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EVALUATION OF SURFACE WATER RESOURCES FROM MACHINE-PROCESSING OF ERTS MULTI-SPECTRAL DATA

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Evaluation of Surface Water Resources from Machine-Processing of ERTS Multispectral Data[1]

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ABSTRACT

Water resource data that are useful to environmental scientists and planners frequently are missing, incomplete, or obtained irregularly. A new source of surface hydrological information can be obtained as often as every 18 days in some areas through machine-processing of Earth Resources Technology Satellite (ERTS) multispectral scanner data. This research focused on the surface water resources of a large metropolitan area, Marion County (Indianapolis), Indiana, in order to assess the potential value of ERTS spectral analysis to water resources problems.

The results of the research indicate that all surface water bodies over 0.5 ha were identified accurately from ERTS multispectral analysis. Five distinct classes of water were identified and correlated with parameters which included the i) degree of water siltiness; ii) depth of water; iii) presence of macro and micro biotic forms in the water; and iv) presence of various chemical concentrations in the water. The machine-processing of ERTS spectral data used alone or in conjunction with conventional sources of hydrological information can lead to the monitoring of the i) area of surface water bodies; ii) estimated volume of selected surface water bodies; iii) differences in degree of silt and clay suspended in water; and iv) degree of water eutrophication related to chemical concentrations. Water resources information obtained from ERTS analysis will be useful in helping to solve or better understand selected pollution, erosion, and planning problems in metropolitan and other environments.

Additional Index Words: water pollution, water management, water quality monitoring.

Water resources are vitally important to large metropolitan areas because industries, commercial establishments, and residences depend upon the amount and quality of a region's water supply. Hydrological data are used to give insight into many aspects of water supply and quality, drainage and flood control, water recreation, and sewage processing in most metropolitan areas; however, severe problems of data acquisition are common in many types of environmental water studies. A total or partial paucity of surface hydrological data inhibits a good regional assessment and evaluation of water resources. This paper explores the use of the Earth Resources Technology Satellite (ERTS) as a source of information which provides regional surface water data suitable to use independently or in conjunction with existing water resource data in order to evaluate better water quality and uses in metropolitan environments. It will be shown that machine processing of ERTS multispectral scanner data provides a valuable method to obtain hydrological information that can be used to help monitor and evaluate various surface water characteristics such as depth, surface area, volume, and turbidity simultaneously as often as every eighteen days in a given study area. Theoretically over 31 million km² of surface area can be scanned every day by ERTS from its orbital altitude of 925 km. These ERTS capabilities add greatly to the ability of the environmental scientist and regional planner to make rational water resources decisions.

MATERIALS AND METHODS

Marion County, (Indianapolis) Indiana (Fig. 1) was selected as an area for water resources analysis utilizing ERTS multispectral scanner data because: i) the county is one of the ten largest metropolitan areas in the United States, thus positive results gained from ERTS analysis will be significant to many individuals and ii) the diversity of surface water features presents a good opportunity to assess the ERTS system in a hydrological application. The largest water bodies are Eagle Creek and Geist Reservoirs in the northwestern and northeastern sections of the county respectively. Geist Reservoir is the major supply of water for the inhabitants of the county. There are approximately 60 ponds or small lakes of more than 0.5 ha (1.2 acres) in the study area. Several of these ponds are active or inactive gravel pits, some of which are associated with lowlands that receive overflow from adjacent creeks and the West Fork White River. Sewage disposal and water treatment facilities use water bodies (maintained by man) adjacent to the West Fork White River. Many ponds or small lakes are found in depressional topographic locations not associated with reservoirs, floodplains, or gravel pits. The width of the major river of the county (West Fork White River) rarely exceeds 150 m, while the

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average width of smaller tributary streams (i.e. Fall Creek) is less than 60 m.

Four bands of high-quality digitized, multispectral data were obtained from an ERTS pass over the study area on 30 September 1972 (Band 4, .5-.6 µm; Band 5, .6-.7 µm; Band 6, .7-.8 µm; and Band 7, .8-1.1 µm). Computer implemented processing of spectral data was used to assess the distribution and characteristics of surface water in Marion County. Selected implications of the research results obtained from the ERTS hydrologic analysis are explored.

