22b	1.19a
Pre-Plant (n=116)	1.9a	34.77a	23.59a	0.23a	8.43a	2.03a							
Split (Pre-Plant and Out of Season) (n=81)	1.88a	20.5a	22.4a	0.11a	0.59a	0.70a							
9.4 South-Central Semi-Arid Prairies													
Grass in Growing Season (n=60)	1.15a	0.2a	1.76a	0.18a	0.1a	0.22ab							
Pre-Plant (n=79)	3.12ab	5.51b	9.43b	0.44a	4.46b	4.30a							
Split (At Plant and Side/Top Dress) (n=82)	2.77b	0.71a	5.90b	0.41a	0.22a	1.19b							
At Plant (n=83)	-	-	-	0.27a	-	1.10ab							

[a] For ecoregion, median values followed by the same letter are not significantly different (α = 0.05). [b] For category, median values followed by the same letter are not significantly different (α =0.05).

3.3.5 Impact of fertilizer placement on N and P runoff

The average annual runoff loads for three categories of fertilizer placement (surface, incorporated, injected) in each ecoregion (based on the number of site years, minimum of 25) are presented in Table 3.5. When analyzing fertilizer placement, it became apparent that several treatments used split applications with different placement; therefore, these combinations were presented in Table 3.5 when more than 25 site years of data were available.

3.3.5.1 Key results on fertilizer placement impacts – within ecoregions

For the Southeastern USA Plains, split application with surface placement and either incorporation or injection had higher particulate and total N and P loads than surface placement, which can be partially attributed to the prevalence of surface placement treatments on grassland sites with low erodibility in the Southeastern USA Plains (Harmel et al., 2022). For the Ozark-Ouachita/Appalachian Forests, incorporation produced higher dissolved N, total N, and dissolved P loads than surface application (Figure 3.6). This counterintuitive result, however, can be explained by higher N and P rates for the incorporated treatments (262 kg/ha/yr and 183 kg/ha/yr, respectively) and many of the surface placement treatments occurred on grasslands with application during the growing season with active nutrient uptake (Table 3.5). The same phenomena occurred in the South-Central Semi-Arid Prairies with fertilizer incorporation tending to produce higher N and P loads possibly due to the tillage soil disturbance during fertilizer incorporation (Harmel et al., 2009). Fertilizer placement did not seem to impact N and P loads in the Mixed Wood Plains or Temperate Prairies.

3.3.5.2 Key results on fertilizer placement impacts between ecoregions.

No significant differences between ecoregions were observed for surface fertilizer application. The impacts of fertilizer incorporation on N and P runoff did vary between ecoregions, with the Temperate Prairies producing the highest particulate and total N and P loads but relatively low dissolved N and P loads and the Ozark-Ouachita/Appalachian Forests producing the highest dissolved P loads. For fertilizer injection, dissolved and total P losses were higher for the Temperate Prairies than for the Ozark-Ouachita/Appalachian Forests. This difference likely occurred because the injection treatments in the Ozark-Ouachita/Appalachian Forests were all in corn production with winter cover crops and because application occurred at planting, whereas the Temperate Prairies sites were in corn production without cover crops and were fertilized out-of-season (Harmel et al., 2022).

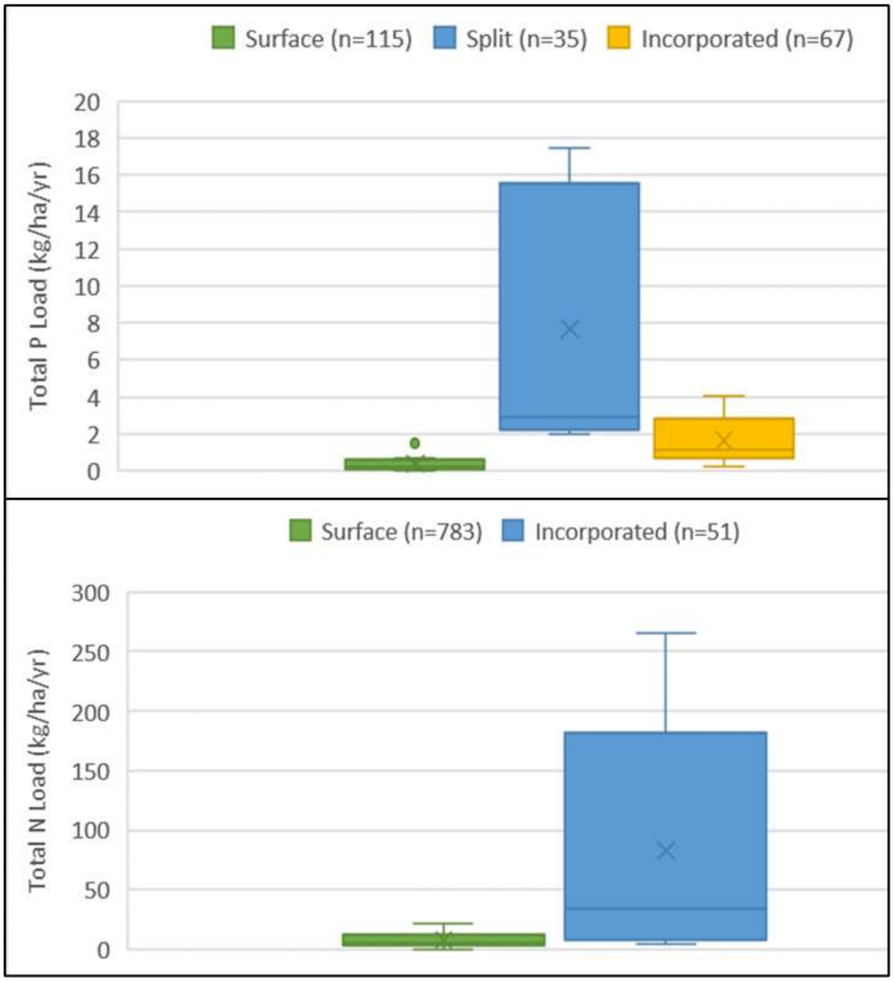

Figure 3.6. Annual runoff loads from sites with fertilizer incorporation and sites with surface placement: a) total P loads in the Southeastern USA Plains, and b) total N loads in the Ozark-Ouachita/Appalachian Forests.

Table 3.5. Median annual dissolved, particulate, and total N and P runoff load (kg/ha/yr), weighted by site years) based on fertilizer placement (minimum of 25 site years) for Level II ecoregions, sorted by ecoregion (left) and by fertilizer placement (right).

	Diss. N	Part. N	Total N	Diss. P	Part. P	Total P
Level II ecoregion – Fertilizer Placement[a]	**----------- kg/ha/yr -----------**					
8.1 Mixed Wood Plains						
Split (Surface and Incorporated) (n=43)	3.0a	-	-	0.14a	0.79a	0.86a
Incorporated (n=50)	2.27a	-	-	0.09a	0.04a	1.3a
Surface (n=31)	7.07a	-	-	0.24a	1.13a	1.51a
8.2 Central USA Plains						
Surface (n=52)	1.07	-	2.18	0.13	0.13	0.35
8.3 Southeastern USA Plains						
Incorporated (n=67)	3.96a	0.27a	3.23ab	0.30a	0.59ab	0.99ab
Split (Surface and Incorporated or Injected) (n=35)	4.6a	6.80b	11.4a	0.50a	1.90a	2.9a
Surface (n=115)	2.23a	-	0.54b	0.17a	0.09b	0.40b
8.4 Ozark-Ouachita/App. Forests						
Incorporated (n=51)	3.90a	-	34.7a	4.0a	0.24a	0.99ab
Surface (n=783)	0.95b	1.16	2.9b	0.86c	0.15a	0.97b
Injected (n=44)	-	-	-	0.05b	0.10a	0.15a
9.2 Temperate Prairies						
Incorporated (n=110)	2.42a	34.77a	35.95a	0.23a	8.43a	5.25a
Injected (n=65)	1.46a	3.22a	5.35a	0.17a	-	2.03a
Surface (n=64)	1.15a	32.05a	8.89a	0.3a	8.1a	1.21a
9.4 South-Central Semi-Arid Prairies						
Incorporated (n=118)	5.34a	4.6a	9.72a	1.0a	1.04a	2.51a
Split (Surface and Incorporated or Injected) (n=68)	2.54ab	5.9ab	7.2a	0.3a	1.9ab	2.20ab
Surface (n=215)	1.15b	1.52b	2.7b	0.17a	0.16b	1.11b

	Diss. N	Part. N	Total N	Diss. P	Part. P	Total P
Fertilizer Placement - Level II ecoregion[b]	**----------- kg/ha/yr -----------**					
Surface						
8.1 Mixed Wood Plains (n=31)	7.07a	-	-	0.24a	1.13a	1.51a
8.2 Central USA Plains (n=52)	1.07a	-	2.18a	0.13a	0.13a	0.35a
8.3 Southeastern USA Plains (n=115)	2.23a	-	0.54a	0.17a	0.09a	0.40a
8.4 Ozark-Ouachita/App. Forests (n=783)	0.95a	1.16a	2.9a	0.86a	0.15a	0.97a
9.2 Temperate Prairies (n=64)	1.15a	32.05a	8.89a	0.3a	8.1a	1.21a
9.4 South-Central Semi-Arid Prairies (n=215)	1.15a	1.52a	2.7a	0.17a	0.16a	1.11a
Incorporated						
8.1 Mixed Wood Plains (n=50)	2.27a	-	-	0.09a	0.04a	1.3a
8.3 Southeastern USA Plains (n=67)	3.96a	0.27a	3.23a	0.30abc	0.59a	0.99ab
8.4 Ozark-Ouachita/App. Forests (n=51)	3.90a	-	34.7b	4.0b	0.24a	0.99ab
9.2 Temperate Prairies (n=110)	2.42a	34.77b	35.95ab	0.23ac	8.43a	5.25ab
9.4 South-Central Semi-Arid Prairies (n=118)	5.34a	4.6ab	9.72ab	1.0bc	1.04a	2.51b
Injected						
8.4 Ozark-Ouachita/App. Forests (n=44)	-	-	-	0.05a	0.10	0.15a
9.2 Temperate Prairies (n=65)	1.46	3.22	5.35	0.17b	-	2.03b

[a] For each ecoregion, median values followed by the same letter are not significantly different ($\alpha = 0.05$).

[b] For each fertilizer placement category, median values followed by the same letter are not significantly different ($\alpha = 0.05$).

3.4: Conclusions

The present meta-type analyses of N and P runoff from agricultural lands for Level II North American ecoregions produced several interesting results related to land management factors such as land use, tillage, and fertilizer timing and placement. While many of the differences were expected based on prevailing science and echoed in practice recommendations, several differences in annual N or P runoff loads were counter to current understanding. For example,

- Annual particulate N loads were significantly higher for the Temperate Prairies (21.0 kg/ha/yr) than for the much wetter Ozark-Ouachita/Appalachian Forests (1.2 kg/ha/yr), likely because most of the Ozark-Ouachita/Appalachian Forests data were from grasslands whereas most of the data from the Temperate Prairies were from potentially highly erodible cultivated lands.
- The highest annual dissolved P losses occurred in the Mississippi Alluvial/Southeast USA Coastal Plains (0.48 kg/ha/yr) and Ozark-Ouachita/Appalachian Forests (0.80 kg/ha/yr) as influenced by high annual precipitation, although the relatively wet Southeastern USA Plains, Mixed Wood Plains, and Central USA Plains had lower annual dissolved P loads (0.12-0.17 kg/ha/yr).
- Annual particulate P loads from the Ozark-Ouachita/Appalachian Forests (0.13 kg/ha/yr) were significantly lower than other ecoregions likely because much of the data were from grassland or corn with winter cover crops.
- Tillage did not seem to impact annual N and P loads in the Mixed Wood Plains and Central USA Plains, which was surprising. For the Southeastern USA Plains and Temperate Prairies, no-till had the highest dissolved P loads and conventional the lowest,

which was consistent with prevailing science; however, the conventional tillage produced the highest dissolved P loads in the Ozark-Ouachita/Appalachian Forests. These differences in tillage impacts occurred despite similar rainfall and the prominence of corn production in these ecoregions.

- Split fertilizer applications tended to have higher loads than pre-plant applications in the Southeastern USA Plains. This counterintuitive result was especially surprising since pre-plant application in this ecoregion tended to incorporate fertilizer with tillage thus increasing erosion potential. In contrast, pre-plant applications tended to produce higher annual particulate and total N and P loads than split applications in the South-Central Semi-Arid Prairies.
- In the South-Central Semi-Arid Prairies, fertilizer application to grass in the growing season tended to produce the lowest N and P loads, likely due to reduced erodibility and application during the period of active nutrient uptake. In contrast, in the Ozark-Ouachita/Appalachian Forests, dissolved, particulate, and total P loads were significantly higher for fertilizer application to grass in the growing season than to cropland at planting. This was likely due to the effectiveness of winter cover crops in reducing N and P losses in corn production and to higher P application rates on grassed lands (avg = 255 kg/ha) than cropland (avg = 40 kg/ha).
- In the Ozark-Ouachita/Appalachian Forests, fertilizer incorporation produced higher dissolved N, total N, and dissolved P loads than surface application. This seemingly counterintuitive result can be explained by higher N and P rates for the incorporated treatments and because many of the surface placement treatments occurred on grasslands with application in the growing season with active nutrient uptake. The same phenomena

occurred in the South-Central Semi-Arid Prairies with fertilizer incorporation tending to produce higher N and P loads possibly due to the tillage soil disturbance during fertilizer incorporation.

Understanding the differences in edge-of-field N and P runoff between ecoregions is needed to better inform policy and guide regional management decisions to reduce nutrient pollution and resulting eutrophication. The present study lays the groundwork for future analyses that should consider the following observations.

- Much more annual P runoff load data are available than N data. This could be because P is often the limiting nutrient in eutrophication of North American fresh waters, thus warranting more contemporary research funding and attention.
- There is a large disparity in the amount of N and P runoff data among ecoregions. Out of the 50 North American Level II ecoregions, only nine had more than 25 site years of data. Few data are available from west of the Rocky Mountains, even though many areas of the western US are major agricultural regions, likely due to the prominence of irrigated agriculture because of low rainfall and thus little runoff. Only 31 sites years total are available and only from the Marine West Coast Forest and Mediterranean California ecoregions. In contrast, the Temperate Prairies, South-Central Semi-Arid Prairies, and Ozark-Ouachita/Appalachian Forests produced 2533 site years of data (76% of available data) because of the prominence of rainfed agriculture in the “US Breadbasket”.
- All results presented in the present study are based on single factor analyses. Additional multi-factor analyses (e.g., multiple regression, mechanistic modeling, artificial intelligence/machine learning, spatial statistics, causal statistics) evaluating the interactions between ecoregion factors and land use/management decisions will likely

produce valuable understanding to guide management decisions to mitigate N and P runoff losses.

- The results observed and discussed in the present study apply only to the field-scale; however, they should also be evaluated/expanded to the watershed-scale in the context of downstream waterbodies. Linking edge-of-field nutrient runoff with downstream water quality along with related factors and complications (e.g., biological responses, fate and transport processes, spatial variability, lag times) is critical for sensitive water bodies (Daniels et al., 2018; Harmel et al., 2018). Because of likely differences in the impact of management decisions on receiving waterbodies, the present ecoregion analyses should prove valuable developing regionally appropriate nonpoint source mitigation research, policies, and management programs.

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Chapter 4: Agricultural Management Practice Interaction Effects On Nitrogen And Phosphorus Runoff: A Meta-Analysis Of The MANAGE Database

4.1: Introduction

Each year, an estimated 75 billion tons of soil is eroded annually from arable lands worldwide; in the US this represents an estimated financial loss of ~ US $400 billion per year (Borrelli, 2017). Much of that soil loss is correlated with nitrogen (N) and phosphorus (P) loss. The USDA estimates that “each year farmers apply over 18 million tons of manufactured fertilizer, of which 40-80% is lost to the environment” (USDA, 2016). Similarly, other research has shown that a significant portion of N applied as fertilizers can be lost to the environment through processes like leaching, volatilization, and runoff. Estimates suggest that N losses from fertilizers can range from 20-50% (or even greater; Zhang, 2021). This concept is particularly significant when the North American fertilizer market was recently valued at US $26.8 billion (Spherical Insights, 2023), and in 2021 N and P consumption reached over 15 million metric tons (Statista Research Department, 2023). Using agricultural conservation practices, loss can be mitigated to help preserve soil health and its utility for future growing seasons and generations. However, if land managers were able to protect 100% of their topsoil, offsite N and P would still be lost via leaching or gaseous losses (Tahat et al., 2020).

Offsite N and P transport from agricultural fields is often a substantial contributor to accelerated eutrophication, as both N and P are often the limiting factors in algal growth in North American waterbodies (Beman et al., 2005; White et al., 2014; de Baar, 1994). On a small scale, producer actions may seem inconsequential, but they influence global nutrient cycling and ecosystems (Kleinman and Harmel, 2023). Thus, mismanagement can become a negative reinforcement loop across agriculture at the regional, national, and global scale. Management practices that aim only toward maximizing yield in the short-term may result in poor soil health, increased runoff, and nutrient and soil loss as well as an increase in the perceived need for increased fertilizer application, exacerbating agriculture's contribution to accelerated eutrophication.

Various management decisions, along with soil, topographical, and climatic characteristics, can affect nutrient loss. However, the ecological and soil health bottom line exists and has its own intrinsic value beyond the monetary goals of producers. Many producer programs aim to improve overall soil health like the state of Colorado's STAR program. STAR is a soil health program that launched in 2022 to encourage the adoption of healthy soil management practices such as conservation or no-till tillage (Colorado Department of Agriculture, 2023). Extension and education as well as tradition has brought soil health and management back into the forefront of soil stewardship. The Dust Bowl and the advent of modern-day fertilizers demonstrated how much potential soils have as a resource and what they can do when properly managed and when mismanaged. Management decisions and best management practices are not a cookie cutter program. Soils and their needs and limitations are both temporally and spatially variable and what works generally will not work for all (Rochette et al., 1991). Modern day soil, water, and nutrient management need to be regionally tailored to topographical, climatological, and soil physical and chemical features. White et al. (2015) developed a national database of localized export coefficients for Level III U.S. ecoregions (Omernik, 1987) using the Soil and Water Assessment Tool model, which included land use, topography, climate, management, conservation practice, and soil data to stochastically represent annual N and P load distributions, then used the MANAGE data for validation.

Agricultural management decisions are typically made at the field-scale, thus tracking and quantifying runoff and water quality data at that scale is critical for improving the understanding of nutrient fate and transport following land application (Reba et al., 2013; Sharpley et al., 1987, 2001; Daniels et al., 2018) and ultimately reducing nutrient losses. However, while reducing nutrient loss from agricultural lands is important, no specific federal policies set target values for edge-of-field nutrient loss. While some nutrient loss is a reality and is unavoidable, Harmel et al. (2018) assessed nutrient runoff from fields across the United States, concluding that certainty programs offer the most promise for ensuring acceptable nutrient runoff and that field-scale models linked with watershed decision support tools are the most promising for assessing impacts on downstream water quality.

Past research on the connection between management practices and nutrient loads from the "Measured Annual Nutrient loads from AGricultural Environments" (MANAGE) database across North American Ecoregions has focused on tillage, fertilizer timing, fertilizer method, and land use (Austin Hopkins Dissertation, Chapter 3). However, this present work expanded the analyses to include inherent field scale variables (e.g., site-specific rainfall, slope, soil test P). Estimating the effect of conservation practices on reducing nutrient loss using observational data can be confounded by factors such as differing crop types and management practices. Qian et al. (2016) discussed two methods outside of conventional statistics to estimate effects with confounding variables: *propensity score* method in which a sub-set of data was formed for a treatment group and another for a control group with similar distributions of confounding variables, and a *multilevel modeling* method in which data were stratified based on important confounding factors with the conservation practice effect evaluated for each stratum. The methods of Qian et al. (2016) should prove valuable for future exploration and application of

MANAGE to improve water quality and soil and nutrient conservation. However, our aim was to explore how these factors interact to influence edge-of-field nutrient loss. Understanding these interactions is essential for making informed and effective management decisions.

We hypothesized that practices such as conservation tillage, fertilizer injection, and split application of fertilizer will reduce nutrient loss. Conversely, high initial soil P concentrations may diminish the benefits of these conservation practices. We also hypothesized that conventional tillage, fertilizer incorporation, corn production, and pre-plant or out-of-season fertilizer applications, especially when combined with high slopes, high rainfall, and high soil test P concentrations, will increase nutrient losses. Additionally, we hypothesized that inherent differences between North American ecoregions will influence the effectiveness of both conservation and conventional agricultural practices on annual nutrient loss, resulting in significant variations between ecoregions.

4.2: Materials and Methods

This work presents a meta-analysis of 94 published studies that researched the inputs and drivers of edge-of-field agricultural nutrient loads. Specifically, this work analyzes regional nutrient runoff data from agricultural land in North American to better inform and improve on-farm management decisions. The MANAGE database was created to provide up-to-date field-scale N and P load data from published studies of agricultural land uses in North America, including cultivated and grassland (i.e., improved pasture and rangeland; Harmel et al., 2006). The initial version was built off an effort in the early 1980’s to gather and compile nutrient export coefficients or annual nutrient losses for a variety of land uses (Beaulac, 1980; Reckhow et al., 1980; Beaulac and Reckhow, 1982). Subsequent revisions included N and P concentrations in runoff water, crop yield and nutrient uptake, fertilizer application timing, and additional runoff studies from forest lands (Harmel et al., 2008, 2016, 2022).

To complete the present analysis, we used the recent MANAGE update Harmel et al. (2022). The update added 27 studies representing an additional 1,346 site years of data and delineated the Level II EPA ecoregion (Omernik, 1987; Omernik and Griffith, 2014) for each study. Of the 50 Level II ecoregions in the US and Canada, annual N and P runoff load data were available for 11 ecoregions (Table 4.2).

Specifically, from MANAGE, we compiled annual N and P runoff load data (i.e., dissolved, particulate, and total N and P, in kg/ha/yr) for each ecoregion and for various agricultural management practices (i.e., land use, tillage, fertilizer timing, fertilizer placement) within each ecoregion. We evaluated potential differences in N and P runoff loads across broad management practices within North America with statistical and graphical approaches. As this data was nutrient load water quality data, it was right skewed and not normally distributed. Thus, we conducted Kruskal-Wallis non-parametric analyses followed by Dunn's tests (for pairwise comparisons, α=0.05) on median values weighted by the site years of data, utilizing R (R Core Team, 2024). We created box-and-whisker plots to visually evaluate load differences across management decisions within the continent (Helsel and Hirsch, 1993). We used this same methodology to examine statistically significant differences amongst crop yield and management practices.

To enhance the understanding of differences in interactions between management practices and site characteristics, a linear model (LM) analysis was conducted. The interactions between five explanatory variables (ecoregion, tillage, land use, fertilizer timing, and fertilizer placement) along with several site-specific characteristics (Table 4.1) and their effects on nutrient loads were analyzed. Pairwise interactions were the focus of this research to avoid overly complex discussions of multiple factor interactions, controlling for confounding interacting variables when possible. All data were shown to meet assumptions for linearity, independence, and homoscedasticity prior to running the LM. The LM along with all other statistics was performed with R version 4.3.3 ($\alpha=0.05$). The linear regression model equation used for our analysis was:

$$\log(\mu) = \beta_0 + \beta_T T + \beta_F F + \beta_P P + \beta_L L + \beta_E E + \epsilon \qquad (1)$$

where $\log(\mu)$ is the natural log of the nutrient load μ. β_0 is the intercept term. β_T represents the vector of coefficients for the categorical tillage variable (T). β_F represents the vector of coefficients for the fertilizer timing variable (F). β_P represents the vector of coefficients for the fertilizer placement variable (P). β_L represents the vector of coefficients for the categorical land use variable (L). β_E represents the vector of coefficients for the categorical ecoregion variable (E), and ϵ represents the error term.

Table 4.1. List of numeric variables utilized from the MANAGE database for statistical analysis.

