THE USE OF THE LANDSAT MSS IN THE STUDY OF LAND USE/COVER AND WATER QUALITY RELATIONSHIPS:

A CASE STUDY OF THE LAKE ANNA WATERSHED

by

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TABLE OF CONTENTS

Page

LIST OF TABLES

Table Page

Table Page

LIST OF FIGURES

Chapter 1

Problem Statement

LANDSAT monitors the land resources of earth by means of a multispectral scanner (MSS), a sensor which images and records radiation reflected by the earth's surface in four spectral bands. Although the MSS was designed for mapping land rather than water resources, a growing number of researchers have devoted their efforts to water quality monitoring with the use of LANDSAT MSS data. The research interests of Mather (1981) and Munday et al (1979) are examples of the increased use of the LANDSAT MSS data in monitoring water quality.

Munday et al use chromaticity analysis, an established technique within the science of colorimetry, to measure the turbidity of water bodies as represented on LANDSAT imagery. This technique is used to develop chromaticity coordinates, values derived from normalized radiances recorded by measurements in the green, red, and near infrared spectra. The chromaticity coordinates are plotted onto x and y axes, the chromaticity diagram. The positions of the coordinates on the diagram are compared with a calibrated locus to estimate the turbidity of a water body. Munday et al (1979) used chromaticity analysis with LANDSAT MSS data to monitor sediment flow in the Minas Basin, Bay of Fundy, Nova

Scotia--information used by Canadian officials to estimate the life span of a tidal barge power project in that area.

The purpose of this research is to extend the use of chromaticity analysis as applied to LANDSAT MSS data by focusing on the following questions:

1. What degree of accuracy can be achieved by applying chromaticity analysis to geographic environments different from those studied previously?
2. Can chromaticity analysis of LANDSAT MSS data be used to monitor accurately the relationship between land use/cover patterns and the sediment discharge of a watershed?
3. What is the relationship between different combinations of land use/cover patterns within a watershed to the level of sediment that is produced from this watershed?

A second premise of this research is based on a study by Haugen, McKim, and Marlan (1977). These authors studied the feasibility of using high altitude aerial photography to assess effects of land use patterns on the sediment discharge of streams within three watersheds in the Great Lakes Basin. The authors concluded:

> The comparison of land use to stream sedimentation demonstrated that a relationship could be shown based primarily upon data derived by remote sensing means. This type of data is necessary for the prediction of impact on streams and harbors of land use changes within a watershed (Haugen, McKim, and Marlan, 1977; p. 65).

The goal of this research is similar to that of Haugen et al - the comparison of land use/cover to stream sedimentation -- but the methods and techniques use LANDSAT MSS data instead of aerial photographs. Research by Munday (1974), Scarpace et al (1979), Khorram (1980), Holyer (1978), and others who have used LANDSAT to assess the quality of various water bodies has remained distinct from that of scientists, such as Rogers, Hollyday, and Solomon, who have used LANDSAT to investigate the land use and land cover of various watersheds. No study has been found similar to the Haugen et al study in which LANDSAT MSS data were used to simulatenously examine turbidity levels in relation to land use/cover patterns. As a result, LANDSAT MSS data is used here to research the relationship between these two parameters.

A. Advantages of LANDSAT MSS Data for Watershed Management

A problem within watershed management is the control of nonpoint source pollution. Nonpoint source pollution has been defined as "any pollutant whose specified point of generation cannot be traced to any discrete, identifiable facility and whose exact point of entry into a water course cannot be defined" (Cox, 1979). Nonpoint pollution is the result of both natural and human activities, but such land uses as agriculture, silviculture, logging, urbanization, construction, and mining-related activities often produce greater amounts of sediment than natural sedimentation processes.

The magnitude of water quality degradation from nonpoint sources is immense. The problem is equal to or greater than the total effect from all point sources. The EPA has estimated that 15 percent of the nation's waters are failing to meet water quality standards because of nonpoint sources (Cox, 1979). Further degradation is predicted unless action beyond point source control is taken.

How can the problem of nonpoint source pollution be managed? The first step in managing the nonpoint source pollution is the idenfication of problem areas. The LANDSAT MSS offers a possible means to identify problem areas.

LANDSAT provides an excellent view of the land use and land cover of a watershed. Two LANDSAT orbiters circle the earth in nearly polar, sun-synchronous orbits of 18 days duration. Since LANDSAT 3 is in the same position as LANDSAT 2 on the ninth day of the cycle, repetitive coverage of the same spot on earth is possible every nine days. This repetitive and seasonal coverage by LANDSAT provides the researcher with an historical record of the earth's resources and associated land uses.

The accumulation of visual and digital information from LANDSAT can be used to inventory the land use and land cover of a watershed for any season of the year. In addition, when a stream empties into a larger water body, MSS data can form the basis for an estimate of the suspended sediment in the larger water body. These characteristics make the LANDSAT MSS a potentially useful tool in studying the relationship between land uses/covers of a watershed and water quality.

Other advantages of the LANDSAT MSS with respect to the monitoring of water quality include synoptic coverage, timely data and less labor-intensive information (Richason, 1978).

B. Justification for Research

Researchers have called for new techniques to monitor the causes and extent of the sedimentation of water bodies. Many of the needs for new techniques are within the capability of LANDSAT. A NASA-sponsored conference, Remote Sensing and Problems of the Hydrosphere: A Focus for Future Research (1979), examined potential applications of remote sensing in monitoring causes and impacts of sedimentation. Recommendations from the conference included a need for 1) accurate data collection systems which can rapidly detect changes in urban and rural land use activities, 2) improved measurements of sediment in aqueous systems, 3) measurements of the eutrophication of lakes and reservoirs, and 4) observations on the location and characterization of the movement of sediment within water bodies (Goldberg, 1979).

A Tennessee Valley Authority study of man-made reservoirs called for further investigation of the relationship between land use and land cover surrounding a reservoir and the water quality of the reservoir. A recommendation of the study stated, "Further studies should also be made [with the use of LANDSAT] to locate and present water quality changes within particular reservoir areas" (Meinert et al, 1981).

This research applies these recommendations by studying relationships between land use/cover patterns and turbidity levels within the Lake Anna watershed. The Lake Anna watershed is located in north-central Virginia within the counties of Orange, Louisa, and Spotsylvania (Figure 1.1). Lake Anna was formed in 1972 to act as a cooling source for the North Anna Nuclear Power Plant.

The Lake Anna watershed was selected as the study area for four principle reasons. First, with the inundation of the lands now forming the Lake Anna reservoir, natural barriers to nonpoint source pollution, such as vegetation along the tributaries of the watershed, were destroyed. Second, Lake Anna will eventually become filled with

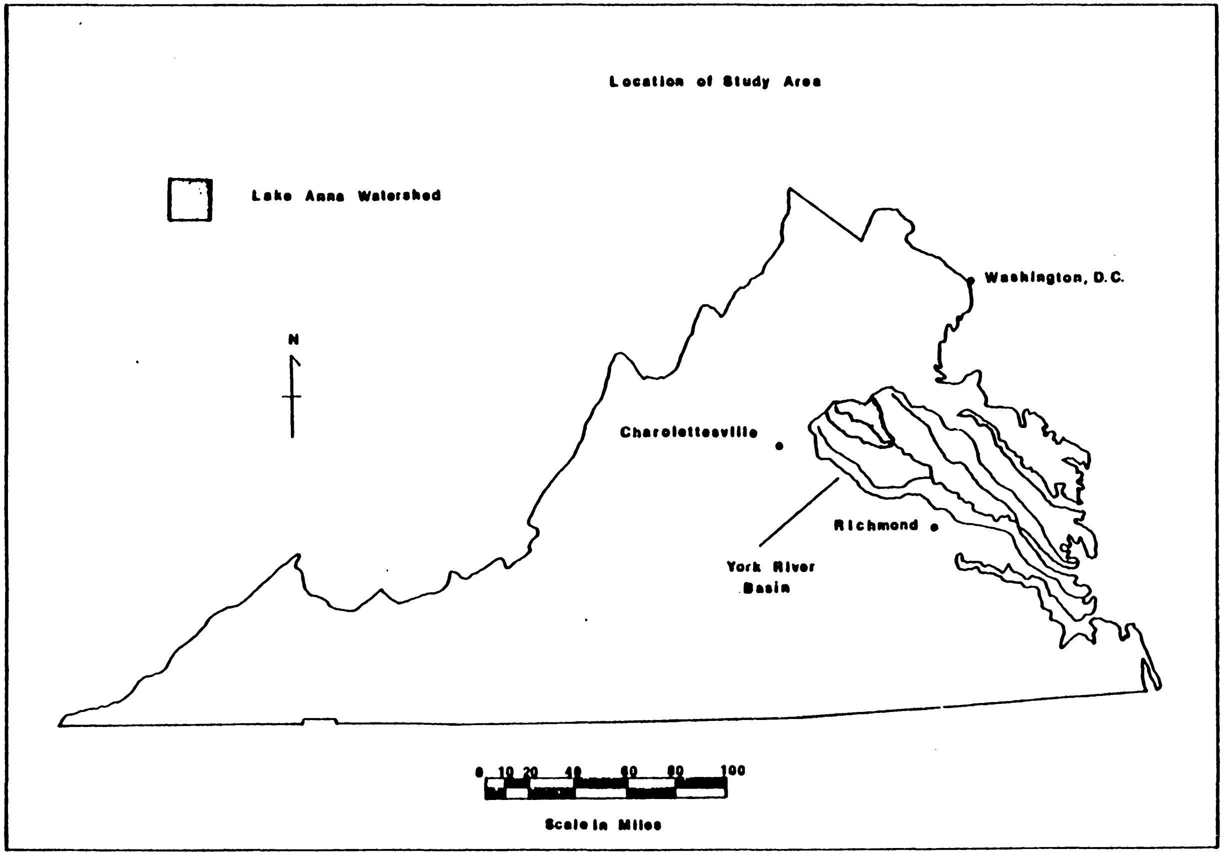

Figure 1.1. Location of Study Area: North-Central Virginia

sediment. Therefore, the inflow of sediment into the reservoir can be reduced by the management of potential sources of nonpoint pollution. Third, many potential sources of nonpoint pollution are within the Lake Anna watershed. These sources include agricultural land, logging operations, residential developments, and mining operations. Fourth, physical characteristics of the study area, such as rolling topography and highly erodible soils, increase the probability of erosion. Therefore, the most important justification for this research is that a case study of relationships between land use/cover patterns and turbidity levels in the Lake Anna watershed can provide useful economic, engineering, ecological, recreational, and geologic information for proper watershed management.

This research emphasizes one basic theme in geographic thought -- human/environment relationships. Because LANDSAT imagery and data provide systematic records of the earth's land cover, they can be used to monitor the physical artifacts of man's occupation of earth. This research also addresses the issue of analyzing human/evnironment relationship problems from a broad perspective. The synoptic coverage capabilities of the LANDSAT MSS can provide information about a watershed on a scale that can enhance the efficiency for managing the resource. Such research results can be used by land use planners, water resource managers, engineers, limnologists, and soil and water conservationists.

C. Summary of Problem

Researchers have called for new techniques to monitor relationships between land use/cover patterns and water quality. Previous research has used aerial photography to study this relationship. Data from LANDSAT's MSS also offers a means to monitor this relationship. Studies have shown that MSS data can be used to measure the sediment loads of water bodies and land use/cover patterns within a watershed. However, the land use/cover and water quality detection capabilities of LANDSAT are often used in isolation from one another. This research integrates these capabilities by using LANDSAT MSS data to explore relationships between land use/cover patterns and water quality.

Chapter 2

Review of Previous Research

Research which has utilized the LANDSAT MSS to study hydrologic problems can be separated into two broad areas: the use of remote sensing techniques for monitoring water quality and the use of remote sensing techniques for watershed management. While the former focuses on remote sensing techniques as a means to estimate water quality, the latter emphasizes the use of remote sensing devices to define land use and land cover patterns within a watershed as they influence the character and quality of streamflow.

Research in both areas has found the LANDSAT MSS to be an effective tool for monitoring water resources. A weakness in existing research is the lack of correlation between the two sets of data for watershed and water quality management. Chapter 2 reviews this previous research (Sections A and B), identifies its strengths and weaknesses (Section C), and discusses how this present study contributes to the previous research (Section C).

A. Remote Sensing as a Means to Monitor Water Quality

Early Research

The interests of Strandberg (1966) and Scherz et al (1969) are typical of early research which used remote sensing techniques to identify water pollution. Strandberg was one of the first to recognize the utility of remote sensing techniques in monitoring water quality.

> Aerial photographic-interpretation techniques can play a valuable role in helping to protect our national water resources. A vast amount of aquatic ecological information can be imaged photographically. Perhaps in no other way can large water areas be examined and the interactions which occur in them be studied as thoroughly (Strandberg, 1966; p. 240).

Strandberg's research interests concentrated on "signature" identification of water pollutants, based on the assumption that pollutants have a distinct appearance on an aerial photographs. Water pollution signatures were classified into three groups: municipal wastes, industrial wastes, and land drainage wastes. As for the utility of these signature classifications, Strandberg suggested:

> Investigators who examine water in test tubes or by the drop on microscope slides cannot see whole rivers and lakes, nor can investigators studying aerial photography taxonomically classify the aquatic organisms that are present, nor conduct qualitative and quantitative chemical analysis. However, the two investigators can work together as a team to their mutual benefit (p. 245).

Scherz et al (1969) expanded Strandberg's research by converting water pollution signatures into digital format. While Strandberg had studied signatures by visual interpretation, Scherz et al correlated signatures with laboratory reflectance data. Hence, Scherz et al continued the research on the signature characteristics of different types of pollutants.

Researchers recognized soon after the launch of LANDSAT 1 that MSS data could be used to estimate and map water quality. The Symposium on Significant Results Obtained From ERTS - 1 provided one of the first opportunities for users of ERTS data to meet together and share the accomplishments of their investigations. An example of this early use of LANDSAT is the work by Yarger et al (1973), who correlated the suspended sediment load of two Kansas reservoirs with points of known sedimentation on LANDSAT imagery. Their study indicated that MSS bands 5 and 6 exhibited a strong correlation with suspended sediment data.

The significance of this early water quality research is illustrated by two accomplishments. First, Strandberg recognized that remote sensing techniques could be used to assist traditional methods of water quality monitoring. The synoptic coverage of remote sensing could reduce field work and costs by quickly locating water quality problem areas.

Second, and most important, the signature categorization research of Scherz et al and Yarger et al found that certain water quality pollutants are highly correlated with signatures from aerial photographs and satellite imagery.

Estimation of Water Quality from LANDSAT MSS Data

Water resource researchers have found the LANDSAT MSS to be an effective tool in recording water quality trends of selected water bodies. Most of this previous research presented methodologies for using LANDSAT MSS data in the detection of water pollution. Four different methods of water quality analysis and their contributions to the development of signature analysis are examined here. These methods include regression analysis, supervised classification, chromaticity, and identification of a universal algorithm for suspended sediment detection by means of the LANDSAT MSS. A common objective of all these methodologies is an attempt by researchers to develop accurate and efficient techniques for estimating water quality levels from LANDSAT MSS data.

Regression: Researchers have used a number of multivariate analysis techniques to study relationships between MSS data and surface water quality data. Three groups of research used regression analysis to correlate water quality data with MSS data. Their primary contributions included the use of regression analysis in image interpretation, atmospheric correction algorithms, and the use of pixel blocks to characterize the quality of a water body.

Rogers et al (1976) used stepwise regression analysis to investigate relationships between MSS data and each of seven water quality parameters. The results of their research revealed that a ratio of LANDSAT bands most accurately measured the overall water quality within Saginaw Bay. Secchi disc depth and temperature were most accurately correlated with Band 5. In addition, the authors noted that the distribution and concentration of other water quality variables could be correlated to detectable parameters.

Scarpace et al (1979) extended the research of Rogers et al by correlating surface water quality data with radiometric information such as atmospherically corrected MSS data, the average variance of the corrected signal, and the variance in the spectral signature from the average signature over time. Although the water quality of almost all the Wisconsin lakes studied was classified correctly, the Scarpace et al study concluded that their regression equations were applicable only to the specific water bodies examined and that individual regression equations would have to be developed for different regions. In an earlier, similar study, Scarpace et al (1979) successfully classified the trophic status of reservoirs within the TVA system, using similar treatment and analysis of LANDSAT MSS data.

Supervised Classification: Supervised classification is another multivariate technique used by researchers to study relationships between MSS data and surface water quality samples. The supervised classification procedure classifies areas of unknown water quality on the basis of known water quality. Supervised classification algorithms have well documented successes in land use analysis, but Smith and Addington (1977) and Khorram (1980) have demonstrated that the method can be applied to water quality analysis of LANDSAT MSS data.

Smith and Addington (1978) used a supervised classification algorithm in their study of temporal changes in water quality of Lake Mead, Nevada. Lake Mead was selected because a fifteen percent sidelap of LANDSAT coverage allowed water quality to be monitored on consecutive days. As input into the classification algorithm, Smith and Addington used an average value from a block of pixels to represent water quality. The results of the study showed a moderate level of correlation between MSS-derived data and surface data.

Khorram (1980) also applied this technique in an effort to locate biologically active zones in the San Francisco Bay Region on LANDSAT imagery. Like Smith and Addington, Khorram averaged the values from a nine-by-nine block of water pixels taken from a multi-band image. Regression analysis between actual water quality data and the predicted values yielded a correlation coefficient of 0.67. Khorram suggested that the low coefficient probably was caused by bottom reflection.

Chromaticity: Chromaticity analysis, an established technique within colorimetry, defines the quality of color and is based on the hue and saturation of a color rather than brightness. The potential utility of chromaticity analysis has been tested in many areas. Most recently, Munday and Alfoldi (1975; 1977), Munday et al (1979), and Mather (1981) applied the technique to estimate water quality levels on LANDSAT imagery. While Munday and Alfoldi and Munday et al confirmed the accuracy and utility of chromaticity analysis for estimating water quality levels, Mather applied the technique to a different geographic setting.

The objective of Alfoldi and Munday's research (1977) was to develop a LANDSAT water quality monitoring system using chromaticity analysis. Such a system would require only initial correlation of LANDSAT data with water quality samples; thereafter, turbidity could be assessed on the basis of the initial calibration. Alfoldi and Munday built on previous research to combine the techniques of band normalization, chromaticity analysis, and atmospheric adjustments to LANDSAT data in order to determine sediment load and movement in the Minas Bay Region, Bay of Fundy. Sediment levels were estimated by plotting normalized brightness values (chromaticity coordinates) on a chromaticity diagram and then comparing the locations of these values to a sediment locus, as an index to sediment levels.

The results of their study revealed that chromaticity analysis of LANDSAT data was quite accurate in estimating the water quality of the Minas Bay Region. In a later study Munday et al (1979) confirmed the results of their study of the Minas Bay Region. Although the chromaticity technique previously had been perfected and used in an operational context as a water quality monitoring system, their research addressed the impact of sediment size, chlorophyll, dissolved organic matter, solar angle, system noise and atmospheric adjustments on the position of chromaticity points within the diagram. The authors concluded that: 1) such factors as sediment size, chlorophyll, dissolved organic matter, and solar angle had little effect on the position of chromaticity points; 2) system noise was reduced through the averaging of smaller, four-by-six blocks of pixels; 3) less error occurred in the middle range of particle sizes as compared with extremely small or large sediment particles; and 4) the atmospheric adjustment of the chromaticity points improved the measurement of sediment loads over unadjusted chromaticity points.

The accuracy of chromaticity analysis of water pixels was further confirmed by Mather's application (1981) of the technique in a different geographic environment. Mather applied chromaticity analysis to the study of suspended sediment off the coast of southeast Lincolnshire, Great Britain. Although Mather did not apply an atmospheric correction algorithm, his results proved to be as successful as those achieved by Munday et al. Mather stated:

> The additional information provided by the LANDSAT-based suspended sediment contour maps unquestionably 'improved the validity of the Bay of Fundy model' (Mather, 1981; p. 1061).

These research findings have four implications for LANDSAT research of water quality problems. First, the results firmly established the chromaticity technique as a statistically valid tool. Second, a higher level of correlation between surface water quality samples and the results of chromaticity analysis than had been achieved in previous research was accomplished by the chromaticity technique and atmospheric corrections. Third, the successful application of chromaticity analysis to LANDSAT MSS data proved that techniques other than multivariate analysis could be used to estimate water quality levels from LANDSAT MSS data. Fourth, the technique has been proven successful in different geographic environments.

Universal Algorithm: A major weakness in the research reviewed thus far is the restricted geographic applicability of the technique. In other words, surface data is needed and atmospheric corrections must be made for each new study area. The objective of Holyer's research (1978) was to develop a universal algorithm for detecting suspended sediment from LANDSAT MSS data.

A major goal of Holyer's research was "to examine the variability of sediment-reflectance relationships to determine if it is feasible to make quantitative remote measurements of sufficient accuracy for U.S. EPA monitoring purposes with little or no ground truth" (Holyer, 1978; p. 323). Holyer studied the spectral reflectance of a variety of sediment types that flow into Lake Mead, Nevada. He determined that transferable multispectral algorithms can be developed for nephometric turbidity, an optical measurement technique which is related to the scattering absorption of light from suspended sediments in a water body (Holyer, 1978).

Evaluation of Water Quality Monitoring Methods

The studies discussed here exemplify a concerted effort by researchers to use remote sensing techniques, and more specifically, to use LANDSAT MSS data as a means to estimate water quality. Although individual techniques vary in style and approach, researchers have assessed the success of their technique by the correlation of LANDSAT brightness values to surface data. Other similarities among the studies include the investigation of large, dynamic water bodies, multiple scenes analysis, and the use of surface data.

Each individual body of research has contributed to the study of water quality. However, the level of success that Munday et al achieved make their methodology particularly useful for further water quality research. Mather supported their results with the findings of his research. Two principle advantages of chromaticity analysis include accuracy and the broad geographic applicability of the technique. Therefore, based on the success of chromaticity analysis as achieved by Munday et al and Mather, chromaticity analysis is used to assess turbidity levels in this study.

Problems can be found in the methodologies of the other research reviewed. The most significant problems result from inaccuracies between water quality levels as estimated from LANDSAT MSS data and surface water quality levels. Khorram and Smith and Addington found that only a moderate relationship could be established between the results of supervised classification of LANDSAT MSS data and surface water quality levels. Although Rogers et al were successfully correlated brightness values with surface data, their method was not as accurate in assessing water quality as the band normalization techniques devised by Munday et al. A second problem is the limited geographic applicability of several of the techniques. The regression equations used by Scarpace et al could only be applied to water bodies within their study area. New regression equations had to be calculated for other geographical areas. A related problem is that Scarpace et al studied the overall quality of a water body, thereby limiting the utility of this technique for sections of a water body. A final problem involves the application of the technique to water quality problems outside the laboratory. Holyer's universal multispectral suspended sediment algorithm was proven successful only in the laboratory. Other problems with this technique arise with the correlation of his research results with water quality measurement techniques other than nephometric turbidity.

B. Remote Sensing Techniques as a Means to Detect Nonpoint Sources of Pollution

Early Research

Fewer researchers have applied remote sensing techniques to study sources of nonpoint pollution than to monitor water quality. This emphasis is partially the result of the lack of importance assigned by the Environmental Protection Agency (EPA) to the implementation of policies to control nonpoint sources of pollution. March et al stated:

> Although the legislative history of the Federal Water Pollution Control Act of 1972 (FWPCA) called for the area-wide water quality and management program mandated by Section 208 (the section which governs nonpoint source water pollution) 'the most important aspect of a water pollution control strategy,' the EPA placed little importance on implementation of Section 208 planning in the period immediately following the passage of the 1972 Act (March, Kramer, and Geyer, 1981; p. 324).

