DETECTION AND CLASSIFICATION OF WATER BODIES WITH HIGH SPECTRAL RADIANCE USING LANDSAT MULTISPECTRAL DIGITAL DATA

By

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DETECTION AND CLASSIFICATION OF WATER
BODIES WITH HIGH SPECTRAL RADIANCE
USING LANDSAT MULTISPECTRAL
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PREFACE

This study examines the degree to which high spectral reflectance of water, as a result of suspended sediment or bottom reflectance, affects the classification accuracy of water pixels using Landsat multispectral digital data. Several techniques for classifying the data are also compared and analyzed regarding water detection capabilities.

Much appreciation goes to Dr. John D. Vitek, my major advisor, for the direction, confidence, and encouragement he gave me throughout graduate school. I have been continuously inspired by his contagious enthusiasm for the study of geography.

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INTRODUCTION

Overview

Computer classification of digital data from the Landsat multispectral scanner is an effective means for locating and analyzing water bodies within a large study area. Landsat digital data can provide information such as the location of water bodies, surface area, relative turbidity, approximate shape, surrounding land cover, and in many cases, clues about pollution or eutrophication problems within water catchments.

The employment of Landsat data for a regional inventory and analysis of water bodies has proven to be cost effective in both time and money when compared to other means of collecting similar types of data (Rogers and McKeon, 1979). Landsat, however, because it senses the surface of the earth remotely, does have disadvantages which other 'in situ' data collection techniques may not have.

Landsat records surface reflectances which are integrated into picture elements or 'pixels'. The amount of energy reflected from land cover features within a .62 hectare land area is displayed on the imagery as a cell representing a .45 hectare land area.

Oftentimes a Landsat pixel, containing reflectance values determined by water reflectance, is classified as a land cover type other than water. One reason for such misclassification of water pixels is that high levels of suspended sediment or bottom reflectance cause water reflectance values to appear similar to those of other land cover types with low reflectance. Water, because it absorbs visible and infrared light energy, has a low spectral reflectance which is quite distinct from most other land cover types; however, if depth decreases to the point that reflectance from the bottom can be detected by the satellite or if the suspended sediment load increases, the water reflectance will also increase. When bottom reflectance or suspended sediment increases substantially, the amount of energy backscattered from below the water surface may approach and even surpass the amount of energy radiated by dark or wet soil. This causes an overlap of reflectance values which contributes to the misclassification of water.

In areas such as central Oklahoma, turbidity levels and water depths can vary significantly from pond to pond. Turbidity and depth also vary among regions of Oklahoma depending on soil type, surrounding land cover, and terrain characteristics. The detection of water bodies displaying certain characteristics depends on the particular Landsat spectral bands used in classification (Witzig and Whitehurst, 1981). The technique used for water body classification may also affect the accuracy with which water surface area is classified. Use of a particular classification technique over the relatively clear water bodies of eastern Oklahoma may not produce the same level of accuracy in water delineation when used for water classification of relatively turbid water bodies in western Oklahoma.

The degree to which the factors of high sediment and bottom reflectance affect water classification has been neglected in studies dealing with the remote sensing of water although they have been cited as problems. Work and Gilmer (1976) explained that shallow ponds with high suspended sediment concentrations may be erroneously classified as other low reflecting land cover types such as wet or dark soil. Boland (1976) stated that bottom reflectance does affect the amount of energy reflected from a water body to the satellite, and that studies were needed to analyze such affects.

Mixed pixels, another problem which causes water to be misclassified on Landsat data, has been dealt with frequently in studies and will not be studied extensively herein. Even so, an understanding of mixed pixels is important because they are a major cause of pixel misclassification (Grabau, 1976 and Smedes et al., 1975) and complicate the study of suspended sediment and bottom reflectance effects on water classification.

A mixed pixel is one in which the reflected energy from two or more land cover features combines to create an average reflectance value for the pixel. This average reflectance value may cause the pixel to be classified as some feature other than those which actually contributed to the value recorded for the pixel.

When using Landsat for the detection of water bodies, mixed pixels may be considered a problem if the pixel is classified as some land cover other than water when in actuality the majority of the .62 hectare detected for that pixel is comprised of water. Such an error in classification would cause underestimation of actual water body size. A reversed situation in which a pixel representing mostly land reflectance and little water reflectance is classified as water would be equally undesirable because it would cause overestimation of water body size.

High reflectance from water, as a result of suspended sediment or bottom reflectance, may cause erroneous classification of mixed pixels as well as pixels which contain only water reflectance. A mixed pixel containing the reflectance from a .62 hectare area which is comprised of 90 percent water and 10 percent grass may be classified as water if the water within the instantaneous field of view (IFOV) has a very low reflectance because of depth and clarity. If the water reflects a high amount of energy because of suspended sediment or bottom reflectance, the average reflectance detected within the IFOV may cause the pixel to be classed as a land cover other than water.

The erroneous classification of water pixels because of suspended sediment, bottom reflectance, or mixed pixels is common near the perimeter of lakes and also for entire small ponds. Work and Gilmer (1976) state that almost all ponds less than .4 hectare are not detected, ponds over .4 hectare and less than 1.6 hectares are only occasionally detected, and size and shape of margins of larger water bodies are often misrepresented.

An accurate classification of small ponds may often be essential for water studies over large areas. In Oklahoma, for instance, approximately 1800 lakes over 10 acres in size exist, far fewer than the approximately 190,000 ponds which are less than 10 acres (Johnson et al., 1979). Because the large majority of water bodies are less than 10 acres, these small water bodies must be considered as an important water resource.

Objectives

The major objective of this study is to determine the effect that high suspended sediment loads and bottom reflectance have on the accuracy of water classification using Landsat MSS digital data. The results of such an analysis may provide helpful insights regarding the use of particular classification techniques and Landsat spectral bands for the classification of water bodies which display such characteristics. Understanding the affects of high turbidity and bottom reflectance on the detection of water bodies is necessary for better resource assessment through the use of Landsat data.

Three classification techniques will be performed on the same scene of data. First, the significance of the relationship between high suspended sediment loads and pixel misclassification will be determined. Second, the significance of the relationship between water depth (as a measure of bottom reflectance) and pixel misclassification will be determined. Third, each of the classification techniques will be analyzed to determine the technique which provided the most accurate surface area classification of water bodies.

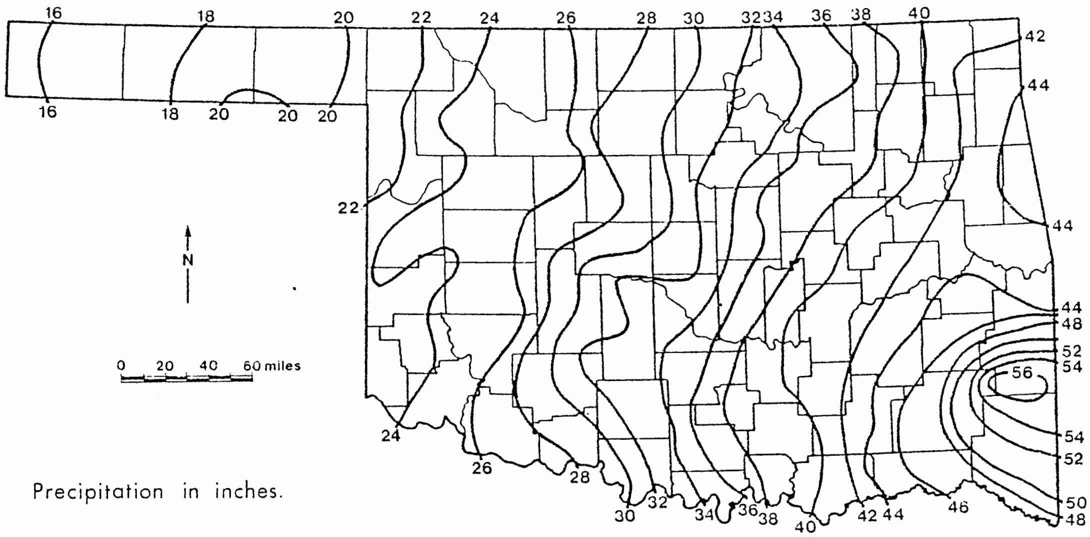
The classification techniques will be ranked according to their capability to separate water pixels from those of other low reflecting land cover. The techniques to be used include a standard unsupervised classification, which will actually provide three different classifications by changing selected training field statistics for each, a standard band 7 threshold routine, and a band average routine using bands 6 and 7. The first two techniques are chosen because they are standard routines employed for classification of land and water features. The band average technique is chosen because it is expected to enhance the separation between land and water.

Study Justification

Many communities in the western United States have experienced an increasing demand on limited water resources. Today, maintaining adequate water supplies for human consumption, industry, generation of electricity, recreation, and agriculture is a major resource problem for these communities.

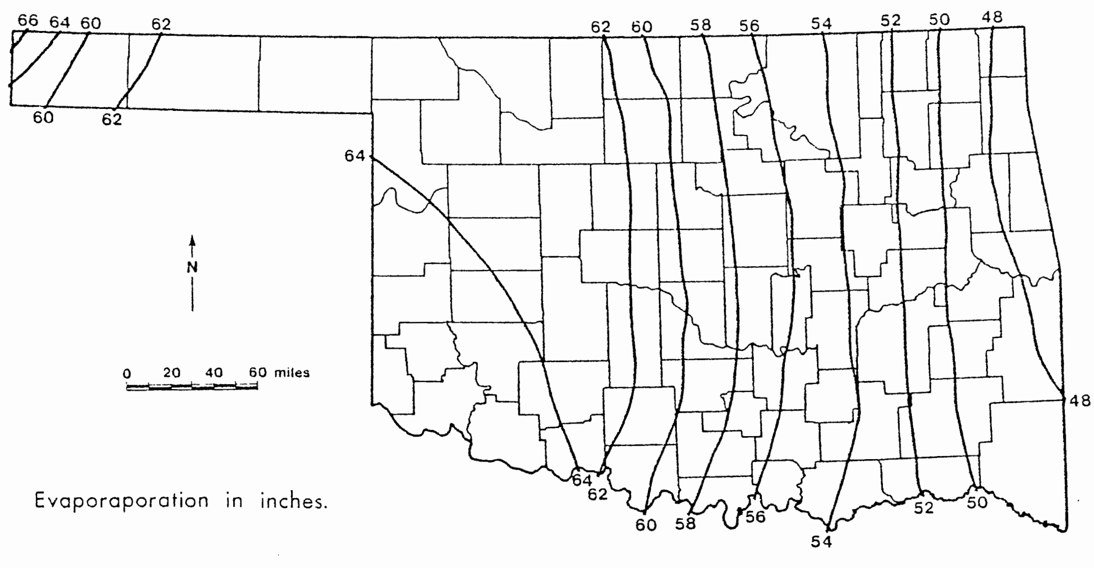
The construction of surface water impoundments, ranging in size from major reservoirs to farm ponds, is a vital means of coping with water demands in the state of Oklahoma as it is throughout the western states. Eighty percent of the water used by cities and industry in Oklahoma is taken from surface water catchments (Johnson et al., 1979)

Growing water demands and climatic variability, despite development of watershed programs aimed at increasing water supplies through the construction of ponds and reservoirs, often deplete community reserves to the point that water use must be rationed. This is particularly true in western Oklahoma where average annual precipitation ranges from approximately 35 inches in the center of the state to less than 16 inches in the Panhandle (Figure 1). Evaporation compounds the problem of maintaining a surplus of surface water throughout central and western Oklahoma. As precipitation decreases westward through the state, average annual lake evaporation increases to over 64 inches in southwestern Oklahoma (Figure 2).



Source: Oklahoma Water Resources Board, 1980, p. 48.

Figure 1. Average Annual Precipitation in Oklahoma



Source: Oklahoma Water Resources Board, 1980, p. 49.

Figure 2. Average Annual Lake Evaporation in Oklahoma

Climate plus heavy sedimentation rates contribute to the reduction of reservoir water-holding capacity and to water quality problems. High sediment concentrations in water contribute directly to the reduction in reservoir volume through sediment deposition and gradual filling of the reservoir. Indirectly, sediment containing high levels of nitrogen, phosphorus, and other nutrients from crop or range lands increases eutrophication and ultimately reduces reservoir capacity.

Because demand on water supplies is a major concern over such a large area of Oklahoma, the evaluation and monitoring of existing surface water impoundments is often necessary on a regional and state-wide scale. The regional assessment of water catchments facilitates watershed management decisions pertaining to maintainence of existing water bodies and planning for future reservoirs.

The task of monitoring existing water bodies on a regional scale can be quite costly with only in situ data gathering techniques. Information regarding water bodies, however, can be acquired on a regional basis at relatively low cost with Landsat MSS data. In fact, the collection of data similar to that provided by Landsat can cost 2 to 10 times more when alternative collection techniques are employed (Rogers and McKeon, 1979). Landsat is a very cost effective tool when monitoring water bodies over a large area. In situ measures, however, may be necessary for comprehensive evaluations.

In summary, problems exist with the use of Landsat data which may influence research conclusions. The need exists for determining to what degree high suspended sediment loads and bottom reflectance resulting from shallow water affect the classification of water pixels. It would also be advantageous to determine how different classification techniques perform with regard to detection of water bodies which are shallow or contain high levels of suspended sediment. Knowledge of these relationships may provide a more accurate classification of water features for regional planning purposes.

If high suspended sediment loads or bottom reflectance are found to significantly increase water misclassification for particular classification routines, a regional assessment of water bodies may necessitate a priori analysis of a sample of water bodies within the study area. Such an investigation may determine whether significant geographic variation exists among water characteristics within the study region. If regions within the study area are found to display distinctly different depths or turbidity levels, the interpreter may wish to classify the subregions using different Landsat bands or different classification techniques.

The undertaking of this study should aid in the assessment of water resources by providing a better understanding of the effects of suspended sediment and depth on classification of Landsat digital data. The results will be applicable to regional Landsat studies not only in Oklahoma but in areas where high turbidity levels or high bottom reflectance provide the potential for water misclassification. Improvement of the assessment of water resources on a regional scale is important if proper water management decisions are to be made in areas of increasing water demand.

CHAPTER II

LANDSAT

Landsat Satellites

Landsat 1, formerly ERTS-1, was launched on July 23, 1972 as an earth resources satellite, to provide remotely sensed data for public use. To date, four Landsat satellites have supplied data for many applications including land use monitoring, water management, forestry and range management, agriculture, and oil and mineral exploration. Landsat 2, 3, and 4 were launched on January 21, 1975, March 5, 1978, and July 16, 1982 respectively. At present only Landsat 3 and Landsat 4 are operational.

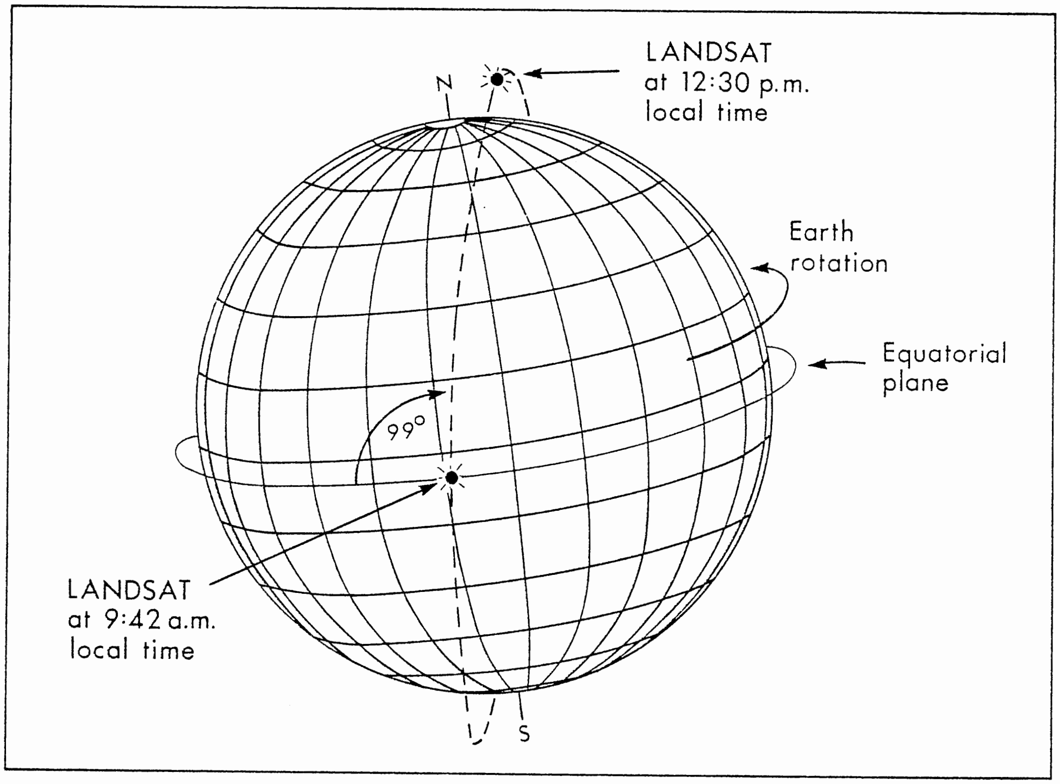
Landsats 1 and 2 collected data from return beam vidicon cameras and a multispectral scanner (MSS). Landsat 3 has similar systems with the addition of a thermal infrared band in the MSS which functioned only a short while. Landsat 3, at present, is capable of sending back only limited data. Landsat 4 recently became operational and is sending back data from its four band MSS with the addition of smaller resolution data from the seven channel thematic mapper (TM). The TM, with a resolution of 30 meters, senses in seven bands - the first six primarily in the visible and near infrared and the seventh in the thermal infrared range.

Satellite Orbit

Landsat 1, 2, and 3 operate at an altitude of 920 kilometers in a circular, near north-to-south orbit which is near polar and sun-synchronous; an orbit which allows each satellite to repeat its coverage every 18 days. Each orbits the earth in a plane which is inclined 99 degrees in a clockwise direction from the equator or nine degrees from each pole (Figure 3). Sun-sychronous means that the movement of the satellite's orbit about the earth is at the same angular rate that the earth revolves around the sun. This allows repeat coverage to be produced over a particular area at the same time of day. Also, to help reduce effects of varying sun angle, a constant angle of 37.5 degrees is kept between the satellite, the center of the earth, and the sun (Figure 4). Landsat 4 has a similar orbit but revolves around the earth at an altitude of 705 kilometers giving repeat coverage every 16 days.

