EFFECTS OF LAND USE ON LAKE WATER QUALITY IN CENTRAL FLORIDA

by

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ABSTRACT

Land use affects the water quality of lakes. Different land use types yield different effects due to varying amounts and constituents of runoff. In this study, the effects of surrounding land use on the water quality of 50 lakes in Seminole County, Florida was assessed. Using GIS, I placed buffers of 100 and 500 m around each lake. The percentages of land use type were calculated within these buffers for 1990 and 1995. An ordination of lakes was done using Canonical Correspondence Analysis (CCA) to determine if the surrounding land use patterns were adequate to describe the trophic status of the lakes. Correlations between land use and water quality were found to be significant for the 1990 100 and 500 m buffers. Inter-set correlations showed that among land use types: residential, urban, agriculture, hardwoods, and wetlands were the most influential in determining water quality in that they had the most positive or negative correlation with the WA scores depending on the year and buffer zone. Excessively drained and very poorly drained soils were the most influential of the soil types. A Discriminant Function Analysis (DFA) was also performed to determine which land use and soil variables were effective in discriminating between oligotrophic, mesotrophic, and eutrophic lakes. Wetlands and very poorly drained soil were the most effective in discriminating between the groups of lakes. A multiple regression analysis was performed that determined correlations for 1990 and change in land use 100 m buffers contributed to our understanding of the relationship between land use and water quality. Effects of land use on water quality need to be considered when attempting to restore a lake or subjecting it to future land development.

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1. INTRODUCTION

Lakes are ecological systems that are affected by the surrounding landscape and changes that occur in the landscape (Riera et al. 2001). It has been suggested that landscape pattern may be the best way to determine the source of pollutants and the process by which they enter a body of water (Cairns Jr. and Niederlehner 1996). A landscape is defined, in part, by its composition, i.e., the different types of land use present in an area. Land use alters drainage, in particular, the flow rates of nutrients and sediment loads, which contribute to the improvement or degradation of water quality (Stewart et al. 2000). Water quality in this study refers to the trophic status of a lake.

1.1 Conversion of Forests

To understand water quality drivers, correlations between land use practices and water quality must be determined. Previous attempts have been made to correlate certain land use patterns with water quality. A study performed in the Buffalo River watershed in Arkansas, determined that the conversion from forest to agriculture was the main contributing factor in water quality degradation (Scott and Udouj 1999). It is perceived that forested lands are important in preventing further degradation of water quality by reducing erosion and taking up nutrients (Sliva and Williams 2001). The conversion of forested land to agriculture or industrial lands alters the pathways and rates of water flow, which lead to changes in erosion rates (Bhaduri et al. 2000). It was found that suspended sediment from forests was one-third of that from agricultural land (Turner and Rabalais 2003). Phosphorus and nitrogen are the main nutrients that find their way into lake waters as a result of this erosion (Reynolds and Edwards 1995). Phosphorus tends to be attached to sediment particles that were washed into the lake (Karr and Schlosser 1978), where as nitrogen, in the form of nitrate, easily leaches through the soil (Reynolds and Edwards 1995).

1.2 Agriculture

In agricultural lands, the potential for excess nutrients leaching into surface waters is high, and high rates of runoff are associated with eutrophication (Riera et al. 2001). Poor agricultural practices are a concern due to the fact that crop growers tend to apply more phosphorus or nitrogen than is necessary. The application of phosphorus in excess of what plants require leads to saturation of phosphorus in the soil and a high potential for loss by transport into surface waters (McDowell and Sharpley 2001). Sediment that reaches a lake may continue to release phosphorus into the water (Gulati and Donk 2002). The addition of nutrients not only increases algal growth but also changes the composition of algal communities already present in the lake (Delong and Brusven 1992), usually to species that are considered to be a nuisance.

1.3 Minimizing Eutrophication

To prevent eutrophication or slow down its rate, a means of reducing nutrient input in the lake must be in place. A way to minimize nutrient input is through the establishment of riparian zones. These help to buffer a lake or stream from nutrient runoff (Xiang 1996). Hornbeck and Swank (1992) mention that logging adjacent to streams altered the quantity and quality of inputs and that leaving a 13-30 meter strip of vegetation between a stream and clearing was the best way to protect water quality. In another study, Correll et al. (1992) showed that a hardwood forest bordering cropland removed over 80 percent of the nitrate and total phosphorus in overland flows. The surrounding vegetation in that forest would absorbs much of the nutrient runoff.

1.4 Wetlands

Wetlands are also known to act as filters and should be protected to prevent the acceleration of eutrophication of receiving waters (Kazda 1995). Wetlands include flood plain forests, swamps, and marshes. Each of these types of wetlands can either act as a sink and trap nutrients or act as a source. This is typically dependent on how much they receive (Correll et al. 1992). The various vegetative surfaces mentioned, modify not only the land surface, but also the water quality of rivers or lakes through their filtering abilities (Tong and Chen 2002).

1.5 Urbanization

The biggest threat to water quality and the loss of forest and wetlands is urbanization, which has been shown through various studies to contribute to poor water quality. Sorrano et al. (1996) were able to show that the largest increase in phosphorus concentration in lakes and rivers was associated with urbanization. This is typically the result of urbanization creating an increase in flat surfaces, making it easier for stormwater runoff to reach the lake by allowing drainage to become more efficient (Sonneman et al. 2001). Stormwater runoff carries oxygen-demanding organic material, pesticides and fertilizers thereby increasing the rate of both phosphorus and nitrogen runoff (Horne and Goldman 1994). Stormwater runoff contributes to non-point source pollution, which is usually the main cause of poor water quality in urban settings, and is more difficult to identify and measure since the sources are spread out over a large extent. Examples include street and parking lot wash-off, sediment runoff from construction sites, and wet and dry deposition (Bhaduri et al. 2000). The greater the degree of urbanization, the less vegetation likely present to buffer the lake (Cairns Jr. and Niederlehner 1996), thus more nutrients reach their waters (Sliva and Williams 2001). Sorrano et al. (1996) stated that if a watershed were to be entirely urbanized, the annual loading of phosphorus would double.

1.6 Relationship of Land Use to Water Quality

Prior studies appear to demonstrate a clear link between land use and water quality. However, most of the studies that suggested this relationship was focused on rivers. The question addressed by this study is to what extent do land use practices correlate with water quality of lakes in Central Florida. A Geographic Information System (GIS) was used to determine this relationship because it allows for the assessment of the percentage of each landcover type and whatever changes that may have occurred in the landscape (Tong and Chen 2002). Along with the knowledge of the relationship between land use and water quality, GIS can be used in developing management strategies and creating models (Baban 1999). These strategies can then be implemented to improve the quality of water and reduce the threat of further degradation (Basnyat et al. 2000).

2. METHODS

2.1 Lakes and Water Quality Indices

Fifty lakes in Seminole County were analyzed to determine land use relationships to water quality (Figure 1). These lakes ranged in size from 2.024 to 3617 hectares and represented a variety of origins. Some of them are connected to other water bodies such as rivers or streams. Others are landlocked and possibly formed as a result of a sinkhole, which is typical of karst geologic formations found in central Florida (Waltham and Fookes 2003). Landlocked lakes are replenished through ground water and surface runoff (Lee 2002). Three of the lakes, Cranes Roost, Kiwanis Lake and Catherine Lake, are reservoirs. The 50 lakes were selected based on the availability of water quality data from the Watershed Atlas of Seminole County (2003). Water quality information included chlorophyll a, nitrogen, and phosphorus concentration as well as Secchi depth. The database contained water quality, hydrological, and ecological information on the lakes in Seminole County. The sampling period for this study extended from 1970 until 2002. Lakes in Seminole County that were missing water quality data were not included.

Each sampling period, volunteers collected water samples from two to six mid-lake locations. At the collection site, a standard Secchi disk was used to measure Secchi depth. Samples were collected and brought to the Department of Fisheries and Aquatic Sciences Water Laboratory at the University of Florida. Total phosphorus (TP), total nitrogen (TN), and chlorophyll a (Chl a) concentrations were determined using the procedures of Murphy and Riley (1962). TN concentrations were determined by oxidizing water samples with persulfate.

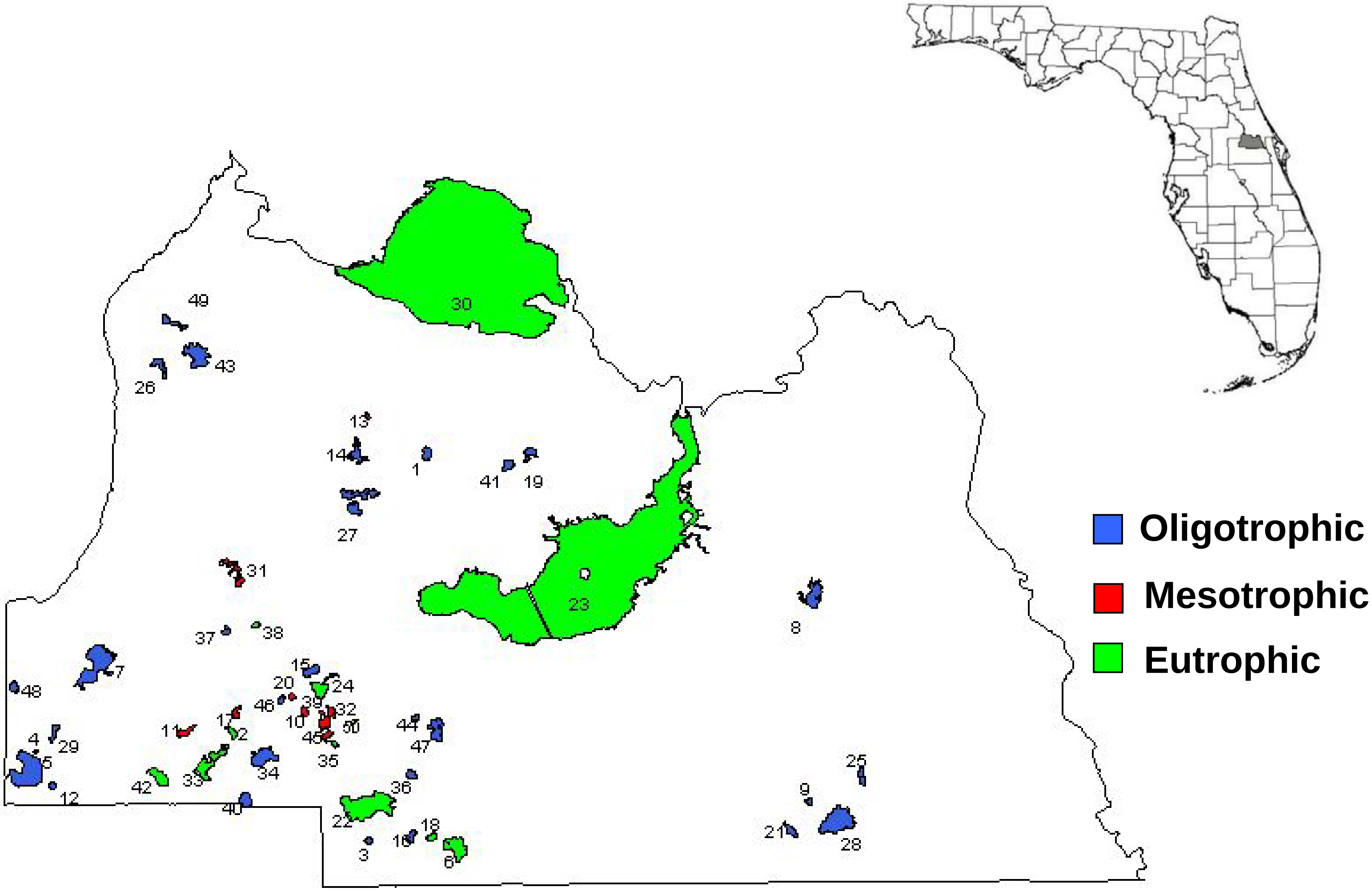

Figure 1: Seminole County and its lakes. Lakes are categorized according to trophic status and are identified by number corresponding to Tables 1-3

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Prior to 1993, Chl a concentrations were determined spectrophotometrically following pigment extraction using acetone as the extractant. After 1993, hot ethanol was used to extract chlorophyll pigments from filters. The samples were filtered in order to concentrate the chlorophyll (Canfield, Jr. et al. 2000). Water quality variables were averaged over the sampling period, which varied with each lake (Tables 1-3).

Water quality variables were mostly obtained through the LakeWatch (LW) volunteer program on a monthly basis. Lakes that were monitored by Seminole County Division of Water Resources, Florida Department of Environmental Protection (FDEP), Florida Fish and Wildlife Conservation Commision (FFWCC), and/or the City of Casselberry were sampled quarterly. Lakes sampled by Volusia County (Vol. Co.) were sampled four times per month. Those sampled by Watershed Action Volunteers (WAV) were sampled every 1-2 weeks. Those sampled by the St. Johns River Water Management District (SJRWMD) were sampled several times in one day per month. The trophic state index (TSI) of each lake was calculated for each of the water quality variables using the following formulas:

$\text{Chl a}_{TSI} = 16.8 + [14.4 * LN (\text{Chl a})]$ (Equation 1)

$TN_{TSI} = 56 + [19.8 * LN (TN)]$ (Equation 2)

$TP_{TSI} = [18.6 * LN (TP * 1000)] - 18.4$ (Equation 3)

And finally the overall TSI value was calculated by

$TSI = (\text{Chl a}_{TSI} + (TP_{TSI} + TN_{TSI}))/2$ (Equation 4)

The TSI was designed to create a standard to indicate the trophic status of lakes by creating one value that would represent the trophic state of a lake, which is more objective than defining trophic status by a nomenclature scale. However, a single criterion for trophic status does not exist (Carlson 1977). For this reason, the FDEP developed an equation based on the concepts presented by Carlson. This is a result of the FDEP being required by the Florida Watershed Restoration Act under Section 303 of the Federal Clean Water Act to develop an index that would indicate trophic status (Joyner 2002). TSI values for oligotrophic lakes ranged from 0-49. Those that were mesotrophic had values ranging from 50-60, and those that were eutrophic had values greater than 60. The index is based on equations developed by Carlson (1977). In all, there were 26 oligotrophic, 12 mesotrophic, and 12 eutrophic lakes (Tables 1-3). To better understand the TSI, lakes were also plotted based on the various water quality variables. This was to indicate how trophic status related to these variables and which variables or combination of variables would give a better indication of trophic status (Figures 2-7).

2.2 Surrounding Land Use Measures

Land use data surrounding each lake were obtained from the SJRWMD for 1990 and 1995. Using ArcView 3.3 GIS software (ESRI 1995), 100 and 500 meter buffer zones were created around each lake under study. Once the buffers were made, the proportions of each land use category (Table 4) in the buffer surrounding the lake were calculated. Some classes were modified. High, medium, and low residential were all combined under a single residential category. The industrial category was lumped with the urban category. The rangeland class was combined with the wooded areas class. The roads, highways, and airports classes were combined into a single transportation category. These combinations were done to simplify the analysis.

Table 1. Oligotrophic lakes and mean water quality variables for the time period sampled. Standard Deviation is in parenthesis. Numbers correspond to Figure 1.