However, many researchers recognized the potential of remote sensing techniques in the detection of nonpoint sources of pollution prior to the passage of the Federal Water Pollution Control Act of 1972. Robinove (1966) suggested that remote sensing techniques could be used to locate sources of erosion.

> Intensification of land use for a wide variety of purposes, including urban development, has increased the erosion of the land surface and consequent sedimentation in rivers and lakes, reservoirs, and estuaries. Regular gauging-station records of sediment discharge of streams can measure sediment produced, but the problem of determining its sources and temporary local deposition is more difficult. It seems probable that synoptic and repetitive surveys from aircraft or spacecraft would contribute importantly to analysis of the extent and location of culturally accelerated erosion and sedimentation (Robinove, 1966; p. 31).

The results of North's research (1971) confirmed Robinove's ideas. North's methodology included the preparation of land use maps from aerial mosaics, which he used to identify, extract, and plot sources and potential sources of pollution. He suggested that the advantage of remote sensing in pollution detection is the ability to monitor the sources, movement, and destinations of pollutants. North concluded that by using the synoptic capabilities of remote sensing techniques, potential sources of nonpoint pollution can be identified and, thus, eventually controlled.

Salomonson et al (1975) found that certain watershed data could be obtained by remote sensing techniques. They determined that six out of twenty six input parameters in watershed modelling were obtainable with existing remote sensing techniques. Those parameters detectable by remote sensing techniques included fraction of impervious area, fraction of water surface, fraction of forested area, maximum volume of interception, overland flow surface length, and overland flow surface slope. Hence, based on remote sensing data, researchers can identify those watersheds which might need further management.

Haugen et al (1977) applied this previous research in a comprehensive study of nonpoint source pollutants within three watersheds of the Great Lakes basin. They attempted to determine whether a regional relationship could be found between land use categories and the sediment loading of streams within specific watersheds based on remotely sensed data.

Haugen et al concluded that as the percentage of agricultural land increases in the Great Lakes Basin, the amount of sediment in streams also will increase. This study set a precedent in two respects. First, while remotely sensed data had previously been used to classify land use and land cover, this study was one of the first to link these data with variations in the turbidity levels. Second, the relationship between land use and stream sedimentation was based solely upon remotely sensed data.

These studies domonstrated increased application of remote sensing techniques in the detection of nonpoint sources of pollution. A basis for these research efforts is that remote sensing techniques offer an efficient method to detect potential areas of nonpoint source pollution. Once these areas are identified, measures can be taken to manage the problem.

The Application of the LANDSAT MSS in Watershed Management

Researchers proved soon after the launch of LANDSAT that the satellite could be used to detect potential sources of nonpoint pollution more efficiently than traditional remote sensing techniques. A number of studies presented at the Symposium on Significant Results Obtained from ERTS-1 suggested that LANDSAT MSS data could be used to distinguish between several similar land use types. Horton and Heilman (1973) found that they could differentiate between corn and soybeans with MSS bands six and seven; Safir and Meyers (1973) were able to separate mature crops from dense forests on a LANDSAT image; and Johnson and Coleman (1973) detected such land use conditions as growing crops, wet soils, seed crops, plowed soil, bare soil, and harvested stubble.

Researchers such as Hollyday and Rogers built on these early findings to study watershed characteristics with LANDSAT MSS data. Hollyday (1976) researched the applicability of LANDSAT imagery and data to the measurement of streamflow characteristics. LANDSAT MSS data were used to classify land cover and land use within watersheds of the

Delmarva Peninsula. Hollyday hypothesized that such land use and land cover information would assist in the prediction of runoff and streamflow characteristics of the study area. Regression analysis was used to correlate streamflow characteristics with the watershed land use and land cover characteristics. Hollyday found that LANDSAT MSS data improved estimates of streamflow characteristics. Although this study did not use LANDSAT to measure the sediment discharge of a watershed or locate sources or potential sources of nonpoint pollution, the study did verify that MSS data and imagery can be used to monitor watershed characteristics.

In contrast to Hollyday, Rogers (1976) studied the utility of LANDSAT as a means to inventory land use and land covers for Section 208 areawide planning, which includes nonpoint pollution control. In one of the first studies of the kind, Rogers (1976) used LANDSAT to locate sources and potential sources of nonpoint pollution in the Triangle J region of North Carolina (Raleigh, Durham, and Chapel Hill).

Rogers' unique methodology included the production of map overlays for the various land use and land cover categories -- a useful tool in watershed management which allows a planner to place certain land use categories in higher priority for further observation or controls than other categories. Another unique step in Rogers' methodology was the combination of the LANDSAT data with information from a geo-based information system. The field verification of the laboratory results proved the LANDSAT-based data to be ninety percent accurate. In addition to this favorable result, the cost of this study was significantly less than the cost of manual aerial photographic interpretation for a similar project.

In a separate study, Rogers (1978) examined the impact of land use and land cover on the water quality of the Great Lakes with LANDSAT MSS data. Sediment loading rates were assigned to each land use and land cover category. Again, Rogers found that classified LANDSAT data closely correlated with ground truth information.

In conclusion, researchers have found that LANDSAT represents an accurate and cost effective means to monitor watershed land use/cover characteristics. Because EPA has placed little emphasis on nonpoint pollution, there has been little regulatory incentive to pursue the full potential of LANDSAT as a means to monitor sources and potential sources of nonpoint pollution. However, research has indirectly indicated that LANDSAT and other types of remote sensing equipment can be used for this purpose. The early LANDSAT studies provided evidence of the satellite's utility in broad-scale land use classification. Hollyday verified futher that LANDSAT can be used to monitor the impact of land use and land cover on processes within a watershed. Finally, Rogers' research illustrated that LANDSAT MSS data can accurately and economically detect potential sources of nonpoint pollution. LANDSAT represents a system that can provide useful information for watershed management.

C. Evaluation of Previous Research

Two major themes can be found in previous research. Hollyday and Rogers directed their investigations toward sources or potential sources of pollution, while Rogers et al, Scarpace et al, Smith and Addington, Khorram, Munday et al, and Holyer used LANDSAT MSS data to study the quality of water bodies. Although weaknesses exist in individual research methodologies, the major weakness of the previous research is the independence of the separate themes. Analysis of LANDSAT MSS data has the capability to provide researchers with information about both watershed land use/cover patterns and water quality.

While researchers have applied LANDSAT MSS data to the study of water quality problems, they have not investigated potential sources of nonpoint pollution. Because nonpoint sources of pollution degrade the quality of our water bodies more than any other source, a need exists to research further the relationship between nonpoint sources of pollution and water quality.[1] The Haugen et al research attempted to use aerial photography to study this relationship. However, the use of aerial photography for the long-term monitoring of watershed land uses has certain inherent weaknesses; including the expense of surveying large regions on a multi-date basis and the fact that aircraft are limited somewhat by weather conditions.

Weaknesses exist in the individual research efforts. Although Rogers' research demonstrated that analysis of LANDSAT MSS data can accurately and economically detect potential sources of nonpoint pollution, the actual influence of nonpoint pollution on water quality is not evaluated. Rogers' research would have been more comprehensive if his study had measured the actual impact of watersheds on the quality of water bodies. The Scarpace et al study demonstrated how the water quality of an entire lake or reservoir might be surveyed and classified, but the Munday et al, Holyer, and Khorram research projects are more useful because the quality of individual areas within water bodies was estimated. The Khorram and Smith and Addington

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[1] Since discharge quality is regulated by recent state and federal legislation, point source polluters, such as industries and sewage treatment plants, no longer degrade water quality on a regular basis.

research provided information about assessing and managing problems in water quality detection. Both research groups applied supervised classification techniques to LANDSAT MSS data in order to estimate water quality, and both groups experienced problems in their studies. In review, the problems that Khorram encountered were the result of bottom reflectance. Although Smith and Addington initially found that surface water quality samples did not match water quality levels as estimated by MSS data, this problem was eventually corrected through normalizing the MSS data.

In conclusion, these studies provide other researchers with valuable information about technique in water quality signature analysis and watershed management. The major weakness in the existing research is the separation of watershed land use and water quality detection. Of the research evaluated, chromaticity analysis and Rogers' methodology for watershed management seem to provide the best basis for further research.

This present research attempts to combine the strengths of these two major themes -- chromaticity analysis and Roger's methodology -- by studying relationships between land use/cover and water quality. By studying the relationship between land use/cover patterns and turbidity levels, I will be able to determine if a basis exists for the two separate research themes.

Chapter 3

Methodology

This research uses LANDSAT MSS data to examine land use/land cover patterns in the Lake Anna, Virginia, watershed and attempts to relate these patterns to levels of suspended sediment in Lake Anna. In an attempt to establish this relationship, turbidity levels within Lake Anna are estimated by the chromaticity technique used by Munday et al. Then, to determine the validity of the chromaticity technique, I compare the results to two groups of ground-based data -- surface turbidity levels and the product of the universal soil loss equation (USLE). Figure 3.1 is a flow chart of this methodology.

Surface turbidity levels obtained from Virginia Electric and Power Company's Environmental Laboratory at Lake Anna are used to assess the accuracy of chromaticity analysis. AMOEBA (Bryant, 1979), an unsupervised classification algorithm, is used to delineate spectral categories from the LANDSAT MSS data. Spectral categories are assigned to land use/cover categories within the Anderson et al classification system. Finally, the USLE is used to predict the sediment yield of each Lake Anna watershed on the basis of land use/cover information as

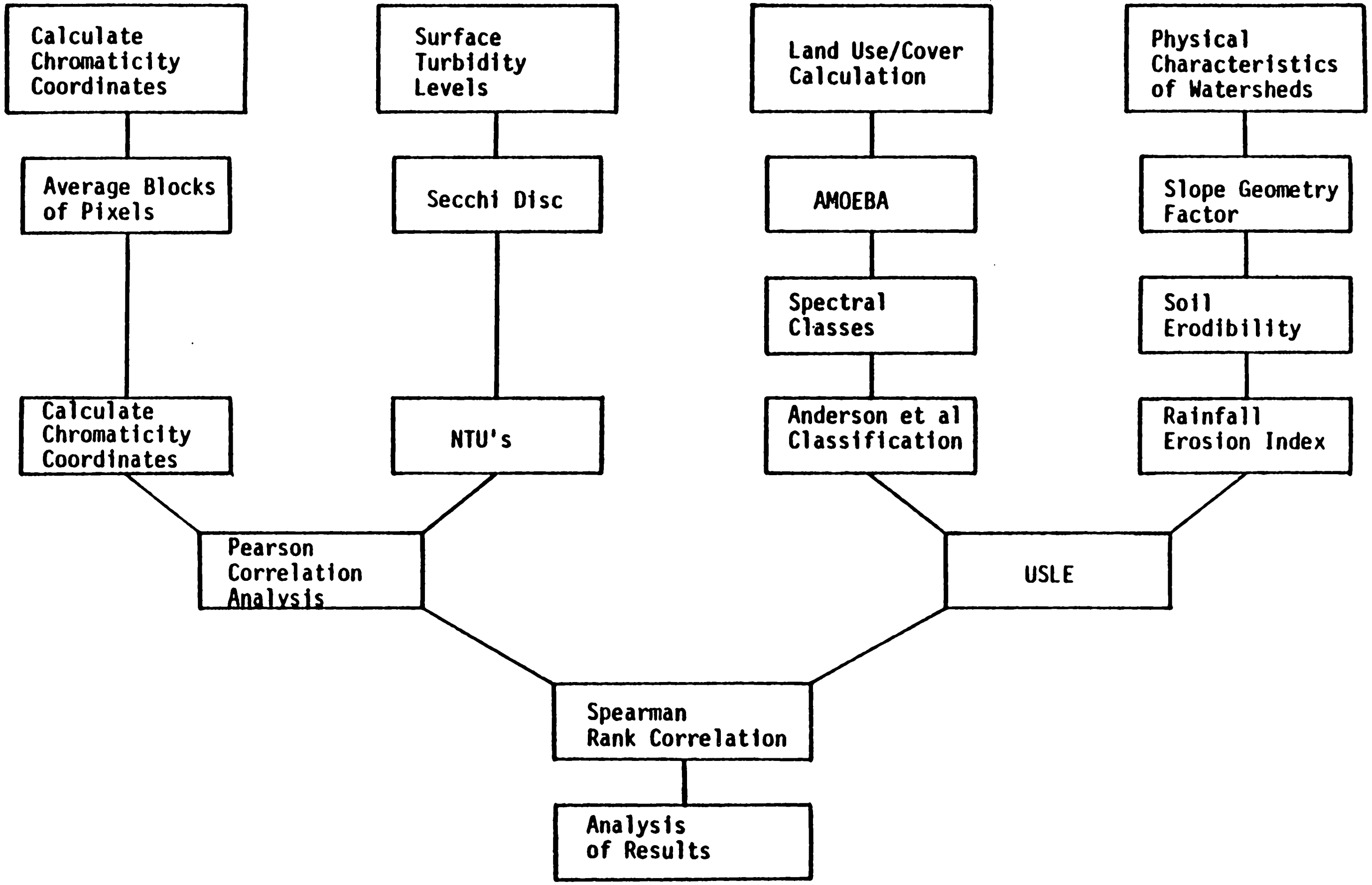

Figure 3.1

Flow Chart of Methodology

delineated from LANDSAT MSS data and the physical characteristics of each watershed. Predicted sediment yield based on the results of USLE is compared to estimated turbidity levels.

The technical objectives of this research are:

1. to assess the utility of chromaticity analysis as applied to LANDSAT MSS data;
2. to extend previous signature analysis research of water pollutants by applying chromaticity analysis of LANDSAT MSS data to a different geographic setting; and
3. to explore more uses of remote sensing for water quality assessment and to investigate the relationship of turbidity levels with land use/ land cover patterns.

A. Background

The study area includes the entire Lake Anna watershed from the Lake Anna dam near Partlow, Virginia, to the headwaters of all its tributaries (Figure 3.2). The Lake Anna watershed, a tributary of the York River watershed, covers 82,957.3 hectares and includes sixteen smaller tributries. Thirteen of these watersheds are studied in this research (Table 3.1; Figure 3.2). The 5,180 hectares of Lake Anna and its 322 kilometers of shoreline are the most prominent features of the watershed (Figure 3.2). The lake was formed in 1972 to form a cooling source for the North Anna Nuclear Power Plant.

Virginia Electric Power Company (VEPCO) officials have been conducting water quality tests on Lake Anna since 1972

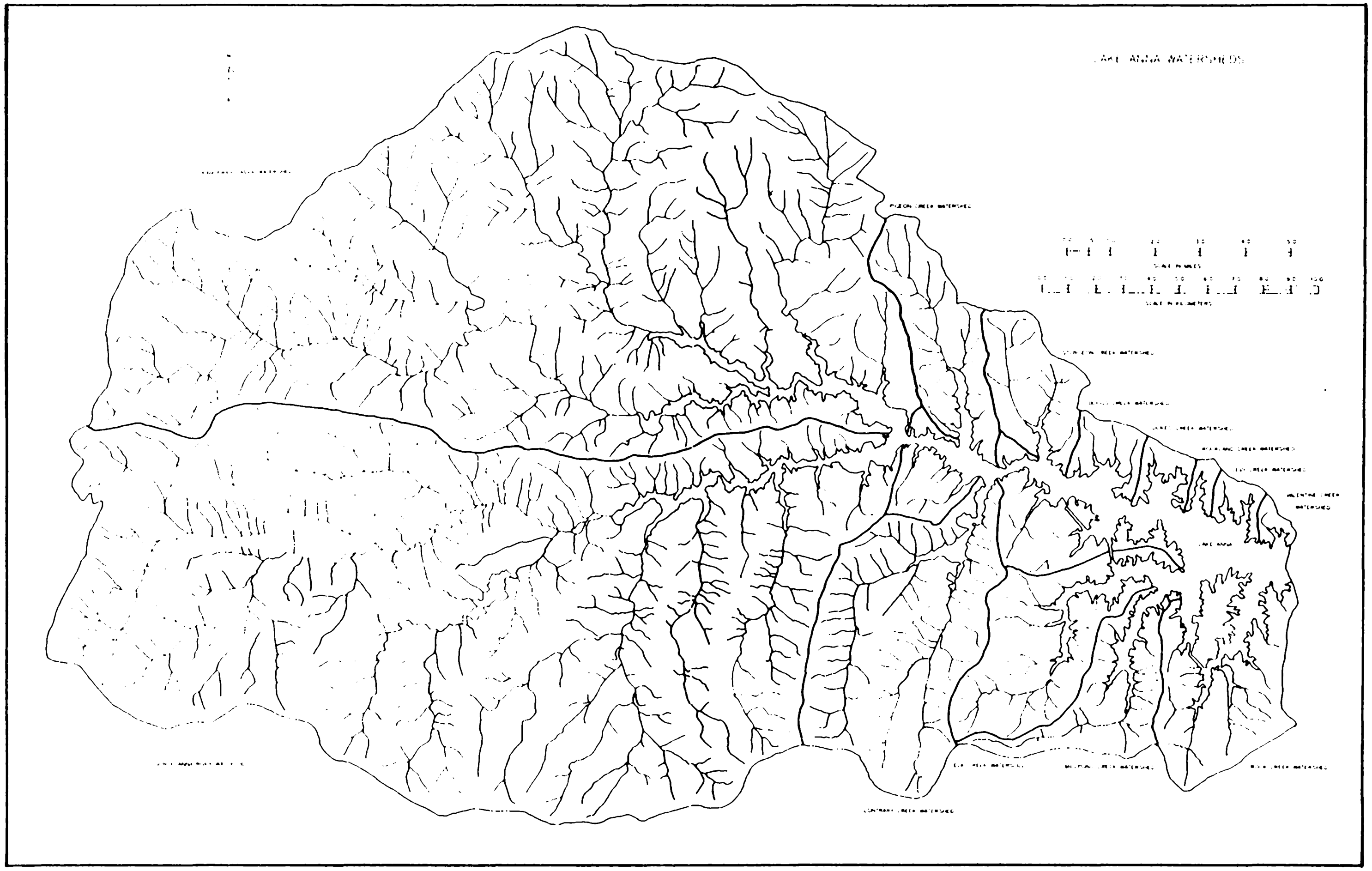

Figure 3.2. Lake Anna Watersheds

The Lake Anna watershed covers 82,957.3 hectares and includes sixteen sub-watersheds. The thirteen sub-watersheds considered in this research are shown on this figure.

TABLE 3.1

Lake Anna Watersheds Included in Research

Watershed	Hectares
Boggs	535.76
Contrary	5,366.45
Dukes	359.11
Elk	2,444.54
Levy	215.41
Millpond	1,592.84
North Anna	29,163.22
Pamunkey	30,227.75
Pigeon	1,828.53
Rock	2,483.80
Rockland	124.44
Sturgeons	1,346.79
Valentine	136.46

when the lake was formed. During this period, stations have monitored a variety of water quality parameters, but the measures of interest for this research include secchi disc depth and nephometric turbidity units (NTU). Although both parameters are used to monitor the level of suspended sediment, they differ markedly in the analysis of the suspended sediment level.

Secchi disc depth was monitored at fourteen stations from 1972 to 1976 (Figure 3.3). The secchi test estimates the level of turbidity by measuring from the surface to the point where the disc can no longer be seen. As the sediment level increases, the depth of the disc from the surface will decrease.

Nephometric turbidity units are measured by the level of light that will pass through a water sample. A high NTU indicates more sediment in the water than a low NTU. Nephometric turbidity has been measured at thirteen stations since 1977 (Figure 3.4).

The launch of LANDSAT 1 in 1972 coincided with the initial development of Lake Anna and the surrounding watersheds. Therefore, LANDSAT MSS data is available to cover the interval from inundation in 1972 to present. Lake Anna surface water quality data are used to evaluate the accuracy of these estimates. A geocorrected, reformatted LANDSAT digital tape was procured for analysis of the land

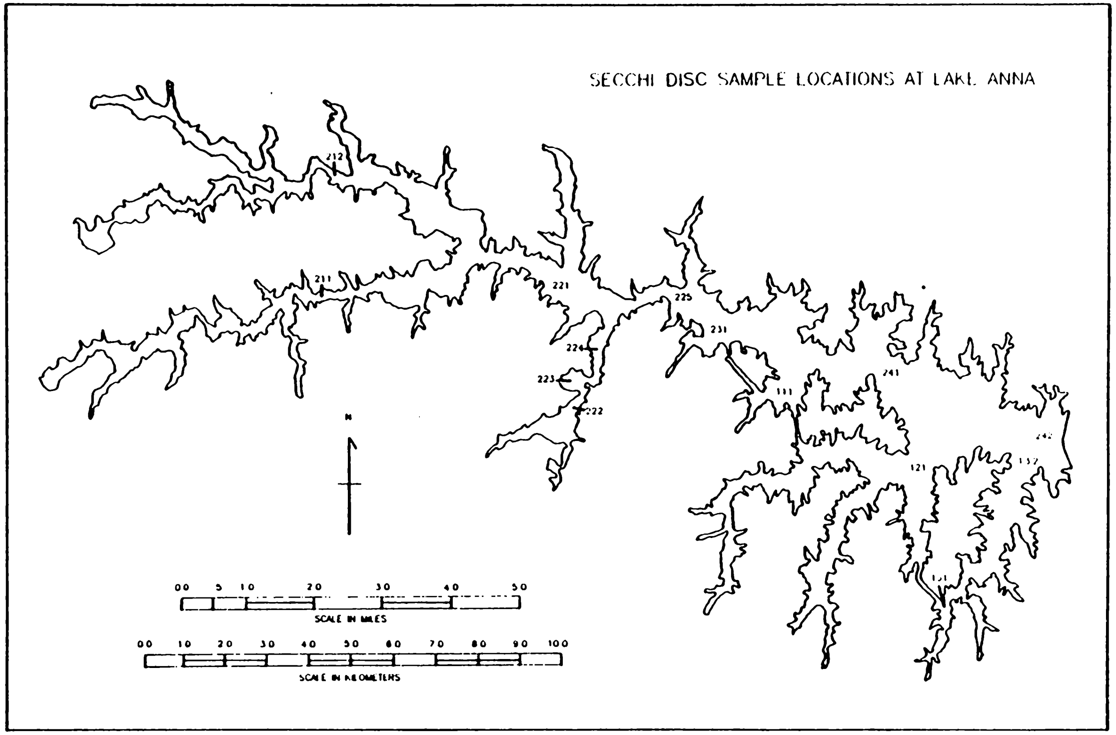

Figure 3.3. Secchi Disc Sample Locations at Lake Anna

Secchi disc depth was monitored at fourteen sample stations from 1972 to 1976. The number assigned to each station represents the approximate position of each sample site.