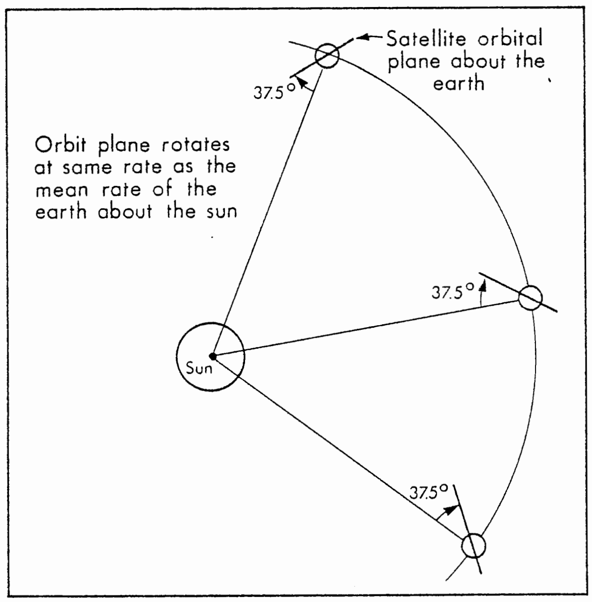
The Multispectral Scanner

Landsat records spectral reflectance for individual picture elements. A knowledge of the procedure in which the MSS collects and records reflectance data for these picture elements is necessary for understanding the major cause of pixel misclassification, mixed pixels.



Source: Walsh, 1979, p. 2-3.

Figure 3. Near Polar Landsat Orbit



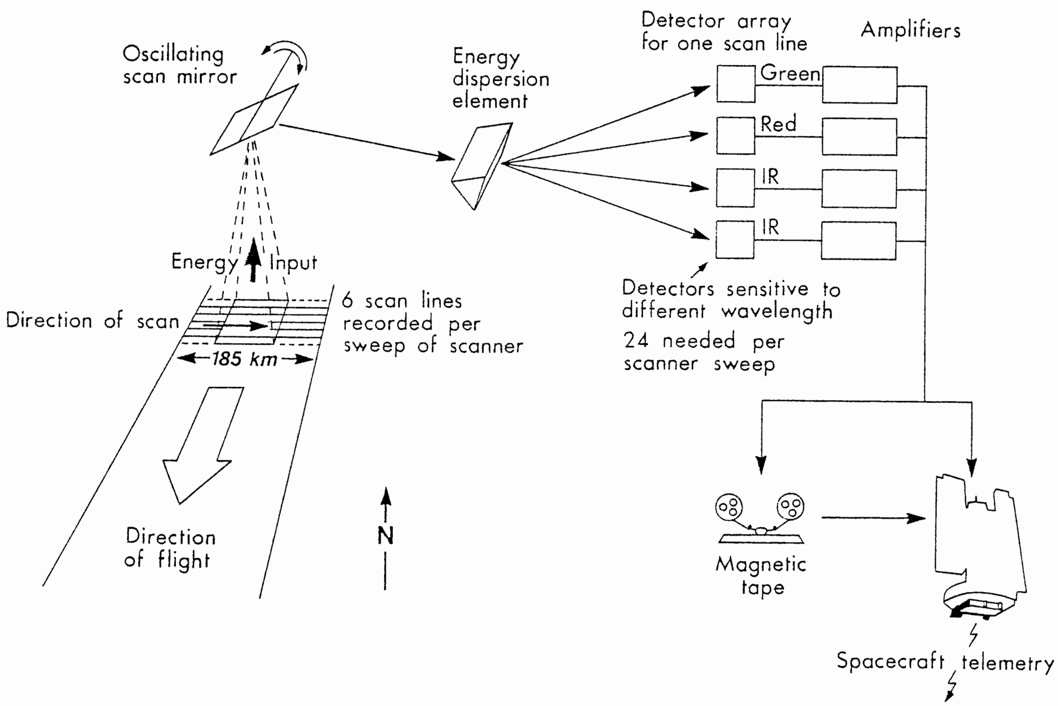
Source: Walsh, 1979, p. 2-3.

Figure 4. Sun-synchronous Landsat Orbit

Each scene of Landsat data compiled by the multispectral scanner covers a geographic area 185 by 185 kilometers with a resolution of .62 hectare. The cell on the MSS image which represents this area is called a picture element or pixel. For each pixel in the image, the amount of reflected electromagnetic energy from that .62 hectare area is recorded in four bands of the electromagnetic spectrum.

The sensors for bands 4 and 5 are sensitive to a portion of the visible spectrum from .5 μm to .6 μm (green light) in band 4, and from .6 μm to .7 μm (red light) in band 5. Bands 6 and 7 detect energy in the near-infrared portion of the spectrum from .7 μm to .8 μm and from .8 μm to 1.1 μm respectively.

The scanner is equipped with an oscillating mirror which sweeps the earth from west to east. The earth reflectance from the mirror is sensed by six parallel detectors for each of the four spectral bands (24 total), therefore, each sweep of the mirror causes the detector to record six scan lines of pixels with four reflectance values for each pixel (Figure 5). The resulting swath of data is six pixels wide and approximately 3300 pixels long having been created from reflectance values over a ground swath 474 meters wide and 185 kilometers long. This process continues with the next sweep of the mirror producing the next six scan lines as the satellite proceeds southward in its orbit.



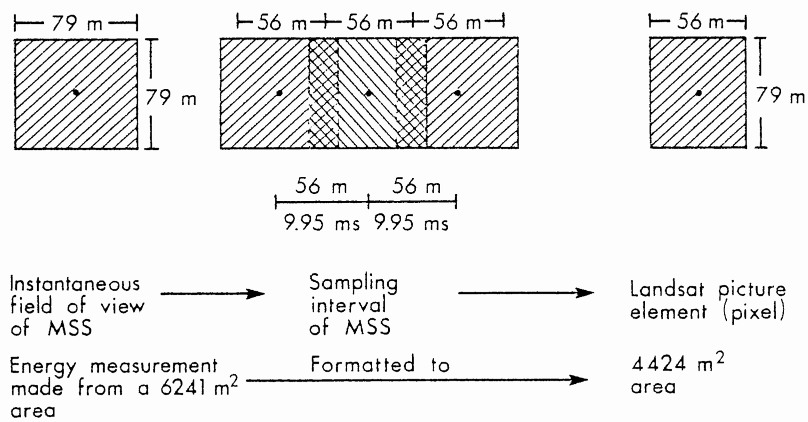
Source: Walsh, 1979, p. 3-4.

Figure 5. Data Collection by the MSS

The .62 hectare represented by each pixel is a 79 by 79 meter area of land. This 79 by 79 meter area is the amount of the earth's surface detectable by each photoelectric cell or sensor at any one time and is called the instantaneous field of view (IFOV). Once the reflectance from the IFOV is reflected onto a sensor, an analog signal (or electrical voltage) is generated which is proportional to the average amount of spectral radiation reaching the sensor.

The analog signal is not recorded continuously but is sampled every 9.95 milliseconds. This time interval in relation to the mirror speed (one oscillation every 73.42 milliseconds) is equivilant to a sample of land cover reflectance every 56 meters. Since the IFOV is sampled every 56 meters, the pixel is recorded as an area being only 56 by 79 meters (.45 hectare) even though the actual area sampled was 79 by 79 meters. Figure 6 demonstrates how 23 meters of pixel overlap contribute to the reflectance recorded by each 56 by 79 meter pixel cell.

The sample analog signals are converted by the satellite into digital values for transmission to earth. The digital values for bands 4, 5, and 6 range from 0 to 127 and for band 7 from 0 to 63. The greater the amount of reflected energy reaching the sensors, the higher the digital value assigned; for example, zero is totally black and 127 represents a totally white reflectance for bands 4, 5, and 6.



Source: Walsh, 1979, p. 4-1.

Figure 6. Formation of the MSS Picture Element

Techniques for Water Class Selection

Unsupervised Classification

Digital classification is a process in which a computer identifies clusters of spectral signatures for pixels which represent land cover with similar reflectance. The computer compares individual pixel signatures to the statistics developed for each cluster of signatures to determine the cluster (or class) in which that pixel best fits. These classes are produced in order to group pixels which represent similar land cover features. Once the classification is complete, an interpreter can display the areas of a particular land cover simultaneously.

An unsupervised classification is a commonly used technique which examines the spectral signatures of the pixels and searches for natural clusters of spectral values through computer analysis. Each pixel has a spectral signature which consists of a set of reflectance values, one for each of the four wavelength ranges of the electromagnetic spectrum in which Landsat senses (Figure 7). The amount of reflectance for each band characterizes the signature for that pixel. A homogeneous land cover area reflects a different amount of energy in each band; yet, the amount of reflectance for a particular band may remain fairly constant for each pixel containing reflectance values from that land cover. Hence, that distinct land cover produces a unique spectral signature.

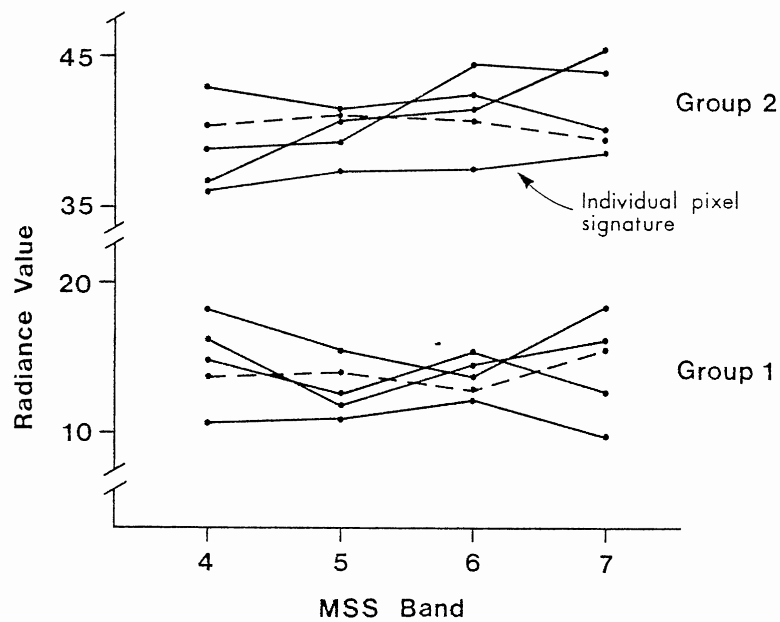


Figure 7. Clusters of Similar Reflectance Signatures

Figure 7 depicts classes derived by grouping spectral reflectance values through an unsupervised classification. Groups 1 and 2 show spectral signatures in which reflectance values fall near those of the mean values (joined by a dashed line) for two unique land features. Signatures of group 1 produce clusters of values which are distinct from those of group 2 since they display a lower reflectance for each band. Consequently, these groupings are assigned by the computer as different classes. The amount of variation from mean class values can be adjusted by statistical parameters which are determined before the computer classification is run. These parameters include a range of standard deviation, coefficient of variation, and a divergence statistic to measure separability.

Walsh (1979) states that separability of classes can be adjusted by altering the variation allowed within classes. By increasing the interclass distance (between class means) and decreasing the intraclass distance (deviation of variables around class means), overlap between classes can be reduced; thereby, reducing the chance of confusing classes. He goes on to explain, however, that "means and variances are usually not controllable except through trial and error" (Walsh, 1979, p. 3-1).

After classes are determined by the computer, the interpreter must decide through his knowledge of the study area, which land cover type each class represents. Classes may then be further combined to provide a more general classification. Depending on statistics used, several classes within the water category can be separated based on turbidity or bottom reflectance.

The unsupervised classification technique is useful for identifying water features because it takes into account reflectance values in all four MSS bands instead of relying, as do some techniques, on just one or two bands. Malila et al. (1975) found that an unsupervised classification using only bands 4, 5, and 7 proved to be 85 percent accurate in the classification of ponds. He did not discuss the range of water body sizes or their characteristics except to mention that a number of large water bodies were included in the study. The addition of band 6 to Malila's classification may have increased the accuracy of the study.

An unsupervised classification will be used in this study instead of a supervised classification in which the interpreter pre-selects training fields from pixels containing representative spectral signatures of land cover types to be classified. The supervised classification requires a priori knowledge of the study area in order to choose homogeneous land features as training samples. If the classification of small water bodies is important, difficulties arise when the interpreter must locate homogeneous training fields for the small water bodies (i.e., less than three hectares) which are usually more turbid and more shallow than larger water bodies. Edge pixels of these water bodies are almost always contaminated by other land cover, causing the selection of representative small water body reflectance values to be difficult. The use of larger water bodies for training field selection may eliminate the problem of mixed reflectance but may still preclude the selection of small water body reflectance because of deeper, less turbid water.

Band 7 Threshold Technique

Classification of band 7 values alone has often proved to be a simple and fairly accurate technique for determining water classes. Band 7 (.8 μm to 1.1 μm) shows water features well because very little electromagnetic energy in this wavelength is backscattered from water to the scanner. Water features, therefore, appear characteristically dark in band 7. Work and Gilmer (1976) found band 7 to be satisfactory for water body classification but noticed that shallow ponds with high sediment loads were occasionally missed. Because reflectance values in band 7 were the same as those recorded for dark prairie soils, some soil pixels were classed as water and some water pixels were classed as soil. Overlap of reflectance values presents a problem for the interpreter choosing the cut off value between soil and water.

Band Average

Another means of classification of water features is band averaging. This routine is performed on the MSS bands (usually two) which highlight the features of a particular land cover type the interpreter wishes to detect (National Space Technology Laboratories, 1979). Through the averaging of these two bands, the feature which is prominent on the individual bands is often spectrally enhanced more than other features. The band average can be performed by a computer by adding, for each pixel in the study area, the reflectances in each desired band and dividing by the number of bands used.

A band average produces results similar to those obtained through a band ratio which divides values in one band by values in another band and multiplies by a constant (National Space Technology Laboratories, 1979). A band average has advantages over the band ratio however, in that it allows averages of reflectance values to maintain their meaning in regards to the level of spectral reflectance detected by the pixel (Blanchard, 1982).

Several findings have been made which are useful for determining the bands to average for detection of water. Because band 7 is the best individual band for detection of water, it should be used in a band average. Certain circumstances should be considered before choosing another band to average with band 7. Moore (1978) and Sabins (1978) state that band 5 gives the best contrast between turbid and clear water and also shows relative sediment levels. When Gilmer and Colwell (1977) performed band averages using bands 4 and 7 and bands 5 and 7, they detected little or no advantage over the use of only band 7. Moore (1978) and McCauley et al. (1973) state that bands 6 and 7 are useful by themselves for mapping the land water interface. If Gilmer and Colwell had used these two bands together in an averaging technique they may have found significant results.

Band 6 is also useful for determining relative suspended sediment levels in water bodies (McCauley et al., 1973). Ritchie et al. (1976) states that band 6 is the best band for suspended sediment analysis. Rogers et al. (1975, p. 441) concludes from his study that "band 6 is the single most important band for prediction of almost all water quality parameters."

McCauly and Ritchie disagree with Moore and Sabins about the best band for suspended sediment analysis. Band 5 gives the most accurate and detailed indication of relative turbidity levels within a reservoir while band 6 shows different turbidity levels with more gradual variation in reflectance values. Values from band 5 are more exact measures of turbidity because the .6 μm to .7 μm wavelength penetrates water deeper than the .7 μm to .8 μm wavelength of band 6. Values from band 6 tend to generalize these values into larger areas of similar turbidity since variations in turbidity are less visible in the .7 μm to .8 μm wavelength range (Blanchard, 1983).

CHAPTER III

LITERATURE REVIEW

General Application of Landsat for Water Study

Since the first Landsat images became available, use in water studies has proven quite valuable. The imagery not only displays water bodies over a large area of the earth surface but also provides information pertaining to the characteristics of water bodies. Landsat imagery is a useful tool for the inventory of water bodies in forested areas (Erb, 1973) as well as in grasslands (Work and Gilmer, 1976). The employment of Landsat data for measuring and monitoring sediment density and transport, water levels, eutrophication and other environmental conditions has also proven worthwhile (Moore, 1978; Ritchie et al., 1976; and Brooks, 1975).

Factors Affecting Pixel Reflectance Values

Several factors affect the amount of reflected energy recorded by the MSS over water. Depending on the type of information a researcher is seeking to obtain from MSS data, some factors may prove to be a hindrance to accurate analysis of water bodies or may actually enhance information regarding the characteristics of water bodies. Sun elevation, atmospheric effects, surface roughness, and physical characteristics of water bodies are factors which determine the amount of reflected energy reaching the scanner from water (Moore, 1978). Pixel size affects the way the reflected energy reaching the scanner is actually recorded (Grabau, 1976).

Sun Elevation and Atmospheric Effects on Water Detection

The amount of solar radiation which reaches a water body is affected by the atmosphere and sun elevation. As the sun angle decreases, less direct solar radiation reaches the water body because it must travel through more of the earth's atmosphere and therefore has a greater chance to be backscattered and absorbed before reaching the water. The spectral energy which is backscattered by the atmosphere can be detected by the scanner causing 'contamination' of reflectance values (Moore, 1978). Atmospheric scattering increases the signal received by the scanner and is a more serious problem with shorter wavelengths (Sabins, 1978).

Backscatter of spectral energy results from the interaction between light and the molecules and particulates in the atmosphere. Sabins (1978) describes selective scattering as that which occurs when light interacts with molecules and particulates which are approximately the same size or smaller than the spectral wavelength. Nonselective scattering is caused by the interaction of light with particulates such as fog and dust which are greater than 10 times the spectral wavelength (Sabins, 1978).