Lake Name	Origin of Lake	Area	Sampler	Range of Sample	Sec. Dep (m)	Chl. a (ug/L)	Total N (mg/L)	Total P (ug/L)
1. Ada	Sinkhole	20.78	LW	5/16/90-7/29/02	3.28 (1.84)	5.32 (3.32)	0.62 (0.09)	18.09 (2.93)
3. Ann	Sinkhole	6.11	LW/Sem. Co.	4/12/97-11/19/02	4.24 (1.95)	6.10 (5.64)	0.50 (0.32)	15.05 (6.10)
4. Asher	Sinkhole	1.96	LW	7/23/98/-10/22/02	2.58 (0.87)	10.02 (17.69)	0.60 (0.22)	18.87 (11.26)
5. Bear	Stream	125.32	LW/Sem. Co.	6/7/73-10/27/02	5.47 (3.36)	4.01 (2.29)	0.52 (0.11)	13.96 (3.08)
7. Brantley	Sinkhole	115.37	LW/Sem. Co.	10/2/73-12/5/02	3.50 (2.12)	7.94 (5.94)	0.49 (0.49)	13.54 (6.95)
8. Buck	Sinkhole	64.29	Sem. Co.	11/30/98-12/11/02	2.23 (0.68)	7.57 (2.77)	0.87 (0.14)	30.90 (14.65)
9. Catherine	Sinkhole	5.60	Sem. Co.	4/12/72-10/8/02	5.69 (0.71)	2.64 (1.71)	1.45 (2.78)	16.11 (12.10)
12. Cub	Stream	6.02	Sem. Co.	2/17/99-10/31/02	3.63 (1.15)	6.43 (4.17)	0.75 (0.29)	17.43 (5.79)
14. E. Crystal	Stream	51.75	LW/Sem. Co.	8/22/91-3/12/02	3.54 (6.34)	6.17 (2.35)	1.04 (0.27)	20.03 (11.34)
15. Fairy	Stream	20.32	Sem. Co.	9/9/85-3/12/02	1.58 (4.07	18.93 (0.72)	0.72 (0.19)	20.07 (6.46)
16. Florence	Sinkhole	11.47	LW/Sem. Co.	6/21/99-11/19/02	3.15 (2.04)	8.67 (3.49)	0.55 (0.12)	17.74 (8.78)
19. Golden	Sinkhole	19.85	LW/Sem. Co.	9/16/74-11/25/02	2.49 (1.76)	15.27 (1.58)	0.54 (0.126)	29.31 (20.49)
21. Horseshoe S.	Sinkhole	13.77	LW/Sem.Co	1/20/98-10/15/02	1.75 (2.08)	4.87 (2.85)	0.68 (1.16)	12.71 (5.95)
25. Kiwanis	Reservoir	12.72	Sem. Co.	5/19/99-4/16/02	2.36 (3.23)	11.80 (9.12)	1.40 (0.95)	22.96 (13.61)
26. Markham	Sinkhole	28.14	Sem. Co.	10/19/98-10/3/02	1.79 (0.25)	7.71 (2.80)	0.96 (0.41)	33.08 (28.87)
27. Mary	Sinkhole	60.61	LW	4/3/72-10/18/02	4.07 (2.38)	4.25 (2.27)	0.64 (0.08)	13.00 (3.19)
28. Mills	Stream	93.55	Sem. Co.	4/14/99-4/16/02	2.97(0.73)	3.48 (1.82)	0.58 (0.24)	15.35 (6.60)
29. Mirror	Sinkhole	11.49	Sem. Co.	10/24/94-10/31/02	2.27(2.18)	11.65 (14.71)	0.92 (0.33)	25.29 (9.94)
34. Prairie	Stream	49.51	LW	3/9/82-11/25/02	3.41 (2.43)	8.532 (3.17)	0.65 (0.11)	17.10 (4.20)
36. Red Bug	Sinkhole	11.83	Sem. Co.	2/1/82-11/14/02	2.32 (2.94)	5.14 (3.70)	0.95 (0.33)	21.55 (16.85)
37. Rock	Sinkhole	7.73	LW	12/1/91-10/22/02	4.33 (2.23)	3.96 (2.78)	0.51 (0.07)	10.28 (2.77)
40. Seminary	Sinkhole	22.30	LW/Sem.Co	3/9/82-11/26/02	6.47 (2.30)	3.21 (1.84)	0.45 (0.23)	11.36 (8.46)
41. Silver	Sinkhole	14.88	LW	1/31/98-4/30/02	4.20 (1.16)	3.72 (1.86)	0.45 (0.07)	11.93 (2.26)
43. Sylvan	Sinkhole	76.03	Sem. Co.	2/15/82-10/1/02	2.19 (1.42)	6.80 (2.94)	0.64 (0.23)	26.24 (39.97)
44. Tony	Stream	9.48	LW/Sem.Co	7/27/99-11/19/02	2.41 (2.16)	12.49 (8.49)	0.97 (0.33)	28.68 (17.68)
46. Trout	Stream	5.98	Casselberry/WAV	10/4/94-5/14/01	4.24 (5.59)	1.82 (1.06)	0.45 (0.09)	15.13 (8.34)
47. Tuskawilla	Sinkhole	40.40	LW	2/1/82-9/19/02	2.58 (1.60)	6.207 (3.53)	0.58 (0.04)	17.89 (3.90)
48. Wekiva	Sinkhole	16.38	LW/Sem.Co	3/19/82-12/15/02	1.92 (0.79)	13.36 (8.69)	0.92 (0.19)	22.85 (15.22)
49. Yankee	Sinkhole	19.98	Sem. Co.	10/19/98-10/1/02	1.79 (0.55)	5.49 (3.50)	0.68 (0.30)	24.86 (14.15)

Table 2. Mesotrophic lakes and the water quality variables for the time period sampled. Standard deviation is in parenthesis. Numbers correspond to Figure 1.

Lake Name	Origin of Lake	Area	Sampler	Range sampled	Sec. Dep (m)	Chl. a (ug/L)	Total N (mg/L)	Total P (ug/L)
10. Concord	Stream	7.55	LW/Casselbury	6/22/93-10/18/02	1.44 (0.34)	33.41 (18.12)	0.78 (0.47)	45.75 (14.58)
11. Cranes Roost	Reservior	10.61	LW	8/17/95-9/21/02	1.85 (0.42)	13.87 (9.67)	0.67 (0.22)	49.45 (35.57)
13. DeForest	Sinkhole	4.79	LW/Sem. Co.	10/14/96-9/2/98	2.10 (2.02)	22.58 (47.08)	1.47 (1.40)	45.25 (48.26)
17. Florida	Stream	10.03	LW	2/28/73-11/15/02	2.31 (1.24)	15.60 (15.91)	0.85 (0.92)	50.95 (7.14)
20. Griffen	Stream	4.65	Casselberry	5/23/92-3/28/01	2.23 (2.74)	14.82 (15.93)	1.53 (2.64)	105.35 (164.08)
31. Myrtle	Sinkhole	22.09	Sem. Co.	1/31/98-9/16/02	1.57 (1.79)	14.26 (7.91)	1.38 (0.62)	42.07 (45.38)
32. NorthTrip	Stream	9.23	LW	5/30/96-10/18/02	1.44 (0.64)	24.04 (9.74)	0.90 (0.18)	40.17 (9.37)
39. Secret	Sinkhole	2.02	LW	6/22/93-10/18/02	1.97 (1.35)	18.13 (10.66)	0.68 (0.27)	32.10 (14.70)
45. Triplet	Stream	34.09	LW	5/30/96-10/18/02	1.31 (0.34)	24.97 (10.99)	0.84 (0.16)	48.80 (26.60)
50. Yvonne	Stream	2.87	Casselberry	6/21/93-3/28/01	2.01 (1.55)	18.75 (23.81)	0.76 (0.22)	48.22 (48.91)

Table 3. Eutrophic lakes and the water quality variables for the time period sampled. Standard Deviation is in parenthesis. Numbers correspond to Figure 1.

Lake Name	Origin of Lake	Area	Sampler	Range Sampled	Sec Dep (m.)	Chl a. (ug/L)	Total N (mg/L)	Total P (ug/L)
2. Adelaide	Stream	8.59	LW	2/14/82-11/15/02	1.49 (1.03)	33.42 (34.07)	1.03 (0.29)	46.40 (17.37)
6. Bear Gully	Stream	56.43	LW	2/1/82-10/19/02	1.01 (.34)	41.15 (9.46)	1.20 (0.21)	40.30 (6.52)
18. Garden	Stream	9.27	Sem. Co.	11/9/99-11/19/02	1.05 (0.45)	13.59 (18.91)	1.33 (0.18)	43.25 (13.21)
22. Howell	Stream	165.01	LW/SJR/WAV	3/15/73-11/14/02	1.05 (0.89)	34.87 (16.64)	1.03 (0.29)	75.09 (49.06)
23. Jesup	Stream	3287.59	Vol. Co./SJRWMD /FDEP/FGFC	3/9/70-9/19/02	0.92 (0.82)	98.27 (62.88)	2.00 (1.02)	138.54 (70.44)
24. Kathryn	Stream	31.51	Casselberry	2/20/73-3/28/012	2.54 (12.41)	35.63 (23.42)	1.00 (0.45)	47.63 (17.17)
30. Monroe	Stream	3624.76	Vol. Co.	2/10/70-4/8/02	0.96 (0.62)	37.54 (43.96)	1.57 (0.58)	87.76 (52.35)
33. Orienta	Sinkhole	57.55	LW	6/17/95-2/28/02	0.87 (1.01)	54.19 (22.92)	1.25 (0.40)	43.10(11.49)
35. Queens Mirror	Sinkhole	4.73	LW	5/30/96-10/18/02	1.27 (0.83)	36.88 (17.55)	0.87 (0.23)	55.62 (15.82)
38. Searcy	Sinkhole	4.61	LW	2/24/98-11/23/02	1.36 (0.76)	38.05 (23.31)	1.24 (0.28)	56.79 (17.93)
42. Spring	Stream	35.63	LW/Sem. Co.	2/26/73-11/26/02	1.05 (0.30)	1.88 (17.00)	1.56 (0.34)	41.65 (7.45)

Table 4 describes the land use types used in this study, which were based on the land use codes provided by the Florida Department of Transportation (1999).

Soil data were obtained from the SJRWMD. The different soil types were categorized according to their drainage abilities and were incorporated along with the land use data. The average percentages for Seminole County are excessively poorly drained soil: 14.8, for moderately well: 14.7, for poorly drained: 16.8, for somewhat poorly drained: 34.1, and for very poorly drained soil: 18.5. Runoff is the most common way for phosphorus and nitrogen to reach a nearby water body, which is affected by how well the soil drains. Land use data and soil data are both needed to estimate runoff (Melesse and Shih 2002). For example, a low drainage ability will result in a higher erosion rate, thereby increasing the nutrient load into a lake. TIGER (Topologically Integrated Geographic Encoding and Referencing) road data were obtained from U.S. Census Bureau (1990). As roads can influence ecological functions (Forman 2003) road density (km/ha) within each buffer zone of a lake was calculated.

In addition to these static classes, changes in the proportion in buffer classes surrounding a lake were calculated from 1990 to 1995. However, because Cranes Roost lake was not constructed until after 1990 it was not included in the land use change analyses.

2.3 Data Analysis

The purpose of this study was to determine what correlations exist between land use and overall water quality and the correlation between each water quality variable and land use. However, we were not testing how the strongest water quality variables were related to the land use data.

Table 4. Land use classes with description and average percentage across the county

Land Use Class	Description	Average Percentage
Residential	Defined as number of dwelling units per acre, includes low-density, medium density, and high density.	0.556
Urban	Defined as the areas predominately associated with the distribution of products and services, where manufacturing, assembly, and processing of materials occurs, and includes institutional, recreational and open land. Institutional embraces facilities of education, religion, health, medical, governmental, and military. Open land is defined as undeveloped land within urban areas and inactive land with street patterns but no structures.	0.098
Agriculture	Includes cropland, improved and unimproved pastureland, row, field, and tree crops, feeding operations for cattle, poultry, and swine, nurseries, vineyards, and other open land. Improved pasture is land that has been cleared, tilled reseeded with specific grass types and involves brush control and fertilizer application. Unimproved pasture includes cleared land with major stands of trees and brush where native grasses have been allowed to develop. Open land includes those agricultural lands whose intended usage cannot be determined.	0.054
Hardwoods	Includes the both rangeland and upland forests. Rangeland is land where natural vegetation is predominately grasses, grass-like plants and shrubs and is generally not fertilized, cultivated or irrigated. Upland forests support a canopy closure of ten percent or more and can include timber harvesting.	0.093
Water	Includes lakes, reservoirs, streams, rivers, canals, and creeks. Does not include portions with emergent vegetation or observable submerged vegetation.	0.034
Wetlands	Areas where the water table is at, near, or above the land surface for a significant portion of most years.	0.1453
Barren Land	Little or no vegetation and limited potential to support vegetative communities. An area of bare rock or soil.	0.0007
Transportation and Communication	Includes roads, highways, railroads, airports, and ports. Radar television, antennas, and transmission towers are all under communication.	0.0198
Electricity	Includes power facilities and power transmission lines. Power facilities include hydropower, thermal, and nuclear.	0.0021
Sewage	Includes sewage treatment and solid waste disposal plants.	0.00044

For the first part of the study, it was decided that CCA would be the best statistical method in which two matrices are tested to see if any correlation exists between them (McCune and Grace 2000).

Six different matrices were evaluated with CCA. Land use matrices were created for both the year and the size of the buffer zone. Soil cover data were incorporated into the matrices. These soil types were categorized according to their drainage abilities in Tables 5-7. Another matrix containing the lakes and water quality parameters for each lake was created.

The centering method was used for scaling in CCA analysis. Scores were derived from land use variables and displayed. These scores are the weighted average (WA) scores and were chosen in order to reduce the probability of interference from environmental noise. Weighted average means that the scores for rows in the main matrix are derived from the columns in the main matrix, as oppose to the environmental variables in the second. A Monte Carlo test was run to test the null hypothesis: There was no relationship between the first matrix and any of the other matrices. The null hypothesis was rejected or accepted based on the p-value given. The CCA was completed using 100 randomizations in order to obtain a more accurate result. This is an acceptable technique as mentioned in (Turner et al. 1996).

In addition, Discriminant Function Analysis (DFA) was performed to determine if the land use variables can indeed separate the lakes based on trophic status. Lakes were split into three trophic groups and then into two trophic groups for both the year and size of the buffer zone. Land use and soil data were transformed using Arcsine as suggested by Fry (2002). Discriminant function analysis was also used to determine which land use or soil variable could be used to distinguish between the groups of lakes. The significance of each variable in contributing to the discrimination among groups of lakes was reported as well as the percentage of lakes that were classified correctly.

Once I obtained the CCA and DFA results of the land use to overall water quality analysis, I then narrowed the study to determine correlations between each water quality variable and land use and test whether there were any differences between sinkhole originated lakes and stream-fed lakes. Step-wise regression was used to test individual water quality variable relationships. Lakes included in the multiple regression analysis were those that had data from 1996 and before. Land use data were normalized with arcsin times the square root of x to reduce error and was tested for each year/buffer zone. DFA was then used to test differences between sinkhole originated lakes and stream-fed lakes. All lakes other than those considered reservoirs were included and data was tested for year/buffer zone. Land use data were also normalized for DFA to reduce error. Step-wise regression was not permitted for this analysis.

Table 5. Soil series of Volusia County used and their drainage abilities

Soil Series	Drainage Ability
Basinger	Very poorly
Bluff	Very poorly
Chobee	Very poorly
Daytona	Medium well
Eaugallie	Poorly
Electra	Somewhat poorly
Farmton	Poorly
Fluvaquents	Poorly
Gator	Very poorly
Immokalee	Poorly
Orsino	Medium well
Paisley	Poorly
Paola	Excessively well
Placid	Very poorly
Pomona	Very poorly
Quartzip Samments	Poorly
Riviera	Poorly
Samsula	Very poorly
Terraceia	Very poorly
Urban land	Somewhat poorly
Wabasso	Poorly
Wauchula	Poorly
Winder	Poorly

Table 6. Orange County soil series and their drainage abilities

Soil Series	Drainage Ability
Archbold	Medium well
Basinger	Very Poorly
Candler	Excessively well
Florahome	Medium well
Hontoon	Very poorly
Immokalee	Poorly
Pomello	Medium well
St. John's	Poorly
St. Lucie	Excessively well
Tavares	Medium well
Urban Land	Somewhat poorly

Table 7. Seminole County soil series used and their drainage abilities

Soil Series	Drainage Ability
Adamsville	Somewhat poorly
Arents	Somewhat poorly
Astatula	Excessively well
Basinger	Poorly
Canova	Very poorly
Eaugallie	Very poorly
Felda	Very poorly
Immokalee	Poorly
Brighton	Very poorly
Malabar	Poorly
Manatee	Very poorly
Myakka	Poorly
Nittaw	Very poorly
Paola	Excessively well
Pineda	Poorly
Udorthents	Medium well
Pomello	Medium well
Pompano	Poorly
St. John's	Poorly
Seffner	Somewhat poorly
Tavares	Medium well
Terra Ceia	Very poorly
Urban Land	Somewhat poorly
Wabasso	Poorly