The first step in the analysis was to generate a gray scale lineprinter map of the county in band 6 (0.7-0.8 µm). Histograms that had been calculated previously allowed the map to show sixteen data ranges, each of which was represented by a different alphanumeric symbol. Band 6 was selected for display because of the high probability that the lowest spectral reflectance values (darkest tone) in that portion of the spectrum would be water. The printout was compared with color air photography ground information (Indianapolis Power and Light Company, Indianapolis/Marion County Color Airphoto Mosaic, 1972) to determine which of those dark tone areas were water and which were cloud shadow. After locating the water bodies in the county on the gray scale map, line and column coordinates were chosen and recorded for rectangular training sample areas of water. Because of the irregular shape of the reservoirs, a number of samples were selected, 16 from Geist Reservoir and seven from Eagle Creek Reservoir. A single sample was also chosen from each of ten smaller surface water bodies. Care was taken in selection of the 33 samples in order to obtain a representative sampling from all of the area's surface water. The spectral responses of these water samples in each one of the four ERTS bands were used to help train a computer to identify automatically water everywhere throughout the study area.

These samples were submitted to a clustering algorithm program (Wacker, A. G., and D. A. Landgrebe, 1971. A minimum of distance approach to classification. LARS Information Note 100771, p. 129-133. Purdue University) which requested delineation of the spectral responses of water data into five spectral classes using all four bands of data. The output from the clustering program was maps of each of the 33 sample areas which indicated the cluster class of all points (each point is an area of approximately 60 m by 80 m and is known as a Remote Sensing Unit or RSU) in the samples by different alphanumeric symbols. The characteristics of four of the clusters (each cluster represented a distinct spectral class of water) indicated that they had informational value, but the fifth was considered to be a non-informational (non-water) spectral class. Training samples representative of each one of the four water classes were delineated directly from the cluster maps, and were used ultimately to train a computer to identify automatically different classes of water.

It was not advisable at this stage in the analysis to classify all of the data points in the county, because training samples were not yet defined for other types of land cover. Some of these features, particularly cloud shadow, could easily be misclassified as water. Thus, training samples were chosen for the other land cover types in the county, including single-family (newer) residential, multi-family (older) residential, grassy (open) areas, trees, commercial/industrial, cloud, and cloud shadow. Statistics of the relative spectral responses (means, standard deviations, and covariance matrices) were calculated for the four water classes and the seven other classes. All of the data points in the county were then classified by a Gaussian maximum likelihood classifier (Phillips, T. H. 1973. LARSYS users manual. LARS, Purdue University) into one of the eleven classes. The results were displayed by a lineprinter using different alphanumeric symbols for each class. Figure 2 contains a synthesized photographic display of the complete (11 class) classification of Marion County.

RESULTS AND DISCUSSION

Virtually 100% of all standing water bodies over 0.5 ha were identified in the ERTS classification analysis. The shape and surface area of the large water bodies (particularly the two reservoirs and to a lesser degree the largest ponds) were determined very accurately from the

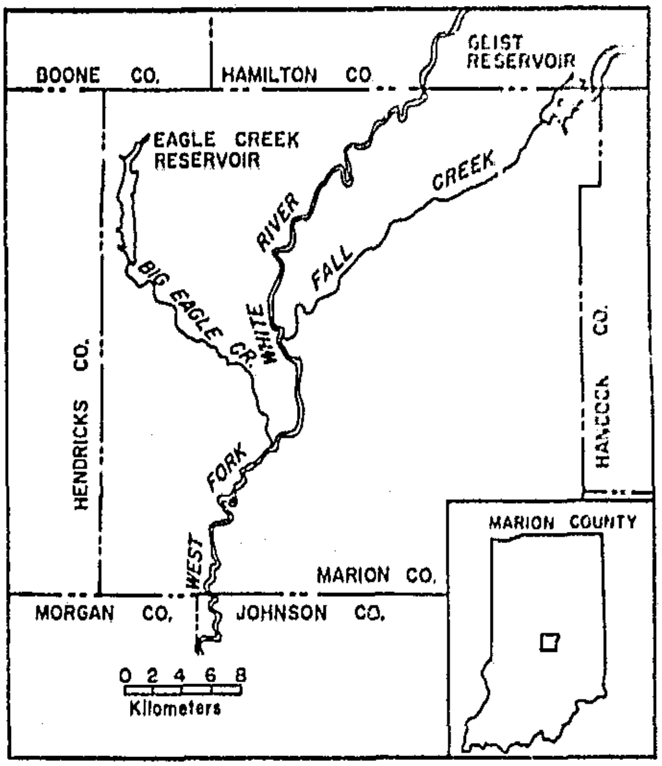

Fig. 1—Indianapolis metropolitan study area.