Effects of atmospheric scattering are greatly reduced through correction techniques performed on the data before it is received by the user; however, some contamination still exists. If only one Landsat scene is used in a study, any remaining atmospheric contamination, unless abnormally high, should have very little affect on analysis because in most cases the contamination is fairly constant over the entire scene. The problem of atmospheric contamination will be greatest when several Landsat scenes are compared. This is brought about by the variation in atmospheric conditions over time which cause the amount of absorption and backscatter to vary from scene to scene (Moore, 1978).

Effects of Water Body Characteristics on Detection

When solar radiation reaches water, three types of interaction may occur: (1) the light may be reflected by the water surface, (2) it may be absorbed by the water, or (3) it may be backscattered by water molecules or other matter below the surface (Scherz and Van Domelen, 1975). Energy reflected by the water surface is white light and when viewed by a scanner is referred to as sun glint. The amount of sun glint detected is determined by the elevation of the sun or roughness of the water surface. Although more light is reflected from the water surface at low sun angles, less sun glint is detected by the scanner than when reflected at high sun angles. This occurs because the light reflected from the water surface is mirrored more directly back toward the scanner (Moore, 1978 and Strong, 1973).

Strong (1973) found that imagery over rough ocean surfaces contained much sun glint when the sun-elevation angle exceeded 55 degrees from the horizon. On the other hand, Work and Gilmer (1976) had no trouble with sun glint when studying relatively calm water surfaces of ponds when sun angle was 59.5 degrees. A rough water surface increases glint very little between sun angles of 20 to 70 degrees and decreases glint at angles less than 20 degrees when compared to measurements over calm water (Moore, 1978).

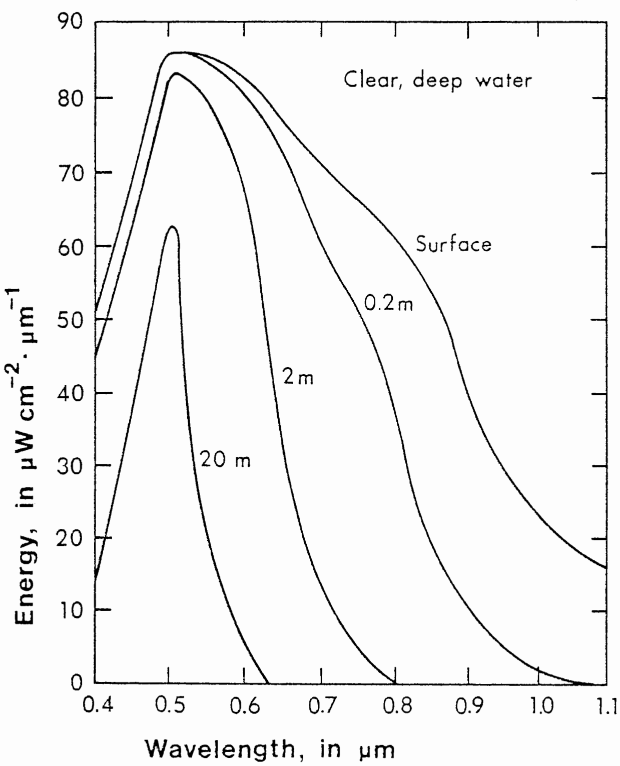
Sun glint is usually considered undesirable for remote sensing purposes because the spectral energy is reflected from the water surface rather than radiated by the constituents within the water which are often the focus of analysis. Although it has not been noted as a major problem in water turbidity studies, sun glint may affect the absolute level of radiation measured by the scanner (Moore, 1978). For this reason it should be taken into consideraton when choosing imagery for water body analysis.

Energy which is not reflected by the water surface is refracted through the water and may either be absorbed or backscattered. The amount of absorption or backscatter is a function of certain water characteristics.

Absorption is caused by the continued downward refraction of solar energy through the water. The depth to which solar energy can be transmitted is strongly dependent on wavelength. Figure 8 illustrates the effect of pure water on the absorption rates of different spectral wavelengths. MSS band wavelengths in the visible spectrum (.4 μm to .7 μm) penetrate much deeper than near infrared wavelengths (.8 μm to 1.1 μm). In fact, the band 4 wavelength (.5 μm to .6 μm) is the only wavelength of light viewed by the MSS which penetrates pure water below 20 meters; whereas, most red light (.6 μm to .7 μm) is absorbed within two meters of the surface and most infrared light within .2 meters (Moore, 1978).

If water bodies were pure water (i.e. without suspended particulates), little problem would exist with misclassification of water features because they would truly radiate a unique signature. In reality many constituents occur within water bodies which contribute to a substantial increase in the amount of light backscattered by the water. These constituents may cause water to be confused with spectral reflectance of other land cover types (Work and Gilmer, 1976).

Physical characteristics of water such as concentration of suspended sediment, sediment particle size and shape, depth, and phytoplankton concentration influence MSS

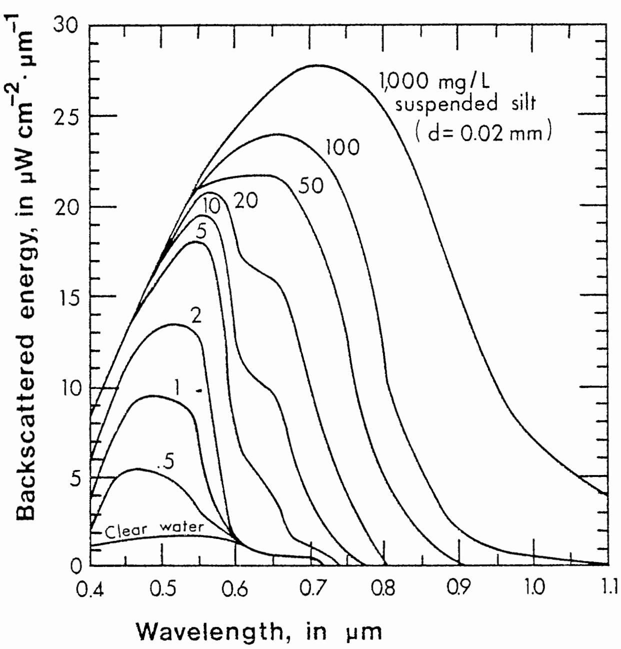


Source: Moore, 1978, p. 458.

Figure 8. Effects of Pure Water on Absorption Rates of MSS Wavelengths

reflectance values because they actually affect the amount of light backscattered from below the water surface (Scherz and Van Domelen, 1975 and Moore, 1978). Suspended sediment has a major effect on the solar flux which is backscattered to the scanner. Numerous studies, for example Scarpace et al. (1979) and Kritikos et al. (1974), have been carried out for the purpose of correlating suspended sediment loads with spectral reflectance detected by the satellite. At present, however, standard quantitative measures of sediment cannot be derived depending on Landsat MSS reflectance values because of the differing affects of the atmosphere on absorption and backscattering over time and the varying combinations of physical characteristics which change from pond to pond (Moore, 1978). Relative measures of suspended sediment, on the other hand, can be fairly well determined for a scene of MSS data (Brooks, 1975).

Brooks (1975) explains that in clear water the backscatter of light peaks at .45 μm; yet, with increasing turbidity the peak shifts toward longer wavelengths. The effect of suspended sediment on backscatter is apparent in Figure 9. The curves, indicating different concentrations of suspended silt, illustrate how the rise in suspended sediment load increases the backscattered flux for different wavelengths of the MSS. Moore (1978) notes that for low to medium concentrations of sediment, the shapes of all curves are similar because of absorption characteristics of water; but, for high concentrations, the shapes of the curves are a



Source: Moore, 1978, p. 460.

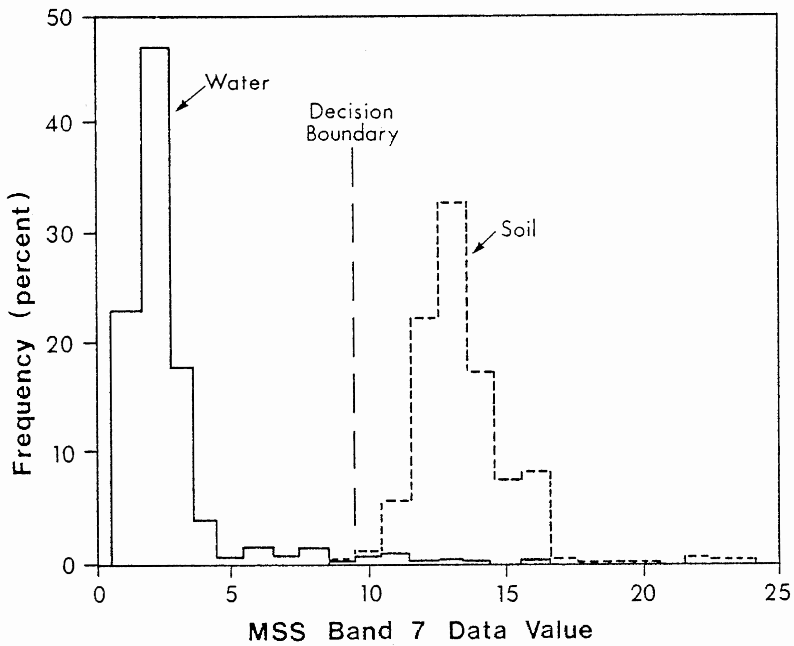
Figure 9. Effects of Suspended Sediment on Backscatter of MSS Wavelengths

result of the absorption characteristics of the sediment particles.

Figure 9 illustrates how an increase in sediment concentration causes a water body to increase in reflectance to the point where it may be confused with other low reflecting land cover such as wet or dark soil. It should also be noted that MSS band 7 is least affected by high sediment concentrations because it is almost entirely absorbed within the top twenty centimeters of water. For this reason band 7 is often used individually for classification of water bodies.

Work and Gilmer (1976) state that bottom reflectance and suspended sediment have little or no affect on the amount of reflected energy received in band 7. Their deduction is based on spectral transmission curves of near-infrared wavelengths in clear water and does not indicate that consideration was made regarding the findings of many others, that shallow water or increasing suspended sediment concentrations increase backscatter in these wavelengths.

They later explain, however, that in their studies of prairie ponds in North Dakota, reflectances of dark Mollisols often approached the reflectance values of water in band 7 and eventually conclude that, in frequency histograms of band 7, soil and water reflectance values overlap because of shallow or sediment loaded water (Figure 10). The decision boundary in Figure 10 indicates the cutoff value chosen to separate the majority of water



Source: Work and Gilmer, 1976, p. 688.

Figure 10. Overlap of Water and Dark Soil Radiance

reflectance values from soil reflectance values within the overlapping region.

Work and Gilmer do not discuss whether an abnormally high number of ponds in their study contain high concentrations of suspended sediment. A greater overlap between water and soil reflectance values might exist in a frequency distribution of numerous ponds with high suspended sediment concentrations.

Suspended sediment varies in size from sand to colloids. Sand (.02 mm to 2.0 mm in diameter) within a water body is usually only detectable through remote sensing when the water is clear enough to allow light to reflect off sand on the bottom. In water catchments containing high sediment concentrations, sand particles would not contribute to water reflectance values unless an in-flowing or out-flowing current were swift enough to pick the sand up in suspension. Silt (.002 mmd to .02 mmd) and clay (less than .002 mmd) particles are more easily suspended in water catchments, especially in shallow areas where wind can stir the water. These particles contribute significantly to the amount of backscattered light from water. Dissolved constituents called colloids produce little backscattered light unless present in very high concentrations (Moore, 1978).

Moore (1978) explained that a few milligrams per liter of suspended fine clay produced the same amount of backscattered light as several thousand mg/l of suspended sand. A greater amount of scatter is caused by clay because a fine-grained material is made of more particles than an equal weight of coarse-grained sand. Furthermore, at high concentrations (over 200 mg/l of sand or 2 mg/l of clay and colloids) the suspended particles produced a distinctive spectral signature; whereas, at lesser concentrations the signature is dependent on the water characteristics affecting light absorption.

If enough light is transmitted to the bottom of a pond and reflected to the scanner, the reflectance from the bottom of the pond may be detected. The depth at which this is possible decreases as the wavelength of light increases or as suspended sediment increases (Moore, 1978). Bottom detection decreases as wavelength increases because of water penetration characteristics explained previously. If the water body is fairly clear and shallow, some solar energy reflected from the bottom can be recorded by the satellite. Table I indicates the depth at which bottom reflectance is detectable in water containing no suspended sediment.

Changes in phytoplankton content can also increase backscatter which, in turn, increases water reflectance. Phytoplankton concentrations increase in the spring and decrease in the fall with the peak of concentration in late summer (Scherz, 1977). Witzig and Whitehurst (1981) explain that only very high concentrations of phytoplankton, occurring in late August or September, produce a significant correlation with water reflectance values detected by

Landsat. If eutrophication levels are the focus of study, imagery should be selected near the end of August or early September. If suspended sediment is to be studied, imagery should not be selected during the late summer months because high algae concentrations will strongly influence the spectral reflectance of water bodies.

TABLE I

BOTTOM DETECTION BY MSS BANDS

MSS Band	Depth at which Detection of Bottom is Possible	Depth at which Bottom Reflectance is easily recognized
4	38 m	18 m
5	6 m	3 m
6	2 m	1 m
7	.1 m	---

Secchi Disk

Many studies have used a variety of methods for gathering and correlating water turbidity measurements with water reflectance values detected by Landsat. One of the simplest and most common methods of gathering turbidity data for this purpose is the Secchi disk.

Although the Secchi disk provides a good relative measure of turbidity for correlation with Landsat data, it has some disadvantages because it is merely a visual measure. It does not indicate the degree to which each particular factor, such as concentration and particle size of suspended material, water color, and phytoplankton, contribute to overall turbidity. Moore (1978) points out that because Secchi depths are visual measures, observed values are based on average reflectances across the visible spectrum; whereas, Landsat imagery views the turbidity in more precise wavelength ranges. Moore (1978) also explains that Landsat often detects beyond Secchi depths. Hence, bottom reflectance may contribute to the reflectance recorded by Landsat, eventhough, Secchi depth may be less than water depth. McCluney (1975) states that Secchi depths can be influenced by surface waves which disrupt the view of the disk. Furthermore, significant differences in depth readings may occur among viewers at times of observation.

Despite these disadvantages, Klemas et al. (1973) and Scarpace et al. (1979) have successfully used Secchi depth readings to correlate turbidity with Landsat MSS bands 5 and 6 reflectance values. Both Brooks (1975) and McCauley et al. (1973) have found that concentrations of suspended solids correspond well to Secchi depth readings. McCauley determined that the inverse of secchi depth varies linearly with suspended sediment in concentrations up to 100 ppm when fitting the data with a least squares straight line.

Relative measures of depth and turbidity among water bodies should remain fairly constant over time except in situations where the watershed has been significantly disturbed or during periods of heavy precipitation or high winds. Blanchard (1983) found that secchi disk readings on large reservoirs correlated well with reflectance values from Landsat data taken six years earlier.

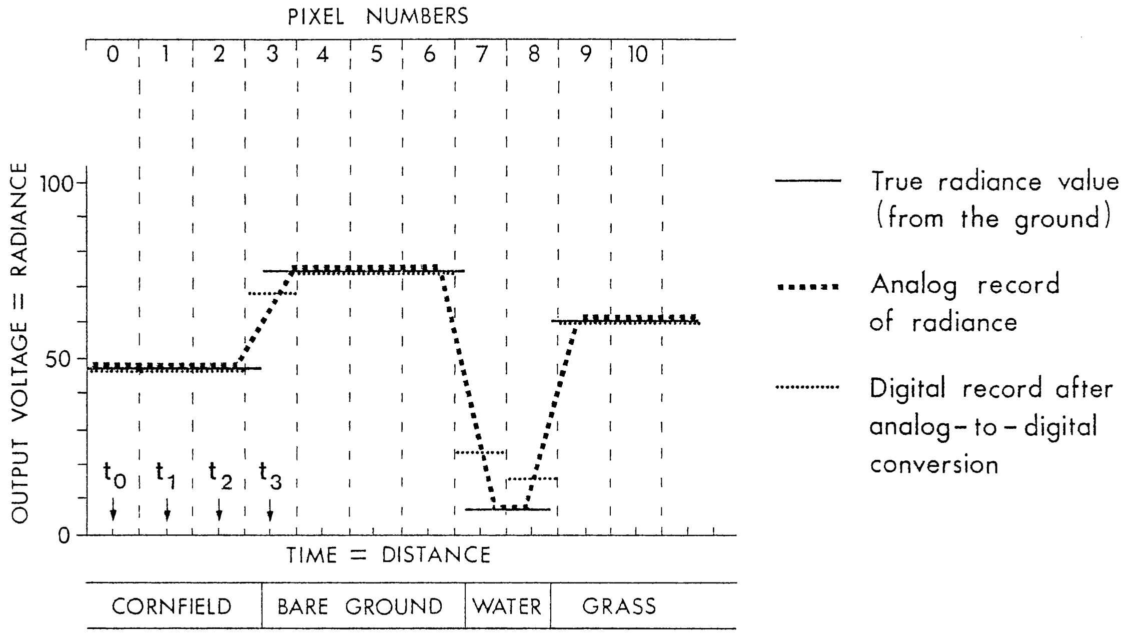
The atmosphere, sun elevation, and a variety of water characteristics can affect the reflectance values recorded by Landsat. When using Landsat data for water study each of these factors should be analyzed and used for the greatest benefit of the study.