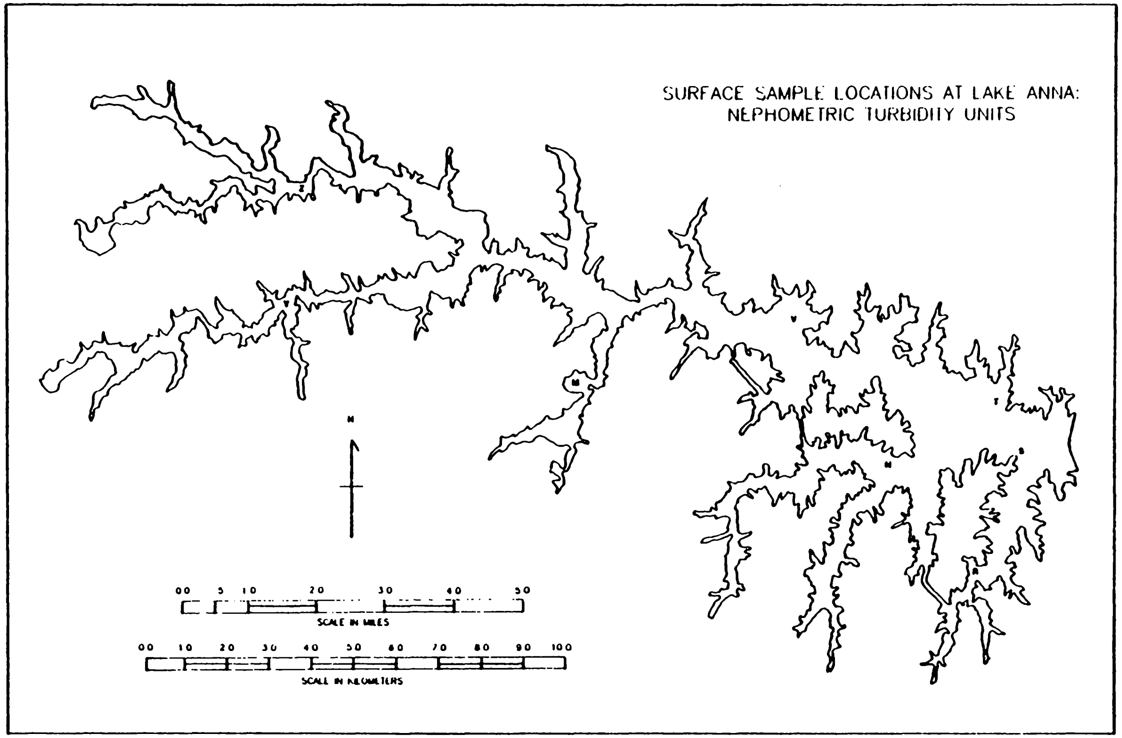

Figure 3.4. Surface Sample Locations at Lake Anna: Nephometric Turbidity Units

Neophometric turbidity has been measured at thirteen stations since 1977. The number assigned to each station represents the approximate position of the sample site.

cover inventory. Consequently, a March 1981 scene was selected for its cloud-free cover and because the scene presents good contrasts between land use categories.

B. Analysis of LANDSAT MSS Data

Characteristics of the LANDSAT System

LANDSAT monitors the land resources of the earth by means of a multispectral scanner (MSS), a sensor which records solar radiation reflected by the surface of the earth in four spectral bands. Bands four and five are sensitive to visible radiation, and bands six and seven are sensitive to radiation in the near infrared spectrum (Table 3.2). Each band provides separate forms of information.

A mirror within the MSS scans the earth from west to east. Each scan of the mirror collects data for a strip of ground approximately 185 kilometers from east to west and 474 meters from north to south. The MSS separates each 474-meter strip into six lines of data, with each line representing 79 meters on the ground. The 79-by-79 meter area represents the instantaneous field of view (IFOV) (U.S.G.S., 1979). The 79-by-79 meter area is formatted during processing to represent a ground area about 79-by-57 meters. The 79-by-57 meter block has been termed a pixel or

TABLE 3.2

Characteristics of LANDSAT

Multispectral Scanner Sensors

LANDSAT 1

Band	Spectral Sensitivity	
4	0.5 - 0.6 μm	green
5	0.6 - 0.7 μm	red
6	0.7 - 0.8 μm	near IR
7	0.8 - 1.1 μm	near IR

LANDSAT 2

Bands and spectral sensitivity are same as LANDSAT 1

LANDSAT 3

Band	Spectral Sensitivity	
4	0.5 - 0.6 μm	green
5	0.6 - 0.7 μm	red
6	0.7 - 0.8 μm	near IR
7	0.8 - 1.1 μm	near IR
8	10.4 -12.6 μm	thermal IR

picture element. The term pixel can refer to the actual pixel on an image, to the digital value that represents a pixel, and the ground area represented.

MSS products include photograph-like images and computer capatible tapes (CCT) which carry the MSS data. Each CCT holds four bands of data, each with 2400 scan lines containing 3240 pixels each. Brightness values for each pixel ranges from 0 reflectance (black) to a brightness value of 127, which represents the highest measured reflectance. The difference in brightness values provides information about an area of the earth's surface and is the mechanism that allows the user to analyze the image. For example, clear water absorbs all wavelengths. Therefore, clear water has a brightness value near zero in all spectral bands. Turbid water has a higher reflectance value, because the sediment in the water tends to reflect a greater amount of radiation.

The imagery for this research was selected on the basis of availability, quality, and date. Coverage is available from the early development of the Lake Anna watershed to present (Table 3.3). Data for each scene are available in the form of CCTs and are used in this research.

The General Image Processing system (GIPSY) is used to analyze the LANDSAT MSS data (Haralick et al, 1981).

TABLE 3.3

LANDSAT Computer Compatible Tapes Selected For Study

Scene Date	Identification Number	Path and Row
03-26-81	82225515114X0	17-13
04-28-78	82119214434X0	16-34
02-09-74	8156615153500	16-34
01-20-73	8117015200500	16-34

Currently, the system can access over two hundred commands to study the imagery.

Water Quality Analysis of LANDSAT MSS Data

In June 1981 during conversation John Munday stated, "There is a need to test this technique on water bodies in other geographical areas." Lake Anna differs from the Alfoldi and Munday study area in three respects. First, unlike the large, open expanses of the Bay of Fundy, Lake Anna is long and in some areas quite narrow. Second, the Bay of Fundy is in a tidal zone, whereas Lake Anna is not influenced by tides and is quite static by comparison. Third, while the water in the Bay of Fundy is brackish to salty, Lake Anna contains fresh water. A goal of this research, therefore is to assess the effectiveness of chromaticity analysis in this setting. (Specific details of the Alfoldi and Munday procedure and chromaticity analysis are addressed in Chapter 4.)

Alfoldi and Munday (1977) found that LANDSAT MSS data could also be used to estimate both secchi disc depth and the turbidity level of a water body. The water quality tests at Lake Anna include measurements of secchi disc depth, 1972 to 1976, and turbidity level, 1977 to present. Water quality sample sites at Lake Anna correspond to inlets and other land features. These features are used to locate the water quality sample sites on the LANDSAT imagery.

Alfoldi and Munday also developed an algorithm to adjust the chromaticity coordinates for atmospheric interference. While the Alfoldi and Munday algorithm adjusts chromaticity coordinates, a similar algorithm, GIPSY's DEHAZE command, adjusts the pixel values. Chromaticity coordinates are calculated for both dehazed and unadjusted pixels in this research.

In order to confirm the accuracy of the chromaticity analysis as it is applied to LANDSAT MSS data, water quality data are compared with the chromaticity coordinates data to determine if LANDSAT MSS data provide information about secchi disc depth and nephometric turbidity level with the same degree of accuracy as the surface samples. Simple regression analysis is used to determine the relationship between chromaticity coordinate X and the log of surface turbidity levels:

$$y = ax + b$$

where,

y = chromaticity coordinate X
a = slope
x = the log of NTUs or secchi disc depth
b = intercept.

The results of this analysis are evaluated for both the accuracy of chromaticity analysis as applied to the study area and the accuracy of the chromaticity transformation of dehazed and unadjusted MSS data.

Unsupervised Classification of LANDSAT MSS Data

Land use/land cover patterns are mapped from the LANDSAT MSS data using AMOEBA, an unsupervised classification procedure (Bryant, 1979). AMOEBA uses a spatially modified, nearest-neighbor-classifier algorithm that assigns pixels to a spectral category on the basis of boundary and field within data space. Proper program execution is based on two assumptions. First, the user must know the approximate number of land use/cover categories within an image. Second, categories must be present in spatial associations. This procedure considers all four MSS bands of a scene. The algorithm is applied to a scene until all pixels are assigned to a spectral category. All pixels within a category are assigned an identification number.

Spectral categories are assigned to land use/cover categories within the Anderson land use and land cover classification system. Anderson et al (1976) recommend classification at level I for LANDSAT MSS data. Ancillary information, such as aerial photographs, topographic maps, and field observations, is employed in the classification of land use/land cover in the study area.

The number of pixels for each category and watershed is calculated using GIPSY's MHIST command. This number is multiplied by the approximate land area of a pixel. The following equation can be used to calculate the approximate land area of each category from the output of the MHIST command:

$$A = .3249 * L(C)$$

where,

A = area in hectares
.3249 = hectares in a pixel for a geometrically corrected image
L(C) = number of pixels in a particular land use category.

The approximate area of each land use/cover pattern is divided by the total area of each respective watershed. This procedure standardizes data for each land use/cover pattern within a watershed and assists in the comparison of watershed land use/cover patterns and turbidity levels.

C. An Assessment of the Impact of Land Uses on Water Quality

The utility of chromaticity analysis for watershed management is assessed further by comparing the results of the universal soil loss equation (USLE), as applied to the

Lake Anna watersheds to the results of chromaticity analysis. The USLE is used to predict which watersheds are likely to produce the greatest amount of sediment.

Variables for the USLE include the slope geometry factor, soil texture, rainfall erosion index, and land use/cover data for each watershed. The USLE can be expressed in the following form:

$$A = K * R * C * S$$

where,

A = estimate of soil loss in tons per acre
K = erodibility factor
R = rainfall erosion Index
C = plant cover factor
S = slope geometry factor.

The erodibility factor is primarily a function of soil texture and runoff potential of soil. Two soil textures are dominate in the Lake Anna watersheds: silty and sandy loam. Both soils are similar in terms of runoff potential and erodiblity (Figure 3.5) (Marsh, 1978; Edmunds, 1982; Carter et al, 1971; Carter, 1976; and Elder et al, 1976). Because of this similarity, the K variable is initialized to 1.0 for both of these soil textures. The rainfall erosion index is an indication of the relative intensity of erosion for areas in the eastern United States (Marsh, 1978). The index value for the Lake Anna watershed is approximately 175. This value is based on the erosive energy of the total annual

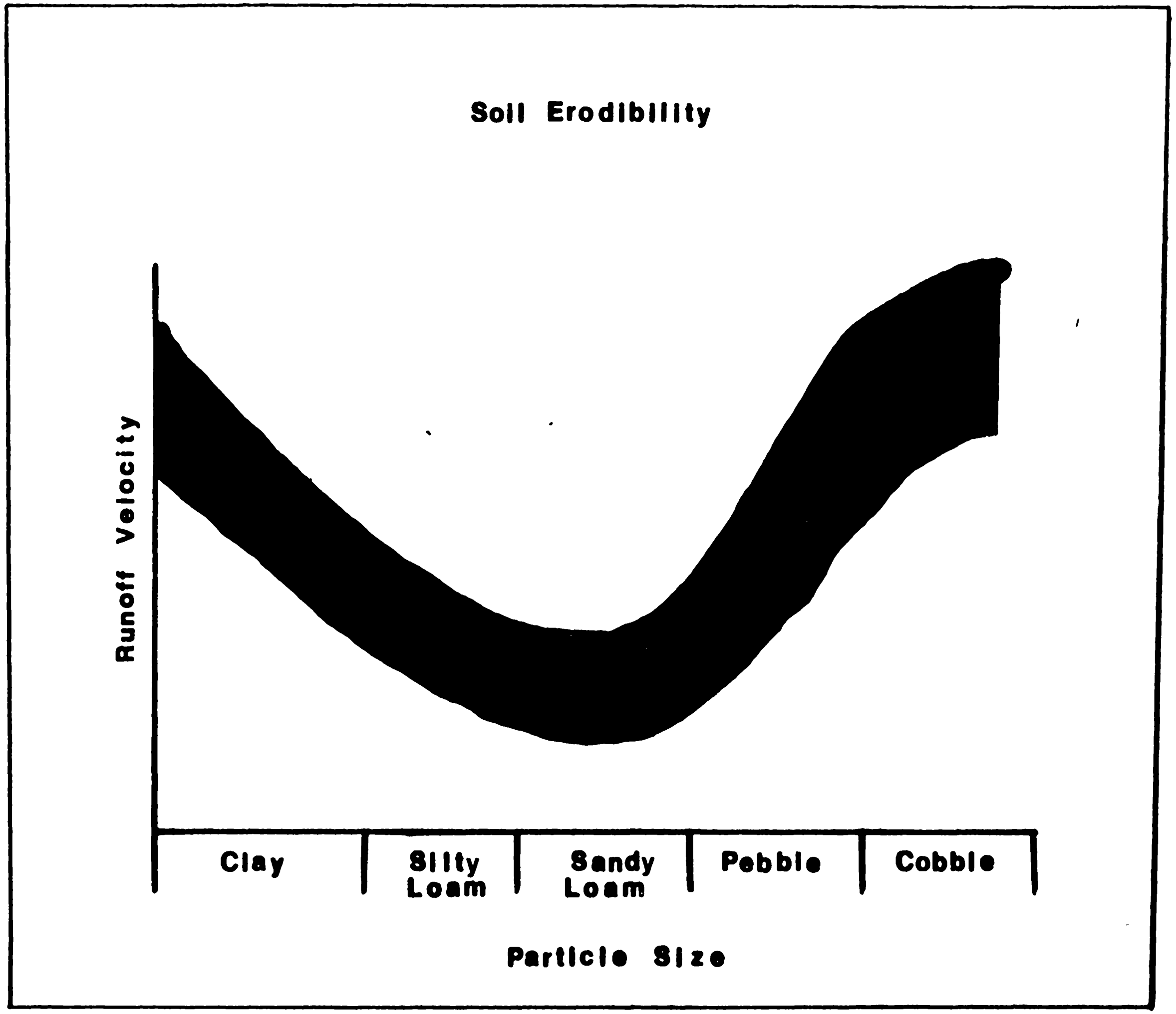

Figure 3.5. Soil Erodibility

Silty and sandy loam are the two dominate soil textures in the Lake Anna watershed and are almost equally susceptible to erosion.

rainfall times the average annual maximum intensity of a thirty-minute rainfall for the location under consideration. The slope geometry factor, variable S, is the ratio of increase in sediment production as a function of slope steepness and length (Marsh, 1978).

Land use/cover patterns as delineated from LANDSAT MSS data are used to calculate the value for variable C. Variable C is derived by the following equation:

$$C = (P * L) + T$$

where,

C = plant cover factor
P = percent of watershed covered by land use/cover category
L = land use/cover erodibility factor
T = total plant cover factor for a watershed.

Predicted sediment yield, per the results of USLE, is compared to estimated turbidity levels, per the results of chromaticity analysis, for each watershed. To assess the utility of chromaticity analysis in studying land use/cover patterns and turbidity relationships, watersheds are arranged in sequential order on the basis of predicted sediment yield and estimated turbidity levels. The Spearman rank correlation method is then used to assess the relationship between these variables:

$$Rs = 1 - 6 \Sigma^{n}_{i = 1} Di^{2}/N^{3} - N$$

where,

Rs = Spearman correlation coefficient

Di = difference in rank between variables
N = number of observations.

The strength of the relationship is evaluated by the level of correlation between estimated turbidity levels and predicted sediment yield.

D. Hypotheses

LANDSAT MSS data are used to study relationships between land use/cover patterns within selected Lake Anna watersheds and the turbidity levels of the lake. The expected results of this study include:

1. A relationship exists between turbidity levels as estimated by chromaticity analysis and surface turbidity levels.
2. Estimated turbidity levels of the Lake Anna tributaries are influenced by land use/cover patterns within the Lake Anna watershed.
3. High turbidity levels are expected to occur in those tributaries draining from watersheds that have large amounts of agricultural and nonforested land cover. Conversely, low turbidity levels are expected to occur in those tributaries draining from watersheds that have small amounts of agricultural and and nonforested land use/cover.

Hypothesis 1 is tested by correlating chromaticity coordinate X with the log of the surface turbidity levels, and hypothesis 2 is tested by rank correlation of the USLE results with the results of chromaticity analysis. In both instances, the validity of these statements is evaluated by analyzing the relationship between the respective variables. The validity of hypothesis 3 is dependent on the strength of the relationship between estimated turbidity levels and land use/cover patterns, and is tested by evaluating the relationship between the rank ordering of the results of the USLE and chromaticity analysis. The rank order is analyzed for relationships between land use/cover patterns and turbidity levels.

E. Summary

The technical reasons for selecting Lake Anna as the study area include: 1) the availability of water quality data; 2) the availability of LANDSAT MSS data since the inundation by Lake Anna; 3) the diversity of land use/cover patterns, and 4) the assorted watershed sizes within the larger Lake Anna watershed. The methodology for this research uses chromaticity analysis of LANDSAT MSS data to study the relationship between land use characteristics of watersheds and the influences of these land use/cover patterns on the turbidity levels of the reservoir.

Water quality on the LANDSAT imagery is estimated by chromaticity analysis, and then regression analysis is used to correlate estimated turbidity levels with surface water quality data. Land use/cover patterns are classified on LANDSAT imagery by GIPSY's AMOEBA command, which uses a spatial-spectral clustering algorithm. AMOEBA's clustering algorithm is considered an unsupervised classification technique since no prior knowledge of land use is required as input into the algorithm. In order to assess the impact of land use/cover patterns on water quality, the land use/cover patterns of each watershed are integrated into the USLE. The strength of the relationship between the results of the USLE and chromaticity analysis is evaluated by means of the Spearman rank correlation coefficient.

Chapter 4

Chromaticity Analysis of LANDSAT MSS Data

Munday (1974) found that some techniques of colorimetry can be applied in the processing and analysis of LANDSAT MSS data. One such technique, chromaticity analysis, was used by Munday to measure and map sediment flows in water bodies. This chapter outlines principles of chromaticity analysis and discusses the application of this technique in the analysis of water pixels on LANDSAT imagery.

A. Chromaticity Analysis

Chromaticity can be defined as:

> The color quality of light that can be defined by its chromaticity coordinates; depends only on hue and saturation of a color, and not on its luminance (brightness) (Lapedes, 1978; p. 293).

Chromaticity analysis evolved from the two hundred year old principle that a normal observer can duplicate the effect of any color stimulus by combining in the proper proportions the light from the three primary sources -- red, green, and blue. A primary source can be defined as a color that cannot be matched by a mixture of any other two colors. The proportion of each primary source that combines to form another color is called a tristimulus value.

In 1931, the Commission International de l'Eclairage (C.I.E.) used this principle to establish a clear basis for a standard colorimetric system for the visible spectrum (Stimson, 1974). A large group of carefully selected observers were tested on the proportions of each primary that composed another color of interest. The observers were asked to combine different amounts of each primary color until the test color was matched. In addition, the selected observers were instructed to keep two principles in mind during this color-matching exercise. First, one primary cannot be obtained by a mixture of the two other primaries. Second, negative amounts of a primary cannot be used in forming a color (MacAdam, 1981).

The results of this color-matching test established the first standard colorimetric system and standardized a set of tristimulus values for each spectral color. A main benefit of this standardization of tristimulus values was that exact duplication of a color became possible. The red tristimulus value was designated by x, the green tristimulus value by y, and the blue tristimulus value by z.

Another goal of the 1931 C.I.E. was to establish a graphical representation of the quality of a color, enabling comparision of colors. Chromaticity analysis was the method selected for color comparison. Chromaticity coordinates can be calculated for any visible light and represent the hue and saturation of color, and not the luminance or brightness of color.

Chromaticity analysis involves two steps. First, the tristimulus values are used to calculate chromaticity coordinates. This calculation is accomplished by defining three new quantities:

$$X = x / x + y + z$$

$$Y = x / x + y + z$$

$$Z = x / x + y + z$$

where,

x = tristimulus value for red
y = tristimulus value for green
z = tristimulus value for blue
X, Y, Z = chromaticity coordinates.

In actuality, only two of the quantities of X, Y, and Z are needed, because $X + Y + Z = 1$. X and Y are generally selected to represent the chromaticity coordinates of a color.

The second step is to represent the chromaticity of a color by plotting X and Y coordinates on the chromaticity diagram (Figure 4.1). The chromaticity coordinates for the visible spectrum are represented by the locus on Figure 4.1. The locus was developed by calculating chromaticity coordinates for the spectrum of colors and represents the

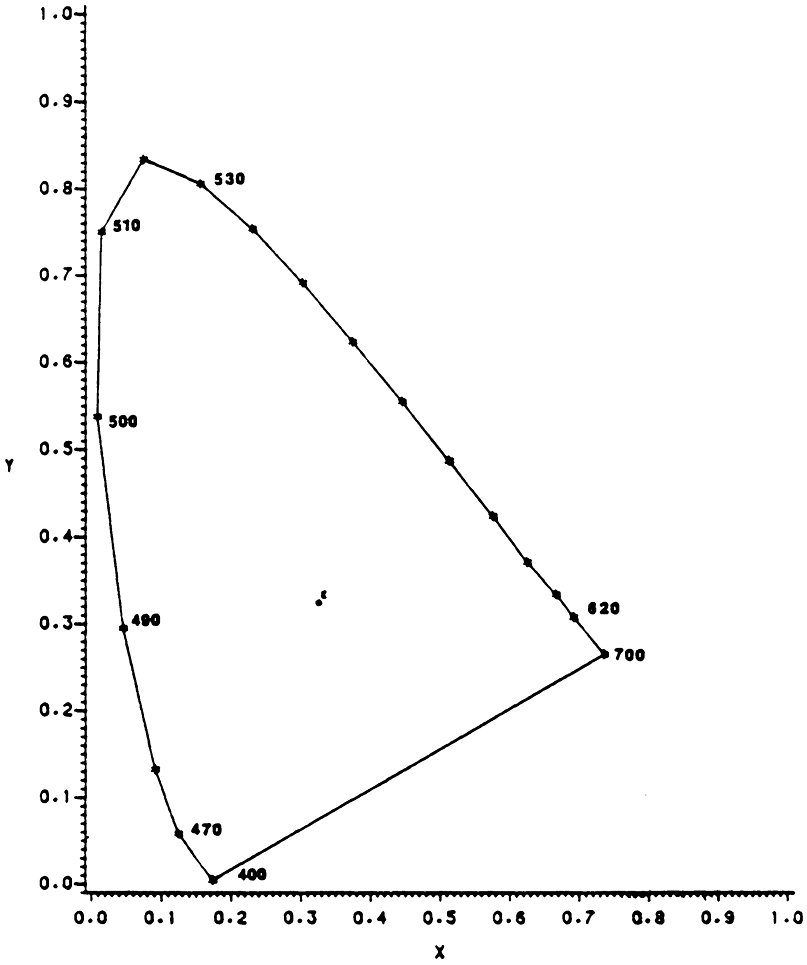

FIGURE 4.1: THE CHROMATICITY DIAGRAM.

SOURCE: MACADAM, 1981.

Chromaticity diagram, showing the locus of the color spectrum and also the location of the point of equal energy, E.

spectrum of colors as defined by the CIE color-matching test. The number next to each point represents the wavelength for that point. Equal proportions of X, Y, and Z equal the white illuminant. E represents white or the point of equal energy on the diagram.[2]

Other properties of the diagram allow additional assessments about the quality of a color. For instance, the tristimulus values of an additive color mixture are the sum of the tristimulus values of the component colors (MacAdam, 1981). Points G and R on Figure 4.2 are connected by line segment Q. Any mixture of G and R, regardless of proportions, will yield chromaticity coordinates that lie on line segment Q.

Two additional properties of the chromaticity diagram are the dominant wavelength calculation and the excitation purity of a color (Stimpson, 1974). Dominant wavelength, hue, can be determined by connecting points E and A with the spectrum locus (Figure 4.3). The intersection of line R with the spectrum locus is the dominant wavelength of point A. The dominant wavelength is 498 nm in this case.

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[2] Since the spectral quality of light, including either artifical illumination or daylight, incident upon an object or surface influences the color that an observer sees, the C.I.E. also developed a standardized system of all categories of illumination. Daylight was selected as the standard illuminate for colorimetry, because it has all the components of the visible spectrum in nearly equal proportions (MacAdam, 1981).