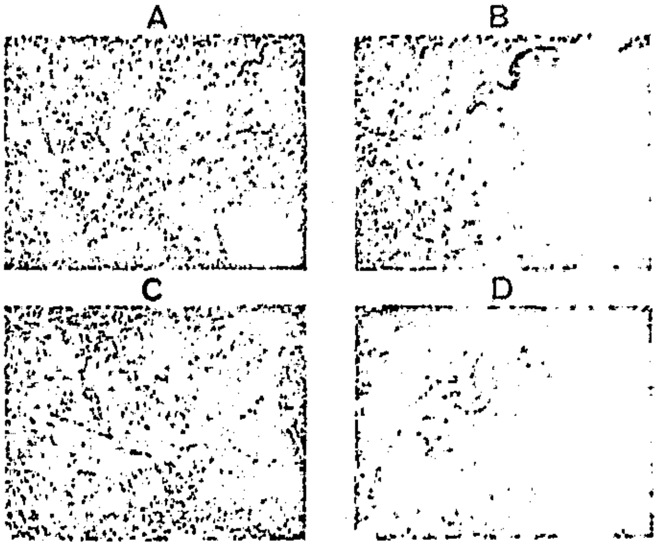

Fig. 2—Digital images of Marion County, Indiana land use classification. Each one of eight (seven non-water and one water) classes of phenomena identified in Marion County through machine processing of ERTS spectral data was displayed using an assigned gray-scale tone on a cathode ray tube (CRT). All classes of water were combined into one class to facilitate photographic clarity; however, water subclasses are possible to obtain in this image form. Figure 2a encompasses all of Marion County and small portions of adjacent counties (> 900 km²). The largest water bodies, Eagle Creek and Geist Reservoirs, are seen ... in the western and northeastern portions of the image. Figures 2b and 2c are digital display enlargements (4X) of the Geist and Eagle Creek reservoir areas respectively. Figure 2d is a maximum size digital display enlargement (16X) of the Geist Reservoir area.

ERTS computer-implemented classification of the study area. The shape and surface area of the smaller standing water bodies were less accurately determined, although the identification of the water bodies themselves was nearly 100% accurate. Distortion of shape and area of water bodies generally increases as the size of the water body [illegible] decreases.

River areas more than 60 m wide were generally identified in ERTS analysis. Streams or rivers 30 to 60 m wide were identified occasionally, while those under 30 m wide were not identified. Consequently, due to the resolution limits of ERTS data, only the West Fork White River was consistently identified, although portions of smaller running water features were classified as water.

Four spectrally distinct classes of water were identified in Marion County (water 1 through water 4). A fifth class of water (referred to as water 5 throughout this discussion) was not spectrally identified, but nevertheless seems to exist as part of the class *commerce*. Variations in the parameters that affected the spectral response of water phenomena have resulted in a pattern of water class distribution that is not random. The distribution of the five classes of water helps to give insight into the parameters that affect the spectral responses of water features that were obtained from the four bands of ERTS data.

The areal distribution of the spectral classes of water in Marion County was complex. Water 1 through water 3 were found in a similar sequence in both Eagle Creek and Geist Reservoirs. The extreme northern section of each reservoir was characterized by water 1; the north-central section contained water 2; and most of the remaining area was water 3 (Figs. 3-4). Water 5 was often found adjacent to the reservoir shoreline. Virtually no water 4 was found in reservoir areas.

All four spectral classes (and the partial water class water 5) characterized the water associated with standing water bodies (excluding reservoirs). Frequently standing water bodies were dominated by one class of water only, while in other cases two or three classes of water were more characteristic. Approximately 15%, 25%, 20%, and 40% of the standing water bodies (excluding reservoirs) were dominated by water 1, water 2, water 3, and water 4, respectively (Fig. 5). The distribution of the lakes and ponds dominated by a given water class appeared to be nearly random.