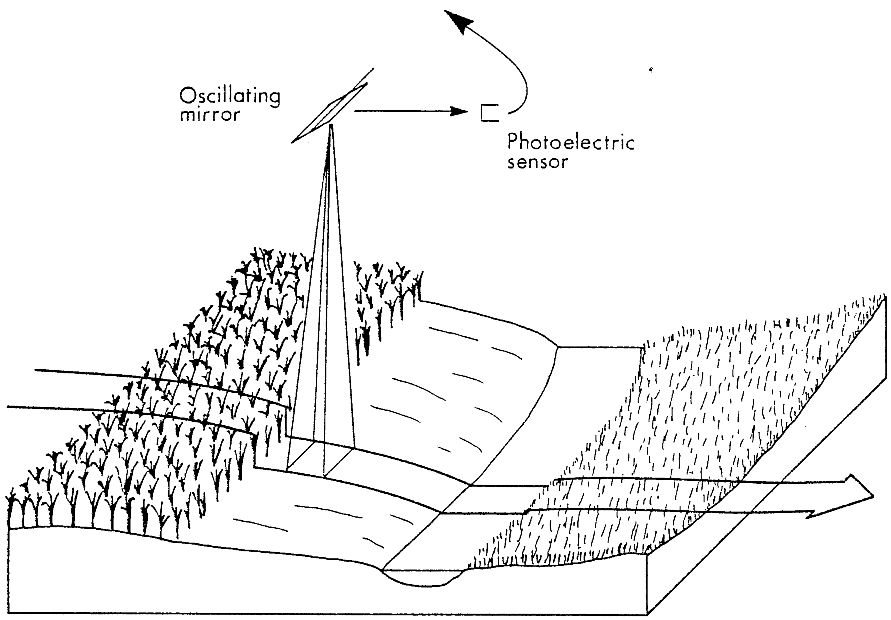
Effects of Pixel Size on MSS Recording of Water Reflectance

Mixed pixels are a major reason water features remain unrecognized on Landsat imagery. As noted earlier, the reflected energy from two or more land cover types frequently combines to give an average reflectance value to a pixel. Such a pixel is termed a mixed pixel (Grabau, 1976). The reflectance values of a mixed pixel depend on the proportion of area within the IFOV that each land cover type dominates and also on the amount of energy each land cover type radiates in the wavelength range for each band.

Mixed pixels cause a problem for the recognition of water bodies when the IFOV for a pixel views the reflectance of water and also the reflectance of one or more land cover types along the shoreline. Figure 11 depicts values for a single photoelectric sensor within a scanner as it views the surface of the earth. The upper portion of the illustration indicates the amount of energy radiated by individual land cover types, the analog signal (voltage output by the sensor), and the sampled analog signal which is converted to a digital value for each pixel.

Because the reflected energy from only one land cover type, a cornfield, is within the IFOV of pixels 0, 1, and 2, the reflectance within the IFOV, and hence, the analog signal remains constant as the scanner sweeps the earth. This allows the sampled analog signal (the recorded pixel value) to also remain constant for each pixel viewing only the cornfield. Pixel 3, however, detects reflected energy from two land features, the cornfield and bare ground. As the scanner sweeps the ground the proportion of bare ground area to cornfield area within the IFOV increases causing the analog signal to increase because the bare ground reflects a greater amount of spectral energy than does the cornfield. At time t_3 , the sample time for pixel 3, the IFOV views an area composed of about three-fourths bare ground and one-fourth cornfield; therefore, the pixel takes on a value closer to that of bare ground. The reflectance that was recorded for pixel 3, 69, was determined by adding together the products of the reflectance values for each land feature times the areal proportion each feature occupies within the IFOV.





Adapted from: Grabau, 1976, pp. 45, 48.

Figure 11. Radiance Values at Three Stages

A mixed pixel will be classified as one of the land cover types which actually contributed to its reflectance values or it may be classified as a totally different land feature from those viewed within the IFOV (Grabau, 1976). Figure 11 illustrates why mixed pixels are often erroneously classified. Instead of resembling the reflectance of a cornfield or bare soil, the value of pixel three is closer to that of grass. Granted this illustration depicts only the reflectance detected by one MSS band; but, the inclusion of the reflectance values for the other three MSS bands during classificaton may complicate the problem even more.

Grabau (1976) explains that the ratio of pixel size to terrain unit size is very important when considering the effect mixed pixels will have on a study. When the size of features in the landscape are smaller than the .62 hectare IFOV, all the pixels will be mixed pixels. When the size of the IFOV and the areal extent of land cover features are approximately the same, the majority of pixels will be mixed. Mixed pixels become less of a problem only when the size of terrain units becomes much larger than the size of the IFOV.

Erb (1973) and Work and Gilmer (1976) discuss the omission of small ponds on Landsat images caused by mixed pixels. Erb found that ponds in forested areas were almost always detected on Landsat black and white images if they were greater than one hectare in size. Work and Gilmer concluded from their study of prairie ponds that water features greater than 1.6 hectares were almost always detected on Landsat band 7 images. They also concluded that detection of a pond in the .4 to 1.6 hectare range was dependent on whether the pond was included in the entire IFOV for a pixel or whether its reflectance was fractionally divided over several pixels. Ponds less than .4 hectare were not recognized at all.

Depending on the orientation of the pixel grid with respect to water features, several things can happen to the size and shape of the features on the imagery. Grabau (1976) explains that mixed pixels around the perimeter of the feature may change the shape of the feature or may cause two distinct features to fuse into one. The feature may also be enlarged or reduced depending on the amount of reflectance it contributes to the mixed pixels and also on the method in which the image was classified.

Work and Gilmer (1976) found that the surface area of ponds was underestimated because mixed pixels containing some water reflectance did not exhibit a definite water irradiance. Furthermore, this error was found to be greater for small ponds and water bodies with irregular shapes, for example, those with a high ratio of perimeter to area.

Irregularly shaped water bodies were underestimated by Work and Gilmer because long shorelines increased the occurrance of mixed pixels. In addition, Grabau (1976) states that long linear arms extending from water bodies are often too narrow to contribute only water radiance to entire pixels. This may cause the arm to disappear when the data is classified.

Summary

Water reflectance values are determined by a variety of factors. Some of these factors have a tolerable effect in that they, by themselves, do not change water reflectance to the point that the water feature may be misclassified. The factors of mixed pixels, high suspended sediment levels, and bottom reflectance because of shallow water may change water radiance values enough to cause an erroneous classification of water pixels. Although several methods have shown some success in reducing the problem of mixed pixels, the effects of suspended sediment and bottom reflectance on water body detection have received little attention.

CHAPTER IV

METHODOLOGY

Overview

An analysis of the effects of suspended sediment and depth on the detection of water bodies by Landsat requires that data be collected from a study area that exhibits a wide range of pond sizes, depths, and levels of turbidity. Factors which affect these variables need to be similar during the collection of observations for each variable. This entails that climatic factors must be the same prior to collection of the data and that watershed characteristics are not disturbed or changed within the period between collection dates. Such a task is difficult when a period of years lapses between dates of data availability.

Data chosen for this study are from ponds within forest or rangeland surrounding Stillwater, Oklahoma. The data consists of measurements of pond surface area determined from the most recent aerial photos dated April 4 and 8, 1979, Landsat imagery taken June 12, 1979, and field measurements of suspended sediment and depth collected March 12-15, 1983. Measurements of surface area from the photos were used to represent actual surface area of the ponds at the time of satellite overpass. Depth and Secchi disk measurements were also used to represent the conditions of each on the Landsat date.

The data were analyzed regarding the amount of error in detection of pond surface area for five Landsat classifications. Linear regressions were performed to determine the effect of suspended sediment levels and depth on the amount of error in water surface area detected by Landsat.

Study Area

The study area (Figure 12), located in central Payne County and southeastern Noble County in north-central Oklahoma, encompasses approximately 355 square miles. This size of study area was necessary to insure that the variables studied would exist in a variety of combinations and that enough water bodies would appear on the imagery for statistical analysis. Not all ponds within the area were studied. By studying aerial photographs, 42 sections were selected which contained 124 ponds suitable for study.

The water catchments within the study area provided the variety of study factor combinations required by this study. An ample number of water bodies exist within the area; most ranging in size from small ponds less than one acre (.41 hectare) to lakes of approximately 15 acres (6.03 hectares). Water depth and suspended sediment also vary from pond to pond.

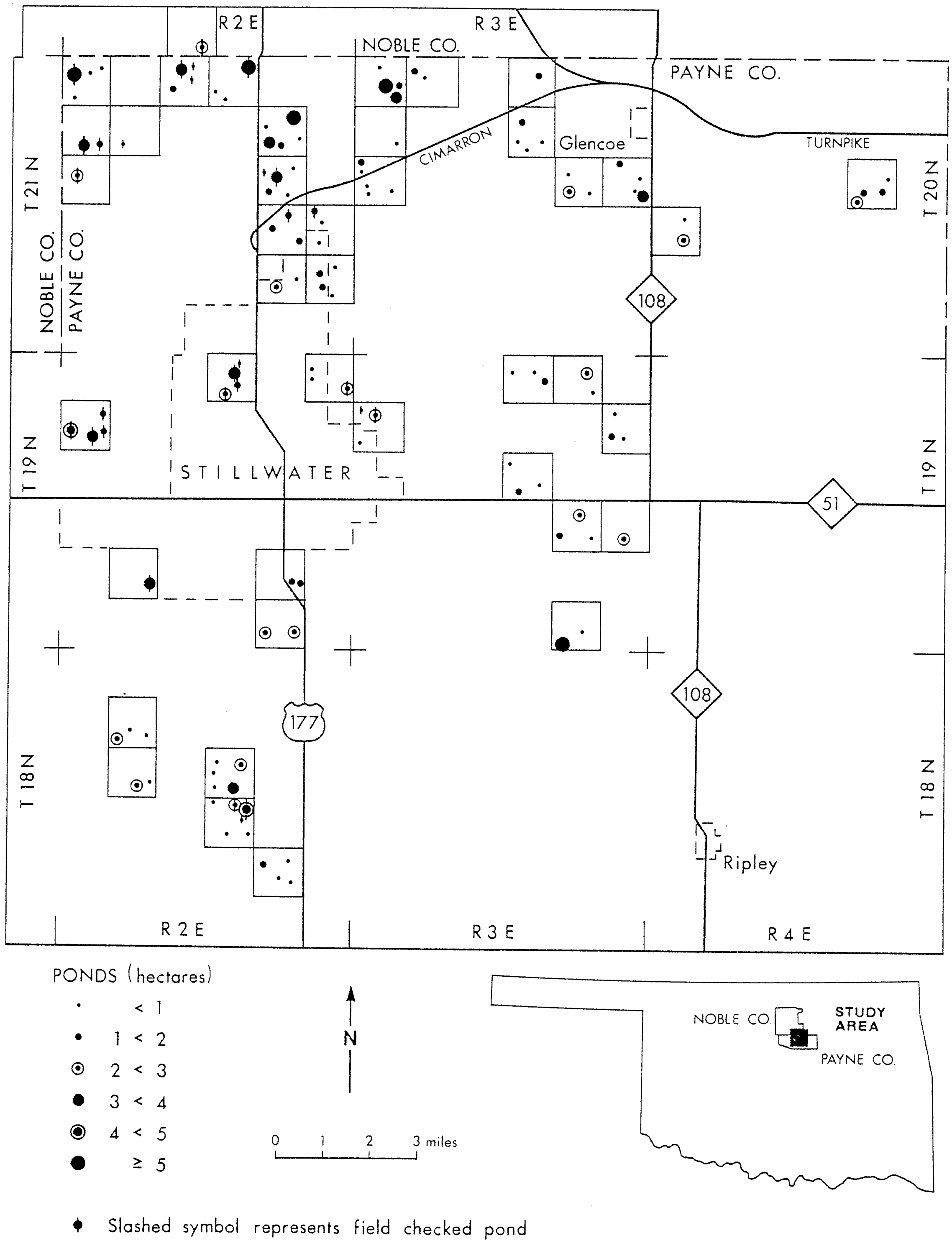


Figure 12. Study Area

Landsat Data

Landsat Scene

The Landsat data chosen for this study is the Guthrie, Oklahoma scene dated June 12, 1979. This scene most closely corresponds to available aerial photography of Payne County. Computer compatible tapes (CCTs) supplied the digital data for the scene analysis performed at the Center for Applications of Remote Sensing (CARS), Oklahoma State University. The classification techniques were generated on a Perkin Elmer 8/32 mini-computer through the use of the Earth Resources Laboratories Applications Software (ELAS). The digital data were reformatted for use with the ELAS software and were geographically referenced to Universal Transverse Mercator (UTM) coordinates from United States Geological Survey (USGS) 7.5 minute quadrangle maps. Resampling of the data through geographic referencing converted the data to 50 meter cells.

Visual analysis for water classification was possible with image display on a COMTAL image processor and a Versatec electrostatic printer/plotter. Visual interpretation for determining and combining final water classes was facilitated by referring to USGS 7.5 minute quadrangle maps dated 1979 and to water bodies traced from aerial photographs supplied by Payne County Agricultural Stabilization and Conservation Service (ASCS) dated April 4 and 8, 1979.

Selection of the Water Class

When water classes were being determined, care had to be taken to insure that the cutoff values or classes between water and wet soil were as accurate as possible. In order to choose the most accurate cutoff point, classes or values were combined until pond sizes on the imagery resembled pond sizes known from the photographs. The high reflectance values of water in the band 7 and band average routines, and certain classes for the unsupervised classifications added more surface area to some ponds, but at the same time, introduced a large number of cells representing wet soil. The point at which the ponds were classified as accurately as possible without introducing more wet soil pixels than water pixels was chosen as the cutoff value or class for each classification.

Unsupervised Classifications

Three unsupervised classifications were performed on the scene. By adjusting the upper-bound standard deviation parameter for each classification, the resulting classes were generated differently. The upper bound of the standard deviation for the first unsupervised classification (UC1) was allowed to default to 1.0. The upper bound of the standard deviation for the second unsupervised classification (UC2) and the third (UC3) was set at 1.5 and .7 respectively. The search routine in ELAS was used to create training fields of homogeneous pixel signatures. Statistical parameters other than upper-bound standard deviation were allowed to default to ELAS generated values.

The search routine operates by passing a three-by-three pixel window through the data. Based on the statistical parameters set, the routine determines whether the pixels in the three by three window provide a homogeneous training field by which to group similar pixels. If pixel signatures within this window fall within the statistical boundaries, the statistics of that training field (the mean and covariance matrix) are held in computer memory until 60 bins are filled. When the bins containing the statistics for individual training fields are filled, the pair of statistics with the smallest scaled distance between them is merged to make room for one more three-by-three window. The search routine continues to collect a new training field and merge pairs with smallest scaled distance throughout the scene. The MAXL routine in ELAS then uses the principal of maximum likelihood to put each pixel into the class, or training field, in which it best fits.

UC1 created 45 classes, seven of which were interpreted as water. UC2 created 50 classes of which eight were categorized as water and UC3 created 42 classes with five interpreted as water. Even if the number of classes had not changed for each classification, the pixels belonging to each class would probably have changed because of the difference in sampling brought about by the standard deviation upper bound.

The adjustment of the standard deviation upper bound for these unsupervised classifications provides a means for 'fine tuning' the technique for a more accurate classification of shallow or turbid water bodies. After water classes were determined, electrostatic plots were produced for each classification. Only classes which were comprised of mostly water pixels were displayed on the plots.

Band 7

The band 7 threshold technique required only visual interpretation for determining the water class. The classes were determined by highlighting individual reflectance values in relation to the rest of the scene and determining through geographic location whether they represented water reflectance. As with the unsupervised classifications, pixels with definite water values were combined and printed on the electrostatic plotter.

Band Average

Band 6 has the potential to produce a significant visual enhancement of water when averaged with band 7 because it displays a good land-water interface and shows relative suspended sediment levels well. The programmable calculator module (PCAL) in ELAS was employed to average band 6 pixel values with band 7 values. The resulting pixel values were then classified and plotted in the same method used for the band 7 routine.

Collection of Analysis Variables

Water Surface Area

Measurements of water body surface area were taken from black and white aerial photographs supplied by the Payne County ASCS office. The photos were flown on April 4 and 8, 1979 at a scale of 1:7,920. All the ponds within 42 selected sections were carefully traced from the photos and digitized in order to determine the surface area of each. The large scale of the photos helped minimize any error incurred from the tracing of the water bodies.

Work and Gilmer (1976) determined the smallest pond detectable by Landsat to be .4 hectare. Because no ponds smaller than .4 hectare were detected by Landsat in this study, only ponds above this size were included in this analysis. Had a pond less than .4 hectare appeared on the Landsat plots, the lower size limit of ponds used in this study would have been changed to account for that pond.

Once ponds less than .4 hectare were eliminated, 124 ponds ranging in size from .41 to 6.03 hectares were available for study. Figure 13 is a histogram of water body surface areas for the 124 ponds studied.

Depth and Suspended Sediment

Water depth and suspended sediment measures were taken in the field for a sample of 29 ponds on March 12-15. Most of these ponds appeared on at least several of the Landsat

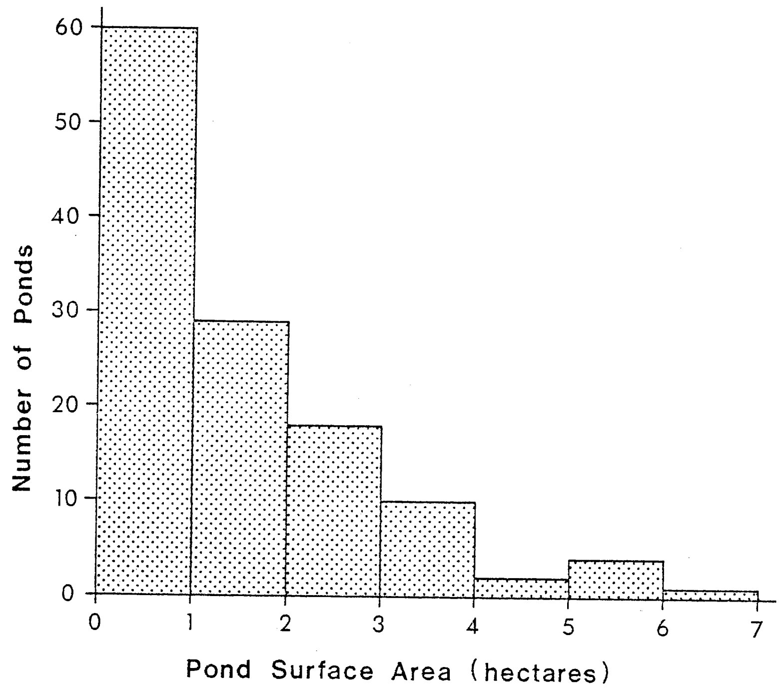


Figure 13. Frequency of 124 Study Ponds by Size

plots; although, several did not appear on any of the plots. All the 124 ponds available for study were analyzed prior to field checking regarding the accuracy of the classification of surface area by calculating the amount of error between pond sizes from photos and those from Landsat. This insured that the majority of ponds sampled for depth and turbidity measures were classed as water by at least several of the routines.