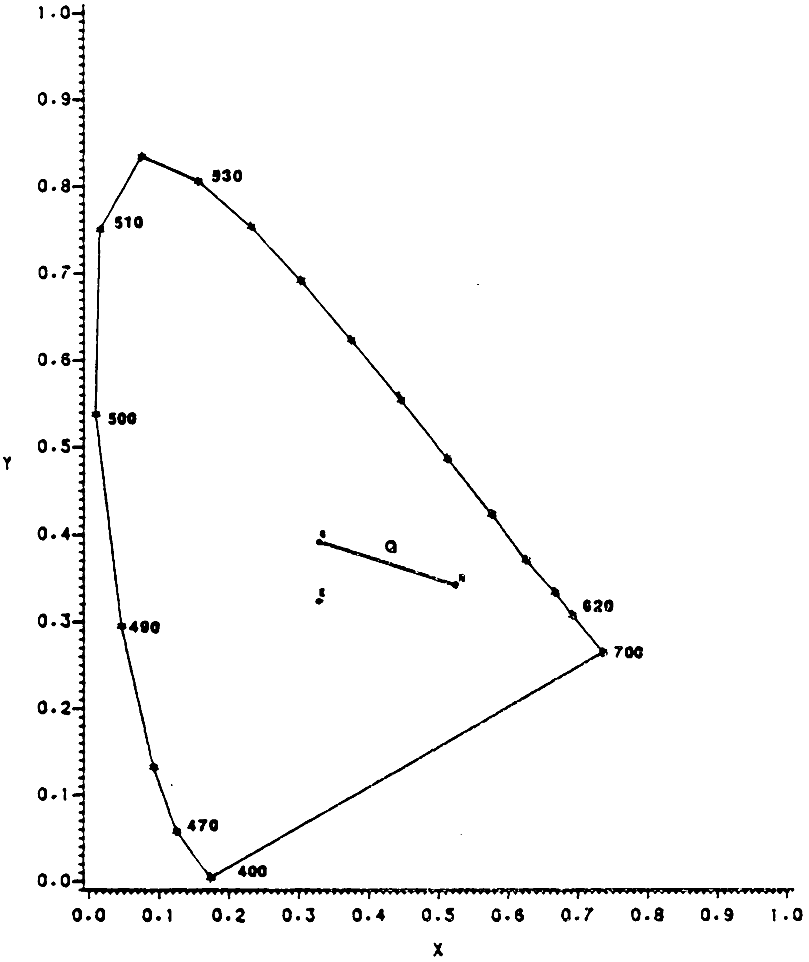

FIGURE 4.2: ADDITIVE MIXTURE PROPERTY OF THE CHROMATICITY DIAGRAM.

SOURCE: MACADAM, 1981.

Additive mixtures of R and G lie on the line Q in the chromaticity diagram.

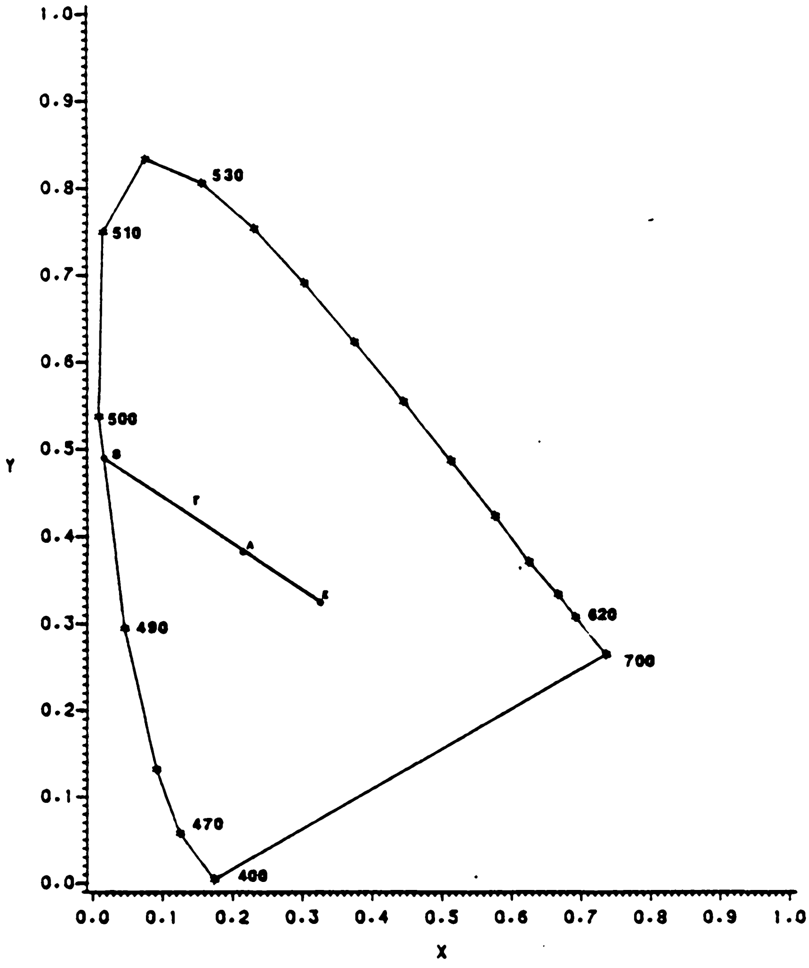

FIGURE 4.3: DOMINATE WAVELENGHT AND EXCITATION PURITY PROPERITIES OF THE CHROMATICITY DIAGRAM.

SOURCE: MACADAM, 1981.

The intersection of line R with the spectrum locus is the dominant wavelength, 498 in this case. Excitation purity is the distance ratio of line segment EA to ES.

Excitation purity, saturation, is the distance ratio of line segment EA to ES.

B. Chromaticity and Water Quality Assessment

The potential utility of chromaticity analysis has been tested in many areas. Most recently, Munday (1974) applied chromaticity analysis to estimate turbidity levels on LANDSAT imagery. Munday's research closely followed the procedure outlined in the previous section and used the same equations to calculate chromaticity coordinates for LANDSAT MSS data as colorimetry uses. Munday's application of chromaticity analysis to LANDSAT MSS data differs in one respect from colorimetry. Since the LANDSAT MSS does not have a spectral channel sensitive to blue light, data from the infrared band are substituted for blue.

Munday eliminated MSS band 7 for water quality mapping, because the wavelength of this band is highly absorbed by atmospheric water vapor. The remaining MSS bands 4, 5, and 6 are analogous to the x, y, and z tristimulus values for green, red, and blue respectively. The near infrared wavelength of band 6 is substituted for the z in this case.

MSS digital numbers from each band are indicative of the brightness level reflected by each 79-by-79 meter area of a water body. Munday converted these MSS digital numbers to radiance values:

$$R = DN/255 * (\max - \min) + \min$$

where,

R = radiance value
DN = digital counts from the MSS
255 = total possible number of brightness values
max = maximum LANDSAT sensor calibration factor (Table 4.1)
min = minimum LANDSAT sensor calibration factor (Table 4.1).

Next, the chromaticity coordinates for each band's radiance values were calculated:

$$X4 = R4 / \Sigma(Ri)$$

$$X5 = R5 / \Sigma(Ri)$$

where,

Ri = summed radiance values for bands 4, 5, and 6
X4 = chromaticity coordinate for band 4
X5 = chromaticity coordinate for band 5.

The chromaticity transformation is a ratio normalization of the LANDSAT radiance values. This transformation has the effect of enhancing spectral details by suppressing total brightness variations and enhancing spectral variations. Brightness variation is caused by such factors as sunglint, sunlight reflections, changing atmospheric transmissions, translucent and opaque clouds, and sensor outputs. Since chromaticity analysis normalizes or removes the radiometric variation from the MSS data, the data can be analyzed based on color and not brightness. Munday found that the chromaticity transformation of LANDSAT MSS data is the optimal method for suppressing this total radiance variation in water pixels and, thus, enhancing color (Munday and Alfoldi, 1975).

TABLE 4.1

LANDSAT Sensor Calibration Factors

		Channel			
		4	5	6	7
LANDSAT 1	min	2.48	2.00	1.76	*
	max	0.00	0.00	0.00	0.00
LANDSAT 2	min	2.63	1.76	1.52	3.91
	max	0.08	0.06	0.06	0.11
LANDSAT 3	min	2.50	2.00	1.65	4.50
	max	0.04	0.03	0.03	0.03

(values in mw cm^{-2} sr)

* not given

Source: Mather, 1981

As in color theory, only two coordinates need to be plotted on the chromaticity diagram. Again, X and Y (X4 and X5) are selected for this purpose. Plotted coordinates are compared to a sediment locus (Figure 4.4). The points of the sediment locus are derived from pixels of known water quality and represent a wide range of sediment conditions in a water body. The far left point of the locus is near the point of equal energy. This position on the locus indicates radiance values for reflectance of water with a high sediment content. Each progressive step to the right on the sediment locus indicates a slightly different color for less turbid water. The far right position on the locus indicates clear water.

The sediment locus may be explained by the color additive mixture property within color theory. All points that lie within the two extremes of the locus are additive mixtures of either high sediment (the far left) or low sediment (the far right). If plotted chromaticity coordinates fall on the sediment locus, the coordinate pair was derived from a pixel with spectral qualities similar to that point on the locus.

In some cases, plotted coordinates fall below the locus. Such a location indicates a movement of the point toward the equal energy point. A positon below the sediment

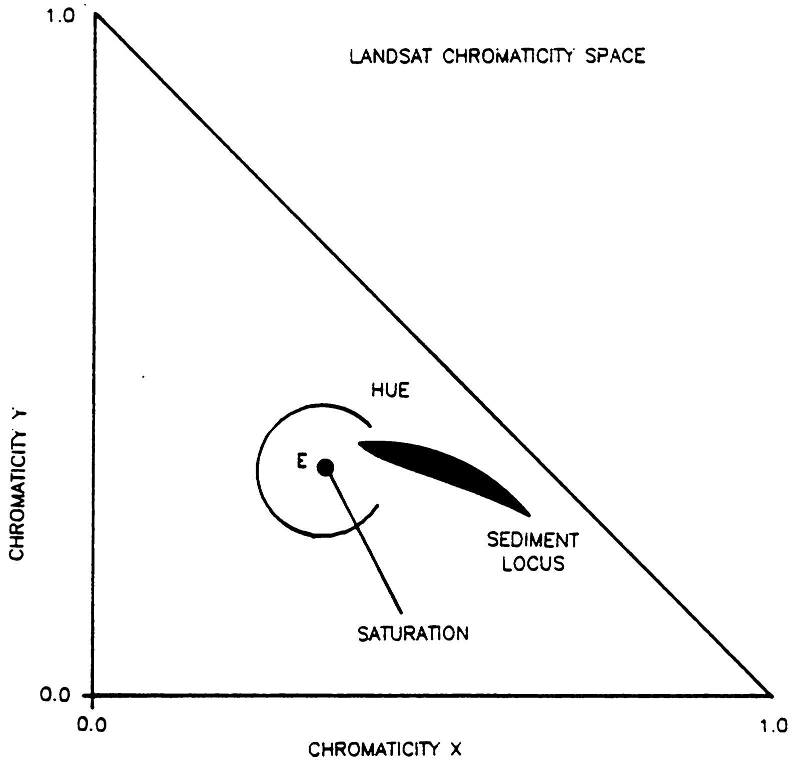

Figure 4.4. LANDSAT Chromaticity Space

A plot of X4 and X5 results in a curve termed a "sediment locus." The radial dimension (outwards from E) contains spectral purity information, and radial shifts in the position of the sediment locus are attributed to atmospheric variations, thin clouds, air pollution, or white caps (Munday et al, 1979).

locus is an indication of spectral impurity and can be caused by such factors as atmospheric variations, thin clouds, air pollution, white caps, thin snow, or ice cover. The level of spectral purity for a water pixel can be measured by color theory techniques. A line is drawn to intersect the equal energy point, the coordinate point of interest, and the sediment locus. A ratio is calculated between the two line segments. For example, if the point falls directly on the locus, the spectral purity of this point is one hundred percent. Spectral purity decreases with distance from the locus. GIPSY's DEHAZE command is used in this research to adjust points that did not fall on the locus.

C. Summary

Chromaticity analysis of LANDSAT MSS data is based on principles of colorimetry. Munday used chromaticity transformation of MSS data to estimate turbidity levels within water bodies. Chromaticity coordinates were calculated from three MSS spectral channels -- green, red, and infrared -- which are analogous to the three primary colors in colorimetry. Then, chromaticity coordinates were represented graphically on a chromaticity diagram and compared with a sediment locus to determine turbidity level.

Munday found that the advantages of water quality estimation by chromaticity analysis include color enhancement and suppression of total radiance variation in water pixels.

Chromaticity transformation of MSS data is used to estimate turbidity levels within Lake Anna. Chromaticity coordinates are calculated by the same procedure that Munday used in his research. Turbidity levels as estimated by this method are compared with surface data and the product of the USLE in order to assess the utility of chromaticity analysis for watershed management. The results of the chromaticity calculations and an analysis of these results are presented in Chapter 5.

Chapter 5

Land Use/Cover Patterns and Water Quality:
A Case Study of the Lake Anna Watershed

LANDSAT MSS data were used to study the relationship between the turbidity levels of Lake Anna and the land use/cover patterns of selected watersheds draining into the lake. In an attempt to establish an association between these two variables, turbidity levels of Lake Anna as estimated by chromaticity analysis were related to two different kinds of ground-based data -- surface water quality data and the product of the universal soil loss equation (USLE).

The results of chromaticity analysis correlate moderately well with surface turbidity levels, but correlate poorly with the product of the USLE. This chapter presents a comparative analysis of turbidity levels with these ground-based data and explores some of the practical and conceptual problems that might have influenced these relationships. Practical problems can be defined as data collection problems and include LANDSAT system and data accuracy problems. Conceptual problems are problems based on theoretical issues of using LANDSAT MSS data for watershed management purposes. These conceptual problems remain even after the practical problems have been solved.

A. Analysis of Turbidity Levels as Estimated by Chromaticity Analysis

General Procedure

Two groups of water quality sample data were extracted from the four LANDSAT scenes selected for this research:[3] those that correspond to the positions sampled by the VEPCO Environmental Laboratory, referred to here as 'surface sample sites' (Figure 5.1), and those that are used to assess the influence of land use/cover patterns on water quality, or 'LANDSAT sample sites' (Figure 5.2). The purpose of the former is to assess the accuracy of chromaticity analysis in estimating turbidity levels in Lake Anna, while the turbidity levels of the latter are correlated to the product of the USLE in order to assess the impact of land use/cover patterns on turbidity levels.

The color image display in the Spatial Data Analysis Laboratory at Virginia Tech was used to sample the MSS data from the LANDSAT image. Pixel values for surface sample

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[3] January 9, 1973, February 9, 1974, April 28, 1978, and March 23, 1981 were the four scenes selected for this research.

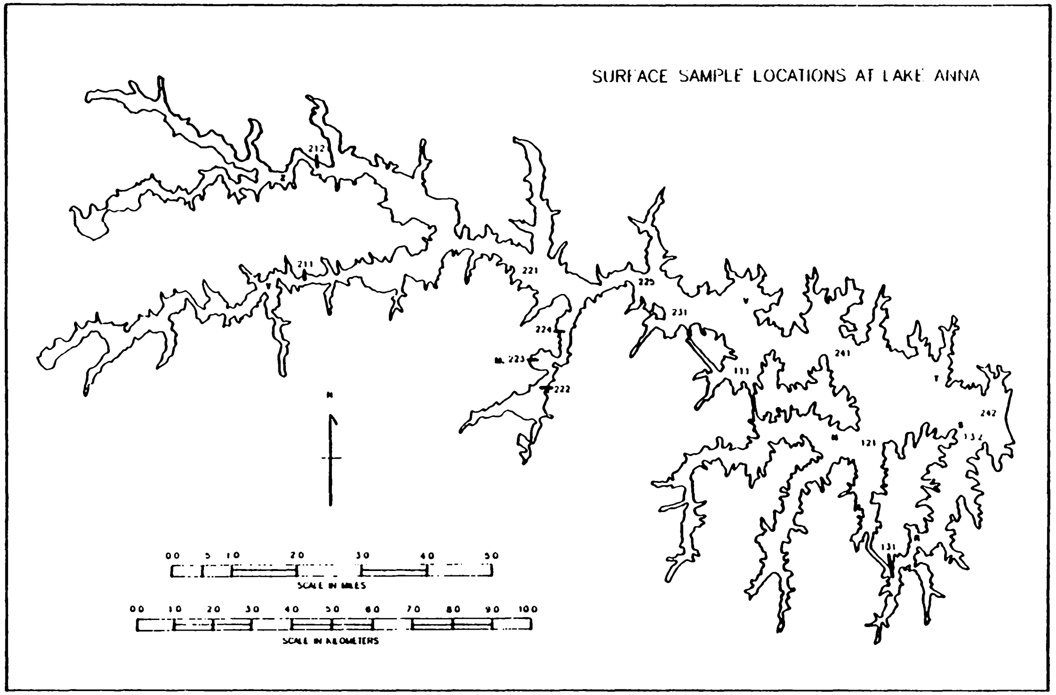


Figure 5.1. Surface Sample Locations at Lake Anna

Surface sample locations include both section disc depth (numbers) and nephometric turbidity unit stations (letters). These stations are used to assess the accuracy of turbidity levels as estimated by chromaticity analysis.

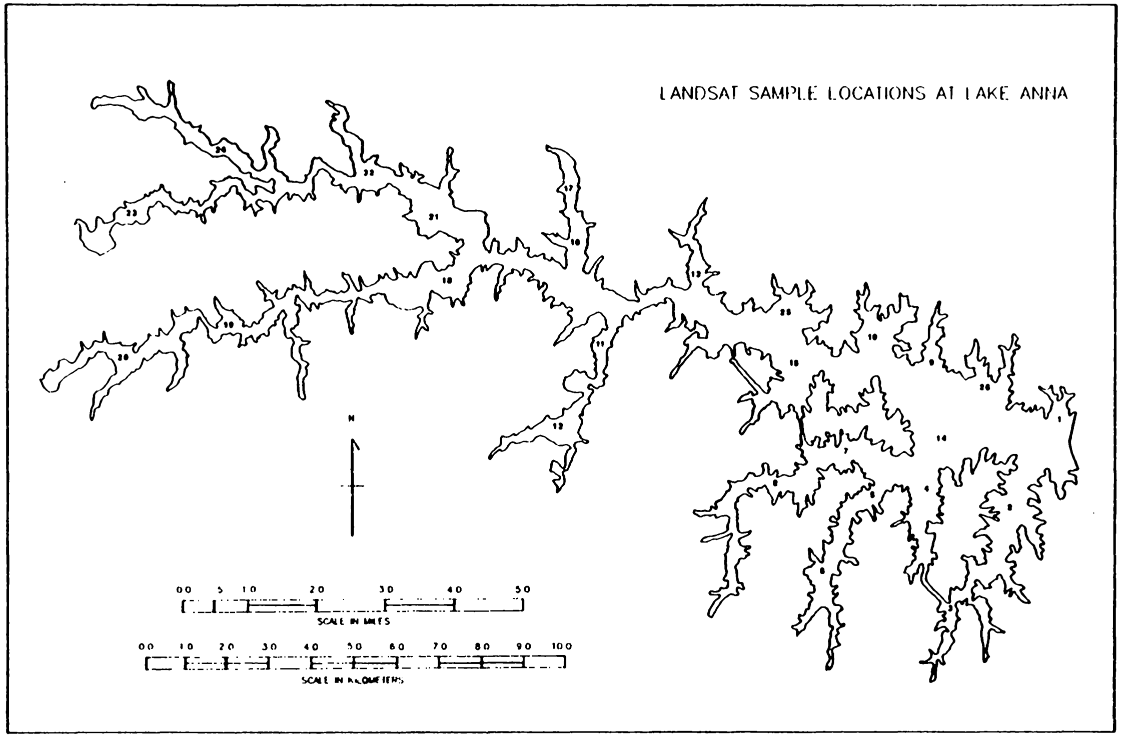


Figure 5.2. LANDSAT Sample Locations at Lake Anna

The turbidity levels of the LANDSAT sample locations are correlated to the product of the USLE in order to assess the impact of land use/cover patterns on turbidity levels. See page 71 for an index to the numbered sample sites.

Key to Figure 5.2

1. Valentine
2. Rock (Lower)
3. Rock (Upper)
4. Moody
5. Millpond (Lower)
6. Millpond (Upper)
7. Elk (Lower)
8. Elk (Upper)
9. Rockland
10. Dukes
11. Contrary (Lower)
12. Contrary (Upper)
13. Sturgeon
14. Main Lake 1
15. Main Lake 2
16. Pigeon (Lower)
17. Pigeon (Upper)
18. North Anna (Lower)
19. North Anna (Middle)
20. North Anna (Upper)
21. Pamunkey (Lower)
22. Pamunkey (Middle)
23. Pamunkey (Upper)
24. Terrys Run
25. Boggs
26. Levy

locations were extracted from LANDSAT data on the basis of the approximate ground location on the image. For the LANDSAT sample sites, the upper, middle, and lower regions of each tributary were sampled. Easily recognizable features such as distinct coves, points, dikes, and bridges permitted convenient location of the surface sample sites and the LANDSAT sample sites on imagery.

Each sample area was positioned the distance of 1 1/2 pixels from the nearest shoreline, island, or man-made feature. At each sample site, square or rectangular blocks of two, three, or four pixels were averaged for each MSS channel. Munday et al (1979) found that such pixel averaging suppressed residual MSS striping effects and recovered additional radiometric resolution. Chromaticity coordinates were calculated for the averaged pixels.

An average of chromaticity coordinates for all LANDSAT sample sites within an arm of the lake was used to represent the overall level of turbidity for that particular arm of the lake. Chromaticity coordinates for both LANDSAT sample sites and surface sample sites were plotted on the chromaticity diagram, and the position was then compared to the sediment locus for each respective date. The position of the plotted chromaticity coordinate in relation to the sediment locus is an estimate of the level of turbidity for an area or arm of the lake.

GIPSY commands were used to select sample sites and calculate chromaticity coordinates (Table 5.1). Documentation for these commands, with the exception of CHROM, is available at the Spatial Data Analysis Laboratory. Documentation for the CHROM command can be found in Appendix 1 of this study.

