A SPATIAL ANALYSIS OF PHOSPHORUS IN THE MISSISSIPPI RIVER BASIN

BY

LINDA M. JACOBSON

THESIS

Submitted in partial fulfillment of the requirements
for the degree of Master of Science in Natural Resources and Environmental Sciences
in the Graduate College of the
University of Illinois at Urbana-Champaign, 2010

Urbana, Illinois

Master's Committee:

Professor Mark B. David, Director of Research
Assistant Professor Jennifer Fraterrigo
Associate Professor Emeritus Gregory F. McIsaac

ABSTRACT

Phosphorus (P) in rivers and streams in the Mississippi River Basin (MRB) is a contributing nutrient to hypoxia in the Gulf of Mexico and impacts local water quality. Although nitrogen has been extensively studied and attributed to be the main nutrient causing the Gulf hypoxic zone, P has increasingly been recognized as having more of an effect than was previously thought. The primary inputs of P to rivers and streams are through surface runoff or tile drainage from agricultural fields and from point sources, primarily sewage effluent. The objective of this study was to analyze the spatial pattern of P inputs and outputs in the MRB as they relate to riverine P yields to the Gulf of Mexico and to determine the counties in the MRB that have the highest yields of P and the most critical factors causing this P loss. A database of factors contributing P to the environment was constructed for each county in the MRB from 1997 through 2006 including data on fertilizer application, major crop acreage and harvest, animal numbers for manure inputs and human population. Landscape and climate characteristics of tile drainage, soil characteristics, slope and precipitation were also included. Riverine yields of total P (TP), dissolved reactive P (DRP) and particulate P (PP) for 113 watersheds within the MRB were related to these factors to create multiple regression and spatial error regression models to predict P yields throughout the basin. The fraction of the land planted in crops, sewage effluent P inputs and precipitation were found to best predict TP yields with a spatial error model (R^2=0.47). Dissolved reactive P yields were predicted by fertilizer P inputs, sewage effluent P inputs and precipitation in a multiple regression model (R^2=0.46), whereas PP yields were explained by crop fraction, sewage effluent P inputs and soil bulk density in a spatial error regression model (R^2=0.499). Inputs of P from animal manure were not found to be significant in any model predicting P yields, which contrasts with the results of the USGS SPARROW

model. Overall, the Cornbelt region of the upper Midwest, where there is a large amount of cropland and fertilizer application, had the counties with the greatest P yields. This analysis of P in the MRB helps to point out specific areas where P reductions are needed to limit the occurrence of Gulf hypoxia and improve local water quality.

ACKNOWLEDGEMENTS

I would like to foremost thank my advisor, Dr. Mark David, for all his help and guidance. He has taught me a great deal and his feedback was always immensely helpful. I would also like to thank my other committee members, Drs. Jennifer Fraterrigo and Greg McIsaac. I really appreciate all the time they both spent with me. Dr. Fraterrigo was always available to help with my GIS issues and statistics, and Dr. McIsaac answered my numerous questions about phosphorus. Having such a helpful committee made my research experience as a graduate student very enjoyable, and as they have all shared their knowledge with me they have helped me to become a better scientist.

In addition, I am grateful to all those in the biogeochemistry lab group for all they have done for me. In particular, thank you to Corey Mitchell and Krishna Woli for their assistance in the many tedious parts of my GIS work. Also, thank you to Jenwei Tsai for her encouragement, friendship and many baked goods; going through this graduate program with a great friend has been a real blessing. I am also thankful to Dr. Robert Darmody for his help with formatting portions of the thesis and to Dr. George Gertner for his help with the spatial regression models.

With much gratitude, I would also like to thank my parents, Bob and Janet Jacobson, and my sister, Amy Jacobson, for all their support and love. They have been there for me just a phone call away whenever I needed them. Their joy in my successes and encouragement in my trials has helped me through everything, and I am very thankful for such a wonderful family.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

Phosphorus (P) is an important element and plays a vital role in the environment. It is often a limiting nutrient for plant growth and is an essential component of DNA and RNA which store, replicate and transcribe genetic information and as a result form living organisms (Pierrou 1976). Therefore, P is necessary for both plant and animal life. Phosphorus is also present in aquatic ecosystems where it is necessary for the survival of plants and aquatic organisms. There are several forms of P that are commonly analyzed in aquatic ecosystems, such as dissolved reactive P (DRP), particulate P (PP) and total P (TP). Dissolved reactive P is defined as the portion that passes through a 0.45-μm cellulose membrane filter, while PP is the material that does not pass through a 0.45-μm filter (Broberg and Persson 1988). Total P consists of both the dissolved and particulate forms of phosphorus. Particulate P is sediment bound, and DRP, also known as orthophosphate, is the only form that is available to be taken up and used by plants, bacteria and algae (Correll 1999).

Phosphorus also has a distinct cycle. Phosphorus comes primarily from the weathering of sedimentary rocks, most notably apatite (Schlesinger 1997). Rivers, as the largest flux of P in the global cycle, carry P to the ocean where it is eventually incorporated into the sediments of the ocean. The largest pool of P in the global cycle is found in these ocean sediments. The P cycle is different from many other nutrient cycles in that the atmosphere is not a major component of the P cycle since P is not present in a gaseous phase. However, P can be transported through the air adsorbed on particles and deposited as dust. The P cycle has been altered over time with P becoming increasingly available due to the mining of phosphate rocks by humans for fertilizer. As a result of this human activity, fertilizer runoff, erosion and other pollution has greatly impacted rivers by increasing the loads of P transported by rivers (Schlesinger 1997).

As increased amounts of P have been transported to rivers and streams over time a major impact has been the creation of coastal hypoxic zones. With increased nutrient loads of both nitrogen (N) and P, eutrophication has been intensified in coastal waters (Carpenter et al. 1998, Vitousek et al. 1997 and Alexander et al. 2008). As a result of the algae growth caused by eutrophication, the oxygen level of the water is depleted when the algae die and decompose, and hypoxic conditions develop. Decomposition uses oxygen, and as the organic material is decomposed, oxygen is used faster than it can be replaced by mixing from the top layer (Rabalais and Turner 2001, Turner et al. 2006). A hypoxic zone is characterized by a concentration of dissolved oxygen that is less than 2 mg O_2 L^{-1} (Diaz 2001).

Rabalais et al. (1996) show that as primary production increases, the severity and amount of hypoxia increases. This is especially seen in the Gulf of Mexico where nutrient loads from the Mississippi River Basin have been attributed to widespread hypoxia (USEPA 2007). The Mississippi River Basin drains a large portion of the United States and various sources contribute nutrients, especially N and P, to the Mississippi River which then flows to the Gulf of Mexico. One of the main contributors of N and P is runoff from fertilizers and manures applied to agricultural fields. The use of fertilizer in the United States has increased since the 1940s and has been shown to correlate with the changing N loads in the Mississippi River (Platon et al. 2005). Conley (2000) demonstrated increasing nutrient loads in rivers that flow into estuaries with nutrient loads having increased 6-50 times for N and 18-180 times for P as compared to pristine conditions. A major governmental study performed in 1999 by the National Science and Technology Council found a significant link between N pollution of rivers and hypoxia in the Gulf of Mexico (CENR 2000). As a result, N has been extensively studied for its source, trends and effects on hypoxia.

While N has been determined to be a major contributing nutrient in the creation of hypoxia, P has been found to have an important effect on hypoxia as well (USEPA 2007). Phosphorus becomes a limiting nutrient in the coastal waters of the Gulf of Mexico in the spring and summer due to drastic changes that have occurred in the N to P ratio from excessive N loading over many years (USEPA 2007). Sylvan et al. (2006) assert that P is limiting for phytoplankton growth in the spring and summer and as a result should be included in strategies that are being developed to decrease the occurrence of hypoxia. Bierman et al. (1994) also found primary productivity to be controlled to a greater extent by P than by N in several areas of the Mississippi Delta. Therefore, P seems to have more of an effect on hypoxia in the Gulf of Mexico than was previously thought.

There are various sources contributing P to the Mississippi River throughout the MRB with mostly nonpoint sources accounting for the movement of P from both fields and pastures. In the Midwest, agriculture dominates most of the land with corn and soybeans being the predominant crops. In a nationwide analysis, the US EPA found P to enter rivers and streams from nonpoint sources due primarily to agriculture (USEPA 1998). Coming from agricultural fields, P predominantly moves due to surface runoff or tile drainage. Sharpley et al. (1994) determined runoff and erosion to be the principal means of transporting P from agricultural fields to rivers and streams. In a study performed on three streams in Illinois, tile drainage was determined to be a major source of P to surface waters with larger DRP concentrations occurring with greater discharge (Gentry et al. 2007). Tile drainage was also an important source of P export in agricultural watersheds in Delaware, Indiana and Canada (Sims 1998). Fraterrigo and Downing (2007) found the agricultural landscape to have a similar effect on P concentrations in lakes in Iowa. Total P concentrations in the lakes correlated with the amount of surrounding land dominated by agriculture as well as commercially developed land, which included industrial and residential land (Fraterrigo and Downing 2007).

A comparative watershed study performed by Domagalski et al. (2008) examined five watersheds, including two located in the MRB. A Nebraska basin with a corn-soybean rotation was used to characterize the land use of the Midwest, and a basin located in Indiana was utilized for its tile drainage. The watershed located in Nebraska exported more P relative to the amount applied than any of the other watersheds. This was explained by the highly erodible soils in the area and a large amount of surface runoff. Surface runoff was not found to be as important in Indiana due to the contribution of tile drainage (Domagalski et al. 2008). Therefore, soil type and land use, which differs between regions, has a noticeable effect on the movement of P in watersheds.

To further examine the effect of soil type and land use, the soils of pastures and cultivated areas were studied by Ballantine et al. (2009). The pasture soils sampled in this study were found to have a higher TP content than cultivated soils with organic P being the dominant form of P in pastures due to the high organic matter content and contribution of animal manure. Inorganic P was the dominant form in cultivated areas due to fertilizer application. The sediment transported by surface runoff had greater concentrations of TP than the source soils from both the cultivated and pasture land with a greater increase in TP in the sediment from the cultivated land. Deposited sediments were also analyzed and had greater P concentrations when cultivated soils were the source while P concentrations in deposited sediments from pasture source soils were variable. Therefore, land use had a greater effect for deposited sediments from cultivated soils, while soil type and physical properties had more of an effect for deposited sediments from pasture soils (Ballantine et al. 2009).

Phosphorus is transported through soils of fields and pastures and into rivers and streams mostly through surface runoff, macropore flow and matrix flow (Nash and Halliwell 1999). However, surface runoff has been found to transport the highest concentration of P (Nash and Halliwell 1999). The most important factor in the amount of P that is lost through surface runoff has been found to be the amount of water that leaves the pasture or field, not the concentration of P in the water (Burwell et al. 1975). Therefore, the amount of water in surface runoff entering rivers has the most effect on the concentration of P transported.

The occurrence of different forms of P depends on the type of transport. Particulate P is bound to soil particles and organic matter and therefore enters rivers and streams mostly through runoff and erosion. The majority (75-95%) of the P coming from runoff of conventionally tilled land consists of PP (Sharpley et al. 1994). Dissolved reactive P is not sediment bound and therefore is transported from runoff of grass or forested lands which produce less erosion (Sharpley et al. 1994). As shown by Gentry et al. (2007) the loads of DRP, PP and TP in streams depend greatly on precipitation and stream discharge. During years without major storm events resulting in high discharge, DRP consisted of 50 to 73% of the TP riverine loads, while during a wet year DRP was 35% of the TP load. Overall, concentrations of both DRP and TP rose during storm events and were significantly lower during the low flow of summer and fall. During the large discharge event, PP concentrations were two to five times greater than DRP as a result of large amounts of surface runoff and erosion into the streams. Large DRP loads were found in rivers in January 2001 due to P fertilizer that was applied to frozen soils and a precipitation event that transported the P to rivers through surface runoff. However, in most years large discharge events did not occur and most P was transported in the form of DRP to streams through tile drainage (Gentry et al. 2007).

Another important source of P within the MRB is point sources, particularly sewage effluent. Point sources were found to contribute 34% of the average annual P flux in the Gulf of Mexico and 27% of the spring flux of P over the five year period from 2001 to 2005 (USEPA 2007). The annual effluent load of TP from eight sewage treatment plants located in Illinois was measured and ranged from 8 to 1,105 tons P for the year 2004 (USEPA 2007). For the period from 1980 through 1997, 47% of the TP loads occurring in rivers in Illinois was attributed to sewage effluent (David and Gentry 2000). Sewage effluent can contribute a large amount of P to rivers and streams if limits on P concentrations for sewage effluent released from sewage treatment plants are not utilized. Therefore, rivers located in the MRB and receiving sewage effluent likely contain high concentrations of P and transport the P to the Gulf of Mexico.

Due to increased nutrients in the MRB and Gulf of Mexico, hypoxia has become a greater issue and work has been done in an attempt to limit the occurrence of hypoxia. The Mississippi River Gulf of Mexico Watershed Nutrient Task Force created an Action Plan in which goals for reduction of N and P were developed in an effort to reduce the size of the hypoxic zone (Mississippi River/Gulf of Mexico Watershed Nutrient Task Force 2008). The major goals consist of reducing both total N and total P loads in rivers by 45% to decrease the size of the hypoxic zone in the Gulf of Mexico to 5000 square kilometers averaged over five consecutive years by 2015. Various stakeholders are involved in the plan and are expected to make changes to limit nutrient loss into the Mississippi River. Also, the winter and spring months (January through June) were determined to contribute the nutrient loads which create the hypoxic zone in the Gulf of Mexico in the spring and summer. Therefore, the winter and spring months are an important focus for nutrient load reductions. Further research will also be performed to monitor the hypoxic zone and to further understand the role of N and P in hypoxia (Mississippi

River/Gulf of Mexico Watershed Nutrient Task Force 2008). In order to achieve these goals, a more extensive study of the location and cause of the loss of P to the Mississippi River is necessary. Therefore, the objectives of this study were to analyze the spatial pattern of P inputs and outputs in the MRB as they relate to riverine P yields to the Gulf of Mexico and to determine the counties in the MRB that have the highest yields of P and the most critical factors causing this P loss.

MATERIALS AND METHODS

Data Sources

A ten year data set from 1997 through 2006 of factors contributing P to the environment was constructed for each county in the MRB (1,768 counties). The National Agricultural Statistics Service (NASS) provided data on the acres of crops planted and amount of biomass produced each year in every county for corn, soybean, wheat (*Triticum aestivum* L.), rice (*Oryza sativa* L.), cotton (*Gossypium gursutum* L.) and sorghum (*Sorghum bicolor* (L.) Moench) (USDA 2008). The crop fraction for each county was calculated as the percent of the county that was planted in these crops. Alfalfa (*Medicago sativa* L.) and other hay acres planted and biomass produced were also available from NASS data (USDA 2008). The number of animals including hogs, cattle, broilers, layers and turkeys were available from county level data from the 1997 and 2002 Census of Agriculture, which was used to interpolate animal numbers for the remaining years for my ten year study period (USDA 2008). Fertilizer P inputs for each county were estimated from yearly states' sales of P fertilizer (AAPFCO 2008) and then estimated at the county level using Census of Agriculture fertilizer expenditure data from 1997 and 2002 (USDA 2008), interpolating for the other years. Human population numbers were from the US Census Bureau (US Bureau of the Census 2008).