An attempt was also made to collect data from several ponds in different size ranges (Figure 14). In this respect, the sample of ponds field checked was not randomly chosen; however, the final selection of ponds can be considered random because they were chosen on the basis of accessibility and permission from land owners.

A stratified random sample was taken for each pond in the field study. The ponds were sampled for both depth and suspended sediment at points which were approximately equal distances apart. The number of samples for each pond depended on pond size. Generally, one sample location occurred within every .62 hectare; a distribution chosen because it corresponds with the land area detected by the IFOV of the multispectral scanner.

Measurements of pond depth and turbidity were collected from a kayak so that sediment would not be disturbed in shallow areas. At each sample location, turbidity was measured with a Secchi disk. Depth was then measured with a weighted cord. Both measurements were recorded in meters.

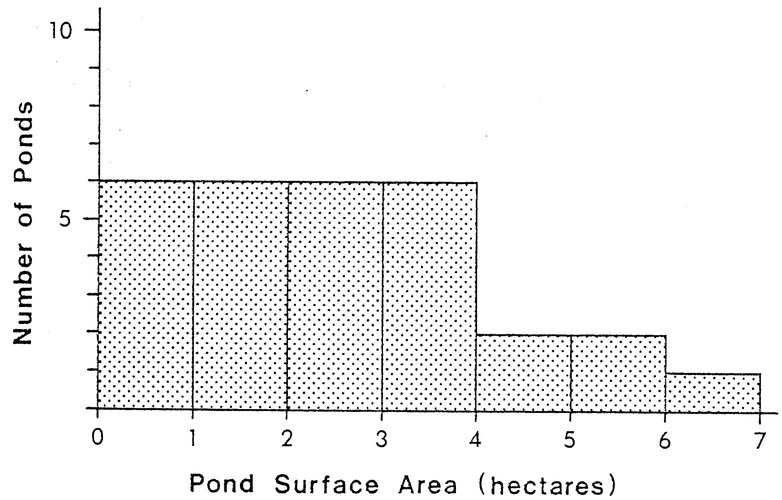


Figure 14. Frequency of 29 Sampled Ponds by Size

Factors Influencing the Data

The analysis variables for this research were collected at different times. The external factors which influence the independent variables of depth and turbidity should be measured at the time the Landsat observations are recorded; but, the data used in this study are from different dates, even years apart. By analyzing the factors which affect the study variables at each date, several assumptions were made. The time period between data collection dates for each variable introduces an opportunity for significant change within the variables. For this reason care had to be taken to account for changes in the study variables that may have been produced by variations in the external factors. Watershed characteristics and weather conditions previous to data collection, and season of data collection are the factors which most strongly influence the variables of surface area, depth, and turbidity within the study.

Sun angle at the time of Landsat overpass was 40 degrees while the sun angle at 12:00 a.m. during the days of in situ data collection was approximately 39 degrees. Because Secchi disk measurements were taken throughout the day, sun angle was less than that at the time of Landsat overpass; hence, less direct solar radiation was available for disk detection. This is not of great concern because relative Secchi disk levels would be affected very little by the change of sun angle between the collection dates. Also, because of the low sun angle, sun glint was not found to be a problem on the Landsat data.

Daily variation of sun angle may have produced only slight error of Secchi disk readings. Solar energy penetrates water at a greater depth when more directly overhead. The observed Secchi disk readings taken in the morning or afternoon, however, showed little if any reduction in disk visibility as a result of sun angle. In fact, one of the shallowest Secchi readings was taken near noon and the deepest was taken toward late afternoon. Little problem existed with waves obstructing the visibility of the disk. If waves were a problem, the boat was turned so as to block the wind from the side in which the reading was taken.

Watershed conditions were not studied for the date of the Landsat scene but were visually analyzed on the aerial photography and in the field for the 29 field checked ponds. Watershed characteristics which would have had the most influence on the research variables are those dealing with soil or vegetation disturbances. Observations of construction were sought within the watershed on the photography and in the field. Exposed soil within the watershed of a pond could produce above normal sediment loads from precipitation runoff and could reduce depth over time. No signs of construction or distrubed soil were evident on the photos or in the watersheds of the 29 ponds sampled.

The majority of the land cover within the watersheds is pasture. Some cropland and some forest also surround a few of the ponds. The land cover type surrounding the ponds was checked in the field to determine whether a change had occurred since the photo date. No noticeable change had occured in the vegetation types surrounding the water bodies visited.

In watersheds covered mostly with pasture, the amount of grazing would have affected the ability of precipitation runoff to transport sediment into the ponds. The amount of grazing within pasture surrounding ponds is not assessable for the Landsat date. Although the degree of grazing during the collection of the field data can be determined, its affect on the turbidity of ponds cannot be compared with the affect of grazing on turbidity during Landsat overpass. For this reason, grazing effects on turbidity are considered constant.

Another important factor which influences the variables in this study is the amount of precipitation prior to data collection. Precipitation affects the depth and surface area of ponds and may affect suspended sediment concentrations if rain occurs prior to data collection.

Pond sizes measured from the aerial photos are probably representative of pond sizes during Landsat overpass. The absolute measures of suspended sediment and depth for each collection date are not considered constant; however, the relative differences between ponds for each variable are assumed similar to the relative pond to pond differences detected by Landsat. If only relative suspended sediment levels and water depths are similar for each collection date, statistical analysis would still show whether an increase in suspended sediment or bottom reflectance decreased the water classification accuracy of Landsat data.

The amount of precipitation for three months prior to the aerial photography totaled approximately 5.3 inches. Precipitation between the date of aerial photography and the Landsat date totaled approximately 11 inches and that for three months prior to collection of depth and Secchi disk measures totaled approximately 6 inches. Because ponds were near volume capacity on the photos and during in situ data collection, the greater amount of rain prior to Landsat overpass should not have produced much of an increase in water surface area and depth. Any increase in water in the ponds during the Landsat date could not have increased depth much over that existing during the depth collection date because any excess water would have drained over spillways. Relative measures between ponds should be consistent with those at the time of Landsat overpass. Also, because rainfall amounts were similar for several stations around the study area at each collection time, it was assumed that the water depths varied similarly for each date.

Relative suspended sediment concentrations at satellite overpass also need to be similar to those at the time of Secchi disk measurements. The effects of precipitation on suspended sediment prior to data collection dates are more difficult to assess than the precipitation effects on depth.

The amount of rain in the week prior to satellite overpass averaged 2.7 inches; whereas, precipitation prior to collection of secchi disk measures averaged .9 inches. The 1.8 inches difference between the two dates may have increased the suspended sediment load to a greater yield for the Landsat scene than for the Secchi disk measures.

The last day of rain before the image date was June 10. This allowed approximately two days for suspended sediment to settle out before the imagery was taken. The amount of suspended sediment contributed by the rain would depend on the amount and proximity of exposed soil and the density of vegetation within the watershed. The amount of exposed soil should be less during Landsat overpass than during in situ data collection because of the increased vegetation growth from March to June. The increase in vegetation reduced the amount of soil available for transport and decreased the velocity and, hence, the sediment carrying capability of the surface runoff. This reduced the effect of the greater precipitation amount on turbidity prior to the Landsat overpass. The degree of grazing within watersheds may have affected the level of turbidity in the ponds; however, for reasons previously mentioned, grazing effects are considered constant for this study.

Most of the sediment, especially the larger particles, should have settled out prior to overpass. Any remaining turbidity resulting from runoff should consist primarily of some clay and increases in colloid concentrations.

Wind speeds for three days prior to Landsat overpass averaged four miles per hour; whereas, speeds for three days prior to the first day of Secchi depth measures averaged five miles per hour. Wind speeds on the day of Landsat overpass averaged 1.3 mph. The lowest average wind speed during in situ data collection was 1.3 mph, while the highest average was 4.5 mph. The effect of winds on turbidity prior to and during Landsat overpass was slightly less than that during in situ data collection. The differences in turbidity resulting from the wind should not be great considering the small differences between the speeds at each date and the relatively low wind speeds overall.

Phytoplankton levels should have only limited effects on water reflectance differences between each collection date. Witzig and Whitehurst (1981) noted that only extensive concentrations of phytoplankton contributed to a change in reflectance levels of water. They also stated that such concentrations occured in late July or August. This suggests that any difference in phytoplankton concentration at each collection date may have only a slight, if any, affect on water reflectance values at each collection date.

In summary, actual surface area estimated for the Landsat date by digitizing the aerial photos should be fairly accurate. Pond depths should be similar at in situ and Landsat collection dates. The effects of turbidity levels on water reflectance should result primarily from suspended sediment. Factors which affect the amount of suspended sediment in the ponds, such as wind, precipitation, and exposed soil, may have varied enough within individual ponds at each collection date to have caused the turbidity data at in situ collection to be unrepresentative of that at the time of Landsat overpass. Precipitation just prior to Landsat overpass was greater than that just prior to in situ data collection; however, the greater vegetation density and lower wind speeds during Landsat overpass should have helped to compensate for this difference. Any association between suspended sediment levels and water classification error should show up even if only the relative turbidity differences among ponds are the same for each collection date. It is possible, however, that the factors affecting turbidity levels may have produced enough variation in relative turbidity levels at each collection date to cause any relationships to disappear.

CHAPTER V

ANALYSIS

Procedure

This analysis seeks to determine if differences in the accuracy of water classification exists between several classification routines. An analysis is also made to test the hypothesis that high suspended sediment levels and bottom reflectance, resulting from shallow water, increase erroneous classification of water bodies. The first phase of the analysis will utilize surface area measures determined for 124 ponds from aerial photos and from five Landsat classifications. Raw data and descriptive statistics for these variables are listed in Table II and Table III in the Appendix. The second phase of the analysis will introduce Secchi disk measures and depth measures for 29 of the 124 ponds. Raw data and descriptive statistics for these variables are listed in Tables IV, V, and VI in the Appendix.

The surface area of each pond digitized from the aerial photos was assumed to be the actual pond size during Landsat overpass. Pond surface areas determined from Landsat were checked for accuracy by calculating an error value for each of the 124 ponds (Table VII, Appendix) The error was determined by the equation:

$$E = \frac{p - L}{p}$$

in which: E = the degree of error

p = the surface area determined from photos

L = the surface area determined from Landsat.

The nature of the error factor makes it suitable for use in regression analysis. If Landsat overestimated the actual surface area, a negative number would result. If underestimation occurred, a positive number resulted with a maximum of one, meaning the pond was not detected at all. Zero would of course mean that the pond was detected by Landsat at its actual size. This equation was calculated for each of the 124 ponds and for each classification.

Secchi disk measures varied greatly from pond to pond; yet, within pond readings were quite similar. Depth was also found to vary considerably between ponds and in a few instances, within ponds; however, for the majority of ponds it was relatively consistant. Because of the homogeneity of the within pond readings, the Secchi disk and depth measures were averaged for each pond sampled (Table V and Table VI). This simplified the analysis even though it generalized the data.

Several methods of analysis were used to compare the accuracy of each classification routine. Linear regression was then performed on the observations from the group of 29 ponds to determine the correlation between depth and the error in surface area for each Landsat classification. Linear regression was also performed with Secchi depths and surface area error for each classification.

Analysis Results

Comparison of Landsat Classifications for Water Detection

The classification routine which most accurately identified ponds was evident in the early stage of analysis eventhough all the routines underestimated most ponds. A comparison of the average error for each classification technique showed the band 7 routine to be superior to the other classifications. The average error for 124 ponds in the band 7 routine was 62 percent. The band average produced a mean error of 73 percent and UC1, UC2, and UC3 produced significantly higher error means of 88 percent, 87 percent, and 87 percent, respectively.

These average error values indicate that approximately 38 percent of water surface area for the study ponds was classified as water through a band 7 routine. Only 27 percent of the water surface area for the ponds studied was classified as water by the band average. UC1 provided only 12 percent accuracy and UC2 and UC3 were only slightly better with 13 percent accuracy for each. The amount of error for at least the band 7 and band average routines is not high considering the majority of ponds studied were less than two hectares in size. Because of the small pond sizes, a high probability existed that the majority of the pixels would contain mixed reflectance of water and land. This brought about a high probability that these ponds would be underclassified. Studies of much larger water bodies (i.e., Malila et al., 1975) produce a much higher accuracy because the ratio of pixels containing mixed reflectance to those pixles containing only water reflectance is much lower than that ratio existing in this study. Also, several of the ponds studied were long and narrow or had long linear arms which increased the possibility of mixed land/water pixels and increased the probability of misclassification.

The method by which the water class was selected for the band 7 and band average routines insured that the highest possible accuracy was obtained for these classifications. Reflectance values were added to the classifications up to the point in which pond sizes were most accurately represented without introducing a large number of extraneous pixels.

Table VIII, in the Appendix, displays results of paired t-tests performed on several variables. The Means procedure in the Statistical Analysis System (SAS) software was used to determine if the means for the variables are the same. The Mean procedure calculates a t-statistic from the differences between two sets of observations. The t-statistic is generated for the hypothesis that the mean of the differences is equal to zero.

The first five sets of comparison variables indicate that the means of the pond sizes from photos are significantly less than those from the Landsat classifications. This was determined at the .05 significance level for 23 degrees of freedom in a one-tail test. The critical t-value at this level is 1.645 which causes the rejection of the null hypothesis because all observed values of t were above this value. It can be concluded from the first five tests that each Landsat classification significantly underestimated the pond sizes.

The ten other comparison variables were analyzed to determine whether significant differences existed between the detection capabilities of each Landsat classification. A one-tail test was used at the .05 significance level to produce the critical t-value of 1.645. All the Landsat classification routines were found to be significantly different from each other with their relationships indicated by the accepted hypothesis in Table VIII. The classifications from highest to lowest rank in accuracy are, band 7 routine, band average routine, UC2, UC1, and UC3.

As a summary of the t-tests, all the classification routines significantly underestimated the actual pond sizes. A significant difference also exists between each of the classification routines in terms of accuracy of water classification.

The reason for the difference in water classification accuracy among the routines is because of the depth at which the wavelengths of the MSS bands used in a particular classification are absorbed by water. Band 7 alone is absorbed in the upper 20 centimeters of water; therefore, suspended particles in the water must exist in very high concentrations to cause much backscatter. Band 6 wavelengths are absorbed mostly within the upper 2 meters of water and have more chance to be backscattered to the scanner. Wavelengths in bands 4 and 5 can penetrate much deeper than those in bands 6 and 7. This gives bands 4 and 5 the greatest capability of detecting energy backscattered by suspended particles in the water.

Band 7 detects less backscatter than the other bands; therefore, it obtains very low reflectance values for water. The average of bands 6 and 7 caused the reflectance values to increase to the point that they overlapped with wet or dark soil more than those for just band 7. This resulted in a greater classification error for the band average.

The unsupervised classifications added bands 4 and 5 to the classification which introduced even more overlap between water and wet soil values, thus decreasing the separability of the two land cover types. By increasing the upper-bound standard deviation, UC2 provided only slightly more accuracy than the other unsupervised classifications; whereas, UC3 provided the greatest classification error.

Table IX, in the Appendix, displays a breakdown in percent error by actual pond sizes for each classification. Ponds between .4 and one hectare in size were classified with the least accuracy. Average error for the band 7 routine holds fairly constant between 41 percent and 47 percent for each class size over one hectare; whereas, the errors for the other classification techniques display more variation with pond size.

This breakdown in size ranges (Table IX) suggests a possible negative correlation between pond size and classification error in the unsupervised classifications. The correlation procedure in SAS was used to determine whether such a relationship actually exists.

Correlation coefficients generated by the procedure show some negative relationships, at a .0001 significance level, between actual pond size and the amount of classification error for that pond. The coefficient for band 7 is -.349. UC1, UC2, and UC3 produced correlation coefficients of -.394, -.458, and -.57, respectively. The band average correlation coefficient was not found to be significant.

These correlation coefficients indicate that classification error does increase some as pond size decreases. This relationship is explained by Grabau (1976) as being a result of mixed pixels. Much misclassification will be caused by mixed pixels when the IFOV is larger than the land feature to be detected. This study was concerned with relatively small water features. The correlation coefficients may have shown stronger relationships if larger water bodies had existed in the sample.

Figures 15-19 are plots of water bodies within the study area which were generated by the five classification routines. The 42 sections from which ponds were selected are indicated on each plot. By referring back to Figure 13 a visual comparison can be made between the ponds classified and those which actually exist.

Effects of Water Depth and Suspended Sediment on Water Classification

The observations of the dependent variable, Landsat error, and the independent variables, pond depth and Secchi disk depths, were analyzed through the univariate procedure in SAS to determine if they were taken from a normal distribution. A W-statistic was produced for the Shapiro-Wilk test of the null hypothesis that the data are a random sample from a normal distribution. This test is appropriate for sample sizes containing less than 51 observations. W is always greater than zero and less than or equal to one with small values of W leading to rejection of the null hypothesis (SAS Institute Inc., 1982). All the variables in this study displayed a W-statistic greater than .82; hence, the null hypothesis was accepted. Each variable contains a random sample of observations taken from a normal distribution.

