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ADAPTIVE SHORT-TERM WATER QUALITY FORECASTS
USING REMOTE SENSING AND GIS

DISSERTATION

Presented in Partial Fulfillment of Requirements for
the Degree Doctor of Philosophy in the Graduate
School of The Ohio State University

by
Ming-Der Yang, B.S., M.S.

The Ohio State University
1996

Dissertation Committee: Approved by
Dr. E. T. McDonald
Dr. C. J. Merry
Dr. R. M. Sykes

Advisors
Department of Civil and Environmental
Engineering and Geodetic Science
ABSTRACT

Water quality modeling has been developed for more than three quarters of a century, but is limited to the study of trends instead of making accurate short-term forecasts. A major barrier to water quality modeling is the lack of an efficient system for water quality monitoring. Traditional water quality sampling is time-consuming, expensive, and can only be taken for small size samples. Also, instant and accurate water quality data cannot always be provided to satisfy the demands of water quality modeling and parameter calibration. Remote sensing provides a revolutionary technique to monitor water quality repetitively over a large area. The major concerns regarding the use of remote sensing for water quality monitoring are: 1) suitable spectral channels for deriving various characteristics of water quality variables, and 2) appropriate and efficient image processing techniques to convert image brightness to traditional water quality indices.
The first objective of this research is to use SPOT satellite imagery to remotely detect water quality variables, such as chlorophyll a, Secchi depth, and phosphorus. A geographic information system (GIS) software — ERDAS IMAGINE — was integrated into the monitoring system to enhance the display of predictions from the water quality model QUAL2E. The short-term forecasting system was applied to a case study at the Te-Chi Reservoir, Taiwan. All water quality variables from simulations are displayed on a geographically registered map and in color to correspond with varying water quality levels. The visualizing technique is helpful for rapid understanding of water quality conditions. The complete integrated system being developed is designed to be economical and to efficiently answer "what-if" questions whenever pollutant sources change in the system.

The second objective of this research is to calibrate relevant biological parameters by incorporating remote sensing data into the modeling system. The most important biological parameters, the maximum growth rate and respiration, were calibrated by using least squares estimation and SPOT satellite data. The results yield data of algal biological parameters that provide engineers with fundamental information about the interactions within the ecosystem for use in controlling eutrophication.
To My Parents
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Purchase of the SPOT imagery was made possible by the Department of Civil and Environmental Engineering and Geodetic Science and the College of Engineering, The Ohio State University.

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VITA

November 11, 1967.............................. Born in Taiwan, R.O.C.

1990......................................................... B.S., Civil Engineering
National Chiao-Tung University
Hsing-Chu, Taiwan, R.O.C.

1990-1991............................................... Research Assistant,
Water Resources Laboratory
National Taiwan University
Taipei, Taiwan, R.O.C.

1993........................................................... M.S., Civil Engineering
The Ohio State University
Columbus, Ohio

1996........................................................... Intern, Division of Surface Water
Ohio Environmental Protection
Agency
PUBLICATION

Research Publication


FIELDS OF STUDY

Major Field: Civil and Environmental Engineering
   Studies in Environmental Engineering and Remote Sensing
Minor Field: Geodetic Science
   Studies in Photogrammetry
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CHAPTER 1

INTRODUCTION

Eutrophication is the most important problem of water quality for developed and developing countries. Thomann (1987) broadly defined eutrophication as:

• • • “the input of organic and inorganic nutrients into a water body which stimulates the growth of algae or rooted aquatic plants resulting in the interference with desirable water uses of aesthetics, recreation, fish maintenance, and water supply”. (p. 386)

Problems with eutrophication include bad odors, funny tastes, and scum in the water supply.