Phosphorus Estimates

The production amounts for the crops were utilized to obtain the amount of P harvested each year for every crop. The estimated rate of P removed for harvested corn, soybean, wheat, sorghum, alfalfa and hay were 0.068 kg P bushel^{-1}, 0.163 kg P bushel^{-1}, 0.091 kg P bushel^{-1}, 0.082 kg P bushel^{-1}, 2.1 kg P ton^{-1} and 6.94 kg P ton^{-1}, respectively (Goolsby et al. 1999). The estimated rate of P harvested in rice and cotton was calculated from the USDA Crop Nutrient Tool, and the rate was 0.115 kg P hundred weight^{-1} for rice and 0.862 kg P bale^{-1} for cotton (USDA, NRCS 2010). The amount of P harvested in each of the crops for each county was found by multiplying these conversion factors by the amount of the crop harvested and dividing by the area of the county.

The amount of P in animal manure was calculated with estimates made by Goolsby et al. (1999). Hogs, cattle, broilers, layers and turkeys were estimated at 0.012, 0.053, 0.0003, 0.0006 and 0.0013 kg P day^{-1}, respectively (Goolsby et al. 1999). These values were multiplied by the number of animals in each county for each year to obtain the amount of P contributed through animal manure for each animal.

The amount of P consumed by humans in each county was estimated by multiplying the population in the year 2000 in each county by 0.46 kg P yr^{-1}, the per capita value of P consumed by humans (David and Gentry 2000).

Phosphorus Balances

A P balance, called net P inputs was calculated based on the database. The components of the P balance were crop P harvested, animal manure P, human consumption of P and fertilizer P. Crop P harvested was the sum of corn, soybean, wheat, sorghum, rice and cotton P harvested. Animal manure P consisted of the sum of hog, cattle, broiler, layer and turkey manure P. The net P inputs were calculated as (fertilizer P + animal manure P + human consumption of P) – (crop P harvested).

Landscape and Climate Characteristics

Tile drainage, soil bulk density, soil clay content, slope and precipitation were obtained or estimated for each county. The percent of each county that is tile drained was obtained from Sugg (2007) which was based on the locations of row cropped areas and poorly drained soils. Changes to the data where tile drained estimates seemed too low were made in a few counties in Illinois and Minnesota based on a map of tile drainage in Illinois in 1913 and a discussion with a state expert for Minnesota (G.W. Randall, personal communication, 2007). The soil bulk density and clay content were obtained from the DNDC model developed by Li (2010).

The average slope was calculated from Digital Elevation Models (DEMs) using GIS. DEMs at 1 arc second (30 meter resolution) were downloaded for each state from the USGS *The National Map* Seamless Server (USGS 2010) and projected to the Universal Transverse Mercator (UTM) projection based on the UTM zone of the state's location. If a state was located in more than one UTM zone, the DEM was clipped and projected according to each zone. A raster of the percent slope was created in GIS with the Spatial Analyst tool from the projected DEMs for each state. The mean percent slope of each county was then calculated with the Spatial Analyst tool through zonal statistics. For counties that were located in multiple UTM zones, the slopes for each UTM zone in the county were averaged to obtain the mean percent slope.

Precipitation data were obtained from Daymet as an 18 year mean of total annual precipitation from the years 1980 through 1997 in a grid form at one kilometer resolution for the entire United States (Thornton et al. 1997). Using GIS, the precipitation data were averaged by county using zonal statistics.

Riverine P Concentrations and Yields

A subwatershed analysis was conducted using 113 unique watersheds located throughout the MRB. A watershed was considered to be unique if its boundaries were not within the boundaries of another watershed. Flow and P concentration data for each watershed were utilized to calculate yield estimates from 1997 to 2006 for January 1st to June 30th. The months from January to June were chosen to show the winter/spring time period, which is the time period that contributes nutrients that cause the hypoxic zone in the Gulf of Mexico. Flow data were available from the USGS, and TP and DRP data were from the USGS and the USEPA STORET database (USGS 2010, USEPA 2009). I only selected those sites for which there was continuous flow data available from the USGS and at least 3 TP concentrations between January and June for the majority of the years during the 1997 to 2006 time period. However, data collection varied by state and year with some years having more concentration data available than others. There were typically about 40 TP concentration measurements at each location. Total P was measured at 101 of the 113 sites, and DRP was measured at 73 of the 113 sites. Particulate P (PP) concentrations were calculated by subtracting the DRP concentration from the TP concentration, and PP concentrations were measured at 61 sites. The TP, DRP and PP concentrations were averaged for the six month period, multiplied by the average flow during the six months from 1997 to 2006 and then divided by the watershed area to obtain an estimate of the yield. Watersheds were also chosen to be a variety of areas, and the range in watershed size in this analysis was from 79 to 50,360 km^2, and the median watershed area was 1,994 km^2. The watershed boundaries were delineated using GIS by clipping and merging the HUC8 or HUC12 watersheds that contained the flow path of the river up to the point of data collection.

Modeling

Models were created to relate the independent variables to the yields of TP, DRP and PP of the unique watersheds. Estimates of the independent variables averaged from 1997 through 2006 were made for each unique watershed using GIS. A weighted average of the variables was calculated based on the area of each county that was located in the watershed. The important independent variables were compared for the counties in the MRB and the 113 unique watersheds to verify that these watersheds were representative of the entire basin. Correlation analysis was utilized to analyze correlation between the independent variables and the January to June yields of TP, DRP and PP for each unique watershed. The independent variables that were found to be highly correlated with the watershed TP, DRP and PP yields were used in creating models.

Several statistical models were developed. All models were run using the TP, DRP and PP yield data with and without a square root transformation in an attempt to correct for the non-normality of the yield data. Multiple regression models were constructed for the TP, DRP and PP yields, using the SAS PROC REG procedure. I then examined whether the residuals of each model were spatially autocorrelated to determine the need for spatial regression models using GeoDa (Anselin et al. 2006).

Spatial autocorrelation of the residuals of the multiple regression models was examined with the global Moran's I. The equation for the Moran's I follows:

$$I = \frac{n}{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}}$$

where n is the number of units, X is the residual value, $\overline{X}$ is the mean of the residuals and W_{ij} is the weight matrix. The rook contiguity spatial weights matrix created by GeoDa was used in this analysis. In rook contiguity, neighbors are defined by sharing a common boundary.

I examined two formulations of spatial regression models to account for spatial autocorrelations: a spatial lag model and a spatial error model. The spatial lag model accounts for spatial trends in the data by incorporating an autocorrelation term in the regression model structure, while the spatial error model does so by incorporating an autocorrelation term in the error term. The spatial lag model follows the equation below:

$$Y = X\beta + \rho WY + \varepsilon$$

where Y is the yield of TP, DRP or PP (dependent variable), X is the independent variable, β is the regression coefficient, ρ is the spatial autoregression coefficient, W is the spatial weight matrix, WY is the spatially lagged dependent variable and ε is the random error term.

The spatial error model follows:

$$Y = X\beta + \varepsilon \qquad \varepsilon = \lambda W\varepsilon + \xi$$

where Y is the yield of TP, DRP or PP (dependent variable), X is the independent variable, β is the regression coefficient and ε is the random error term where λ is the spatial autoregression coefficient, W is the spatial weights matrix, $W\varepsilon$ is the spatially lagged error term and ξ is the independent error term.

The multiple regression models and spatial lag and error models were compared to determine which best fit the data to show the most critical factors controlling riverine P yields. The best model based on having the highest R^2 and log likelihood values and the lowest Akaike's information criterion (AIC) value for each constituent was then applied to each county in the MRB, and TP, DRP and PP yields for each county were visualized using GIS.

RESULTS

County Level Characteristics

Inputs of fertilizer P were greatest in the Cornbelt of the MRB (Figure 1). This is where the largest crop fraction was located (Figure 2) with the crops predominantly in a corn and soybean rotation which is highly characteristic of the Midwest. The percent of tile drainage was also greatest in the Cornbelt region (Figure 3) due to the need to artificially drain the poorly drained soils of the area. The Pearson correlation coefficients (Table 1) further demonstrated the relationship between these variables with fertilizer P inputs and crop fraction highly correlated ($r=0.89$, $p<0.0001$) as well as the percent of tile drainage significantly correlated with fertilizer P inputs ($r=0.54$, $p<0.0001$) and crop fraction ($r=0.47$, $p<0.0001$). Crop P harvested was also highly correlated with crop fraction ($r=0.95$, $p<0.0001$), fertilizer P inputs ($r=0.92$, $p<0.0001$) and tile drainage ($r=0.57$, $p<0.0001$) as would be expected. Therefore, fertilizer can be used as an indicator of row crop intensity.

Animal manure P inputs were greatest in the western part of the MRB (Figure 4) where there is little rainfall. Human P consumption was greatest near large cities but otherwise did not show any spatial trends (Figure 5). Net P inputs were greatest in the western part of the MRB and negative in Illinois (Figure 6). Animal manure P inputs and net P inputs were highly correlated ($r=0.81$, $p<0.0001$; Table 2) which explains their similar spatial trends. Net P inputs were significantly correlated ($p<0.0001$) with crop fraction and crop P harvested, but the association was low ($r=-0.1$ and -0.14, respectively). Net P inputs were not correlated with fertilizer P inputs and human P consumption. Therefore, many of the counties with high net P inputs had large animal manure P inputs, rather than fertilizer or effluent sources.

Subwatersheds' Yields and County Level Characteristics

The TP, DRP and PP yields for the subwatersheds were variable throughout the MRB (Figures 7, 8 and 9). The yield for the subwatersheds ranged from 0 to 1.27 kg P ha^{-1} for TP, 0 to 0.4 kg P ha^{-1} for DRP and 0 to 1.04 kg P ha^{-1} for PP. For the most part, all three yields were greatest in the Cornbelt region and lowest along the eastern and western edges of the MRB.

The TP, DRP and PP yields for the subwatersheds were related to the county level characteristics averaged for the subwatersheds as shown with Pearson correlation coefficients (Table 3). Crop fraction and fertilizer P were highly correlated with the TP yields (r=0.37 and r=0.36, respectively, p<0.0001). Crop fraction was also significantly correlated with the yields of DRP (r=0.24, p=0.04) and PP (r=0.3, p=0.02), while fertilizer P inputs were significantly correlated with DRP yields (r=0.29, p=0.01). Crop P harvested was significantly correlated with all yields of P but most highly correlated with the yield of TP (r=0.36, p=0.0003). Tile drainage fraction was only significantly correlated with the yield of TP (r=0.26, p=0.0099).

Animal manure P inputs were significantly correlated with the yields of TP (r=0.3, p=0.0024) and DRP (r=0.27, p=0.023) but were not significantly correlated with PP yield (r=0.03, p=0.84). Human P consumption was significantly correlated with TP (r=0.34, p=0.0006), DRP (r=0.27, p=0.023) and PP (r=0.39, p=0.0019) yields and had greater correlations than animal manure P inputs. The net P inputs in the MRB were not significantly correlated with TP, DRP or PP yields.

The percent slope of the subwatersheds was highly negatively correlated with the subwatersheds' yields of TP (r=-0.34, p=0.0005), DRP (r=-0.31, p=0.0071) and PP (r=-0.34, p=0.007). Precipitation was highly correlated with yields of TP (r=0.31, p=0.0019) and DRP (r=0.36, p=0.0015) and was not significantly correlated with PP yield (r=0.21, p=0.1035). The percent clay and the bulk density of the soils of the subwatersheds were both highly correlated with the yield of PP (r=0.38, p=0.0023 and r=0.36, p=0.0046, respectively). Percent clay was also significantly correlated with TP yield (r=0.29, p=0.0037), and bulk density was also significantly correlated with DRP yield (r=0.29, p=0.0114). The areas of the watersheds were significantly negatively correlated with DRP yields (r=-0.33, p=0.0047) but not with TP (r=-0.12, p=0.2299) or PP yields (r=-0.08, p=0.5656).

Modeling Distributions

To determine that the subwatersheds used as the model for the MRB were representative of the MRB, the distribution of the county characteristics was compared to the characteristics averaged for the watersheds (Table 4). The median values were similar between the model and MRB for most of the characteristics. However, the entire MRB had a median crop fraction that was about double the crop fraction for the modeled watersheds, but the rest of the distribution was similar. The distributions and medians for the other characteristics were similar, but the maximum was greatest for the MRB counties for all the characteristics except for the bulk density, which was less than but close to the model maximum. The minimums were predominantly the same for the model and MRB characteristics with the exception of precipitation having a noticeably smaller minimum for the model and clay having a noticeably smaller minimum for the MRB. Even with these differences, the model watershed characteristics compared well to the overall MRB and are assumed to be representative of the entire basin.

The distribution of the areas for the watersheds of the model ranged from 79 to 50,360 km^2 with a median of 1,994 km^2. The flows for the watersheds ranged from 0.1 to 58.8 cm with a median of 16.8 cm. The variability in the watershed areas and flows created a random sample of watersheds that would be representative of the MRB. The watersheds had median yields of 0.23, 0.09 and 0.20 kg P ha^{-1} for TP, DRP and PP, respectively.

Ordinary Least Squares Multiple Regression Models

Many ordinary least squares multiple regression models were created to predict TP, DRP and PP yields from the county characteristics of P inputs and landscape and climate factors. For non-transformed TP yields, human P consumption, crop fraction and precipitation gave the best fit model with all three factors significant at the 0.01 probability level and an R^2 of 0.355 (Table 5). A square root transformation of the TP yields was then utilized to better meet the normality and heteroskedasticity assumptions of the multiple regression model. The same variables were used in the multiple regression model, and there was no change in their significance (Table 6). The R^2 increased to 0.432.

The DRP yields were best predicted by human P consumption, fertilizer P inputs and precipitation in the multiple regression model (Table 7). In this model, human P consumption was significant at the 0.05 probability level, and fertilizer P inputs and precipitation were significant at the 0.01 probability level. The R^2 of the model was 0.273. With a square root transformed DRP yield, the variables had the same significance, and the R^2 of the model improved to 0.46 (Table 8).

The best fit multiple regression model to predict the PP yields contained human P consumption, crop fraction and bulk density (Table 9). Human P consumption and crop fraction were both significant at the 0.01 probability level, whereas bulk density was not statistically significant. The R^2 of the model was 0.329. Using a square root transformation for the PP yield, human P consumption and crop fraction remained significant, and bulk density became significant at the 0.05 probability level (Table 10). The R^2 also increased to 0.373.

The Jarque-Bera test and Breusch Pagan test were used to determine the normality and heteroskedasticity of the residuals of the ordinary least squares multiple regression models (Table 11). The Jarque-Bera test and Breusch Pagan test were both significant at the 0.01 probability level for the non-transformed TP yield multiple regression model indicating a non-normal distribution of the residuals as well as the presence of heteroskedasticity, or a non-constant error variance. Using the square root transformation for the TP yields improved the normality of the residuals, since the Jarque-Bera test became significant only at the 0.05 level. A constant variance of the error was also achieved as the Breusch Pagan test was not statistically significant.