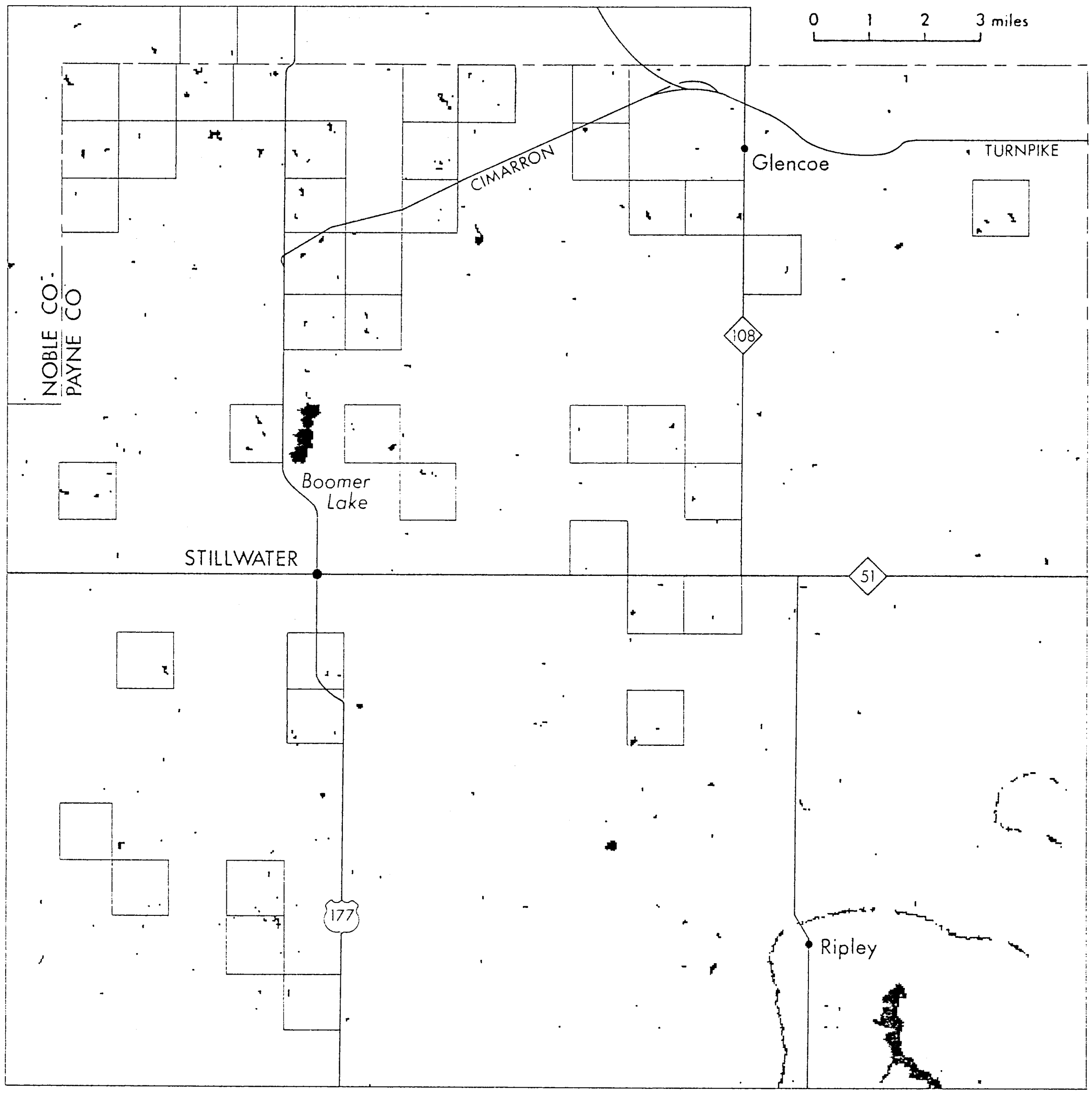


Figure 15. Plot of Water Bodies from the Band 7 Classification Routine

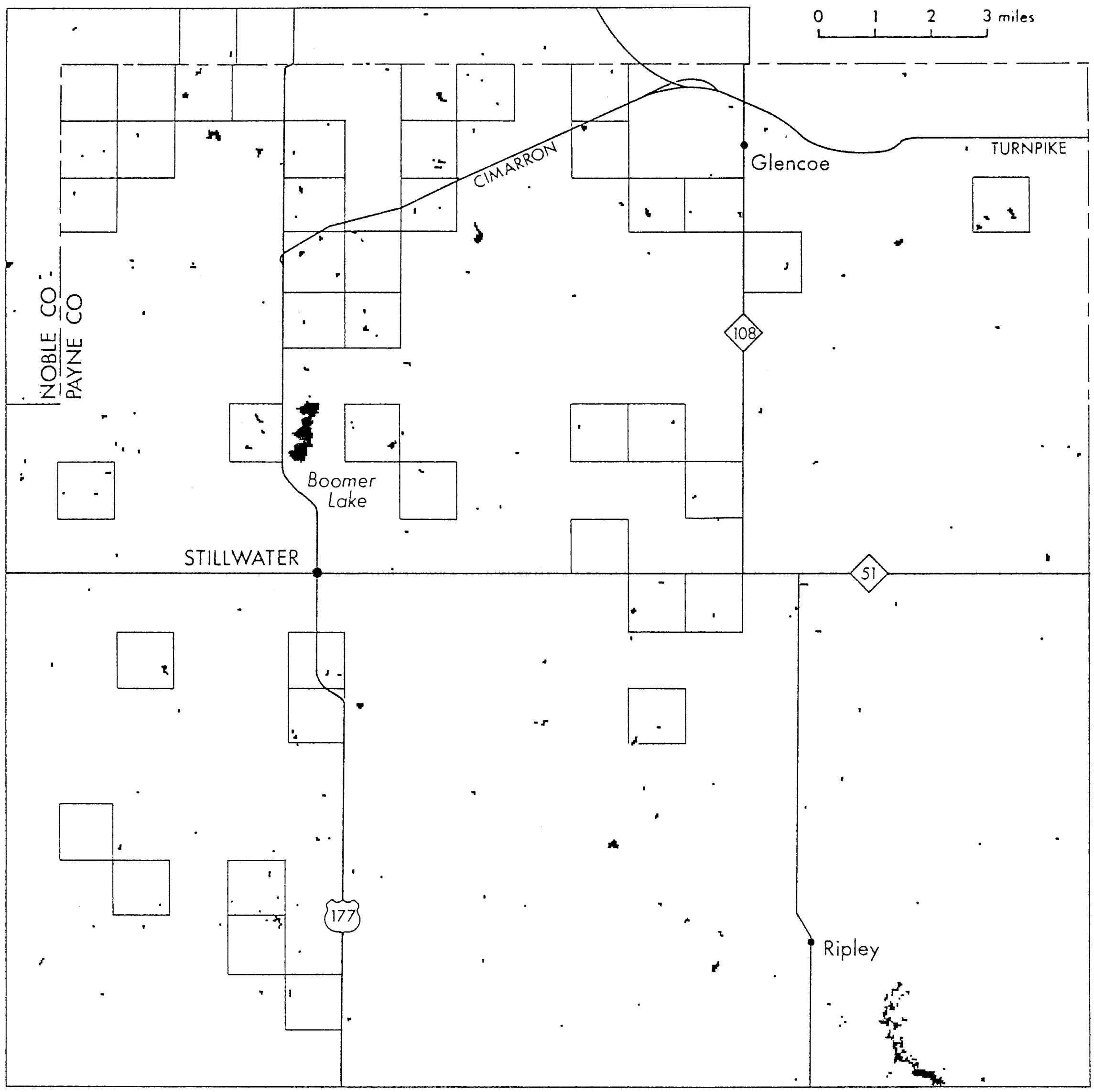


Figure 16. Plot of Water Bodies from the Band Average Classification Routine

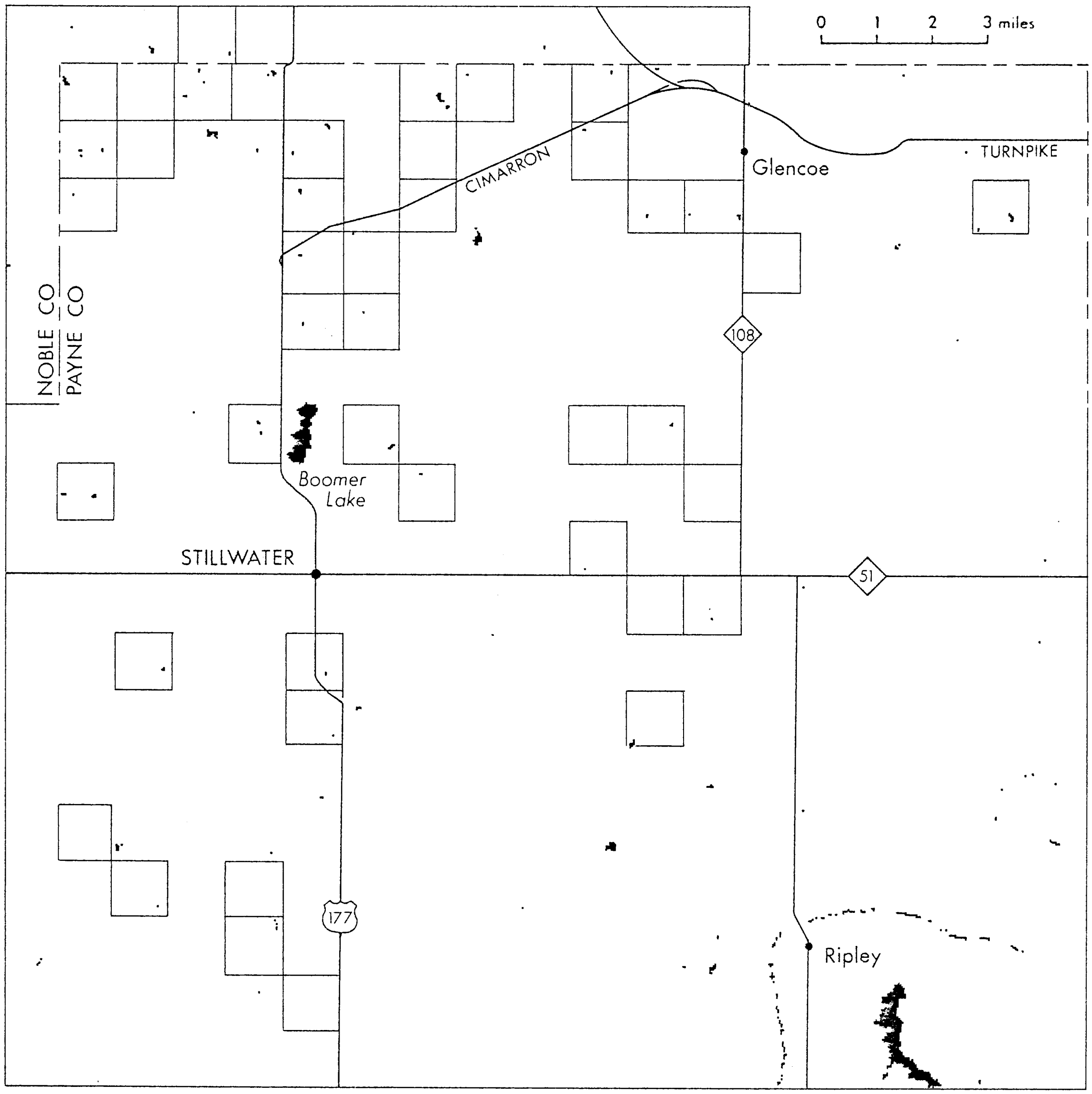


Figure 17. Plot of Water Bodies from UC1

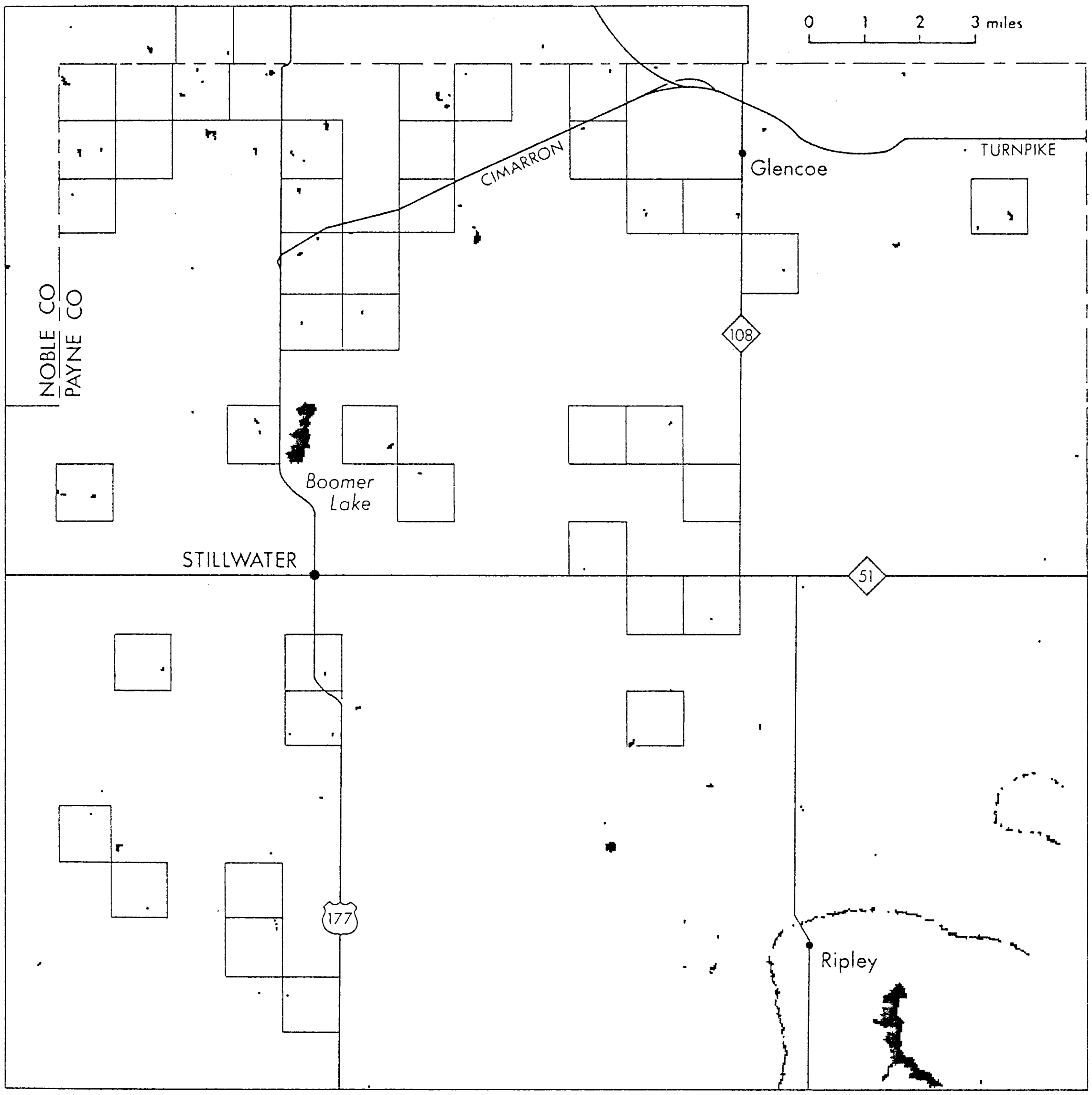


Figure 18. Plot of Water Bodies from UC2

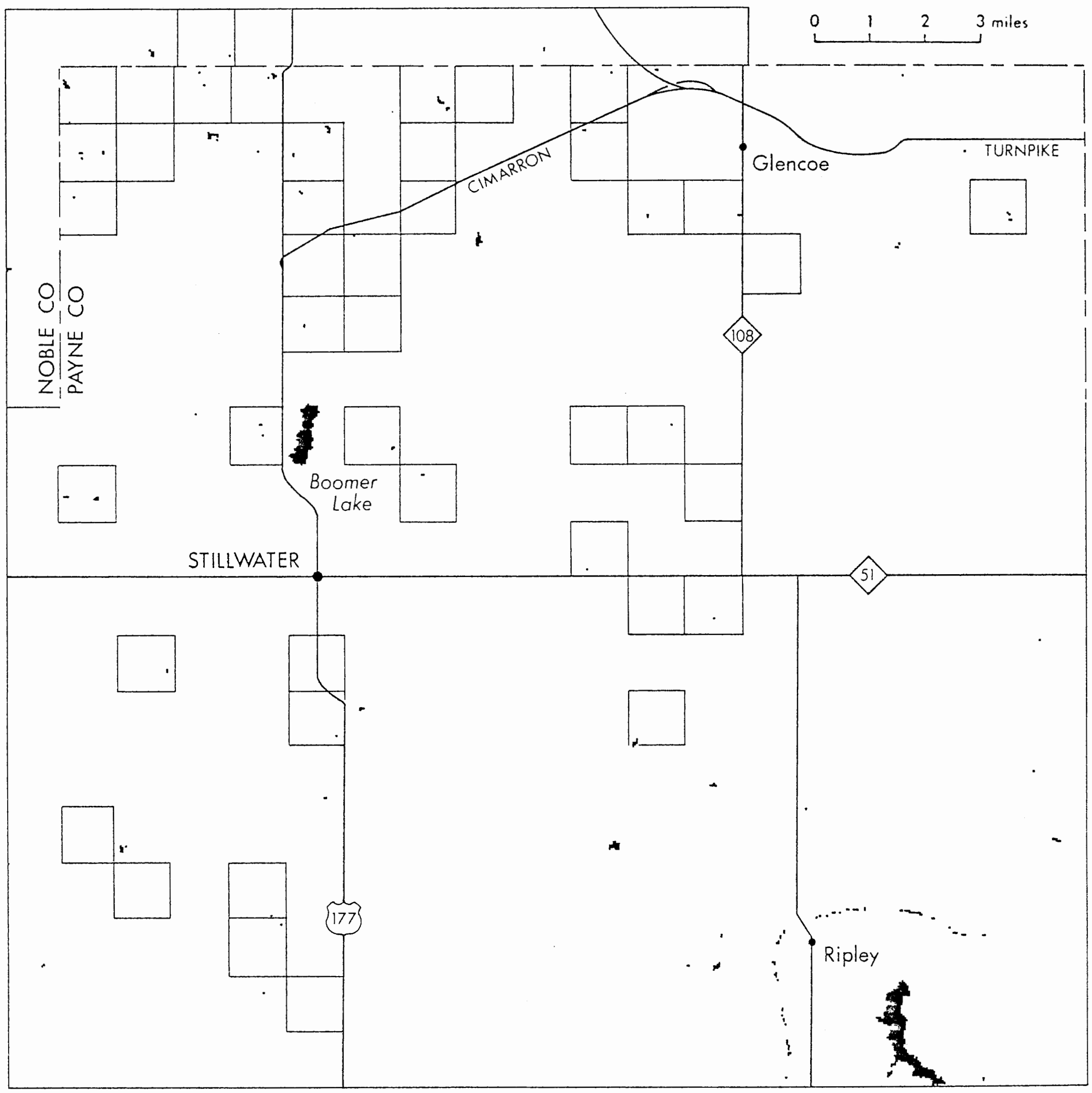


Figure 19. Plot of Water Bodies from UC3

The variables of Secchi depth and water depth were tested to determine whether any association existed between the variables. The correlation procedure in SAS produced a correlation coefficient of .80 at the .01 significance level; therefore, less than one percent chance for error exists in concluding that Secchi disk depths increase as water depths increase. Because turbidity exists in an inverse relationship with Secchi depths, the conclusion can be stated that as depth of ponds increases within the study area, turbidity decreases.