Rivers that were sufficiently wide to permit the ERTS identification of a spectral class of water were always

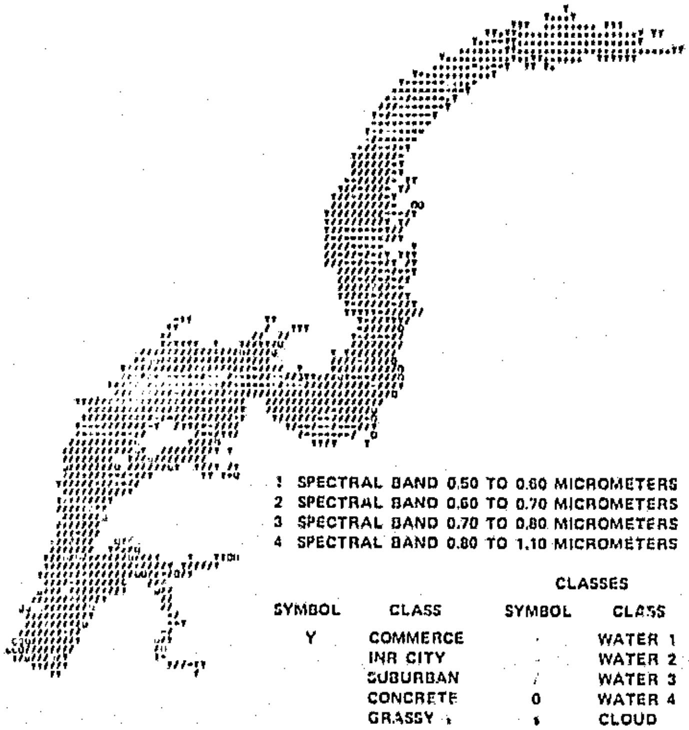

Fig. 3—Alphanumeric representation of Geist Reservoir water classes as determined from computer-implemented classification of water using four ERTS spectral bands. Each alphanumeric symbol is equivalent to an area of approximately 60 by 80 m.

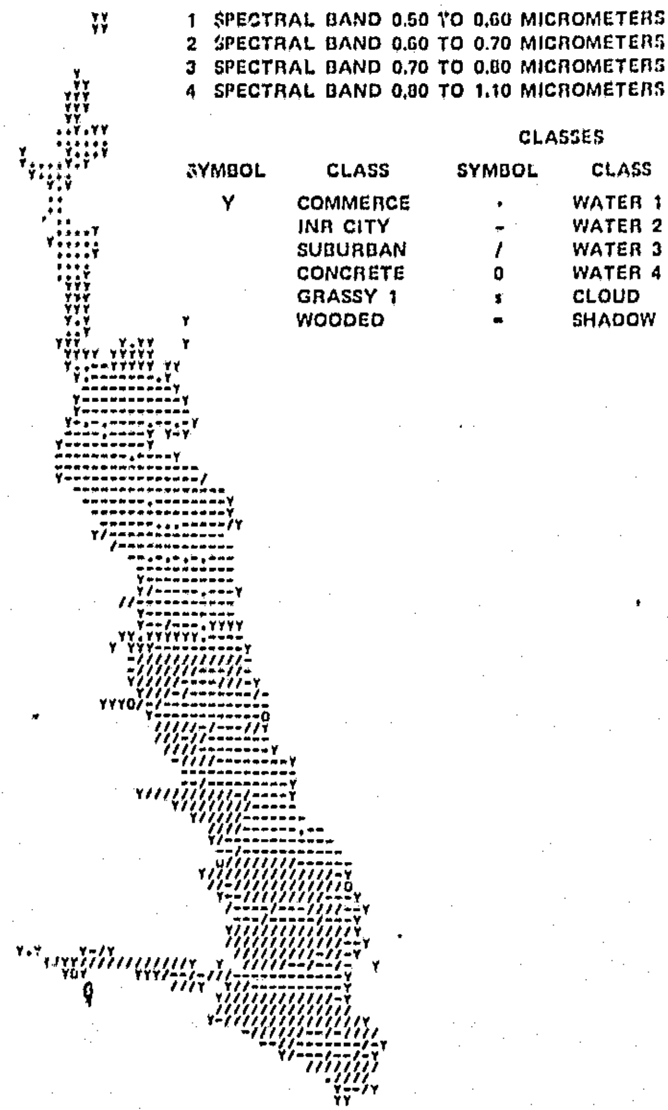

Fig. 4—Alphanumeric representation of Eagle Creek Reservoir water classes as determined from computer-implemented classification of water using four ERTS spectral bands. Each alphanumeric symbol is equivalent to an area of approximately 60 by 80 m.