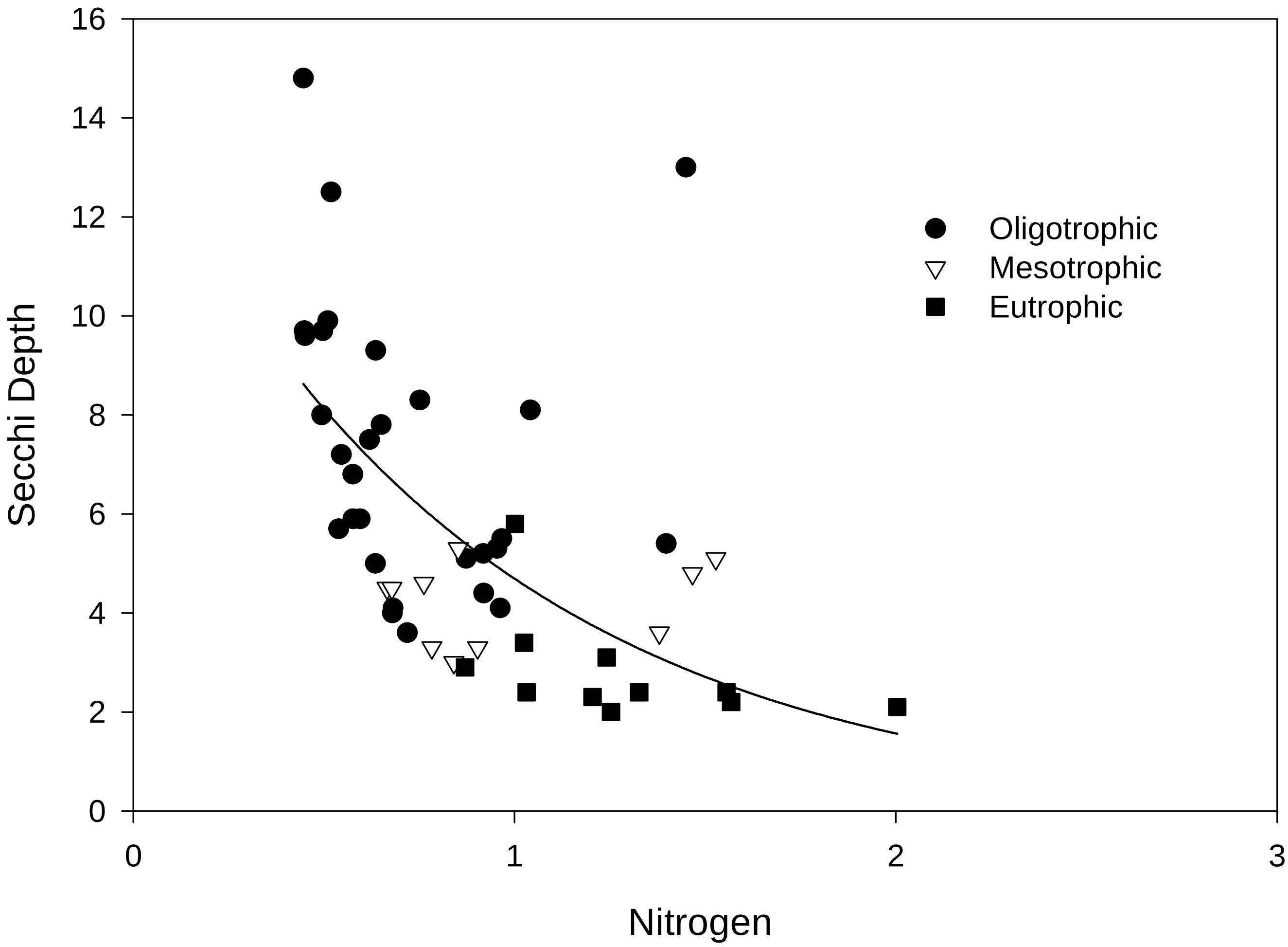

Figure 2. Graph of nitrogen vs. Secchi depth to describe the trophic status of a lake.

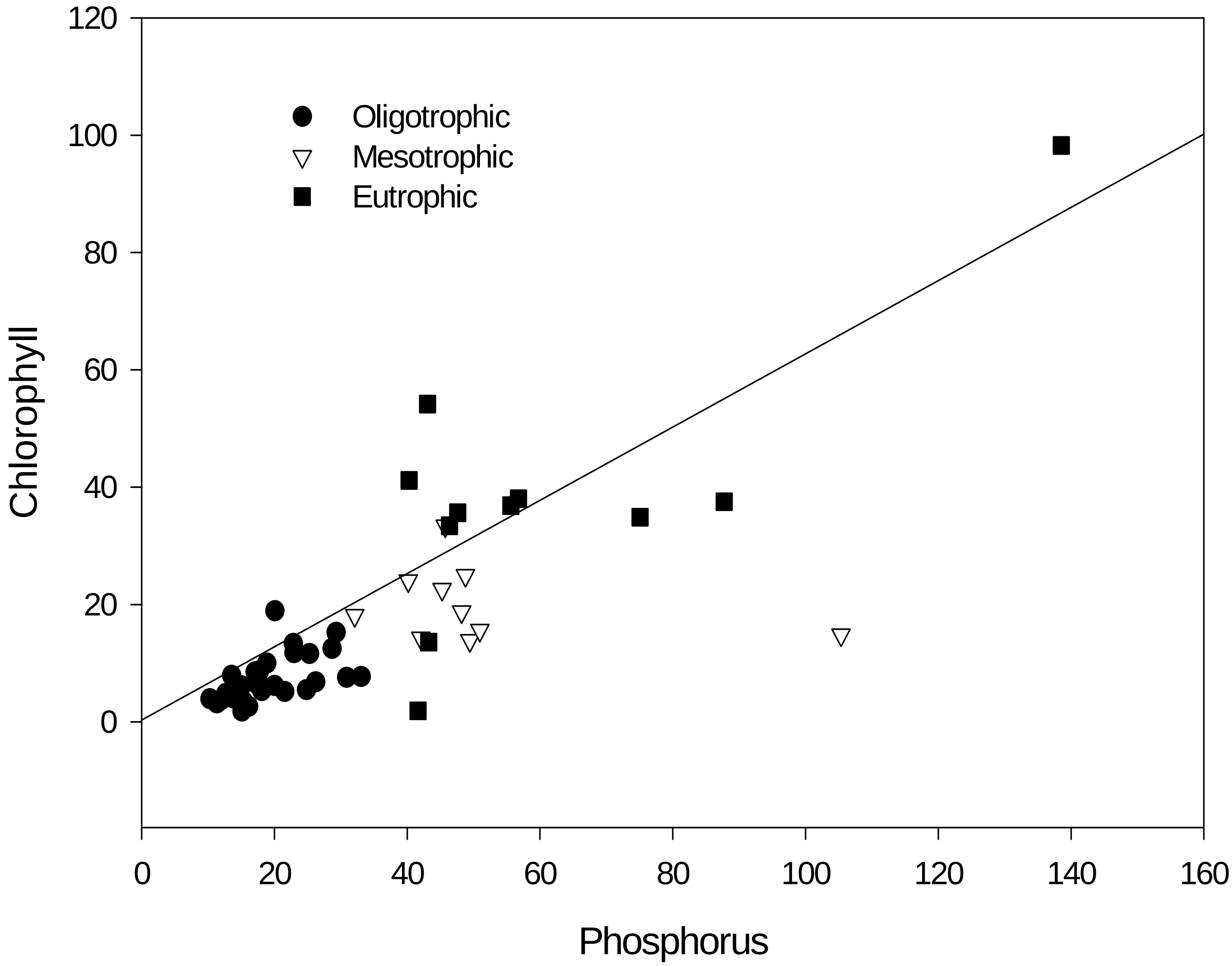

Figure 3. Graph of phosphorus vs. chlorophyll to describe the trophic status of a lake.

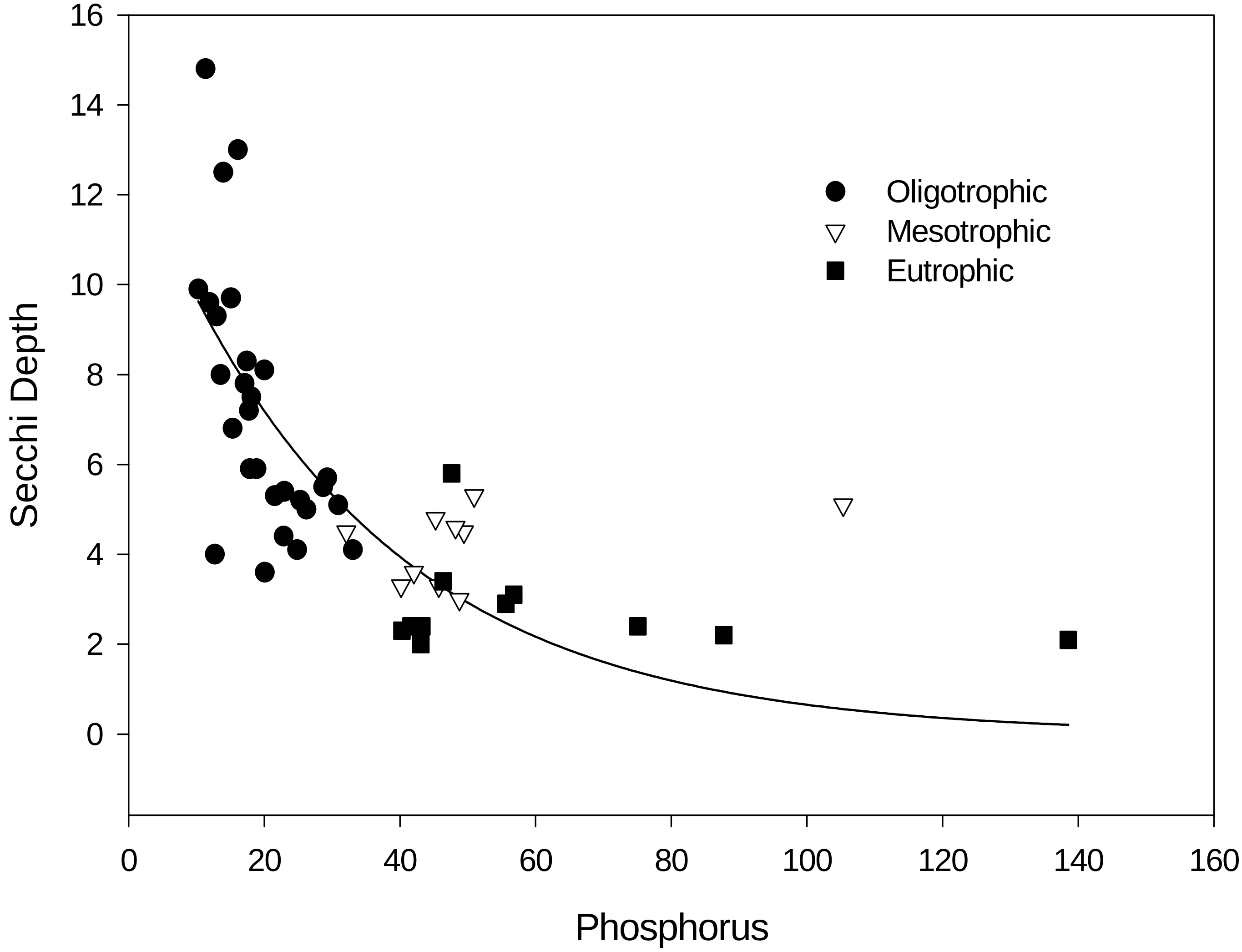

Figure 4. Graph of phosphorus vs. Secchi Depth to describe the trophic status of a lake.

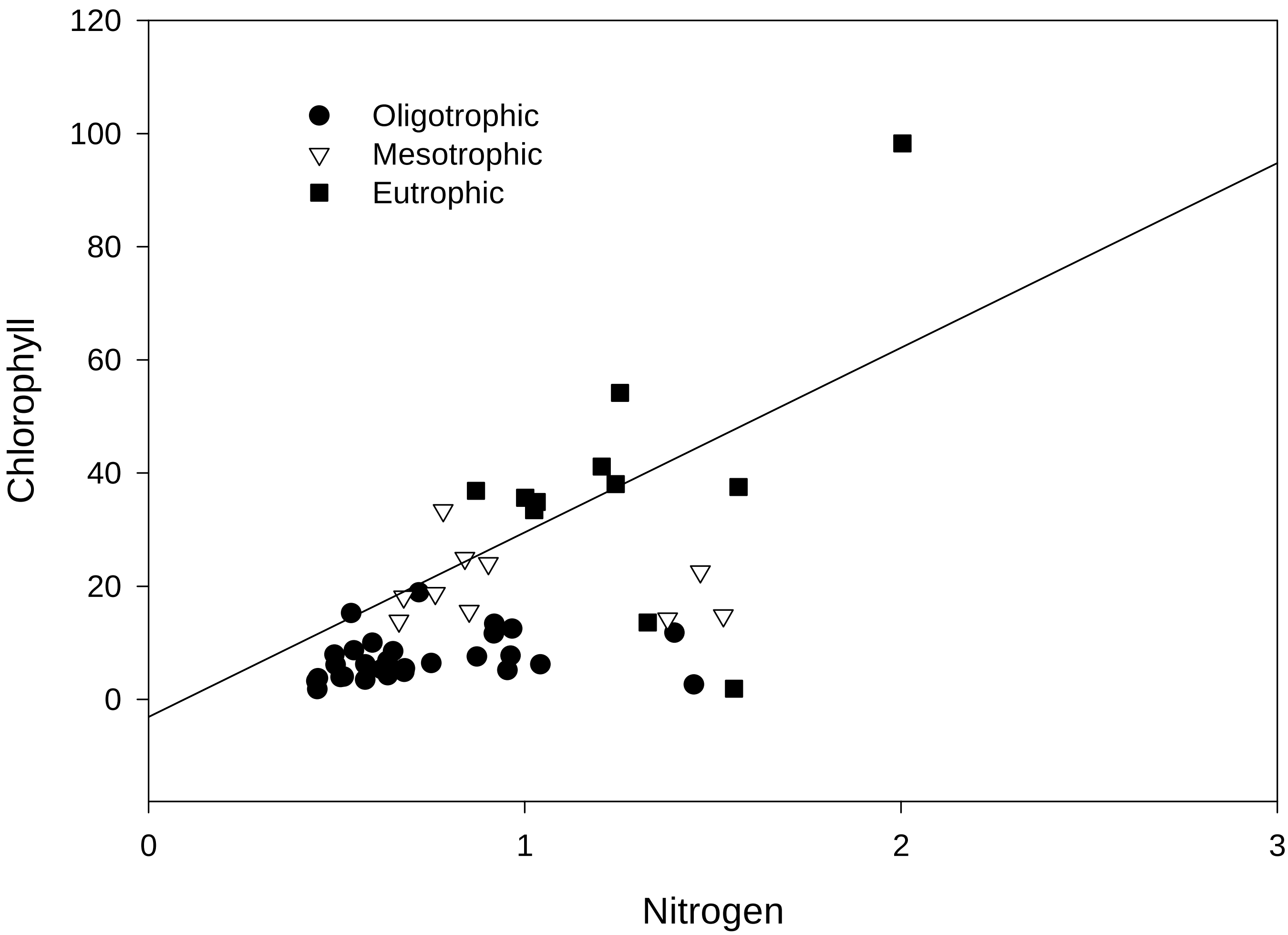

Figure 5. Graph of nitrogen vs. chlorophyll to describe the trophic status of a lake.

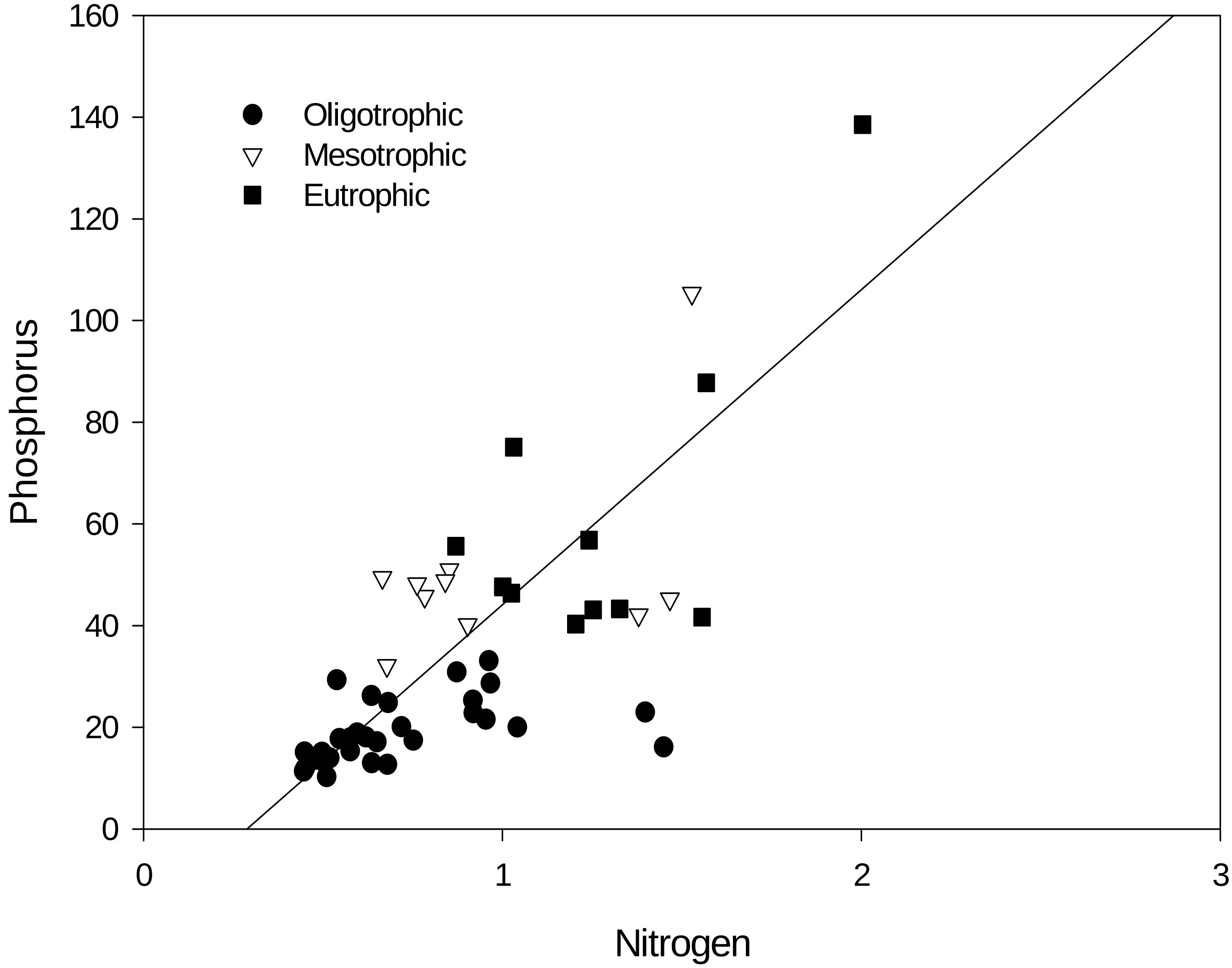

Figure 6. Graph of nitrogen vs. phosphorus to describe the trophic status of a lake.