This increases the cost of water treatment and causes an unbalanced ecosystem. In aquatic trophic systems, algae play a significant role in an aquatic ecosystem because of their role in primary production (Shubert, 1984). Excessive growth of algae is caused by the over-discharge of nutrients into water bodies, such as lakes and rivers. Therefore, nutrient reduction is the essential solution for
controlling eutrophication. Environmental engineers can reduce the concentration of input nutrients by pre-treating wastewater before it is discharged into lakes and rivers. However, building and maintaining water treatment plants is very expensive. Therefore, ecologists have proposed another solution to eutrophication problems from the trophic-dynamic viewpoint. This method includes biological regulation by introducing natural predators of algae, aquatic insects, into the ecosystem to reduce the growth of algae. In some cases, biological regulation can efficiently control eutrophication problems. But in other cases, it cannot function very well because of the appearance of another higher trophic species — fish. "Which one is the first regulator controlling the ecological structure, either nutrient control or biological regulation?" has been a controversial question (Ward, 1992). In my previous research, a trophic-dynamics model was built to answer this question (Yang, 1993). The research concluded that in a two-link food chain system, algae can be controlled by biological regulation because algae is predator-limited. But in a three-link food chain system, algae only can be controlled by nutrient reduction because algae are food-limited. When engineers know what the trophic structure is (two- or three-link), then they can determine whether nutrient reduction or biological regulation is the best strategy to control eutrophication problems. In summary, an investigation of the aquatic ecosystem has to be carried out because an ecosystem will develop into a two- or three-link food chain.
depending on biological parameters of trophic species, such as maximum growth rates, respiration rate, and growth affinity constants.

Unfortunately, those parameters usually are a mystery for a specific water body due to insufficient water quality data. The only information available are reports from research laboratories. Suggested values from these reports do not carry much information on local characteristics. Furthermore, since those biological parameters are included in water quality modeling, researchers can only adopt a set of suitable values from a customary range obtained in a laboratory. Calibration of these parameters is difficult in most cases because of the lack of field data. Moreover, the procurement of water quality data is a severe barrier for water quality modeling to become more practical.

1.1 The Nature of The Problem

Conventional measurement of water quality requires on-site sampling and laboratory work, which is expensive and time consuming. Also, due to these two limitations, the sample size is very often small and reduces the reliability of the results. A revolutionary technique to monitor water quality — remote sensing — can overcome this problem. A number of studies have shown that applications of
remote sensing meets the demands of a large sample and provides a complete spatial and temporal view of water quality (Ritchie et al., 1990).

In short, problems that exist in water quality modeling are briefly stated as:

- water quality sampling is difficult because conventional manual field investigations are time-consuming;
- water sampling only covers a limited area;
- a wide-cover water quality test is extremely expensive;
- environmental and biological parameters in water quality models have no field data as a reference;
- the simulated result is displayed only in numerical figures without any association with geographic spatial information.

1.2 Water Quality Monitoring Systems With Remote Sensing

The application to remote sensing on water quality monitoring has been demonstrated by several authors. A semi-automatic data acquisition and handling system was developed by Scarpace et al. (1979) to employ multidate Landsat imagery for the assessment of the trophic status of inland lakes in Wisconsin. Lillesand et al. (1983) and Verdin (1985) used Landsat Multispectral Scanner (MSS) images in lake and reservoir water quality studies. Khorram and Cheshire
(1987) also used MSS digital data to compare 75 surface samples to monitor water quality variables, such as salinity, chlorophyll a, turbidity, and total suspended solids for the Neuse River Estuary in North Carolina. Through regression techniques, Landsat Thematic Mapper (TM) data were used to assess water quality conditions in Green Bay (Lathrop and Lillesand, 1986). Later SPOT data were also tested (Lathrop and Lillesand, 1989). Temperature is a very fundamental factor in hydrodynamics and biological reactions. Satellite data have been used to describe the thermal variation in lakes and rivers (Bolgrien et al., 1995). Multispectral remote sensing techniques have been used to measure suspended sediment concentrations in lakes (Merry et al., 1988; Lyon et al., 1988; Liedtke et al., 1995). A radiometric model for determination of water depths from remote sensing data has been successfully developed based on physical and chemical processes of light penetration (Lyon and Hutchinson, 1995). Many studies have also contributed to developing algorithms for remote sensing to measure chlorophyll concentration (Harding et al., 1995).

Most previous studies have focused on the investigation of the relationship between remote sensing data and field measurements. However, advantages of remote sensing, such as covering a wide area and providing instant information, can add a valuable data for water quality management. To improve the application of remote sensing to a practical level, the integration of remote sensing and water
quality modeling needs to be done before a water quality forecasting system can be established.