Results

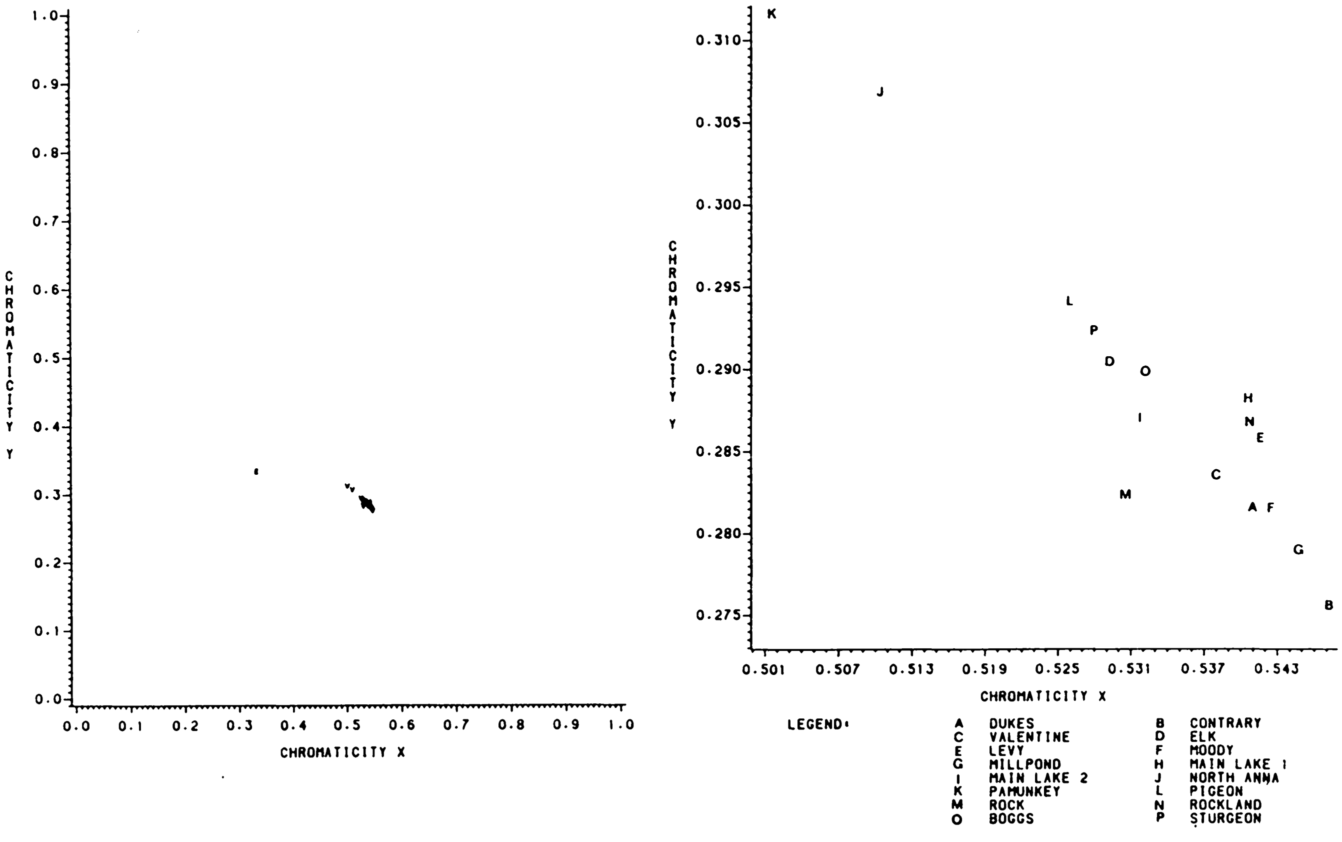
Sediment loci were calculated for all unadjusted chromaticity coordinates (Appendix 2 - Figures 1, 2, 3, and 4). These data were combined into one figure by averaging the LANDSAT sample site chromaticity coordinates for the four scenes (Figure 5.3). A dehazed locus was also calculated for the April 28, 1978, MSS data in order to assess the utility of GIPSY's DEHAZE command as applied to chromaticity analysis (Figure 5.4). For each locus, the end nearest "E" is an indication of turbid water, whereas the opposite end of the locus is an indication of less turbid water. The sediment locus forms an indication of relative turbidity. Turbid water in Lake Anna might be relatively clear water in other water bodies or vice versa.

Most coordinates from LANDSAT and surface sample sites fall on the lower end of the sediment locus, an indication of relatively clear water (Figure 5.3; See Appendix 2 for

TABLE 5.1

GIPSY Commands Used to Estimate Water Quality
from LANDSAT MSS Data

Command	Description
SBIMG	Subdivides a single or multiband standard image format (SIF) file.
PRNCP	Forms the principle components of a multiband SIF. The output from this command is the covariance matrix and mean values and eigenvectors and eigenvalues.
DEHAZE	Removes atmospheric path-radiance (haze) from a multi-band image. The inputs for this command include a multi-band image and the output from the PRNCP command. The command calculates the amount of haze in each band and then subtracts it.
CURSOR	Manipulates censor on light display to label points on an image.
CHROM	Calculates chromaticity coordinates from Bands 4, 5, and 6 of a LANDSAT image.
EXSIF	Examine standard image file: allows examination and modification of identification records or any pixel within a SIF file.



A.

B.

Figure 5.3. Average for Each LANDSAT Sample Site: All Scenes

Most coordinates of the LANDSAT sample sites fall on the lower end of the sediment locus, an indication of relatively clear water (A). B represents a smaller scale of A.

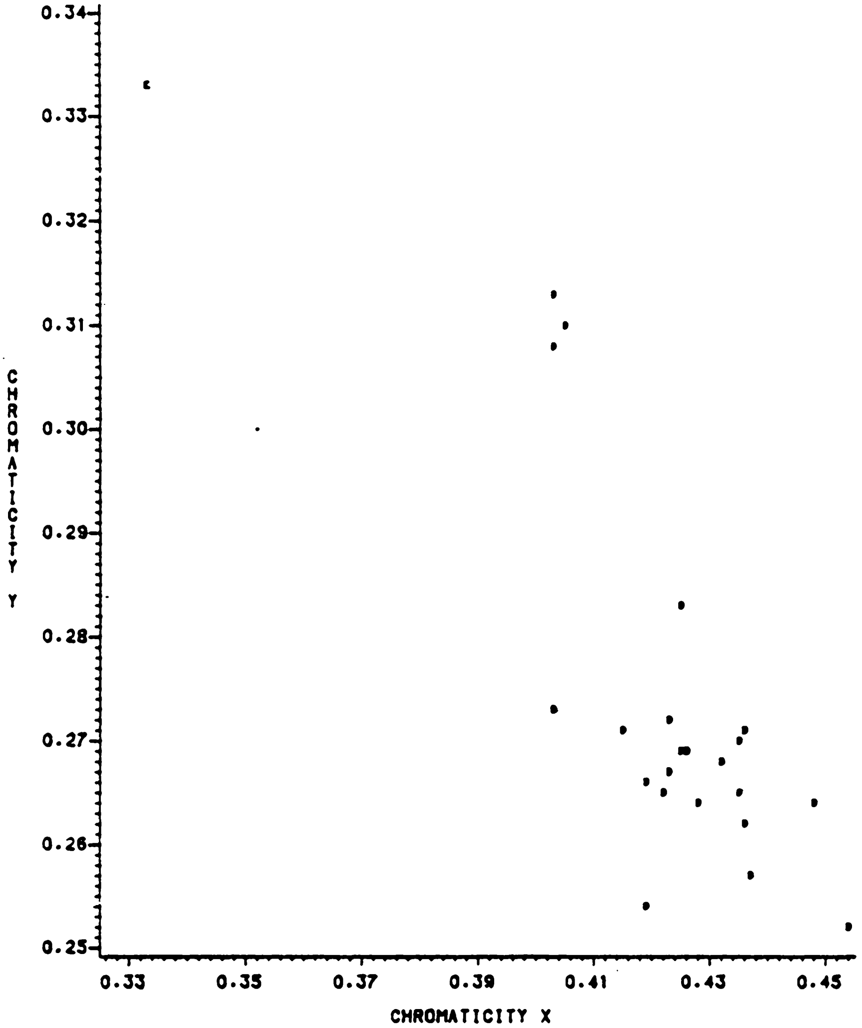


FIGURE 5.4: DEHAZED CHROMATICITY COORDINATES: APRIL 28, 1978.

D REPRESENTS CHROMATICITY COORDINATES THAT WERE CALCULATED FROM DEHAZED PIXELS.
E REPRESENTS THE POINT OF EQUAL ENERGY.

A dehazed locus was calculated for the April 28, 1978 MSS data in order to assess the utility of GIPSY's DEHAZE command as applied to chromaticity analysis.

plots of surface sample sites). The Pamunkey, North Anna, Sturgeon, and Pigeon tributaries tend to be the most turbid while the Contrary, Millpond, and Dukes tributaries tend to be the least turbid overall. Table 5.2 lists the Lake Anna tributaries in order of level of turbidity level as estimated by chromaticity analysis. The sequence of the tributaries in this list is based on the position of the plotted chromaticity coordinates for a Lake Anna tributary in relation to the sediment locus. In Table 5.2, the most turbid tributaries are listed first, and least turbid tributaries are listed last for each scene.

Accuracy Assessment of Unadjusted Coordinates. Munday et al (1979) tested the accuracy of chromaticity analysis by correlating chromaticity coordinate X with the log of turbidity.[4] Their procedure was followed in this study in order to test hypothesis 1:

1. A relationship exists between turbidity levels as estimated by chromaticity analysis and surface turbidity levels.

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[4] Munday et al (1979) found that a higher correlation coefficient was achieved by using chromaticity coordinate X as the dependent variable rather than the Y or Z coordinate. Turbidity levels were transformed to a logarithmic scale because the exponential curve of the data becomes more of a linear trend, and the heteroscedastic variance, changing variance, becomes more constant about the trend.

TABLE 5.2

LANDSAT Sample Sites Listed in Order of Turbidity Level as Estimated by Chromaticity Analysis: By Individual Date and Average

Jan. 09 1973	Feb. 09 1974	Apr. 28 1978	Mar. 23 1981	Average
Pamunkey	Pamunkey	Pamunkey	Pamunkey	Pamunkey
North Anna	North Anna	North Anna	North Anna	North Anna
Sturgeon	Pigeon	Elk	Rockland	Pigeon
Pigeon	Boggs	Sturgeon	Pigeon	Sturgeon
Main Lake 2	Elk	Rock	Levy	Elk
Elk	Sturgeon	Boggs	Boggs	Boggs
Main Lake 1	Main Lake 1	Contrary	Moody	Main Lake 2
Dukes	Rock	Pigeon	Rock	Rock
Boggs	Moody	Levy	Elk	Main Lake 1
Valentine	Main Lake 2	Millpond	Millpond	Rockland
Rock	Valentine	Valentine	Sturgeon	Valentine
Levy	Rockland	Rockland	Dukes	Levy
Rockland	Levy	Main Lake 2	Main Lake 2	Dukes
Contrary	Millpond	Main Lake 1	Main Lake 1	Moody
Millpond	Dukes	Dukes	Contrary	Millpond
Moody	Contrary	Moody	Valentine	Contrary

Chromaticity coordinate X from each respective scene and surface sample location was correlated with the log of turbidity for the corresponding surface sampling date.[5] Because the turbidity level of Lake Anna has been measured by two different methods, secchi disc depth (1972 to 1976) and nephometric turbidity units (1976 to present) two separate groups of correlation coefficients were calculated. The X chromaticity coordinates from the January 1973 and February 1974 scenes were correlated with the log of secchi disc level, and the X chromaticity coordinates from the April 1978 and March 1981 scenes were correlated with the log of nephometric turbidity units (Table 5.3). Although the results of chromaticity analysis have a moderately high level of correlation with surface turbidity levels for three of the four dates analyzed, these results are not as successful as those achieved in previous research (Munday, 1974; Munday et al, 1979; Mather, 1981). Possible factors influencing this moderate level of correlation can be grouped into two broad areas, practical and conceptual problems.

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[5] As in the Munday et al research (1979), Pearson product moment correlation analysis was applied to the data in this research.

TABLE 5.3

Correlation of Unadjusted Chromaticity Coordinates X With Log of Turbidity

Scene Date	Correlation	Number of Samples
	Secchi Disc	
January 09, 1973	.64	11
February 09, 1974	.76	7
	Nephelometric Turbidity Units	
April 28, 1978	-.27	8
March 23, 1981	-.76	7

Three major practical issues have been identified. First, because satellite overpass and water quality test dates differ by as much as two weeks in some cases, meterological events could have changed turbidity levels during the intervening time period. In the case of the April scene, 2.97 inches of rain fell on the study area between the satellite overpass and water quality test date (Table 5.4). The low level of correlation for this date (-0.27) could have been influenced by the amount of rainfall between the satellite overpass and the surface sample date. Conversely, the March 23, 1981, satellite overpass and surface sample date coincide exactly. The chromaticity coordinates from the March scene have a high level of correlation with surface turbidity levels. Second, the small number and range of surface turbidity sample levels that are available for any one date might have influenced the moderate level of correlation for all scene dates. A greater number of surface samples and range of turbidity levels would have allowed for a more through accuracy assessment. Third, because the LANDSAT MSS has coarse resolution capabilities, pixel values are sampled from a larger section of the water body than the surface sample. Pixel values represent a generalized spectral signal of an area, whereas a surface water quality sample indicates the turbidity level of a single point in the lake.

TABLE 5.4

Satellite Overpass Dates, Water Quality Test Dates and Rainfall Accumulation During Intervening Time Period

Satellite Overpass Date	Water Quality Test Date	Rainfall Accumulation	Date of Previous Rainfall
3-26-81	3-23-81	.15 in.	3-23-81
4-28-78	4-20-78	2.97 in.	4-27-78
2-09-74	1-26-74	1.20 in.	2-09-74
1-09-73	1-20-73	.12 in.	1-09-73

One conceptual problem has also been identified. While other researchers have successfully used chromaticity analysis to estimate turbidity levels, their study areas included such large, open water bodies as Lake Ontario and the Bay of Fundy. This research attempted to estimate turbidity levels in a small, man-made reservoir, Lake Anna. Several characteristics of small, man-made reservoirs, such as Lake Anna, might influence the accuracy of chromaticity analysis of water quality. First, the narrow arms of these reservoirs might influence the spectral purity of water pixels. Although all samples were taken from a distance at least 1 1/2 pixels from the nearest shoreline, spectral overlap between shoreline and water pixels could have occurred at the sample site. Second, small, man-made reservoirs are characterized by slow-moving waters and generally are not as dynamic as water bodies studied previously. Slow-moving waters allow sediment to settle rapidly, resulting in an observation of lower correlations between actual surface data and estimated turbidity.

Dehazed Chromaticity Coordinates. Munday et al (1979) found that the correction of chromaticity coordinates for atmospheric interference shifted the coordinates toward the sediment locus. In this research, water pixels were adjusted for any possible atmospheric interference using

GIPSY's DEHAZE command (Switzer et al, 1981). This command differs from the Munday et al procedure in that the pixels are dehazed prior to the calculation of the chromaticity coordinates, while the Munday et al procedure corrects the chromaticity coordinates for any possible atmospheric interference.

The April scene date was selected for dehazing, because, of the four scenes, chromaticity coordinates from this scene have the lowest correlation with surface turbidity levels. Haze or high levels of humidity in the atmosphere could have altered the spectral signal received by the LANDSAT MSS. Dehazing the April pixel values did not cause a shift of the coordinates either toward the sediment locus developed from adjusted pixels or toward the locus developed from unadjusted pixels (Figure 5.5). Rather, dehazing pixel values had three effects on the chromaticity coordinates. First, dehazing caused the chromaticity coordinates and the sediment locus to shift toward "E". Second, dehazing had the effect of scattering coordinates around the dehazed sediment locus rather than drawing the pixels closer to the locus. Third, dehazing pixel values did not substantially improve the correlation between chromaticity coordinate X and the log of turbidity (Table 5.5).

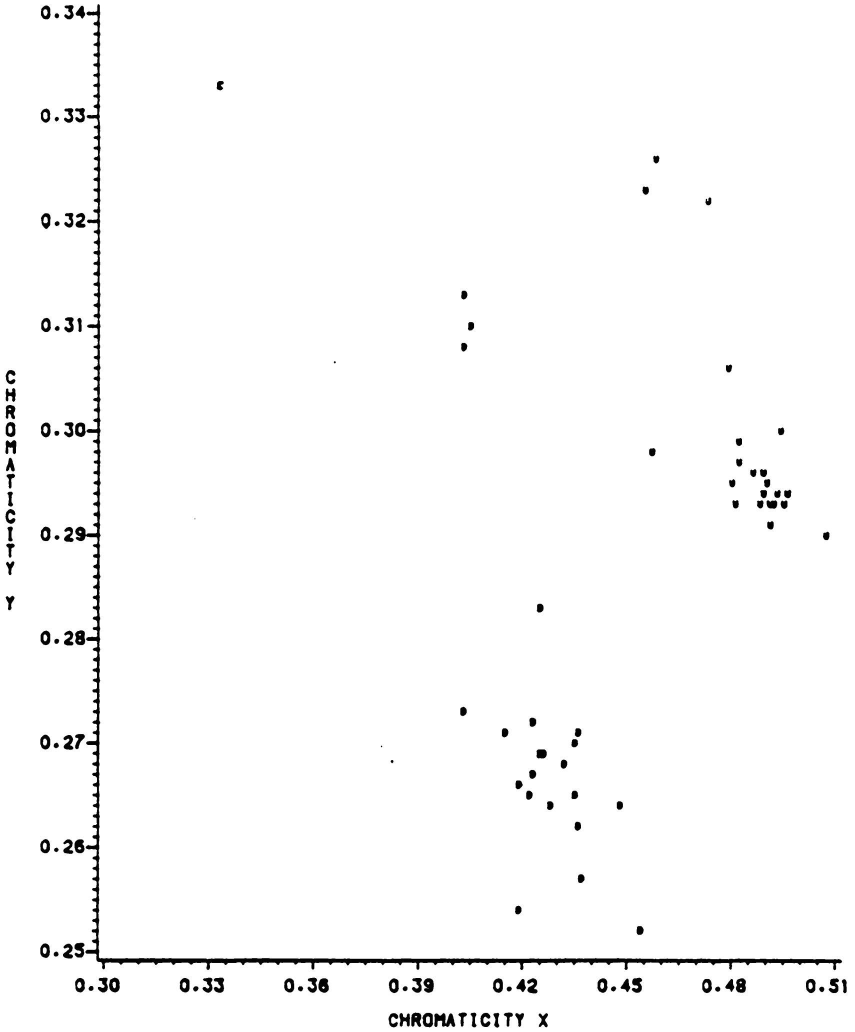

FIGURE 5.5: DEHAZED AND UNADJUSTED CHROMATICITY COORDINATES.

U REPRESENTS UNADJUSTED COORDINATES.
D REPRESENTS CHROMATICITY COORDINATES THAT WERE CALCULATED FROM DEHAZED PIXELS.
E REPRESENTS THE POINT OF EQUAL ENERGY.

Dehazing the April pixel values did not cause a shift of the coordinates either toward the sediment locus developed from unadjusted pixels or toward the locus developed from unadjusted pixels.

TABLE 5.5

Correlation of Unadjusted and Dehazed Chromaticity Coordinate X With Log of Nephelometric Turbidity Units

	Correlation	Number of Samples
Dehazed	-0.277	8
Unadjusted	- .274	8

An explanation for the first two effects might be that the Lake Anna area had a low humidity level during the week prior to the overpass, April 28, 1978, and that dehazing the image might have distorted the unadjusted pixel values. As for the third effect, the 2.97 inches of rainfall received during the interval between the satellite overpass and surface sample date could have also influenced the low correlation.

Evaluation of Results

Although the level of correlation between chromaticity coordinate X and the log of turbidity is not as high in this research as the level achieved in previous research, the strength of the relationship should allow for an accurate analysis of the influence of land use/cover patterns on turbidity levels within the Lake Anna watershed. With the exception of the April scene, the results of chromaticity analysis have a moderately high level of correlation with surface turbidity levels. Meterological events seem likely to have influenced the low level of correlation between the April chromaticity coordinates and surface turbidity levels. However, on the basis of the strength of the relationship between the chromaticity coordinates from the other dates and surface turbidity levels, an argument could be made that the April turbidity level estimates are an accurate indication of surface turbidity levels.

B. An Analysis of the Impact of Land Use/Cover Patterns on Turbidity Levels of Lake Anna

Land Use/Cover Classification Procedure

The same four LANDSAT scenes (See Footnote 3) were evaluated to determine which scene best represents the land use/cover of the Lake Anna watersheds. Only three land use/cover categories (coniferous forest, deciduous forest, and nonforested cover) are visible on the winter color composite images. The land area percentages of the nonforested land use/cover category probably are inflated for the winter dates because, deciduous forests without growing season foliage can acquire the spectral appearance of pasture or nonforested land. Difficulties also arise in the separation of pasture and cropland on the winter imagery. Because both land use/cover types are void of living vegetation, the spectral appearance is quite similar for both of these covers.

Four distinct land uses/cover categories (deciduous forest, coniferous forest, pasture, and cropland) are apparent on the April scene. The land use/cover types on this scene are heavily influenced by mid-spring plant growth, which can cause some spectral overlap between categories. Two examples are apparent. First, mid-spring plant growth gives pasture and cropland the same spectral appearance in several cases. This condition makes category separation difficult. Second, overall pasture area is decreased by thick, lush deciduous foliage.

The March scene has the best spectral representation of the land use/cover of the Lake Anna watershed. Four dominant land use/cover categories (deciduous forest, coniferous forest, pasture, and cropland) are visible on the color composite, and very little spectral overlap is observed between classes. Because growing season foliage is in an early stage, pasture and forest cover and pasture and cropland are all spectrally distinct. Therefore, the March scene was used to delineate land use/cover in the Lake Anna watershed.

AMOEBA (Bryant, 1979), a data clustering program available on GIPSY, was used to calculate regions or land use/cover categories within the March scene of Lake Anna.[6] A

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[6] Data clustering programs, such as mode clustering, assign values to a cluster on the basis of value similarity in data space. AMOEBA operates in a similar fashion, but in addition, values are clustered on the basis of spatial relationships. Clustering error, error which is caused in the process of spatial clustering, can be assessed by a percentage that is calculated by the program. The percentage is calculated for all clusters within an image rather than each individual cluster. Less than 25 percent is an indication of good clustering. A value greater than

description of GIPSY commands used in this calculation process is presented in Table 5.6. AMOEBA found ten data clusters in the March scene.

Land use/cover classification analysis was completed for thirteen catchments within the Lake Anna watershed. These watersheds were selected on the basis of the size of the lake arm extending into the watershed, the size of the watershed, and the proximity of the watershed to the main body of the lake.

Region or land use/cover classification was accomplished with the use of aerial photographs, field observations, and topographic maps. A color-coded image of the Lake Anna watershed was displayed on the color CRT. Land uses/cover patterns on the MSS image were identified by matching corresponding patterns on the aerial photographs and the topographic maps. Easily recognizable features, such as peninsulas and distinctive arms of the, lake were effective as reference points for associating patterns visible on aerial photographs and topographic maps with those on the MSS image.

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twenty-five percent is an indication of two possible errors. First, a pair of similar values may be assigned to different clusters, or second, the values may be different and assigned to the same cluster. The March scene received a percentage of 18 percent, an indication of relatively good clustering.

TABLE 5.6

GIPSY Commands Used in Image Segmentation

Command	Description
SBIMG PRNCP DEHAZE CURSOR EXSIF	These five commands were used for image segmentation as well as for estimating water quality from LANDSAT MSS data. For a further description of these commands please see Table 5.1.
AMOEBA	Performs a completely unsupervised clustering and classification of a multi-band image using a spatial spectral algorithm.
ELIMRG	Creates a symbolic image in which pixels in a region having a specified property with values greater or smaller than a threshold are eliminated. This command can be used to reduce the noise in symbolic images.
FILL	Takes the output from ELIMRG and grows the zero values of a symbolic image by labeling these values with the label of the pixel closest to it.
MHIST PRPMBI	Computes a property list for a multi-band image. This command computes the number of pixels, maximum gray level, the minimum gray level, the mean, and the variance for each category. The input for this command is a symbolic image and a numeric image.
PRTPF	Print a property file.
PRTSYM	Prints an image in symbolic form on the line printer.
PRTSYM	Generates a sequential file, which can be plotted on the line printer, from a symbolic SIF.
MHIST	Counts the number of pixels in each category within a symbolic image.

From the ten AMOEBA clusters, five land use/cover categories were established based on information from the topographic maps, field observations, and aerial photographs. These five classes are water, deciduous and coniferous forests, and nonforest cover and cropland. In cases where more than five clusters were generated, the additional categories belonged to one of the five major land use/cover categories. Aerial photographs, as well as topographic and spectral information were used to assign these additional categories to the five major land use/cover categories.