Variable	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**	**25th (%)tile**	**75(%)tile**	**Count (n)**
Max soil test P. (ppm)	86	100	32	3.4	630	15	140	1479
Min. soil test p (ppm)	48	69	25	2.8	550	14	60	1477
Max slope %	7.2	6.2	6.1	0.10	40	3.0	8.0	2950
Min. Slope %	4.8	3.6	3.9	0	35	2.0	8.0	2950
Max watershed size (ha)	3.9	11	0.60	0.0009	100	0.14	3.8	3347
Min. watershed size (ha)	3.7	11	0.60	0.0009	100	0.14	3.0	3347
Avg. N fertilizer applied (kg/ha/yr)	190	520	97	0	4900	33	180	1752
Avg. P fertilizer applied (kg/ha)	68	210	25	0	2500	6.0	64	2750
Avg. Crop Yield (Mg/Ha)	6.9	5.8	5.0	0.94	30	3.6	8.5	420
Max Precipitation (mm/yr)	1300	510	1200	290	2100	940	1700	1641
Avg. Precipitation (mm)	940	310	950	230	1900	720	1200	2094
Max Runoff (mm/yr)	180	130	160	1.0	900	78	230	1673
Avg. Runoff (mm/yr)	87	78	67	0.80	560	36	120	2954
Max Soil Loss (kg/ha/yr)	3000	7700	400	4.0	69000	120	2200	1425
Avg. Soil Loss (kg/ha/yr)	2100	5300	290	0	71000	58	1400	2495
Diss. N (kg/ha/yr)	2.8	4.0	1.5	0	43	0.69	3.3	1679
Part. N (kg/ha/yr)	12	28	2.1	0	150	0.92	6.0	580

Total N (kg/ha/yr)	14	32	4.5	0	270	1.9	12	1443
Diss. P (kg/ha/yr)	0.70	2.3	0.23	0	31	0.10	0.72	2489
Part. P (kg/ha/yr)	2.6	6.2	0.30	0	33	0.10	1.2	812
Total P (kg/ha/yr)	1.8	3.9	0.88	0	33	0.27	1.7	2544

Unfortunately, a large difference in the amount (counts) of data for various management practices within the MANAGE database existed (e.g., see Table 4.2 for observation counts). This phenomenon caused difficulty in statistical analysis because of the frequency of missing values. For all pairwise interactions and stepwise multiple linear regression modeling, all possible variable combinations were defined, and missing observations were filtered out. The data gaps in MANAGE resulted from the use of publications with differing metrics and objectives, not all studies reporting the same information limiting full scale application of multiple linear regression.

Table 4.2. List of categorical variables and their counts, used in the statistical analysis of the MANAGE database.

Categorical Variables	**Count (N)**
Tillage	No-Till: n=494
	Conventional: n=829
	Conservation: n= 704
Fertilizer Placement	Incorporated: n=414
	Injected: n=268
	Surface: n=1281
Fertilizer Timing	Grass in growing season: n=742
	PrePlant: n=305
	Split (At Plant and Side/Top Dress): n=145
	Split (PrePlant and Out of Season): n=130
Land Use	Corn: n=394
	Pasture: n=275
	Pasture (Grazed): n=735
	Various corn/soybean/grain/alfalfa rotations: n=42
	Wheat and small grains: n=376
Level II Ecoregions (observations and % of total)	7.1 Marine West Coast Forest (n=12, < 1%)
	8.1 Mixed Wood Plains (n=218, 7%)
	8.2 Central USA Plains (n=110, 3%)
	8.3 Southeastern USA Plains (n=289, 9%)
	8.4 Ozark-Ouachita/Appalachian Forests (n=964, 29%)
	8.5 Mississippi Alluvial/Southeast USA Coastal Plains (n=65, 2%)

	9.2 Temperate Prairies (n=675, 20%)
	9.3 West-Central Semi-Arid Prairies (n=75, 2%)
	9.4 South-Central Semi-Arid Prairies (n=884, 27%)
	9.5 Texas-Louisiana Coastal Plain (n=15, <1%)
	11.1 Mediterranean California (n=19, < 1%)

The categorical variables in Table 4.2 are defined as follows (Harmel et al., 2016). For tillage, no-till involves leaving the soil undisturbed from harvest to planting, except for nutrient injection; conventional tillage includes plowing and harrowing that thoroughly turns and loosens the soil; and conservation tillage is an intermediate approach, maintaining at least 30% crop residue cover on the soil surface post-planting while still involving some soil disturbance for seedbed preparation. For fertilizer placement, incorporation involves broadcasting fertilizer on the soil surface followed by mechanical mixing into the soil; injection placement involves directly placing the fertilizer into the soil at a specific depth; and surface application refers to spreading fertilizer on the soil surface without subsequent incorporation. For fertilizer timing, grass in growing season refers to fertilizer application during the active growth period of pasture grasses, excluding establishment or dormancy phases; preplant application occurs from two months to one week before planting; split (at plant and side/top dress) involves applying fertilizer at planting (within one week of planting) and again during the growing season; and split (preplant and out-of-season) entails an initial application preplant and a second application out of season, defined as more than two months before planting.

For ease of analysis, all observations within the MANAGE database were duplicated according to the weight or number of site years. For example, if an observation only had 2 site years, all data on that row would be duplicated into a total of two rows. If an observation had 12 site years, then the one row was duplicated to 12 total rows. This data weighting was performed using a macro within Excel. This aided in analysis and visualization when weighting by a specific variable was not feasible. This process did not artificially inflate observations as one entry within the database may represent multiple observations via site or watershed years as defined by Harmel et al. (2006). The process above was essentially the same as weighting our observations by site years within the observations of the data within MANAGE (Hirsch et al., 2010).

4.3: Results and Discussion

4.3.1: Nutrient Load Effects from Agricultural Management Decisions Across North American Ecoregions

In previous research, agricultural management practices in MANAGE were compared across and within EPA level II ecoregions of North America. There were different outcomes across the spatially variable landscape depending on factors such as temperature, precipitation, and soil fertility. However, the current meta-analysis and results span all ecoregions, thus providing additional insight. There are typically not one size fits all management approaches, but all results presented within this chapter were significant when data from all ecoregions were combined across North American.

Kruskal-Wallis tests on all data comparisons possible showed statistically significant differences between all field characteristics and management decisions (i.e., $p < 0.05$). These results support the hypothesis that the distributions of nutrient loads are the same across all management decisions. To determine what those statistically significant differences were, we performed a Dunn's test on all management comparisons to determine what differences were present. All Dunn's tests were statistically significant, suggesting that there were significant pairwise differences between at least some group comparisons, as discussed below.

4.3.1.1: Tillage

The tillage practices examined were conservation, conventional, and no-till (Table 4.3). Pairwise comparisons between tillage groups for dissolved N were non-significant (values ranged from 2.14 to 2.42 kg/ha/yr) with tillage impacts more readily observed in particulate and total N loss. For particulate and total N, conventional tillage (14.8 and 19.5 kg/ha/yr, respectively) produced greater loads than conservation (2.44 and 5.90, respectively) and no-till (1.54 and 6.80 kg/ha/yr, respectively) (Figure 4.1); there were no differences between no-till and conservation tillage. For P, no-till produced greater dissolved P loads than conservation or conventional tillage (0.34 compared to 0.21 to 0.22 kg/ha/yr). Conventional tillage contributed to the greatest particulate P load, followed by conservation tillage, and then no-till (3.80, 0.56, 0.11 kg/ha/yr, respectively). Conventional tillage also contributed to the greatest total P load as compared to the other tillage practices (1.70 compared to 0.91 and 0.95 kg/ha/yr).

In line with current scientific research (e.g., Tiessen et al., 2010; Angle et al., 1984), conventional tillage across all crops and ecoregions often produced significantly greater nutrient loss than conservation tillage and no-till. Similarly, Munodawafa (2007) found that total N losses were significantly greater under conventional tillage (16 kg/ha) compared to mulch ridging (2.3 kg/ha) and tied ridging (2.3 and 0.6 kg/ha), two conservation tillage methods. This is additionally noteworthy because soils studied by Munodawafa (2007) in a study were relatively nutrient-poor sandy soils. DeLaune et al. (2012) evaluated no-till, conventional tillage, and soil aeration using with various angles. Their results showed that conversion from no-till to conventional tillage increased runoff volume by 38% and that total sediment losses were at least 3 times greater from conventional tillage plots than no-till and aerated treatments. They also reported that total P and ammonium-N loads were significantly greater from conventional till plots than the other tillage treatments.

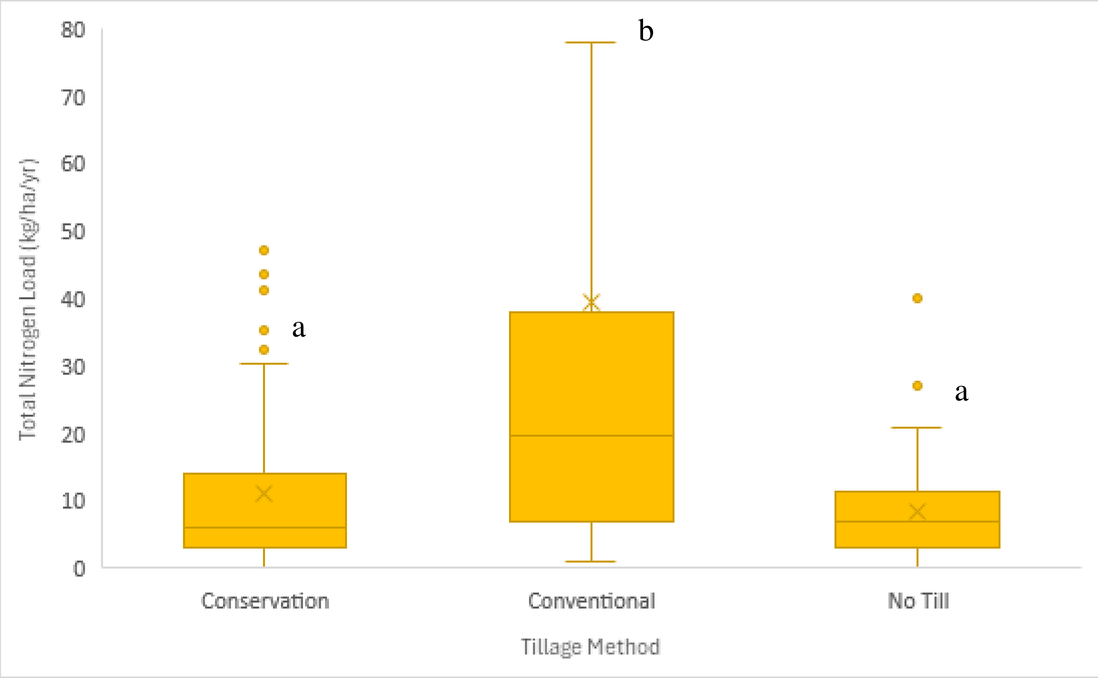

Figure 4.1. Total N load (kg/ha/yr) compared across tillage practices. Box and whisker plots with different lowercase letters above the bars indicate statistically significant differences between treatments (α = 0.05). Statistical significance was determined using Kruskal-Wallis non-parametric tests followed by Dunn's tests.

Table 4.3. Median annual dissolved, particulate, and total N and P runoff loads (kg/ha/yr, weighted by site years) grouped by management practices.

	Diss. N	**Part. N**	**Total N**	**Diss. P**	**Part. P**	**Total P**
Tillage	**------------------------------ kg/ha/yr ------------------------------**					
Conservation	2.14a	2.44a	5.90a	0.21a	0.56b	0.91a
Conventional	2.42a	14.8b	19.5b	0.22a	3.80c	1.70b
No-till	2.20a	1.54a	6.80a	0.34b	0.11a	0.95a
Fertilizer Placement						
Incorporated	2.72b	5.80b	23.59c	0.39a	4.46c	2.50c
Injected	1.46a	3.22b	5.35b	0.34b	0.10a	1.30b
Surface	1.07a	1.21a	3.20a	0.20a	0.20b	0.97a
Fertilizer Timing						
Grass in growing season	0.95a	1.16a	2.76a	0.93c	0.2a	0.97a
PrePlant	2.42bc	5.8b	12.3b	0.24b	5.01c	2.98c
Split (At Plant and Side/Top Dress)	3.13c	2.55b	6.8c	0.41ab	0.9b	1.7b
Split (PrePlant and Out of Season)	1.89b	20.5c	16.0c	0.11a	0.59b	0.48a
Land Use						
Corn	1.88c	30.5d	33.0c	0.14a	0.12b	1.75c
Pasture	0.50a	0.66a	1.6a	0.08a	0.11a	0.21a
Pasture (Grazed)	0.92a	1.28b	2.25a	0.67c	0.23b	0.60b
Various corn/soybean/grain/alfalfa rotations	1.26bc	-	-	0.14a	-	0.37b
Wheat and small grains	1.22b	5.9c	5.9b	0.19b	5.01c	0.44b
Total site years by constituent	n=1679	n=680	n=1443	n=2391	n=812	n=2446

[a] For each constituent, median values followed by the same letter are not significantly different ($\alpha = 0.05$) within a particular management practice or land use.).

4.3.1.2: Fertilizer Placement

The impact of fertilizer placement (i.e., incorporated, injected, and surface application) on nutrient loads is presented in Table 4.3. Dissolved N exhibited significant variation with values ranging from 1.07-2.72 kg/ha/yr. Notably, fertilizer incorporation tended to produce the highest dissolved, particulate, and total N loads (Table 4.3; Figure 4.2) compared to injected and surface application. Alternatively, surface placement tended to produce the lowest runoff loads for dissolved, particulate, and total N. Additional studies have demonstrated that injected N fertilizer in the spring may increase yields compared to surface broadcast placement, but it may also escalate N loss (Jeong and Bhattarai, 2018).

Similar to N, fertilizer incorporation tended to produce significantly greater dissolved, particulate, and total P loads compared to injected or surface applications. Alternatively, fertilizer injection tended to produce the lowest dissolved, particulate, and total P loads. These findings emphasize the potential for nutrient retention and runoff mitigation with alternative placement strategies. Incorporating fertilizer might intuitively seem to ‘trap’ nutrients within the soil, but major soil disruption via incorporation and tillage releases more nutrients offsite than if N and P fertilizers were applied to the soil surface or injected.

In support of the findings above, Smith et al. (2016) explored P loss with various fertilizer sources and placements. They compared broadcast and banded subsurface applications and found that banding fertilizer and poultry litter below the surface decreased soluble P by 98% and 84%, respectively. However, in research on swine manure injection in corn, Kovar et al. (2011) observed that losses of dissolved P were greater in both fall and spring following low-disturbance injection; however, application method had no effect on total P loads in runoff when comparing no manure, knife injection, and low-disturbance injection. They also observed that low-disturbance injection of swine manure into a standing cover crop can minimize plant damage and P losses in surface runoff while providing optimum P availability. In another study testing the incorporation of surface-applied poultry litter and inorganic fertilizer by rotary tillage and their effects on runoff quality, Nichols et al. (1994) found that total N and P runoff loads from surface applications of fertilizer to pasture land were not significantly different between litter and traditional fertilizer treatments. This was contrary to our meta-analysis findings that incorporated fertilizer methods typically are significantly greater in loads than other methods. Lastly, in an evaluation of P loss from agricultural lands to water bodies, Sharpley et al. (2001) found that the effect of application method and timing of rainfall was significant for the concentration of P in surface runoff from grasslands. They observed that surface broadcast applications and plowed/incorporated applications were significantly more susceptible to nutrient loss especially given rainfall soon after application than a subsurface placement. Subsurface placement showed no variability in loss regardless of time of rainfall after P applications (Sharpley et al., 2001).

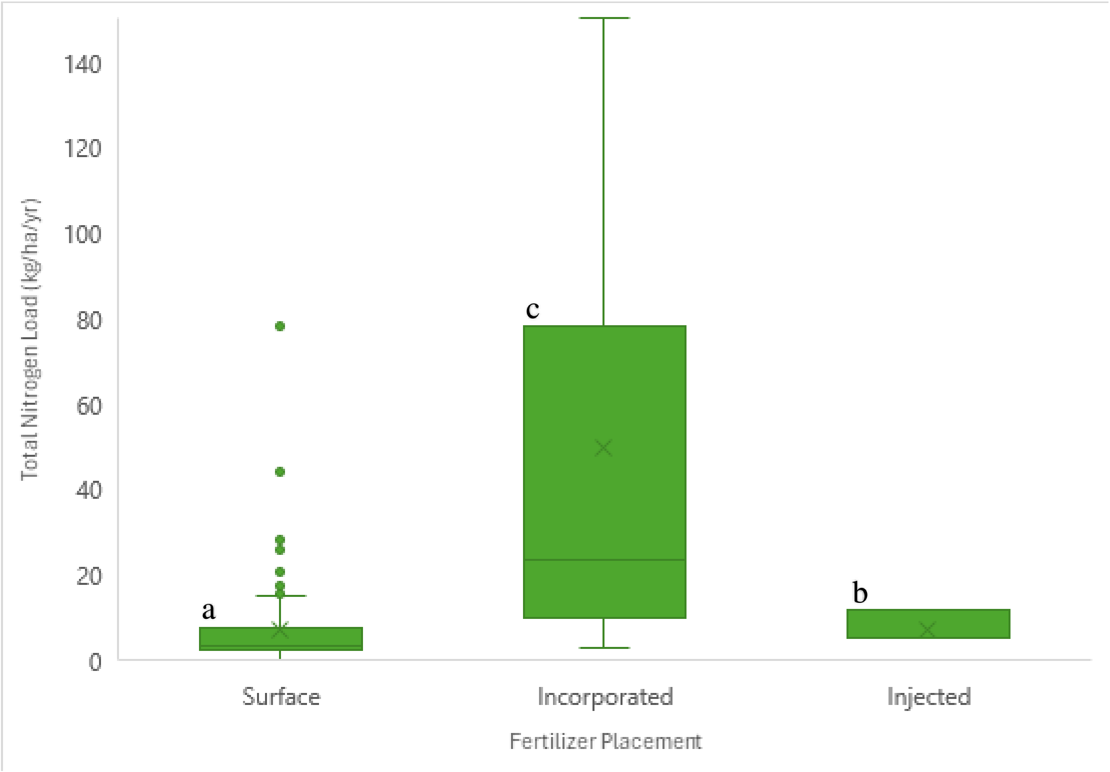

Figure 4.2. Total Nitrogen loads (kg/ha/yr) compared across fertilizer placement practices. Box and whisker plots with different lowercase letters above the bars indicate statistically significant differences between treatments (α = 0.05). Statistical significance was determined using Kruskal-Wallis non-parametric tests followed by Dunn's tests.

4.3.1.3: Fertilizer Timing

The influence of fertilizer timing (i.e., grass in the growing season, pre-plant, split application using at planting and side/top dress, and split application preplant and out of season) on N and P nutrient loads was also examined (Table 4.3). Dissolved N loads exhibited considerable variability across fertilizer timing options (0.95-3.13 kg/ha/yr). For example, pre-plant application and split application (at plant and side/top dress) showed significantly greater dissolved N loads than other timing options. Additionally, pre-plant and split (preplant and out of season) applications resulted in substantially greater loads at particulate N loads (5.8 and 20.5 kg/ha/yr, respectively) and total N loads (12.3 and 16.0) kg/ha/yr, respectively (Figure 4.3) compared to other timing options. Split application (plant and side/top dress) showed lower loads for both particulate and total N (2.55 and 6.80 kg/ha/yr) respectively, indicating a potential for reduced nutrient runoff. Application to grass in the growing season led to the lowest total N load. Grass in growing season produced significantly lower loads (2.76 kg/ha/yr total N) compared to preplant (12.3 kg/ha/yr), split (at plant and side/top dress) (6.8 kg/ha/yr), and split (preplant and out of season) (16.0 kg/ha/yr) to cropland.

Regarding P loads, application to grass in growing season led to significantly greater dissolved P loads (0.93 kg/ha/yr) compared to other fertilizer timing options. This result was likely due to the prevalence of grass land studies in MANAGE from the Ozark-Ouachita/Appalachian Forests that have high rates of poultry litter application. Notably, split application (pre-plant and out-of-season) showed the lowest dissolved P loads. For particulate P, pre-plant fertilizer application resulted in the greatest median load (5.01 kg/ha/yr). Finally, pre-plant application produced the greatest median total P loads (2.98 kg/ha/yr), significantly greater than split applications or at plant applications. The patterns observed in this study suggest that the timing of fertilizer application plays a vital role in determining edge-of-field nutrient loads. Therefore, split (at plant and side/top dress) and grass in growing season applications potentially offer greater success in reducing nutrient losses.

Similar trends have been observed in other research focused on fertilizer timing. In an 11-year study, Liu et al. (2017) found that out-of-season application produced 12-16% increases in total P loads and 19-40% increases in dissolved P loads compared to fertilizers applied at planting. However, they also pointed out that the impact of application timing was dependent on precipitation events and field-scale characteristics. Grant et al. (2012) compared the N use efficiency of preplant banded N applications and split applications of N at planting and in season in corn, finding that there was no statistically significant difference between split applications of urea and urea banded at the time of seeding. They additionally found that effects were consistent across all environments and across all tillage systems they tested.

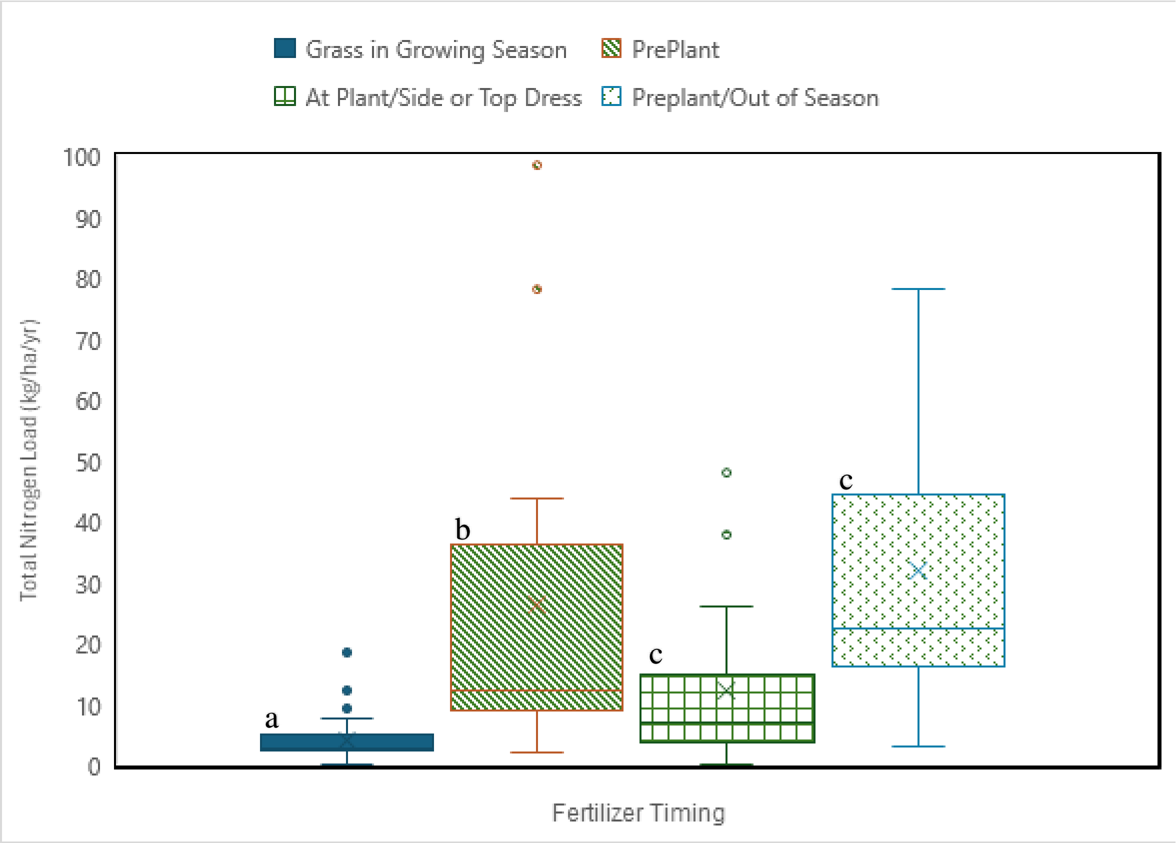

Figure 4.3. Total Nitrogen loads (kg/ha/yr) compared across fertilizer application timings. Box and whisker plots with different lowercase letters above the bars indicate statistically significant differences between treatments ($\alpha = 0.05$). Statistical significance was determined using Kruskal-Wallis non-parametric tests followed by Dunn's tests.