1.3 Purpose of The Study

Remote sensing provides a revolutionary alternative for water quality monitoring for a range of temporal and spatial scales. Therefore, the first goal of this research is to integrate water quality modeling with remote sensing techniques to enhance the contribution of water quality modeling in practical water quality management. The second purpose of this study is to calibrate relevant biological parameters by the incorporation of remote sensing data.

The benefits from the application of remote sensing are expected to:

- provide synoptic and repetitive monitoring for a large area with a broad range of sample sites;
- obtain water quality data instantly and economically;
- periodically calibrate and verify the water quality model with remote sensing data;
- display predicted water quality conditions temporally and spatially by means of pictorial and graphic presentations;
• establish a water quality management system and provide decision-makers useful information.

This dissertation is divided into six chapters. Chapter 1 states the nature of the problem and the primary objectives of this research. Chapter 2 presents related literature and a theoretical background of satellite remote sensing and geographic information systems associated with water quality assessment. Chapter 3 describes the methodology used to calibrate water quality parameters using remotely sensed data in water quality modeling. Chapter 4 shows a study case on the Te-Chi Reservoir in Taiwan for which a detailed study plan, study site delineation, data collection, and image processing of the data are included. A procedure of how to integrate remote sensing into water quality modeling and then how to store and display the data with GIS software is also discussed in this chapter. Chapter 5 provides and discusses the results of the simulation and calibration. The final products from the monitoring system and the integrated forecasting system are presented. Chapter 6 presents a conclusion of this research and addresses the perspective of the applications of water resources monitoring and management.
CHAPTER 2

WATER QUALITY ASSESSMENT AND PRESENTATION USING REMOTE SENSING AND GIS

Traditional methods of monitoring water quality are dependent on the collection of \textit{in situ} samples, which are taken from discrete locations. This relatively small portion of water is transported to laboratories and tested using various chemical and physical procedures. In the real world, open water usually covers a considerably wide area. Hence, the analytical results from several collection bottles of water seldom represents the entire water body. A large number of samples, of course, can yield a better confidence level. However, a large-scale sampling is unfeasible most of the time due to either economical limitations or physical difficulties. Remote sensing with its synoptic and repetitive coverage provides a valuable assessment technique to examine a broad-area water body. The applications of remote sensing imagery include assessing ecological changes, changes in moisture regimes over a growing season, vegetation or soil
types, and land cover classification (Lachowski and Bergsvik, 1990; Evanisko, 1990; Bullock et al., 1994; Lachowski et al., 1994; Johnsson, 1994). Incorporating remote sensing as an instantaneous water quality monitoring tool into water quality models can be used to simulate or even forecast the water quality variations. Furthermore, integration of remote sensing with the data structure of a GIS (Geographic Information System) can provide a visual presentation of water quality variables throughout a water body. The purpose of this chapter is to briefly introduce the knowledge background of how remote sensing, water quality modeling, and GIS are applied in water resources engineering, especially for water quality applications.

2.1 Remote Sensing in Water Resources

2.1.1 Spectral Characteristics of Water Bodies

As light reaches an object, it must be reflected, absorbed, or transmitted. The distribution and proportion of solar energy is determined by the nature of the surface, the wavelength of the electromagnetic energy, and the angle of illumination. For example, spectral reflectance received by remote sensors from
water bodies depends on several interactive factors, including the radiation incident to the water surface, roughness of the surface, angles of observation and illumination, reflection of light from the bottom in some cases, optical properties of the water, and atmospheric scattering (Campbell, 1987). Those major sources of electromagnetic energy reflected from water bodies and recorded by satellite sensors are illustrated in Figure 2.1. In the figure, \( E_0 \) is solar energy; \( \theta_0 \) is the solar zenith angle; \( L_r \) is radiance reflected from the water surface; \( L_w \) is radiance reflected from the water body; \( L_a \) is radiance from the atmosphere; and \( L_s \) is radiance recorded by the sensor.