The multiple regression model for the DRP yield was significant at the 0.01 probability level for both the Jarque-Bera and Breusch Pagan tests, while the square root transformed DRP yield remained significant at the 0.01 probability level for the Jarque-Bera test and was not statistically significant for the Breusch Pagan test. Therefore, the normality of the residuals did not seem to be improved, but the assumption of constant error variance was reached with the square root transformation.

The Jarque-Bera test was significant at the 0.01 probability level for the non-transformed PP yield multiple regression model, and the Breusch Pagan test was significant at the 0.05 probability level. With the square root transformation, neither test was significant, indicating a normal distribution of the residuals and the removal of heteroskedasticity, meaning a constant variance of the error.

To test for spatial dependence in the residuals of the ordinary least squares multiple regression models, the Moran's I was analyzed and Lagrange Multiplier Lag and Error diagnostics were utilized (Table 12). The Moran's I tests for spatial autocorrelation in the residuals, and the Lagrange Multiplier Lag and Error test statistics were used to help determine the use of either the spatial lag or spatial error model. For the non-transformed TP yield multiple regression model, the Moran's I had a value of 0.068 and was not significant, which indicated that the residuals were not spatially autocorrelated. However, the Lagrange Multiplier Lag test was significant at the 0.05 probability level, so the use of the spatial lag model may be appropriate. The square root transformed TP yield multiple regression model also did not have spatially autocorrelated residuals with a Moran's I value of 0.096, which was not statistically significant. The Lagrange Multiplier Lag test was significant at the 0.05 probability level; therefore, the spatial lag model should be used for the square root transformed TP yields as well.

The non-transformed and square root transformed DRP yield multiple regression models had the same spatial dependence results. Both had Moran's I scores that were not statistically significant, indicating that the residuals of the models were not autocorrelated. The Lagrange Multiplier Lag and Error tests were also not statistically significant for both models, which meant that a spatial regression model should not be necessary in predicting the DRP yield.

The non-transformed PP yield multiple regression model had a Moran's I score of 0.145, which was significant at the 0.05 probability level. Therefore, the residuals of the model were spatially autocorrelated and a spatial regression model would be necessary to remove the spatial autocorrelation in the residuals. The Lagrange Multiplier Error test was significant at the 0.05 probability level, while the Lagrange Multiplier Lag test was not statistically significant. As a result, this test shows the spatial error model to be the best spatial regression model to use in predicting the PP yield. The multiple regression model for the square root transformed PP yield had a Moran's I score of 0.218, which was significant at the 0.01 probability level. The Lagrange Multiplier Error test was significant at the 0.01 probability level and the Lagrange Multiplier Lag test statistically was not significant, which resulted in the conclusion to utilize the spatial error model for the square root transformed PP yield model as well.

Spatial Regression

Both the spatial lag and spatial error models were created to predict the TP, DRP and PP yields despite the results of the Lagrange Multiplier Error tests to ensure that the best model was utilized. For the non-transformed TP yields, the spatial lag model added a spatial lag term with the coefficient ρ, which indicated the spatial dependence of the data. Since ρ was positive and significant at the 0.01 probability level, it helped to improve the fit of the model (Table 13). The spatial error model added a spatially correlated error term with the coefficient λ. The λ coefficient was also positive and significant at the 0.01 probability level, improving the model fit from the ordinary least squares multiple regression model. The spatial lag and spatial error models had the same R^2 (0.388), and the spatial lag model had a slightly larger log likelihood, while the spatial error model had a lower AIC value. Compared to the multiple regression model, both spatial models had larger R^2 and log likelihood values and smaller AIC values indicating the need for a spatial regression model to improve the model fit.

The square root transformed TP yields had a positive ρ value that was significant at the 0.01 probability level for the spatial lag model as well as a positive λ value also significant at the 0.01 probability level for the spatial error model (Table 14). However, in contrast to the results of the non-transformed TP yield spatial regression models, the spatial error model for the square root transformed TP yields had a larger R^2 and log likelihood and a smaller AIC than the spatial lag model. Both spatial models for the square root transformed TP yields were better fits than the multiple regression model for the square root transformed TP yields with larger R^2 and log likelihood and lower AIC values. The square root transformed TP yield spatial models were also better fits than those for the non-transformed TP yields as they had larger R^2 and log likelihood values and lower AIC values.

The spatial lag and spatial error models for the non-transformed DRP yield did not improve the fit of the multiple regression model as was expected (Table 15). The ρ value was not statistically significant in the spatial lag model, and the R^2, log likelihood and AIC values were very similar to those in the multiple regression model. While the λ value in the spatial error model was positive and significant at the 0.01 probability level, the R^2, log likelihood and AIC values were also not much larger than those for the multiple regression model.

The square root transformed DRP yield spatial models also were not necessary to improve the fit of the model (Table 16). The ρ value in the spatial lag model was not significant, and the R^2, log likelihood and AIC values of both the spatial lag and error models were similar to those of the multiple regression model for the square root transformed DRP yields.

For the PP yields, the non-transformed data had positive ρ and λ values that were significant at the 0.01 probability level for the spatial lag and error models, respectively (Table 17). The spatial error model had a larger R^2 and log likelihood and lower AIC than the spatial lag model as well as the multiple regression model, indicating that the spatial error model was a better fit.

The square root transformed PP yields also had positive ρ and λ values with ρ significant at the 0.05 probability level and λ significant at the 0.01 probability level (Table 18). The spatial error model had a larger R^2 and log likelihood value and a lower AIC value than the spatial lag model as well as the spatial models for the non-transformed PP yields. Therefore, the spatial error model using square root transformed PP yields was the best fit model for the PP yields.

Heteroskedasticity and spatial dependence of the residuals for the spatial models were tested with the Breusch Pagan test and the Moran's I, respectively (Table 19). Since the Breusch Pagan test was significant at the 0.01 probability level for both spatial models for the non-transformed TP yields, heteroskedasticity was not removed. However, the square root transformed TP yield spatial models were not significant in the Breusch Pagan test, so heteroskedasticity was removed by using the transformation. The Moran's I values for the square root transformed TP yields were reduced from the multiple regression model with the spatial lag Moran's I value closest to zero. This indicates a reduction in spatial autocorrelation.

For the DRP yield spatial models, heteroskedasticity remained for both non-transformed DRP yield spatial models and the square root transformed DRP yield spatial lag model. Heteroskedasticity was removed in the square root transformed DRP yield spatial error model. The Moran's I values were reduced for all the DRP spatial models as compared to the multiple regression model.

In the non-transformed PP yield spatial lag and error models, heteroskedasticity was not removed. However, heteroskedasticity was removed in the square root transformed PP yield spatial lag and error models. The Moran's I values were smaller for all the spatial models for PP yields compared to the multiple regression models with the square root transformed spatial error model Moran's I value closest to zero.

Models Applied to the MRB

The spatial error regression model was chosen to best predict the yield of TP, the ordinary least squares multiple regression model for the yield of DRP and the spatial error regression model for the yield of PP. The models all used the square root transformation as it helped to better meet the statistical assumptions of regression. For the TP yield the model was:

$$\text{TP Yield (January to June kg P ha}^{-1}\text{)} = \\ 0.116 + 0.139 \times \text{Human P} + 0.004 \times \text{Crop Fraction} \\ + 0.002 \times \text{Precipitation} + 0.789 \times W\varepsilon$$

The model for the DRP yield was:

$$\text{DRP Yield (January to June kg P ha}^{-1}\text{)} = \\ -0.003 + 0.063 \times \text{Human P} + 0.016 \times \text{Fertilizer P} + 0.002 \times \text{Precipitation}$$

For the PP yield the model was:

$$\text{PP Yield (January to June kg P ha}^{-1}\text{)} = \\ -0.322 + 0.162 \times \text{Human P} + 0.003 \times \text{Crop Fraction} \\ + 0.491 \times \text{Bulk Density} + 0.847 \times W\varepsilon$$

The chosen models were applied to each county in the MRB to show the predicted TP, DRP and PP yields (Figures 10, 11 and 12, respectively). The classes in the figures showed the number of counties with the highest yields with the three largest classes having about 100 counties in each, the fourth class having about 400 counties and the last class having about 1,050 counties.

Predicted TP yields were highest in the Midwestern Cornbelt region through southern Minnesota, Iowa, Illinois, Indiana and Ohio. There were also large TP yields predicted in counties along the Mississippi River in the southern part of the MRB in Arkansas, Louisiana, Tennessee and Mississippi. The lowest predicted TP yields were in the counties in the western part of the MRB as would be expected due to their small crop fraction.

The spatial distribution of the predicted DRP yields was similar to that of the predicted TP yields. Predicted DRP yields were largest in the Cornbelt region of the MRB, particularly in Illinois, Indiana and Ohio. There were also some counties with large predicted DRP yields in Louisiana near the Gulf of Mexico. The smallest predicted DRP yields were in the western and eastern regions of the MRB.

The predicted PP yields had a more variable spatial distribution. The largest predicted PP yields were in the Cornbelt, but there were fewer counties with high values in that area as compared to the predicted TP and DRP yields. The lowest predicted PP yields were along the western and eastern border of the MRB; however Nebraska, Kansas and Oklahoma had more counties with larger predicted PP yields than was predicted for TP or DRP yields.

Figures and Tables

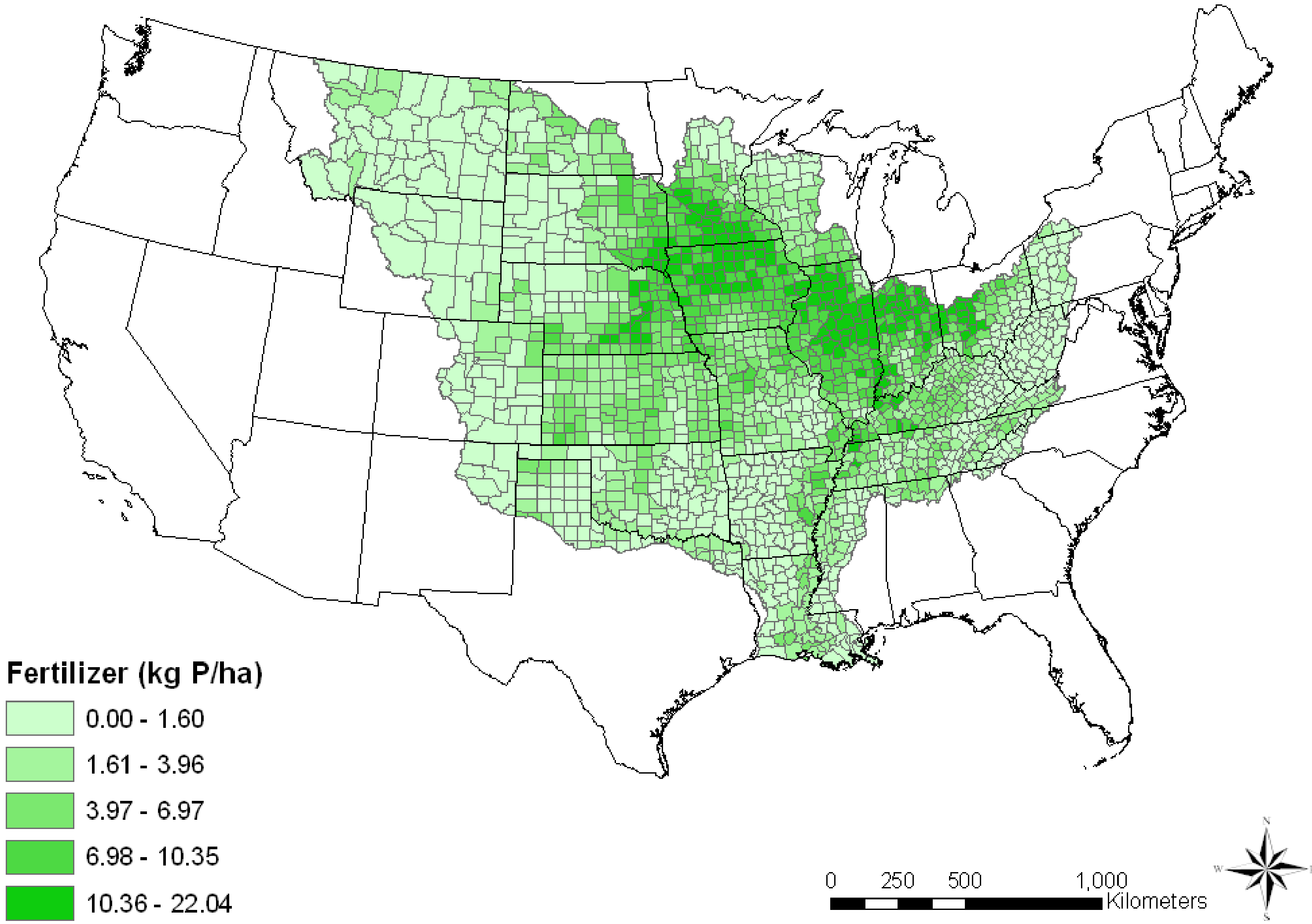

Figure 1. Average annual fertilizer P inputs by county for the Mississippi River Basin from 1997 to 2006.

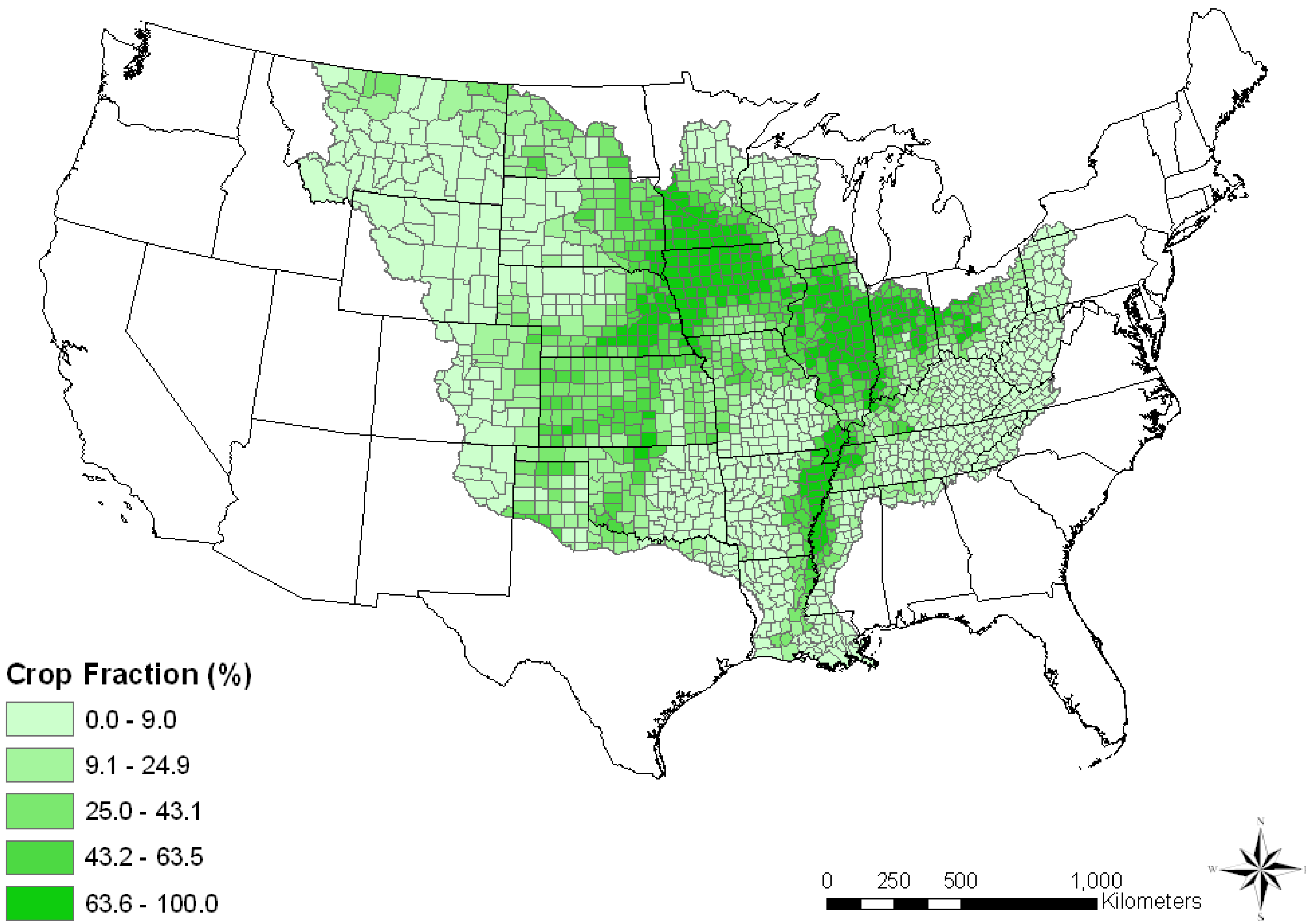

Figure 2. Fraction of county area that was planted in crops in the Mississippi River Basin from 1997 to 2006.