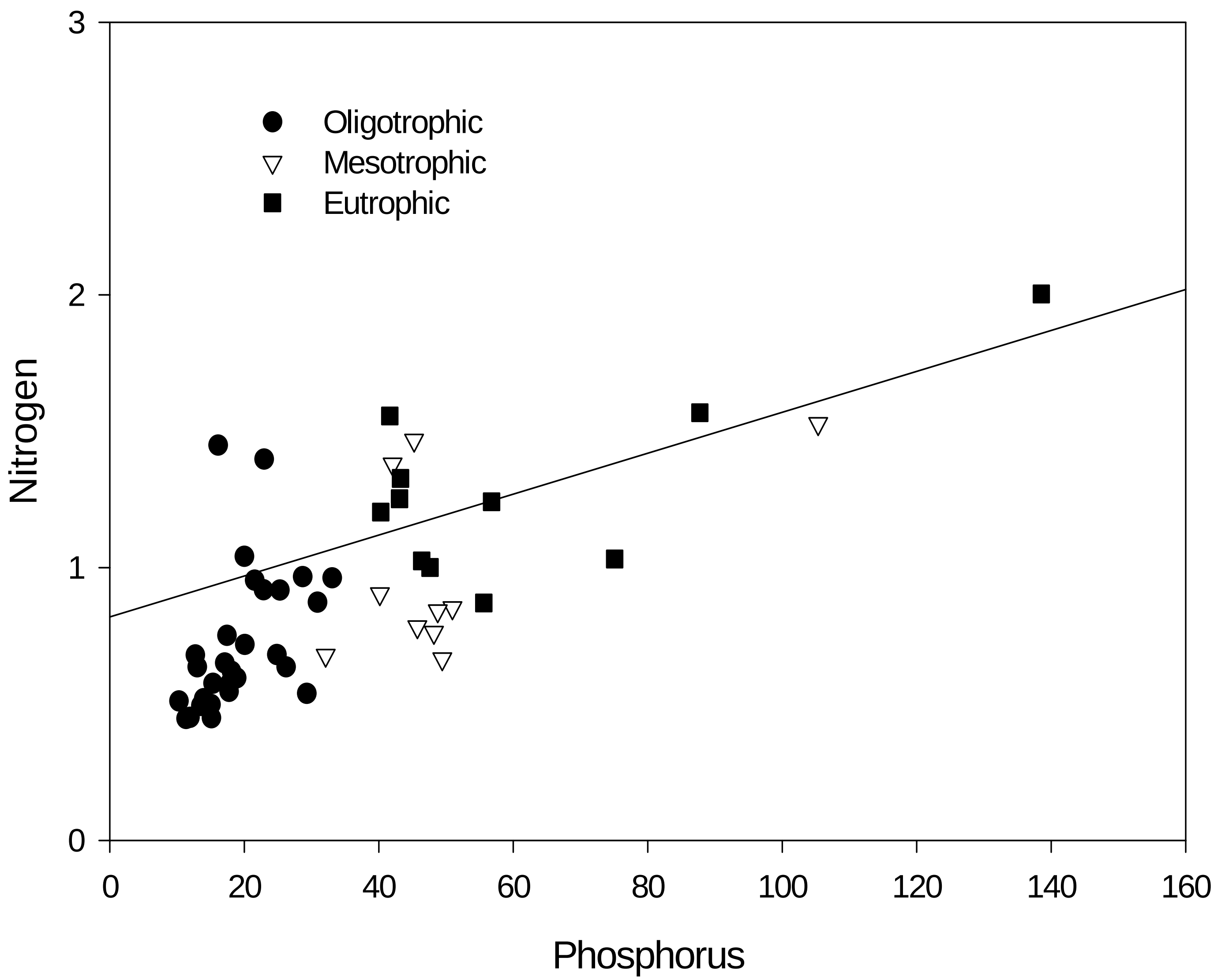

Figure 7. Graph of phosphorus vs. nitrogen to describe the trophic status of a lake.

3. RESULTS

3.1 Relationship among water quality variables

Each of the preceding graphs show the relationship among water quality variables and how each can be used to describe the trophic status of a lake (Figures 2-7). Phosphorus seems to be the dominant factor in determining trophic status. Phosphorus was able to discriminate between lakes of different trophic states better than the other water quality variables. Chlorophyll also provided distinction among groups of lakes although not quite as well as phosphorus. Nitrogen and Secchi depth were not able to separate out lakes as distinctly as phosphorus or chlorophyll. However, in each graph, oligotrophic lakes separated out very well, indicating that all the water quality variables contribute to defining the trophic state of a lake.

3.2 CCA Results

CCA was performed on the land use and soil type for each year and buffer zone. Only land use for 1990 100 m and 1990 500 m buffers was found to be significant for the correlation between land use and water quality. The insignificant results are found in appendix A.

3.2.1 1990 Land use data from 100 m buffer

3.2.1.1 Corrrelations among land use variables (CCA)

Raw data scores were weighted and averaged for variables in the second matrix, to determine correlation among variables. Among land use variables, strong correlations existed between road density and residential and also between agriculture and hardwoods. For this analysis, electricity and sewage land use categories were absent.

3.2.1.2 Correlations between water quality variables and land use (CCA)

Eigenvalues for the first two axes were 0.275 and 0.082. The eigenvalue for axis 1 was found to be significant using the Monte Carlo test and had a p-value of 0.05. The eigenvalue for the second axis was not significant. The first axis explained 46 percent of the variance while the second axis explained 9.3 percent (Table 8). Each axis represents a landscape variable.

The Pearson correlation was 0.903 suggesting a high correlation between water quality and land use. The correlation between the two matrices for the first axis was found to be significant by the p-value of 0.05 (Table 34). The inter-set correlations showed that hardwood and agriculture had the strongest correlation with the WA scores for axis 1, while residential and urban had the strongest correlation for axis 2, suggesting a correlation between land use and water quality. The first axis appeared to represent a more natural setting while the second axis represented the impact of urbanization (Table 8). Residential and urban had a high positive correlation with axis 2, while agricultural, hardwood, and excessively drained soil had a high positive correlation with axis 1. Barren land and very poorly drained soil had a strong negative correlation with axis 1.

Table 8. CCA results for 1990 100 m based on buffers.
Results include the eigenvalue associated with each axis, the variance explained by that eigenvalue and the inter-set correlations.

Land-Use/Drainage Category	**Axis 1**	**Axis 2**
Residential	0.311	0.259
Urban	-0.389	0.295
Agricultural	0.636	0.004
Hardwood	0.745	-0.03
Water	-0.281	-0.164
Barren land	-0.444	-0.201
Transportation	-0.038	0.137
Electricity	-0.13	0.116
Road Density	0.36	0.011
Excessively drained	0.552	-0.036
Medium well drained	-0.051	-0.058
Poorly drained	0.341	-0.017
Somewhat poorly drained	-0.037	0.123
Very poorly drained	-0.516	-0.027
Eigenvalue	0.294	0.059
Percent Variance explained	46	9.3
Pearson Correlation	0.903	0.611

3.2.2 1990 Land use data from 500 m buffer

3.2.2.1 Correlations among land use variables (CCA)

Residential and urban both had high correlations with road density. Urban areas also had a high correlation with water and sewage had a strong correlation with electricity.

3.2.2.1 Correlations between land use and water quality variables (CCA)

The first two CCA axes accounted for 49.3 % and 8.5 % of the variance with eigenvalues of 0.315 and 0.054. Based on the Monte Carlo tests, the eigenvalue for axis 1 was significant ($p<0.05$) while the eigenvalue for axis 2 was not ($p>0.05$). The Pearson correlation for axis 1 was 0.936 indicating a high correlation between water quality variables and environmental variables. The correlation between the two matrices was found to be significant ($p= 0.01$) (Table 34). Inter-set correlations show excessively drained soils having the strongest correlation with the WA scores for axis 1 while residential had the strongest correlation for axis 2 (Table 9). The other inter-set correlations showed that road density had a high positive correlation with axis 2, while wetlands had a strong negative correlation with axis 2. Urban and hardwoods had a strong positive correlation with axis1, while very poorly drained soil had a strong negative correlation with axis 1. The WA scores were plotted to show if the water quality variables were adequate to describe the effects of land use (Figure 9). Oligotrophic and eutrophic lakes were loosely separated into groups. Mesotrophic lakes were spread randomly throughout the plot. Lakes were separated mostly along axis 2. I conclude land-use variables were not sufficient to describe water quality for the lakes given.

Table 9. CCA results for 1990 500 m based on buffers.
Results include the eigenvalue associated with each axis, the variance explained by that eigenvalue and the inter-set correlations.

Land Use/Drainage Category	Axis 1	**Axis 2**
Residential	-0.127	0.287
Urban	0.481	0.082
Agricultural	0.212	-0.131
Hardwoods	0.386	0.007
Water	0.291	0.008
Wetlands	-0.414	-0.233
Barren land	-0.268	-0.043
Transportation	0.104	0.102
Electricity	-0.147	0.005
Sewage	-0.189	-0.129
Road Density	0.126	0.239
Excessively drained	0.552	-0.052
Medium well drained	-0.051	-0.056
Poorly drained	0.34	-0.023
Somewhat poorly drained	-0.044	0.144
Very poorly drained	-0.511	-0.026
Eigenvalues	0.315	0.054
Percent variance explained	49.3	8.5
Pearson Correlation	0.936	0.605

3.3 Classification Accuracy for All Lakes in Seminole County

Lakes were classified based on the land use and soil type for each year and buffer zone. Altogether there were twenty-nine oligotrophic lakes, ten mesotrophic lakes, and eleven eutrophic lakes. All the lakes were tested with DFA and the results include, Wilk's lambdas, F-value, significance of each variable in discriminating between the trophic state of each lake and the classification table. For each year and buffer zone, lakes were separated into three groups and then into two groups.

3.3.1 1990 100 m buffer zone

For lakes separated into three groups, Wilk's lambda was significant for road density, and moderately drained soils. Both were determined to be variables that describe the discriminating functions 1 and 2 (Table 10). In the classification matrix, 67 % of the lakes were classified correctly as oligotrophic, 75 % of the lakes were classified correctly as mesotrophic, and 72.5 % of the lakes were correctly classified as eutrophic. Overall, 69.4 % of the lakes were classified correctly (Table 12).

For lakes separated into two groups, Wilk's lambda was significant for moderately well drained soils only (Table 11). In the classification matrix, 76.7 % of the oligotrophic lakes were classified correctly, while 68.4 % of the mesotrophic and eutrophic lakes were classified correctly. Overall, 73.5% of the lakes were classified correctly (Table 13).

Table 10. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are separated into three groups.

Land Use variables (3 groups)	**Wilk's lambda**	**F-value**	**Significance (<0.05)**
Residential	0.978	0.518	0.599
Urban	0.945	1.340	0.272
Agricultural	0.996	0.094	0.910
Hardwoods	0.922	1.935	0.156
Water	0.949	1.246	0.297
Wetlands	0.922	1.933	0.156
Road Density	0.878	3.205	0.050
Excessive	0.963	0.894	0.416
Moderately	0.878	3.917	0.050
Poorly	0.948	1.266	0.291
Somewhat Poorly	0.962	0.918	0.407
Very Poorly	0.951	1.189	0.314

Table 11. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are separated into two groups.

Land Use variables (2 groups)	**Wilk's lambda**	**F-value**	**Significance (<0.05)**
Residential	0.986	0.677	0.415
Urban	0.980	0.975	0.329
Agricultural	0.998	0.083	0.775
Hardwoods	0.968	1.536	0.221
Water	0.987	0.603	0.441
Wetlands	0.963	1.781	0.188
Road Density	0.935	3.257	0.078
Excessive	0.998	0.117	0.734
Moderately Well	0.892	5.712	0.021
Poorly	0.948	2.583	0.115
Somewhat Poorly	0.963	1.827	0.183
Very Poorly	0.998	0.081	0.777

Table 12. Accuracy of DFA classification of lake trophic status based on surrounding land use. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (29)	66.7	13.3	20
Mesotrophic (9)	12.5	75	12.5
Eutrophic (11)	18.2	9.1	72.7

Table 13. Accuracy of DFA classification of lake trophic status based on surrounding land use. Numbers in parentheses indicate the number of lakes in that category.

	Predicted	
Observed	**Oligotrophic**	**Meso-Eutrophic**
Oligotrophic (29)	76.7	23.3
Meso-Eutrophic (20)	31.6	68.4

3.3.2 1990 500 m buffer zone

For lakes separated into three groups, Wilks's lambda shows that wetlands and poorly drained soil were significant in discriminating between groups and were adequate to describe discriminant functions 1 and 2. (Table 14) Classification results show 70 % of oligotrophic, 87.5 % of mesotrophic, and 72.7 % of eutrophic lakes were classified correctly. Overall, 73.5 % of lakes were classified correctly (Table 16).

For lakes separated into two groups, Wilk's lambda shows that urban and road density were significant in discriminating between groups and were used to describe functions 1 and 2 (Table 15). Classification results show that 66.7% of oligotrophic lakes and 68.4 % of mesotrophic and eutrophic lakes were classfied correctly. Overall, 67.3% of lakes were classified correctly (Table 17).

Table 14. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are split into three groups.

Land Use variables (3 groups)	Wilk's lambda	F-value	Significance (<0.05)
Residential	0.991	0.214	0.808
Urban	0.968	0.751	0.478
Agricultural	0.954	1.112	0.337
Hardwoods	0.895	2.706	0.077
Water	0.946	1.311	0.280
Wetlands	0.819	5.084	0.010
Road Density	0.997	0.077	0.926
Excessive	0.926	1.844	0.170
Moderately Well	0.958	1.015	0.370
Poorly	0.868	3.495	0.039
Somewhat Poorly	0.925	1.877	0.165
Very Poorly	0.912	2.207	0.122

Table 15. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are split into two groups.

Land Use variables (2 groups)	**Wilk's lambda**	**F-value**	**Significance (<0.05)**
Residential	0.956	1.073	0.350
Urban	0.829	4.843	0.012
Agricultural	0.993	0.157	0.855
Hardwoods	0.931	1.733	0.188
Water	0.929	1.790	0.178
Wetlands	0.947	1.326	0.275
Road Density	0.872	3.461	0.040
Excessive	0.980	0.474	0.625
Moderately Well	0.965	0.864	0.428
Poorly	0.997	0.064	0.938
Somewhat Poorly	0.967	0.798	0.456
Very Poorly	0.890	2.906	0.065

Table 16. Accuracy of DFA classification of lake trophic status based on surrounding land use. Numbers in parentheses indicates the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (29)	70	16.7	13.3
Mesotrophic (9)	12.5	87.5	0
Eutrophic (11)	18.2	9.1	72.7

Table 17. Accuracy of DFA classification of lake trophic status based on surrounding land use. Numbers in parentheses indicates the number of lakes in that category.

	Predicted	
Observed	**Oligotrophic**	**Meso-Eutrophic**
Oligotrophic (29)	66.7	33.3
Meso-Eutrophic (20)	31.6	68.4

3.3.3 1995 100 m buffer zone

For lakes separated into three groups, Wilk's lambda was significant for urban and road density in discriminating between groups (Table 18). Classification shows that 71 % of oligotrophic, 100 % of mesotrophic, and 70.0 % of eutrophic lakes were correctly classified. Overall, 76 % of lakes were correctly classified (Table 20).

For lakes separated into two groups, Wilk's lambda was significant for road density in discriminating between groups (Table 19). Classification shows that 71 % of oligotrophic lakes and 68.4 % of mesotrophic and eutrophic lakes were correctly classified. Overall, 70.0 % of lakes were correctly classified (Table 21).

Table 18. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are split into three groups.