Of those ponds tested for Secchi depth and water depth, only one of the sampling locations produced a Secchi depth which was the same as the water depth. In other words, only one sample location existed where detection of the bottom was possible by the observer. For all other sample locations, Secchi depths were less than water depths. Because of the difference between these two measures within most of the ponds sampled, it is unlikely that bottom reflectance contributed much to the energy which was backscattered from below the water surface. Moore (1978) stated that the scanner can often detect below Secchi depths. For this reason, the factor of water depth was analyzed as an indicator of bottom reflectance to determine any possible affect on pixel misclassification.

Normal distributions of the data allowed the use of linear regression for determining if significant causal relationships exist between the independent variables of

Secchi depth and water depth and the dependent variable Landsat error. Coefficient of determination values for all the linear regressions were very low. Table X, in the Appendix, identifies the correlation coefficients for each of the analyses. The r-square values indicate that suspended sediment levels and water depth as a measure of bottom reflectance do not affect the amount of error for individual ponds which are classified by a particular routine. The hypotheses of this study must, therefore, be rejected if the assumptions made herein are true. Affects of external factors, especially weather conditions, on the turbidity levels existing for each collection date are only speculative, eventhough, based upon comparison of climatic records for each date. Enough variability may have existed between each data collection date to create fallacies within the latter analysis.

In summary, analysis of average error factors among classifications supported findings in the literature. The analysis indicates that the inclusion of bands in a classification routine which detect a greater amount of backscattered flux than band 7 (i.e., bands 4, 5, and 6), causes water bodies to be less accurately classified overall.

The average error factors in Table IX and results of the correlation procedure indicate that as pond size classes increase, the average error tends to decrease for every classification but the band average. This supports Grabau's

(1976) findings that when pixel size is similar to the size of the land feature, a greater amount of misclassification occurs than when the pixel size is smaller than the land feature. The majority of the error within the classification routines studied herein, is a result of mixed pixels and is largely determined by pond size.

The major hypotheses of this study, which state that high suspended sediment levels and high bottom reflectance, measured by water depth, cause an increase in water misclassification, had to be rejected. Rejection of these hypotheses leads to the conclusion that the misclassification of individual ponds within a particular classification routine is not dependent on turbidity levels or on water depths as a measure of bottom reflectance. Because of the possibility of significant differences in these variables for each collection date; however, this conclusion may not be valid.

CHAPTER VI

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This study was carried out to determine (1) whether suspended sediment or bottom reflectance causes variation in the accuracy of water detection among several classification routines, (2) to what degree bottom reflectance resulting from shallow water affects the accuracy of water detection, and (3) to what degree suspended sediment levels affect the accuracy of water detection. Accuracy of water classification varied significantly between classification routines in this study. The accuracy of each classification was a result of the water penetration characteristics of MSS band wavelengths used in the particular routines. Accuracy within classification routines was found to vary from pond to pond but not as a result of suspended sediment or depth. The classification accuracy varies only with pond size, suggesting that the error is a result of a large number of mixed land/water pixels.

Of those classification routines analyzed, the band 7 routine was found to have produced the least amount of error in water classification. The band average routine using bands 6 and 7 was shown to be more accurate than unsupervised classifications in which the upper-bound standard deviation was adjusted to alter the amount of variation allowed within classes.

The band average was expected to produce a better separation between water and land than the band 7 routine. The band 7 values, instead of being enhanced by the addition of band 6 values, were contaminated by the values in band 6. This contamination occurred because band 6 is not as capable as band 7 in producing a distinct separation between water and wet soil reflectance. Moore (1978) and McCauley et al. (1973) state that band 6 provides a good land/water interface although not as clear as that in band 7. This study found that the band 6 land/water definition was not distinct enough to produce a better classification when averaged with band 7, than when band 7 was used alone.

The results of this study also indicate that suspended sediment and bottom detection capabilities of MSS bands 4, 5, and 6 were responsible for the low percentage of water surface area delineated by the unsupervised classifications. The low accuracy of the unsupervised classifications may also be a result of an incapability of the three by three pixel window, used in the ELAS Search routine, to identify the reflectance of small ponds. Many ponds in this study contributed water reflectance to only a few of the cells in the three by three window, thereby, allowing only larger water bodies to contribute to training field selection of water reflectance.

The reason such a low percentage of water surface area was classified by each routine is because of the high ratio of mixed pixels to pixels containing values of reflectance from water only. A small pond, say two hectares, may be detected within the IFOV of four adjacent pixels; however, each of these pixels would most likely be mixed, increasing the possibility of misclassification. If this study had been concerned with large water bodies, the ratio of mixed pixels to those containing only water reflectance would have decreased, thereby, reducing error in water classification.

Mixed pixels have been determined to be a major reason for the variation in classification error between ponds (Grabau, 1976). For each classification routine, except the band average, it was found that classification error varies depending mostly on the size of the water body because of the effect of the mixed reflectance values. Suspended sediment and shallow water have also been blamed for some erroneous classification of water bodies on Landsat digital data; yet, the extent of the problem had not been determined (Work and Gilmer, 1976 and Boland, 1976). The findings of this research suggest that areas with water characteristics which are similar to the fairly high suspended sediment levels and fairly shallow water bodies analyzed in this study will not experience erroneous classification of water pixels as a result of suspended sediment or bottom reflectance. Fallacies may exist; however, concerning assumptions regarding the conditions of the independent variables during Landsat and in situ data collection dates.

Because of the collection of data over a period of time, enough change may have occurred in the variables to cause any existing relationships to disappear. This must be considered a possibility eventhough care was taken to sample at a time when the factors influencing the variables were as similar as possible to those at Landsat overpass. The possibility exists that high suspended sediment levels or high bottom reflectance may significantly reduce the accuracy of water classification using Landsat data.

Ponds analyzed in this study ranged up to 6.3 meters in depth and from .5 to 1.3 meters in Secchi disk turbidity measures. Areas with ponds which display even higher suspended sediment loads or consistantly shallower water than those in this study may be more suitable for determining significant effects on pixel misclassification as a result of these factors.

In areas displaying water characteristics similar to those in this study, a band 7 classification routine should provide the most accurate detection of water bodies. The band 7 routine, however, does not provide the interpreter with much more information about the water body than approximate pond size and shape. If information regarding surrounding land cover or relative turbidity levels is more important than accurate surface area, classification techniques which employ other MSS bands should be used. An average of bands 6 and 7 should provide water classification which is superior to that of an unsupervised classification and at the same time give an indication of water body characteristics.

Recommendations

Several assumptions had to be made regarding the data used in this study because of the differences between collection dates. The need for these assumptions could be eliminated if the data for each variable were collected at the same time of satellite overpass. Any error incurred by in-situ data collection during overpass would be minimal; thereby, increasing the validity of the analysis results.

The acquisition of such data would be expensive. It would require that aerial photography be flown over the study area and that in-situ data measurements be made on the desired sample of water bodies as close as possible to the Landsat date.

It is also recommended that ponds larger than one hectare be used in the sample. This study found that, on the average, only about six percent of the ponds between .4 and one hectare are detected. The other 94 percent was misclassified primarily because of mixed pixels. The low detection in this size range may bias the analysis. The collection of in-situ measurements from a sample larger than 29 may also affect the analysis results. Because of the high number of mixed water pixels inherent within a study of small water bodies, a substantial increase in the sample size may be necessary to detect any significant correlation between the dependent and independent variables.

In summary, this study shows no significant relationship between bottom reflectance or suspended sediment and water classification error within individual classification routines using Landsat digital data; however, the change in the data over time may have caused existing relationships to disappear for this particular analysis. The change in classification error with the change in pond size suggests that mixed pixels account for most of the error in water classification.

The results of the study do describe the greater reliability of a band 7 classification routine over an average of bands 6 and 7 and unsupervised classifications for the detection of water bodies. This is because bands detecting in the longer wavelengths receive less backscatter from water causing, the water pixels to appear much darker than other land cover types. Producing this study in an area with a greater range of suspended sediment concentrations or water body depths, may result in significant relationships regarding the affects of high levels of suspended sediment and bottom reflectance on water classification error using Landsat data.

The search for a more accurate means of studying the landscape is often the task of the physical geographer, and is a necessary step toward understanding and dealing with current problems within the human environment. The hypotheses posed within this study were formulated through an analysis of documented, state of the art research. The questions although technical in nature were in need of study; not merely for the sake of satisfying curiosity, but for the sake of what an answer might mean in terms of a more accurate method of assessment of vital water resources in Oklahoma and similar areas of the western United States.

This study answers questions regarding the application of certain classification techniques for water study. Further study of the effects of bottom reflectance and high turbidity levels on water misclassification is necessary. If signigicant relationships are found, Landsat classification techniques can be assigned to provide greater water classification accuracy depending on the physical characteristics of water bodies within the study area. A priori knowledge of the geographic variation of physical characteristics of water bodies should prove beneficial for a more accurate classification and assessment of water resources using Landsat digital data on a regional scale.

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TABLE II

POND SURFACE AREAS FROM PHOTOS AND PLOTS
(HECTARES)

Township, Range, Section	Photo	Band 7	Band Average	UC1	UC2	UC3
18 02 08	2.42	2.50	1.00	1.75	2.00	2.00
18 02 08	.65	--	--	--	--	--
18 02 08	.57	.25	--	--	--	--
18 02 15	.53	--	--	--	--	--
18 02 15	.60	--	--	--	--	--
18 02 15	.64	--	--	--	--	--
18 02 15	3.02	.50	.25	--	--	--
18 02 15	2.10	.75	.75	--	--	--
18 02 17	2.96	.25	--	--	--	--
18 02 17	.53	.25	.25	.25	--	--
18 02 22	.51	.25	--	--	--	--
18 02 22	2.46	.75	.25	--	--	--
18 02 22	4.75	3.25	.25	1.00	1.00	.25
18 02 22	.70	--	--	--	--	--
18 02 22	.60	--	--	--	--	--
18 02 22	.45	--	--	--	--	--
18 02 26	1.34	1.00	1.00	--	.25	--
18 02 26	.84	--	--	--	--	--
18 02 26	.49	--	--	--	--	--
18 02 26	.72	--	--	--	--	--
19 02 01	.54	.25	.25	--	--	--
19 02 01	.44	.25	.25	--	--	--
19 02 01	2.09	3.00	3.00	1.50	1.75	.75
19 02 03	.53	--	--	--	--	--
19 02 03	2.41	1.50	1.50	--	--	--
19 02 03	3.01	2.50	2.25	.75	1.25	.50
19 02 03	1.98	1.00	.75	.50	.50	.25
19 02 07	4.35	2.25	.25	.75	1.25	.75
19 02 07	1.43	.75	.75	--	--	--
19 02 07	1.61	.25	--	--	--	--
19 02 07	3.03	1.25	.50	1.25	1.25	1.25
19 02 26	1.44	.75	1.00	.50	.50	--
19 02 26	1.27	.50	.75	--	--	--
19 02 29	3.62	2.25	2.25	.75	.75	.50
19 02 35	2.68	.50	--	.25	.50	.25
19 02 35	2.00	1.25	1.25	--	.25	--
19 03 02	2.40	1.50	.75	.75	.50	.25
19 03 02	.44	.25	--	--	--	--
19 03 03	.80	.50	.50	--	--	--
19 03 03	.51	--	--	--	--	--
19 03 03	1.90	--	--	--	--	--

TABLE II (Continued)

Township, Range, Section	Photo	Band 7	Band Average	UC1	UC2	UC3
19 03 07	.85	1.50	.75	.75	.50	.25
19 03 07	2.39	.75	.75	.50	.50	.50
19 03 07	.41	--	--	--	--	--
19 03 12	.99	.25	--	--	--	--
19 03 12	1.70	1.00	--	--	--	--
19 03 12	.42	--	--	--	--	--
19 03 15	1.50	.25	.50	.50	.50	.50
19 03 15	.54	--	--	--	--	--
19 03 15	.55	--	--	--	--	--
19 03 23	2.02	.75	.75	--	--	--
19 03 23	.42	--	--	--	--	--
19 03 23	1.28	1.50	1.50	--	--	--
19 03 24	2.50	.50	.50	.25	.25	.25
19 03 35	5.00	3.00	1.75	2.00	1.75	2.00
19 03 35	.68	.50	.50	.50	--	--
20 02 03	.57	--	--	--	--	--
20 02 03	.64	--	--	--	--	--
20 02 03	5.10	2.25	--	1.50	1.75	1.50
20 02 04	3.11	2.50	1.50	.50	.50	.25
20 02 04	.89	.50	--	.25	.25	.25
20 02 04	1.23	1.75	1.75	.50	1.00	--
20 02 04	.43	--	--	--	--	--
20 02 06	6.03	3.00	--	2.25	1.25	2.25
20 02 06	.66	--	--	--	--	--
20 02 06	.55	--	--	--	--	--
20 02 06	.53	--	--	--	--	--
20 02 07	3.16	2.25	.25	.75	1.00	.75
20 02 07	1.54	1.00	.25	.50	.25	.50
20 02 08	.66	--	--	--	--	--
20 02 11	.60	--	--	--	--	--
20 02 11	3.33	1.50	.50	.50	.75	.50
20 02 11	1.30	.50	--	--	.25	--
20 02 11	.86	--	--	--	--	--
20 02 11	5.59	2.75	.25	1.25	2.00	1.75
20 02 14	3.37	2.25	1.50	1.25	1.25	.75
20 02 14	.65	--	--	--	--	--
20 02 14	1.11	1.00	.25	--	--	--
20 02 14	.62	--	--	--	--	--
20 02 14	.61	--	--	--	--	--
20 02 18	2.03	.50	.50	.25	.25	.25
20 02 23	1.45	1.50	1.50	.50	1.00	--
20 02 23	1.29	.50	.75	--	--	--
20 02 23	1.49	2.00	1.00	--	.50	--

TABLE II (Continued)

Township, Range, Section	Photo	Band 7	Band Average	UC1	UC2	UC3
20 02 24	1.47	.50	.75	.25	.50	.25
20 02 24	.58	--	--	--	--	--
20 02 24	.51	--	--	--	--	--
20 02 25	1.82	1.25	.50	.25	.50	--
20 02 25	.41	--	--	--	--	--
20 02 25	1.17	1.50	1.50	--	--	--
20 02 25	.72	.25	.25	--	--	--
20 02 26	2.50	1.00	2.00	.50	.50	.50
20 02 26	.62	.25	--	--	--	--
20 03 03	1.46	.50	.50	.50	.50	.25
20 03 05	1.16	1.00	.25	.25	.25	--
20 03 05	.56	.25	.25	--	--	--
20 03 06	.68	--	--	--	--	--
20 03 06	5.10	4.25	3.75	3.00	2.75	1.75
20 03 06	1.08	.25	--	--	.25	--
20 03 06	3.65	1.00	--	.75	1.25	.75
20 03 07	.72	.25	--	--	--	--
20 03 10	1.78	1.75	1.75	.50	.50	.50
20 03 10	.72	--	--	--	--	--
20 03 10	.60	--	--	--	--	--
20 03 10	.51	--	--	--	--	--
20 03 13	3.15	2.00	1.25	1.00	1.00	.50
20 03 13	.41	--	--	--	--	--
20 03 12	1.03	.25	.25	--	--	--
20 03 13	1.11	.50	.25	.25	--	--
20 03 14	.47	--	--	--	--	--
20 03 14	2.88	2.50	2.50	.25	.75	.50
20 03 14	.64	--	--	--	--	--
20 03 18	1.13	.25	--	--	--	--
20 03 18	.54	--	--	--	--	--
20 03 18	.66	--	.50	--	--	--
20 03 18	.45	--	.25	--	--	--
20 03 18	.48	.25	--	--	--	--
20 04 14	1.52	2.75	2.75	2.00	2.00	1.00
20 04 14	.67	--	--	--	--	--
20 04 14	1.55	1.00	1.00	--	--	--
20 02 14	2.39	1.50	1.50	.50	.50	--
20 04 19	.98	--	--	--	--	--
20 04 19	2.04	1.00	--	--	.25	--
21 02 33	2.41	.75	.75	.50	.50	.25

TABLE III

DESCRIPTIVE STATISTICS FOR SURFACE AREAS OF PONDS FROM PHOTOS AND PLOTS (HECTARES)

Variable	Number of Observations	Mean	Standard Deviation	Range
Photo	124	1.52	1.25	5.62
Band 7	124	.75	.93	4.25
Band Average	124	.48	.73	3.75
UC1	124	.28	.53	3.00
UC2	124	.31	.55	2.75
UC3	124	.20	.45	2.25

TABLE IV

WATER DEPTH AND SECCHI DISK MEASURES FOR 29 PONDS

Township, Range, Section	Pond Surface Area from Photos (ha)	Secchi Depth (meters)	Water Depth (meters)
18 02 22	2.46	.25	1.8
		.25	1.9
		.25	2.7
18 02 22	4.75	.20	1.6
		.20	1.8
		.20	1.0
		.20	1.5
		.20	2.5
		.20	2.5
		.20	4.7
18 02 22	.45	.90	2.6
		1.05	4.0
19 02 01	2.09	.40	3.4
		.40	1.2
		.30	1.0
		.40	2.0
		.35	1.8
19 02 03	2.41	.40	2.0
		.30	1.7
		.35	1.2
		.30	1.3
19 02 03	3.01	.90	2.1
		1.00	3.8
		1.00	2.0
		1.20	1.5
19 02 03	.53	.25	1.9
		.21	2.1
		.25	.4
19 02 03	1.98	.30	.4
		.30	1.2
		.20	1.0
19 02 07	4.35	.30	2.7
		.30	2.2
		.25	.8
		.25	1.1
		.20	.8
		.20	.2