4.3.1.4: Land Use

The impact of land use on nutrient loads was measured across several common land uses, including corn, pasture, pasture grazed, various corn/soybean/grain/alfalfa rotations, and wheat/small grains. Dissolved N loads exhibited substantial variability across land use, with values ranging from 0.50-1.88 kg/ha/yr (Table 4.3). Corn and various corn/soybean/grain/alfalfa rotations had significantly greater dissolved N loads compared to other land uses. Additionally, corn resulted in substantially greater median particulate N (30.5 kg/ha/yr) and total N loads (33.0 kg/ha/yr, respectively Table 4.3; Figure 4.4) than other land uses. Pasture grazed exhibited significantly lower loads for both particulate and total N, which was likely attributed to reduced erosion due to perennial cover. The low dissolved N losses from pasture was likely due to rapid plant N uptake, keeping dissolved N concentrations relatively low. Grasslands that are mown or cut for hay or silage also have very low leaching losses because grass and pasture plants are usually very efficient at capturing the N applied in fertilizer or N fixed by legumes; while traditional crops generally have greater N losses because of the shallower root systems and increased inputs (Cameron et al., 2013). Traditional corn production results in significant nutrient losses (total N of 33 kg/ha/yr and total P of 1.75 kg/ha/yr), and thus pairing corn production with minimal tillage and conservation techniques such as utilizing cover crops may aid in mitigating the risk of nutrient loss (Kaspar et al., 2011; Thapa et al., 2018; Wang et al., 2020).

Regarding P loads, pasture (grazed) and wheat/small grains exhibited significantly greater dissolved P loads compared to other land uses, at 0.67 and 0.19 kg/ha/yr respectively. For grazed pastures, the high P losses were likely due to the prevalence of studies in MANAGE from the Ozark-Ouachita/Appalachian Forests that have high rates of poultry litter application. Such excessive manure applications can lead to increased edge-of-field nutrient losses (Jarvis et al., 1987). It has been shown that days since fertilization was inversely related to the flow weighted mean P loss, accounting for more than 50% of the variance in P loss (Nash et al., 2000). Nash et al. (2000) also observed that days since grazing and total storm flow were less important in the variance of P loss from grazing pasture systems. Lastly, they concluded that management of fertilizer application in relation to the timing of runoff events appears to be the main method by which P export can be decreased in pasture based grazing systems. On the other hand, ungrazed pastures displayed the lowest dissolved P loads among land uses. For particulate P, wheat and other small grains resulted in the greatest load (5.01 kg/ha/yr). Finally, corn produced the greatest total P loads at 1.75 kg/ha/yr, significantly more than all other land uses. The reversal of land uses from wheat and small grains producing the greatest particulate P load to corn producing the greatest total P loads was likely influenced in part by research prioritization. There were 812 site year observations for particulate P and 2,446 site years observations for total P. Corn land use produced some of the lowest overall dissolved and particulate P loads. Depending on the inherent soil nutrient N and P concentrations as well as local soil moisture and seasonal rainfall, corn typically has higher input requirements than wheat, but this needs to be definitively researched before stating that as the reason for particulate P being greater in load in wheat and dissolved and total P being greater in corn. These trends across variable land use types suggest that different agricultural practices contribute to variation in nutrient loads, with specific land uses associated with greater nutrient outputs, while others may offer greater success in reducing nutrient losses.

When we consider the results in Table 4.3 in the context of land use, we can conclude that corn should be planted with cover crops or other forms of nutrient recapture to hold and retain N (Hanrahan et al., 2018). When we consider P loads as related to land use, total P load loss from corn stands out as the largest potential concern. However, in Table 4.3 we see the total P load not coming from the dissolved or particulate fractions but from total P, which suggests organic P likely plays a large role in this loss. Increased organic P loss from corn land use production can be attributed to, in part, manure applications. Manure is often used in corn production regions with nearby concentrated livestock operations. Grande et al. (2005) observed these practices may have implications for nutrient losses from agricultural lands. They reported that: 1) total and dissolved P loads were inversely related to percent residue cover, but both total and dissolved P concentrations were unaffected by residue level; 2) manure application increased dissolved P concentrations in spring runoff two to five times but did not significantly affect dissolved P loads, since higher concentrations were offset by lower runoff volumes; 3) manure application increased the total P concentration in sediments as particle size decreased; and 4) manure application increased the total P concentration of the 0- to 2-µm fraction by 79-125%, while elevating the 2- to 10- and 10- to 50-µm fractions to a lesser extent. Recent manure additions were most influential in enriching transported sediments with P (Grande et al., 2005).

In a study examining management practice effects on P runoff in corn production, Bundy et al. (2001) found in no-till corn that: 1) both dissolved P load and concentration increased as soil test P increased from 8 to 62 mg/kg; 2) a 5-year history of manure or biosolids application greatly increased soil test P and dissolved P concentrations in runoff; and 3) manure applications had higher dissolved P concentration but lower dissolved P loads than the 5-year biosolids treatment, probably due to residue accumulation and lower runoff in manure treatment. Additionally, tillage and manure effects on P losses showed that tillage compared to incorporated manure lowered runoff dissolved P concentration but increased total P concentration and loads due to increased sediment loss (Bundy et al., 2001). If organic P makes up close to 70% of total P loads as Oberson et al. (1996) suggests, emphasis needs to be placed on mineralizing organic P to keep it in place within agricultural fields and not lost through edge-of-field runoff. Oberson et al. (1996) suggest that organic P can be captured and mineralized to mineral P by several factors including higher levels of biological activity through microbial and enzyme activity, increased organic matter quality, acidic soil pH, diverse crop rotations, and cover crops.

Additionally, in Table 4.3 we notice that wheat and small grains had a relatively high portion of load loss as particulate N, likely due to high sediment and organic matter loss from runoff and erosion (Shi and Schulin, 2018). Wu et al. (2019) reported that switching from high coverage grassland to dryland agriculture with crops such as millet and sorghum led to a sharp increase of particulate N and P. Knowing this, combining wheat production with no-till practices and off-season cover crops may greatly reduce particulate nutrient losses.

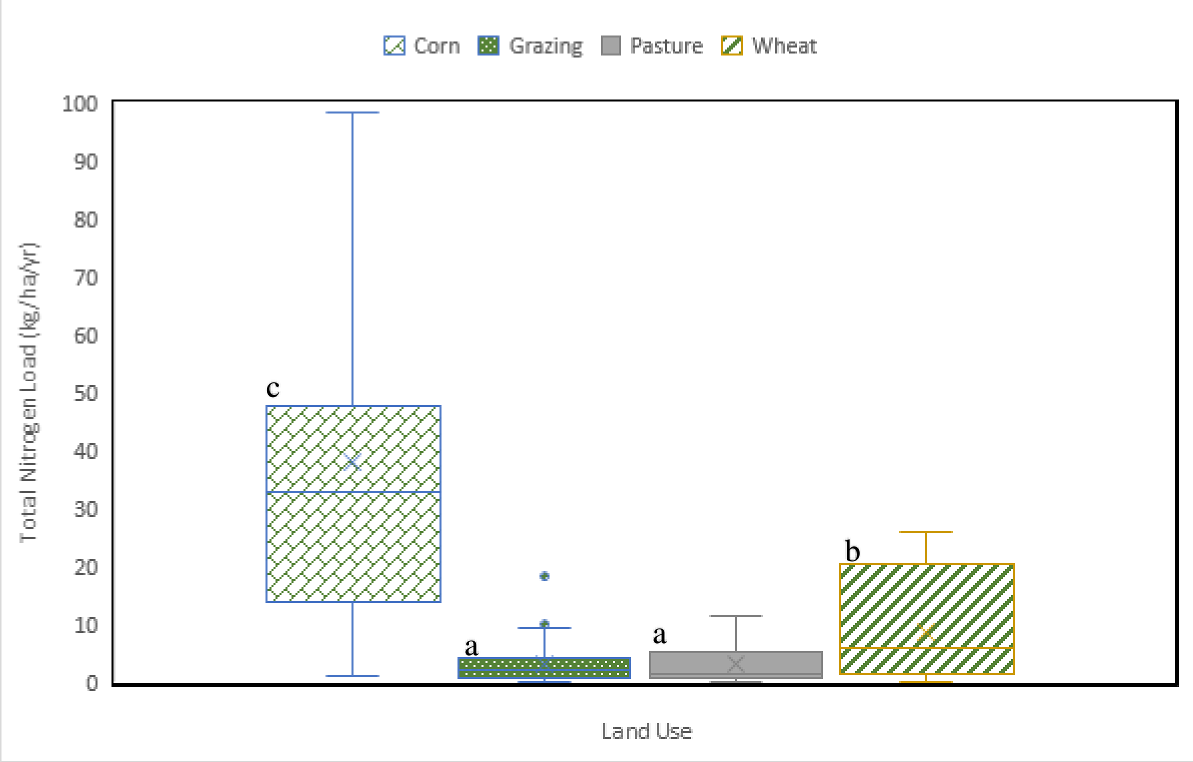

Figure 4.4. Total Nitrogen Loads (kg/ha/yr) compared across land use. Box and whisker plots with different lowercase letters above the bars indicate statistically significant differences between treatments (α = 0.05). Statistical significance was determined using Kruskal-Wallis non-parametric tests followed by Dunn's tests.

Figures 4.5, 4.6, and 4.7 aid in visually identifying agricultural management trends and their influence on dissolved, particulate, and total N and P loads. These figures visually represent the median results listed in Table 4.3. In addition to the statistical significance listed in Table 4.3, we can identify some 'dual threats', or practices that lead to both high N and P loads. In Figure

4.5 we see that incorporating fertilizer and split (at plant and side/top dress) application lead to greater median load values of dissolved N and P. Concerning particulate N and P, in Figure 4.6 we see that conventional tillage, incorporating fertilizer, preplant fertilizer timings, and wheat and small grain production leads to relatively high losses. We also see another interesting trend in that split (preplant and out of season) application and corn production tend to produce less overall particulate P than those methods just mentioned, yet those methods produce more than double the amount of N load. Lastly, concerning total N and P load, we observe the greatest risk factors are preplant fertilizer timing, conventional tillage, corn production, and fertilizer incorporation (Figure 4.7).

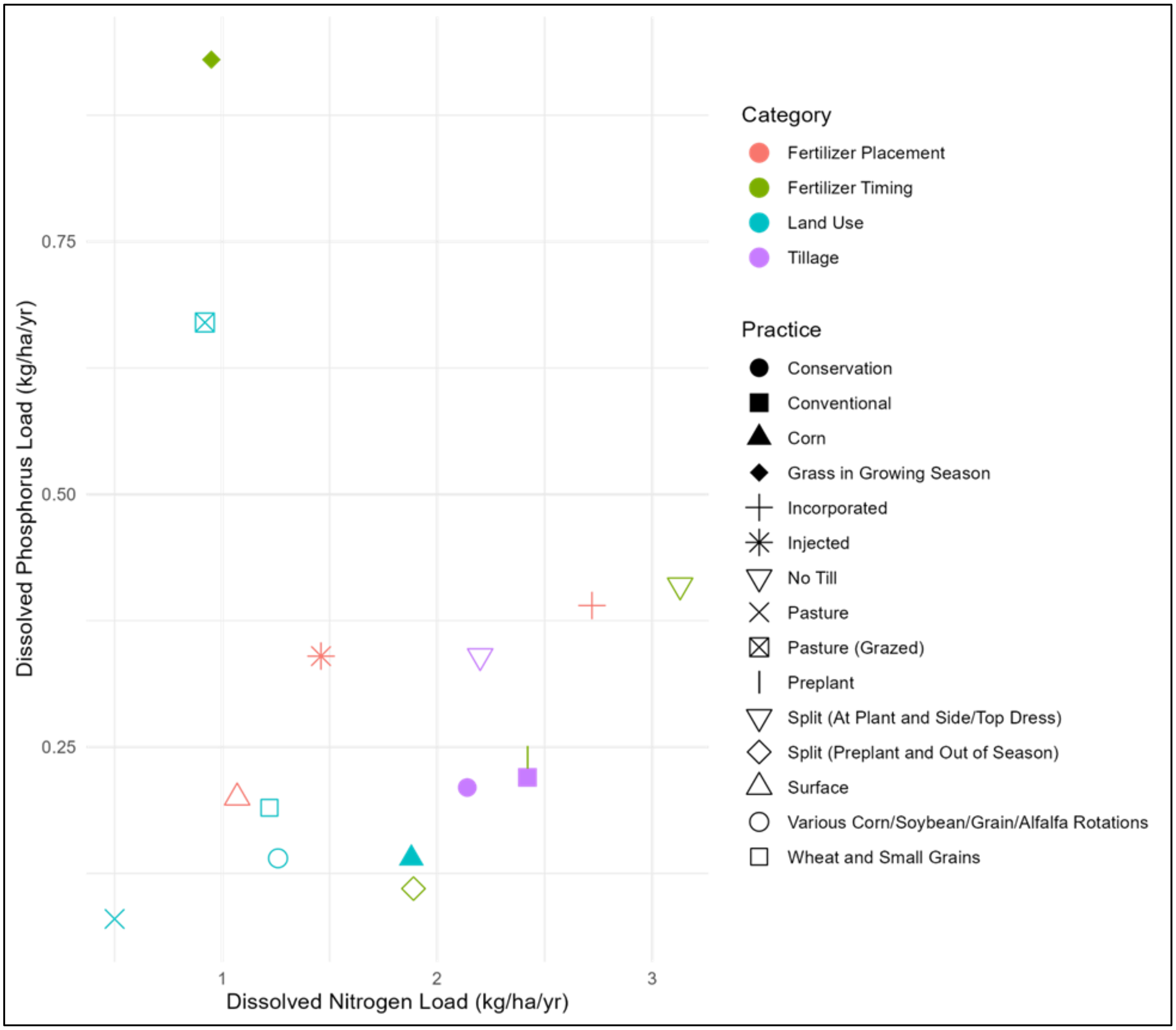

Figure 4.5. Median load (weighted by site years, kg/ha/yr) for dissolved nitrogen and phosphorus by selected management decisions.

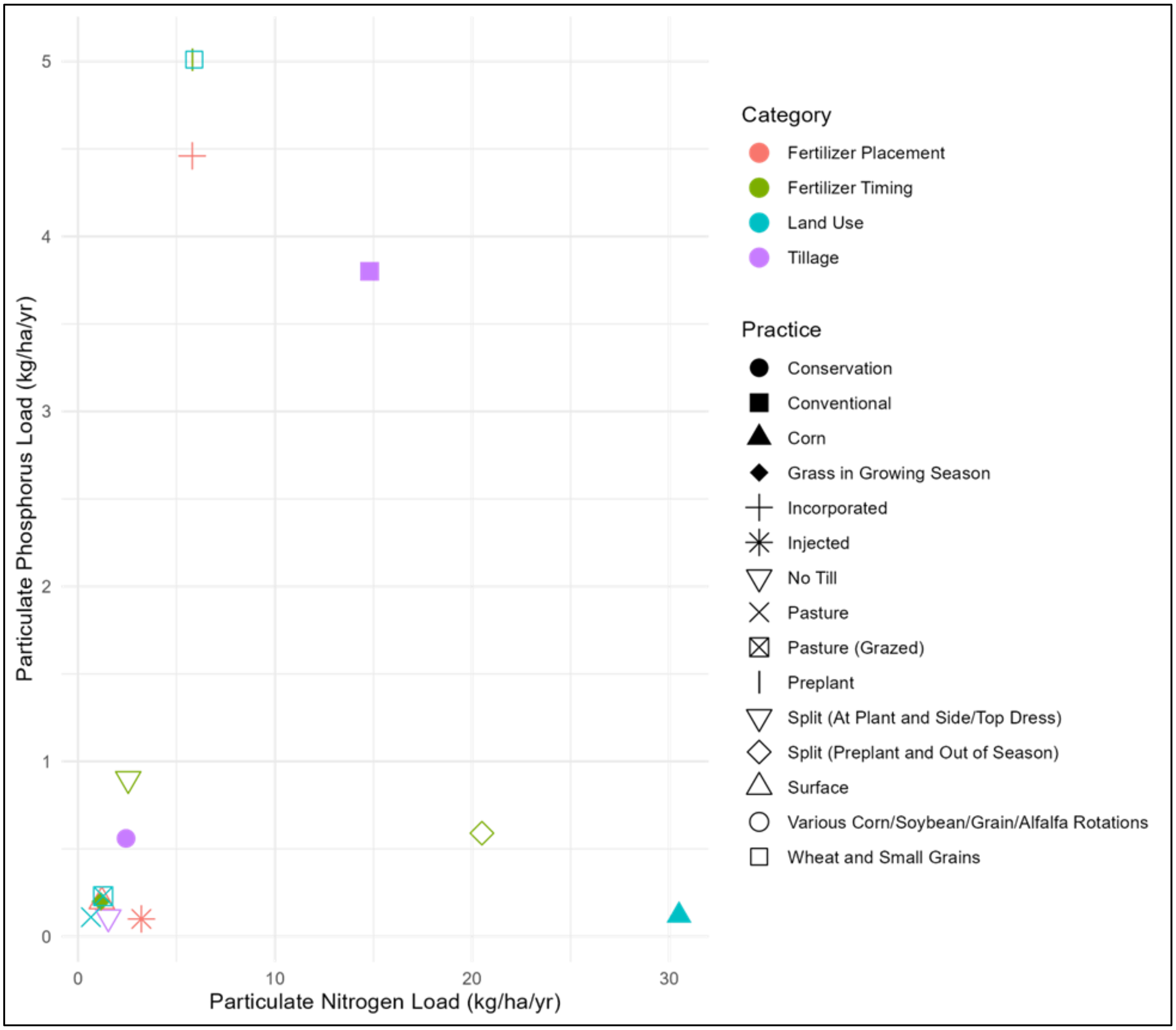

Figure 4.6. Median load (weighted by site years, kg/ha/yr) for particulate nitrogen and phosphorus by selected management decisions.

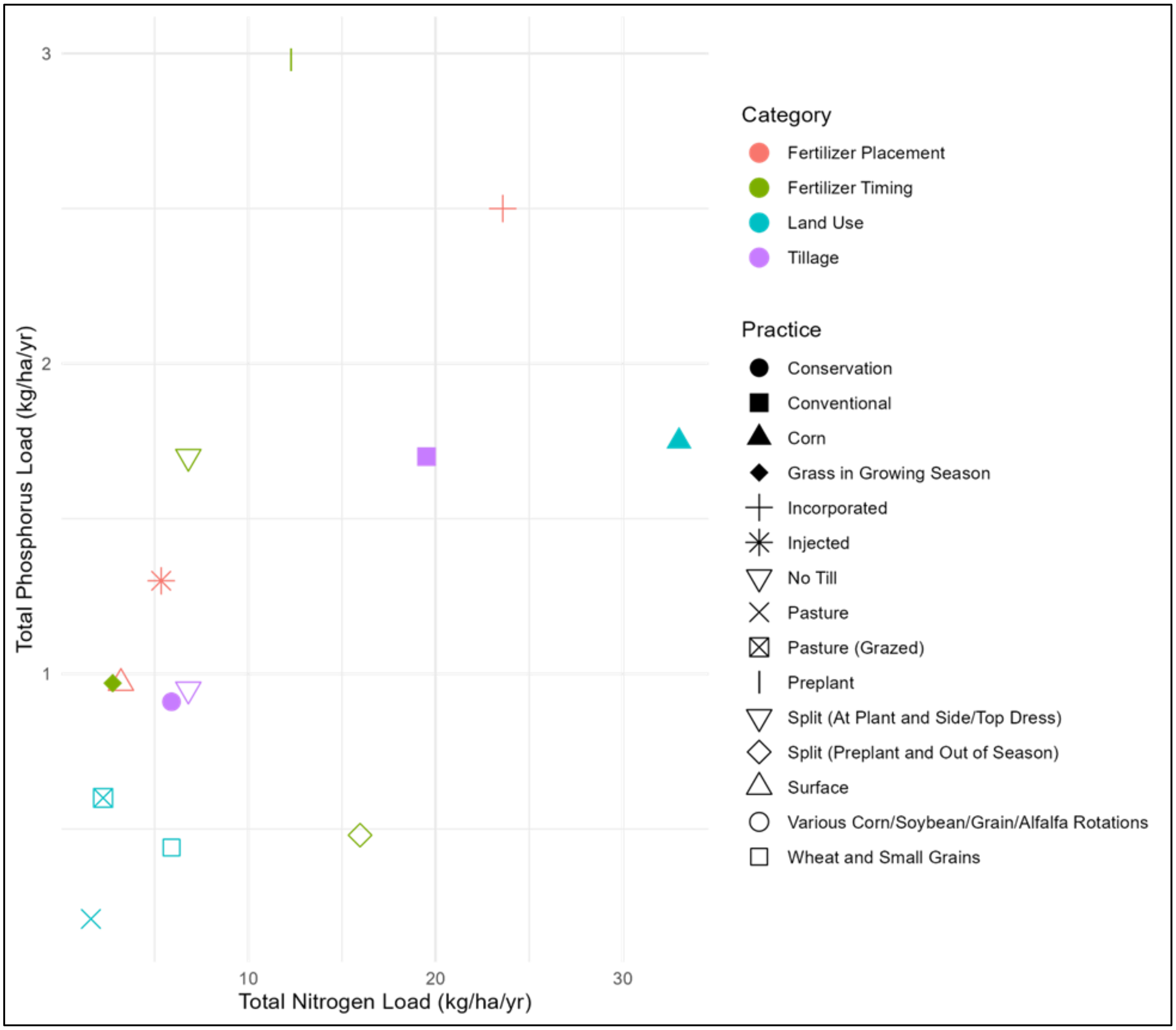

Figure 4.7. Median load (weighted by site years, kg/ha/yr) for total nitrogen and phosphorus by selected management decisions.

4.3.1.5: Crop Yield

Agricultural management practices are often aimed towards maximizing crop yield. Significant yield differences amongst all crop type yields as a function of management type/practices is presented in Table 4.4. Conventional tillage produced significantly greater yields (7.5 Mg/ha) compared to conservation tillage (4.0 Mg/ha) and no-till practices (5.0 Mg/ha). As shown in Figure 4.8 and Table 4.5, tillage had a variable (yet not significant) effect across various crop types. No-till has been shown on average to reduce yields by 5% across 50 crops and over 6000 paired observations; however, under rainfed conditions in dry climates, no-till can match conventional tillage yields (Pittelkow et al., 2015). Corn, one of the largest components of MANAGE, was evaluated under a 20-year continuous tillage study by Kapusta et al. (1996). The authors found that corn yield was lower in no-till compared with conventional regardless of fertilizer treatment. Additionally, there was no difference in yield among tillage systems when N and P fertilizer was surface applied, with the conclusion drawn that for these circumstances, continuous no-till did not reduce corn yield (Kapusta et al., 1996). He et al. (2022) observed that in areas with mean annual temperatures below 3°C, crop yields were significantly higher under conservation till compared with conventional tillage, whereas yields reduced under no-till by approximately 4%. The majority of the observations under MANAGE come from areas under dryland cropping systems that are rain-fed, and this follows previous findings that conservation and no-till practices are most effective in boosting yields under those climatic conditions (Hansen et al., 2016). This suggests that conventional tillage may enhance yields due to (for example) better soil aeration and weed control (Locke et al., 2002), while conservation and no-till practices offer sustainable alternatives with comparable yields, potentially promoting improved soil health and erosion control.

Fertilizer placement further influenced yields, with injection (9.95 Mg/ha) outperforming incorporation (6.49 Mg/ha), and incorporation outperforming surface application (5.09 Mg/ha). Fertilizer timing was crucial, as application during the growing season (10.3 Mg/ha) and preplant (9.70 Mg/ha) were most effective, while split applications at planting and side/top dress resulted in significantly less yields (4.40 Mg/ha). However, there were no significant differences between grass in growing season, preplant, and split (preplant and out of season). Considering this snapshot of data from MANAGE, it is likely that there are confounding variables affecting the yield reduction of split (at plant and side/top dress) application. Research on the 4R methodology has shown that breaking up fertilizer applications makes more efficient use of nutrients and thus boosts crop yield. For example, in a study examining growth and yield responses in corn to split and delated fertilizer applications, Sitthaphanit et al. (2010) found that three to four split applications of fertilizer increased the grain yield from 2.7 to 3.3-4.5 Mg/ha. They also reported a greater crop growth rate and relative growth rate with split applications 30-60 days after emergence. This suggests that fertilizer applications to minimize nutrient loss increased the growth and nutrient use efficiency of corn. Additionally, Johnston and Bruulsema (2014) observed that 4R nutrient stewardship improved overall nutrient use efficiency, while applying too much fertilizer leads to residual nutrients in the soil and losses to the environment. The authors found that using a split timing of in season application, slow and controlled release fertilizer technology, stabilizers, and inhibitors all add to better timings for increased efficient crop uptake and improved crop yield.