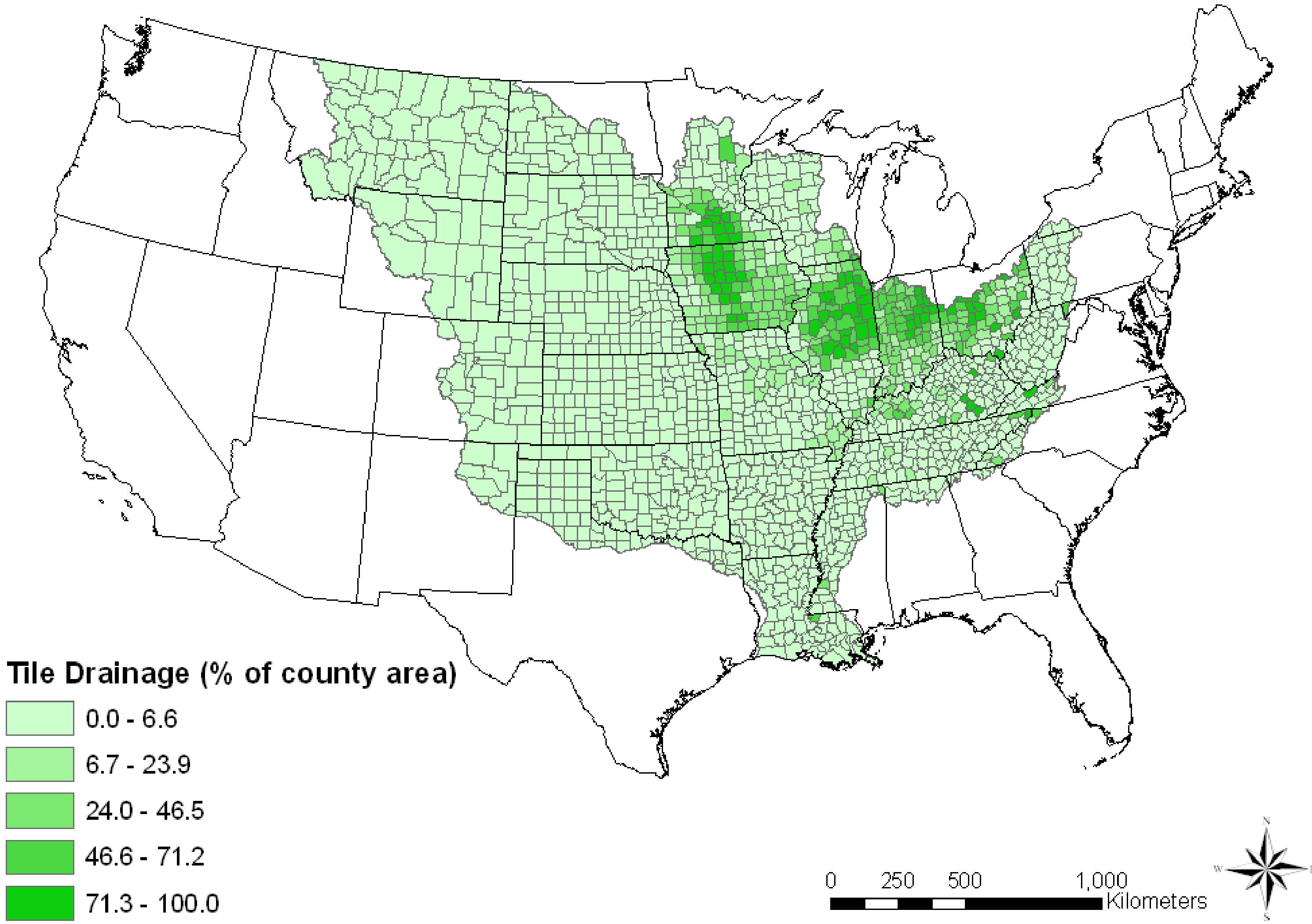

Figure 3. Percent of county area that is tile drained in the Mississippi River Basin.

Table 1. Pearson correlation coefficients (r) showing associations between Mississippi River Basin county crop, tile drainage, and fertilizer characteristics (n=1768).

	Crop P Harvested	Crop Fraction	Tile Drainage
Crop Fraction	0.95**		
Tile Drainage	0.57**	0.47**	
Fertilizer P	0.92**	0.89**	0.54**

**significant at the 0.01 probability level

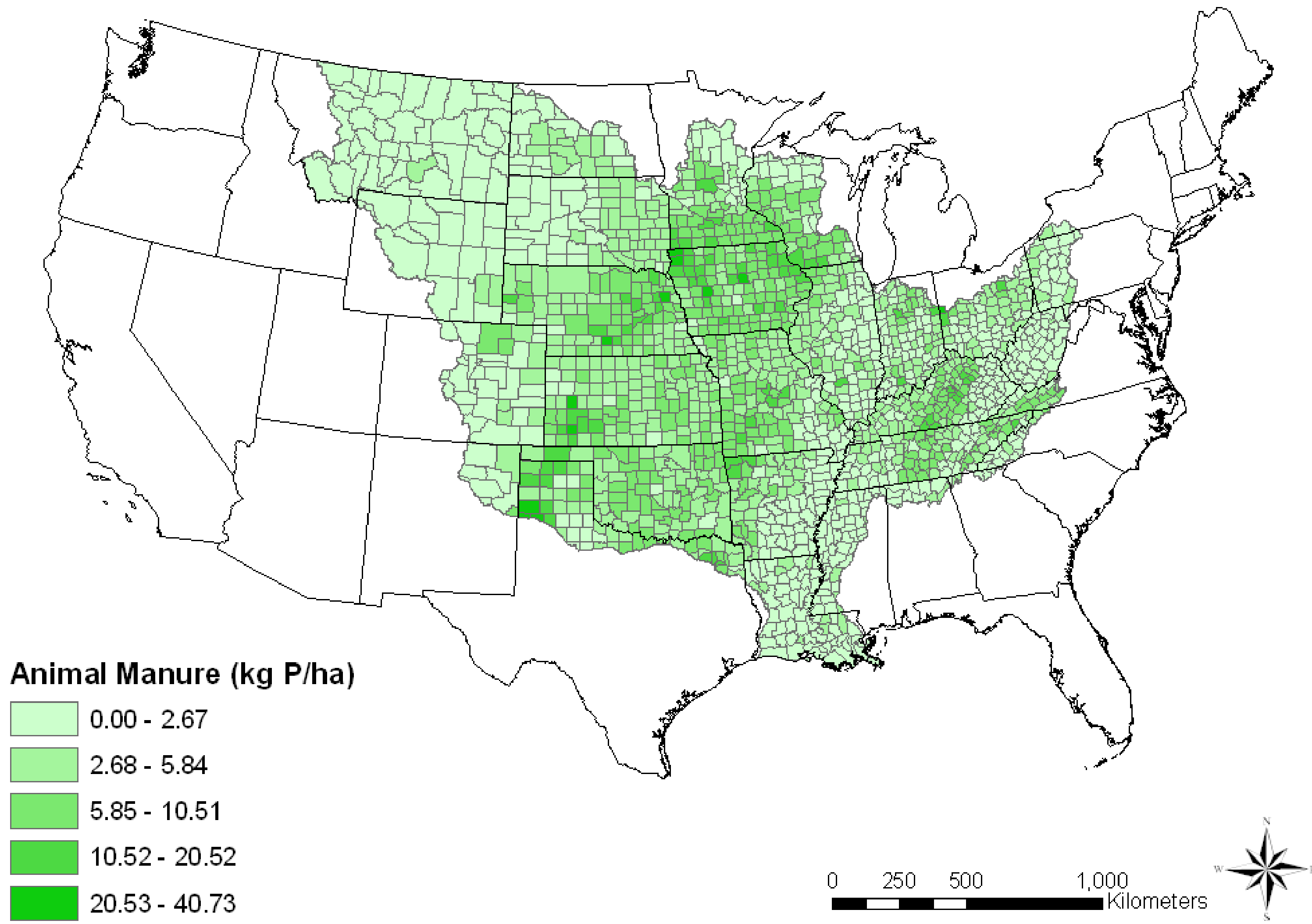

Figure 4. Average annual animal manure P inputs by county for the Mississippi River Basin from 1997 to 2006.

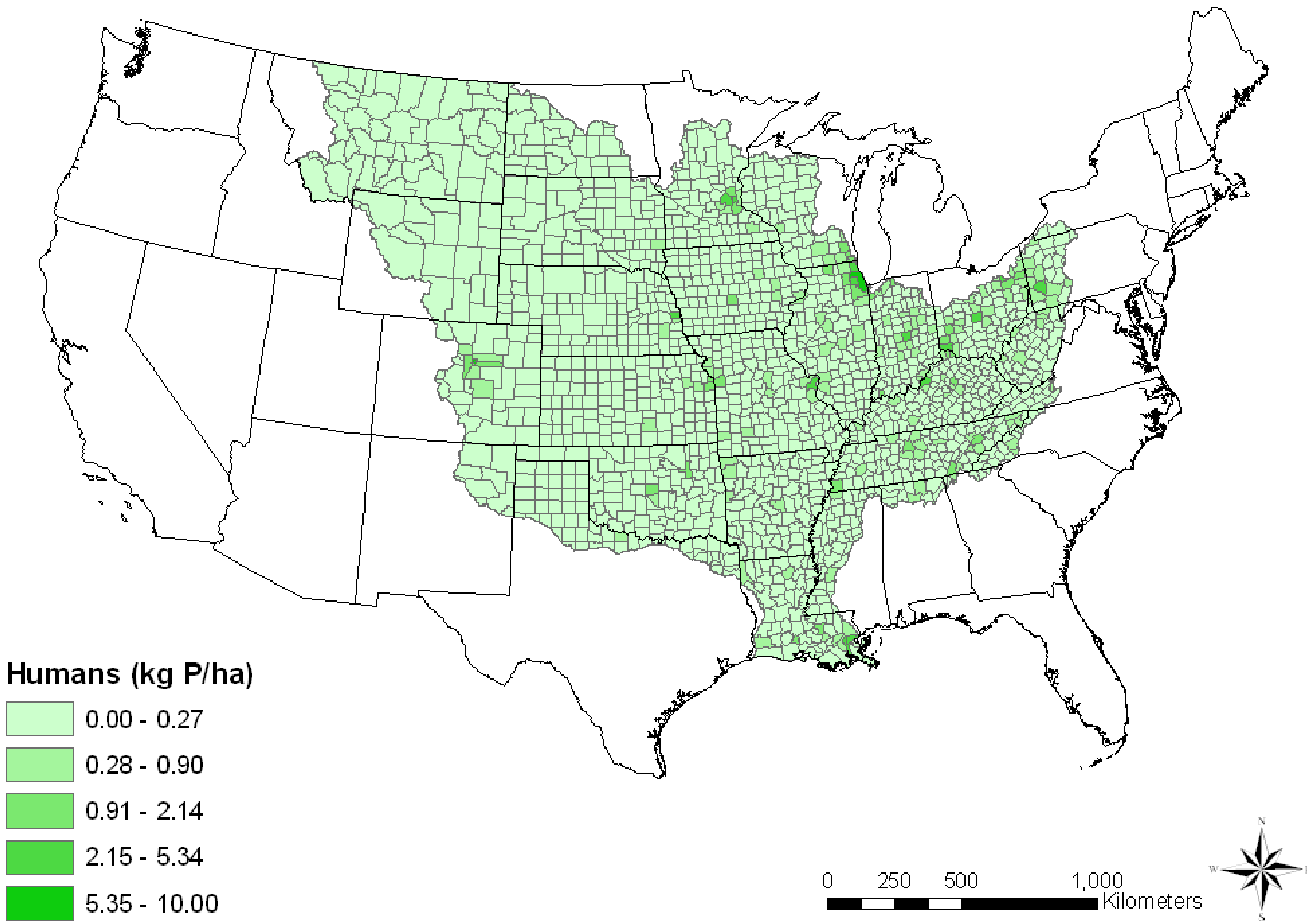

Figure 5. Average amount of P consumed by humans by county for the Mississippi River Basin.