The area for each land use/cover category was calculated by one of two procedures. The two larger watersheds, North Anna and Pamunkey, are somewhat rectangular in shape, and, thus, the MHIST command within GIPSY could be used to count the number of pixels in each category for these two watersheds. In the second method, a coded printout of the other watersheds was produced by the PRTSYM program, and the number of pixels in each land use/cover category was counted by hand. For either method, the number of pixels in each category was multiplied by .3249, the number of hectares in a pixel for a geometrically corrected scene. The overall area for each land use/cover category was standardized by dividing the number of hectares in each category by the total number of hectares in a watershed. This produces a measure of the proportion of each watershed occupied by each category. These data are applied further in this section to assess the impact of land use/cover patterns on turbidity levels of Lake Anna.

In general, the dominant land use/cover is forested land, and more specifically, deciduous forest cover dominates almost all the watersheds (Table 5.7). Cropland is the least dominant cover in terms of area.

Assessing the overall accuracy of this classification is beyond the scope of this paper. However, a detailed comparison of selected areas within each watershed subimage to aerial photographs and topographic maps revealed the classification scheme to be accurate in the separation of deciduous and coniferious forests. Agricultural land was classified accurately, but the changing uses of agricultural land, made differentiation between pasture and cropland difficult in some cases.

Results

Tributary turbidity levels as estimated by chromaticity analysis were analyzed in relation to the product of the universal soil loss equation (USLE) in order to test hypothesis 2 and 3 or:

TABLE 5.7

Land Use/Cover Patterns: Lake Anna Watersheds

Watershed	Coniferous	Deciduous	Mixed	Total Forested	Pasture	Crop	Total Agricultural	Total[1] Area
Boggs	97.79	162.77	207.94	468.50	63.03	4.2	67.33	535.76
Percent	18.25	30.38	38.81	87.45	11.76	.79	12.55	
Contrary	1959.47	2790.89	--	4750.36	409.70	28.92	438.62	5188.97
Percent	37.76	53.78	--	91.54	7.90	.56	8.45	
Dukes	41.26	115.01	88.70	244.97	97.15	16.89	114.04	359.11
Percent	11.26	32.04	24.71	68.24	27.06	4.71	30.68	
Elk	418.79	1726.52	--	2145.31	529.59	41.91	571.50	2716.81
Percent	15.41	63.55	--	78.96	19.49	1.54	21.04	
Levy	55.88	68.55	86.10	210.53	4.9	--	4.9	215.41
Percent	25.94	31.83	39.97	97.74	2.26	--	2.26	
Millpond	488.97	968.2	--	1457.17	350.24	17.54	367.78	1824.96
Percent	26.79	53.05	--	79.85	19.19	.96	20.15	
North Anna	13235.57	14438.86	--	27674.43	6051.62	500.67	6552.29	35259.79[2]
Percent	37.54	40.95	--	78.49	17.16	1.57	18.58	
Pamunkey	11672.47	17172.56	--	28845.03	11191.07	650.75	11041.82	41726.80[3]
Percent	26.82	41.16	--	69.13	26.82	1.56	28.38	
Pigeon	673.19	878.2	1007.51	2558.9	96.17	--	96.17	2655.08
Percent	25.35	33.08	37.95	96.38	3.62	--	3.62	
Rock	593.27	1673.88	--	2267.15	437.32	43.86	481.18	2748.33
Percent	21.58	60.91	--	82.49	15.91	1.60	17.51	
Rockland	69.85	21.44	32.49	123.78	.65	--	.65	124.44
Percent	56.14	17.23	26.11	99.47	.53	--	.53	
Sturgeons	203.71	374.32	396.38	947.41	272.92	5.85	278.77	1226.17
Percent	16.61	28.33	32.33	77.27	22.26	.48	22.74	
Valentine	31.84	42.56	49.06	123.46	7.15	5.84	13.02	136.46
Percent	23.33	31.19	35.95	90.47	5.24	4.29	9.54	

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[1] Area is in hectares and does not exactly match the true ground area.

[2,3] Total area includes shadow areas which are not included as category on this figure.

2. Estimated turbidity levels of the Lake Anna tributaries are influenced by land use/cover patterns within the Lake Anna watershed.

3. High turbidity levels are expected to occur in those tributaries draining from watersheds that have large amounts of agricultural and nonforested land cover. Conversely, low turbidity levels are expected to occur in those tributaries draining from watersheds that have small amounts of agricultural and nonforested land use/cover.

The product of the USLE was used to answer the question, "Which tributaries would be expected to be turbid based on land use/cover patterns, the slope geometry factor, rainfall, and soil erodibility?" As described in the previous section, land use/cover patterns were delineated from LANDSAT MSS data. Additional data for the USLE were gathered from rainfall and slope indices (Marsh, 1978), topographic maps, and soil surveys (Carter et al, 1971; Carter, 1976; and Elder et al, 1976). Chaper 3 presents a more complete description of the variables and procedures of the USLE.

Watersheds were arranged in order of predicted level of sediment discharge, per the results of the USLE, and estimated turbidity, per chromaticity analysis (Table 5.8). Next, these results were correlated and plotted on the basis of rank (Table 5.9; Figure 5.6).[7] A low level of correlation

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[7] Spearman rank correlation analysis was used in this research.

TABLE 5.8

Rank Order of the Results of Chromaticity Analysis and the USLE[1]

Chromaticity Analysis	USLE
1. Pamunkey	1. Dukes
2. North Anna	2. Elk
3. Pigeon	3. Pamunkey
4. Sturgeons	4. Pigeon
5. Elk	5. Contrary
6. Boggs	6. North Anna
7. Rock	7. Sturgeons
8. Rockland	8. Millpond
9. Valentine	9. Valentine
10. Levy	10. Boggs
11. Dukes	11. Rock
12. Millpond	12. Levy
13. Contrary	13. Rockland

[1] Most turbid are listed first, and least turbid are listed last.

TABLE 5.9

Rank Correlation of the Results of Chromaticity Analysis and USLE

Correlation	.23
Number of Samples	13

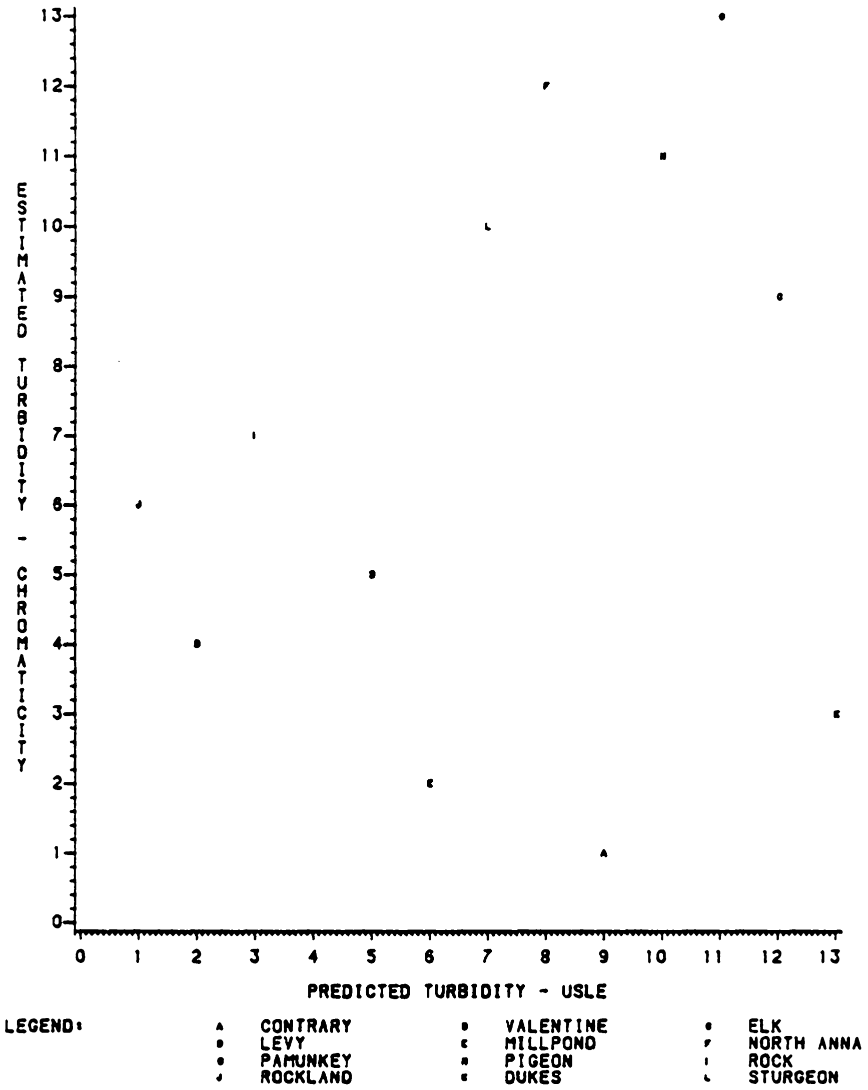

FIGURE 5.6: RANKED RESULTS OF CHROMATICITY ANALYSIS AND USLE.

was found between the results of chromaticity analysis and the USLE.

The relationship between these two variables was then evaluated by comparing the spatial and physical characteristics of each watershed (Table 5.10). Two patterns are evident from Table 5.10 and Figure 5.6. First, slope geometry seems to influence turbidity levels. The most turbid tributaries drain from watersheds with high slope geometry factors while the least turbid tributaries drain from watersheds with a low slope geometry factor. Second, as the level of nonforested land and cropland increases and the level of forested land decreases, an increase in turbidity levels is apparent. This pattern is most apparent in the Pamunkey, the most turbid tributary, and Levy, the least turbid tributary. Haugen et al (1977) reached similar conclusions from their study of several watersheds within the Great Lakes drainage basin.

Although similarites between predicted and estimated turbidity levels also occur in other watersheds, the number and range of inconsistencies produces a number of questions as to the strength of the relationship between land use/cover patterns and turbidity. Practical and conceptual problems probably influenced these inconsistencies and can be found both in using LANDSAT MSS data and the USLE to study this relationship.

TABLE 5.10

Physical Characteristics of Each Watershed[1]

Watershed	Slope Geometry	USLE	Coniferous	Deciduous	Mixed	Total Forested	Pasture	Crop	Total Agricultural	Total[2] Area
Pamunkey	5.4	25.09	11672.47	17172.56	--	28845.03	11191.07	650.75	11841.82	41726.8[3]
Percent			26.82	41.16	--	69.13	26.82	1.56	28.38	
North Anna	5.4	24.15	13235.57	14438.86	--	27674.43	6051.62	500.67	6552.29	35259.79[4]
Percent			37.54	40.95	--	78.49	17.16	1.57	18.50	
Pigeon	6.9	24.58	673.19	878.2	1007.51	2558.9	96.17	--	96.17	2655.08
Percent			25.35	33.08	37.95	96.38	3.62	--	3.62	
Elk	6.1	28.03	418.79	1726.52	--	2145.31	529.59	41.91	571.50	2716.81
Percent			15.41	63.55	--	78.06	19.49	1.54	21.04	
Dukes	5.6	35.18	41.26	115.01	88.70	244.97	97.15	16.89	114.04	359.11
Percent			11.26	32.04	24.71	68.24	27.06	4.71	30.68	
Sturgeon	5.4	22.28	203.71	347.32	396.32	947.41	272.92	5.85	278.77	1226.17
Percent			16.61	28.33	32.73	77.27	22.26	.48	22.74	
Contrary	6.2	24.26	1959.47	2790.89	--	4750.36	409.70	28.92	438.62	5188.97
Percent			37.78	53.78	--	91.54	7.90	.56	8.45	
Boggs	3.7	15.14	97.79	162.77	207.94	468.50	63.03	4.2	67.33	535.76
Percent			18.25	30.38	38.81	87.45	11.76	.79	12.55	
Valentine	2.8	15.94	31.84	42.56	49.06	123.46	7.15	5.54	13.02	136.46
Percent			23.33	31.19	35.95	90.47	5.24	4.29	9.54	
Millpond	3.9	16.79	488.97	968.2	--	1457.17	350.24	17.54	367.78	1824.96
Percent			26.79	53.05	--	79.85	19.19	.96	20.15	
Rock	3.1	14.14	593.27	1673.88	--	2267.15	437.32	43.86	481.18	2748.33
Percent			21.58	60.91	--	82.49	15.81	1.60	17.51	
Rockland	1.9	6.67	69.85	21.44	32.49	123.78	.65	--	.65	124.44
Percent			56.14	17.23	26.11	99.47	.53	--	.53	
Levy	2.1	7.43	55.88	68.55	86.10	210.53	4.9	--	4.9	215.41
Percent			25.94	31.83	39.97	97.74	2.26	--	2.26	

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[1] Watersheds are listed in approximate order of estimated and predicted turbidity.

[2,3,4] Total area includes shadow areas which are not included as category on this figure.

Practical and Conceptual Problems of LANDSAT MSS Data. Inconsistencies in the results of this study could generate questions as to the relationships between land use/cover patterns and turbidity levels. However, other research has been successful in relating land use/cover patterns to turbidity levels (Knott, 1973; Wolman and Schick, 1967). Therefore, the relationship inconsistencies in this study might be the influence of various practical and conceptual problems in using LANDSAT MSS data to study the relationship between land use/cover patterns and turbidity levels.

Three practical problems have been identified in using LANDSAT MSS data to study this relationship. First, the most significant problem is that four scenes are insufficient to establish a relationship between turbidity levels and land use/cover patterns. Previous research attempts have used a large number of surface samples over a two year period to establish a relationship between land use/cover patterns and turbidity levels (Knott, 1973). Perhaps a larger number of scenes would have been useful in defining land use/cover pattern and turbidity relationships. Second, LANDSAT imagery of the quality needed for such an in depth study would be difficult to obtain. Five years of LANDSAT imagery, 1972 to 1976, were viewed at the Browse File, Goddard Space Flight Center. Because of cloud cover and poor image quality, only six scenes were considered acceptable for this time period. Of the six, only two scenes could be selected for use in this study.

Third, because of the low spatial resolution capabilites of the LANDSAT MSS, significant areas of residential and recreational development within the Lake Anna watershed were not discernable on the satellite imagery. Only five land use/cover categories (nonforest cover, cropland, water, and deciduous and coniferous forest cover) could be delineated from the March 23, 1981, LANDSAT scene. Additional cover types, such as residential and recreational development, would have been useful in the analysis of land use/cover patterns and water quality relationships within the Lake Anna watershed.

I identified two conceptual problems in using LANDSAT MSS data to study relationships between land use/cover patterns and turbidity levels. First, a cause and effect relationship does not always exist between land use/cover patterns and turbidity levels. Rather, turbidity levels can be influenced by a broad range of factors other than those considered in this research. These additional factors include water depth and currents, wind, and channel width.

Second, even after the practical problems of this study are solved, several charactersitics of the LANDSAT data collection system limit its utility in studying land use/cover patterns and water quality relationships. First, surface sample crews would have to be available and ready to take water quality samples on each satellite overpass date. Cloud cover or extreme atmospheric haze influences spectral signals received by LANDSAT and thus, could delay surface sampling activities. If this occurs, time and money would be wasted. Second, because high levels of humidity create atmospheric haze along the eastern coast of the U.S. from mid-May through mid-September, the utility of LANDSAT as a water quality monitoring device for Lake Anna would be limited during this time period. Surface water quality samples would be more practical during this time period.

Other problems with the LANDSAT system include difficulty in timing surface sample collection to coincide with satellite overpass and locating surface sample sites on LANDSAT data. A combination of these problems limits the LANDSAT data collection system in the study of land use/cover pattern and water quality relationships. For these reasons, LANDSAT MSS data are not a substitute for surface water quality data.

Conceptual Problems of the USLE. Two conceptual issues were identified in using the USLE to study relationships between land use/cover patterns and turbidity levels.

First, in the sediment loss prediction, the equation does not consider how much eroded material is redeposited before it reaches streams or lakes, nor does it consider the position of vegetation or other natural or man-made obstructions that possibly can influence the movement of sediment (Kling and Olson, n.d.). For example, both the Valentine and Contrary creek watersheds contain over 90 percent forested cover. The equation does not consider the position of this forested cover in relation to the areas that are likely to erode nor does the equation consider the position of the forest in relation to the source of sediment and a water body. The forest cover for both of these watersheds could be in such a position as to isolate the nonforested area and the cropland from the lake. Second, USLE predicts gross sediment loss per year, rather than for a particular rainfall event. Results of chromaticity are based on each individual date. Therefore, chromaticity analysis provides a more accurate estimate of turbidity levels for a particular date than the USLE.

C. Evaluation of Results

Two premises of this research are that a relationship exists between tributary turbidity levels and land use/cover patterns, and that LANDSAT MSS data can be used to study this relationship. MSS data were transformed to chromaticity coordinates to estimate turbidity levels in Lake Anna. The accuracy of turbidity levels as estimated by chromaticity analysis was assessed by relating the results to two individual groups of ground-based data, surface turbidity levels and the product of the USLE. In this section, the relationship between the results of chromaticity analysis and the two groups of ground-based data was evaluated further by analyzing these three variables (Table 5.11).

In Table 5.11, an inconsistency is apparent. The results of chromaticity analysis relate moderately well with surface turbidity levels, but a weak relationship exists between turbidity levels as estimated by chromaticity analysis and the product of the USLE. Two conclusions are suggested by this weak relationship:

1. Turbidity levels as estimated by chromaticity analysis are not influenced by watershed characteristics.
2. The methodology of this research, the use of LANDSAT MSS data to study the relationship between land use/cover patterns, influences the weak relationship.

Because previous research has determined that a relationship exists between particular land use/cover patterns and turbidity levels (Knott, 1973; Wolman and Schick, 1967), the

TABLE 5.11

Comparison of the Results of Chromaticity Analysis with Two Ground-Based Data

	Surface Turbidity Levels	USLE	Land use/ cover Patterns
Results of Chromaticity Analysis	M	L	L

M = Moderate level of correlation

L = Low level of correlation

former conclusion can be discounted. Rather, the weak relationship was probably the result of the methodology of this research. Practical problems include the small number of LANDSAT scenes available for this research and the low resolution capabilities of the LANDSAT MSS. Even after the practical problems are solved, conceptual problems remain. Because of cloud cover and timing problems, LANDSAT imagery of the quality needed for an in depth study of land use/cover and turbidity level relationships is difficult to obtain.

Such conclusions raise questions as to the best possible application of LANDSAT MSS for watershed management. Alternative applications of LANDSAT MSS data for watershed management are discussed in Chapter 6.

Chapter 6

Summary and Conclusions of Research

The purpose of this research was to extend the use of chromaticity analysis as applied to LANDSAT MSS data by focusing on the following questions:

1. What degree of accuracy can be achieved by applying chromaticity analysis to geographic environments different from those previously studied?
2. Can chromaticity analysis of LANDSAT MSS data be used to monitor accurately the relationship between land use/cover patterns and the sediment discharge of a watershed?
3. What is the relationship between different combinations of land use/cover patterns within a watershed to the level of sediment that is produced from that watershed?

While previous research applied LANDSAT MSS data in estimating turbidity levels and detecting land use/cover patterns, a weakness in existing research was the lack of correlation between these two sets of data for watershed and water quality management. This research attempted to integrate these capabilities.

Turbidity levels within Lake Anna were estimated by the chromaticity technique used by Munday et al and were related to two groups of ground-based data -- surface turbidity levels and the product of the universal soil loss equation (USLE). Estimated turbidity levels correlated moderately well with surface data, but only a slight relationship could be established between land use/cover patterns and turbidity levels. The Pamunkey watershed, which has the highest percentage of agricultural land, tends to produce the most sediment, while the Levy watershed, which has one of the highest percentages of forest cover, generates the least amount of sediment. However, inconsistencies can be found in relating particular land use/cover patterns and turbidity levels for other Lake Anna watersheds. For example, the Pigeon tributary, which drains from a watershed with a high percentage of forest cover, tends to be highly turbid, while the Millpond tributary, which drains from a watershed with a high percentage of agricultural land, tends to be less turbid.

On the basis of these results, the above questions can be answered, and the hypotheses of this research can be accepted or rejected:

1. Because a moderately strong relationship can be established between chromaticity coordinate X and the surface turbidity levels of Lake Anna, hypothesis 1 can be accepted.
2. Because land use/cover patterns did not relate to the results of chromaticity analysis, and because only a weak relationship can be established between particular land use/cover patterns and turbidity levels, hypotheses 2 and 3 must be rejected.

Therefore, based on these results, the separation of the two themes within previous research referred to in Chapter 2 may be a necessity rather than a weakness. Possible explanations for these results can be grouped into two categories, practical and conceptual problems (Tables 6.1 and 6.2).

A. Theoretical Implications: The Utility of LANDSAT for Watershed Management

A combination of practical and conceptual problems markedly influenced the results of this research. Practical problems were defined in this research as data collection problems and can be classified into three categories -- date difference, data availability, and LANDSAT system problems (Table 6.1). Problems within these categories can be solved by collecting new or different kinds of data. Conceptual problems were based on theoretical issues of using LANDSAT MSS data for watershed management purposes and remain even after the practical problems have been solved. Conceptual problems can be classified into two broad categories -- technique application problems and constraints of the LANDSAT system (Table 6.2). Problems within these two categories indicate that LANDSAT MSS data is not a substitute for surface data. Instead, LANDSAT MSS data can more properly supplement surface water quality data.

TABLE 6.1

Summary of Practical Problems of This Research

Ground-based data	Surface data	USLE
Date Differences	Satellite overpass and water quality collection date differences	Chromaticity analysis estimates turbidity for one date. USLE predicts gross sediment loss per year
Data Availability	Small number of surface sample sites and limited range of turbidity levels	Four scenes are insufficient to establish a relationship between land use/cover patterns and turbidity levels Sufficient high quality imagery would be difficult to acquire for a more in-depth study
System Problems	LANDSAT MSS samples a larger area of the water body than the surface sample, which could account for differences between surface turbidity and estimated turbidity	The coarse resolution of LANDSAT prevents a more thorough land use/cover inventory

TABLE 6.2

Summary of Conceptual Problems of This Research

Ground-based data	Surface data	USLE
Technique Application	Physical characteristics of Lake Anna might have influenced results of chromaticity analysis	The USLE does not consider how much material is redeposited before it reaches water body The USLE does not consider the position of vegetation or other natural or man-made obstructions which can influence the movement of sediment
Constraints of LANDSAT MSS System		After practical problems are solved fundamental characteristics of the LANDSAT system limit the availability of sufficient imagery and the quality of information necessary to study land use/cover pattern and turbidity level relationships Land use/cover is one of many problems which influence turbidity levels

An analysis of the problems under the technique application and system constraints categories reveals some disadvantages in using these data for turbidity estimates and suggests alternative applications of LANDSAT MSS data for watershed management. Characteristics of small, man-made reservoirs and of the LANDSAT system limit the application of chromaticity analysis as a means to estimate turbidity levels on a regular basis. The narrow arms of reservoirs (such as Lake Anna) can influence the spectral purity of water pixels, and the slow-moving water of these reservoirs allows sediment to settle rapidly. In combination these physical characteristics can reduce the accuracy and, therefore, the utility of chromaticity analysis for the management of small, man-made reservoirs.

The LANDSAT system is limited in the type of information that it can provide about the earth's resources, and in addition, detectable resources can be obscured through atmospheric conditions. The LANDSAT system can provide spectral information about water bodies, but because of meterological conditions, this information might not be available on a regular basis.