When we examine the findings in both Tables 4.3 and 4.4 we see that, for instance, surface applications of N and P fertilizers resulted in some of the lowest N and P load losses. However, we can also examine the crop yield as a result of surface fertilizer applications and see that those yields are significantly less than other application methods (5.1 Mg/ha compared to 10.0 and 6.5 Mg/ha respectively). Surface application of fertilizers leaves the fertilizer more exposed on the soil surface. When surface N fertilizer placement is a concern, N can be lost via volatilization to the atmosphere. In a study on ammonia volatilization following surface application of urea to tilled and no-tilled soils, Rochette et al. (2009) found that broadcasting of urea to agricultural soils can result in considerable losses by NH_3 volatilization. They also reported that higher atmospheric losses occurred from no-tilled systems. No-tilled systems are typically associated with surface applications of fertilizer while those cropping systems that utilize tillage traditionally incorporate their fertilizers. Rochette et al. (2009) reported that mean cumulative NH_3 losses were greater in no-till (3.0 g N/m^2) than in conventionally tilled fields (0.52 g N/m^2). While they found that surface fertilizer applications lead to less nutrient losses, the nutrients that are retained in the soil or fertilizer are used less efficiently when it comes to crop yield and atmospheric losses. These findings highlight the importance of optimizing management practices for enhanced productivity, advocating for context-specific decisions that balance yield and sustainability.

Table 4.4. Median crop yield weighted by site years distributed by management practice. Significance is denoted as differences in lowercase letters (after crop yield) between management practice within a management type.

Management Type	Management Practice	Crop Yield (Mg/ha)
Tillage	Conservation	4.00a
	Conventional	7.50b
	No-till	4.97a
Fertilizer Placement	Incorporated	6.49b
	Injected	9.95c
	Surface	5.09a
Fertilizer Timing	Grass in Growing Season	10.3b
	PrePlant	9.70b
	Split (At Plant and Side/Top Dress)	4.40a
	Split (PrePlant and Out of Season)	8.00b
Land Use	Corn	8.50b
	Pasture	11.4b
	Pasture Grazed	5.05ab
	Various Corn/soybean/small grain or alfalfa rotations	12.4ab
	Wheat and Small Grains	3.87a

The above results compared crop yield across different crop types which is not as informative as a discussion of crop yield within uniform crop types. Thus, Table 4.5 focuses primarily on corn and wheat as these crops are the most significant yield and monetary value driven crops found frequently in the MANAGE database. For corn yield, no significant differences were observed between tillage management practices, suggesting that all tillage practices can be effective for corn production depending on other management factors (e.g., see Figure 4.8). For wheat crop yield, differences in tillage practices were compared between conservation and conventional tillage methods. Conservation tillage was associated with significantly greater wheat yields than conventional tillage (7.17 and 0.94 Mg/ha respectively) (Table 4.5 and Figure 4.8).

Additionally, fertilizer placement was crucial; both incorporated (9.70 Mg/ha) and injected (9.95 Mg/ha) placements resulted in significantly greater corn yields than surface application (4.97 Mg/ha), emphasizing the importance of integrating fertilizer into the soil for optimal nutrient uptake (Table 4.5 and Figure 4.8). We observed in Table 4.3 that injecting fertilizer leads to greater nutrient and soil conservation in agriculture, additionally in Table 4.5 when we see that there are no statistically significant differences in overall crop yield among application method practices. Thus, we can prioritize both nutrient conservation and maximum yields by utilizing fertilizer injection methods where possible.

Fertilizer timing significantly impacted corn yields, with pre-plant application correlating to the highest yield (9.85 Mg/ha) as compared to split application (preplant and out of season; 8.00 Mg/ha). This indicates that applying fertilizer before planting may be more beneficial for corn productivity; however, crop yield was not the overall objective of the MANAGE database and thus we need to rely on the body of science to clarify our understanding. In a comparison of various split applications and preplant application timings, a study found that compared to fall and preplant application timings, corn grain yield with a two way in season split was 12.6 to 15.7 Mg/ha (among years) and significantly greater than preplant and fall applications (Davies et al., 2020). However, the authors found that these trends were variable across locations, and some fields where split applications improved other soil/agricultural metrics like agronomic efficiency, yet overall did not produce significantly higher crop yield compared to preplant fertilizer applications. Additionally, Preza-Fontes et al. (2021) found that split applications of N, especially when combined with cover crops, reduced N loss while maintaining corn crop yields. They found that corn yield did not differ among N fertilized treatments that included preplant, out-of-season, and split applications in any year. Overall, research supports that split applications are likely optimal in terms of timing fertilizer applications, especially when considering the 4R methodology.

For wheat, conservation tillage resulted in a significantly greater median yield (7.17 Mg/ha) compared to conventional tillage (0.94 Mg/ha) (Table 4.5 and Figure 4.8). This substantial difference underscores the benefits of conservation tillage for wheat, likely due to improved soil structure and moisture retention. One trend that was noteworthy was the difference in crop yield between conservation and conventional tillage in both wheat and corn where consistent trends are not evident (Table 4.5). These findings are consistent with what others have observed. In a 15-year study on the effect of conservation tillage on soil structure and wheat cultivation, Li et al. (2007) found that crop yield and water use efficiency tended to be higher under conservation tillage practices than under conventional tillage, especially in years of low rainfall, suggesting that the change in soil structure has provided a more suitable environment for crop development. Partly contrary to our meta-analysis results, Copec et al. (2015) found that there were significant boosts in yield for both corn and wheat over multiple years when conservation tillage was used compared to conventional tillage. They reported 8.5 Mg/ha and 7.9 Mg/ha for corn using conservation and conventional respectively, and they reported 5.4 and 4.9 Mg/ha for wheat using conservation and conventional tillage. Although we lack a definitive explanation for there being no significant differences between crop yields in corn tillage systems, the aggregate results suggest that there are not one size fits all practices and all practices must be considered within the system utilized.

Overall, these the differences in crop yield suggest that conservation practices may enhance yields, yet the choice of tillage, fertilizer timing, and placement must be appropriate to specific crop requirements. Corn benefits from pre-plant fertilizer applications and incorporating or injecting fertilizer, whereas wheat significantly benefits from conservation tillage. For example, research has been performed to examine the effect the 4R methods have on crop yield and nutrient use efficiency and crop yield. In a study examining 270 distinct soil-climate regions focused on corn yield and N loss, Banger et al. (2020) found that surface fertilizer applications had the highest environmental N loss; when injected at planting or side dress, the N loss was reduced considerably. When examining the effects of conservation tillage approaches on soil nutrients and dryland wheat yield, Shao et al. (2016) found that conservation tillage improved organic matter, available nutrients in topsoil, as well as increased wheat yields and water use efficiency. The authors also reported a wheat yield increase of 8-12% on average when using conservation tillage compared to conventional tillage. Banger et al. (2020) reported that their results emphasized that N rate adjustment following improvements in placement, use of inhibitors, and application timings can mitigate N loss by 42-57% and result in 3-4% greater yields compared to baseline scenarios in corn production. The above insights are crucial for developing sustainable and effective agricultural practices to maximize crop productivity.

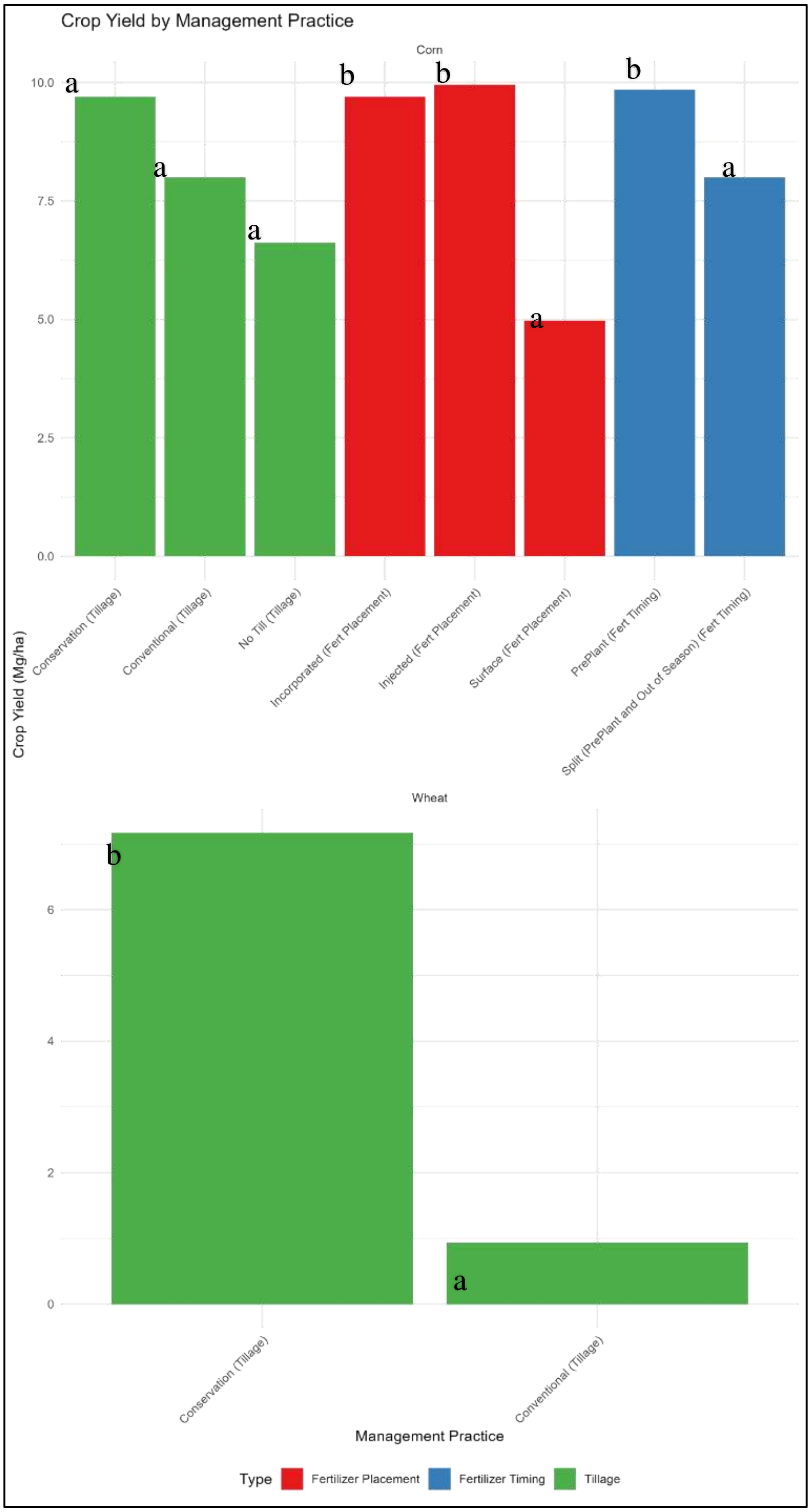

Figure 4.8. Bar graphs show median crop yield as affected by management choices for corn (top) and wheat (bottom) in Mg/Ha. Bar plots with different lowercase letters above the bars indicate statistically significant differences between treatments (α = 0.05). Statistical significance was determined using Kruskal-Wallis non-parametric tests followed by Dunn's tests.

Table 4.5. Median corn and wheat yield weighted by site years distributed by management practice. Significance is denoted as differences in lowercase letters (after crop yield) between management practice within a management type.

Management Type	**Management Practice**	**Crop Yield (Mg/ha)**
Corn		
Tillage	Conservation	9.70a
	Conventional	8.00a
	No-till	6.62a
Fertilizer Placement	Incorporated	9.70a
	Injected	9.95a
	Surface	4.97b
Fertilizer Timing	PrePlant	9.85a
	Split (PrePlant and Out-of-Season)	8.00b
Wheat		
Tillage	Conservation	7.17a
	Conventional	0.94b

4.3.2: Pairwise Management Practice Interactions on Nutrient Load Across North American Ecoregions

It has been demonstrated that tillage, land use, fertilizer timing, fertilizer placement, and ecoregion location across North America all play a vital role in nutrient runoff from agricultural lands (Hopkins Dissertation 2024, Chapter 3). Table 4.6 lists the correlation between numerical explanatory variables and nutrient loads. Many of the relationships were statistically significant ($p < 0.05$).

Concerning dissolved N, maximum and average annual runoff were the most highly correlated, with Pearson values of 0.31 and 0.47. In support, Manninen et al. (2018) observed that annual dissolved N loads were affected by discharge volume and seasonal weather conditions. Loads in the work by Manninen et al. (2018) varied between 0.8–3.2 kg/ha for three sites of permanent grassland and were comparable to those from boreal forests with similar soil types.

For particulate N, the single highest correlated relationship was between particulate N and maximum soil loss with a Pearson correlation of 0.82. Additionally, average soil loss had a correlation value of 0.59. Particulate N and crop yield also had a relatively high correlation of 0.66. This was likely driven by the fact that crop yields are, to a certain degree, tied to soil fertility and overall fertilizer applied. Bechman et al. (2009) found that reduced nutrient application and the presence of stubble during autumn and winter led to the largest decrease in particulate N risk loss. Concerning annual total N loads, maximum soil loss, maximum runoff, and average crop yield had correlation values of 0.54, 0.51, and 0.40, respectively. Rocha et al. (2012) showed an average annual runoff (35 mm), sediment yield of 46 Mg/ha, 3.2 Mg/ha of total N, and 1.4 Mg/ha of total P. However, when Rocha et al. (2012) considered the adoption of conservation practices, results showed an increase in water infiltration in the watershed and reductions in runoff (-18%), sediment (-66%), total N (-25%), and total P (-30%). Overall, their results were similar to our meta-analysis results in that total N loads were related to soil loss and runoff, and mitigating those losses correlated to lower total N loads.

Concerning dissolved P, the greatest Pearson correlation univariate values were maximum soil test P and average precipitation, with values of 0.51 and 0.35. Dissolved P load has been previously shown to be influenced by soil test P. Bundy et al. (2001) found that soil test

P was the greatest driver, more so than fertilizer applied or fertilizer application method, of dissolved P loads.

For particulate P, some of the most highly correlated variables were maximum runoff, maximum soil loss, average soil loss, and average precipitation. These had respective Pearson values of 0.62, 0.52, 0.61, and -0.45. Heathwaite et al. (2000) observed that the magnitude and composition of the P load transported in surface and subsurface hydrological pathways from a grassland catchment depends on the discharge capacity of the flow route and the frequency with which the pathway operates. Surface runoff is an important pathway for P loss, but this pathway is spatially limited and temporarily confined to high magnitude, high intensity rainfall events (Heathwaite et al., 2000). Interestingly average annual precipitation was the only variable in our meta-analysis that was negatively correlated with particulate P load.

The univariate variables most greatly correlated to total P were maximum runoff, maximum and average soil loss (0.46 and 0.48 respectively) as previously discussed before as well as supported by previous research (Sharpley et al., 2001), who showed that loss of total P in both surface runoff and subsurface flow originates primarily from small areas within watersheds during a few storms. These areas occur where high soil P, or P application in mineral fertilizer or manure, coincide with high runoff or erosion potential. Interestingly, average N and P fertilizer input weights were typically poorly correlated with nutrient loads, leaving field site characteristics to determine edge-of-field loads more significantly than management input decisions.

It is noteworthy to mention how interrelated the N and P loads were to one another. For example, particulate N was highly correlated to particulate P and total P with Pearson values of 0.97 and 0.96. Additionally, total P was highly correlated to particulate N and total N with

Pearson values of 0.96 and 0.95. These are vital, if not already intuitive observations, indicating to soil and nutrient conservationists that practices which assist in the retention of one can improve the retention of the other.

Table 4.6. Pearson correlation results (r and significance) between nitrogen (left half) and phosphorus (right half) nutrient load and MANAGE variables. Dissolved nitrogen (DN), particulate nitrogen (PN), total nitrogen (TN), dissolved phosphorus (DP), particulate phosphorus (PP), and total phosphorus (TP).

y_x	x	Equation	r (Pearson Corr.)	Sign. (p < 0.05)	y_x	x	Equation	r (Pearson Corr.)	Sign. (p < 0.05)
DN	PN	y=0.03x+-0.05	0.03	0.422	DP	DN	y=0.21x+0.15	0.21	<0.001
DN	TN	y=0.26x+0.21	0.26	<0.001	DP	PN	y=-0.23x+-0.32	-0.23	<0.001
DN	DP	y=0.21x+0.15	0.21	<0.001	DP	TN	y=0.76x+0.73	0.76	<0.001
DN	PP	y=-0.06x+-0.15	-0.06	0.209	DP	PP	y=-0.19x+-0.25	-0.19	<0.001
DN	TP	y=0.09x+0.03	0.09	0.002	DP	TP	y=0.1x+0.05	0.10	<0.001
DN	Max soil test P	y=0.1x+-0.01	0.10	0.084	DP	Max soil test P	y=0.51x+0.47	0.51	<0.001
DN	Min soil test P	y=0.1x+-0.01	0.10	0.085	DP	Min soil test P	y=0.25x+0.19	0.25	<0.001
DN	Max slope %	y=-0.06x+-0.11	-0.07	0.010	DP	Max slope %	y=0.04x+0	0.04	0.056
DN	Min slope %	y=-0.05x+-0.1	-0.05	0.030	DP	Min slope %	y=0.04x+0	0.04	0.064
DN	Max watershed size	y=-0.02x+-0.07	-0.02	0.329	DP	Max watershed size	y=-0.06x+-0.1	-0.06	0.002
DN	Min watershed Size	y=-0.02x+-0.07	-0.02	0.390	DP	Min watershed Size	y=-0.06x+-0.1	-0.06	0.003
DN	Avg N applied	y=-0.02x+-0.08	-0.02	0.474	DP	Avg N applied	y=0.06x+0.01	0.06	0.019
DN	Avg P applied	y=-0.04x+-0.09	-0.04	0.155	DP	Avg P applied	y=0.11x+0.06	0.11	<0.001
DN	Crop yield	y=0.13x+0.01	0.13	0.033	DP	Crop yield	y=-0.24x+-0.34	-0.24	<0.001
DN	Max precipitation	y=-0.07x+-0.13	-0.07	0.037	DP	Max precipitation	y=0.28x+0.23	0.28	<0.001
DN	Avg precipitation	y=0.19x+0.14	0.19	<0.001	DP	Avg precipitation	y=0.35x+0.31	0.35	<0.001
DN	Max runoff	y=0.31x+0.24	0.31	<0.001	DP	Max runoff	y=0.17x+0.12	0.17	<0.001
DN	Avg runoff	y=0.47x+0.43	0.47	<0.001	DP	Avg runoff	y=0.1x+0.06	0.10	<0.001
DN	Max soil loss	y=0.09x+0.01	0.09	0.027	DP	Max soil loss	y=-0.14x+-0.2	-0.14	<0.001
DN	Avg soil loss	y=0.06x+0.01	0.06	0.032	DP	Avg soil loss	y=0.15x+0.1	0.15	<0.001
PN	DN	y=0.03x+-0.05	0.03	0.422	PP	DN	y=-0.06x+-0.15	-0.06	0.209
PN	TN	y=0.99x+0.99	0.99	<0.001	PP	PN	y=0.97x+0.96	0.97	<0.001
PN	DP	y=-0.23x+-0.32	-0.23	<0.001	PP	TN	y=0.97x+0.96	0.97	<0.001
PN	PP	y=0.97x+0.96	0.97	<0.001	PP	DP	y=-0.19x+-0.25	-0.19	<0.001

PN	TP	y=0.96x+0.96	0.96	<0.001	PP	TP	y=1x+0.99	1.00	<0.001
PN	Max soil test P	y=-0.01x+-0.2	-0.01	0.912	PP	Max soil test P	y=-0.19x+-0.28	-0.19	<0.001
PN	Min soil test P	y=0.3x+0.12	0.30	0.001	PP	Min soil test P	y=0.11x+0.02	0.11	0.017
PN	Max slope %	y=0x+-0.08	0.00	0.960	PP	Max slope %	y=-0.12x+-0.19	-0.12	0.001
PN	Min slope %	y=0.04x+-0.04	0.04	0.332	PP	Min slope %	y=-0.01x+-0.08	-0.01	0.707
PN	Max watershed size	y=-0.1x+-0.17	-0.10	0.009	PP	Max watershed size	y=-0.12x+-0.18	-0.12	0.001
PN	Min watershed Size	y=-0.09x+-0.17	-0.09	0.014	PP	Min watershed Size	y=-0.12x+-0.18	-0.12	0.001
PN	Avg N applied	y=-0.08x+-0.17	-0.08	0.093	PP	Avg N applied	y=-0.2x+-0.27	-0.20	<0.001
PN	Avg P applied	y=-0.12x+-0.19	-0.12	0.005	PP	Avg P applied	y=-0.12x+-0.18	-0.12	0.001
PN	Crop yield	y=0.67x+0.55	0.67	<0.001	PP	Crop yield	y=0.27x+0.11	0.27	0.002
PN	Max precipitation	y=-0.26x+-0.34	-0.26	<0.001	PP	Max precipitation	y=-0.05x+-0.13	-0.05	0.282
PN	Avg precipitation	y=-0.48x+-0.54	-0.48	<0.001	PP	Avg precipitation	y=-0.45x+-0.51	-0.45	<0.001
PN	Max runoff	y=0.42x+0.33	0.42	<0.001	PP	Max runoff	y=0.62x+0.56	0.62	<0.001
PN	Avg runoff	y=0.07x+-0.01	0.07	0.078	PP	Avg runoff	y=0.27x+0.2	0.27	<0.001
PN	Max soil loss	y=0.82x+0.79	0.82	<0.001	PP	Max soil loss	y=0.52x+0.45	0.52	<0.001
PN	Avg soil loss	y=0.59x+0.53	0.59	<0.001	PP	Avg soil loss	y=0.62x+0.57	0.62	<0.001
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TN	DN	y=0.26x+0.21	0.26	<0.001	TP	DN	y=0.09x+0.03	0.09	0.002
TN	PN	y=0.99x+0.99	0.99	<0.001	TP	PN	y=0.96x+0.96	0.96	<0.001
TN	DP	y=0.76x+0.73	0.76	<0.001	TP	TN	y=0.95x+0.94	0.95	<0.001
TN	PP	y=0.97x+0.96	0.97	<0.001	TP	DP	y=0.1x+0.05	0.10	<0.001
TN	TP	y=0.95x+0.94	0.95	<0.001	TP	PP	y=1x+0.99	1.00	<0.001
TN	Max soil test P	y=0.01x+-0.1	0.01	0.843	TP	Max soil test P	y=0.16x+0.11	0.16	<0.001
TN	Min soil test P	y=0.02x+-0.09	0.02	0.722	TP	Min soil test P	y=0.17x+0.11	0.17	<0.001
TN	Max slope %	y=0.02x+-0.04	0.02	0.542	TP	Max slope %	y=-0.08x+-0.12	-0.08	<0.001
TN	Min slope %	y=0.03x+-0.02	0.03	0.257	TP	Min slope %	y=-0.02x+-0.06	-0.02	0.427
TN	Max watershed size	y=-0.09x+-0.14	-0.09	0.001	TP	Max watershed size	y=-0.1x+-0.14	-0.10	<0.001
TN	Min watershed Size	y=-0.08x+-0.13	-0.08	0.002	TP	Min watershed Size	y=-0.1x+-0.14	-0.10	<0.001
TN	Avg N applied	y=0.27x+0.21	0.27	<0.001	TP	Avg N applied	y=-0.04x+-0.1	-0.04	0.103

TN	Avg P applied	y=0.25x+0.19	0.25	<0.001	TP	Avg P applied	y=-0.01x+-0.05	-0.01	0.682
TN	Crop yield	y=0.4x+0.27	0.40	<0.001	TP	Crop yield	y=0.22x+0.12	0.22	<0.001
TN	Max precipitation	y=-0.13x+-0.21	-0.13	<0.001	TP	Max precipitation	y=0.12x+0.06	0.12	<0.001
TN	Avg precipitation	y=-0.21x+-0.27	-0.21	<0.001	TP	Avg precipitation	y=-0.12x+-0.17	-0.12	<0.001
TN	Max runoff	y=0.51x+0.44	0.51	<0.001	TP	Max runoff	y=0.46x+0.41	0.46	<0.001
TN	Avg runoff	y=0.18x+0.13	0.18	<0.001	TP	Avg runoff	y=0.28x+0.24	0.28	<0.001
TN	Max soil loss	y=0.54x+0.47	0.54	<0.001	TP	Max soil loss	y=0.45x+0.4	0.45	<0.001
TN	Avg soil loss	y=0.39x+0.34	0.39	<0.001	TP	Avg soil loss	y=0.48x+0.44	0.48	<0.001

When taken as a whole, management decisions can have variable effects on nutrient loads. For example, utilizing conventional tillage in a low rainfall and low soil fertility ecoregion would likely lead to lower loads than utilizing conventional tillage in a high rainfall and high soil fertility ecoregion. Thus, Table 4.7 detailed the pairwise interactions that tillage, land use, fertilizer timing, fertilizer placement, and ecoregion have on log transformed annual N and P loads.