identified as water 1 (Fig. 5). Very narrow (under 60 m running water bodies were frequently identified as water 5.

The Remote Sensing Units or RSU's that can be considered water 5 have a pattern of areal distribution that is characteristic of water and they are found in zones where water and non-water interface. This type of water is classified as *commerce* (one of the seven non-water classes), but it can be distinguished accurately from actual *commerce* in the study area through a spatial analysis of spectral data that is combined with available ground observation information. For example, a meandering 1-RSU wide linear pattern of *commerce* in a rural area and a one RSU layer of *commerce* adjacent to an isolated part of a reservoir are incongruous, hence these patterns can be identified as water 5 rather than *commerce*. There are a few areas (primarily within the more highly-urbanized sections of the country) where the spatial and spectral characteristics of water 5 are more difficult but possible to differentiate from *commerce*.

Spatial analysis of the spectral class *commerce* identifies 1-RSU wide bands of water 5 along several narrow (< 60 m) watercourses, adjacent to the banks of wider (> 60 m) watercourses, and on shorelines of standing water bodies. Apparently, water 5 is a mixture of water reflectance combined with reflectance from adjacent non-water phenomena (i.e., soil, vegetation, roads, and other features, found on both sides of a narrow river or similar features along a shoreline in the case of a standing water body). It may be feasible to separate accurately a class water 5 from *commerce* solely through spectral analysis; however, at this time the use of spatial patterns of the spectral class *commerce* supported by available ground observation information provides the most accurate method of delineating a fifth class of water in the study area.

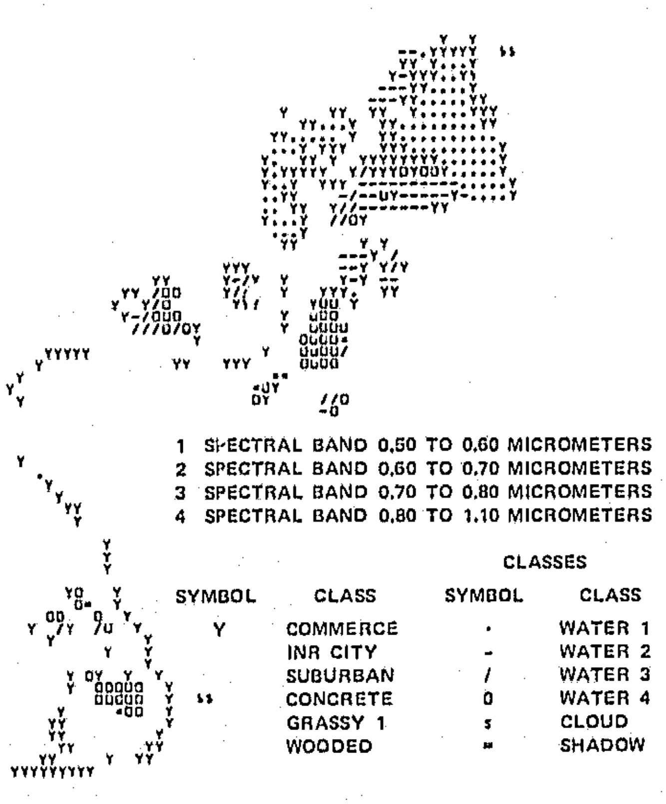

Fig. 5—Alphanumeric representation of water classes of small lakes and narrow stream (the stream is indicated by the winding line of symbol Y in the western part of the figure) as determined from computer-implemented classification of water using four ERTS spectral bands. Each alphanumeric symbol is equivalent to an area of 60 by 80 m.