For clear water, a major portion of light is transmitted or absorbed by a water body as it strikes the water surface. Only a small amount of energy is reflected into the sky and appears as a very low brightness value on remote sensing images. The influence of atmospheric scattering, including Rayleigh scattering, Mie scattering, and nonselective scattering, depends upon the wavelength. For pure and deep water, water is expected to be blue because in this range light penetration is not strong and light is scattered mostly by particles that are small relative to the wavelength (known as Rayleigh scattering). As the wavelength of light gets longer, e.g. red region, absorption of energy becomes much greater and only the reflectance from shallow water bodies can be detected. With a further
Figure 2.1 Sources of radiance recorded by satellite sensors (after Stumpf, 1987)
increase in wavelength, light absorption is so great that pure water reflects almost nothing in the near infrared region. As water becomes polluted, its spectral characteristics change due to the constituents in the water, such as phytoplankton, dissolved organic substances, and inorganic suspended solids. Such spectral characteristics make it possible to distinguish polluted water from pure water. The detailed theoretical knowledge is discussed later, but first we have to review the present performance of satellite remote sensing systems.

2.1.2 Satellite Sensors

Remote sensing information provides a unique perspective that cannot be obtained from ground field investigations. Types of remote sensing data include low- and high-altitude airborne imagery and satellite imagery. Satellite sensors have certain advantages over aircraft photography because of their synoptic view, and repetitive and large area coverage. Such advantages include savings in data acquisition expenses and a decrease of the time required for data collecting and image processing. These advantages are tailored to meet the needs of water resources monitoring.
Originally in the 1960's, the land observation satellites were designed for weather observation. After the first Landsat ("Land Satellite") satellite, designed for the observation of land resources, was launched in 1972, the application of satellite systems to the earth's environment has significantly increased year after year. There is a big difference in satellite orbits between these two systems. Meteorological satellites are positioned in geosynchronous orbits and revolve at an angular rate the same as the earth's rotation and cover the same area all the time. On the contrary, earth observation satellites are placed in sun-synchronous orbits and keep a constant angular orientation with the direction of solar radiation. Therefore, such satellite sensors always overpass a given location and record the reflectance from the ground at the same local time to avoid the variation of solar illumination.

Whether or not a sensor is tailored to record the wavelengths of interest for specific scientific investigations has to be verified by the spectral regions of the instruments. Presently, satellite remote sensing systems, such as the Landsat Thematic Mapper (TM), the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR), and SPOT (Le Système Pour l'Observation de la Terre) HRV (High Resolution Visible) are all potentially useful in monitoring water quality (Lathrop, 1988). As long as the
water quality parameter has a spectral signature located within the desired spectrum window, remote detection is feasible. Figure 2.2 shows the spectral regions for AVHRR, Landsat MSS and TM, and SPOT HRV sensors. Most MSS and TM bands are capable of detecting water quality parameters, depending on the specific purpose. Among the seven bands of TM, Bands 1, 2, 3, and 4 are suitable for assessing the optically-related water quality parameters of chlorophyll a, turbidity, and Secchi depth, and TM band 6 (thermal band) can be used for surface temperature detection (Lathrop, 1985). All three spectral regions of the HRV instrument cover the electromagnetic spectrum that can be used to detect variations in water quality. As a result, Landsat TM and SPOT HRV sensors are broadly used to distinguish different levels of pollutants for water bodies.

2.1.3 Landsat and SPOT

Landsats 1, 2, and 3 revolve around the earth 14 times each day (about 103 minutes per orbit) (Campbell, 1987). It takes 18 days to complete a cycle, which consists of 252 orbits. Since the earth rotates from west to east, each successive Landsat orbit from north to south is offset to the west by 2,875 km at the equator. Landsats 1, 2, and 3 use both analog and digital detectors, which include the return
Figure 2.2 The spectral sensitivity of NOAA AVHRR, Landsat MSS and TM, and SPOT HRV sensors (after Lillesand and Kiefer, 1994)
beam vidicon camera (RBV) system and the multispectral scanner (MSS) to produce images. The MSS uses a west-to-east oscillating mirror to generate an image swath of 185 km. The instantaneous field of view (IFOV) for the Landsat sensor is approximately 79 m x 79 m. The size of a pixel (picture element) for the MSS is 79 m x 56 m. An MSS scene consists of approximately 2,400 scan lines and each line has 3,240 pixels.