Land use variables (3 groups)	**Wilk's lambda**	**F-value**	**Significance (<0.05)**
Residential	0.956	1.073	0.350
Urban	0.829	4.843	0.012
Agricultural	0.993	0.157	0.855
Hardwood	0.931	1.733	0.188
Water	0.929	1.790	0.178
Wetlands	0.947	1.326	0.275
Road density	0.872	3.461	0.040
Excessive	0.980	0.474	0.625
Moderately well	0.965	0.864	0.428
Poorly	0.997	0.064	0.938
Somewhat poorly	0.967	0.798	0.456
Very poorly	0.890	2.906	0.065

Table 19. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are split into two groups.

Land Use Variables (2 groups)	Wilk's lambda	F-Value	Significance (<0.05)
Residential	0.994	0.267	0.608
Urban	0.936	3.266	0.077
Agricultural	0.993	0.317	0.576
Hardwoods	0.989	0.541	0.465
Water	0.988	0.602	0.442
Wetlands	0.998	0.086	0.770
Road Density	0.914	4.522	0.039
Excessively	0.993	0.320	0.574
Moderately Well	0.968	1.588	0.214
Poorly	1.0	0.018	0.893
Somewhat Poorly	1.0	0.000	0.995
Very Poorly	0.973	1.340	0.253

Table 20. Accuracy of DFA classification of lake trophic status based on surrounding land use. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (29)	71	9.7	19.4
Mesotrophic (10)	0	100	0
Eutrophic (11)	30	0	70

Table 21. Accuracy of DFA classification of lake trophic status based on surrounding land use. Numbers in parentheses indicate the number of lakes in that category.

	Predicted	
Observed	**Oligotrophic**	**Meso-Eutrophic**
Oligotrophic (29)	71	29
Meso-Eutrophic (21)	31.6	68.4

3.3.4 1995 500 m buffer zone

For lakes separated into three groups, Wilk's lambda was significant for urban, agricultural, water and poorly drained soil in discriminating between groups (Table 22). Agriculture and poorly drained soil were adequate to describe the discriminant functions 1 and 2. Among oligotrophic lakes, 67.7 % were correctly classified, as well as 100 % of mesotrophic, and 36.4 % of eutrophic lakes. Overall, 66 % of lakes were correctly classified (Table 24).

For lakes separated into two groups, Wilk's lambda was significant for poorly drained soil and agriculture (Table 23). Classification results show that 67.7 % of oligotrophic lakes and 73.7 % of mesotrophic and eutrophic lakes were correctly classified. Overall 70% of all lakes were correctly classified (Table 25).

Table 22. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are split into three groups.

Land use variables (3 groups)	**Wilk's lambda**	**F-value**	**Significance (<0.05)**
Residential	0.985	0.362	0.698
Urban	0.876	3.316	0.045
Agricultural	0.847	4.249	0.02
Hardwoods	0.956	1.080	0.348
Water	0.850	4.149	0.022
Wetlands	0.944	1.385	0.26
Road Density	0.905	2.471	0.095
Excessively	0.984	0.391	0.678
Moderately Well	0.967	0.799	0.456
Poorly	0.847	4.236	0.02
Somewhat Poorly	0.917	2.122	0.131
Very Poorly	0.988	0.277	0.759

Table 23. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are split into two groups.

Land use variables (2 groups)	**Wilk's lambda**	**F-value**	**Significance (<0.05)**
Residential	0.997	0.134	0.716
Urban	0.942	2.957	0.092
Agricultural	0.889	5.994	0.018
Hardwoods	0.959	2.061	0.158
Water	0.956	2.213	0.143
Wetlands	0.980	0.969	0.330
Road Density	0.927	3.784	0.058
Excessively	0.984	0.799	0.376
Moderately Well	0.995	0.261	0.612
Poorly	0.860	7.786	0.008
Somewhat Poorly	0.932	3.519	0.067
Very Poorly	0.992	0.381	0.540

Table 24. Accuracy of DFA classification of lake trophic status based on surrounding land use. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic	67.7	6.5	25.8
Mesotrophic	0	100	0
Eutrophic	36.4	27.3	36.4

Table 25. Accuracy of DFA classification of lake trophic status based on surrounding land use. Numbers in parentheses indicate the number of lakes in that category.

	Predicted	
Observed	**Oligotrophic**	**Meso-Eutrophic**
Oligotrophic (29)	67.7	32.3
Meso-Eutrophic (21)	26.3	73.7

3.3.5 Change in land use for 100 m buffer zone

For lakes separated into three groups, Wilk's lambda was significant for urban (Table 26). The first canonical function explained 61.3 % of the variance and the second 38.7 %. Lakes that were classified correctly include 74.2 % of oligotrophic lakes, 66.7 % of mesotrophic, and 60 % of eutrophic. Overall 70 % of lakes were classified correctly (Table 28).

For lakes separated into two groups, Wilk's lambda was significant for urban (Table 27) and was adequate to describe the first discriminant function. 93.5 % of oligotrophic lakes and 66.7 % of mesotrophic and eutrophic lakes were correctly classified. Overall 87.5 % of the lakes were correctly classified (Table 29).

Table 26. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are split into three groups.

Land Use Variables (3 Groups)	**Wilk's lambda**	**F-Value**	**Significance (<0.05)**
Residential	0.985	0.352	0.705
Urban	0.772	6.959	0.002
Agriculture	0.986	0.332	0.719
Hardwoods	0.932	1.715	0.191
Water	0.907	2.418	0.100
Wetlands	0.960	0.967	0.388
Road Density	0.980	0.474	0.625
Excessively Drained	0.983	0.414	0.663
Moderately Well	0.998	0.047	0.954
Poorly	0.983	0.397	0.675
Somewhat Poorly	0.900	2.615	0.084
Very Poorly	0.937	1.582	0.216

Table 27. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are split into two groups

Land Use Variables (2 Groups)	Wilk's lambda	F-value	Significance (<0.05)
Residential	0.985	0.575	0.453
Urban	0.767	11.534	0.002
Agriculture	0.994	0.215	0.646
Hardwoods	0.938	2.518	0.121
Water	0.962	1.517	0.226
Wetlands	0.957	1.714	0.198
Road Density	1.000	0.005	0.942
Excessively Drained	0.983	0.666	0.42
Moderately Well	0.997	0.100	0.753
Poorly	0.990	0.398	0.532
Somewhat Poorly	0.993	0.252	0.618
Very Poorly	0.934	2.673	0.110

Table 28. Accuracy of DFA classifications of lake trophic status based on surrounding land use. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic	74.2	9.7	16.1
Mesotrophic	33.3	66.7	0
Eutrophic	40	0	60

Table 29. Accuracy of DFA classification of lake trophic status based on surrounding land use. Numbers in parentheses indicate the number of lakes in that category.

	Predicted	
Observed	**Oligotrophic**	**Meso-Eutrophic**
Oligotrophic (29)	93.5	6.5
Meso-Eutrophic (21)	33.3	66.7

3.3.6 Change in Land Use for 500 m Buffers

For lakes separated into three groups, Wilk's lambda was significant for water in discriminating between groups. None of the other variables were significant (Table 30). Classification results showed that 74.2 % of oligotrophic, 50% of mesotrophic, and 63.6% of eutrophic lakes were classified correctly. Overall, 68 % of lakes were correctly classified (Table 32)

For lakes separated into two groups, Wilk's lambda was significant for water in discriminating between groups (Table 31) and was the only variable adequate to describe the function. Classification results show that 90.3% of oligotrophic lakes were correctly classified. 50% of mesotrophic and eutrophic lakes were correctly classified. Overall, 82.1 % of lakes were correctly classified (Table 33).

Table 30. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are split into three groups.

Land use variables (3 groups)	Wilk's lambda	F-value	Significance (<0.05)
Residential	0.985	0.215	0.807
Urban	0.988	0.276	0.760
Agricultural	0.988	0.294	0.746
Hardwoods	0.976	0.574	0.567
Water	0.914	2.205	0.122
Wetlands	0.943	1.433	0.249
Road density	0.994	0.144	0.866
Excessive	0.973	0.653	0.525
Moderately well	0.964	0.888	0.418
Poorly	0.807	5.615	0.007
Somewhat poorly	0.985	0.358	0.701
Very poorly	0.987	0.314	0.732

Table 31. Test for significance of each land use variable in discriminating between groups of lakes. Lakes are split into two groups.

Land use variables (2 groups)	Wilk’s lambda	F-value	Significance (<0.05)
Residential	0.988	0.431	0.516
Urban	0.996	0.144	0.707
Agricultural	0.989	0.399	0.532
Hardwoods	0.991	0.343	0.562
Water	0.990	0.379	0.542
Wetlands	0.946	2.102	0.156
Road density	0.996	0.135	0.715
Excessive	0.994	0.225	0.638
Moderately well	0.990	0.391	0.536
Poorly	0.830	7.605	0.009
Somewhat poorly	0.985	0.573	0.454
Very poorly	0.990	0.387	0.538

Table 32. Accuracy of DFA classification of lake trophic status based on surrounding land use. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic	74.2	6.5	19.4
Mesotrophic	37.5	50	12.5
Eutrophic	36.4	0	63.6

Table 33. Accuracy of DFA classification of lake trophic status based on surrounding land use. Numbers in parentheses indicate the number of lakes in that category.

	Predicted	
Observed	**Oligotrophic**	**Meso-Eutrophic**
Oligotrophic (29)	90.3	9.7
Meso-Eutrophic (21)	50	50

Table 34. Monte Carlo Test of Significance Values for axis 1

Land Use Category	Eigenvalue	Land use – Water Quality Correlation
1990 100 m	0.03	0.05
1990 500 m	0.01	0.01
1995 100 m	0.20	0.23
1995 500 m	0.07	0.07
Change in 100 m	0.13	0.48
Change in 500 m	0.81	0.15

3.4 Multiple Regression Using Land Use and Water Quality Variables

Multiple regression results for 1990 100 and 500 m buffers and for change in land use 100 m buffers contribute to our understanding of the correlation between land use and water quality. Results for the other years and buffer zones were unclear and did not add to our understanding of the analysis. Therefore, they were placed in Appendix B.

3.4.1 Multiple Regression Results for 1990 100 m

When using multiple regression for 1990 land use classes using 100 m buffers, phosphorus was positively correlated with wetlands with a p-value of 0.008. Nitrogen was positively correlated with very poorly drained soil with a p-value of 0.03. Chlorophyll was positively correlated with agriculture and residential land uses and had p-values of 0.018, and 0.005 respectively. Secchi depth was negatively correlated with very poorly drained soil with a p-value of 0.017. All other land use variables were excluded from the analysis (Table 35).

Table 35. Multiple regression results for water quality variables and land use for 1990 100 m based on buffers. Table includes coefficients used in the regression model as well as significant values for each variable used.

Water Quality Variable	**Land Use**	**Significance Value**	**Regression Coefficients (intercept, slope)**
Secchi Depth	Very Poorly drained soil	0.017	(-0.849, 0.787)
Phosphorus	Wetlands	0.008	(0.710, 1.324)
Nitrogen	Very poorly drained soil	0.03	(0.543, -0.123)
Chlorophyll	Residential	0.023	(-0.617, 1.877)
	Agriculture	0.002	(-1.922, 1.877)

3.4.2 Multiple Regression Results for 1990 500 m

When using multiple regression for 1990 land use classes using 500 m buffers, phosphorus was positively correlated with wetlands with a p-value of 0.008. Nitrogen and chl.a were both positively correlated with very poorly drained soil with p-values of 0.03 and 0.01. Secchi depth was negatively correlated with very poorly drained soil with a p-value of 0.017. All other land use variables were excluded from the analysis (Table 36).

Table 36. Multiple regression results for water quality variables and land use for 1990 500 m based on buffers. Table includes coefficients used in the regression model as well as significant values for each variable used.

Water Quality Variables	**Land Use**	**Significance Value**	**Regression Coefficients (intercept, slope)**
Phosphorus	Wetlands	0.008	(0.710, 1.324)
Nitrogen	Very Poorly Drained Soil	0.015	(0.543. –0.123)
Chlorophyll	Very Poorly Drained Soil	0.010	(1.685, 0.924)
Secchi Depth	Very Poorly Drained Soil	0.017	(-0.849, 0.787)

3.4.3 Multiple Regression Results for Change in Land Use 100 m

When using multiple regression for change in land use classes using 100 m buffers, chlorophyll a and nitrogen were positively correlated with agriculture and had p-values of 0.03 and 0.036. Secchi depth was negatively correlated with agriculture and had a p-value of 0.047. All other land use variables were excluded (Table 37).

Table 37. Multiple regression results for water quality variables and change in land use 100 m based on buffers. Table includes coefficients used in the regression model as well as significant values for each variable used.

Water Quality Variables	Land Use	Significance Value	Regression Coefficients (intercept, slope)
Nitrogen	Agriculture	0.036	(8.506, 1.201)
Chlorophyll	Agriculture	0.03	(3.266, -0.0029)
Secchi Depth	Agriculture	0.047	(-4.273, 0.642)

3.5 Classification Accuracy for Sinkhole and Stream-fed Lakes

Lakes were classified based on the land use and soil type for each year and buffer zone. Lakes were separated into two categories; sinkhole-originated and stream-fed and were tested with DFA. There were twenty oligotrophic lakes, three mesotrophic and three eutrophic lakes for sinkhole-originated. There were eight oligotrophic, six mesotrophic, and eight eutrophic lakes for stream-fed.

3.5.1 Classification Accuracy for 1990 100 m

For the 1990 land use classes using 100 m buffers, sinkhole originated lakes were tested with DFA. Out of twenty lakes, 90% of oligotrophic lakes were classified correctly as oligotrophic. Out of three lakes, 100% of mesotrophic, and out of three lakes, 100% of eutrophic lakes were classified correctly. Overall, 92.3% of lakes were classified correctly (Table 38). When stream-fed lakes were tested with DFA, out of eight lakes, 100% of oligotrophic were classified correctly. Out of six lakes, 100 % of mesotrophic lakes were classified correctly and out of eight lakes, 83.3% of eutrophic lakes were classified correctly. Overall 95.5% of lakes were classified correctly (Table 39).

Table 38. Accuracy of DFA classification of lake trophic status based on surrounding land use for 1990 100 sinkhole-originated lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (8)	90	0	0
Mesotrophic (6)	0	100	0
Eutrophic (8)	0	0	100

Table 39. Accuracy of DFA classification of lake trophic status based on surrounding land use for 1990 100 stream-fed lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (20)	100	0	0
Mesotrophic (3)	0	100	0
Eutrophic (3)	16.7	0	85.3

3.5.2 Classification Accuracy for 1990 500 m

For 1990 land use classes using 500 m buffers, 85% of oligotrophic sinkhole-originated lakes were classified correctly, and 100% of mesotrophic and eutrophic sinkhole-originated lakes were classified correctly. Overall 88.5% of lakes were classified correctly (Table 40). For stream-fed lakes, 85% of oligotrophic lakes were classified correctly. 100% of mesotrophic and eutrophic lakes were classified correctly. Overall 88.5% of lakes were classified correctly (Table 41).

Table 40. Accuracy of DFA classification of lake trophic status based on surrounding land use for 1990 500 sinkhole-originated lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (8)	85	10	5
Mesotrophic (6)	0	100	0
Eutrophic (8)	0	0	100

Table 41. Accuracy of DFA classification of lake trophic status based on surrounding land use for 1990 500 stream-fed lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (20)	85	10	5
Mesotrophic (3)	0	100	0
Eutrophic (3)	0	0	100

3.5.3 Classification Accuracy for 1995 100 m buffers

For 1995 land use classes using 100 m buffers, 90% of oligotrophic sinkhole-originated lakes were classified correctly. 100% of mesotrophic and eutrophic sinkhole-originated lakes were classified correctly. Overall 95.5% of lakes were classified correctly (Table 42). For stream-fed lakes, 87.5% of oligotrophic lakes were classified correctly. 100% of mesotrophic and eutrophic lakes were classified correctly. Road density was significant in discriminating between categories of lakes. Overall 95.5% of lakes were classified correctly (Table 43).

Table 42. Accuracy of DFA classification of lake trophic status based on surrounding land use for 1995 100 sinkhole originated lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (20)	90	0	10.0
Mesotrophic (3)	0	100	0
Eutrophic (3)	0	0	100

Table 43. Accuracy of DFA classification of lake trophic status based on surrounding land use for 1995 100 stream-fed lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (8)	87.5	0	12.5
Mesotrophic (6)	0	100	0
Eutrophic (8)	0	0	100

3.5.4 Classification Accuracy for 1995 500 m

For 1995 land use classes using 500 m buffers, 71.4% of oligotrophic sinkhole-originated lakes were classified correctly. 100% of mesotrophic, and eutrophic sinkhole lakes were classified. Overall, 76.9% of lakes were correctly classified (Table 44). For stream-fed lakes, 100% of lakes were classified correctly. Hardwoods had a p-value of 0.051, which is not considered significant. However, it may have been used to describe one of the discriminant functions. Wetlands and very poorly drained soil also appear important in discriminating between groups of lakes (Table 45).