It is important to attempt to identify water 5 as a supplement to information gained from analysis of water 1 through water 4 because: i) improved accuracy in estimation of the surface area of water bodies is attained; ii) more complete and accurate identification of very small water bodies (< 1.0 ha) is assured; iii) many rivers that are of insufficient width to be spectrally identified as water are subject to identification as the partial water class water 5; and iv) semipermanent quasiswampy areas (soil and vegetation forms that periodically are interlaced with shallow standing water during periods of high moisture) that generally are impossible to identify as a spectral class of water, are subject to water 5 identification. Water 5 cannot be used to analyze biological, chemical, or physical characteristics of the water because too many strong non-water influences affect the spectral reflectance of each RSU.

Ground observation information, upon which hypotheses in this study were based, was obtained for the study area water bodies from maps, (Indianapolis and Marion County Map, 1972. Cram Company, Indianapolis), aerial photographs, published reports, (Division of Planning and Zoning Staff. 1972–73. Water quality control program work papers 3–6, 9–12, and Water quality management plan—Indianapolis Metropolitan Area. Department of Metropolitan Development, Indianapolis-Marion County, Indiana), personal interviews, (R. M. Robling, Senior Planner, Indianapolis Department of Metropolitan Development and D. Bochem, Engineer, Indianapolis Water Company, Personal Communication), and visual observations. Equal amounts of data for each water body were not possible to obtain. Some potentially important ground observation data could not be obtained; however, the sum total of all data collected permitted an evaluation of several parameters that affected the spectral characteristics of water. The information gained from this analysis will be valuable to establish ground observation procedures for future Marion County ERTS hydrological studies.

The parameters that appeared to have the greatest influence on the spectral characteristics of water are: i) variability in water depth; ii) degree of water turbidity particularly related to the amount of silt or clay particles in suspension; iii) distribution and amount of macrobotanical forms (aquatic weeds); iv) distribution and amount of microbotanical forms (algae blooms); v) chemical impurities; and vi) influence of adjacent earth surface features that are not an intimate part of a water body (i.e., tree adjacent to a shoreline). Each different class of water was influenced by varying combinations of these major parameters. The results of the water classification analysis are presented in summary form (Table 1).

An analysis of the data presented in Table 1 indicates that water 3 and water 4 were the classes least modified spectrally by non-water phenomena, while the spectral

Table 1. Distribution and selected characteristics of spectral water classes in Marion County, Indiana

Water class	Location	Common water characteristics*
Water 1	(a) Southern areas of reservoirs (b) Numerous ponds and lakes distributed throughout the study area	Shallow (< 2m) water, high percentage of silt and clay in suspension, moderate spectral influence from aquatic biotic lifeforms (a – b) or
	(c) West Fork White River (d) Sewage processing area	High percentage of silt and clay in suspension, chemical impurities, slight spectral influence from nonwater phenomena adjacent to the river (c – d)
Water 2	(a) North central and central sections of the reservoirs (b) Numerous ponds and lakes distributed throughout the study area	Moderate (2 to 4m) water depth, moderate amount of aquatic vegetation and/or silt and clay in suspension
Water 3	(a) South-central and southern sections of the reservoirs (b) Numerous ponds and lakes distributed throughout the study area	Moderate to deep (3 to 5m) water, slight to moderate spectral variations caused by physical, chemical and biological impurities in the water.
Water 4	(a) Numerous ponds and lakes distributed throughout the study area	Variable water depth with large amounts of macro- and/or microaquatic vegetation present at or above the surface of the water. Very little turbidity caused by silting or Generally very deep (> 8m) water associated with numerous gravel pits. Moderate biological activity in the water is possible. Very little turbidity caused by silting
Water 5	(a) Numerous water/nonwater interface areas	Spectral responses from nonwater phenomena dominate

* The terms large, high, moderate, and slight referred to in parts of this table are not quantified. These terms are used subjectively to provide a relative ranking of water impurities found within the five classes of water identified in this analysis.