In Table 4.7, the 'term' represents the pairwise interaction comparison of interest as compared to baseline without those variables. The estimate represents the coefficient value for each term in the model and indicates the expected change in the dependent variable for a one-unit change in the corresponding independent variable, holding all other variables constant at zero. For example, the estimate for total N load when using "Tillage: Conventional : Fertilizer Timing: Split (at plant and side/top dress)" was 1.70, suggesting that the log nutrient load was expected to increase by approximately 1.70 units when tillage was conventional, and the fertilizer timing was a split application compared to the reference category. The estimates of the interaction terms work relatively similarly. For example, in Table 4.7 there was an interaction for log dissolved N between surface fertilizer placement and conventional tillage. The estimate of 1.37 represents the expected change in the nutrient load when both surface placement and conventional tillage are present compared to the scenario when neither of them were present, holding all other variables constant. This implies that the log dissolved N loads increase 1.37 times more than if neither were utilized. The standard error measures the variability or uncertainty of the estimate and indicates the average amount that the estimate differs from the true value due to random sampling variation. For example, considering dissolved N, the standard error for "Tillage: Conventional: Ecoregion 8.3" was 0.3. The statistic value is the t-value associated with each estimate, calculated by dividing the estimate by its standard error. The t-value measures the strength of the evidence against the null hypothesis (i.e., that the true coefficient is zero). Larger absolute t-values suggest stronger evidence against the null hypothesis. For example, the statistic value for logdN "Tillage: Conventional: Fertilizer Placement: Injected" was 7.17, with this carrying more statistical weight as compared to logdN " Tillage: Conventional: Fertilizer Timing: Preplant" which had a t-value of 0.98 and did not have a significant p value. Lastly, the p-value denotes whether an interaction relationship was statistically significant or not ($p < 0.05$).

From the analysis of the pairwise interactions for all log transformed N and P loads, several significant trends can be seen as bulleted below:

Dissolved Nitrogen (logDN)

- Tillage and Fertilizer Placement: The interaction between conventional tillage and surface fertilizer placement significantly increased dissolved N load ($p < 0.05$). The interaction of fertilizer injection and conventional tillage was also significant ($p<0.05$).
- Tillage and Ecoregion: Conventional tillage combined with specific ecoregions, namely the Mixed Woods Plains, Southeastern USA Plains, Ozark-Ouachita/Appalachian Forests, and Temperate Prairies showed a significant increase in dissolved N load ($p < 0.05$).
- No-till: No significant interactions were found between no-till and land use or fertilizer timing, suggesting no-till practices might be less impactful alone on dissolved N loads. However, the Temperate Prairies ecoregion was significant when combined with no-till practices on dissolved N load. This was noteworthy because Temperate Prairies are one of the largest agricultural producing regions, especially for corn.

Particulate Nitrogen (logPN)

- Tillage and Fertilizer Timing: The combination of no-till and pre-plant fertilizer timing increased particulate N load by 2.3 times more when combined.
- Tillage and Ecoregion: Conventional tillage in Mississippi Alluvial/SE USA Coastal Plains, Temperate Prairies, and South-Central Semi-Arid Prairies, and no-till in South-Central Semi-Arid prairies significantly affected particulate N loads. No-till in the South-Central Semi-Arid Prairies reduced log particulate N load by 4.5 times.
- Land Use and Fertilizer Placement: The interaction of wheat and small grains land use with surface fertilizer placement significantly decreased particulate N load by a factor of 2.3. The interaction of preplant application and surface application reduced the particulate N loads by a factor of 3.6.
- Fertilizer Timing and Ecoregion: One of the most significant interaction effects was with preplant applications in the South-Central Semi-Arid Prairies. The particulate N loads increased 5.93 times over when preplant was utilized in South-Central Semi-Arid Prairies.

Total Nitrogen (logTN)

- Tillage and Fertilizer Timing: Both conventional tillage and no-till with pre-plant fertilizer timing significantly reduced total N load.
- Tillage and Ecoregion: Significant positive interactions were observed with conventional tillage and no-till in the Central USA Plains, Ozark-Ouachita/Appalachian Forests, and Temperate Prairies. In the Temperate Prairies, both no-till and conventional increased the total N by nearly the same factor, 2.6 and 2.7 respectively. This suggests that policy and practices for the Temperate Prairies ecoregion need to be aimed at reducing N loss overall.

- Land Use and Fertilizer Timing/Placement: Significant reductions in total N load were observed with wheat and small grains land use combined with pre-plant fertilizer timing and surface fertilizer placement.
- Fertilizer Timing and Placement: The total N load was reduced by a factor of 2.3 when surface applications and preplant timings were utilized overall.
- Fertilizer Timing and Ecoregion: Within the Southeastern USA Plains, the interaction of preplant applications led to a total N reduction of 1.3 times. On a larger scale, preplant fertilizer application typically increased load loss, but within this ecoregion it appears to not be so.

Dissolved Phosphorus (logDP)

- Tillage and Land Use: No-till combined with wheat and small grains land use significantly increased dissolved P load.
- Tillage and Fertilizer Timing: No-till with split (pre-plant and out-of-season) fertilizer timing significantly reduced dissolved P load. Split application (at plant and side/top dress) reduced dissolved P load.
- Land Use and Fertilizer Placement: Surface fertilizer placement in wheat and small grains significantly increased dissolved P load.
- Fertilizer Timing and Ecoregion: Pre-plant fertilizer timing in the Southeastern USA Plains significantly reduced dissolved P load, while split fertilizer timing in the same ecoregion also led to significant reductions. However, pre-plant fertilizer timing in the Mississippi Alluvial/Southeast USA Coastal Plains led to increased dissolved P loads.

Particulate Phosphorus (logPP)

- Tillage and Fertilizer Placement/Timing: Conventional tillage combined with surface fertilizer placement significantly increased particulate P load. Additionally, no-till and split (at plant and side/top dress) application significantly reduced particulate P by 1.72 times.
- Tillage and Ecoregion: Both conventional tillage and no-till significantly increased in particulate P load in the Southeastern USA Plains. No-till also significantly increased particulate P in the Ozark-Ouachita/Appalachian Forests, while conventional tillage significantly increased particulate P in the Temperate Prairies ecoregion.

Total Phosphorus (logTP)

- Tillage and Land Use: No-till with wheat and small grains land use significantly increased total P load, whereas conventional tillage with wheat and small grains significantly reduced total P loads.
- Tillage and Fertilizer Timing: Conventional tillage combined with pre-plant fertilizer timing and with split application (at planting and side/top dress) significantly reduced total P load.
- Tillage and Fertilizer Placement: When combined with conventional tillage, both injected and surface applications increased total P loads by a factor of 0.6 and 0.8, respectively (Table 4.7).
- Tillage and Ecoregion: No-till within the Mixed Woods Plains combined to reduce total P loads by a factor of 1.2, whereas the ecoregion/ no-till interaction of all other ecoregions was not statistically significant.
- Fertilizer Placement and Ecoregion: Surface fertilizer placement in Mixed Wood Plains significantly increased total P load, whereas it decreased total P loads in Southeastern USA

Plains. Injected fertilizer placement in Ozark-Ouachita/Appalachian Forests significantly reduced total P load.

- Land Use and Fertilizer Placement: For wheat and small grains, surface fertilizer applications increased total P by a factor of 1.75. Wheat in other settings has been typically shown to be less of a risk for nutrient loss, yet data in Table 4.7 suggests otherwise.
- Fertilizer Timing and Placement: Akin to previously demonstrated results, preplant and surface application interactions worked together to reduce total P losses, by a factor of 3.6 compared to the effects when considered individually (Table 4.7).

Based on these results, effective nutrient management requires a calculated plan considering the interactions between tillage methods, fertilizer practices, land use, and ecoregional characteristics. Conventional tillage generally increased nutrient loads when combined with surface fertilizer placement, especially in specific ecoregions, while no-till shows mixed effects. Prescribing management decisions to specific conditions or ecoregions may mitigate environmental impacts and support sustainable agriculture, especially nutrient use efficiency.

Table 4.7. Interaction effects between all possible two-way combinations of tillage, land use, fertilizer timing, fertilizer placement, and ecoregion on the impact of log transformed nitrogen and phosphorus loads. * Denotes statistical significance (p value < 0.05).

Nutrient Load	Term	Estimate (Coefficient)	Std. Error	Statistic (t-value)	p value
logdN	Tillage- Conventional : Land Use-Wheat and small grains	0.18	0.28	0.64	5.20E-01
logdN	Tillage- No-Till : Land Use-Wheat and small grains	-0.09	0.42	-0.21	8.34E-01
logdN	Tillage- Conventional : Fertilizer Timing- PrePlant	0.20	0.20	0.98	3.29E-01
logdN	Tillage- No-Till : Fertilizer Timing- PrePlant	0.26	0.52	0.50	6.19E-01
logdN	Tillage- Conventional : Fertilizer Timing- Split (At Plant and Side/Top Dress)	0.04	0.27	0.13	8.94E-01
logdN	Tillage- No-Till : Fertilizer Timing- Split (At Plant and Side/Top Dress)	-0.35	0.40	-0.87	3.83E-01
logdN	Tillage- Conventional : Fertilizer Placement- Injected	0.75	0.32	2.30	2.16E-02*
logdN	Tillage- Conventional : Fertilizer Placement- Surface	1.38	0.19	7.17	2.29E-12*
logdN	Tillage- Conventional : Mixed Wood Plains	0.63	0.32	1.98	4.75E-02*
logdN	Tillage- No-Till : Mixed Wood Plains	-0.52	0.56	-0.92	3.60E-01
logdN	Tillage- No-Till : Central USA Plains	0.44	0.37	1.20	2.30E-01
logdN	Tillage- Conventional : Southeastern USA Plains	1.11	0.30	3.68	2.42E-04*
logdN	Tillage- No-Till : Southeastern USA Plains	0.34	0.37	0.92	3.56E-01
logdN	Tillage- Conventional : Ozark-Ouachita/Appalachian Forests	1.25	0.40	3.14	1.74E-03*
logdN	Tillage- No-Till : Ozark-Ouachita/Appalachian Forests	0.47	0.33	1.41	1.59E-01
logdN	Tillage- Conventional : Mississippi Alluvial/Southeast USA Coastal Plains	0.26	0.72	0.36	7.17E-01
logdN	Tillage- Conventional : Temperate Prairies	1.47	0.21	6.94	7.37E-12*
logdN	Tillage- No-Till : Temperate Prairies	1.38	0.31	4.49	7.85E-06*
logpN	Tillage- Conventional : Land Use-Wheat and small grains	0.73	0.65	1.12	2.66E-01
logpN	Tillage- Conventional : Fertilizer Timing- PrePlant	1.07	1.13	0.94	3.46E-01
logpN	Tillage- No-Till : Fertilizer Timing- PrePlant	2.28	0.98	2.34	2.00E-02*
logpN	Tillage- Conventional : Fertilizer Timing- Split (At Plant and Side/Top Dress)	-0.86	1.22	-0.70	4.83E-01
logpN	Tillage- Conventional : Fertilizer Placement- Surface	0.55	0.90	0.61	5.44E-01
logpN	Tillage- Conventional : Mississippi Alluvial/Southeast USA Coastal Plains	2.87	1.01	2.85	4.61E-03*

logpN	Tillage- Conventional : Temperate Prairies	0.81	0.41	1.98	4.83E-02*
logpN	Tillage- Conventional : South-Central Semi-Arid Prairies	-1.04	0.39	-2.68	7.69E-03*
logpN	Tillage- No-Till : South-Central Semi-Arid Prairies	-4.51	0.50	-9.10	4.95E-18*
logpN	Land Use-Wheat and small grains : Fertilizer Placement- Surface	-2.29	0.43	-5.27	2.99E-07*
logpN	Fertilizer Timing- PrePlant : Fertilizer Placement- Surface	-3.66	1.11	-3.29	1.09E-03*
logpN	Fertilizer Timing- PrePlant : South-Central Semi-Arid Prairies	5.93	0.28	21.02	2.55E-69*
logpN	Fertilizer Placement- Surface : Temperate Prairies	0.35	0.25	1.40	1.61E-01
logtN	Tillage- Conventional : Land Use-Wheat and small grains	1.06	0.35	3.01	2.89E-03*
logtN	Tillage- No-Till : Land Use-Wheat and small grains	0.72	0.49	1.47	1.43E-01
logtN	Tillage- Conventional : Fertilizer Timing- PrePlant	-2.37	0.35	-6.67	1.03E-10*
logtN	Tillage- No-Till : Fertilizer Timing- PrePlant	-1.49	0.56	-2.66	8.10E-03*
logtN	Tillage- Conventional : Fertilizer Timing- Split (At Plant and Side/Top Dress)	-1.71	0.40	-4.22	3.15E-05*
logtN	Tillage- No-Till : Fertilizer Timing- Split (At Plant and Side/Top Dress)	-1.30	0.56	-2.31	2.17E-02*
logtN	Tillage- No-Till : Fertilizer Placement- Injected	0.29	0.51	0.56	5.75E-01
logtN	Tillage- Conventional : Fertilizer Placement- Surface	0.81	0.27	2.96	3.24E-03*
logtN	Tillage- No-Till : Central USA Plains	1.53	0.38	4.06	5.49E-05*
logtN	Tillage- Conventional : Southeastern USA Plains	-0.34	0.55	-0.62	5.35E-01
logtN	Tillage- No-Till : Southeastern USA Plains	-0.28	0.62	-0.45	6.51E-01
logtN	Tillage- Conventional : Ozark-Ouachita/Appalachian Forests	1.36	0.25	5.37	1.04E-07*
logtN	Tillage- No-Till : Ozark-Ouachita/Appalachian Forests	0.95	0.33	2.90	3.85E-03*
logtN	Tillage- Conventional : Mississippi Alluvial/Southeast USA Coastal Plains	-0.65	0.74	-0.88	3.81E-01
logtN	Tillage- Conventional : Temperate Prairies	2.72	0.25	11.04	1.96E-26*
logtN	Tillage- No-Till : Temperate Prairies	2.60	0.34	7.61	7.98E-14*
logtN	Land Use-Wheat and small grains : Fertilizer Timing- PrePlant	-1.23	0.27	-4.47	9.90E-06*
logtN	Land Use-Wheat and small grains : Fertilizer Placement- Surface	-0.91	0.37	-2.47	1.38E-02*
logtN	Fertilizer Timing- PrePlant : Fertilizer Placement- Surface	-2.26	0.73	-3.09	2.14E-03*
logtN	Fertilizer Timing- PrePlant : Southeastern USA Plains	-1.33	0.33	-4.03	6.27E-05*
logtN	Fertilizer Timing- PrePlant : Mississippi Alluvial/Southeast USA Coastal Plains	0.06	0.50	0.12	9.02E-01

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logdP	Tillage- Conventional : Land Use-Various corn/soybean/small grain or alfalfa rotations	-0.24	0.39	-0.60	5.50E-01
logdP	Tillage- Conventional : Land Use-Wheat and small grains	0.04	0.22	0.19	8.49E-01
logdP	Tillage- No-Till : Land Use-Wheat and small grains	1.22	0.29	4.17	3.43E-05*
logdP	Tillage- Conventional : Fertilizer Timing- Split (At Plant and Side/Top Dress)	-0.19	0.27	-0.71	4.78E-01
logdP	Tillage- No-Till : Fertilizer Timing- Split (At Plant and Side/Top Dress)	-1.20	0.47	-2.54	1.15E-02*
logdP	Tillage- Conventional : Fertilizer Timing- Split (PrePlant and Out of Season)	-0.28	0.22	-1.30	1.95E-01
logdP	Tillage- No-Till : Fertilizer Timing- Split (PrePlant and Out of Season)	-2.42	0.53	-4.57	6.75E-06*
logdP	Land Use-Wheat and small grains : Fertilizer Timing- PrePlant	0.23	0.32	0.72	4.72E-01
logdP	Land Use-Wheat and small grains : Fertilizer Placement- Surface	1.59	0.35	4.50	8.22E-06*
logdP	Fertilizer Timing- PrePlant : Fertilizer Placement- Surface	-0.01	0.77	-0.01	9.91E-01
logdP	Fertilizer Timing- PrePlant : Southeastern USA Plains	-3.39	0.32	-10.60	1.02E-24*
logdP	Fertilizer Timing- Split (At Plant and Side/Top Dress) : Southeastern USA Plains	-3.78	0.26	-14.48	1.36E-42*
logdP	Fertilizer Timing- PrePlant : Mississippi Alluvial/Southeast USA Coastal Plains	0.90	0.43	2.10	3.58E-02*
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logpP	Tillage- Conventional : Land Use-Wheat and small grains	-0.75	0.84	-0.89	3.73E-01
logpP	Tillage- Conventional : Fertilizer Timing- Split (At Plant and Side/Top Dress)	-0.91	0.70	-1.31	1.91E-01
logpP	Tillage- No-Till : Fertilizer Timing- Split (At Plant and Side/Top Dress)	-1.73	1.03	-1.67	9.57E-02*
logpP	Tillage- Conventional : Fertilizer Timing- Split (PrePlant and Out of Season)	0.69	1.19	0.58	5.64E-01
logpP	Tillage- No-Till : Fertilizer Placement- Injected	0.79	0.52	1.52	1.30E-01
logpP	Tillage- Conventional : Fertilizer Placement- Surface	1.07	0.37	2.86	4.48E-03*
logpP	Tillage- Conventional : Southeastern USA Plains	1.71	0.64	2.69	7.44E-03*
logpP	Tillage- No-Till : Southeastern USA Plains	3.78	0.57	6.65	8.07E-11*
logpP	Tillage- Conventional : Ozark-Ouachita/Appalachian Forests	1.20	0.93	1.30	1.94E-01
logpP	Tillage- No-Till : Ozark-Ouachita/Appalachian Forests	2.69	0.44	6.14	1.74E-09*
logpP	Tillage- Conventional : Mississippi Alluvial/Southeast USA Coastal Plains	0.28	1.17	0.24	8.13E-01
logpP	Tillage- Conventional : Temperate Prairies	1.35	0.54	2.50	1.28E-02*
logpP	Tillage- Conventional : South-Central Semi-Arid Prairies	0.41	0.56	0.74	4.60E-01

logtP	Tillage- Conventional : Land Use-Various corn/soybean/small grain or alfalfa rotations	-1.66	0.67	-2.48	1.35E-02*
logtP	Tillage- Conventional : Land Use-Wheat and small grains	-0.87	0.35	-2.48	1.32E-02*
logtP	Tillage- No-Till : Land Use-Wheat and small grains	1.65	0.43	3.82	1.47E-04*
logtP	Tillage- Conventional : Fertilizer Timing- PrePlant	-1.63	0.39	-4.21	3.16E-05*
logtP	Tillage- No-Till : Fertilizer Timing- PrePlant	-0.84	0.64	-1.32	1.88E-01
logtP	Tillage- Conventional : Fertilizer Timing- Split (At Plant and Side/Top Dress)	-1.17	0.47	-2.48	1.37E-02*
logtP	Tillage- No-Till : Fertilizer Timing- Split (At Plant and Side/Top Dress)	-0.35	0.66	-0.54	5.90E-01
logtP	Tillage- Conventional : Fertilizer Placement- Injected	0.64	0.35	1.84	6.59E-02*
logtP	Tillage- No-Till : Fertilizer Placement- Injected	0.27	0.24	1.15	2.49E-01
logtP	Tillage- Conventional : Fertilizer Placement- Surface	0.82	0.20	4.16	3.51E-05*
logtP	Tillage- Conventional : Mixed Wood Plains	-0.82	0.71	-1.15	2.52E-01
logtP	Tillage- No-Till : Mixed Wood Plains	-1.23	0.54	-2.30	2.16E-02*
logtP	Tillage- No-Till : Central USA Plains	0.30	0.33	0.91	3.64E-01
logtP	Tillage- Conventional : Southeastern USA Plains	1.03	0.78	1.33	1.85E-01
logtP	Tillage- No-Till : Southeastern USA Plains	0.29	0.48	0.60	5.49E-01
logtP	Tillage- Conventional : Ozark-Ouachita/Appalachian Forests	0.36	0.74	0.48	6.31E-01
logtP	Tillage- No-Till : Ozark-Ouachita/Appalachian Forests	-0.34	0.22	-1.53	1.26E-01
logtP	Tillage- Conventional : Mississippi Alluvial/Southeast USA Coastal Plains	-0.52	0.94	-0.56	5.78E-01
logtP	Tillage- Conventional : Temperate Prairies	0.25	0.69	0.36	7.17E-01
logtP	Tillage- No-Till : Temperate Prairies	0.11	0.22	0.51	6.11E-01
logtP	Tillage- Conventional : South-Central Semi-Arid Prairies	0.34	0.68	0.50	6.16E-01
logtP	Land Use-Wheat and small grains : Fertilizer Timing- PrePlant	-0.34	0.39	-0.86	3.93E-01
logtP	Land Use-Wheat and small grains : Fertilizer Placement- Surface	1.75	0.38	4.65	4.17E-06*
logtP	Fertilizer Timing- PrePlant : Fertilizer Placement- Surface	-3.60	0.84	-4.27	2.23E-05*
logtP	Fertilizer Timing- PrePlant : Southeastern USA Plains	-0.89	0.55	-1.64	1.02E-01
logtP	Fertilizer Timing- Split (At Plant and Side/Top Dress) : Southeastern USA Plains	0.54	0.52	1.04	2.98E-01
logtP	Fertilizer Timing- PrePlant : Mississippi Alluvial/Southeast USA Coastal Plains	-0.21	0.54	-0.40	6.92E-01
logtP	Fertilizer Placement- Surface : Mixed Wood Plains	0.92	0.28	3.25	1.19E-03*

logtP	Fertilizer Placement- Surface : Southeastern USA Plains	-0.68	0.33	-2.02	4.33E-02*
logtP	Fertilizer Placement- Injected : Ozark-Ouachita/Appalachian Forests	-1.58	0.61	-2.59	9.63E-03*
logtP	Fertilizer Placement- Surface : Ozark-Ouachita/Appalachian Forests	0.75	0.59	1.27	2.06E-01

4.3.3: Multiple Linear Regression Analysis and Management Interaction of Nutrient Load

The multiple linear regression (MLR) was populated with the major management decision variables (i.e. tillage, land use, fertilizer timing, fertilizer placement) as well as ecoregion. This was due in part to the nature of the observations within MANAGE, which was populated with data from studies with different aims and objectives; therefore, the same data/ information are not included in all of the studies.

To meet the assumptions of normality for the regression model, it was necessary to focus the analysis on the log transformed nutrient variables. When a stepwise forward linear regression was performed, nearly all the ‘full combination’ models had the lowest Akaike Information Criterion (AIC) values, indicating they were the strongest model for prediction of a particular dependent variable. The model results are presented in Table 4.8 and show that all variables considered led to the strongest model predictions for almost all N and P loads. The exception to this was the logpN model which consisted of tillage, fertilizer placement, and land use.

Particulate N had some of the fewest total observations and thus data points amongst all nutrient load data within MANAGE (Table 4.1). When even the largest groups of nutrient load observations suffer from data scarcity, this impacts the multiple linear regression results of any dependent variable (e.g., particulate N) at least in part by a lack of observations comparing management practice effects on nutrient load loss. This limited dataset for particulate N and in part the MANAGE database, introduces a degree of uncertainty in the regression analysis. As a result, the findings related to particulate N should be interpreted with caution. The scarcity of data points can lead to less robust statistical conclusions and may affect the generalizability of the results. Therefore, while the trends and effects observed in this study provide valuable insights, they should be considered preliminary, and further research with more comprehensive datasets is recommended to confirm these findings.

It is also important to note that there are variables within the MANAGE database that have not yet been quantified in terms of their influence on nutrient loads (e.g., soil test P, slope, fertilizer application rates). Comparisons need to be made on this information, and even given the data scarcity within MANAGE, those field-scale observations with less total entries would lend itself to improving the future accuracy and performance of the optimal models for nutrient load loss.

Table 4.8. Akaike Information Criterion (AIC) values demonstrating optimal model selected via forward stepwise multiple regression models amongst categorical management variables and log transformed nutrient loads.