What is the most useful application of MSS data for watershed management? This question can best be answered by reviewing the conceptual problems which influenced differences between predicted sediment yield, per the results of USLE, and estimated turbidity, per the results of chromaticity analysis. When calculating sediment discharge, the USLE does not use as a variable the position of land use/cover categories in relation to water bodies. As a possible solution to this problem, Campbell (1979) suggested integrating LANDSAT MSS data, geo-based data, and the USLE in the sediment loss prediction. His method involved obtaining land use/cover information from LANDSAT MSS data and rating it as to its potential to contribute sediment to a water body. This rating was based on the character of the land use/cover and its distance from a water body. The rating was then integrated with geo-based data, and sediment loss was calculated through the USLE. The result of this process was a line printer map of land use/cover patterns with potential nonpoint sources of pollution shaded in dark. Although this technique did not estimate turbidity levels from LANDSAT MSS data, the data can be used to infer which areas of a water body are likely to receive the most sediment.

This method fully utilizes the capabilities of the LANDSAT system for watershed management and reduces most of the practical and conceptual issues that were developed in relating land use/cover patterns and turbidity levels.

Practical problems are reduced by this procedure, because the method is not dependent on surface data gathered on a specific overpass date for correlation with LANDSAT MSS data. Rather, ground truth checks can be completed within the approximate time period of satellite overpass. In addition, this procedure probably would reduce conceptual problems, because one or two high quality scenes per year would be sufficient to delineate land use/cover patterns within a watershed. Therefore, meterological events and atmospheric haze would not be as problematical for this technique. The data from this technique combined with a broad base of surface data should be more useful in watershed management than gross land use/cover information and water quality relationships.

B. Extension of Research

The accomplishments of this research include application of chromaticity analysis to small man-made reservoirs, further exploration of the relationships between land use/cover patterns and turbidity levels, and extension of LANDSAT MSS data in watershed management. Most importantly, however, this research exposed limitations in the form of practical and conceptual problems in using LANDSAT MSS data for watershed management. Future research should consider the following modifications in applying LANDSAT MSS data to watershed management problems:

1. Chromaticity analysis should be further tested in small man-made reservoirs. Efforts should be made to include a broader range of surface sample turbidity levels and samples should be gathered on the date of the satellite overpass.
2. Future research could rate land use/cover patterns on the basis of the cover characteristics and distance from a water body. This information could then be used in conjunction with a geo-based data system and the USLE to predict gross sediment loss.
3. Information from the latter recommendation could be used in conjunction with surface water quality data from Lake Anna in order to study relationships between land cover patterns and turbidity levels.

It is hoped that this research has clearly defined the conditons underwhich LANDSAT MSS data can be used for watershed management. Future research can expand the use of LANDSAT for such purposes by considering these recommendations.

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APPENDIX 1

Chromaticity Computer Program

```
#
#                                       APPENDIX    1
#
#       THIS COMMAND COMPUTES CHROMATICITY COORDINATES FROM THREE BANDS
#       OF LANDSAT MSS DATA, BANDS 4, 5, AND 6.  BAND 7 IS NOT USED BECAUSE
        THE WAVELENGTHS OF THIS BAND ARE HIGHLY ABSORBED BY ATMOSPHERIC
#       WATER VAPOR. THE PRINCIPLE UTILITY OF THIS COMMAND IS THE ANALYSIS
#       OF TURBIDITY LEVELS WITHIN WATER BODIES.
#
#
#
#
#
 INCLUDE MACA1
#
 SUBROUTINE DCHROM ( WORK , * )
#
 IMPLICIT INTEGER (A-Z)
#
 INTEGER WORK(.ARB) , IDENT(.IDLENGTH)
#
#
 INCLUDE GIPCOM
 INCLUDE ERROR
#
 CALL PPUSH('DCHROM')
#
#                                       OPEN THE MULTI-BAND INPUT FILE
#
 CALL RDKINL(FDI1, IDENT, .OLD, IEV, %9000 )
#
#                                       COMPUTE SOME SIZE PARAMETERS
#
 NLINES = IDENT(.IDNLINS)
 NPPL = IDENT(.IDNPPL)
 NBANDS = IDENT(.IDNBNDS) - IDENT(.IDNSBNDS)
#
#                                       CHECK FOR CORRECT NUMBER OF NUMERIC BANDS
#
 IF ( NBANDS < 3 )   GOTO 9020
#
#                                       CHECK THAT IMAGE IS IN LINE FORMAT.
#
 IF ( IDENT(.IDNCOLS) ~= IDENT(.IDNPPL) .OR. IDENT(.IDNROWS) ~= 1) GOTO 9030
#
#                                       BEGIN ARRAY ALLOCATION
#
 NXT = 1
#
#                                       INPUT BUFFERS FOR THE THREE INPUT BANDS.
#
 INBUF1 = GETWP( NXT, .INTMODE, NPPL)
 INBUF2 = GETWP( NXT, .INTMODE, NPPL)
 INBUF3 = GETWP( NXT, .INTMODE, NPPL)
#
#                                       OUTPUT BUFFERS FOR THE 2 OUTPUT BANDS.
#
 OTBUF1 = GETWP( NXT, .INTMODE, NPPL)
 OTBUF2 = GETWP( NXT, .INTMODE, NPPL)
```

```
#
#                              SPACE FOR THE BAND NUMBERS IN IMGMXI CALL
#
BANDS = GETWP( NXT, .INTMODE, 3)
#
#                              THE MIN AND MAX OF EACH BAND.
#
IMIN = GETWP( NXT, .INTMODE, 3)
IMAX = GETWP( NXT, .INTMODE, 3)
#
#                              CHECK THAT THERE IS ENOUGH SPACE
#
IF (.OK ~= OSALOC(NXT) )   GOTO 9010
#
#
#                              INITIALIZE BANDS ARRAY FOR IMGMXI CALL
#
DO I = 1 , 3
    WORK(BANDS+I-1) = I
#
#                              GET MIN AND MAX OF EACH NUMERIC IMAGE
#
CALL IMGMXI(FDI1, WORK(IMIN),WORK(IMAX), WORK(BANDS), 3, IDENT,WORK(INBUF1), _
            1, NPPL, IEV, %9000)
#
#                              CLOSE THE INPUT FILE BEFORE CALLING XYZ2YX
#
CALL CLOSE(FDI1)
#
#                              CAL XYZ2YX TO DO THE COMPUTATION
#
CALL XYZ2YX( FDI1, FDO1, WORK(IMIN),WORK(IMAX), WORK(INBUF1), WORK(INBUF2),_
             WORK(INBUF3), WORK(OTBUF1),WORK(OTBUF2),NPPL,IEV,%9000)
#
#
CALL PPOP
#
RETURN
#
#
9000 CONTINUE
#
CALL CLOSE(FDI1)
CALL CLOSE(FDO1)
RETURN 1
#
9010 CONTINUE
IEV = OSGIEV(IEV)
GOTO 9000
#
9020 CONTINUE
IEV= -5051
GOTO 9000
#
9030 CONTINUE
IEV = -5001
GOTO 9000
#
END
```

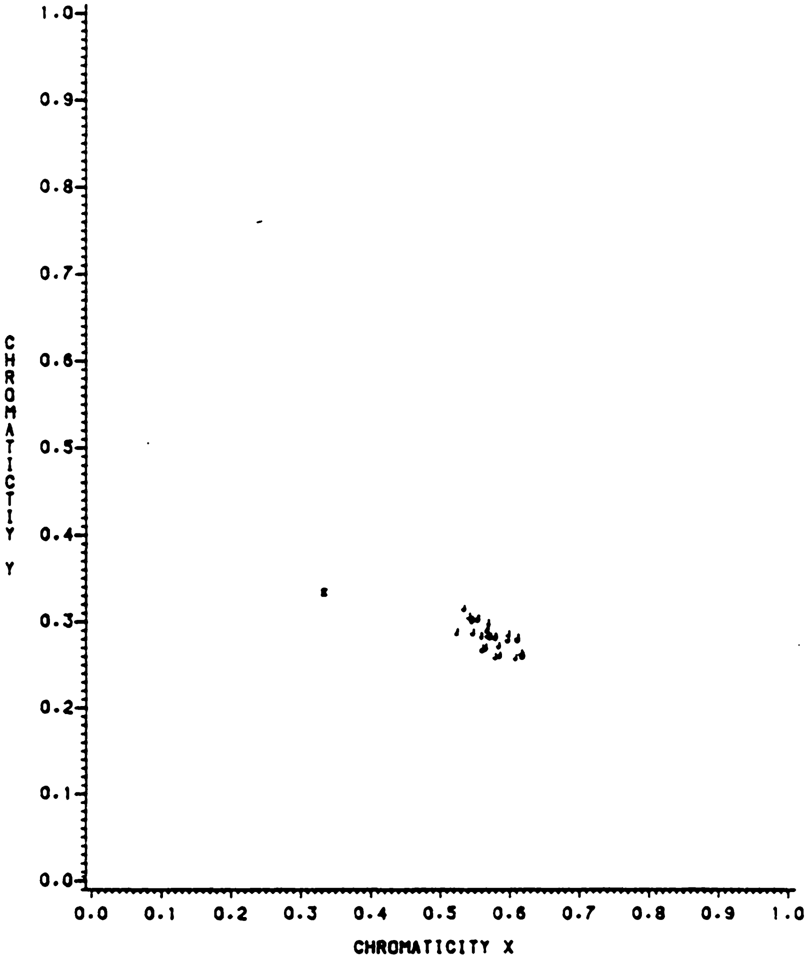
```
#
#
#
#   LANDSAT SENSOR CALIBRATION FACTORS FOR SUBROUTINE XYZ2YX ARE
#   CURRENTLY INITIALIZED FOR LANDSAT 1 MSS DATA.
#
#
 INCLUDE MACA1
#
 SUBROUTINE XYZ2YX ( FDI1, FDO1, IMIN, IMAX, INBUF1, INBUF2, INBUF3, OTBUF1, _
                     OTBUF2, NPPL, IEV, * )
#
#
 IMPLICIT INTEGER (A-Z)
#
 REAL SUMXYZ, X, Y, Z
#
 CHARACTER FDI1(.FDLENGTH), FDO1(.FDLENGTH)
#
 INTEGER IMIN(3), IMAX(3), INBUF1(NPPL), INBUF2(NPPL), INBUF3(NPPL)
 INTEGER OTBUF1(NPPL), OTBUF2(NPPL)
 INTEGER IDENT(.IDLENGTH), JDENT(.IDLENGTH)
#
#
 CALL PPUSH('XYZ2YX')
#
#                                   OPEN INPUT FILE AND COPY DESCRIPTOR RECORDS
#                                   TO A TEMPORARY FILE.
#
 CALL CPYIDR ( FDI1, IDENT, .OPNTMP, IEV, %9000 )
#
#                                   WRITE NAME OF ROUTINE TO DESCRIPTOR RECORDS
#
 CALL DSCNAM ('XYZ2YX', IEV, %9000 )
#
#                                   INITIALIZE JDENT TO ZERO
#
 DO I = 1 , .IDLENGTH
     JDENT(I) = 0
#
#                                   COMPUTE MIN AND MAX VALUES OF OUTPUT FILE
#
 SUMXYZ = ((IMAX(1)/255.*2.48+.00) + (IMAX(2)/255.*2.00+.00)_
          + (IMAX(3)/255.*1.76+.00))
#
 JDENT(.IDMIN)= IFIX(((MINO( IMIN(1), IMIN(2))/255.*2.00+.00)_
                 /SUMXYZ)*1000)
#
 SUMXYZ = ((IMIN(1)/255.*2.48 + .00) + (IMIN(2)/255.*2.00 + .00)_
           + (IMIN(3)/255.*1.76+.00))
#
 JDENT(.IDMAX) = IFIX(((MAXO( IMAX(1), IMAX(2))/255.*2.48+.00)_
                 /SUMXYZ)*1000)
#
#                                   COMPUTE REST OF JDENT
#
 JDENT(.IDNPPL) = IDENT(.IDNPPL)
 JDENT(.IDNLINS) = IDENT(.IDNLINS)
 JDENT(.IDNBNDS) = 2
```

```
JDENT(.IDNSBNDS) = 0
#
#                              COPY THE DESCRIPTOR RECORDS TO THE OUTPUT FILE
#
 CALL COPYDS ( FDO1, JDENT, IEV, %9000 )
#
#                              READ IN THE 3 BANDS FROM THE INPUT FILE, DO
#                              THE TRANSFORMATIONS, AND WRITE THE TWO RESULTING
#                              BANDS OUT.
#
DO ROW = 1 , IDENT(.IDNLINS)
    $(
    CALL RREAD(FDI1,INBUF1,1,ROW,IDENT,.WAIT,IEV,%9000)
    CALL RREAD(FDI1,INBUF2,2,ROW,IDENT,.WAIT,IEV,%9000)
    CALL RREAD(FDI1,INBUF3,3,ROW,IDENT,.WAIT,IEV,%9000)
#
#                              DO COMPUTATIONS FOR EACH PIXEL IN A ROW
#
    DO COL = 1,NPPL
       $(
       SUMXYZ = ((INBUF1(COL)/255.*2.48+.00)+(INBUF2(COL)/255.*2.00+.00)_
                 + (INBUF3(COL)/255.*1.76+.00))
#
       OTBUF1(COL) = IFIX(((INBUF1(COL)/255.*2.48+.00)_
                     /SUMXYZ)*1000.)
#
        OTBUF2(COL) = IFIX(((INBUF2(COL)/255.*2.00+.00)_
                     /SUMXYZ)*1000.  )
       $)
#
#                              WRITE THE OUTPUT BANDS OUT FOR THIS ROW
#
    CALL RWRITE(FDO1,OTBUF1,1,ROW,JDENT,.WAIT,IEV,%9000)
    CALL RWRITE(FDO1,OTBUF2,2,ROW,JDENT,.WAIT,IEV,%9000)
    $)
#
CALL CLOSE(FDI1)
CALL CLOSE(FDO1)
#
CALL PPOP
RETURN
#
#
9000 CONTINUE
CALL CLOSE(FDI1)
CALL CLOSE(FDO1)
RETURN 1
#
#
END
```

APPENDIX 2

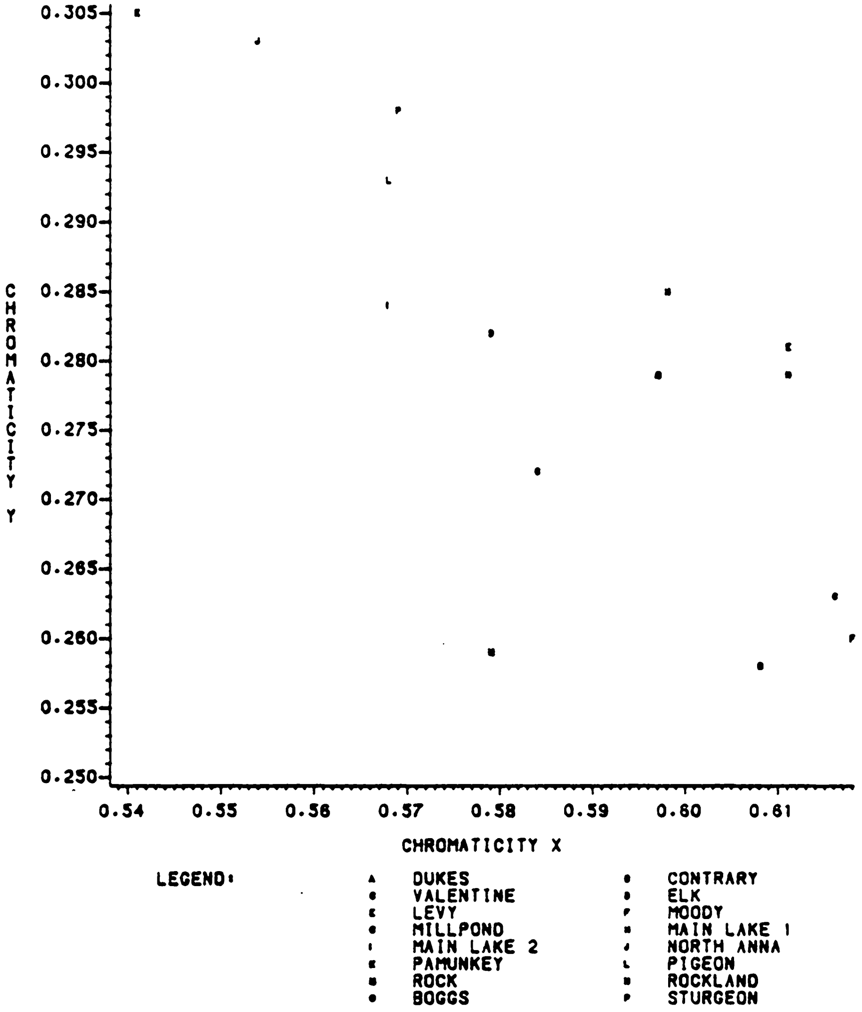
Chromaticity Plots

Figure 1. Chromaticity Diagrams for the January 9, 1973 scene. Plot A includes both LANDSAT and surface sample site chromaticity coordinates for the January 9, 1973 scene. Plots B and C represent a smaller scale of Plot A for the LANDSAT and surface sample sites respectively.

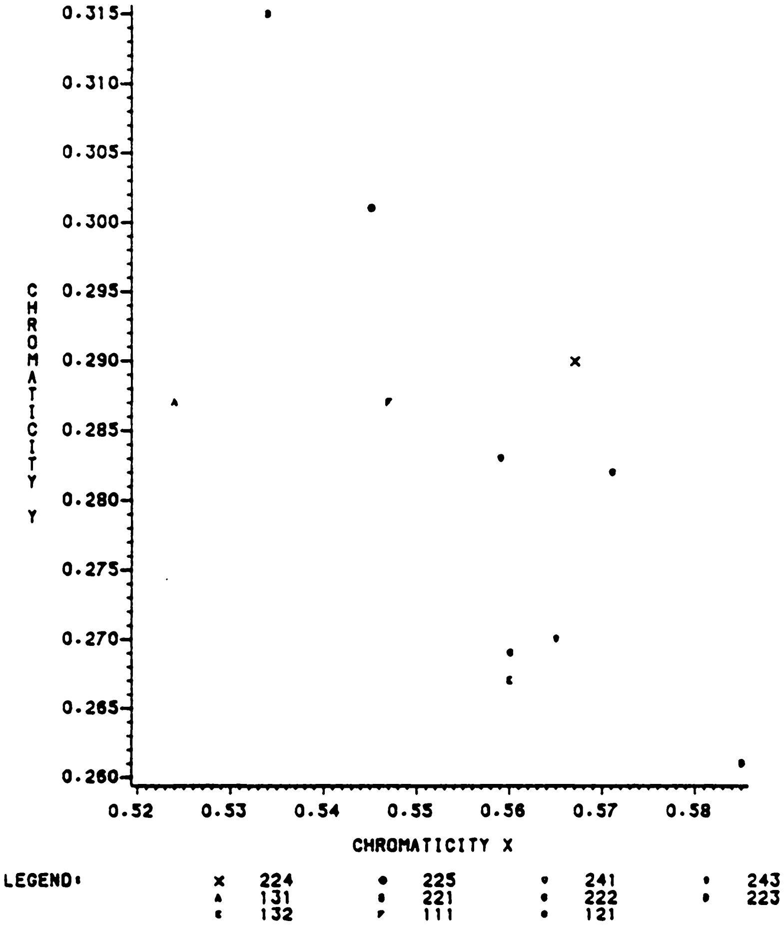


A. PLOT OF ALL CHROMATICITY COORDINATES: JANUARY 09, 1973.

J REPRESENTS CHROMATICITY COORDINATES FOR THE JANUARY SCENE.
E REPRESENTS THE POINT OF EQUAL ENERGY.

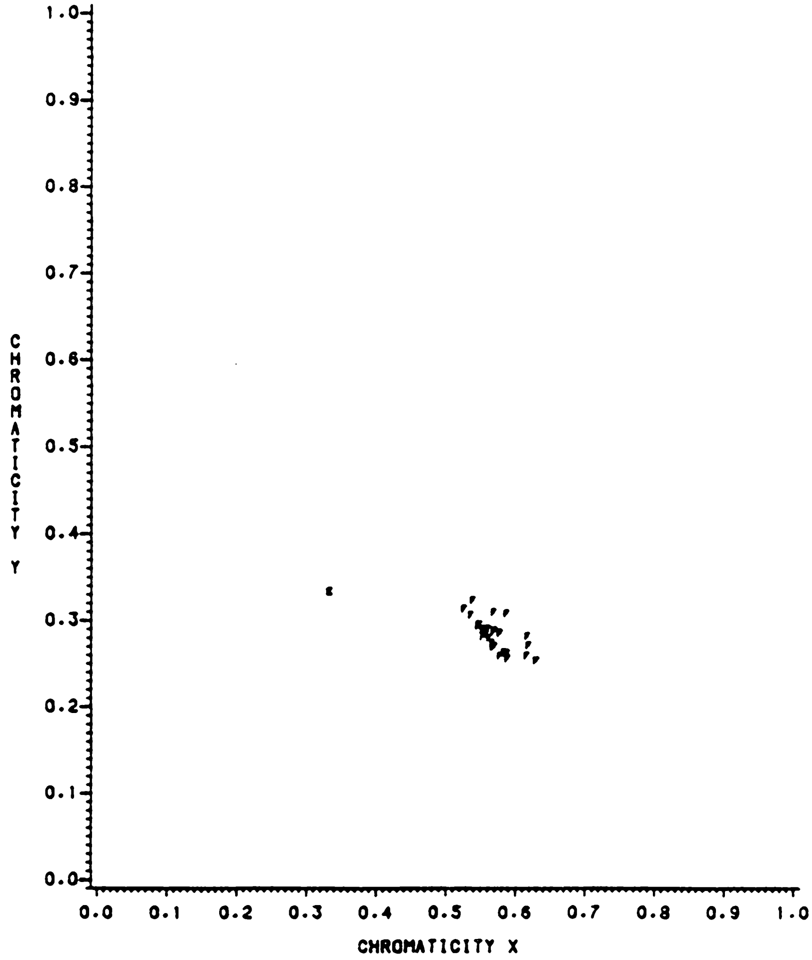


B. LANDSAT SAMPLE SITES: JANUARY 09, 1973 SCENE.



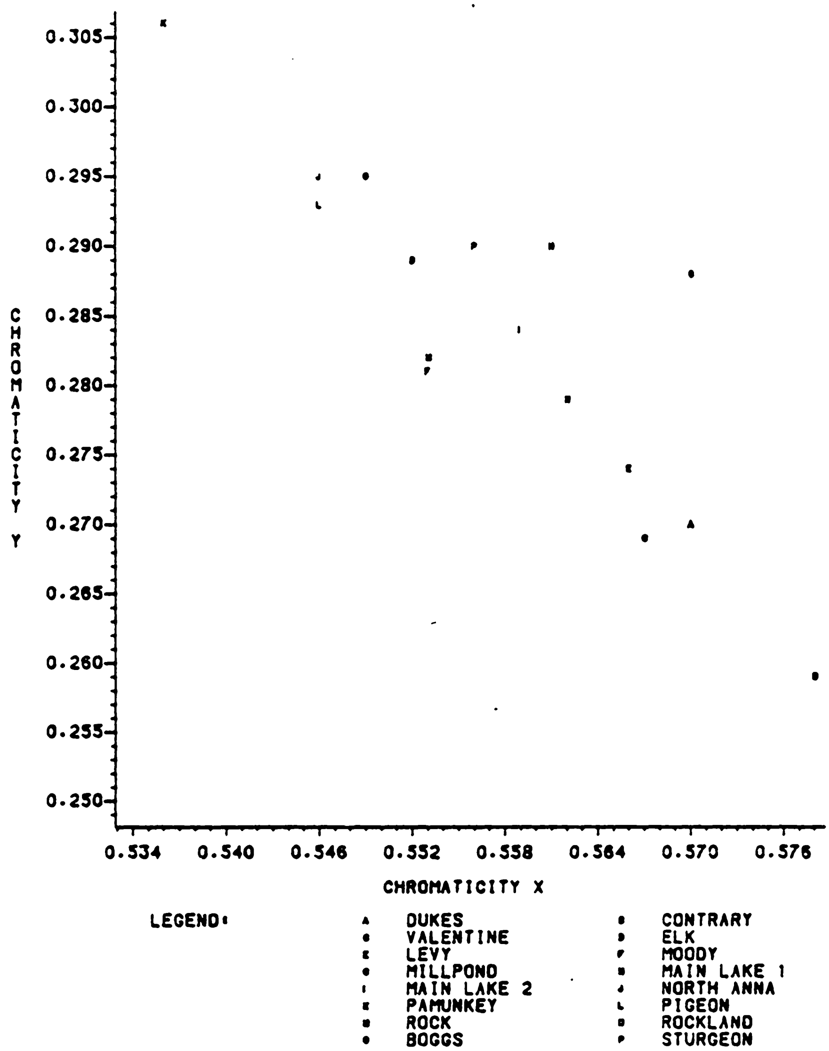
C. SURFACE SAMPLE SITES: JANUARY 09, 1973 SCENE.