characteristics of water 5 reflected most strongly non-water features. Water 1 of the spectral water classes was most noticeably affected spectrally by non-water materials found in the water. High turbidity caused by mixing of silt and clay (via running water, wave action, or human disturbance), particularly in shallow water, was the most common condition associated with water 1. High biomass content in the water (with very little silting) characterize some areas with water 4. Ponds and lakes that were influenced strongly by human activity frequently are prone to a water 4 classification. Many water bodies with water 4 were recipients of inorganic and organic materials (sewage, fertilizer, and some silt) obtained from nearby residential areas and farms. It is speculated by the authors that water 4 is often more nutrient rich overall than are the other standing water body classes. A nutrient rich status in the water could have induced above average biotic activity in these areas. Several gravel pit lakes also have a water 4 classification. In these areas a combination of great depth and moderate biotic activity (with little silting) affects the spectral characteristics of the water. Water 2 appeared to be transitional between the water classes strongly influenced spectrally by water containing suspended solids and water that was relatively free of solids.

The observations made between water classes and water characteristics (Table 1) are supported by electromagnetic wavelength reflectance theory. The water class with the least silt and other solids should have the lowest spectral reflectance because of the great spectral absorption in all ERTS bands. Water mixed with aquatic green vegetation characteristically should have low spectral response also (albeit higher overall than pure water) because of the ability of green vegetation to absorb light moderately to strongly in the visible wavelengths and for water to absorb light very strongly in all ERTS bands. Water that contains large amounts of silt and clay (and possibly chemical precipitates) has relatively high reflectance in the visible part of the spectrum because of the high spectral reflectivity of the silt and clay fraction in the water.

Theoretically, water 1 (high amount of silt and other solids possibly present) should have the highest overall spectral response of the spectral water classes. Water 2 (moderately silty with biotic influences possible also) theoretically should be lower in overall spectral response than water 1, but higher in spectral response than water 3 (less silty than water 2 with biotic influence possible). The lowest spectral response overall of the spectral water classes theoretically should be water 4 which frequently contains aquatic vegetation (low reflectance) and very little silt and clay in suspension. The actual relative spectral water classes generally agree with these theoretical expectations. In theory, the highest spectral responses of all classes that are influenced by water is water 5. The spectral responses of water 5 are determined more by surrounding relatively highly-reflective non-water phenomena than water itself, thus its overall spectral response is higher than that of any of the four spectral classes of water.

These explanations of spectral variations in water classes undoubtedly are valid for a very large majority of all water bodies of Marion County. A dearth of data for some of the known parameters that cause spectral variations in water coupled with the possible exclusion of other parameters that were not considered in this analysis results in conclusions that are subject to slight modification. An analysis of the available data does provide working hypotheses which can be tested, modified, and improved as future ERTS data are analyzed for their hydrological content.

CONCLUSIONS

It has been shown that computer-implemented processing of ERTS data has a potential use for hydrological studies of a metropolitan county. All standing water bodies greater than 0.5 ha are identified, thereby permitting an accurate estimation of the total area of surface water in the county. These area data when combined with topographical information will permit an estimation of volume as well as area of the surface water resources of the country. Temporal variations in area and volume of surface water are available theoretically every 18 days.

A good possibility exists to differentiate between water relatively free of suspended silt and clay from water containing a large silt and clay load. Monitoring this form of turbidity in water bodies can be useful in accessing sources and intensity of erosion in the study area. In selected cases, this information could be used to help make regional planning decisions.

The degree of water eutrophication, as measured by the vegetation content of water bodies, may be possible to monitor using ERTS technology. These data are important for water pollution studies that attempt to trace and analyze the effects of nutrient-rich effluent on the environment.

Planning water use for recreation and residential purposes requires water quality data. The exact pragmatic nature of ERTS spectral analysis applied to water problems remains to be demonstrated, and in part depends on further ERTS hydrological analysis of a study area at different times of the year. However, results from this initial analysis are very encouraging because they indicate that significant practical applications of spectral data are feasible to use to help evaluate water resources.

An 18-day cycle monitoring the water resources is unlikely because of changing weather conditions, but, frequent evaluation of water resources that would be valuable to county planning and environmental officials is [illegible] ible. It is likely that monitoring of computer imple- [illegible] ed processing of ERTS spectral data will be one of [illegible] most effective methods to obtain selected types of [illegible] quality small-scale hydrological data. The ultimate effectiveness of monitoring will depend on the ability to understand better how various parameters affect the spectral responses of water in the study area.