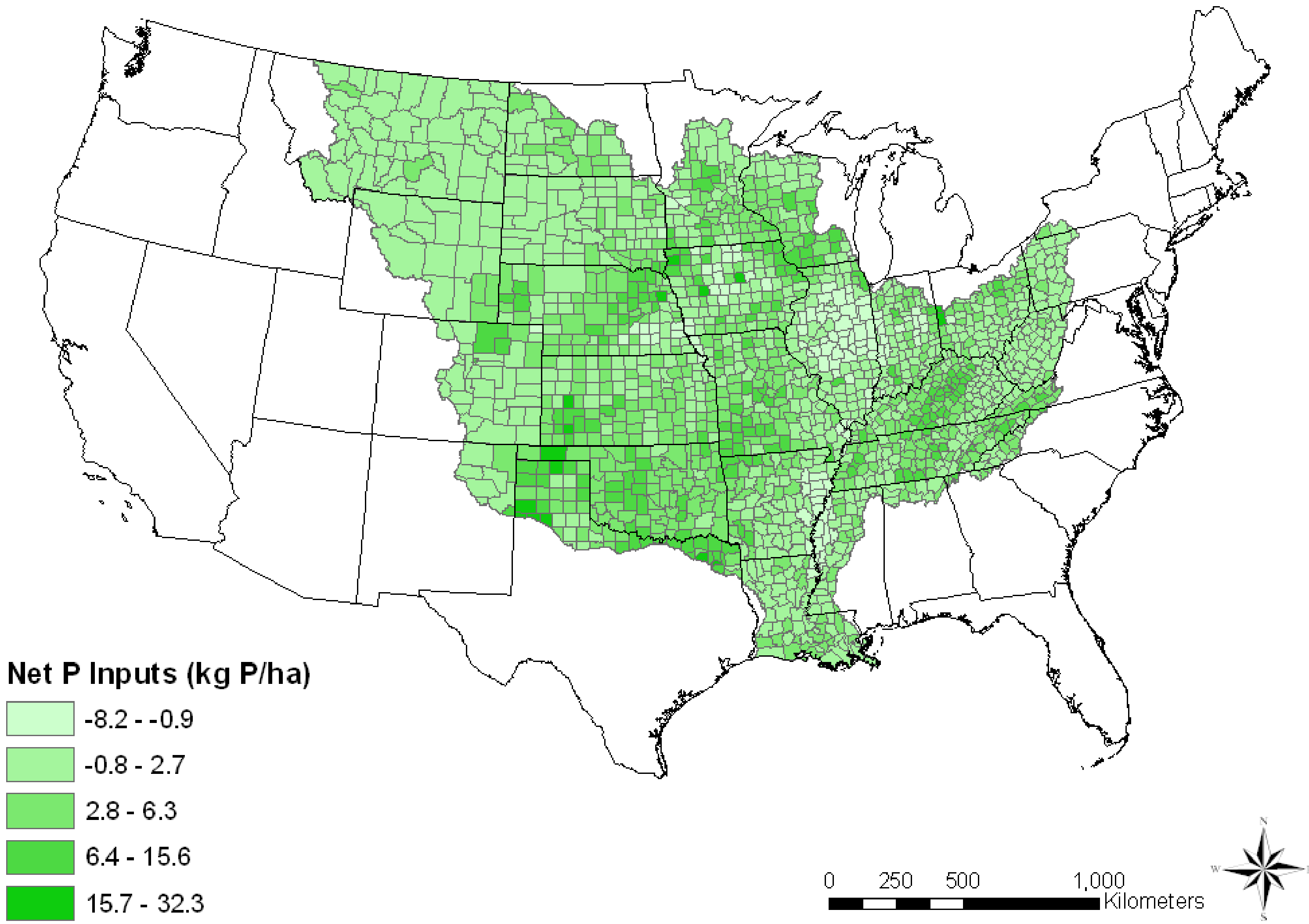

Figure 6. Average annual net P inputs by county for the Mississippi River Basin from 1997 to 2006.

Table 2. Pearson correlation coefficients (*r*) showing associations between net P inputs and Mississippi River Basin county characteristics (n=1768).

	Net P Inputs
Crop Fraction	-0.10**
Fertilizer P	0.02
Animal Manure P	0.81**
Human P	0.04
Crop P Harvested	-0.14**

**significant at the 0.01 probability level

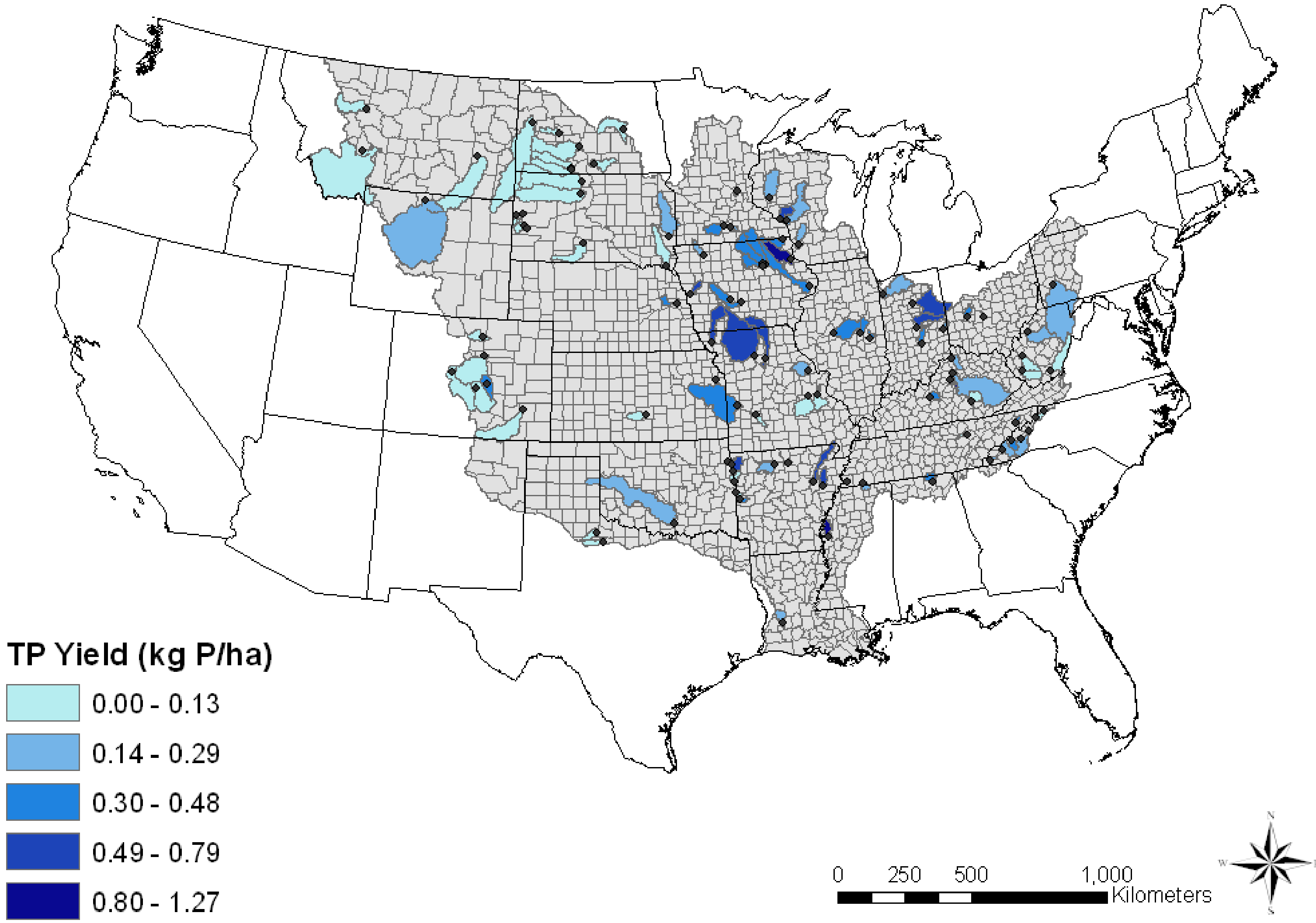

Figure 7. Average annual TP yields for the unique watersheds (n=101).

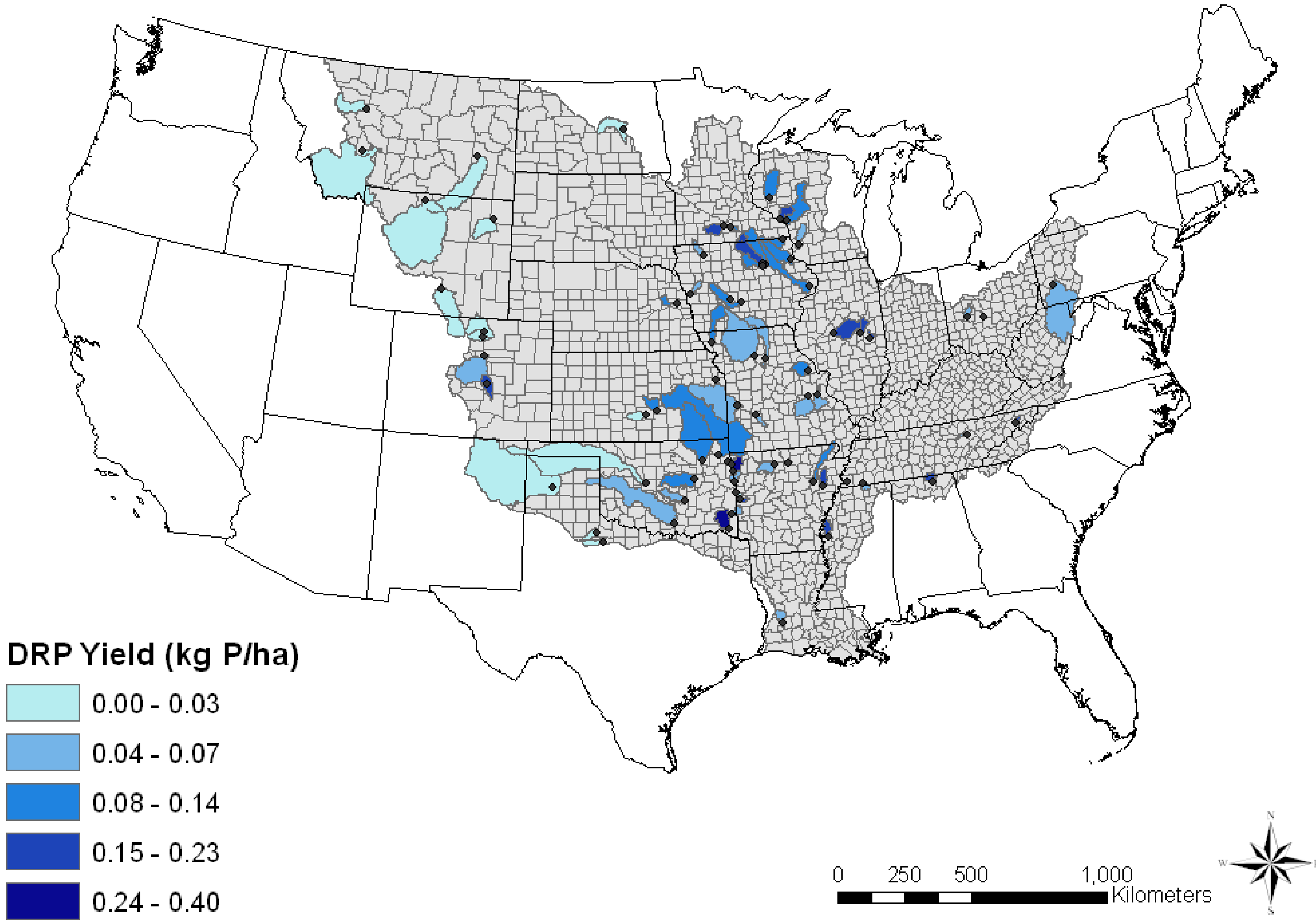

Figure 8. Average annual DRP yields for the unique watersheds (n=73).

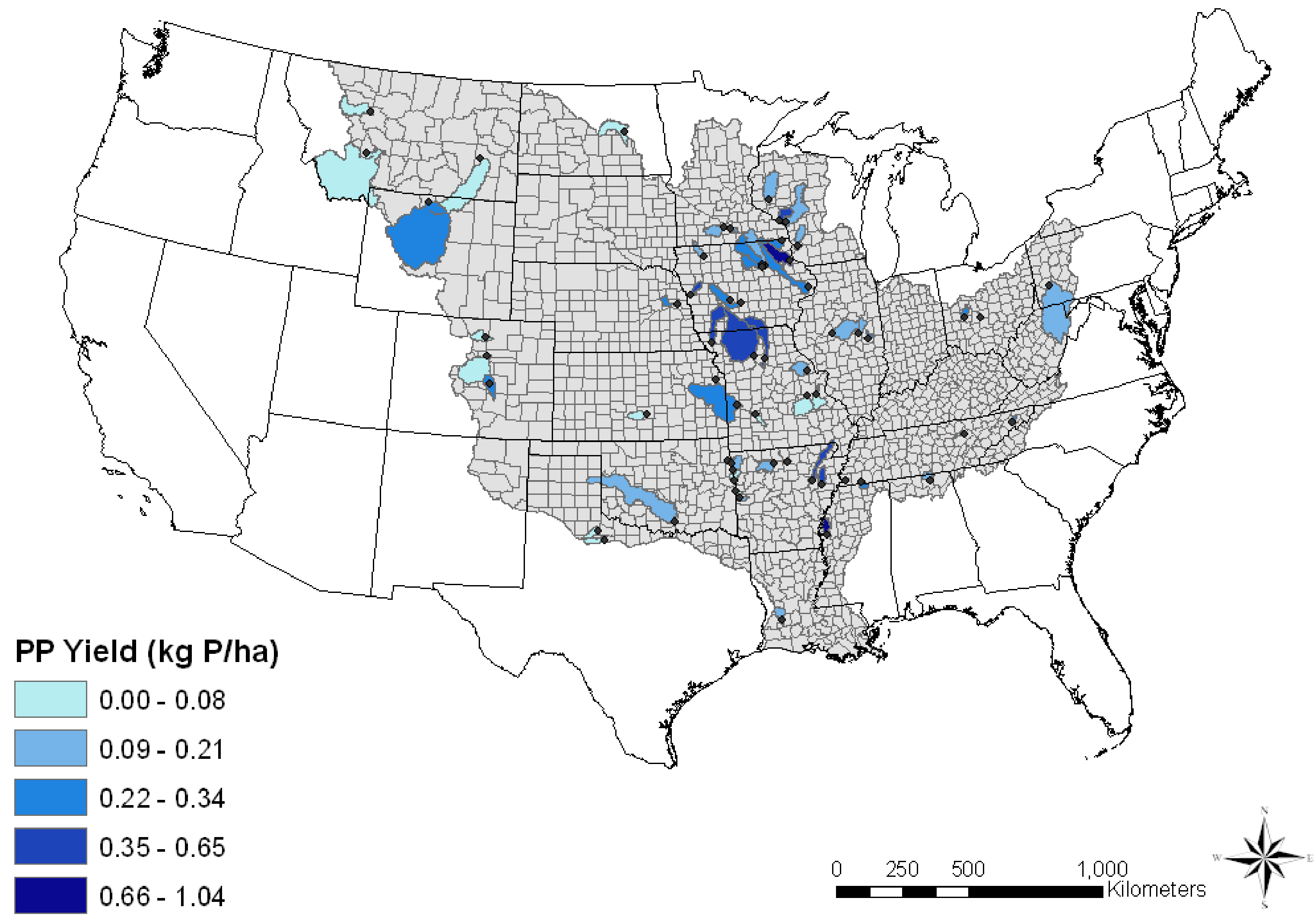

Figure 9. Average annual PP yields for the unique watersheds (n=61).

Table 3. Pearson correlation coefficients (*r*) showing associations between TP (n=101), DRP (n=73) and PP (n=61) yields and Mississippi River Basin county characteristics.

Characteristic	Yield TP	Yield DRP	Yield PP
Crop Fraction	0.37**	0.24*	0.30*
Tile Drainage	0.26**	0.23	0.12
Fertilizer P	0.36**	0.29*	0.20
Crop P Harvested	0.36**	0.25**	0.23*
Animal Manure P	0.30**	0.27*	0.03
Human P	0.34**	0.27*	0.39**
Net P Inputs	0.12	0.09	-0.04
Slope	-0.34**	-0.31**	-0.34**
Precipitation	0.31**	0.36**	0.21
Clay	0.29**	0.08	0.38**
Bulk Density	0.19	0.29*	0.36**
Watershed Area	-0.12	-0.33**	-0.08

*significant at the 0.05 probability level
**significant at the 0.01 probability level

Table 4. Distribution of watershed (Model, n=113) and Mississippi River Basin county (MRB, n=1768) characteristics and P fluxes averaged for 1997 to 2006.