Dependent Variable	**Optimal Model**	**AIC**
logdN	Tillage + Fertilizer Timing + Fertilizer Placement + Land Use + Ecoregion	143.4
logpN	Tillage + Fertilizer Placement + Land Use	163.3
logtN	Tillage + Fertilizer Timing + Fertilizer Placement + Land Use + Ecoregion	92.4
logdP	Tillage + Fertilizer Timing + Fertilizer Placement + Land Use + Ecoregion	80.4
logpP	Tillage + Fertilizer Timing + Fertilizer Placement + Land Use + Ecoregion	173.3
logtP	Tillage + Fertilizer Timing + Fertilizer Placement + Land Use + Ecoregion	296.4

Table 4.9 details all the individual parameters within each multiple linear regression model and their respective coefficients as it relates to predicting log transformed N and P loads. We can observe how relatively simple the model for particulate N is compared to its counterparts and to some extent particulate P.

Table 4.9. Multiple linear regression table showing model parameters and coefficients for optimal model for estimating the log transformed nutrient load values.

Dependent Variable	Multiple Linear Regression Model Parameter	Coefficient
logdN	Intercept	1.66
logdN	Tillage: Conventional	0.48
logdN	Tillage: No-Till	3.61
logdN	Fertilizer Timing: Split (At Plant and Side/Top Dress)	-3.04
logdN	Fertilizer Timing: Split (PrePlant and Out-of-Season)	-0.09
logdN	Fertilizer Placement: Surface	0.27
logdN	Land Use: Wheat and small grains	0.31
logdN	Ecoregion: Temperate Prairies	-1.4
logdN	Ecoregion: South-Central Semi-Arid Prairies	-1.96
logpN	Intercept	1.40
logpN	Tillage: Conventional	2.95
logpN	Fertilizer Placement: Surface	-0.42
logpN	Land Use: Wheat and small grains	-1.95
logtN	Intercept	3.97
logtN	Tillage: Conventional	2.43
logtN	Tillage: No-Till	8.78
logtN	Fertilizer Timing: Split (At Plant and Side/Top Dress)	-6.65
logtN	Fertilizer Timing: Split (PrePlant and Out-of-Season)	-0.49
logtN	Fertilizer Placement: Surface	0.2
logtN	Land Use: Wheat and small grains	-1.43
logtN	Ecoregion: Temperate Prairies	-2.05
logtN	Ecoregion: South-Central Semi-Arid Prairies	-3.33
logdP	Intercept	-1.67
logdP	Tillage: Conventional	0.4
logdP	Tillage: No-Till	4.59
logdP	Fertilizer Timing: Split (At Plant and Side/Top Dress)	-3.7
logdP	Fertilizer Timing: Split (PrePlant and Out-of-Season)	-1.11
logdP	Fertilizer Placement: Surface	1.06
logdP	Land Use: Wheat and small grains	-0.11
logdP	Ecoregion: Temperate Prairies	-0.01
logdP	Ecoregion: South-Central Semi-Arid Prairies	-0.5
logpP	Intercept	-2.84
logpP	Tillage: Conventional	4.18
logpP	Fertilizer Timing: Split (PrePlant and Out-of-Season)	-1.13
logpP	Fertilizer Placement: Surface	0.93
logpP	Land Use: Wheat and small grains	-1.95
logpP	Ecoregion: Temperate Prairies	1.56

logtP	Intercept	2.6
logtP	Tillage: Conventional	2.03
logtP	Tillage: No-Till	5.91
logtP	Fertilizer Timing: Split (At Plant and Side/Top Dress)	-4.68
logtP	Fertilizer Timing: Split (PrePlant and Out-of-Season)	-1
logtP	Fertilizer Placement: Surface	1.3
logtP	Land Use: Wheat and small grains	-1.19
logtP	Ecoregion: Southeastern USA Plains	-3.22
logtP	Ecoregion: Temperate Prairies	-2.39
logtP	Ecoregion: South-Central Semi-Arid Prairies	-3.66

The optimally performing model, when comparing predicted to actual log N load values, was the total N model with $R^2 = 0.92$, MAE = 0.25, and RMSE = 0.36 (Figure 4.9, Table 4.10). The dissolved N and particulate N models had R^2 values of 0.52 and 0.76, as well as MAE and RMSE values of (0.30, 0.50) and (0.79, 0.36).

Dissolved, particulate, and total P models had similar R^2 values (0.78, 0.77, 0.66) (Figure 4.10) although their MAE and RMSE values displayed more variation amongst the models predicted vs. actual error results (0.24, 0.43, 0.62) and (0.32, 0.84, 0.79) (Table 4.10) respectively.

These results indicate that models for dissolved N and P are more precise compared to those for particulate and total N and P; the dissolved and particulate N models are less successful at load prediction compared to the total N model. The lower error values for dissolved nutrient models suggest that these are more straightforward to predict, potentially due to less variability and simpler transport mechanisms. In contrast, greater errors in particulate and total nutrient models point to the complexity and greater variability in these nutrient load forms, indicating a need for more advanced modeling techniques and additional data to improve accuracy. Similar research has shown difficulty in accurately predicting N and P loads, especially particulate and total forms. Kelly et al. (2018) reported lower uncertainty in dissolved N load estimates in streams with a relative error of 1.5-23%; however, uncertainty was greatest in particulate and total N loads, with a relative error of 19-96%.

In comparison to our results, White et al. (2015) aimed to develop sediment and nutrient export coefficients for U.S. ecoregions. They used the Soil and Water Assessment Tool (SWAT) to provide simulations of expected total N and P loads given specific circumstances, and compared those predicted values directly to measured total N and P loads from actual research observation data. Across 60 different sites, they were able to achieve R^2 values of 0.45 and 0.33 for total N and P, respectively.

White et al. (2012) also found similar success when using the Texas Best Management Practice Evaluation Tool (TBET), which is based on SWAT. Across 20 survey sites and over 260 sites years, they were able to produce R^2 values of 0.56 and 0.82 for total N and P in their calibration models, and R^2 values of 0.28 and 0.76 in their validation datasets. The SWAT and TBET models make predictions based on a variety of input variables that modelers can adjust to fit their field characteristics. Considering that we were able to produce similar R^2 value as White et al. (2012, 2015) with less predictor variables but more overall site years and observations, this is promising for future improvement to load loss modeling as well as variable identification when it comes to importance of tracking research variables.

Similar to the data scarcity problem we experienced in this research, Eagle et al. (2017) found that data collection and reporting deficiencies reduce the effectiveness of agri-environmental meta-analysis; therefore, the authors stress the benefits of standardization and consistency across studies enhance data synthesis and meta-analysis. Eagle et al. (2017) emphasized that while there are barriers and challenges in the world of agricultural data, it is important that we do not advocate for uniformity in primary study objectives and design, as each study is unique and needs to be set up and designed to test specific hypotheses. The things we as a community are lacking, however, are both the availability of meta-data and better access to primary data that would allow for extraction of relevant meta-analysis statistics.

In addition, it is important to note that other variables exist within the MANAGE database that may be correlated and statistically significant in their relationship to nutrient load. However, sparse data observations across all numeric field scale variables led to their temporary omission from initial modeling attempts. Future work should focus efforts on data imputation to fill gaps in existing MANAGE data.

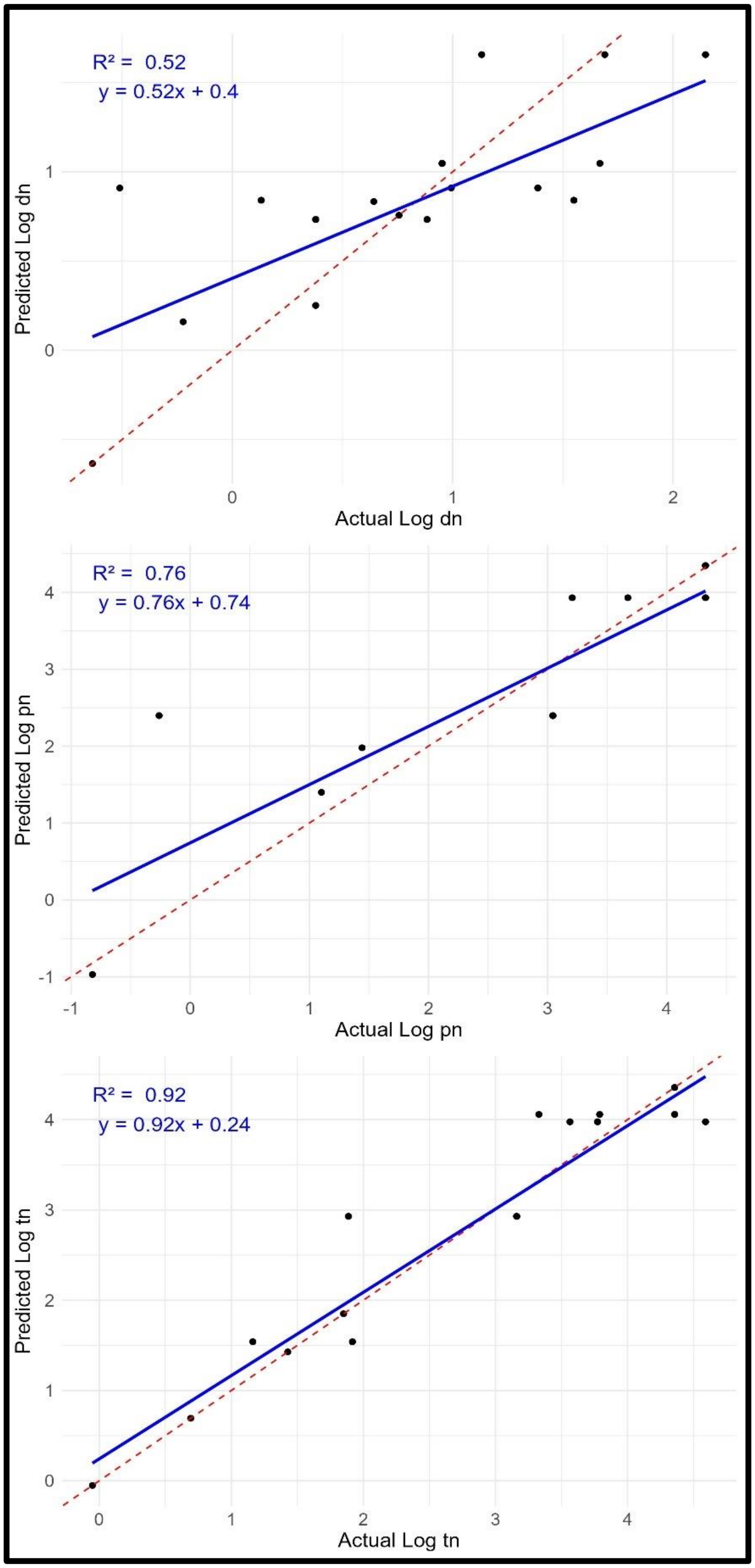

Figure 4.9. Predicted vs. actual plot for the log transformed dissolved, particulate, and total N load (kg/ha/yr).

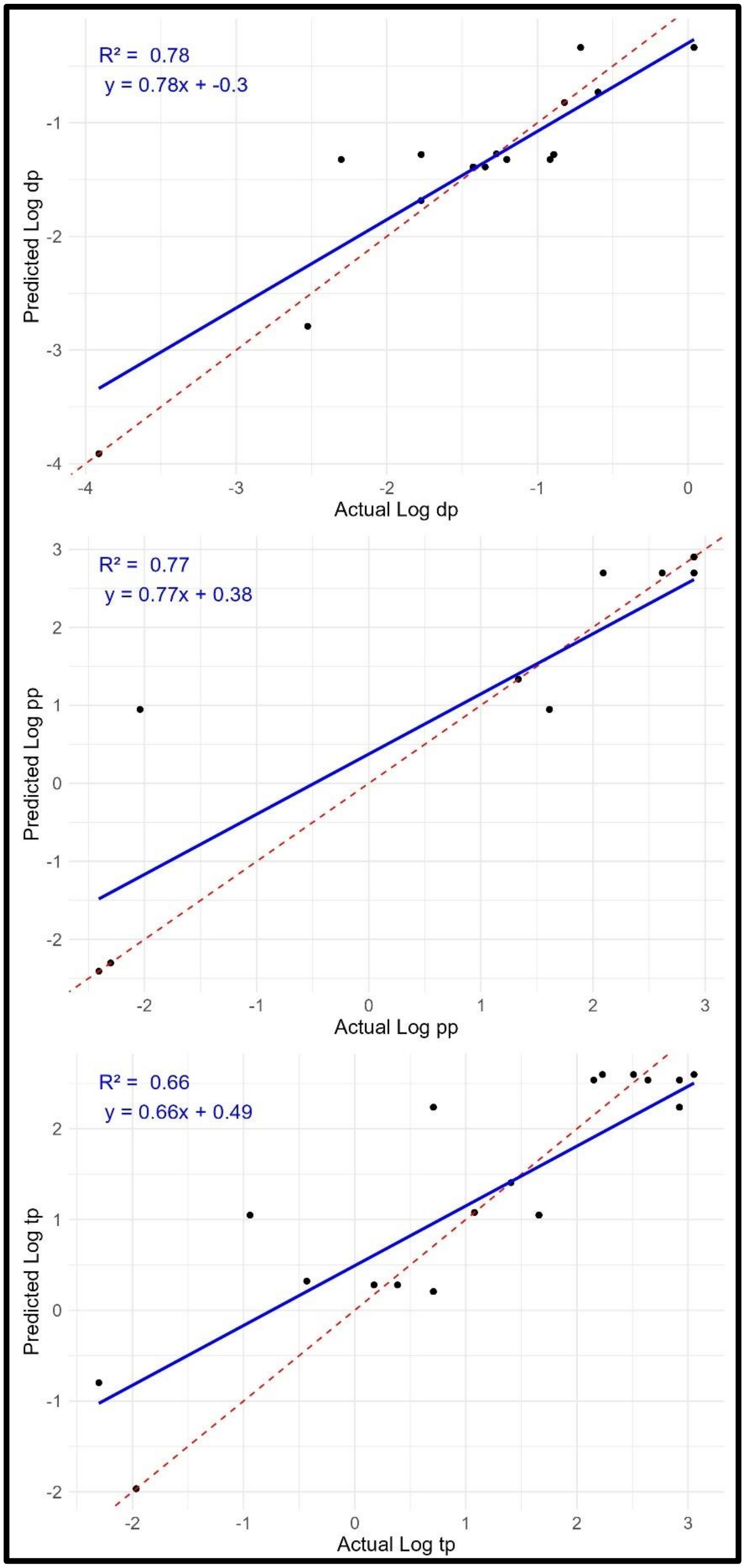

Figure 4.10. Predicted vs. actual plot for the log transformed dissolved, particulate, and total P load (kg/ha/yr).

Table 4.10. Model error results in mean absolute error (MAE) and root mean square error (RMSE) for all transformed nutrient load models.

Dependent Variable	MAE	RMSE
LogdN	0.30	0.41
LogpN	0.50	0.79
LogtN	0.25	0.36
LogdP	0.24	0.32
LogpP	0.43	0.84
LogtP	0.62	0.79

Figures 4.11 and 4.12 show the standardized coefficients from the limited linear regressions of agricultural management decisions and their effects on log nutrient load for N and P, respectively. These are categorical variables and thus require reference variables in the coefficient plots. For both Figures 4.11 and 4.12, the reference variables are Tillage: Conventional, Fertilizer Timing: PrePlant, Fertilizer Placement: Incorporated, Land Use: Corn, Ecoregion: Mississippi Alluvial/SE USA Plains. The reference variables that were selected were those variables that tended to produce greater comparative nutrient load.

Unexpectedly, the coefficients from the linear regression model for no-till was significant on the positive scale for standardized effect on nutrient load fertilizer timing. Split (at plant and side/top dress) application showed significantly less load than the reference preplant and the split (preplant and out of season) application. Conservation tillage was shown to have a negative coefficient for all nutrient load models compared to conventional tillage. Wheat and small grain production was similarly negative in its impacts for modeled particulate and total N and P. Both split application timings (at plant and side/top dress) and (preplant and out-of-season) reduced nutrient load in our models for total N, dissolved P, and total P, although the split (at plant and side/top dress) application showed a much greater numerical reduction than the preplant and out-of-season split. Split application (at plant and side/top dress) reduced dissolved N and the split (preplant and out-of-season) reduced particulate P. When we examined ecoregions for dissolved and total N and P, Temperate Prairies and South-Central Semi-Arid Prairies had reduced loads compared to the Mississippi Alluvial/Southeast USA Coastal Plains. Lastly, the Southeastern USA Plains had signficantly reduced total P loss when compared to the reference ecoregion.

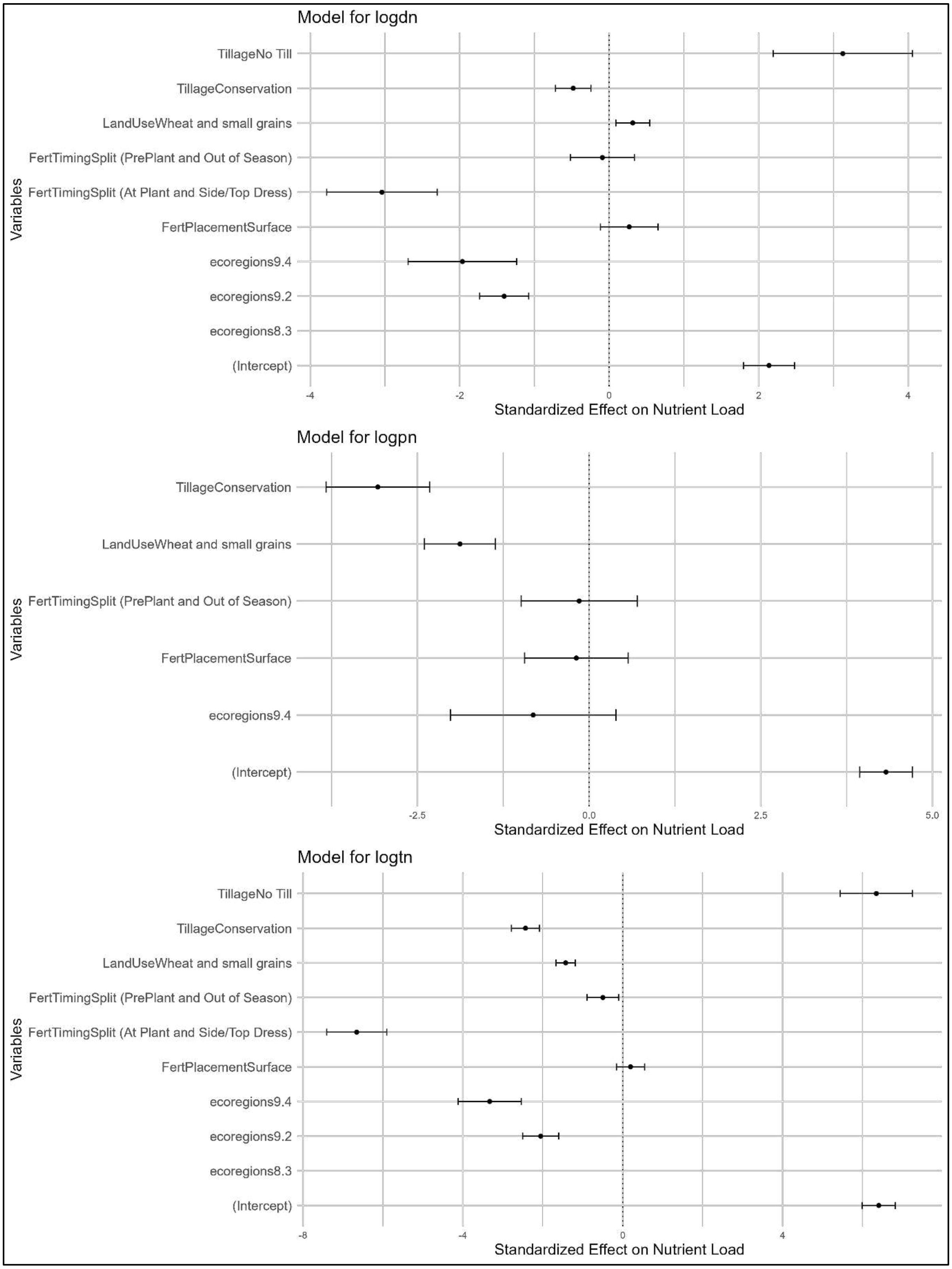

Figure 4.11. Coefficient plot for predictor variables of dissolved, particulate and total log N models. Reference variables set as follows: Tillage: Conventional, Fertilizer Timing: PrePlant, Fertilizer Placement: Incorporated, Land Use: Corn, Ecoregion: Mississippi Alluvial/SE USA Plains (8.5). Those dots, lines and whiskers that are not crossing the 0 dotted line are considered statistically significant from the reference variable and not caused by random chance.

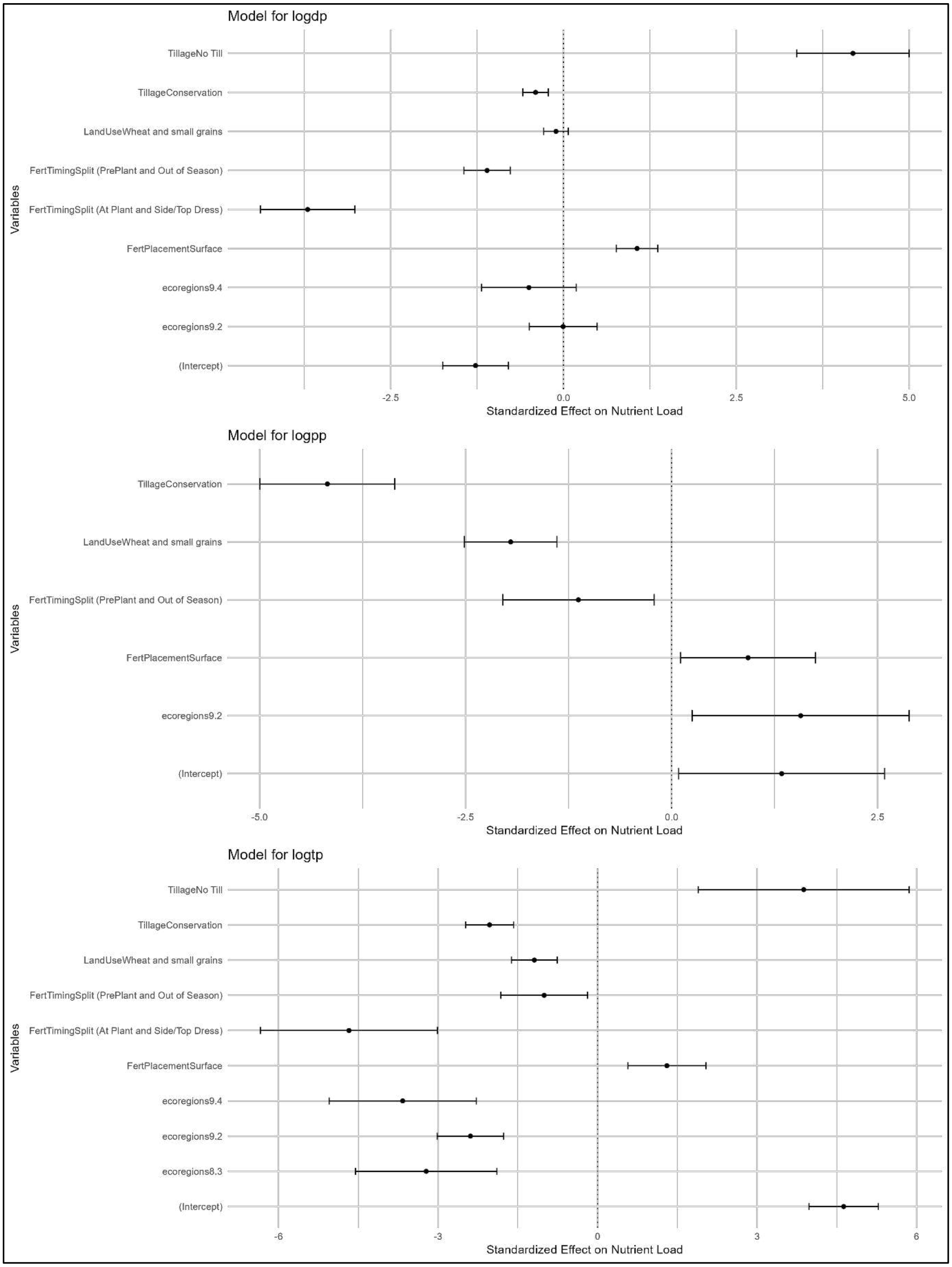

Figure 4.12. Coefficient plot for predictor variables of dissolved, particulate and total log P models. Reference variables set as follows: Tillage: Conventional, Fertilizer Timing: PrePlant, Fertilizer Placement: Incorporated, Land Use: Corn, Ecoregion: Mississippi Alluvial/SE USA Plains (8.5). Those dots, lines and whiskers that are not crossing the 0 dotted line are considered statistically significant from the reference variable and not caused by random chance.