Table 44. Accuracy of DFA classification of lake trophic status based on surrounding land use for 1995 500 sinkhole originated lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (20)	71.4	14.3	14.3
Mesotrophic (3)	0	100	0
Eutrophic (3)	0	0	100

Table 45. Accuracy of DFA classification of lake trophic status based on surrounding land use for 1995 500 stream-fed lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (8)	100	0	0
Mesotrophic (6)	0	100	0
Eutrophic (8)	0	0	100

3.5.5 Classification Accuracy for Change in Land Use 100 m

For change in land use classes using 100 m buffers, change in residential, change in water, and change in wetlands were significant in discriminating between sinkhole lakes. 100% of oligotrophic lakes were classified correctly. 66.7% of mesotrophic and eutrophic lakes were classified correctly. Overall 92.3% of lakes were classified correctly (Table 46). For stream-fed lakes, 62.5 % of oligotrophic, 83.3% of mesotrophic, and 75% of eutrophic lakes were classified correctly. Overall 72.7% of lakes were classified correctly (Table 47).

Table 46 Accuracy of DFA classification of lake trophic status based on surrounding land use for change in 100 sinkhole originated lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (20)	100	0	0
Mesotrophic (3)	33.3	66.7	0
Eutrophic (3)	33.3	0	66.7

Table 47. Accuracy of DFA classification of lake trophic status based on surrounding land use for change in 100 stream-fed lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (8)	62.5	12.5	25
Mesotrophic (6)	16.7	83.3	0
Eutrophic (8)	25	0	75

3.5.6 Classification Accuracy for Change in Land Use 500 m

For change in land use classes using 500 buffers, agriculture and change in water were significant in discriminating between sinkhole-originated lakes. 90% of oligotrophic lakes were classified correctly. 100% of mesotrophic and eutrophic lakes were classified correctly. Overall 92.3% of lakes were classified correctly (Table 48). For stream-fed lakes, 75% of oligotrophic lakes, 66.7% of mesotrophic, and 87.5% of eutrophic lakes were classified correctly. Overall 77.3% of lakes were classified correctly (Table 49).

Table 48. Accuracy of DFA classification of lake trophic status based on surrounding land use for change in 500 sinkhole originated lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (20)	90	0	10
Mesotrophic (3)	0	100	0
Eutrophic (3)	0	0	100

Table 49. Accuracy of DFA classification of lake trophic status based on surrounding land use for change in 500 stream-fed lakes. Numbers in parentheses indicate the number of lakes in that category.

	Predicted		
Observed	**Oligotrophic**	**Mesotrophic**	**Eutrophic**
Oligotrophic (8)	75	12.5	12.5
Mesotrophic (6)	16.7	66.7	16.7
Eutrophic (8)	0	12.5	87.5

4. DISCUSSION

Land use relates to water quality of lakes as it either increases runoff or filters what enters the lakes. The purpose of this study was to test that relationship and our results suggest some direct correlation exists. This study chose CCA and DFA over other statistical procedures to determine correlations between land use and water quality. Several aspects of CCA contribute to our understanding of the various relationships. Weighted correlations indicate the interactions among the land use variables. Such interactions give a better understanding of patterns seen and results of the various correlations in CCA. However, if correlations among variables exist, then applying a statistical analysis that uses multiple regression will cause the correlation with water quality variables to be in doubt, since the land use variables will no longer be acting independently. The WA scores are plotted to see if patterns emerge among groups of lakes and represent the effect land use has on water quality. The inter-set correlations show the correlation between the WA scores and the land use variables, even though it cannot be used as an independent measure of the strength of the correlation between land use and water quality. Our purpose in using the inter set correlations was simply to select the land use variables that were most likely to impact the water quality of lakes. (McCune and Grace 2000). For example, road density was found to be a major factor in determining the structure of the ordination. Not only do roads provide a means of transport, but can be a major source of runoff. Roads can facilitate the spread of fertilizer from farms and even residential areas (Cairns Jr. and Niederlehner 1996). Roads contribute to dry deposition and also provide a conduit for runoff that does not have any vegetative buffer to take up nutrients (Forman et al. 2003). Road density could also be used as a partial measure of the effects of more-specific factors such as logging (Moyle and Randall 1998). Road density more likely represents the amount of urbanization that has occurred.

Some patterns did emerge from the inter-set correlations. It appears that agriculture and hardwoods had the greatest loadings for the 100 meter buffer zones representing non-urban areas. Both of these were positive for 1990 and negative for 1995. This signifies an increase in urbanization and less contribution of each to water quality at the lakefront. Wetlands were the most positively correlated for 1995 and the most negative for 1990. This may be a result of an increase in wetlands due to mitigation efforts or a lowering of lake levels, and may have increased more than the other land use types in replacing agriculture. Stormwater can be sent through wetlands to filter out nutrients as suggested by the SJRWMD (Chapter 40C-42 Regulation of Stormwater Management Systems 1998). Also, the Florida legislature passed the Warren S. Henderson Wetlands Protection Act in 1984, which greatly increased the protection of wetlands (DEP 1998). Our analysis shows that wetlands on average increased from 1990 to 1995 while agriculture decreased. This would further decrease the input of nutrients into lakes. Very poorly drained soil and excessively drained soil had the strongest positive and negative correlations showing a gradient of drainage ability among soils. Very poorly drained soils became more positive as agriculture and hardwoods became more negative again indicating an increase in urbanization.

DFA, in a similar manner to the interset correlations of CCA, selects variables, which are influential in discriminating between groups of lakes. The variables that are significant are used to classify lakes according to trophic status. An advantage to DFA is its flexibility in allowing for assumptions to be violated such as homogeneity and normality. DFA allows for the lakes to be grouped together as a result of the land use and soil variables as well as not making any direct correlations. The discriminating functions then classified lakes according to the trophic state. This classification scheme reflected the pattern seen in CCA with the WA scores. However, the percentage of lakes being classified correctly was relatively low (less than 90 %). A difficulty in classification is a result of lakes being on the border of another trophic state. The TSI range for oligotrophic lakes is also much larger than it is for mesotrophic lakes. For example, Lake Wekiva has a TSI value of 48.72, which is very close to being considered mesotrophic. On the other hand, Lake Monroe has an index of 59.84 making it eutrophic although the difference in the index value is not that great. The chance of a lake being classified as mesotrophic will be much smaller, which shows how the percentage of lakes that are correctly classified increases when lakes are split into only two groups. It must be stated that the TSI is only an index to indicate what the trophic state of a lake is but does not define it (Carlson 1977). The trophic states are continuous and lakes with phosphorus, nitrogen and chlorophyll levels at moderate levels will be difficult to classify as truly one trophic state or another.

In many studies, individual land use categories were tested through the use of multiple-regression that showed which factors were positively or negatively associated with water quality variables (Sliva and Williams 2001). One example, involving streams had stream chemistry as the dependent variable and the various land cover classes as independent variables. Regressions were then run on this data in order to determine the strength of the relationship. Their results suggested that chloride and nitrate were strongly related to land cover (Herlihy et al. 1998). In another study, a regression equation showed residential/urban areas to contribute the most to nitrate levels in a particular stream (Basynat et al. 2000). However, the relationship between land use and water quality is not necessarily linear, which is what CCA evaluates (Tong and Chen 2002). CCA uses multiple regression indicating the effectiveness of environmental variables in structuring the ordination. These values represent the contribution of individual variables to the regression solution. Multiple regression by itself could lead to overfitting. CCA instead, will choose the subset of variables that explain the most variation and allow for correlation among the variables (Palmer 2002). The problem is that the variables are assumed to be independent which in this case; they are not, creating an example of multicollinearity. Each of the land use classes is dependent on the others. Thus a significant correlation may be detected due to the redundancy of the variables when the correlation is not truly significant (Iles 2002). Like CCA, DFA uses multiple regression to determine which land use and soil type variables were the most influential in structuring the ordination, therefore we have the same problems in making these conclusions with DFA as with CCA. Despite this problem, the literature gives numerous examples of multiple regression being used to determine correlations between land use and water quality. Also, CCA can be still used to reflect patterns among lakes based on land use, soil, and water quality variables. CCA selected out variables that contributed the most to the structure of the ordination and these were put into DFA. DFA was then used to verify patterns seen with CCA, in which case oligotrophic lakes were clearly separated out in comparison to mesotrophic or eutrophic lakes.

Every soil type does not contribute equally to nutrient transport (Basynat et al. 2000). Soil types in this study were categorized based on drainage ability. Soils that are well drained have low runoff potential while soils that are poorly drained have high runoff potential. According to DFA, poorly drained soil was very influential in discriminating between groups of lakes. This is in accordance with the fact that much of Seminole County consists of soils that are poorly drained. Such soils allow rainwater to wash down into the lake. These soils tend to consist of clays, sands, sandy loams, and silty clays (USGS). For example, clay has a higher potential for adsorption of minerals, such as phosphorus, than other soil types (Sliva and Williams 2001). When these particles reach the lakes, phosphorus may be released into the waters. This is a result of a lake having low oxygen levels, in which case the phosphorus is desorbed from the particle (Horne and Goldman 1994). Runoff is also a problem for soils that are above an impenetrable surface in which rainwater cannot drain well and washes off the top soil layers (Naef et al. 2002).

Possibly a more accurate methods would be to use GIS to estimate runoff by providing measurements of drainage basin morphology (Melesse and Shih 2002). Slope, soil type, and rainfall can then be incorporated as variables within a given formula. One such formula is $F/S=Q/(P-I)$, where F is actual retention, S is the watershed storage, Q is actual direct runoff, P is total rainfall and I is the initial abstraction. S is found by 25,400/CN –254. CN is a runoff index determined based on soil group, land use, land treatment, hydrologic conditions and antecedent moisture condition (Melesse and Shih 2002). Land covers can then be divided up based on land use, treatment and hydrological conditions. It would then be assumed that different management practices would have different effects on runoff (Melesse and Shih 2002), since changing land use and land management practices is one of the main factors in altering runoff (Tong and Chen 2002). For example, certain agricultural practices may reduce the nutrient load into lakes that would typically be expected. A particular study conducted in the Indian River Lagoon evaluated how land use would affect water quality through runoff. In this study, climate and runoff data were gathered over a 70-year period. Rainfall data were also collected and recorded. Results show that urban and agricultural land use increased. Over this same period, the total runoff depth also increased. It was concluded that runoff increases with forested and wetland areas being converted to urban and agriculture areas (Youngsug et al. 2002). Since rainfall and slope appear relatively uniform across the county, runoff was not calculated for this study. If implemented, runoff would need to be calculated for each lake, which is a direct way to determine how land use is affecting water quality. The failure of Monte Carlo in all but two of the matrix relationships may reflect the exclusion of these factors such as slope, elevation and rainfall patterns that have been found to be relevant in other studies (Turner et al. 1996). Slope was not included since it appeared to be relatively uniform throughout the county. The fact that Seminole County is located on a flood plain results in minimal changes in elevation (Personal communicated J.Osborne). Rainfall patterns were also likely to be relatively constant across the county.

However, changes in runoff volume do not have a simple or linear relationship with land use changes (Bhaduri et al. 2000). Also many lakes in Seminole County originated as sinkholes, which form as a result of dissolution, and are influenced more by seepage than they are by runoff. This leads to most lakes as being seepage lakes, which have no surface water streams flowing in or out (Schiffer 1998). Consequently, they are affected mostly by groundwater (Lee 2002). The groundwater is supplied by the surficial aquifer system. As rain falls, it percolates into the soil, moves downward and replenishes the aquifer system (Schiffer 1998). As a result, fertilizers and other solutes can enter the lakes through groundwater (Lee 2002). This may delay the effect that nutrients will have on lake water quality.

A closer inspection of the data reveals an inconsistency as to when the lakes were sampled. For some lakes, measurements may have been every month, whereas other lakes may have only been sampled a few times a year. Finally, some lakes had one month where samples were frequently taken and then very few sampling dates the next. Such an inconsistency is the purpose behind taking averages for lakes. When sampling, it is important to do so throughout the year, and in a consistent manner since rainfall patterns will vary with season, thus causing fluctuation in the amount of runoff. Much of the runoff occurs as result of smaller-intensity storms that are frequent throughout the year (Youngsug et al. 2002). The fact that very little data exists for some lakes may cause the results not to reflect the relationship between land use and water quality. Analysis of the data shows that concentrations for phosphorus, nitrogen, and chlorophyll were averaged for over a decade for some lakes, while other lakes, had values averaged for a just a few years. For the latter lakes, the water quality data were not collected until several years after land use data had been created. It is not known, how much time passes before a noticeable difference can be detected in the water quality when land use has changed. If the time of effect can be determined, then water quality data could have been used in correspondence with the year that land use data had been gathered.

Water quality of lakes is also dependent on residence time. Retention of various nutrients will vary with the lake. Runoff may be high due to urbanization, but may be compensated by the residence time of the lake. If lakes are flushed with a large volume of low-nutrient water, the residence time decreases significantly, which then allows for a decrease in nutrient levels (p.514 Horne and Goldman). Volume will also influence the vulnerability of a lake to eutrophication. Lakes with larger volumes cause a dilution of any nutrient that enters the body of water. On the other hand, larger volumes also tend to have a longer residence time, increasing the chance of the nutrient being used to propagate algal growth.

Finally, the question of delineating buffer zones cannot be answered in one study. GIS is a tool that can be used for this purpose, as shown in this study. This study indicates a drainage basin approach is best since the land use for 500 m buffers was more significant than 100 m buffers for both years. However, due to the spatial variations in physical, ecological and land use conditions, determining the buffer zone needs to be done on an individual lake basis (Xiang 1996).

4.1 Conclusions

I conclude that CCA is not appropriate to determine if there is a significant correlation between land use and water quality due to the problems with collinearity. Instead, CCA may be more appropriate to determine patterns among lakes and picking out which land use types were the most influential in structuring the ordination. For example, lakes were loosely grouped together according to trophic status based on the most influential land use types. Effects of land use can then be seen in all cases, whether a direct correlation exists or not. However, DFA gave a better indication of correlations between land use and water quality since problems with collinearity are not as strong.

There are questions that still need to be answered. For instance, at what spatial scale does the landscape pattern affect water quality of lakes? Does land use affect water quality within 500 m buffers, the drainage basin of a lake, or the entire watershed? This analysis instead only compares 100 to 500 m buffers. Knowing the amount of runoff each land use will generate and the probability that the nutrients will reach the lake is also important if developers are to minimize impacts of urbanization.

To determine land use effects on water quality, each lake should be studied individually. Other factors such as slope, rainfall, and stormwater management practices can be included. For example, pollution controls have been implemented since the early 1980's starting with the Agricultural NPS Management Plan approved in 1978. The Florida's State Stormwater Rule was adopted by the Environmental Regulation Commission in 1981. Over the course of time, the various regulations that passed designed to decrease effects of point source pollution from wastewater treatment plants and non-point source pollution from agriculture or stormwater from urbanized areas were revised so the effects of urbanization and agriculture were not as strong

(DEP 1998) especially from lakes where data were collected only after these measures were put into place or greatly improved. Some of the methods used to decrease runoff include: turbidity barriers, silt screens, sediment traps, and planting of native vegetation. Other methods include slope stabilization, building of retention ponds, culvert upgrades, raising road elevations, detention ponds, and preservation of wetlands (Dyer, Riddle, Mills, and Precourt Inc. 1995). As development continues, it will become increasingly important to obtain the data needed to make assessments about land use and to the extent that these methods have been applied (Bhaduri et al. 2000). It is important for land use data to be updated and for consistency in sampling in order to reach more accurate conclusions. Our analysis simply shows that in general, land use will impact the water quality of lakes and is one of several factors that needs to be considered when developing around a lake or restoring the water quality of a lake.

APPENDIX A
LAND USE FOR 1995 100 AND 500 M BUFFERS

Land use for 1995 100 and 500 m buffers and the change in land use for both 100 and 500 m buffers were not significantly correlated with water quality using the CCA test. The graphs of the WA scores from all years and buffer zones did not show any distinct patterns. Oligotrophic lakes were loosely grouped together. Mesotrophic and eutrophic lakes were spread throughout the graph. The following discusses the correlations among land use variables and correlations between land use and water quality variables for 1995 100 and 500 m buffers and for change in 500 m buffers.