Characteristic	Basin	Min	25^{th} percentile	Median	75^{th} percentile	Max
Crop Fraction (%)	Model	0	0.5	7.1	51.8	86.1
	MRB	0	1.1	14.3	45.9	100.0
Tile Drainage (% of area)	Model	0	0	0	5.0	99.2
	MRB	0	0	0	4.1	100.0
Fertilizer P (kg P ha^{-1})	Model	0	0.5	1.8	6.2	13.0
	MRB	0	0.9	2.6	6.1	22.0
Crop P Harvested (kg P ha^{-1})	Model	0	0	0.4	8.3	20.0
	MRB	0	0.1	1.4	7.0	22.1
Animal Manure P (kg P ha^{-1})	Model	0.1	1.3	3.0	6.2	14.3
	MRB	0	1.6	3.4	5.8	40.7
Human P (kg P ha^{-1})	Model	0	0	0.1	0.2	3.5
	MRB	0	0	0.1	0.1	10.0
Net P Inputs (kg P ha^{-1})	Model	-6.2	1.1	2.4	4.0	10.3
	MRB	-8.2	0.9	2.4	4.4	32.3
Slope (%)	Model	1.0	3.3	6.8	16.1	42.7
	MRB	0.2	2.6	4.9	10.4	50.2
Precipitation (cm)	Model	16.5	63.7	98.5	124.5	178.7
	MRB	29.9	76.4	103.5	125.1	192.8
Clay (%)	Model	6.0	16.2	19.8	24.2	43.1
	MRB	3.8	16.9	20.2	24.3	50.0
Bulk Density (g/cm^3)	Model	0.4	1.3	1.3	1.4	2.5
	MRB	0.2	1.3	1.3	1.4	1.7
Area (km^2)	Model	79	905	1994	4616	50360
Flow$^+$ (cm)	Model	0.1	5.6	16.8	29.2	58.8
Yield TP$^+$ (kg P ha^{-1})	Model	0.00	0.08	0.23	0.40	1.27
Yield DRP$^+$ (kg P ha^{-1})	Model	0.00	0.03	0.09	0.14	0.40
Yield PP$^+$ (kg P ha^{-1})	Model	0.00	0.07	0.20	0.30	1.04

$^+$January to June

Table 5. Ordinary least squares multiple regression model for non-transformed TP yields in the Mississippi River Basin (Model 1).

Variables	Coefficient
Constant	-0.064
Human P	0.159**
Crop Fraction	0.004**
Precipitation	0.002**
N	101
R^2	0.355
Log likelihood	13.255
AIC	-18.509

Table 6. Ordinary least squares multiple regression model for square root transformed TP yields in the Mississippi River Basin (Model 2).

Variables	Coefficient
Constant	0.084
Human P	0.137**
Crop Fraction	0.004**
Precipitation	0.003**
N	101
R^2	0.432
Log likelihood	25.772
AIC	-43.544

**significant at the 0.01 probability level

Table 7. Ordinary least squares multiple regression model for non-transformed DRP yields in the Mississippi River Basin (Model 3).

Variables	Coefficient
Constant	-0.030
Human P	0.038*
Fertilizer P	0.006**
Precipitation	0.001**
N	73
R^2	0.273
Log likelihood	88.033
AIC	-168.066

Table 8. Ordinary least squares multiple regression model for square root transformed DRP yields in the Mississippi River Basin (Model 4).

Variables	Coefficient
Constant	-0.003
Human P	0.063*
Fertilizer P	0.016**
Precipitation	0.002**
N	73
R^2	0.460
Log likelihood	61.446
AIC	-114.891

*significant at the 0.05 probability level
**significant at the 0.01 probability level

Table 9. Ordinary least squares multiple regression model for non-transformed PP yields in the Mississippi River Basin (Model 5).

Variables	Coefficient
Constant	-0.457
Human P	0.184**
Crop Fraction	0.002**
Bulk Density	0.451
N	61
R^2	0.329
Log likelihood	14.409
AIC	-20.818

Table 10. Ordinary least squares multiple regression model for square root transformed PP yields in the Mississippi River Basin (Model 6).

Variables	Coefficient
Constant	-0.381
Human P	0.163**
Crop Fraction	0.003**
Bulk Density	0.536*
N	61
R^2	0.373
Log likelihood	17.971
AIC	-27.942

*significant at the 0.05 probability level
**significant at the 0.01 probability level

Table 11. Tests for normality and heteroskedasticity of residuals for ordinary least squares multiple regression models.

Model	Jarque-Bera test	Breusch Pagan test
Model 1	67.054**	12.000**
Model 2	7.396*	1.52
Model 3	135.97**	17.841**
Model 4	25.458**	7.785
Model 5	54.354**	8.138*
Model 6	2.214	1.283

Table 12. Tests for spatial dependence of residuals for ordinary least squares multiple regression models.

Model	Moran's I	Lagrange Multiplier Lag	Lagrange Multiplier Error
Model 1	0.068	3.899*	1.499
Model 2	0.096	3.917*	2.978
Model 3	0.028	0.297	0.179
Model 4	0.047	0.057	0.529
Model 5	0.145*	2.821	4.214*
Model 6	0.218**	1.947	9.560**

*significant at the 0.05 probability level
**significant at the 0.01 probability level

Table 13. Spatial lag and spatial error regression models for non-transformed TP yields in the Mississippi River Basin (Models 7 and 8).

Spatial Lag (Model 7)		Spatial Error (Model 8)	
Variables	Coefficient	Variables	Coefficient
Constant	-0.065	Constant	-0.059
Human P	0.163**	Human P	0.161**
Crop Fraction	0.003**	Crop Fraction	0.003**
Precipitation	0.002**	Precipitation	0.002**
ρ	0.392**	λ	0.814**
N	101	N	101
R^2	0.388	R^2	0.388
Log likelihood	15.846	Log likelihood	15.419
AIC	-21.692	AIC	-22.838

**significant at the 0.01 probability level

Table 14. Spatial lag and spatial error regression models for square root transformed TP yields in the Mississippi River Basin (Model 9 and 10).

Spatial Lag (Model 9)		Spatial Error (Model 10)	
Variables	Coefficient	Variables	Coefficient
Constant	0.076	Constant	0.116
Human P	0.140**	Human P	0.139**
Crop Fraction	0.003**	Crop Fraction	0.004**
Precipitation	0.003**	Precipitation	0.002**
ρ	0.208**	λ	0.789**
N	101	N	101
R^2	0.456	R^2	0.47
Log likelihood	27.907	Log likelihood	28.863
AIC	-45.814	AIC	-49.726

**significant at the 0.01 probability level

Table 15. Spatial lag and spatial error regression models for non-transformed DRP yields in the Mississippi River Basin (Models 11 and 12).

Spatial Lag (Model 11)		Spatial Error (Model 12)	
Variables	Coefficient	Variables	Coefficient
Constant	-0.028	Constant	-0.015
Human P	0.039*	Human P	0.037*
Fertilizer P	0.005*	Fertilizer P	0.005
Precipitation	0.001**	Precipitation	0.001**
ρ	0.212	λ	0.673**
N	73	N	73
R^2	0.279	R^2	0.291
Log likelihood	88.319	Log likelihood	88.542
AIC	-166.637	AIC	-169.085

*significant at the 0.05 probability level
**significant at the 0.01 probability level

Table 16. Spatial lag and spatial error regression models for square root transformed DRP yields in the Mississippi River Basin (Model 13 and 14).

Spatial Lag (Model 13)		Spatial Error (Model 14)	
Variables	Coefficient	Variables	Coefficient
Constant	-0.003	Constant	0.037
Human P	0.063*	Human P	0.059*
Fertilizer P	0.015**	Fertilizer P	0.013**
Precipitation	0.002**	Precipitation	0.002**
ρ	0.039	λ	0.66**
N	73	N	73
R^2	0.46	R^2	0.478
Log likelihood	61.486	Log likelihood	62.378
AIC	-112.972	AIC	-116.756

*significant at the 0.05 probability level
**significant at the 0.01 probability level

Table 17. Spatial lag and spatial error regression models for non-transformed PP yields in the Mississippi River Basin (Models 15 and 16).

Spatial Lag (Model 15)		Spatial Error (Model 16)	
Variables	Coefficient	Variables	Coefficient
Constant	-0.371	Constant	-0.341
Human P	0.193**	Human P	0.188**
Crop Fraction	0.002*	Crop Fraction	0.003**
Bulk Density	0.377	Bulk Density	0.355
ρ	0.429**	λ	0.77**
N	61	N	61
R^2	0.375	R^2	0.411
Log likelihood	16.369	Log likelihood	17.506
AIC	-22.739	AIC	-27.011

*significant at the 0.05 probability level
**significant at the 0.01 probability level

Table 18. Spatial lag and spatial error regression models for square root transformed PP yields in the Mississippi River Basin (Model 17 and 18).

Spatial Lag (Model 17)		Spatial Error (Model 18)	
Variables	Coefficient	Variables	Coefficient
Constant	-0.329	Constant	-0.322
Human P	0.169**	Human P	0.162**
Crop Fraction	0.002**	Crop Fraction	0.003**
Bulk Density	0.491*	Bulk Density	0.491*
ρ	0.194*	λ	0.847**
N	61	N	61
R^2	0.397	R^2	0.499
Log likelihood	19.123	Log likelihood	23.564
AIC	-28.245	AIC	-39.128

*significant at the 0.05 probability level
**significant at the 0.01 probability level

Table 19. Tests for heteroskedasticity and spatial dependence of residuals for spatial lag and spatial error models.

Model	Breusch Pagan test	Moran's I
Model 7	16.129**	0.0037[n/a]
Model 8	14.306**	-0.064[n/a]
Model 9	1.751	0.0450[n/a]
Model 10	2.091	-0.09[n/a]
Model 11	19.130**	0.021[n/a]
Model 12	19.235**	-0.015 [n/a]
Model 13	8.138*	0.0466[n/a]
Model 14	7.590	-0.059[n/a]
Model 15	11.416**	0.071[n/a]
Model 16	10.933*	-0.057[n/a]
Model 17	1.086	0.183[n/a]
Model 18	1.047	-0.041[n/a]

*significant at the 0.05 probability level
**significant at the 0.01 probability level
[n/a]significance not available

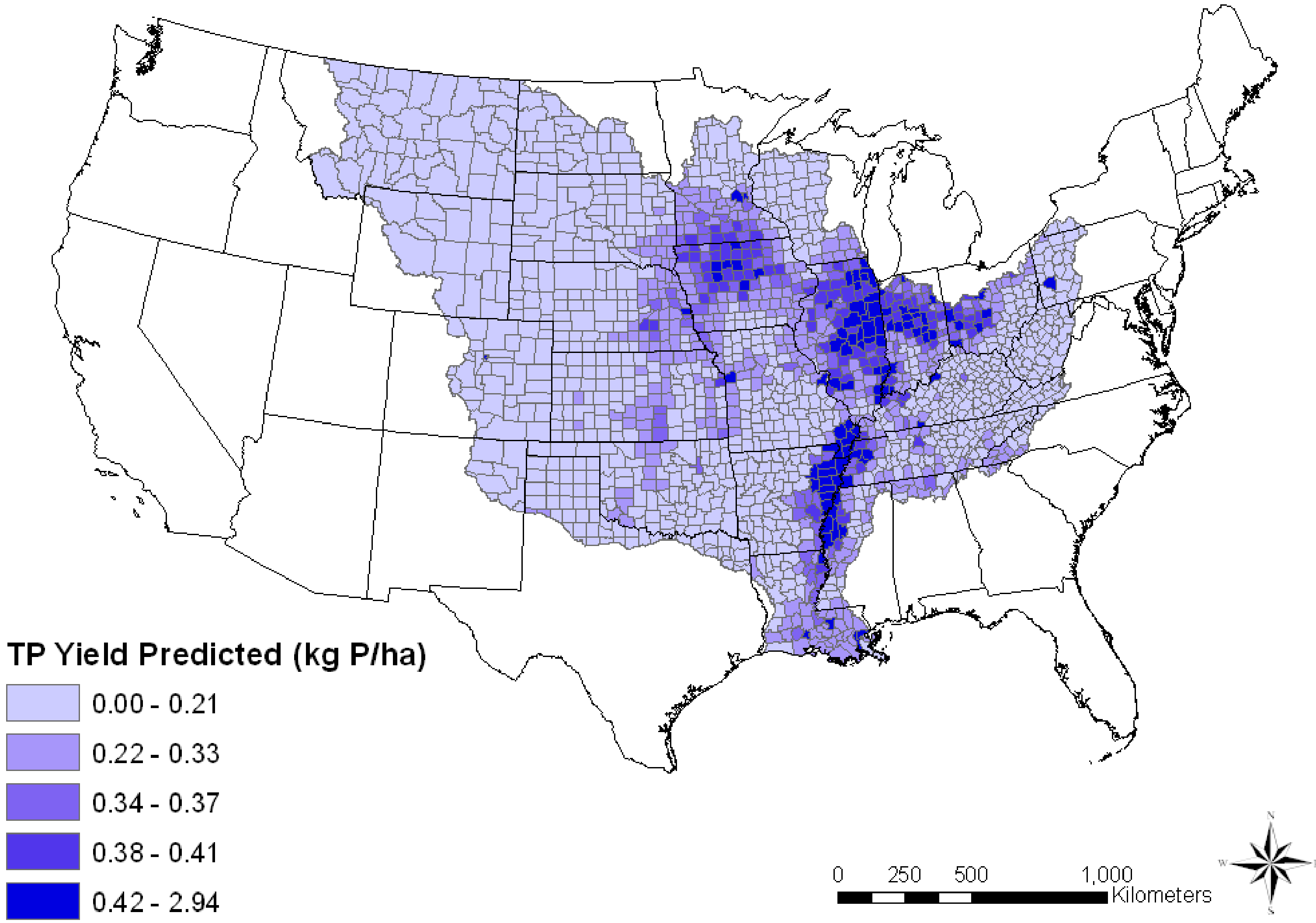

Figure 10. Average annual predicted January to June TP yields for the counties in the Mississippi River Basin from 1997 to 2006.