4.3.4: Nutrient Load Guidelines, Warnings, Exceedances, and Prescriptions

As briefly discussed in the introduction, reducing nutrient loss from agricultural lands is important, and there are many federal policies aimed at nutrient, water, and soil conservation. However, no specific federal policy guidelines exist in terms of an edge-of-field target load value. While some nutrient loss is both a reality and unavoidable, Harmel et al. (2018) assessed nutrient runoff from fields across the United States, concluding that certainty programs offer the most promise for ensuring acceptable nutrient runoff and that field-scale models linked with watershed decision support tools are the most promising for assessing impacts on downstream water quality.

With Harmel et al. (2018) in mind, we explored a potential target based on the 90th percentile of the annual median load under conservation tillage. This allowed us to be inclusive of agriculture where no-till is not an option. It was assumed that if conservation tillage was being utilized, then that producer tends toward using other similar practices in line with the 4R principles aimed at resource conservation and use efficiency. Selecting the 90th percentile of conservation tillage load allows extreme outliers to be excluded and to explore a reasonable target for the agricultural and scientific community. A proposed 90th percentile of conservation tillage is presented in Table 4.11.

Table 4.11. Proposed 90th percentile of conservation tillage nitrogen and phosphorus load targets.

Nutrient Load Form	**Annual Nutrient Load Target (kg/ha)**
Total Nitrogen	10.0
Particulate Nitrogen	6.0
Dissolved Nitrogen	10.5
Total Phosphorus	3.0
Particulate Phosphorus	2.5
Dissolved Phosphorus	0.9

4.3.4.1: Ecoregion Load Target Exceedances

With the proposed and somewhat conservative nutrient runoff load target, there are ecoregions that stand out as the most focus worthy for conservation efforts and policy. With a uniform national target for total N loads of 10 kg/ha/yr, two ecoregions had several annual loads exceeding the target. The Southeastern USA Plains and Temperate Prairies had maximum annual loads up to 47 and 78 kg/ha/yr (Figure 4.13). For the particulate N load target (i.e., 6 kg/ha/yr), the Southeastern USA Plains, Temperate Prairies, and the Mississippi Alluvial/Southeast USA Coastal Plains, and the South-Central Semi-Arid Prairies exceeded the target with maximum load values of up to 7, 75, and 13 kg/ha/yr respectively (Figure 4.14). When we examined the target and potential exceedances of the dissolved N target (10.5 kg/ha/yr), there were no severe exceedances, although the Mixed Woods Plains and Mississippi Alluvial/Southeastern USA Coastal Plains had outliers falling above the target approximately 10 and 14 kg/ha/yr respectively (Figure 4.15).

Concerning total P, with a proposed target of 3 kg/ha/yr, once again the Mississippi Alluvial/Southeastern USA Coastal Plains and the West-Central Semi-Arid Prairies had annual loads exceeding target (4.2-4.7 kg/ha/yr) (Figure 4.16). Several other ecoregions have more outlier observations over the total P target line, namely the Mississippi Alluvial/Southeastern USA Plains, Temperate Prairies, and South-Central Semi-Arid Prairies (Figure 4.16). Concerning particulate P, with a proposed target of 2.5 kg/ha/yr, the Southeastern USA Plains, Mississippi Alluvial/Southeastern USA Coastal Plains, and the Temperate Prairies all drastically exceed the target. These had load values of up to 7, 12.5, and 18 kg/ha/yr, respectively (Figure 4.17). Lastly, concerning dissolved P with a proposed target of 0.9 kg/ha/yr, there were two ecoregions that exceeded the target, the Ozark-Ouachita/Appalachian Forests and the Mississippi Alluvial/Southeastern USA Coastal Plains, with load values of up to 2.8 and 2.6 kg/ha/yr, respectively (Figure 4.18). The Southeastern USA Plains and the South-Central Semi-Arid Prairies had data extreme observations exceeding the target. Identifying these ecoregions with common exceedances of the proposed load target may assist in the prescription of suitable remediation and conservation management choices.

The implications of ecoregions that exceed the nutrient load target are considerable. Those that exceed targets are at risk for poor local water quality, increased fertilizer input requirements, decreased crop yields due to valuable needed nutrients lost from the soil, increased soil erosion from practices that do not promote soil conservation such as conventional tillage, as well as increasing local and government pressure to reduce ecological impacts and improve agricultural efficiency. The reasons the aforementioned ecoregions exceeded targets were often because they prioritized high input - high management requirement crop land uses like corn production, combined with high rainfall, high soil disturbance from conventional tillage, and fertilizer incorporation, all which led to extreme nutrient loads.

Although the 90th percentile of a conservation load target is only a starting point for discussion, further refinement could be made in the future to tailor the load targets to individual ecoregions. The broader ecoregion static target is valuable because it identifies and highlights regional needs for additional policy, energy, and focus for conservation efforts without providing undue flexibility to area with high load loss. However, tailoring the target to individual ecoregions based on spatially variable high soil nutrient fertility and risk of loss is a valuable future step. Having ecoregion prescribed targets could make for allowances for variable soil fertility and production and ultimately ought to be based on temporal variation across production years. Recommending an ecoregion target based on previous years of data was not feasible given the current MANAGE database but could be achieved with strategic and repeated environmental monitoring for each ecoregion.

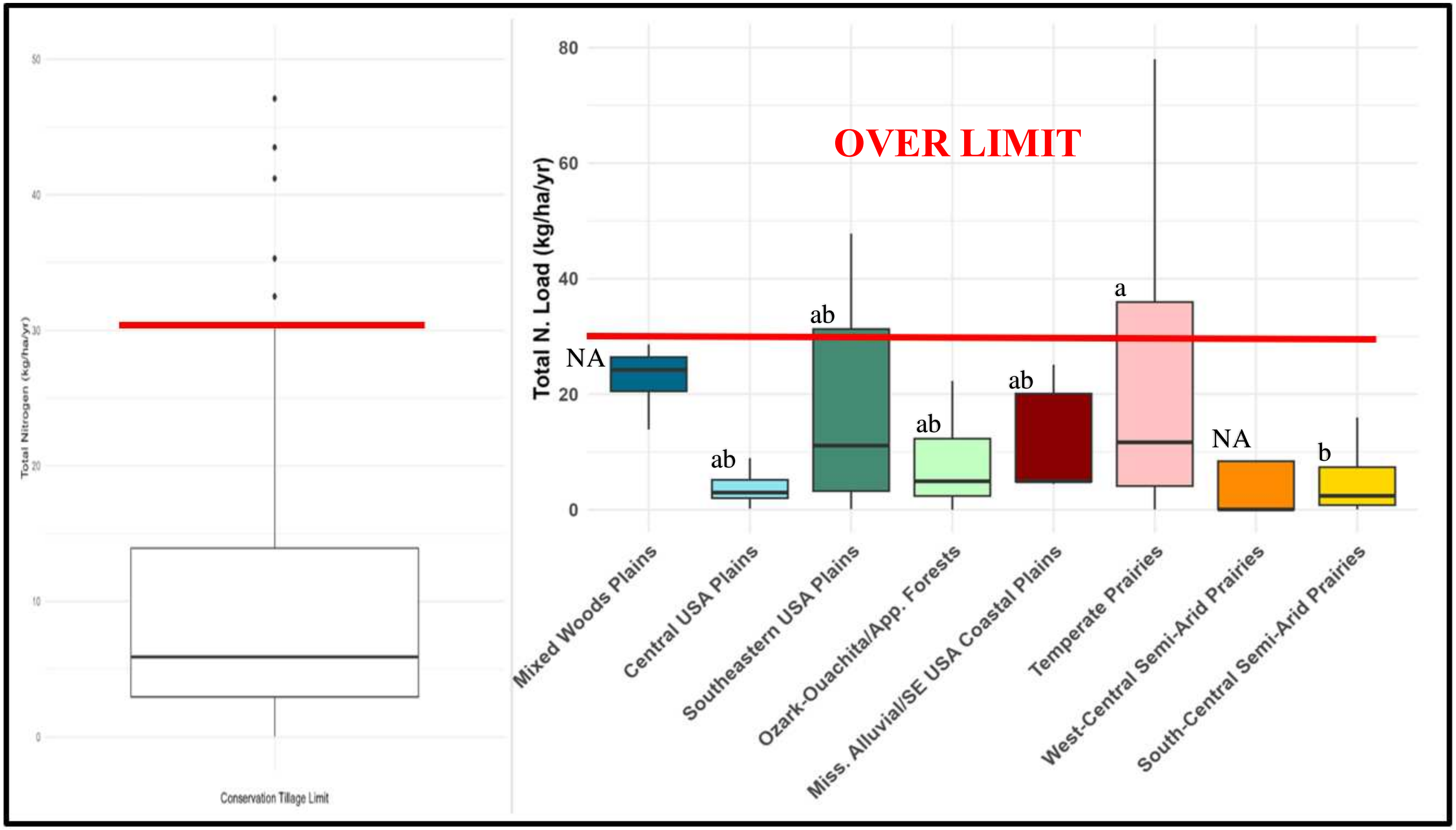

Figure 4.13. Ecoregion exceedances of the 90th percentile load of conservation tillage proposed target for total N load. Left depicts conservation tillage load range and proposed target, right depicts that target applied to the current state of observed load data across ecoregions of North America. For each constituent, median values box and whisker plots with different lowercase letters above the bars indicate statistically significant differences between treatments (α = 0.05). Statistical significance was determined using Kruskal-Wallis non-parametric tests followed by Dunn's tests. Results of statistical analysis presented only for ecoregions with more than 25 site years of data (<25 years = NA).

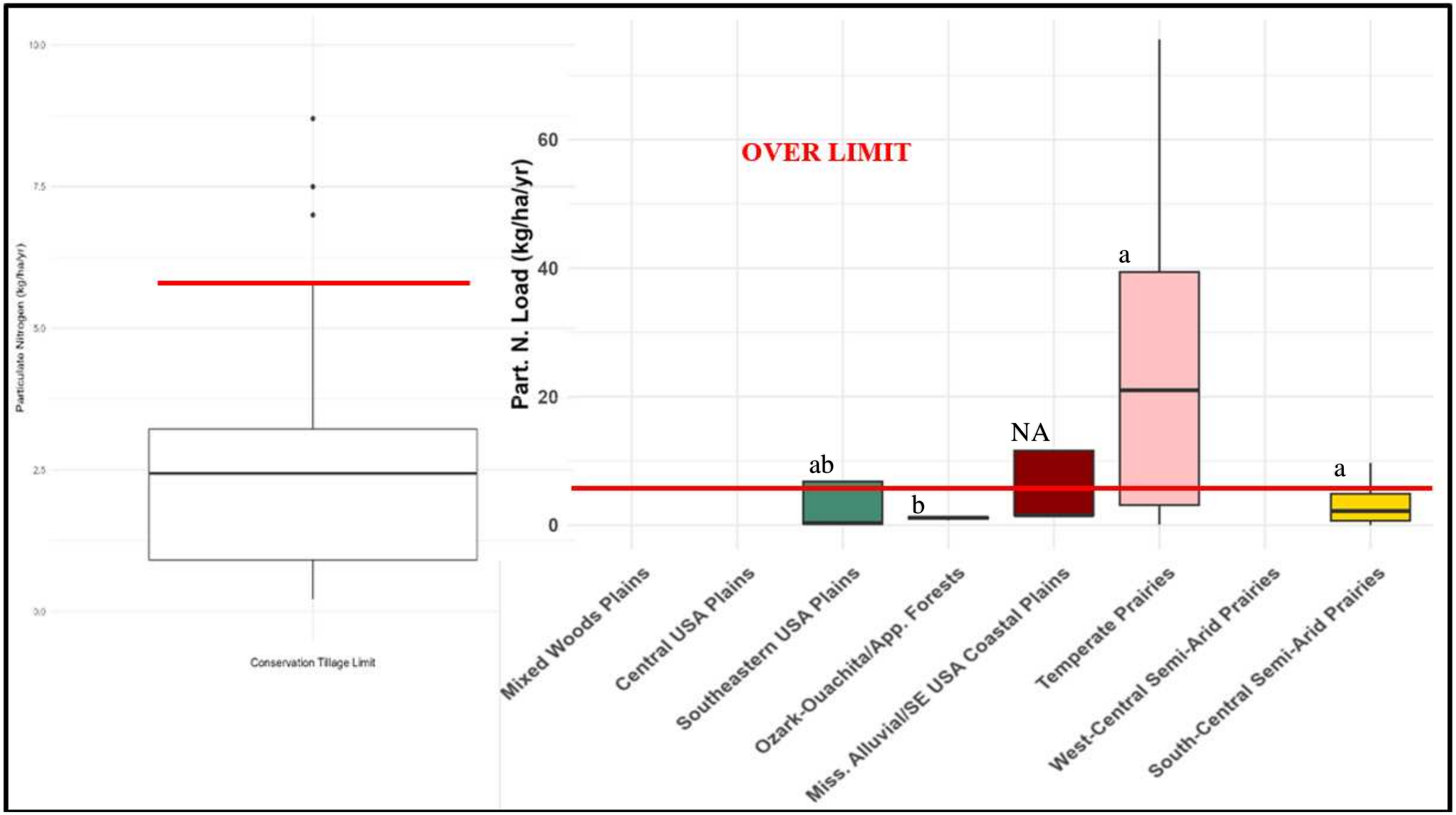

Figure 4.14. Ecoregion exceedances of the 90th percentile load of conservation tillage proposed target for particulate N load. Left depicts conservation tillage load range and proposed target, right depicts that target applied to the current state of observed load data across ecoregions of North America. For each constituent, median values box and whisker plots with different lowercase letters above the bars indicate statistically significant differences between treatments (α = 0.05). Statistical significance was determined using Kruskal-Wallis non-parametric tests followed by Dunn's tests. Results of statistical analysis presented only for ecoregions with more than 25 site years of data (<25 years = NA).

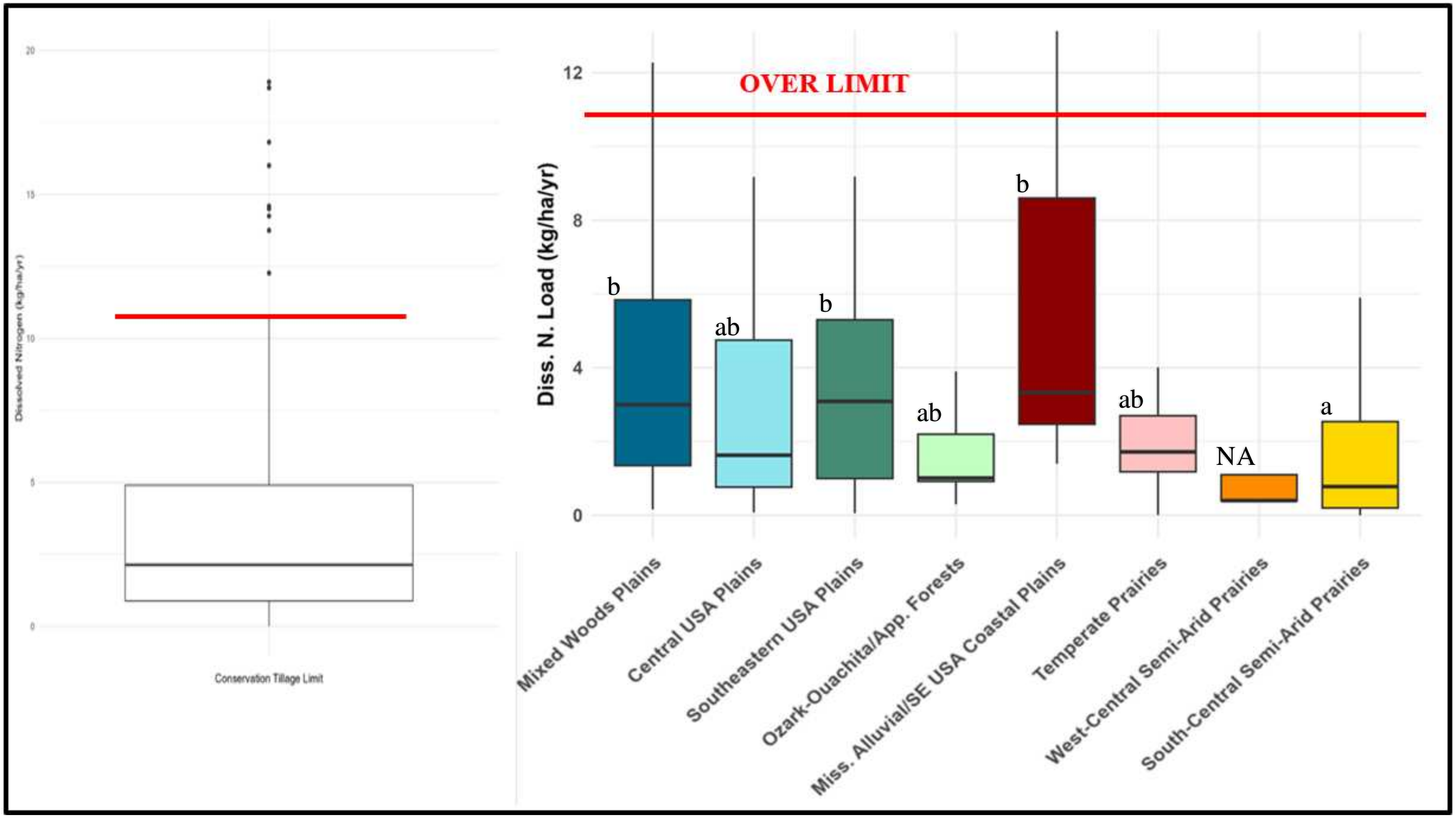

Figure 4.15. Ecoregion exceedances of the 90th percentile load of conservation tillage proposed target for dissolved nitrogen load. Left depicts conservation tillage load range and proposed target, right depicts that target applied to the current state of observed load data across ecoregions of North America. For each constituent, median values box and whisker plots with different lowercase letters above the bars indicate statistically significant differences between treatments (α = 0.05). Statistical significance was determined using Kruskal-Wallis non-parametric tests followed by Dunn's tests. Results of statistical analysis presented only for ecoregions with more than 25 site years of data (<25 years = NA).

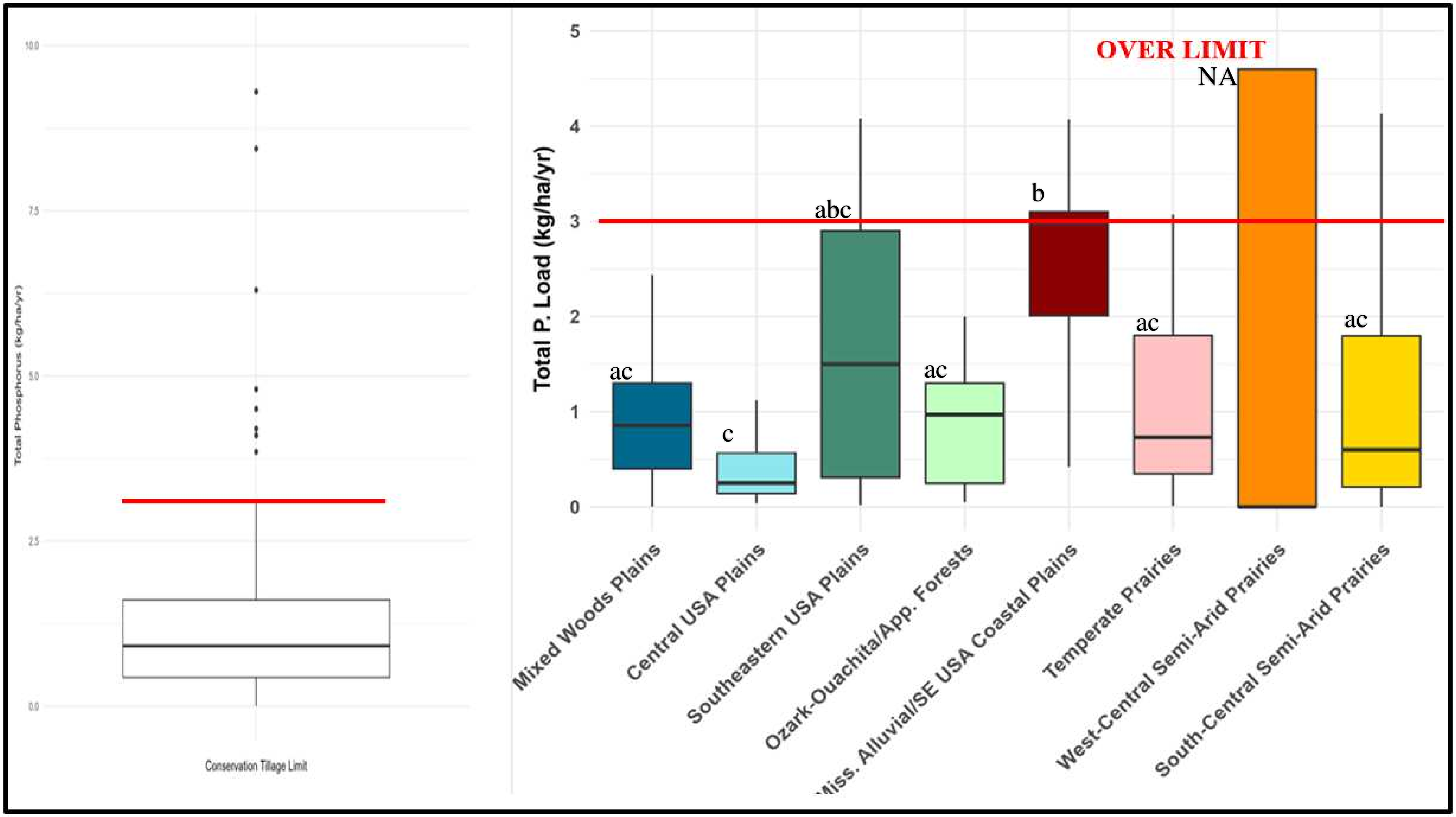

Figure 4.16. Ecoregion exceedances of the 90th percentile load of conservation tillage proposed target for total phosphorus load. Left depicts conservation tillage load range and proposed target, right depicts that target applied to the current state of observed load data across ecoregions of North America. For each constituent, median values box and whisker plots with different lowercase letters above the bars indicate statistically significant differences between treatments (α = 0.05). Statistical significance was determined using Kruskal-Wallis non-parametric tests followed by Dunn's tests. Results of statistical analysis presented only for ecoregions with more than 25 site years of data (<25 years = NA).