Column Studies of Soil Clogging in a Slowly Permeable Soil as a Function of Effluent Quality[1]

T. C. Daniel and J. Bouma[2]

ABSTRACT

Clogging as a function of effluent quality was investigated in cores of the very slowly permeable Almena silt loam soil which offers problems for conventional on-site liquid waste disposal. Undisturbed 60 cm long cores were subjected for approximately 120 days to constant ponding with simulated septic tank effluent, extended aeration effluent and distilled water. Column influents and effluents were monitored with respect to chemical oxygen demand (COD), biochemical oxygen demand (BOD), and solid residue fractions. Column influents differed markedly in COD and BOD content but column effluents had consistently low contents indicating the high renovative capacity of the soil. *In situ* tensiometric, redox, and flow rate measurements indicated development of the most severe barriers to flow in columns ponded with low BOD aerated effluent, followed closely by those ponded with high BOD septic tank effluent. No barriers developed in columns ponded with water. Total concentrations of solid residue fractions in the two effluents and the cumulative load of solids applied to the columns did not differ significantly, but particle sizes in the aerated effluent were smaller. Increased pore clogging in aerated influent treatments points to the significant role of effluent solids in the clogging process in slowly permeable clayey soils. Additional studies are in progress to better define critical waste characteristics as related to soil clogging.

Additional Index Words: septic tank effluent, extended aeration, soil disposal, liquid waste.

Slowly permeable soils, such as the Almena silt loam (Aeric Glossaqualf) and other soils with comparable permeability characteristics comprise approximately 800,000 hectares (2 million acres) in Wisconsin and are defined as unsuitable by the current Health Code for on-site subsurface disposal of septic tank effluent due to the low permeability. Measured percolation rates of 27.5 min/cm (70 min/inch) in the topsoil and 39.4 min/cm (100 min/inch) in the subsoil exceed the critical rate of 23.6 min/cm (60 min/inch) (24, 25). The capacity of a soil to accept and conduct liquid can be better expressed by considering hydraulic conductivity data which is physically well defined (7). Measurements *in situ* in the Almena silt loam yielded K_{sat} values of 4 cm/day (0.98 gal/ft^2 per day) for the topsoil and 2 cm/day (0.49 gal/ft^2 per day) for the subsoil.

The low hydraulic conductivity of Almena silt loam soil can be illustrated by considering the derived theoretical loading rate as a function of the percolation rate according to $Q = 5/\sqrt{t}$ (Q = loading rate in gal/ft^2 per day; t = percolation rate in min/inch) which is the standard equation used to size seepage beds (24). A percolation rate of 39.4 min/cm (100 min/inch) translates into a loading rate of 0.5 gal/ft^2 per day, or 2.04 cm/day, which is equal to K_{sat}, the conductivity at saturation, of the horizon.

Crust formation and clogged layers within drainage beds will appreciably reduce soil permeability (7). Clogging of soil pores by suspended particles from effluent may decrease infiltration (11). Other data suggest that clogging may be due to production of gums, derived from organics in the liquid waste and in the soil pores (1, 5, 14, 15, 16, 17, 23).

Prior research has often assumed that clogging is mainly related to the carbon load of the effluent. It has been suggested, therefore, that aerobic treatment of waste water which can substantially reduce the carbon load could lengthen the life of the system by reducing the clogging problem (12). Investigations have therefore been limited to determinations of ambient factors which induce or alleviate the clogging problem within the seepage bed. Unfortunately, research has been restricted to column studies using artificially aggregated soil fill materials (18), rather than undisturbed cores in which flow patterns of liquid are significantly different (2). In this study large undisturbed cores of the Almena silt loam were extracted in the field and pretreated such that minimal disturbance of structure and soil solution occurred prior to [illegible] column studies. The formation of flow inhibiting layers as a function of carbon load was followed with tensiometers.

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[1]Contribution from the Soil Science Department, College of Agricultural and Life Sciences, Univ. of Wisconsin and the Geol. Nat. Hist. Survey, Univ. Extension, Madison, Wisconsin. This research was part of the Small Scale Waste Management Project, Univ. of Wisconsin funded by the Upper Great Lakes Regional Commission and the State of Wisconsin. Received 9 Dec. 1973

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