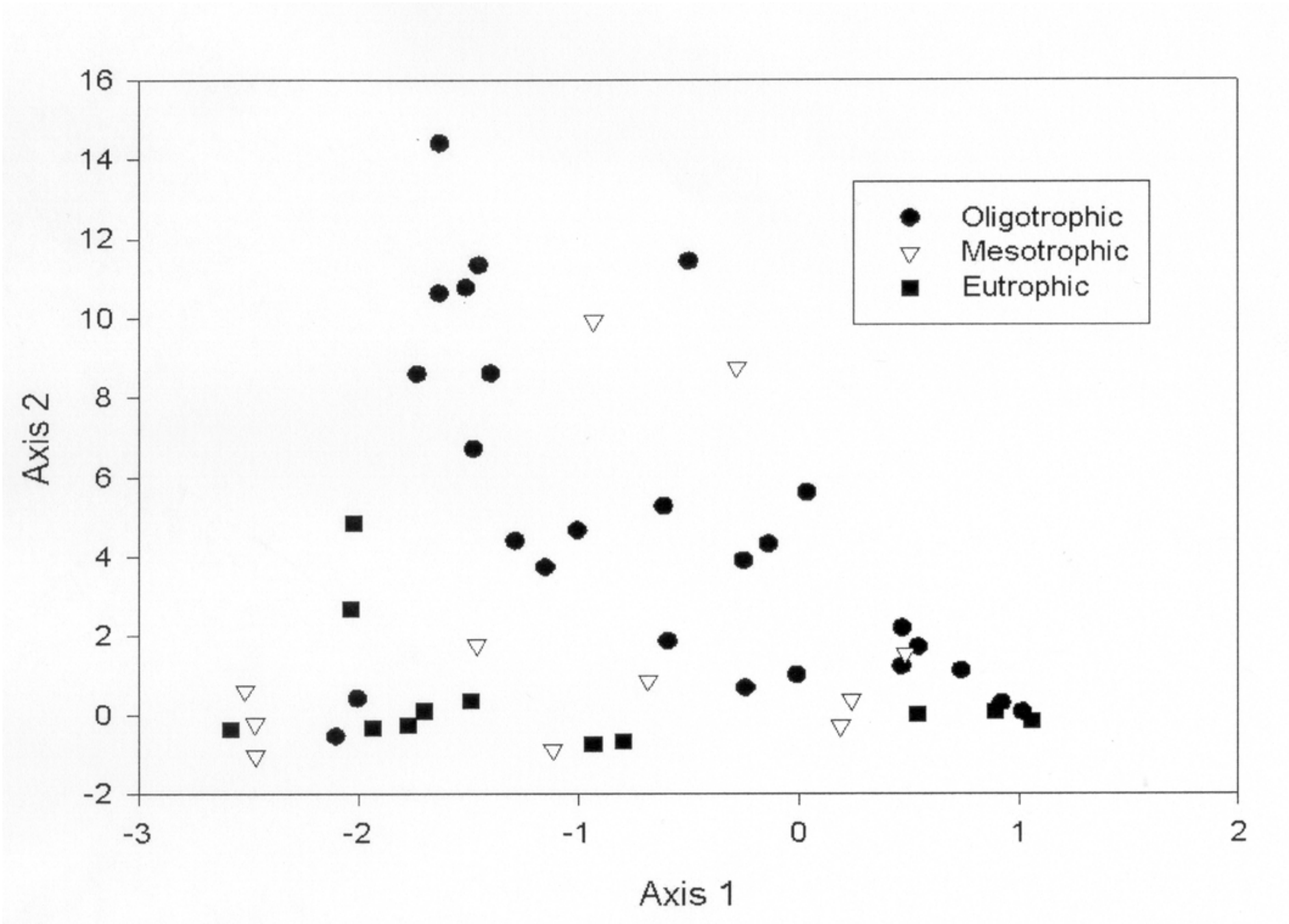

Figure 8. CCA ordination of the lakes based on the WA scores for land use 1990 in surrounding 100 m buffers.

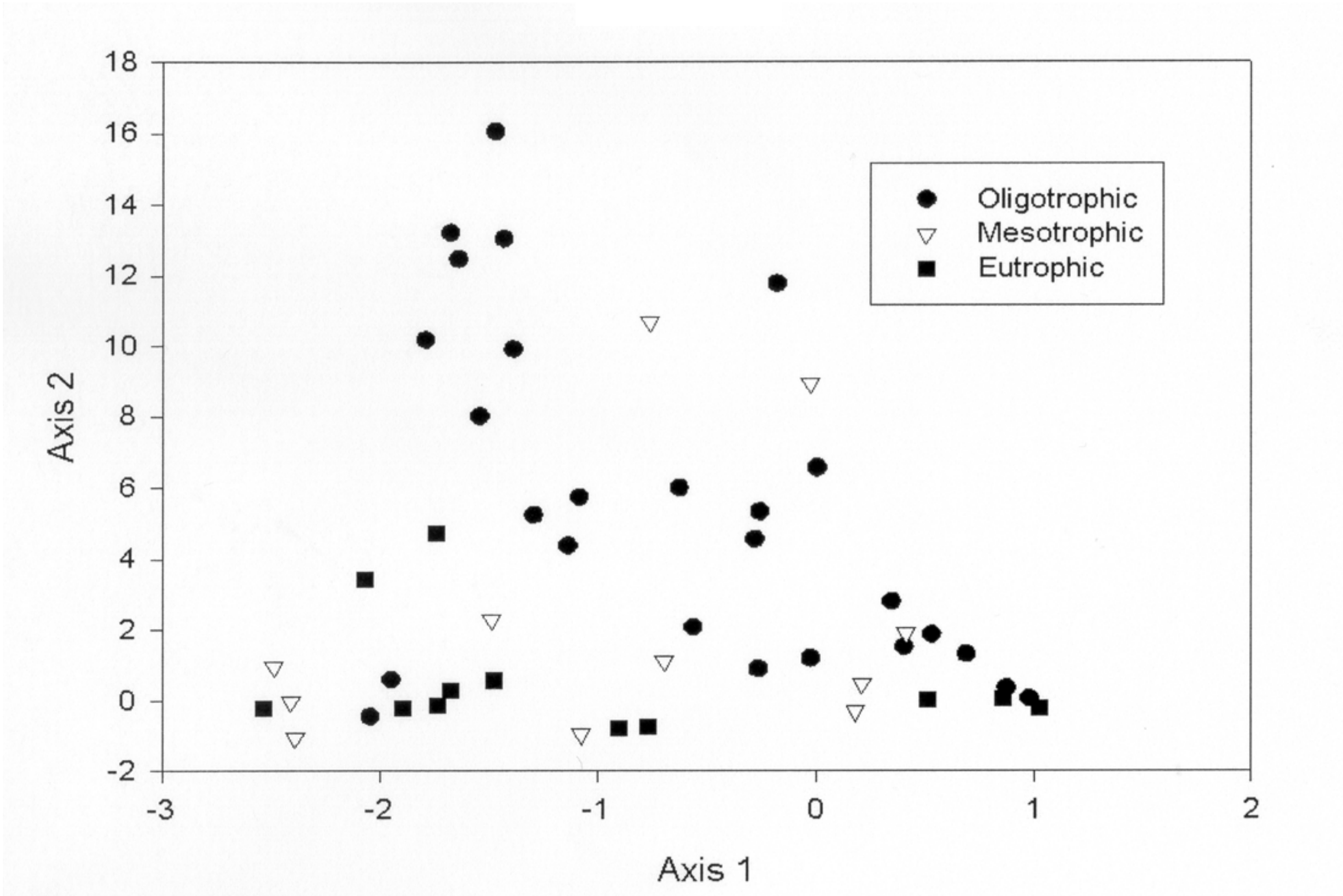

Figure 9. CCA ordination of lakes based on WA scores for 1990 land use in surrounding 500 m buffers.

A.1 1995 Land use data from 100 m buffer

Correlation among land use variables (CCA)

Weighted correlations among land-use variables were strong between road density and residential and also between agriculture and hardwood. There was also a strong correlation between urban and transportation.

Correlation between land use and water quality variables (CCA)

The first two CCA axes accounted for 39.4% and 6 % of the variance. The eigenvalue for axis 1 was 0.25 and was significant while axis 2 was 0.038 and was not significant using the Monte Carlo test. The Pearson correlation was 0.87 indicating a high correlation between land use and water quality variables. The correlation between the two matrices was not found to be significant as suggested by the p-value of 0.28 (Table 34). Inter-set correlations showed very poorly drained soil had the strongest correlation to the WA scores for axis 1 and wetlands had the strongest to axis 2 (Table 50). The other inter-set correlations show there is a strong positive correlation between wetlands and axis 1 while there is a strong negative correlation between hardwood, agriculture, excessively drained soil and poorly drained soil and axis 1. Residential had a strong negative correlation to axis 2. The WA scores were plotted to show if the water quality variables were adequate in describing the effects of land use (Figure 10). Oligotrophic and eutrophic lakes were loosely separated into groups. Mesotrophic lakes were randomly spread throughout the plot. Lakes were separated mostly along axis 2. To conclude, land-use variables were not sufficient to describe water quality.

Table 50. CCA results for 1995 100 m based on buffers.
Results include the eigenvalue associated with each axis, the variance explained by that eigenvalue and the inter-set correlations.

Land Use/Drainage Category	**Axis 1**	**Axis 2**
Residential	-0.1	-0.262
Urban	0.15	-0.117
Agricultural	-0.68	-0.005
Hardwoods	-0.625	0.066
Water	0.21	0.037
Wetlands	0.362	0.202
Transportation	0.048	-0.06
Electricity	0.194	0.139
Road Density	-0.363	-0.09
Excessively drained	-0.548	0.038
Medium well drained	0.076	0.061
Poorly drained	-0.363	0.012
Somewhat poorly drained	-0.069	-0.126
Very poorly drained	0.526	0.038
Eigenvalues	0.25	0.038
Percent variance explained	39.4	6
Pearson Correlation	0.87	0.605

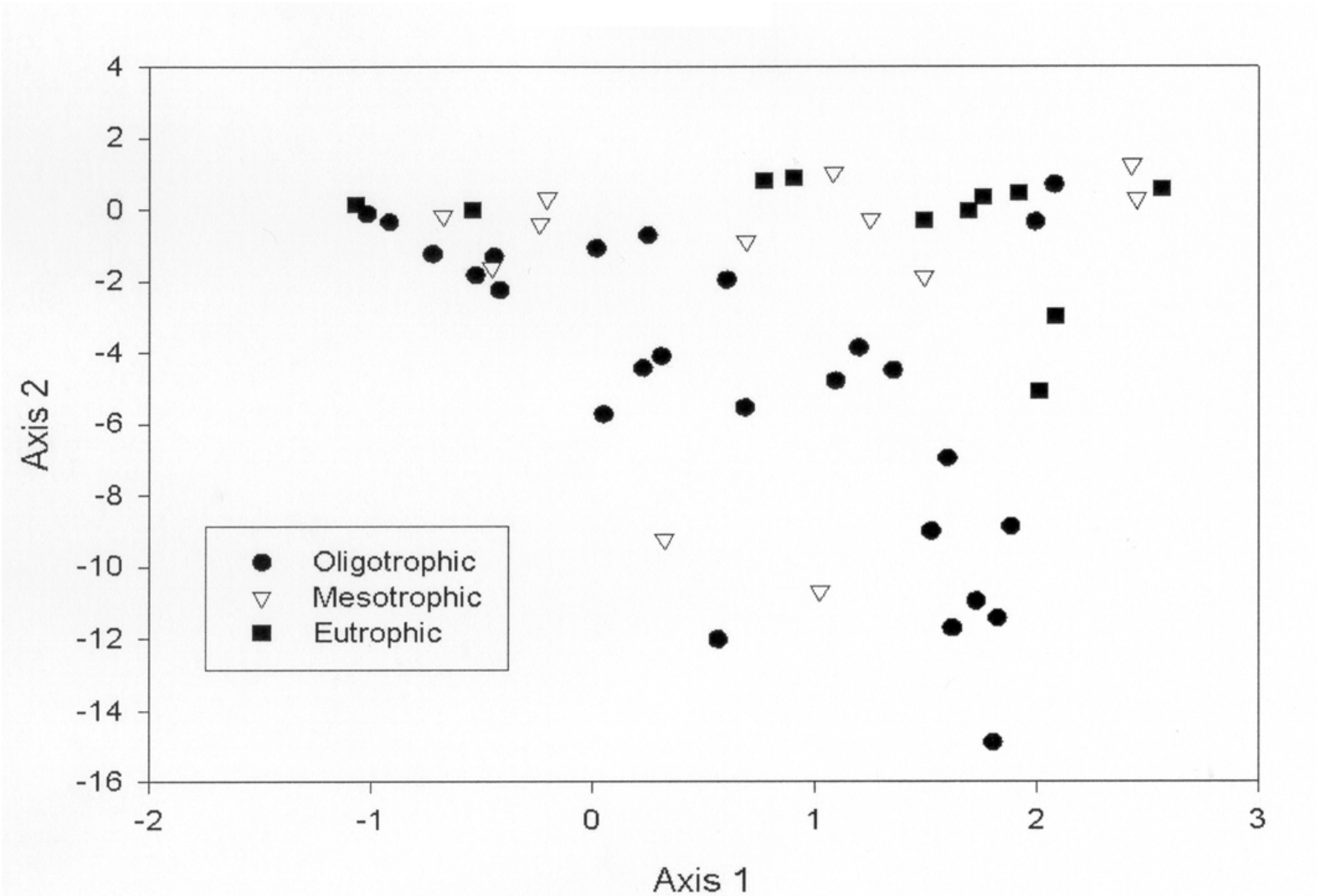

Figure 10. CCA ordination of lakes based on WA scores for 1995 land use in surrounding 100 m buffers.

A.2 1995 land use data from 500 m buffer

Correlations among land use variables (CCA)

Weighted correlations among land-use variables were strong between sewage and urban and between agriculture and poorly drained. There was also a strong correlation between road density and both residential and urban areas.

Correlation between land use and water quality variables (CCA)

The first two CCA axes accounted for 45 % and 9.7 % of the variance. The eigenvalues for the first two axes were 0.286 and 0.061 and the first axis was found to be significant using the Monte Carlo test. The Pearson correlation was 0.893 for axis 1, which indicates a high correlation between land use and water quality variables. The correlation between the two matrices was found to be significant (Table 34). Inter-set correlations show that very poorly drained soil had the strongest correlation with the WA scores for axis 1, while wetlands had the strongest correlation for Axis 2 (Table 51). The other inter-set correlations show that residential and somewhat poorly drained soil had strong negative correlations with axis 2. Wetlands had a strong positive correlation with axis 1, while urban, hardwood, water, and sewage had strong negative correlations with axis 1. The WA scores were plotted to show if the water quality variables were adequate to describe the effects of land use (Figure 11). Oligotrophic and eutrophic lakes were loosely separated into groups. Mesotrophic lakes were also grouped together, but this group overlapped with the other two groups. Lakes are separated mostly along axis 2.

To conclude, land-use variables were not sufficient to describe water quality.

Table 51. CCA results for 1995 500 m based on buffers.
Results include the eigenvalue associated with each axis, the variance explained by that eigenvalue, and the inter-set correlations.