TABLE IV (Continued)

Township, Range, Section	Pond Surface Area from Photos (ha)	Secchi Depth (meters)	Water Depth (meters)
19 02 07	3.03	.10	1.0
		.20	1.8
		.15	1.9
		.15	.5
		.15	1.0
19 02 07	1.61	.25	1.2
		.10	2.2
		.15	2.3
19 02 07	1.43	.30	3.1
		.25	3.3
		.30	1.6
		.30	1.7
		.30	1.3
19 02 29	3.62	.60	1.8
		.60	1.3
		.60	2.6
		.75	3.0
19 03 07	.85	.20	1.3
		.20	1.5
		.20	1.7
19 03 07	2.39	.25	1.2
		.25	1.4
		.25	1.3
		.25	1.0
20 02 03	5.1	.05	.9
		.10	1.1
		.10	1.0
		.10	1.1
		.10	1.2
20 02 04	3.11	.35	2.4
		.30	3.3
		.30	2.0
		.30	1.0
20 02 04	.43	.15	1.5
		.10	1.0
20 02 04	.89	.50	1.9
		.50	4.0
		.60	1.4
		.50	.9

TABLE IV (Continued)

Township, Range, Section	Pond Surface Area from Photos (ha)	Secchi Depth (meters)	Water Depth (meters)
20 02 06	6.03	.40	.5
		.60	.9
		.60	2.4
		.60	2.0
		.50	1.3
20 02 07	1.54	.55	.9
		.50	1.4
		.60	4.0
		.55	4.0
		.55	5.3
20 02 07	3.16	.35	1.0
		.35	1.1
		.30	1.2
		.30	1.6
		.35	1.8
		.30	1.0
20 02 08	.66	.20	1.0
		.20	1.8
		.20	2.3
20 02 14	3.37	.35	1.4
		.30	2.0
		.35	1.5
		.30	4.8
		.30	5.2
		.35	2.2
		.30	1.8
		.30	2.1
		.30	1.6
20 02 14	.61	.10	.8
		.10	2.6
		.05	1.5
		.05	2.9
20 02 18	2.03	1.30	5.0
		1.30	3.3
		1.30	3.8
		1.20	5.4
		1.20	2.8
		1.20	5.2
		1.30	4.0
		1.20	3.8

TABLE IV (Continued)

Township, Range, Section	Pond Surface Area from Photos (ha)	Secchi Depth (meters)	Water Depth (meters)
20 02 23	1.49	.55	1.2
		.50	1.2
		.50	2.3
		.50	1.3
		.55	4.5
20 02 24	1.47	1.20	2.9
		1.30	4.6
		1.20	6.3
		1.20	6.1
		1.30	3.2
21 02 33	2.41	.15	1.2
		.10	.7
		.10	.7
		.10	.8
		.10	1.3

TABLE V

DESCRIPTIVE STATISTICS FOR SECCHI DEPTHS BY POND (METERS)

Township, Range, Section	Pond Surface Area from Photos (ha)	Mean	Standard Deviation	Range
18 02 22	2.46	.25	0.00	0.00
18 02 22	4.75	.20	0.00	0.00
18 02 22	.45	.90	.11	.15
19 02 01	2.09	.37	.04	.10
19 02 03	2.41	.34	.05	.10
19 02 03	3.01	1.00	.13	.30
19 02 03	.53	.24	.02	.04
19 02 03	1.98	.30	.06	.10
19 02 07	4.35	.25	.04	.10
19 02 07	3.03	.15	.04	.10
19 02 07	1.61	.17	.08	.15
19 02 07	1.43	.29	.02	.05
19 02 29	3.62	.64	.08	.15
19 03 07	.85	.20	0.00	0.00
19 03 07	2.39	.25	0.00	0.00
20 02 03	5.10	.09	.02	.05
20 02 04	3.11	.31	.03	.05
20 02 04	.43	.13	.04	.05
20 02 04	.89	.53	.05	.10
20 02 06	6.03	.54	.09	.20
20 02 07	1.54	.55	.04	.10
20 02 07	3.16	.33	.03	.05
20 02 08	.66	.20	0.00	0.00
20 02 14	3.37	.32	.03	.05
20 02 14	.61	.08	.03	.05
20 02 18	2.03	1.25	.05	.10
20 02 23	1.49	.52	.03	.05
20 02 24	1.47	1.24	.05	.10
21 02 33	2.41	.11	.02	.05

TABLE VI

DESCRIPTIVE STATISTICS FOR WATER DEPTHS BY POND (METERS)

Township, Range, Section	Pond Surface Area from Photos (ha)	Mean	Standard Deviation	Range
18 02 22	2.46	2.13	.49	.9
18 02 22	4.75	2.20	1.20	3.7
18 02 22	.45	3.30	.99	1.4
19 02 01	2.09	1.90	.94	2.4
19 02 03	2.41	1.60	.37	.8
19 02 03	3.01	2.40	1.00	2.3
19 02 03	.53	1.50	.93	1.7
19 02 03	1.98	.90	.42	.8
19 02 07	4.35	1.30	.95	2.5
19 02 07	3.03	1.20	.59	1.4
19 02 07	1.61	1.90	.61	1.1
19 02 07	1.43	2.20	.93	2.0
19 02 29	3.62	2.20	.77	1.7
19 03 07	.85	1.50	.20	.4
19 03 07	2.39	1.20	.17	.4
20 02 03	5.10	1.10	.11	.3
20 02 04	3.11	2.20	.95	2.3
20 02 04	.43	1.30	.40	.5
20 02 04	.89	2.10	1.36	3.1
20 02 06	6.03	1.40	.70	1.9
20 02 07	1.54	3.10	1.90	4.4
20 02 07	3.16	1.30	.34	.8
20 02 08	.66	2.60	.66	1.3
20 02 14	3.37	2.50	1.44	3.8
20 02 14	.61	2.00	.88	1.1
20 02 18	2.03	4.20	.94	2.6
20 02 23	1.49	2.10	1.42	3.3
20 02 24	1.47	4.60	1.58	3.4
21 02 33	2.41	.94	.29	.5

TABLE VII

ERROR FACTORS FOR EACH CLASSIFICATION TECHNIQUE (BY POND)

Township, Range, Section	Surface Area (Photo)*	Band 7	Band Average	UC1	UC2	UC3
18 02 08	.65	1.00	1.00	1.00	1.00	1.00
18 02 08	.57	.56	1.00	1.00	1.00	1.00
18 02 15	.53	1.00	1.00	1.00	1.00	1.00
18 02 15	.60	1.00	1.00	1.00	1.00	1.00
18 02 15	.64	1.00	1.00	1.00	1.00	1.00
18 02 15	3.02	.83	.92	1.00	1.00	1.00
18 02 15	2.10	.64	.64	1.00	1.00	1.00
18 02 17	2.96	.92	1.00	1.00	1.00	1.00
18 02 17	.53	.53	.53	.53	1.00	1.00
18 02 22	.51	.51	1.00	1.00	1.00	1.00
18 02 22	2.46	.70	.90	1.00	1.00	1.00
18 02 22	4.75	.32	.95	.79	.79	.79
18 02 22	.70	1.00	1.00	1.00	1.00	1.00
18 02 22	.60	.58	1.00	1.00	1.00	1.00
18 02 22	.45	1.00	1.00	1.00	1.00	1.00
18 02 26	1.34	.25	.25	1.00	.81	.81
18 02 26	.84	1.00	1.00	1.00	1.00	1.00
18 02 26	.49	1.00	1.00	1.00	1.00	1.00
18 02 26	.72	1.00	1.00	1.00	1.00	1.00
19 02 01	.54	.54	.54	1.00	1.00	1.00
19 02 01	.44	.43	.43	1.00	1.00	1.00
19 02 01	2.09	- .44	- .44	.28	.16	.16
19 02 03	.53	1.00	1.00	1.00	1.00	1.00
19 02 03	2.41	.38	.38	1.00	1.00	1.00
19 02 03	3.01	.17	.25	.75	.58	.58
19 02 03	1.98	.49	.62	.75	.75	.75
19 02 07	4.35	.48	.94	.83	.71	.71
19 02 07	1.43	.48	.48	1.00	1.00	1.00
19 02 07	1.61	.84	1.00	1.00	1.00	1.00
19 02 07	3.03	.59	.83	.59	.59	.59
19 02 26	1.44	.48	.31	.65	.65	.65
19 02 26	1.27	.61	.41	1.00	1.00	1.00
19 02 29	3.62	.38	.38	.79	.79	.79
19 02 35	2.68	.81	1.00	.91	.81	.81
19 02 35	2.00	.38	.38	1.00	.88	.88
19 03 02	2.40	.37	.69	.69	.79	.79
19 03 02	.44	.43	1.00	1.00	1.00	1.00
19 03 03	.80	.37	.37	1.00	1.00	1.00
19 03 03	.51	1.00	1.00	1.00	1.00	1.00
19 03 03	1.90	1.00	1.00	1.00	1.00	1.00

TABLE VII (Continued)

Township, Range, Section	Surface Area (Photo)	Band 7	Band Average	UC1	UC2	UC3
19 03 07	.85	- .76	.12	.12	.41	.41
19 03 07	2.39	.69	.69	.79	.79	.79
19 03 07	.41	1.00	1.00	1.00	1.00	1.00
19 03 12	.99	.75	1.00	1.00	1.00	1.00
19 03 12	1.70	.41	1.00	1.00	1.00	1.00
19 03 12	.42	1.00	1.00	1.00	1.00	1.00
19 03 15	1.50	.83	.67	.83	.83	.83
19 03 15	.54	1.00	1.00	1.00	1.00	1.00
19 03 15	.55	1.00	1.00	1.00	1.00	1.00
19 03 23	2.02	.63	.63	1.00	1.00	1.00
19 03 23	.42	1.00	1.00	1.00	1.00	1.00
19 03 23	1.28	- .17	- .17	1.00	1.00	1.00
19 03 24	2.50	.80	.80	.90	.90	.90
19 03 35	5.00	.40	.65	.60	.65	.65
19 03 35	.68	.26	.26	.26	1.00	1.00
20 02 03	.57	1.00	1.00	1.00	1.00	1.00
20 02 03	.64	1.00	1.00	1.00	1.00	1.00
20 02 03	5.10	.56	1.00	.71	.66	.66
20 02 04	3.11	.20	.52	.84	.84	.84
20 02 04	.89	.44	1.00	.72	.72	.72
20 02 04	1.23	- .42	- .42	.59	.19	.19
20 02 04	.43	1.00	1.00	1.00	1.00	1.00
20 02 06	6.03	.50	1.00	.63	.79	.79
20 02 06	.66	1.00	1.00	1.00	1.00	1.00
20 02 06	.55	1.00	1.00	1.00	1.00	1.00
20 02 06	.53	1.00	1.00	1.00	1.00	1.00
20 02 07	3.16	.29	.92	.76	.68	.68
20 02 07	1.54	.35	.84	.68	.84	.84
20 02 08	.66	1.00	1.00	1.00	1.00	1.00
20 02 11	.60	1.00	1.00	1.00	1.00	1.00
20 02 11	3.33	.55	.85	.85	.77	.77
20 02 11	1.30	.62	1.00	1.00	.81	.81
20 02 11	.86	1.00	1.00	1.00	1.00	1.00
20 02 11	5.59	.51	.96	.78	.64	.64
20 02 14	3.37	.33	.55	.63	.63	.63
20 02 14	.65	1.00	1.00	1.00	1.00	1.00
20 02 14	1.11	.10	.77	1.00	1.00	1.00
20 02 14	.62	1.00	1.00	1.00	1.00	1.00
20 02 14	.61	1.00	1.00	1.00	1.00	1.00
20 02 18	2.03	.75	.75	.88	.88	.88
20 02 23	1.45	- .03	- .03	.66	.31	.31
20 02 23	1.29	.61	.42	1.00	1.00	1.00
20 02 23	1.49	- .34	.33	1.00	.66	.66

TABLE VII (Continued)

Township, Range, Section	Surface Area (Photo)	Band 7	Band Average	UC1	UC2	UC3
20 02 24	1.47	.66	.49	.83	.66	.66
20 02 24	.58	1.00	1.00	1.00	1.00	1.00
20 02 24	.51	1.00	1.00	1.00	1.00	1.00
20 02 25	1.82	.31	.73	.86	.73	.73
20 02 25	.41	1.00	1.00	1.00	1.00	1.00
20 02 25	1.17	- .28	- .28	1.00	1.00	1.00
20 02 25	.72	.65	.65	1.00	1.00	1.00
20 02 26	2.50	.60	.20	.80	.80	.80
20 02 26	.62	.60	1.00	1.00	1.00	1.00
20 03 03	1.46	.66	.66	.66	.66	.66
20 03 05	1.16	.14	.78	.78	.78	.78
20 03 05	.56	.55	.55	1.00	1.00	1.00
20 03 06	.68	1.00	1.00	1.00	1.00	1.00
20 03 06	5.10	.17	.26	.41	.46	.46
20 03 06	1.08	.77	1.00	1.00	.77	.77
20 03 06	3.65	.73	1.00	.79	.66	.66
20 03 07	.72	.65	1.00	1.00	1.00	1.00
20 03 10	1.78	.02	.02	.72	.72	.72
20 03 10	.72	1.00	1.00	1.00	1.00	1.00
20 03 10	.60	1.00	1.00	1.00	1.00	1.00
20 03 10	.51	1.00	1.00	1.00	1.00	1.00
20 03 13	3.15	.37	.60	.68	.68	.68
20 03 13	.41	1.00	1.00	1.00	1.00	1.00
20 03 13	1.03	.76	.76	1.00	1.00	1.00
20 03 13	1.11	.55	.77	.77	1.00	1.00
20 03 14	.47	1.00	1.00	1.00	1.00	1.00
20 03 14	2.88	.13	.13	.91	.74	.74
20 03 14	.64	1.00	1.00	1.00	1.00	1.00
20 03 18	1.13	.78	1.00	1.00	1.00	1.00
20 03 18	.54	1.00	1.00	1.00	1.00	1.00
20 03 18	.66	1.00	.24	1.00	1.00	1.00
20 03 18	.45	1.00	.44	1.00	1.00	1.00
20 03 18	.48	.48	1.00	1.00	1.00	1.00
20 04 14	1.52	- .81	- .81	- .32	- .32	- .32
20 04 14	.67	1.00	1.00	1.00	1.00	1.00
20 04 14	1.55	.35	.35	1.00	1.00	1.00
20 04 14	2.39	.37	.37	.79	.79	.79
20 04 19	.98	1.00	1.00	1.00	1.00	1.00
20 04 19	2.04	.51	1.00	1.00	.88	.88
21 02 33	2.41	.69	.69	.79	.79	.79

* Measured in hectares.

TABLE VIII

PAIRED T-TESTS FOR INDEPENDENCE

Compared Pond Size Variables	Observed T	Accepted Hypothesis*
Photo - Band 7	8.78	$\mu_1 - \mu_2 > 0$
Photo - Band Average	10.25	"
Photo - UC1	15.03	"
Photo - UC2	14.99	"
Photo - UC3	15.58	"
Band 7 - Band Average	5.36	"
Band 7 - UC1	11.60	"
Band 7 - UC2	11.47	"
Band 7 - UC3	3.68	"
Band Average - UC1	10.57	"
Band Average - UC2	3.15	"
Band Average - UC3	4.49	"
UC1 - UC2	-1.96	$\mu_1 - \mu_2 < 0$
UC1 - UC3	3.91	$\mu_1 - \mu_2 > 0$
UC2 - UC3	4.67	"

* One-tail test at the .05 significance level producing a critical t value of 1.645.

TABLE IX

AVERAGE CLASSIFICATION ERROR BY POND SIZE

Pond Size (hectares)	Band 7	Band Average	UC1	UC2	UC3	n
0.4 < 1	.84	.90	.96	.99	.99	60
1 < 2	.41	.58	.81	.77	.77	29
2 < 3	.47	.66	.78	.75	.75	18
3 < 4	.43	.74	.73	.70	.70	10
4 < 5	.42	.82	.68	.67	.67	2
>= 5	.42	.77	.63	.64	.64	5

TABLE X

CORRELATION COEFFICIENTS

Classification Routine (error variable)	Secchi Depth	Water Depth
Band 7	0.0002	0.0122
Band Average	0.0396	0.0059
UC1	0.0025	0.0319
UC2	0.0071	0.0122
UC3	0.0038	0.0217

2

VITA

Eric Wayne Constance

Candidate for the Degree of

Master of Science

Thesis: DETECTION AND CLASSIFICATION OF WATER BODIES WITH HIGH SPECTRAL RADIANCE USING LANDSAT MULTISPECTRAL DIGITAL DATA

Major Field: Geography

Biographical:

Personal Data: Born in St. Joseph, Missouri, March 6, 1958, the son of Mr. and Mrs. Charles Constance.

Education: Graduated from Jefferson City High School, Jefferson City, Missouri, in May, 1976; received Bachelor of Science degree from Central Missouri State University, Warrensburg, in May, 1980; completed requirements for the Master of Science degree at Oklahoma State University, in July, 1983.

Professional Experience: Graduate teaching assistant, Department of Geography, Oklahoma State University, September - December, 1980; graduate research assistant, Center for Applications of Remote Sensing, Department of Geography, Oklahoma State University, January, 1981 - May, 1982; graduate research assistant, Department of Geography, Oklahoma State University, January, 1982 - July, 1982; cartographer, Oklahoma State University Cartography Service, Department of Geography, June - October, 1981, September, 1982 - January, 1983.

Professional Organizations: Member, American Congress on Surveying and Mapping; member, American Society of Photogrammetry.