Figure 2. Chromaticity Diagrams for the February 9, 1974 scene. Plot A includes both LANDSAT and surface sample site chromaticity coordinates for the February 9, 1974 scene. Plots B and C represent a smaller scale of Plot A for the LANDSAT and surface sample sites respectively.

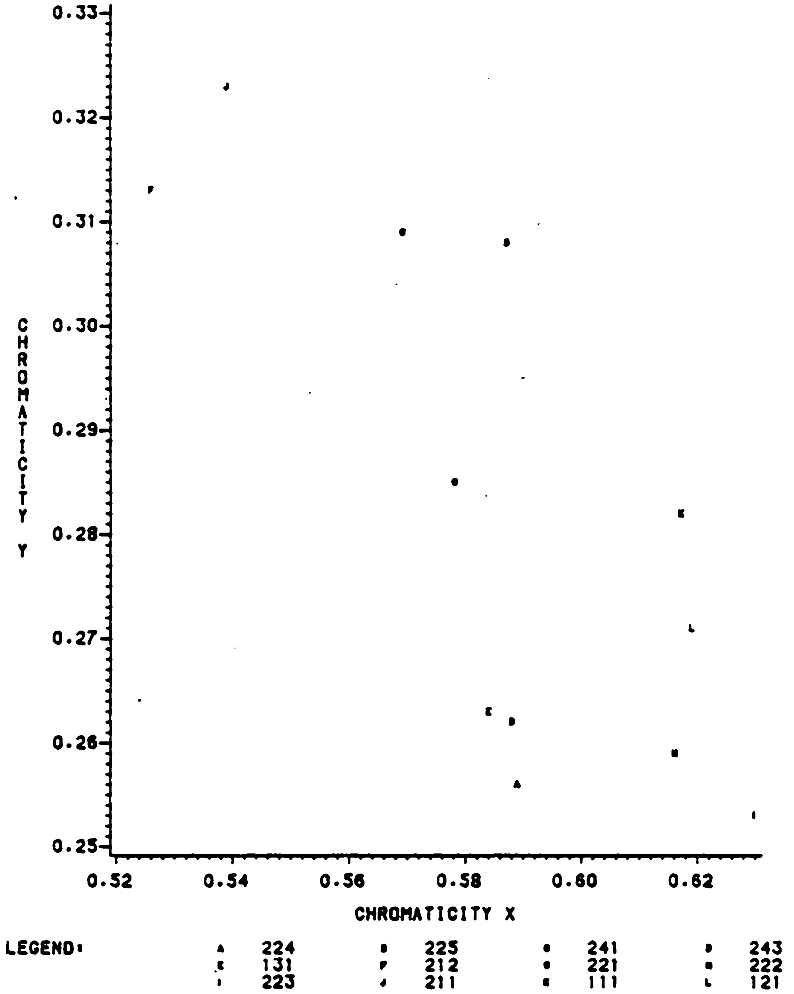


A. PLOT OF ALL CHROMATICITY COORDINATES: FEBRUARY 09, 1974 SCENE.

F REPRESENTS CHROMATICITY COORDINATES FOR THE FEBRUARY SCENE.
E REPRESENTS THE POINT OF EQUAL ENERGY.

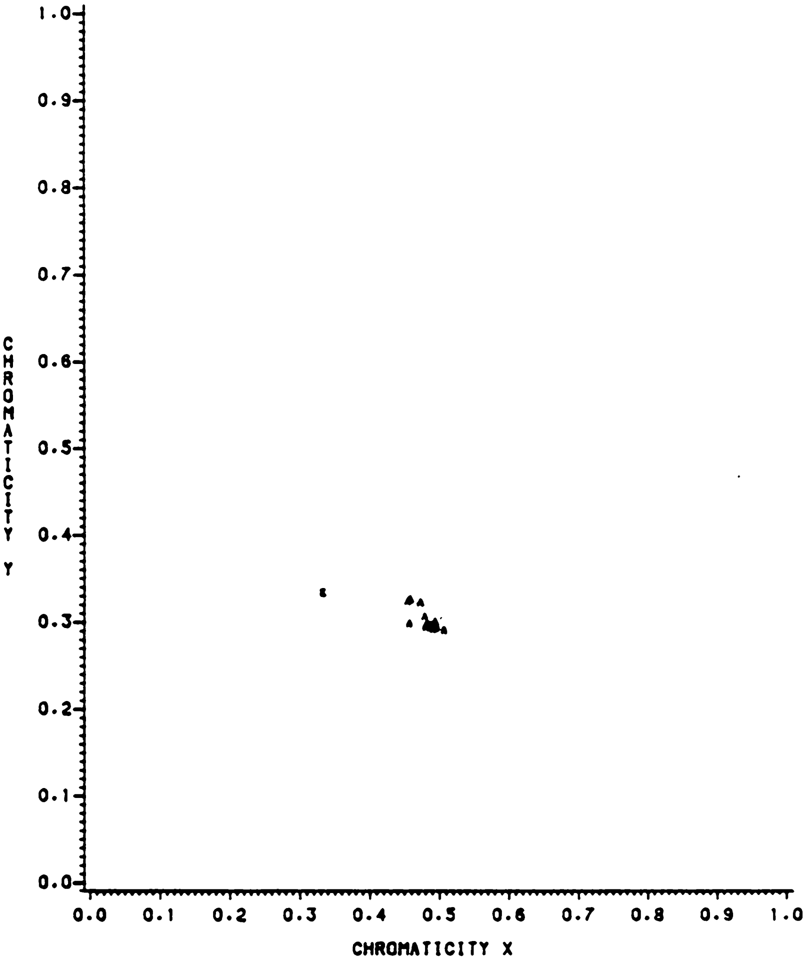


B. LANDSAT SAMPLE SITES: FEBRUARY 09, 1974 SCENE.



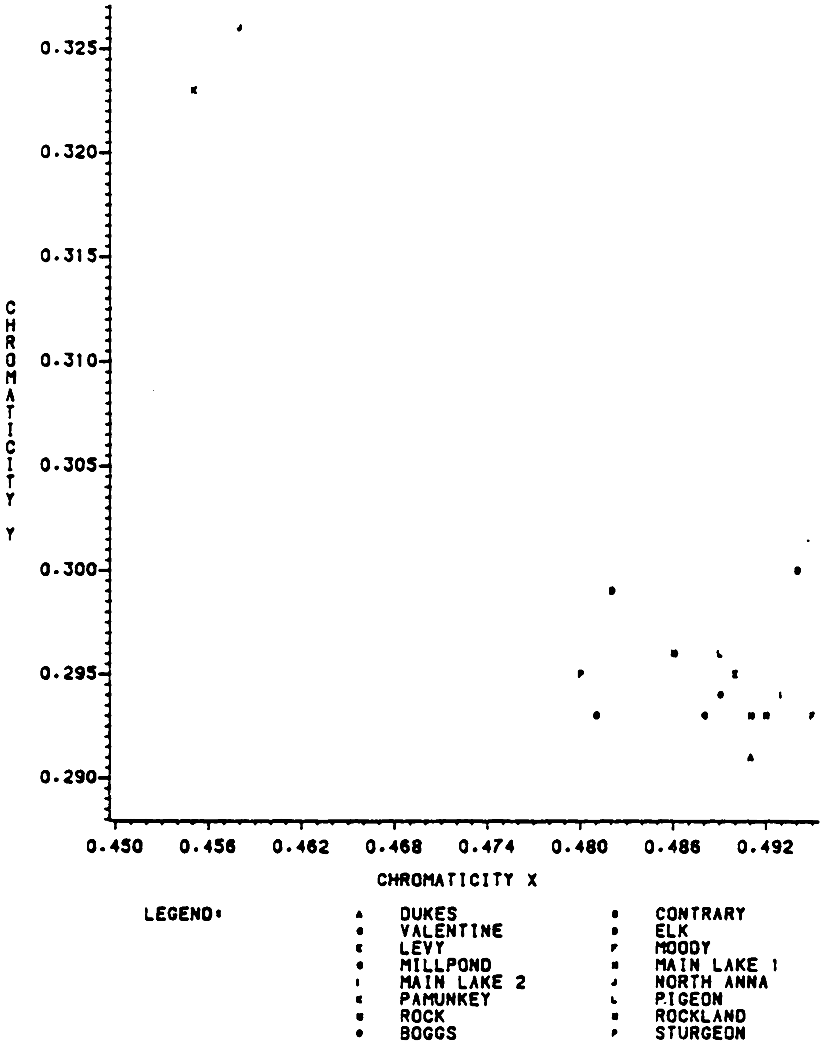
C. SURFACE SAMPLE SITES: FEBRUARY 09, 1974 SCENE.

Figure 3. Chromaticity Diagrams for the April 28, 1978 scene. Plot A includes both LANDSAT and surface sample site chromaticity coordinates for the April 28, 1978 scene. Plots B and C represent a smaller scale of Plot A for the LANDSAT and surface sample sites respectively.

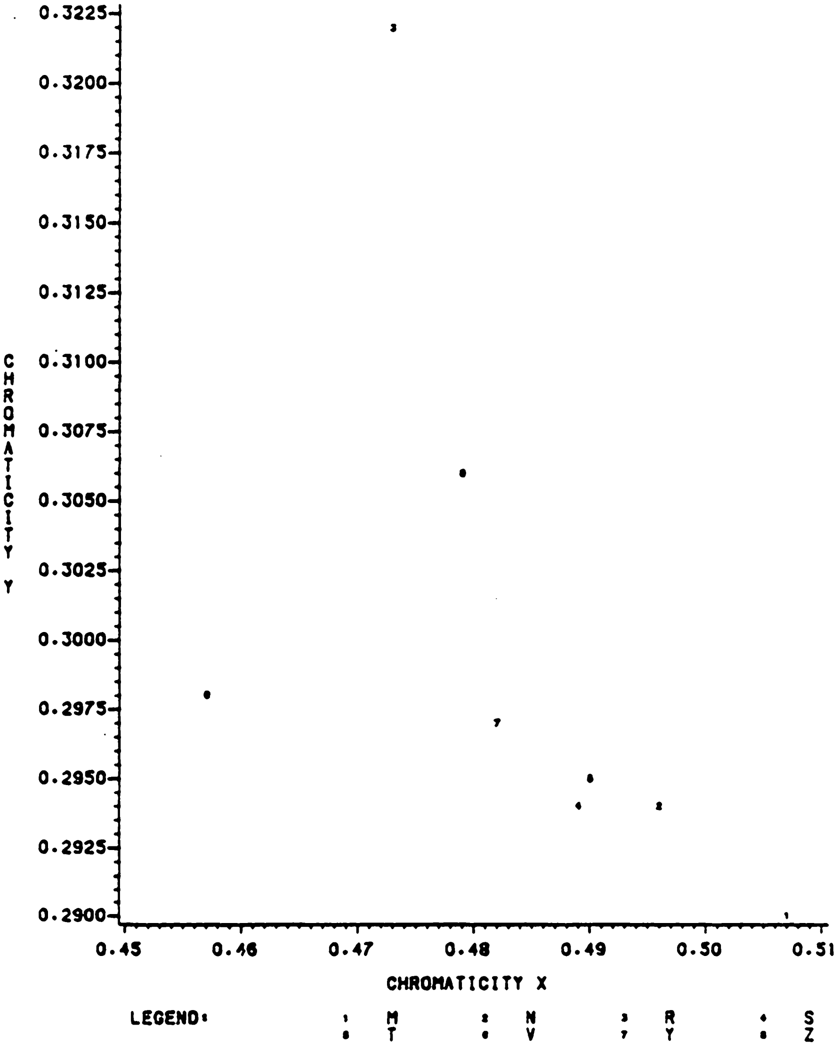


A. PLOT OF ALL CHROMATICITY COORDINATES: APRIL 28, 1978.

A REPRESENTS CHROMATICITY COORDINATES FOR APRIL 28, 1978 SCENE.
E REPRESENTS THE POINT OF EQUAL ENERGY.

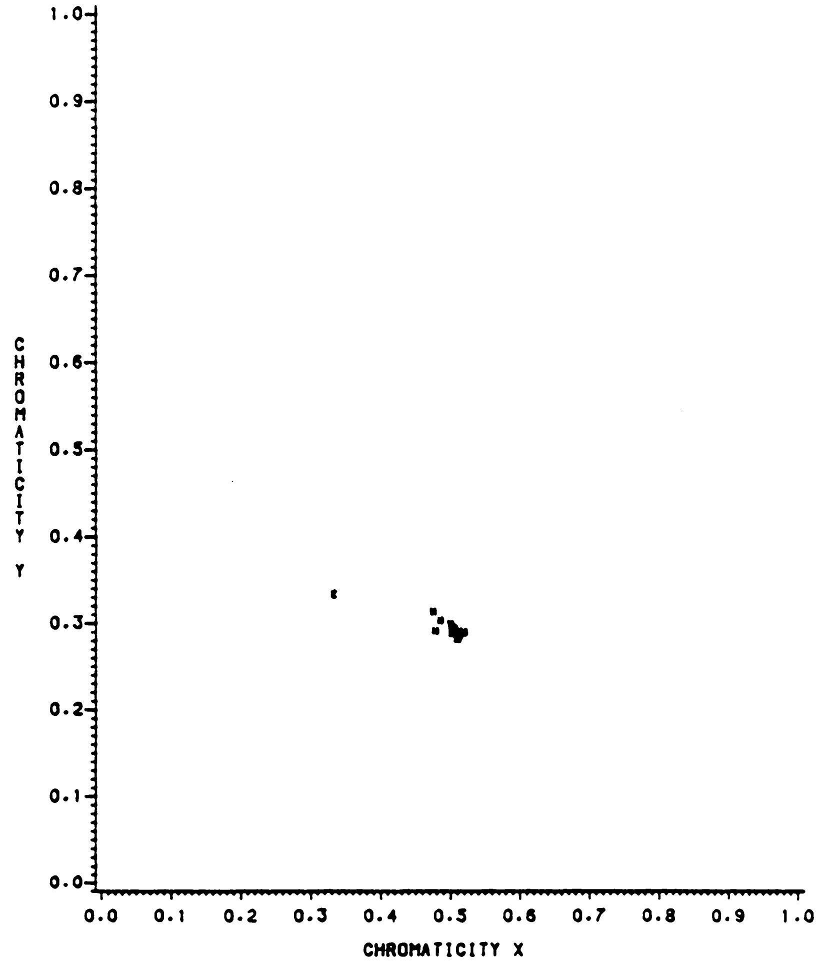


B. LANDSAT SAMPLE SITES: APRIL 28, 1978 SCENE.



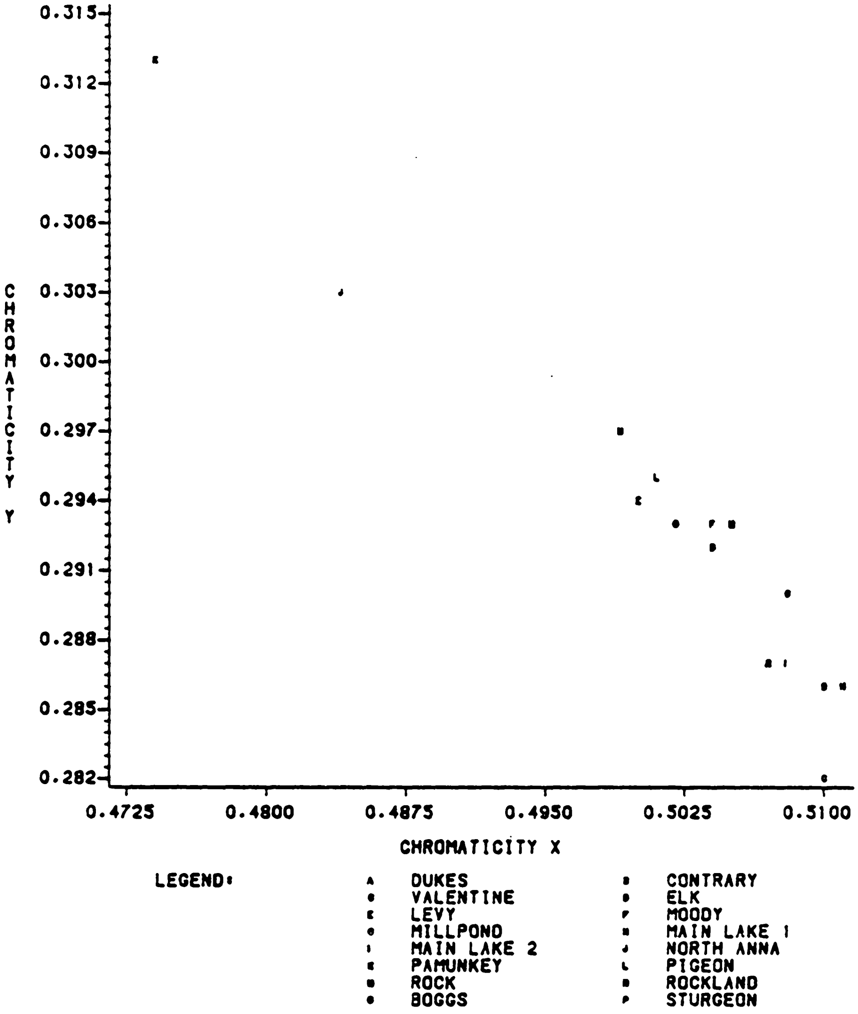
C. SURFACE SAMPLE SITES: APRIL 28, 1978 SCENE.

Figure 4. Chromaticity Diagrams for the March 23, 1981 scene. Plot A includes both LANDSAT and surface sample sites for the March 23, 1981 scene. Plots B and C represent a smaller scale of Plot A for the LANDSAT and surface sample sites respectively.

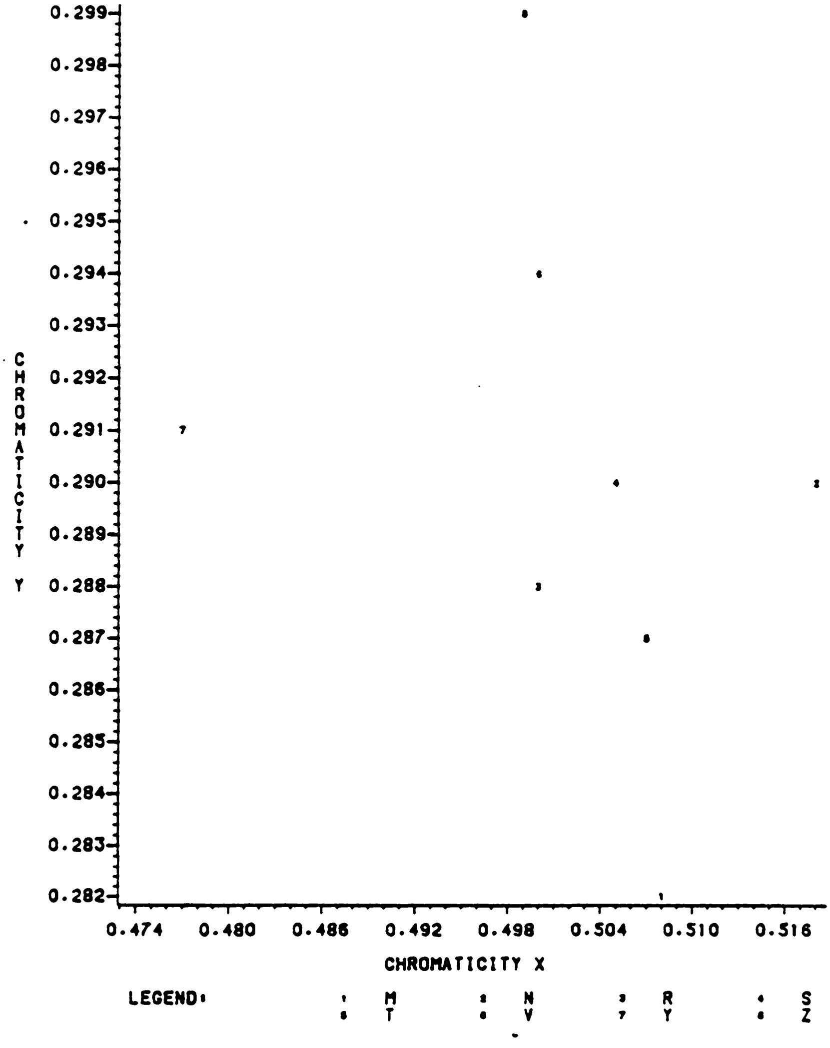


A. PLOT OF ALL CHROMATICITY COORDINATES: MARCH 23, 1981 SCENE.

M REPRESENTS CHROMATICITY COORDINATES FOR MARCH 23, 1981 SCENE.
E REPRESENTS THE POINT OF EQUAL ENERGY.



B. LANDSAT SAMPLE SITES: MARCH 23, 1981 SCENE.



C. SURFACE SAMPLE SITES: MARCH 23, 1981 SCENE.

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THE USE OF THE LANDSAT MSS IN THE STUDY OF LAND USE/COVER AND WATER QUALITY RELATIONSHIPS: A CASE STUDY OF THE LAKE ANNA WATERSHED

by

Stephen Ashton Jones

(ABSTRACT)

The purpose of this research was to explore the potential of using LANDSAT MSS data in the study of land use/cover patterns and turbidity relationships within the Lake Anna watershed. Two premises of this research are that a relationship exists between land use/cover patterns and turbidity levels, and that LANDSAT MSS data can be used to study this relationship. Turbidity levels within Lake Anna were estimated by the chromaticity technique used by Munday et al and were correlated to two groups of ground-based data -- surface turbidity levels and the product of the Universal Soil Loss Equation (USLE).

Estimated turbidity levels correlated moderately well with surface data, but only a slight relationship could be established between land use/cover patterns and estimated turbidity. Possible explanations for these results were grouped into two categories, practical and

conceptual problems. Practical problems were defined as data collection problems and included LANDSAT system and data accuracy problems. Conceptual problems were problems based on theoretical issues of using LANDSAT MSS data to study relationships between land use/cover patterns and turbidity levels. Conceptual problems remained even after the practical problems were solved.

The accomplishments of this research included the application of chromaticity analysis to small man-made reservoirs, further exploration of the relationship between land use/cover patterns, and turbidity levels, and extension of LANDSAT MSS data in watershed management. Most importantly, this research exposed some of the limitations in using LANDSAT MSS data to study relationships between land use/cover patterns and turbidity levels.