Later, a new sensor Thematic Mapper (TM) was added for Landsat-4 and -5. The improved designs of TM include a finer spatial resolution, greater radiometric detail, and more spectral information. The size of a pixel for the TM sensor is 30 m x 30 m. The mirror on TM moves in both the east-west and west-east directions so that the scanning mirror is slowed down and can focus more energy on the detectors over a longer time period to provide more radiometric detail. Landsat-4 and -5 complete the coverage of the earth in 16 days — 233 orbits.

SPOT uses an HRV sensor, which is a pushbroom scanner using charge couple devices (CCDs) that generate an entire line of data instantaneously with no moving parts. Having the detectors on the focal plane results in a higher geometric accuracy. The SPOT linear array is composed of 6,000 detectors for each scan line in the panchromatic mode, for a spatial resolution of 10 m x 10 m. In the
multispectral configuration (3,000 detectors per scan line), SPOT has a spatial resolution of 20 m x 20 m. Moreover, HRV offers a pointing capability up to 27° off-nadir so that the sensors can observe the earth directly beneath the satellite or 950 km on either side of nadir. This technology enables SPOT to gain repeat coverage at intervals of 1 to 5 days, depending on the latitude. Because of such capabilities, SPOT has been successfully applied to research problems in water resources (e.g. Lathrop and Lillesand, 1989).

2.2 Application of Remote Sensing in Water Quality Assessment

As a major data source of geographic information, digital remote sensing presents not only a simple extension of conventional aerial photography, but also an effective approach to the analysis of the earth's surface (Manfred et al., 1991). Because GIS and remote sensing systems use similar equipment and computer programs for analysis and display, remote sensing systems can provide timely information at low cost and in a compatible data form for a GIS. Most traditional methods of monitoring water resources rely on measurements made at specific points. Remote sensing provides a valuable spatial perspective in investigating the
earth's water for broad-scale and systematic patterns that is difficult using traditional methods.

Since the 1960s, remote sensing has been adopted as a hydrologic monitoring tool (Viessman et. al., 1989). Most research has emphasized water quantity, such as precipitation, evaporation, and other types of water circulation. For example, Bhaskar (1991) compiled a GIS with the watershed hydrology simulation (WAHS) model to estimate hydrologic parameters and runoff. Recently, methods of water quality investigation through the application of remote sensing have been developing. For example, Welch and Remilard (1988) used remote sensing data from aerial photographs to monitor aquatic macrophytes and water quality in Lake Marion, South Carolina. Kim and Ventura (1993) and Smith and Vidmar (1994) integrated remote sensing, GIS, and water quality models for the management of water pollution in urban areas.

Water bodies reflect various spectral qualities and quantities, depending on the water surface, optical properties, water temperature, and constituents in the water. Some forms of water characteristics can be remotely observed in a direct or indirect mode (Avery and Berlin, 1992). When the object has a spectral signature within the spectrum window, direct detection is possible. Otherwise, by observing changes in the aquatic environment, indirect detection is possible. For example,
an algae bloom is an indicator showing that the water body is excessively fertilized or eutrophic (Shubert, 1984). When an algal population is largely, the chlorophyll concentration is easily identified in a color infrared image. This characteristic contributes much to the investigation of eutrophication, especially in tropical and subtropical areas. Therefore, the monitoring of water quality can be done using visible, near infrared, and thermal imagery using data the Landsat TM and SPOT HRV sensors. Compared to conventional manual field investigations of water quality, remote sensing provides a synoptic and repetitive coverage monitoring the changes in a water body through time, especially for pollution from non-point sources (Lathrop, 1988).

2.2.1 The Reflectance Characteristics of Water Quality

Water quality is a reflection of the controlling bio- and geo-chemical processes and shows a great variability over a range of temporal and spatial scales (Lathrop, 1988). As long as the water quality parameter has a spectral signature within the spectrum window, remote detection is feasible. There are several major concerns with remote sensing for monitoring water quality. The most important consideration is the spectral range and the optimum band width, which is
important for detecting water quality characteristics. Water quality is considered to be associated with the concentration of three constituents, which are phytoplankton, dissolved organic substances, and inorganic suspended solids.