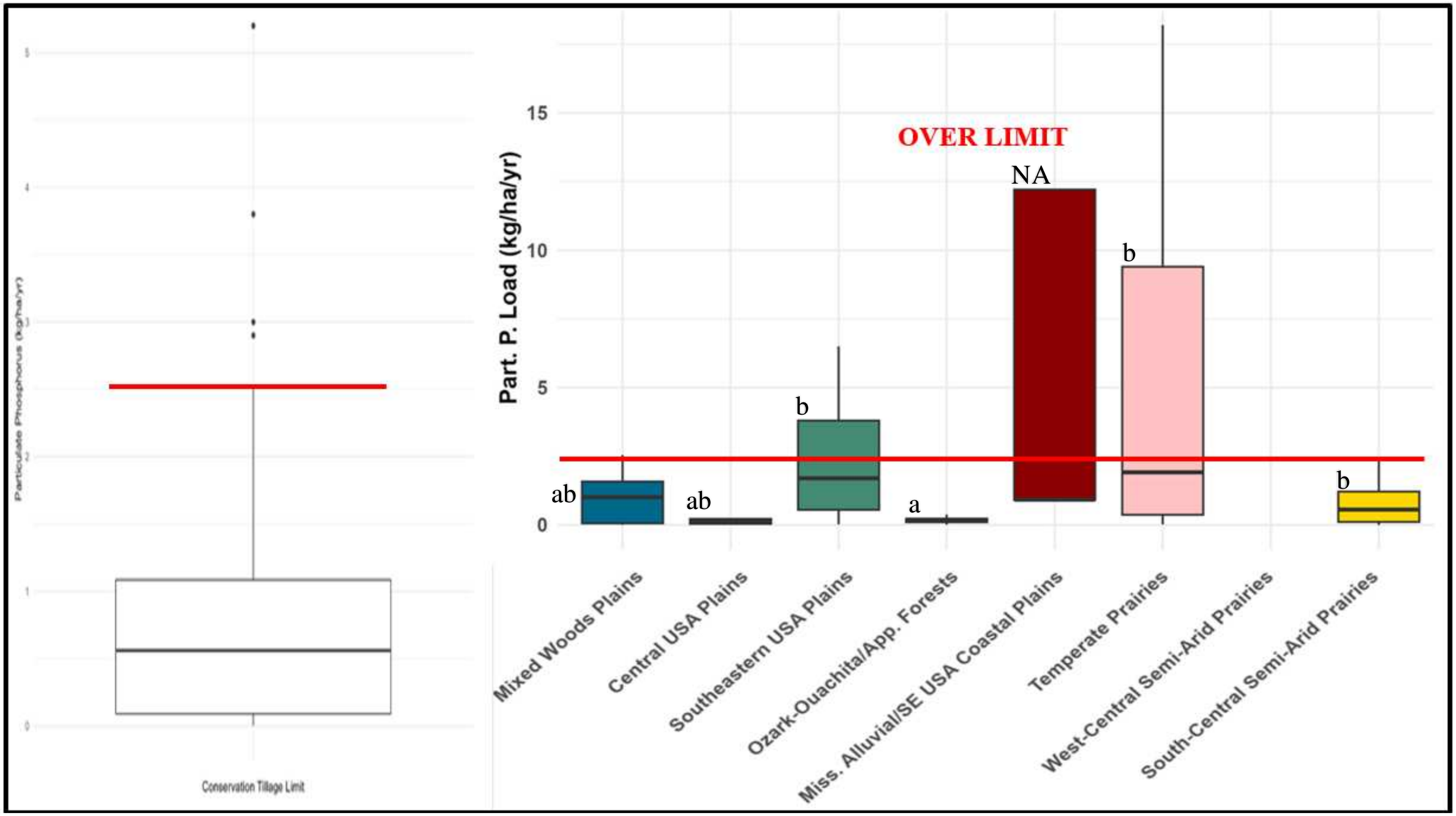

Figure 4.17. Ecoregion exceedances of the 90th percentile load of conservation tillage proposed target for particulate nitrogen load. Left depicts conservation tillage load range and proposed target, right depicts that target applied to the current state of observed load data across ecoregions of North America. For each constituent, median values box and whisker plots with different lowercase letters above the bars indicate statistically significant differences between treatments ($\alpha = 0.05$). Statistical significance was determined using Kruskal-Wallis non-parametric tests followed by Dunn's tests. Results of statistical analysis presented only for ecoregions with more than 25 site years of data (<25 years = NA).

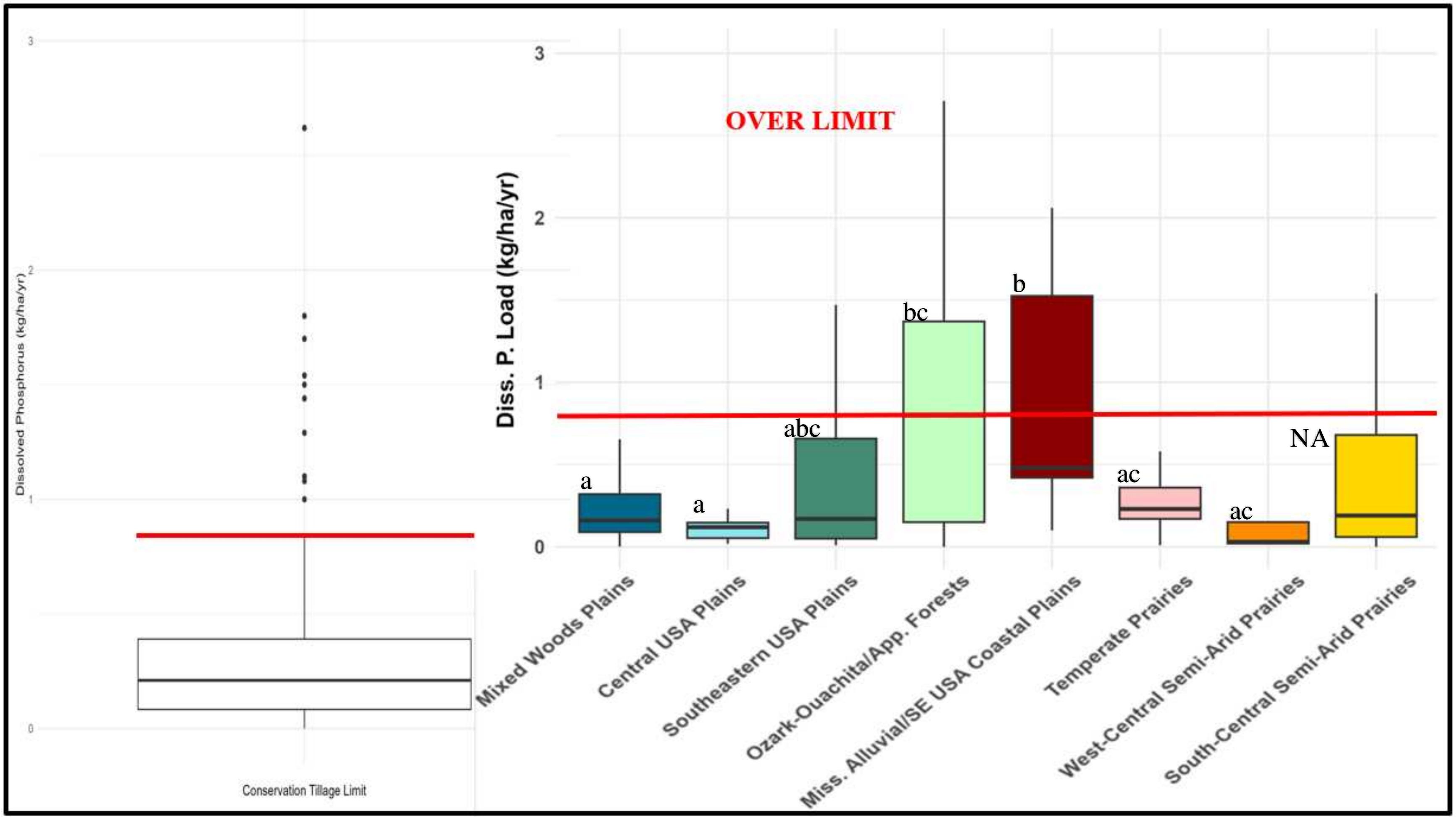

Figure 4.18. Ecoregion exceedances of the 90th percentile load of conservation tillage proposed target for dissolved phosphorus load. Left depicts conservation tillage load range and proposed target, right depicts that target applied to the current state of observed load data across ecoregions of North America. For each constituent, median values box and whisker plots with different lowercase letters above the bars indicate statistically significant differences between treatments (α = 0.05). significance was determined using Kruskal-Wallis non-parametric tests followed by Dunn's tests. Results of statistical analysis presented only for ecoregions with more than 25 site years of data (<25 years = NA).

4.3.4.2: Ecoregion Prescription Strategies to Reduce Nutrient Load Exceedances

Southeastern USA Plains (Ecoregion 8.3):

The Southeastern USA Plains had exceedances of total and particulate N as well as particulate P. The targets for those loads were 10, 6, and 2.5 kg/ha/yr, respectively. However, this ecoregion produced loads of up to 47, 7, and 7 kg/ha/yr, respectively. For total N reduction in the Southeastern USA Plains, utilizing preplant fertilizer application was shown to significantly reduce total N loads by a factor of 1.3. Due to data scarcity, no ecoregion specific recommendations were produced for the Southeastern USA Plains, but utilizing no-till and split application (at plant and side/top dress) has been shown to generally reduce particulate P by a factor of 1.73. Particulate N can similarly be reduced by preplant surface applications of N fertilizer.

Ozark-Ouachita Appalachian Forests (Ecoregion 8.4):

Ozark-Ouachita Appalachian Forests only had a single nutrient load exceedance with dissolved P. The load target was set at 0.9 kg/ha/yr, and this ecoregion produced loads up to 2.7 kg/ha/yr. There were no ecoregion specific recommendations from Table 4.7 for the Ozark-Ouachita/Appalachian Forests; however, it was shown that utilizing no-till and split fertilizer application was able to reduce overall dissolved P by a factor of 2.4. Our recommendation to this and other ecoregions would be to utilize no-till and split application (at plant and side/top dress) combinations to reduce P loss.

Mississippi Alluvial/ Southeastern USA Coastal Plains (Ecoregion 8.5):

Mississippi Alluvial/Southeastern USA Coastal Plains had the greatest number of nutrient load target exceedances, being over the target for particulate N, as well as for total, particulate, and dissolved P (Table 4.11). This ecoregion has reported annual loads up to 12.5, 4, 12, and 2 kg/ha/yr, respectively. For particulate N load reduction in Mississippi Alluvial/Southeastern USA Coastal Plains, avoiding the use of conventional tillage was one of the most significant interactions. When conventional tillage was utilized, the log particulate N increased by a factor of 2.9 times. Similarly, avoiding incorporating fertilizer can lead to a reduction of particulate N. When fertilizers are applied to the soil surface of wheat land for instance, log particulate N was typically reduced by a factor of 2.3. For P in Mississippi Alluvial/Southeastern USA Coastal Plains, avoiding preplant fertilizer applications was shown to increase log dissolved P by a factor of 0.9 times. Overall, one of the largest reduction strategies was utilizing no-till and split applications of fertilizer, leading to a load reduction by a factor of 2.4. No other ecoregion specific interaction was significant for P load reduction in the Mississippi Alluvial/Southeastern USA Coastal Plains. However, the largest successful interaction at reducing total P load was utilizing preplant and surface applications of fertilizer, reducing log total P loss by a factor of 3.6. This interaction is prioritizing not disturbing or dislodging soil particles or sorbed nutrients, keeping soil and nutrients on agricultural lands and out of waterways.

Temperate Prairies (Ecoregion 9.2):

The Temperate Prairies were often over the established load targets (Table 4.11) for total and particulate N as well as particulate P, producing load values of up to 77, 76, and 18 kg/ha/yr, respectively. For particulate N in the Temperate Prairies, avoiding the use of conventional tillage was the single largest driver of reducing particulate N load loss. When conventional tillage was utilized, load was typically increased by a factor of 0.8. This was similarly exhibited for total N. Conventional tillage and no-till increased log total N load by a factor of 2.7 and 2.6, respectively, when compared to conservation tillage. Similar to what has been previously discussed, surface applications and preplant timing of fertilizer was shown to significantly reduce total N load by a factor of 2.3 in the Temperate Prairies. Avoiding the use of conventional tillage was also key in in this ecoregion for reducing particulate P load, increasing by a factor of 1.3 when utilized.

West-Central Semi-Arid Prairies (Ecoregion 9.3):

West-Central Semi-Arid Prairies only had a single nutrient load exceedance. The total P load limit was 3 kg/ha/yr, and this ecoregion had one observation of approximately 4.7 kg/ha/yr. For total P in the West-Central Semi-Arid Prairies, there were no regionally specific interactions in Table 4.7 that were significant. However, combining conventional tillage and preplant fertilizer timing was shown to be significant for total P load reduction by a factor of 1.6. Additionally, both surface and injected fertilizer application were demonstrated to be useful in reducing loads from agricultural lands in other ecoregions like in the Mixed Woods Plains and Southeastern USA Plains.

While the above-mentioned results are specifically tailored for those ecoregions that exceeded the proposed load targets, the body of knowledge typically supports the 4R methods and their effects on agricultural efficiency and conservation. Selecting the appropriate type of fertilizer that matches the nutrient needs of the crop and soil conditions, applying the correct amount of fertilizer to ensure optimal plant growth without excess, which can lead to nutrient runoff. Timing fertilizer application to align with crop nutrient uptake periods, maximizing efficiency and reducing losses. Ensuring fertilizers are applied in a way that minimizes runoff and leaching, often through targeted application techniques.

Together, these practices promote sustainable agriculture by improving nutrient management, enhancing crop yields, and protecting water quality (Snyder, 2017). This alert of specific ecoregions that have exceeded the proposed nutrient load targets, and how to reduce those loads, will enable growers, extension, and government agencies to focus on those areas of

North America that warrant the most critical attention to stem the flow of soil and nutrients from agricultural fields to our waterways.

4.4: Conclusions

- Broad meta-analysis insights across all combined EPA level II ecoregions have value for agricultural production and soil conservation. There were several consistent and significant themes that stood out across the MANAGE database. Conservation tillage led to the greatest nutrient load (except for dissolved N), with total N and P load losses of 19.52 and 1.7 kg/ha/yr.
- Fertilizer incorporation led to the highest overall loads across all metrics measured when compared to injected or surface applications. This led to total N and P loss of 23.59 and 2.50 kg/ha/yr, respectively.
- Fertilizer application at preplant alone or a split tended to produce greater N and P loads. Compared to grass in growing season and at plant and side/top dress application, preplant methods were significantly greater with total N and P load losses of 12.29/15.97 and 2.98/0.48 kg/ha/yr.
- Land use dedicated to corn production, across all measured metrics, produced significantly greater annual N and P loads than pasture, various crop rotations, and wheat. Corn production led to total N and P losses of 33 and 1.75 kg/ha/yr, respectively.
- Many pairwise interactions were significant in their relationship towards affecting N and P load losses from agricultural lands. Conventional tillage generally increased nutrient loads when combined with surface fertilizer placement. No-Till had mixed effects, significantly reducing particulate P when combined with certain fertilizer timings. Greatly reducing the total P load when no-till was used in the Mixed Woods Plains; however, no other ecoregion

interaction was significant. For total N loads, we observed the greatest interaction effect when no-till was applied in the Temperate Prairies. Under normal circumstances, no-till traditionally reduces load; however, when utilized in the Temperate Prairies it had nearly the same effect as conventional tillage, increasing total N load 2.6 times greater than when viewed across all ecoregions. For perspective, conventional tillage increased total N load 2.7 times more when used in the Temperate Prairies ecoregion.

- These meta-analysis insights may assist in driving policy, increasing production efficiency, and providing consistency across multiple growing years as growers and land managers seek to improve their soil fertility and nutrient conservation efforts while simultaneously reducing non-point source pollution risks to large and small watersheds in North America.
- Due to data omissions within the database, reasonably accurate predictions of nutrient loads were able to be achieved with multiple linear regression models populated with data from tillage, land use, fertilizer timing, fertilizer placement, and ecoregion data, with the optimally performing model being total N having an R^2 value of 0.92 and an MAE and RMSE of 0.30 and 0.50 respectively. The best model for P was dissolved P with an R^2 of 0.78 and an MAE and RMSE of 0.24 and 0.32 respectively.

4.5: References

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Chapter 5: Conclusion And Future Directions

5.1: Summary of Findings

- The MANAGE database was started in 2006 with 1,103 site years, 40 publications, and 163 database records. The last time the MANAGE database was updated was in 2016, prior to the work completed here. The last update brought the total number of database records from 330 to 507, watershed site years from 1,980 to 3,326, and covering a total of 94 publications or studies. Additionally, all entries were assigned to an EPA level II ecoregion category. There was significant N and P runoff data available from 11 of the 50 North American level II ecoregions, which represents a large portion of U.S. agriculture. Despite the 2016 update, more data is required from future studies to both fill in the ecoregion data gap and to report additional information.
- In examining annual N and P loads in runoff from agricultural, grasslands, and croplands across ecoregions we observed several notable differences. The Temperate Prairies, which are dominated by highly erodible cultivated land, had significantly higher median annual total N loads (11.7 kg/ha/yr) than the South Central Semi-Arid Prairies (2.4 kg/ha/yr) that are dominated by grasslands. Corn production often produced higher N and P loads than other land uses in the Mixed Wood Plains, Southeastern USA Plains, and Ozark-Ouachita/Appalachian Forests. Additionally, no-till practices produced the highest dissolved P loads in the Southeastern USA Plains and Temperate Prairies, but conventional tillage had the highest dissolved P loads in the Ozark-Ouachita/Appalachian Forests. This spatial variation serves to detail that for nutrient and soil conservation there is often not a one size fits all solution.

- In the meta-analysis of common agricultural practices across high production agricultural ecoregions, we determined that some trends transcended spatial variability. Conventional tillage led to significantly greater total N load (19.52 kg/ha/yr), compared to conservation and no-till practices (5.90 and 6.80 kg/ha/yr). Incorporating N and P fertilizers typically led to significantly higher loads, for example, total N loads were greater than (23.59 kg/ha/yr) other methods such as injection or surface applications (5.35 and 3.20 kg/ha/yr respectively). Fertilizer application timings associated with preplant or out of season applications also led to typically significantly greater loads, with preplant and split (preplant and out of season) producing 12.29 and 15.97 kg/ha/yr in total N load. Lastly, corn production and to a lesser extent wheat and small grains were the most significant drivers of N and P load loss. Corn and wheat produced 33 and 5.9 kg/ha/yr load losses of total N as well as 1.75 and 0.44 kg/ha/yr of total P.
- Crop yield for both corn and wheat had significantly different results which also impacted nutrient load. Tillage produced no significant difference in crop yield; thus no-till would result in similar yields as conventional tillage. Preplant fertilizer timing led to higher crop yields compared to split (preplant and out of season). Surface fertilizer application produced half the amount of yield which was statistically different compared to incorporated and injected. For wheat, conservation tillage had a yield of 7.17 Mg/ha and conventional tillage was significantly less at 0.94 Mg/ha.
- There were many interactions that proved significant for impacting nutrient load. Conventional tillage combined with surface fertilizer significantly increased N loads across all metrics. Conventional tillage in the Southeastern USA Plains, Ozark-Ouachita/Appalachian Forests, and Temperate Prairies showed significant increases in N

loads while no-till in the Temperate Prairies also increased N load. The above-mentioned ecoregions are the Southeastern USA Plains, Ozark-Ouachita/Appalachian Forests, and Temperate Prairies, respectively. The Southeastern USA Plains receive 1342 mm of average annual rainfall and mainly consists of corn, grassland, and cotton production. The Ozark-Ouachita/Appalachian Forests receive 1287 mm of rainfall and produce mostly corn and grazing grassland. Lastly, the Temperate Prairies receive less overall rainfall (787 mm) and are dominated by corn, corn/soybean rotations, and small grain rotations. Preplant fertilizer timing in various land uses generally reduces N loads, particularly in total N.

- A model based on a limited set of categorical agricultural management decisions, namely tillage, land use, fertilizer timing and placement, and ecoregions, was able to predict the log N and P load loss reliably well compared to more establish models based on the Soil Water Assessment Tool. The optimal model was selected using forward stepwise multiple linear regression and resulted in a predicted vs actual R^2 value of 0.92 and an MAE and RMSE of 0.30 and 0.50 respectively for dissolved N. The model being

  $$\log(\mu) = \beta_0 + \beta_T T + \beta_F F + \beta_P P + \beta_L L + \beta_E E + \epsilon \qquad (1)$$

  Where $\log(\mu)$is the natural log of the nutrient load μ. β_0 is the intercept term. β_T represents the vector of coefficients for the categorical tillage variable (T). β_F represents the vector of coefficients for the fertilizer timing variable (F). β_P represents the vector of coefficients for the fertilizer placement variable (P). β_L represents the vector of coefficients for the categorical land use variable (L). β_E represents the vector of coefficients for the categorical ecoregion variable (E), and ϵ represents the error term.

- A proposed N and P load target was set based on the 90th percentile from the data range of load values produced from conservation tillage across all ecoregions. The targets were set as follows: dissolved N of 10.5 kg/ha/yr, particulate N of 6 kg/ha/yr, total N of 10 kg/ha/yr, dissolved P of 0.9 kg/ha/yr, particulate P of 2.5 kg/ha/yr, and total P of 3 kg/ha/yr. These proposed targets allowed our research to focus on specific ecoregion exceedances that warrant further attention from growers, extension, and government agencies aimed at improving agricultural efficiency and conservation. The ecoregions that had the greatest volume of exceedances were the Southeastern USA Plains, Temperate Prairies, and the Mississippi Alluvial/Southeastern USA Plains. Some of the greatest ecoregion exceedances were particulate N in the Temperate Prairies with a particulate N target of 6 kg/ha/yr; however, the median load was 22 kg/ha/yr with observations up to 77 kg/ha/yr. For particulate P, the greatest ecoregion exceedances were the Mississippi Alluvial/Southeastern USA Plains and the Temperate Prairies. The load target for particulate N was set at 2.5 kg/ha/yr. However, large portions of the data observations exhibited load values of up to 12 and 18 kg/ha/yr.
- In conclusion, what can be improved must first be tracked consistently and accurately. This research is applicable across small or large acreage farmers looking to minimize soil erosion and nutrient loss, to large governmental agencies seeking to target N and P driven nutrient pollution and water quality hazards. One of the main goals of MANAGE, to state it simply, is to manage what is at the disposal of North American stakeholders, our soils. This work details how historic big data informed by research and production can be utilized to control soil erosion and nutrient loss across ecoregions in North America. Data driven management decisions and models created from this and other publicly available

sources can aid in active big data applications. The collaboration of scientific research and agricultural production are key to optimizing land, water, and nutrient use efficiency. We are better be able to prescribe management choices and determine nutrient load loss risks given field scale soil, land, and ecological conditions with insights from data and models such as these.

5.2: Directions for Future Research

This research represents an exploratory and explanatory meta-analysis of the Measured Annual Nutrient Loads from Agricultural lands (MANAGE) database. The results and discussion found within provide insights to what practices and inherent field scale characteristics influence nitrogen and phosphorus loads in North American waterways. The work within this dissertation does not represent a comprehensive final analysis and offers potential follow up research opportunities.

First, future research should be directed at first updating the MANAGE database with qualified entries up to the current date to maintain the databases' comprehensive view of nutrient loads in North America. Additionally, data imputation based on existing data could be used to artificially fill the gaps within the database to then lend itself to a more complete modeling application.

Secondly, exploring this dataset with Bayesian statistics and modeling could unveil great insights into nutrient load management. Bayes method is especially suited to this work because it allows one to incorporate prior information about the parameters estimated. There are decades worth of data that can be used to inform the Bayesian model with, and when new research and data are available the model would be able to be updated with the new data. Bayes also provides a natural framework for quantifying and propagating uncertainty through the analysis. In large scale nutrient management, where data can be limited and uncertain, Bayes techniques offer a way to account for and communicate uncertainty. Flexibility in model specification, including complex hierarchical models, can capture the multilevel structure often present in datasets like MANAGE. Bayes allows for accounting for non-independence and spatial correlation which could be present in the data. Finally, Bayes would facilitate future management choices through prediction and decision-making. Bayes analysis can utilize probabilistic inference, allowing researchers to make predictions and decisions based on posterior distributions of model parameters. Stakeholders like the USDA-ARS, USEPA, and land managers/crop producers often need to assess the potential outcomes and associated uncertainties of different management strategies. This could be used in tandem with other models like the Soil and Water Assessment Tool to further buoy conservation efforts aimed at keeping our soil healthy and nutrients in the proper place.

Finally, additional research should be undertaken to seize machine learning (ML) and neural networks (NN) and their role in nutrient management. Given the advent of machine learning and artificial intelligence, a great portion of agricultural research pivots around these tools. Algorithms including NN are deft at detecting complex patterns and relationships in large and multidimensional datasets. With MANAGE containing a wealth of data on nutrient loads, land management practices, soil properties, and environmental conditions, ML can aid in identifying relationships and interactions that would not be readily apparent through traditional statistics. Several environmental processes and functions like nutrient cycling exhibit non-linear relationships with multiple interacting variables. NN are swiftly capable of modeling non-linear relationships, allowing them to capture complex dependencies between nutrient loads and environmental factors. ML can automatically identify relevant variable predictors from a large pool of variables and reduce the total dimensionality of the data. ML algorithms are adept at predictive tasks, making them valuable for predicting future nutrient loads given historic and field scale conditions. ML approaches can also integrate data from multiple sources including remote sensing, climate models, and geospatial data, to enhance the analysis of the MANAGE database. Seizing diverse data sets allows researchers to gain a greater understanding of nutrient cycling processes and drives. Lastly, ML algorithms are often scalable and computationally efficient, allowing researchers to analyze large volumes of data more efficiently. This is crucial for handling the extensive MANAGE database and conducting analyses at different spatial and temporal scales.

While it is more limited than the nutrient load data, data exists in sufficiently large quantities surrounding fertilizer rates applied, N and P taken up by the crops, and crop yield. A large-scale analysis of variable crop rate by fertilizer investigation could be conducted on a larger ecological scale to provide insights into improving crop yield while maximizing the efficiency of our fertilizer applications.