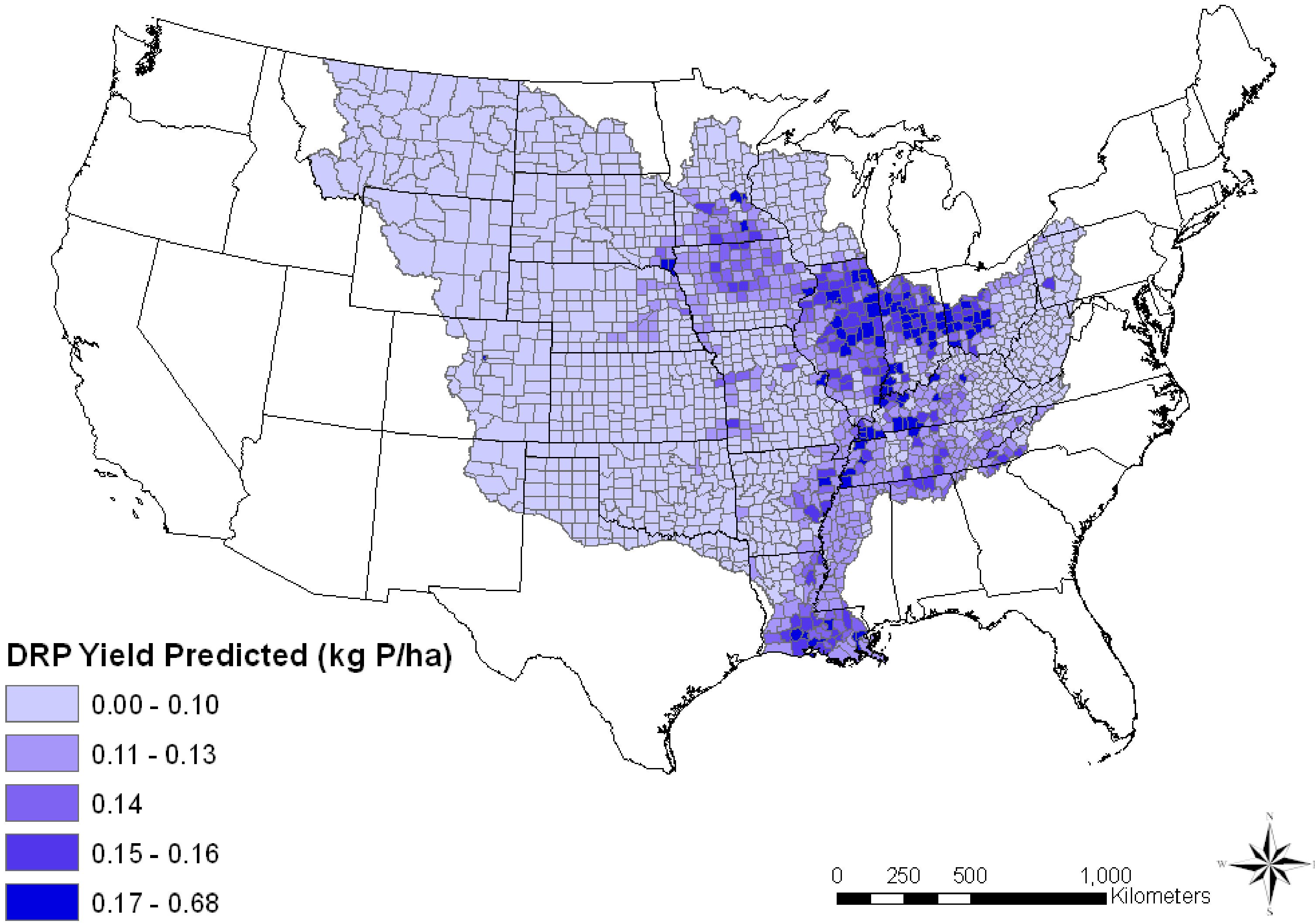

Figure 11. Average annual predicted January to June DRP yields for the counties in the Mississippi River Basin from 1997 to 2006.

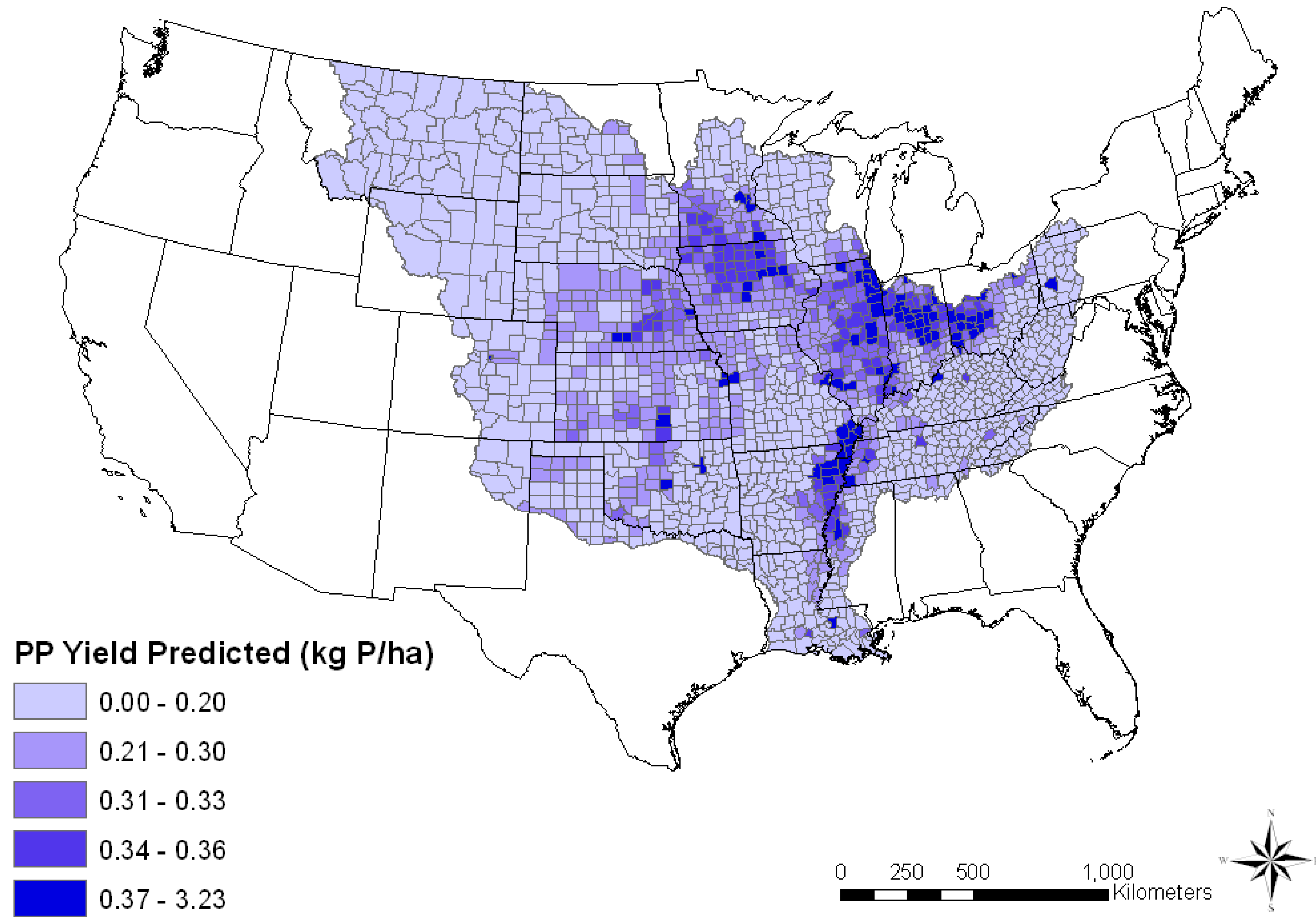

Figure 12. Average annual predicted January to June PP yields for the counties in the Mississippi River Basin from 1997 to 2006.

DISCUSSION

Basin Characteristics Related to P Yields

The importance of agriculture in contributing to TP, DRP and PP yields is clearly shown by the model results. Both models for TP and PP yields had crop fraction as a significant variable, and DRP yield had fertilizer P inputs as a significant variable. Crop fraction and fertilizer P were used to indicate row crop intensity of agriculture. Therefore, agricultural practices of intense row cropping were found to be one of the explanatory variables in contributing all three forms of P to rivers and streams.

Precipitation was significant as a contributing factor in the models for the yields of TP and DRP. These results indicate that the inputs of P from agriculture depended on precipitation to aid in the movement of P from the fields to rivers and streams through surface runoff. Precipitation was also highly correlated with flow ($r=0.9$, $p<0.0001$) and therefore can be used to signify flow. However, precipitation was not significant in models predicting PP yields. Instead, bulk density of the soil was highly significant in the model for PP yields and had the largest coefficient in the model. Therefore, soil characteristics were more important in contributing PP yields, while precipitation was more important in causing TP and DRP yields.

The third variable that was significant in the models for all three forms of P was P consumed by humans. This variable was used as an indicator for sewage effluent P inputs to rivers and streams. Sewage effluent P inputs had the highest coefficient in the TP and DRP yield models and the second highest in the PP yield model. As a result, inputs of P from sewage effluent were a major contributing factor to P yields.

Animal manure P inputs were not significant in any of the models predicting TP, DRP or PP yields. Therefore, animal manure P was not a significant contributor to any of the P yields.

This was likely due to the greatest amount of animal manure being in counties in the western portion of the MRB where precipitation was low. With low precipitation, there was little runoff into rivers and streams. As a result, the animal manure that was present in these counties remained on the land rather than running off into nearby rivers or streams.

Slope had a negative correlation with TP, DRP and PP yields and was not significant in any of the yield models. This is probably because the counties with the highest slope were not used for farming and as a result did not contribute a large amount of phosphorus. In the entire MRB, slope and crop fraction were negatively correlated ($r=-0.52$, $p<0.0001$). Therefore, the counties with the lowest slope were used for agriculture and, as shown by the models, had greater P yields.

Net P inputs were not significantly correlated with any of the P yields and were not utilized in the yield models. This indicated that net P balances, and even negative net P balances, did not explain P losses from counties. Net P balances were negative for 175 counties in the MRB with the majority of these counties located in Illinois, Indiana and along the Mississippi River in Arkansas, Mississippi and Louisiana. A negative net P balance showed that more P was harvested in crops and taken away from a county than was put in through fertilizer, animal manure and sewage effluent. A positive net P balance indicated that more P was being put into a county through fertilizer, animal manure and sewage effluent than was being removed through harvested crops. The positive net P balances did not follow an obvious spatial trend and could not be used to predict P yields.

The watershed areas were not significant in any of the models despite the significant correlation with DRP yields. The negative correlation between DRP yields and the watershed areas indicated that larger watersheds contributed small yields of DRP. However, since the area of the watersheds was not a significant variable in the models, variation in watershed size was not a significant factor in predicting TP, DRP or PP yields.

Use of Spatial Error Regression Model

The spatial error regression models were used to predict the TP and PP yields because they better satisfied the assumptions of the multiple regression model. However, there was not a large difference between the coefficients in the equations created by the multiple regression and spatial error models. The significant lambda coefficient indicated the need to include spatial autocorrelation in the model, but the spatially lagged error term was not included in predicting the county TP and PP yields. This spatially lagged error term could not be included because the errors could not be assumed to be the same at each county location. Therefore, only the coefficients from the spatial error regression models were used to predict the TP and PP yields in the counties, and the predicted yields were not very different from those that would have been predicted by the multiple regression models.

Comparison to the SPARROW Model

The USGS SPARROW (spatially referenced regression on watershed attributes) model was created to determine the sources and processes of transport of total N (TN) and P in the MRB and the delivery of TN and TP to the Gulf of Mexico (Alexander et al. 2008 and Robertson et al. 2009). This model uses a nonlinear statistical method to predict the mean annual flux and yield of TN and TP delivered to the Gulf of Mexico. The mean annual flux and yield of TP was based on eight nutrient sources, five climatic and landscape factors and aquatic nutrient removal. The nutrient sources were 1992 urban sources, corn and soybeans, alfalfa, other crops, pasture/rangeland, forest land, barren/transitional land and shrub land. The climatic and landscape factors were soil permeability, slope, precipitation, catchment area and artificial drainage. Aquatic nutrient removal was included for streams and reservoirs. The model was calibrated by TP loads calculated from TP concentrations and daily flow measured at 425 streams throughout the United States averaged from 1975 to 1995. The mean annual TP loads were then standardized to the 1992 base year.

In the model created by SPARROW to predict TP flux, the parameters of alfalfa, other crops and slope were not significant at the 0.05 probability level (Alexander et al. 2008). This is similar to my model predicting TP yield in that slope was also not a significant explanatory variable. The SPARROW model also predicted that 37% of the P delivered to the Gulf of Mexico was from pasture/rangeland, which included inputs of P from animal manure (Alexander et al. 2008). This result is different from my TP yield model in which P inputs from animal manure were not a significant variable. With SPARROW, Alexander et al. (2008) estimated that corn and soybeans delivered 25.1% of the P to the Gulf of Mexico, and 12.3% of the delivered P was from urban sources. Corn and soybeans is similar to the crop fraction variable in my model and urban sources to sewage effluent inputs. Therefore, these results were consistent with my model since crop fraction and sewage effluent P inputs were both significant and major contributing factors in my models.

The TP yields for the HUC8 watersheds in the MRB determined using the SPARROW model are shown by Robertson et al. (2009) in their figure 4A. Compared to a map showing TP yields predicted from my spatial error model for the HUC8 watersheds (Figure 13), there is a somewhat similar distribution of the highest TP yields being located in parts of Illinois and along the Mississippi River in Arkansas, Tennessee, Mississippi and Louisiana. The maps are also similar in that the lowest TP yields are along the eastern and western edges of the MRB. However, there are differences in the maps with Robertson et al. (2009) having more high TP yields in Oklahoma, Arkansas, Kentucky, Tennessee and Alabama and fewer in Illinois and Indiana as compared to the predicted TP yields from my model.

There may be several reasons for the differences in the P sources and the TP predicted yield maps between my spatial error model and the SPARROW model (Alexander et al. 2008). One may be the difference in time periods for the data. SPARROW used stream data from 1975 to 1995 and nutrient source data from 1992, and I used data from 1997 to 2006. Another could be the way the data were used with SPARROW standardizing the P yield data for just the year 1992. I used a mean value from 1997 to 2006. Finally, the allocation of P inputs from animal manure by the SPARROW model was different than my model. The animal manure P inputs for my model were based on the number of animals in each county, while the SPARROW model allocated animal manure P inputs to pasture and rangelands. A large percentage of P from the manure applied to the pasture and rangelands was then assumed to enter the Mississippi River (Alexander et al. 2008). However, from the results of my models, large amounts of P runoff did not seem to occur from these pasture and rangeland areas.

Top 300 Counties and Management

The 300 counties in the MRB with the greatest predicted P yields were determined to be most in need of management practices to limit P losses. These counties had predicted January to June TP yields greater than 0.34 kg P ha^{-1}, DRP yields greater than 0.14 kg P ha^{-1} or PP yields greater than 0.31 kg P ha^{-1}. Since the majority of these counties were located in the Cornbelt region of the MRB, management in agricultural practices to limit P may be useful. For instance, the USEPA Science Advisory Board (USEPA 2007) recommended the use of complex cropping systems in which a leguminous crop is inter-seeded with the existing corn and grain crops to improve the efficiency of P use. Utilizing perennial cropping systems and cover crops would also help to reduce P in surface runoff (USEPA 2007). However, these are practices that would alter the current agricultural system and can be difficult to implement.

Since the use of fertilizer probably will not completely stop, management in the way it is applied and for potential runoff should be utilized. Phosphorus fertilizer should be applied when storms are unlikely and incorporated into the soil to reduce potential P loss due to runoff. Manure applied to agricultural fields should be integrated into the soil profile to limit P runoff as well (Sharpley et al. 2001). The use of wetlands as well as conservation buffers and riparian areas managed to retain P would be useful in removing P in runoff from agricultural fields (USEPA 2007). However, to be effective in retaining and filtering nutrients, riparian areas need to be managed appropriately for the water flow path (Sharpley et al. 2001). Therefore without altering the current agricultural system, practices can be implemented in the application of fertilizer and in the use of constructed wetland and riparian areas to reduce P in runoff.