Figure 2.3 shows the typical reflectance curves for three basic features: healthy green vegetation, dry bare soil, and clear lake water. In addition to clear water, there could be other materials in a water column, such as some soil, which is called suspended solids, and aquatic vegetation, which is algae in most cases. Generally, these two components significantly influence the reflectance signature from a water body. Thus, non-clear water would have a spectral signature, which depends on the proportion of suspended solids and algae concentration in the water. For example, clear water strongly absorbs energy in wavelengths greater than 0.75 μm, which is the near infrared range. In a eutrophic water body, which means water has a high primary production, the chlorophyll in the algae largely increases the reflectance of a water body in the green and near-infrared spectral regions. The higher the chlorophyll concentration in the water body, the stronger the reflected energy in both wavelength ranges. Moreover, a eutrophic lake contains a high concentration of inorganic materials, such as phosphorus and nitrogen, which increase the water turbidity. Therefore, the spectral curve will be
Figure 2.3 Typical reflectance curves for three basic types of earth features: healthy green vegetation, dry bare soil, and clear lake water (after Lillesand and Kiefer, 1994)
different from the clear water curve and will be a result of the combination of clear water and soil.

With a certain amount of phytoplankton, eutrophic water has a different spectral characteristic. Light that passes through phytoplankton pigments is received by chlorophyll molecules in the algae. A chlorophyll molecule is about 1 nm in diameter, whereas the phytoplankton are about 0.1 mm in diameter (Maul, 1985). Chlorophyll occurs in several forms, mainly including chlorophyll a and chlorophyll b. Chlorophyll a is the most important photosynthetic agent in most green plants and the most common water quality variable tested in a water quality investigation. Chlorophyll preferentially absorbs as much as 70% to 90% of incident light in the blue and red regions (see Figure 2.3). Besides the solar energy, algae also assimilates inorganic nutrients and releases oxygen and some organic matters as a fundamental biological process — photosynthesis. It is evident that a part of the radiance is absorbed because of algal photosynthesis. Moreover, the detritus of dead organisms in phytoplankton cause a complex spectral behavior. A typical spectral variation of phytoplankton is illustrated in Figure 2.4. There are strong absorption peaks at 440 nm and 675 nm.

The spectral behavior of suspended solids is associated with their composition in terms of natural material color and size distribution (Robinson,
Figure 2.4 Typical reflectance curve for phytoplankton (chlorophyll a) dominated water. Arrow shows increasing chlorophyll concentration. The dashed line indicates pure water spectrum. (after Robinson, 1985)
Generally, inorganic suspended solids reflect the most irradiance and have a relatively equal spectral reflectance in the visible and infrared wavelengths. The percentage reflectance was found to increase with a decrease of Secchi depth for different particle sizes and soil types at all wavelengths in the 500 to 1000 nm range (Bhargava and Mariam, 1991). Figure 2.5 shows typical reflectance curves for water with different levels of suspended solids. The reflectance in the yellow region increases while the concentration of suspended solids increases. Moreover, the water color is influenced by dissolved organic matters. Organic matters come from algae and other aquatic species. It has a strong absorption in the blue and a relatively consistent decrease of absorption with wavelength, as shown in Figure 2.6. However, a high concentration of suspended solids could mask the chlorophyll content due to its high reflectance.

This understanding of the spectral characteristics of phytoplankton, dissolved organic materials, and inorganic suspended solids, is important for using remote sensing data in water quality monitoring. To record the distinctive spectral behaviors and to distinguish the brightness values reflected from plankton and suspended solids, multispectral sensors must be employed (Robinson, 1985). Although it is possible that different combinations of chlorophyll and suspended
Figure 2.5 Typical reflectance curve for suspended solids dominated water. Arrow shows increasing suspended solid concentrations. The dashed line indicates pure water spectrum. (after Robinson, 1985)
Figure 2.6 Typical reflectance curve for dissolved organic matters dominated water. Arrow shows increasing dissolved organic matters concentration. The dashed line indicates pure water spectrum. (after Robinson, 1985)
solids present a similar brightness value, a model calibrated with *in situ* samples can provide an approach for the development of interpretive algorithms.