Land Use/Drainage Category	**Axis 1**	**Axis 2**
Residential	0.2	-0.305
Urban	-0.533	-0.054
Agricultural	-0.3	0
Hardwood	-0.504	-0.015
Water	-0.321	-0.013
Wetland	0.388	0.237
Barren land	0.172	0.005
Transportation	-0.115	-0.039
Elevation	0.256	0.009
Sewage	-0.687	0.086
Road Density	-0.205	-0.192
Excessively drained	-0.185	-0.104
Moderately drained	-0.025	0.024
Poorly drained	-0.026	0.125
Somewhat Drained	0.217	-0.457
Very Poorly	0.351	0.109
Eigenvalue	0.286	0.061
Percent Variance explained	45	9.7
Pearson Correlation	0.893	0.633

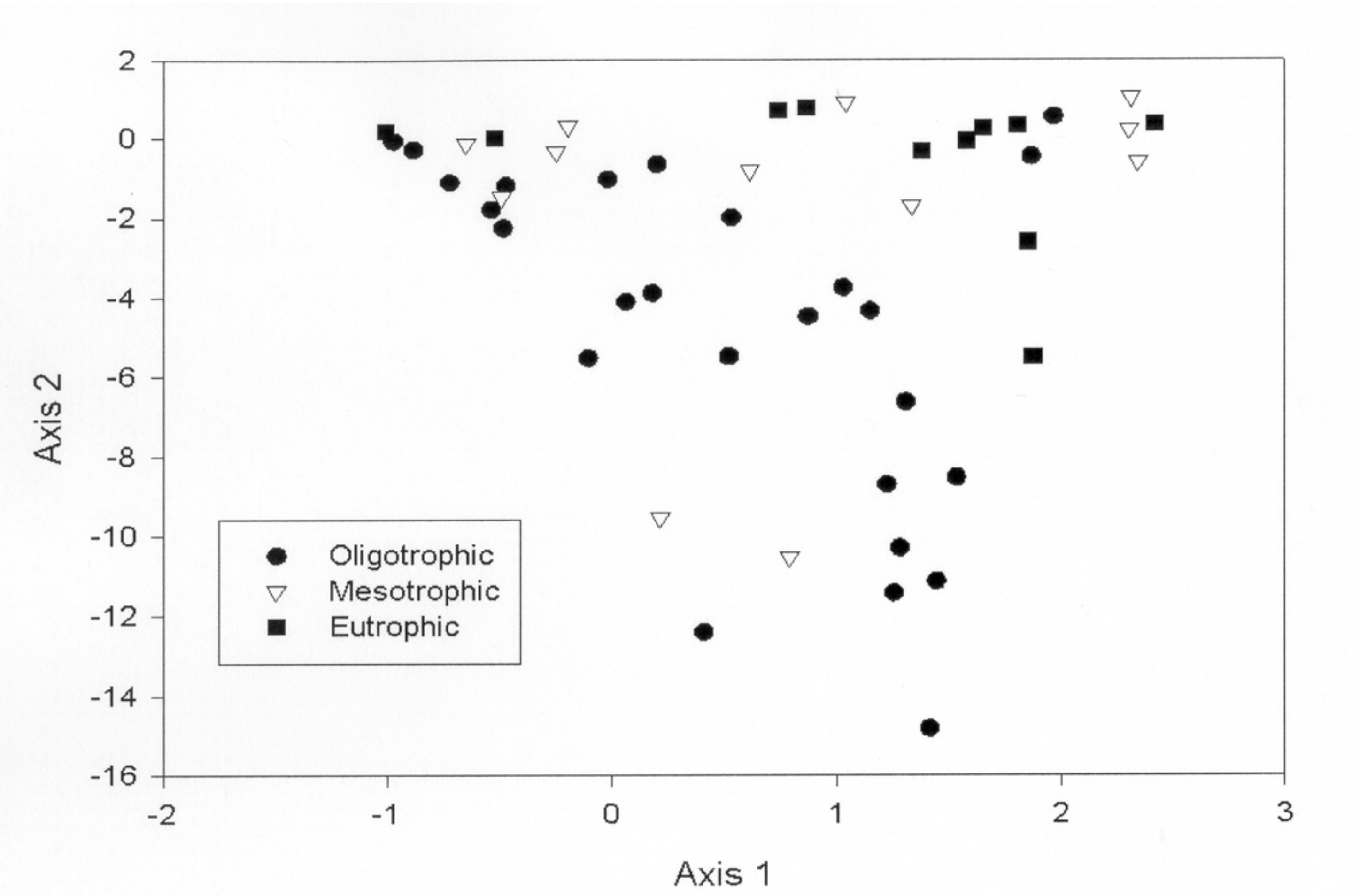

Figure 11. CCA Ordination of Lakes Based on WA Scores for 1995 Land Use in Surrounding 500 m Buffers

A.3 Change in land use 100 m buffer zone

Correlation among land use variables (CCA)

Among land use variables urban and road density, urban and transportation, sewage and electricity, and the relationship between water and wetlands were all highly correlated. Changes in transportation also resulted in changes in residential.

Correlation between water quality variables (CCA)

The first two axes accounted for approximately 41.9 % and 8.1 % of the variance. Eigenvalues for the first two CCA axes were 0.266 and 0.051 and were not found to be significant using the Monte Carlo test. The Pearson Correlation was 0.864 for axis 1 and suggested a relatively high correlation between water quality variables and land use variables. The correlation between the two matrices was not found to be significant as suggested by the p-value of 0.13 for axis 1 (Table 34). Inter-set correlations show that residential had the strongest correlation with the WA scores for axis 1 while transportation had the strongest correlation for axis 2 (Table 52). The other inter-set correlations show that very poorly drained soil had a strong positive correlation with axis 1, while excessively drained soil and poorly drained soil had a strong negative correlation with axis 1. Sewage had a strong positive correlation with axis 2 while road density had the most negative. The WA scores were plotted to show if the water quality variables were adequate to describe the effects of land use (Figure 12). Oligotrophic and eutrophic lakes were loosely separated into groups. Mesotrophic lakes were also grouped together, but this group overlapped with the other two groups. Lakes were separated mostly along axis 2. To conclude, land-use variables were not sufficient to describe water quality.

Table 52. CCA results for the change in land use 100 m. Results include the eigenvalue associated with each axis, the variance explained by that eigenvalue, and the inter-set correlations.

Land Use/Drainage Category	**Axis 1**	**Axis 2**
Residential	0.36	-0.085
Urban	-0.09	0.057
Agriculture	0.073	0.022
Hardwood	-0.005	0.087
Water	-0.104	-0.121
Wetland	-0.275	-0.053
Barren land	-0.018	0.152
Transportation	-0.081	0.045
Electricity	0.195	0.150
Sewage	0.185	0.148
Road density	0.022	-0.127
Excessively drained	-0.531	-0.009
Moderately drained	0.088	0.062
Poorly drained	-0.32	-0.009
Somewhat poorly drained	-0.048	-0.126
Very Poorly drained	0.534	0.077
Eigenvalue	0.245	0.048
Percent variance explained	38.7	7.5
Pearson Correlation	0.828	0.548

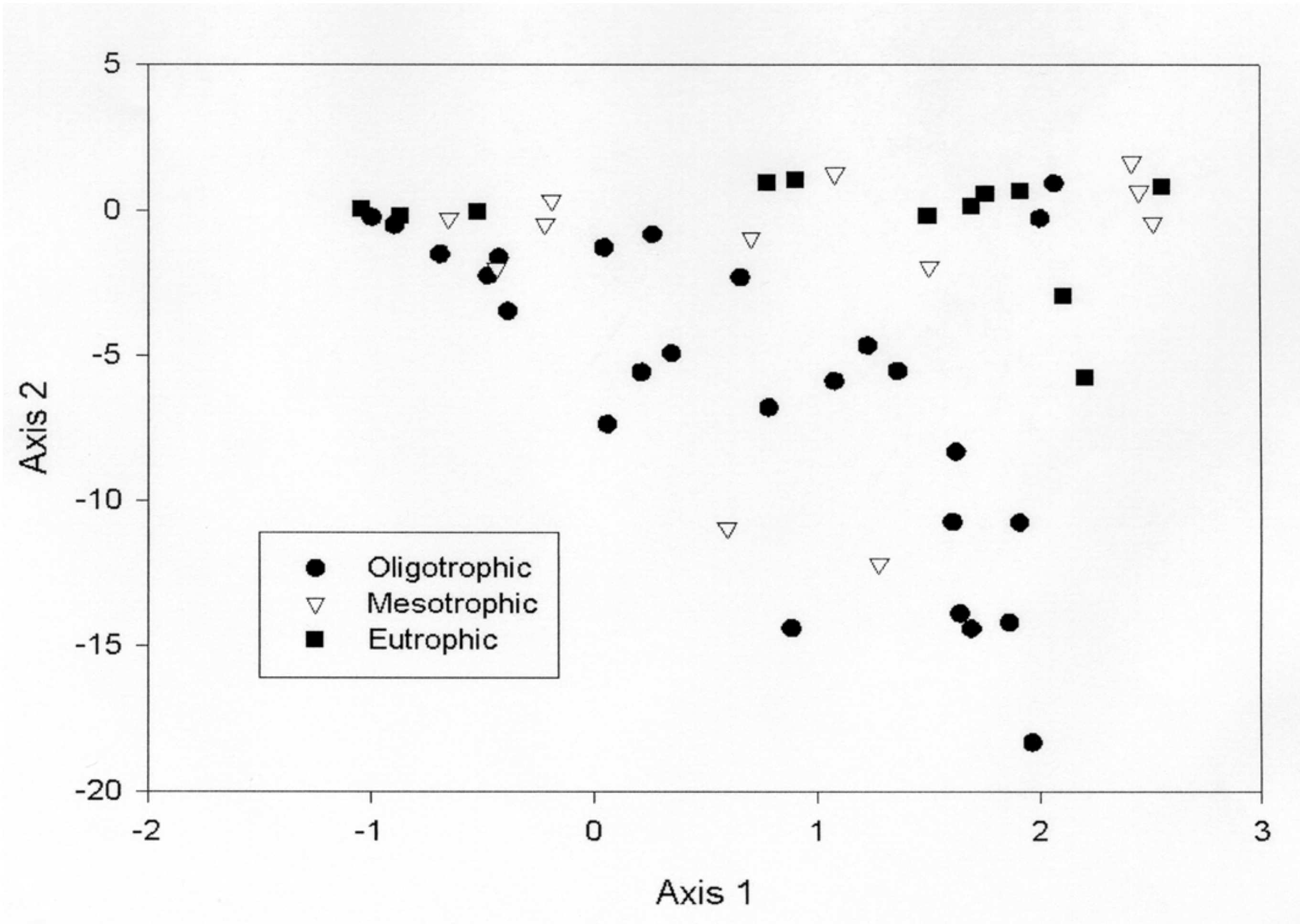

Figure 12. CCA ordination of lakes based on WA scores for 1990-1995 land use change in surrounding 100 m buffers.

A.4 Change in land use data buffer 500 m

Correlation among land use variables (CCA)

Among land-use variables change in urban and change in road density, change in water and change in sewage was highly correlated. The correlation between the change in transportation and change in urban was also strong.

Correlation between water quality and land use variables (CCA)

The first two axes account for 34.1 % and 10.5% of the variation. The eigenvalues for each axis were not considered significant by the Monte Carlo test. The Pearson correlation was 0.784 for axis 1 indicating a somewhat high correlation between water quality and land-use. The correlation between the two matrices for the first axis was not found to be significant (p-value = 0.81) (Table 34). Inter-set correlations show that very poorly drained soil had the strongest correlation with WA scores for axis 1 while transportation had the highest correlation with the WA scores for axis 2. The other inter-set correlations show that residential had the most negative correlation with axis 2, while somewhat poorly drained and excessively drained soil had the most negative correlation with axis 1 (Table 53). The WA scores were plotted to show if the water quality variables were adequate to describe the effects of land use (Figure 13). Oligotrophic and eutrophic lakes were loosely separated into groups. Mesotrophic lakes were spread throughout the plot. Lakes were separated mostly along axis 2. To conclude, land use and soil types were not adequate to describe water quality.

Table 53. CCA results for the change in land use 500 m. Results include the eigenvalue associated with each axis, the variance explained by that eigenvalue, and the inter-set correlations.

Land Use Drainage/Category	**Axis 1**	**Axis 2**
Residential	0.173	-0.218
Urban	0.005	0.126
Agriculture	-0.121	-0.210
Hardwood	-0.005	-0.017
Water	-0.053	0.001
Wetland	0.02	-0.127
Barren land	0.204	0.144
Transportation	-0.052	0.216
Electricity	0.118	0.004
Sewage	0.048	-0.09
Road density	-0.075	-0.025
Excessively drained	-0.234	-0.084
Moderately well drained	-0.013	0.027
Poorly drained	0.016	0.109
Somewhat poorly drained	-0.271	-0.124
Very poorly drained	0.521	0.131
Eigenvalue	0.262	0.066
Percent variance explained	41.2	10.5
Pearson correlation	0.855	0.636

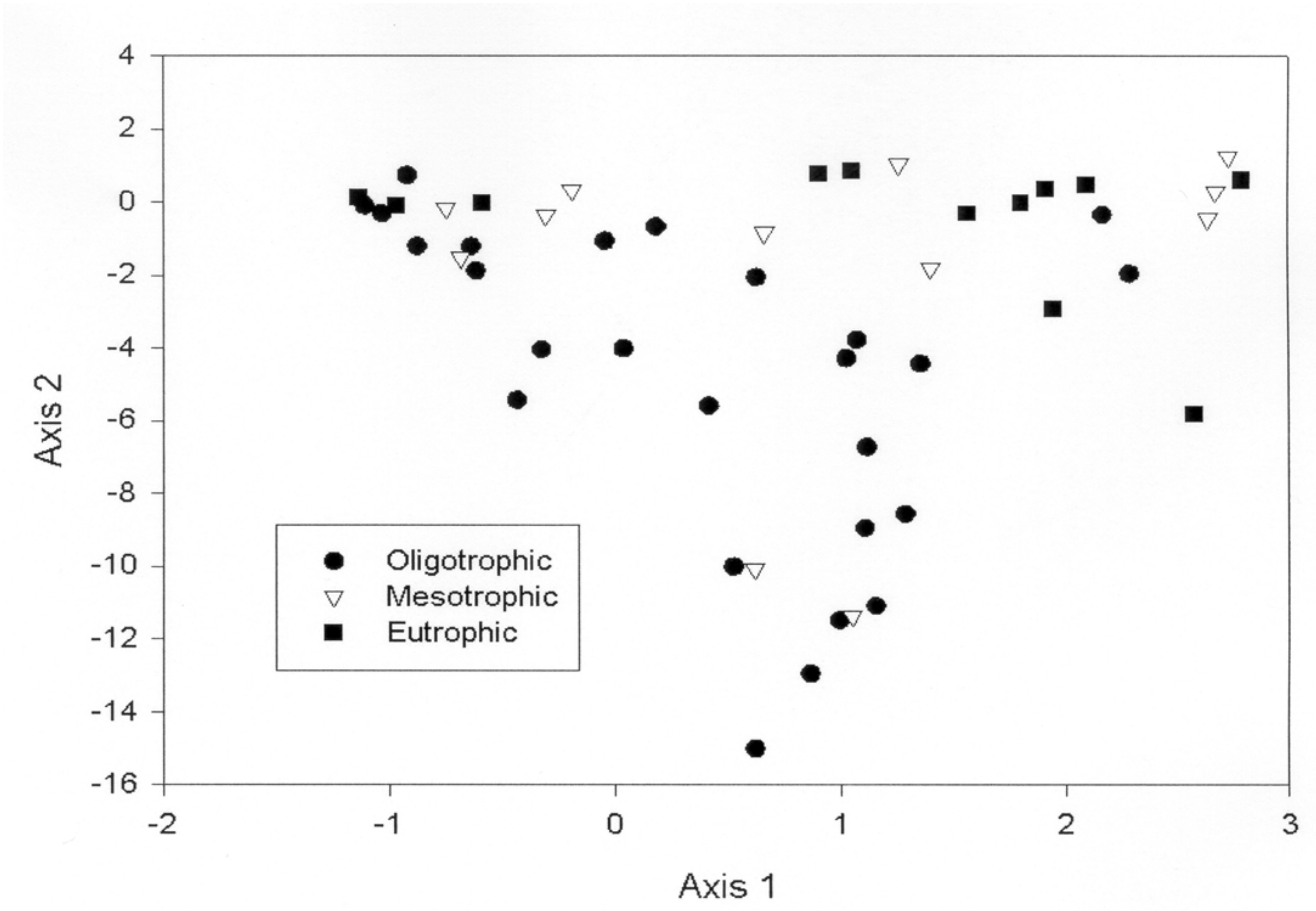

Figure 13. CCA ordination of lakes based on WA scores for 1990-1995 land use change in surrounding 500 m buffers.

APPENDIX B
MULTIPLE REGRESSION RESULTS FOR 1995 LAND CLASSES USING 100 M BUFFERS

B.1 Multiple Regression Results for 1995 100 m

When using multiple regression for 1995 land use classes using 100 m buffers, chlorophyll a was the only water quality variable correlated with any land use variable. It was negatively correlated with moderately well drained soils with a p-value of 0.004. All other land use variables were excluded from the analysis with chl a (Table 54).

Table 54. Multiple regression results for water quality variables and land use for 1995 100 m based on buffers. Table includes coefficients that are used in the regression model as well as significant values for each variable used.

Water Quality Variables	Land Use	Significance Values	Regression Coefficients (intercept, slope)
Chlorophyll	Moderately Well Drained Soils	0.004	(-1.148, 1.428)

B.2 Multiple Regression Results for 1995 500 m

When using multiple regression for 1995 land use classes using 500 m buffers, chlorophyll a and phosphorus were both positively correlated with very poorly drained soil. They had p-values of 0.039 and 0.046. All other land use variables were excluded from the analysis (Table 55).

Table 55. Multiple regression results for water quality variables and land use for 1995 500 m based on buffers. Table includes coefficients that are used in the regression model as well as significant values for each variable used.

Water Quality Variables	Land Use	Significance	Regression Coefficients (intercept, slope)
Phosphorus	Very Poorly Drained Soil	0.046	(0.836, 1.426)
Chlorophyll	Very Poorly Drained Soil	0.039	(1.322, 0.947)

B.3 Multiple Regression Results for Change in Land Use 500 m

When using multiple regression for change in land use classes using 500 m, moderately well drained soil was negatively correlated with chl a. with a p-value of 0.003. Secchi depth was negatively correlated with road density with a p-value of 0.046. All other land use variables were excluded (Table 56).

Table 56. Multiple regression results for water quality variables and the change in land use 500 m based on buffers. Table includes coefficients used in the regression model as well as significant values for each variable used.

Water Quality Variables	**Land Use**	**Significance Value**	**Regression Coefficients (intercept, slope)**
Chlorophylll	Moderately Well Drained Soil	0.003	(-2.016, 1.489)
Secchi Depth	Road Density	0.046	(-0.878, 0.651)

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