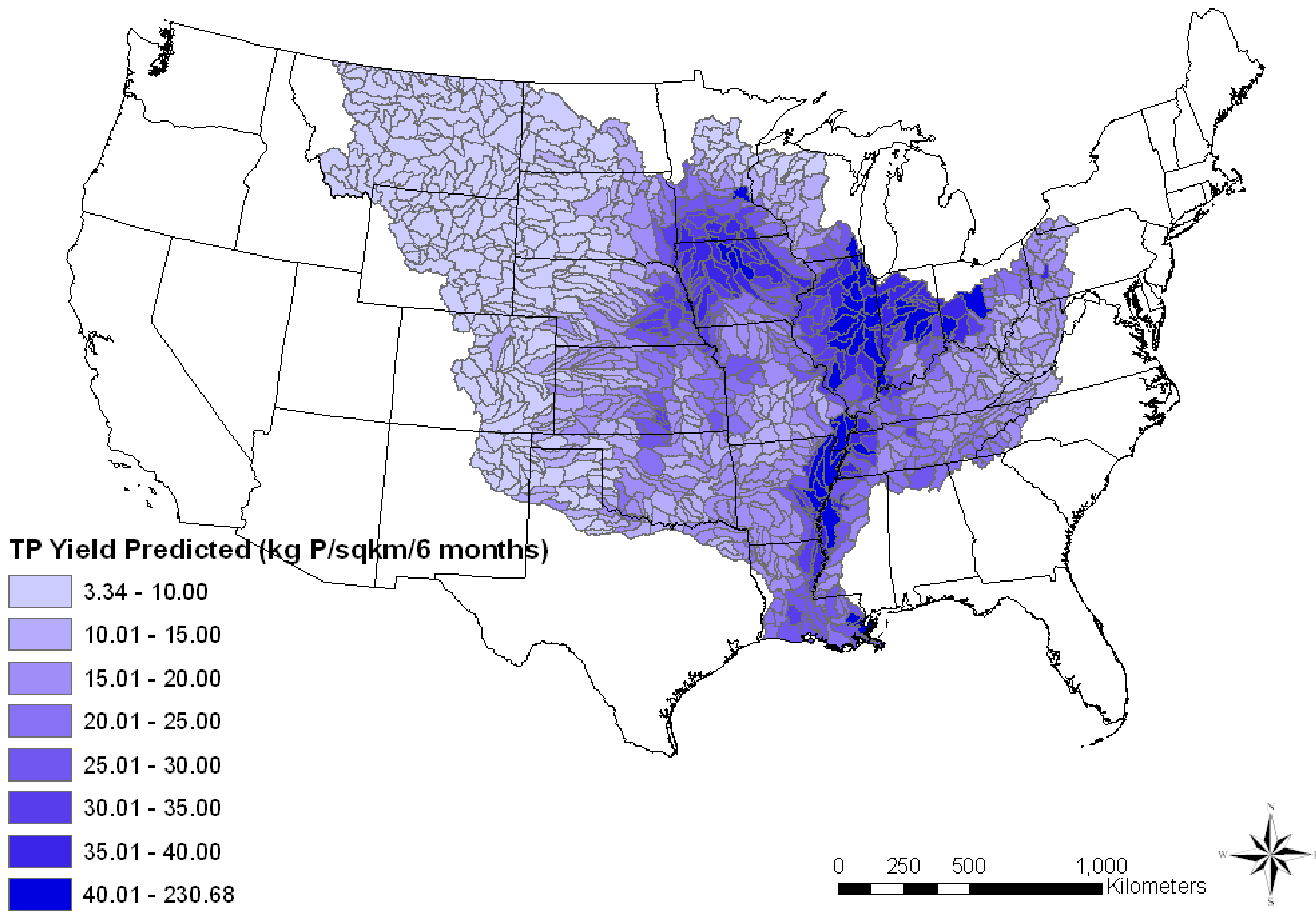

Figure 13. Average annual predicted January to June TP yields for the HUC8 watersheds in the Mississippi River Basin from 1997 to 2006.

CONCLUSIONS

The county level agricultural characteristics of crop fraction, tile drainage and fertilizer P inputs were highly correlated in the MRB and most prominent in the Cornbelt region of the upper Midwest. Due to the high correlation, fertilizer was used to indicate row crop intensity. Animal manure P inputs and net P inputs were largest in the western portion of the MRB. Human P consumption was used to show sewage effluent P inputs and was greatest near large cities.

In the 113 monitored watersheds examined in this study, crop fraction was significantly correlated with the January to June yields of TP, DRP and PP, while fertilizer P inputs were significantly correlated with only the TP and DRP yields. There was also significant correlation between animal manure P inputs and TP and DRP yields as well as between human P consumption and the yields of TP, DRP and PP. Slope was negatively correlated with all three P yields; precipitation was highly correlated with TP and DRP yields and bulk density with DRP and PP yields.

A multiple regression model consisting of human P consumption, crop fraction and precipitation was found to be the best predictor of TP yields. Yields of DRP were best explained by human P consumption, fertilizer P inputs and precipitation. For PP yields, the best multiple regression model included human P consumption, crop fraction and bulk density. Animal manure P inputs were not significant in any of the models due to most of the manure being located in counties in the western region of the MRB where there was little precipitation.

To best satisfy the assumptions of the multiple regression model, a square root transformation of the P yields was utilized for all three models. Also, spatial regression models were determined to be necessary to remove the spatial autocorrelation that was present in the residuals of the multiple regression models for the TP and PP yields. The spatial error regression model, in which a spatially lagged error term was added to the model, was concluded to be the best model to predict the TP and PP yields. Spatial autocorrelation was not present in the residuals of the multiple regression model for the DRP yields; therefore, the multiple regression model was the best model of those evaluated to predict the yields of DRP.

In applying these models to the counties in the MRB, the spatially lagged error term was not included in the calculation of TP and PP yields, since the errors could not be assumed to be uniform throughout the basin. Overall, the spatial distribution of the model estimated yields of TP, DRP and PP were similar throughout the MRB with the largest values located in the Cornbelt of the upper Midwest. Estimated TP yields were also large in counties along the Mississippi River in Arkansas, Louisiana, Tennessee and Mississippi, and there were large DRP yields in several counties in Louisiana near the Gulf of Mexico. Total P, DRP and PP estimated yields were lowest in the counties in the western and eastern regions of the MRB predominantly due to the small crop fraction in these areas.

In a comparison with TP yields predicted for HUC8 watersheds by the USGS SPARROW model, there were similarities in the location of the highest TP yields being located in portions of Illinois and along the Mississippi River in Arkansas, Louisiana, Tennessee and Mississippi. However, there was a difference with the SPARROW model predicting higher TP yields in the western portion of the MRB. This difference is most likely attributable to differing assumptions in the allocation of inputs of P from animal manure.

The 300 counties with the largest predicted P yields were concluded to be most in need of the implementation of management practices. Most of these counties were located in the Cornbelt region where agriculture predominates. Therefore as recommended by the US EPA, various agricultural practices can be utilized to limit P losses, such as utilizing cover crops, creating conservation buffers and incorporating P fertilizer and manure into the soil after application. Implementing such practices in counties with large P yields can help to reduce P losses to rivers and streams and lessen the impact on hypoxia in the Gulf of Mexico as well as improve local water quality.

REFERENCES

AAPFCO. 2008. Commercial fertilizer reports, 1997 to 2007. Association of American Plant Food Control Officials. University of Kentucky, TN.

Alexander, R.B., R.A. Smith, G.E. Schwarz, E.W. Boyer, J.V. Nolan, and J.W. Brakebill. 2008. Differences in phosphorus and nitrogen delivery to the Gulf of Mexico from the Mississippi River Basin. Environ. Sci. Technol. 42:822-830.

Anselin, L., I. Syabri, and Y. Kho. 2006. GeoDa: an introduction to spatial data analysis. Geogr. Anal. 38:5-22.

Bierman, V.J., N.N. Rabalais, S.C. Hinz, D. Zhu, R.E. Turner, and W.J. Wiseman. 1994. A preliminary mass balance model of primary productivity and dissolved oxygen in the Mississippi River plume/inner gulf shelf region. Estuaries 17:886-899.

Broberg, O. and G. Persson. 1988. Particulate and dissolved phosphorus forms in freshwater: composition and analysis. Hydrobiologia 170:61-90.

Burwell, R.E., D.R. Timmons, and R.F. Holt. 1975. Nutrient transport in surface runoff as influenced by soil cover and seasonal periods. Soil Sci. Soc. Amer. Proc. 39:523-528.

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

CENR. 2000. Integrated assessment of hypoxia in the northern Gulf of Mexico. National Science and Technology Council Committee on Environmental and Natural Resources: Washington, D.C.

Conley, D.J. 2000. Biogeochemical nutrient cycles and nutrient management strategies. Hydrobiologia 410:87-96.

Correll, D.L. 1999. Phosphorus: a rate limiting nutrient in surface waters. Poultry Sci. 78:674-682.

David, M.B. and L.E. Gentry. 2000. Anthropogenic inputs of nitrogen and phosphorus and riverine export for Illinois, USA. J. Environ. Qual. 29:494-508.

Diaz, R.J. 2001. Overview of Hypoxia around the World. J. Environ. Qual. 30:275-281.

Domagalski, J.L., S. Ator, R. Coupe, K. McCarthy, D. Lampe, M. Sandstrom, and N. Baker. 2008. Comparative study of transport processes of nitrogen, phosphorus, and herbicides to streams in five agricultural basins, USA. J. Environ. Qual. 37:1158-1169.

Fraterrigo, J.M., and J.A. Downing. 2008. The influence of land use on lake nutrients varies with watershed transport capacity. Ecosystems 11:1021-1034.

Gentry, L.E., M.B. David, T.V. Royer, C.A. Mitchell, and K.M. Starks. 2007. Phosphorus transport pathways to streams in tile-drained agricultural watersheds. J. Environ. Qual. 36:408-415.

Goolsby, D.A., W.A.Battaglin, G.B. Lawrence, R.S. Artz, B.T. Aulenbach, R.P. Hooper, D.R. Keeney, and G.J. Stensland. 1999. Flux and sources of nutrients in the Mississippi–Atchafalaya River basin. Topic 3 Rep. of the Integrated Assessment on Hypoxia in the Gulf of Mexico. NOAA Coastal Ocean Program Decision Analysis Ser. no. 17. NOAA Coastal Ocean Program, Silver Spring, MD.

Li, C. 2010. The DNDC model, ver. 9.3. University of New Hampshire, Institute for the Study of Earth, Oceans, and Space. Complex Systems Research Center, Durham, NH.

Mississippi River/Gulf of Mexico Watershed Nutrient Task Force. 2008. Gulf Hypoxia Action Plan 2008 for reducing, mitigating, and controlling hypoxia in the northern Gulf of Mexico and improving water quality in the Mississippi River Basin. Mississippi River/Gulf of Mexico Watershed Nutrient Task Force. Available on line at: http://www.epa.gov/msbasin/pdf/ghap2008_update082608.pdf

Nash, D.M. and D.J. Halliwell. 1999. Fertilisers and phosphorus loss from productive grazing systems. Aust. J. Soil Res. 37:403-429

Pierrou, U. 1976. The global phosphorus cycle. p. 75-88. In Svensson, B.H. and R. Soderlund (eds.) Nitrogen, phosphorus and sulphur - global cycles. SCOPE Report 7. Ecol. Bull., Stockholm, Sweden.

Platon, E., B.K. Sen Gupta, N.N. Rabalais, and R.E. Turner. 2005. Effect of seasonal hypoxia on the benthic foraminiferal community of the Louisiana inner continental shelf: the 20th century record. Marine Micropaleontology 54:263-283.

Rabalais, N.N., and R.E. Turner. 2001. Coastal hypoxia: consequences for living resources and ecosystems. Coastal and Estuarine Studies, vol. 58. American Geophysical Union, Washington, DC, p. 5.

Rabalais, N.N, W.J. Wiseman., R.E. Turner, D. Justic, B.K. Sen Gupta, and Q. Dortch. 1996. Nutrient changes in the Mississippi River and system responses on the adjacent continental shelf. Estuaries 19:386-407.

Robertson, D.M., G.E. Schwarz, D.A. Saad, and R.B. Alexander. 2009. Incorporating uncertainty into the ranking of SPARROW model nutrient yields from Mississippi/Atchafalaya River basin watersheds. J. Am. Water Resour. Assoc. 45:534-549.

Schlesinger, W.H. 1997. Biogeochemistry: an analysis of global change. Academic Press, San Diego.

Sharpley, A.N., S.C. Chapra, R. Wedepohl, J.T. Sims, T.C. Daniel, and K.R. Reddy. 1994. Managing agricultural phosphorus for protection of surface waters: issues and options. J. Environ.Qual. 23:437-451.

Sharpley, A.N., P. Kleinman, and R. McDowell. 2001. Innovative management of agricultural phosphorus to protect soil and water resources. Commun. Soil Sci. Plant Anal. 32:1071-1100.

Sims, J.T., R.R. Simard, and B.C. Joern. 1998. Phosphorus loss in agricultural drainage: historical perspective and current research. J. Environ. Qual. 27:277-293.

Sugg, Z. 2007. Assessing U.S. farm drainage: Can GIS lead to better estimates of subsurface drainage extent? World Resources Institute, Washington, D.C.

Sylvan, J.B., Q. Dortch, D.M. Nelson, A.F.Maier Brown, W. Morrison, and J.W. Ammerman. 2006. Phosphorus limits phytoplankton growth on the Louisiana Shelf during the period of hypoxia formation. Environ. Sci. Technol. 40:7548-7553.

Thornton, P.E., S.W. Running, and M.A. White. 1997. Generating surfaces of daily meteorological variables over large regions of complex terrain. J. Hydrol. 190:214-251.

Turner, R.E., N.N. Rabalais, and D. Justic. 2006. Predicting summer hypoxia in the northern Gulf of Mexico: Riverine N, P, and Si loading. Marine Pollution Bulletin 52:139-148.

U.S. Bureau of the Census. 2008. Annual population estimates by county, 2000. Available at http://www.census.gov (verified 26 January 2010).

USDA. 2008. National Agricultural Statistics Service State and County data. Available at http://www.nass.usda.gov (verified 26 January 2010). USDA-NASS, Washington, DC.

USDA, NRCS. 2010. Nutrient Content of Crops. Available at http://plants.usda.gov/npk (verified 17 February 2010). National Plant Data Center, Baton Rouge, LA.

USEPA. 1998. National water quality inventory: 1998. Report to congress. Office of Water, USEPA, Washington, DC.

USEPA. 2007. Hypoxia in the Northern Gulf of Mexico, An Update by the EPA Science Advisory Board. EPA-SAB-08-003, December 2007, Washington, DC.

USEPA. 2009. STORET/WQX. Available at http://www.epa.gov/storet (verified 16 February 2010). EROS Data Center, Sioux Falls, SD.

USGS. 2010. The National Map Seamless Server. Available at http://seamless.usgs.gov (verified 16 February 2010).

USGS. 2010. USGS Water Data for the Nation. Available at http://waterdata.usgs.gov (verified 16 February 2010).

Vitousek, P.M., J.D. Aber, R.W. Howarth, G.E. Likens, P.A. Matson, D.W. Schindler, W.H. Schlesinger, and D.G. Tilman. 1997. Human alteration of the global nitrogen cycle: sources and consequences. Ecol. Appl. 7:737-750.