### 2.2.2 Deterministic Radiometric Modeling of Water Bodies

Deterministic models mathematically present natural phenomena based on their physical and chemical properties. By simplifying complex realistic phenomena into several principal interactions, scientists and engineers are capable of simulating the phenomena of interest. Aas (1987) established a deterministic irradiance model to express the vertical attenuation coefficient and the irradiance ratio. An application of a radiometric model was used for evaluation of water depths with a verification of results using aircraft scanner data (Lyon and Hutchinson 1995).

A simple radiometric model for water bodies is briefly stated here based on the knowledge about optical characteristics of water. Among the three reactions (reflection, absorption, and transmission), when electromagnetic energy reaches the water surface, only the reflected energy can be detected by remote sensors. Initially, water volume reflectance ($R$) is defined as the ratio of outgoing radiance to incoming radiance:
where $\lambda$ is the spectral wavelength; $E_u$ is the upwelling irradiance by wavelength $\lambda$ and $E_d$ is the downwelling irradiance by wavelength $\lambda$. Irradiance is the radiance flux incident upon a surface per unit area of the surface, measured in watts per square meter (W/m$^2$). Generally, a diffuse or Lambertian source reflects solar energy equally in all directions. Satellite sensors record the radiance, which is influenced by the angle that the sensor views the feature and the object's spectral characteristic:

$$L = \frac{RE}{\pi A \cos \theta}$$

where

$L$: radiance received by sensors (W/m$^2$/sr);

$R$: the reflectance (dimensionless);

$E$: irradiance (W/m$^2$);

$A$: the object area (m$^2$);

$\theta$: the angle from the sensor to the normal of the object surface (°); and
The solid angle is the ratio of an area \((a)\) on the surface of a sphere, which is the area of the sensors herein, to the square of the radius of the sphere \((r)\):

\[
\omega = a/r^2
\]  

(2.3)

As Figure 2.1 shows, the sources of radianc observed by the satellite's remote sensors include radianc reflected from the water surface \((L_g)\), radianc from the atmosphere \((L_A)\), and the upwelling radianc from the water body \((L_W)\). Thus, the radianc actually measured at the satellite \((L_\star)\) is defined as (Campbell, 1987):

\[
L_\star = (L_g + L_W) \tau + L_A
\]  

(2.4)

where \(\tau\) is the atmospheric transmittance. \(L_g\) depends on both skylight and direct sunlight reflected off the water surface. \(L_A\) and \(\tau\) depend on the scattering and absorption properties of the atmosphere. \(L_W\) represents the contents of the water body, which is the most important parameter in water quality monitoring. In a clear sky, \(L_W\) is the major radianc source that remote sensors can receive from
deep water bodies. $L_W$ is significantly dependent on sensor sensitivity, spectral resolution, and sensor resolution.

The success of a deterministic model is dependent on the verification by one or more data sets. Although the radiometric model delineates the transfer paths of solar energy quite well, there is a certain level of complexity to embrace all the influencing sources of the radiance received at the sensors. Moreover, there is almost no single wavelength or band that can completely detect water quality variables of interest. For example, the green band and NIR band are suitable for detecting the concentration of phytoplankton, but not suspended solids. Therefore, establishing an empirical algorithm could be an alternative for practical applications.

2.2.3 Empirical Modeling of Water Bodies

An empirical approach involves statistical analyses of natural phenomena. By defining relationships between the phenomena and evaluated variables, scientists and engineers can make predictions based on some known variables using statistical model. Typically, through a linear or non-linear regression model, an empirical calibration of the satellite data with concurrent surface reference
information is undertaken to correlate the digital data with water quality variables. Because of its straightforward interpretation, an empirical approach was widely adopted in the determination of water quality variables using remotely sensed data (e.g. Johnson, 1978; Khorram, 1981; Whitlock and Kuo, 1982; Bhargava, 1983; Lillesand et al., 1983; Bukata et al., 1985; Lathrop and Lillesand, 1986 and 1989; Sathyendranath and Trevor, 1989; Ritchie and Cooper, 1991; Lyon et al., 1992; Rundquist et al., 1996).

Besides chlorophyll, these water quality variables could include temperature, suspended solids, and turbidity, which are important considerations in public water supplies. Temperature controls bio-chemical reactions and physical phenomena in water. Suspended solids include inorganic and organic materials, which are released from algal cells and provide nutrients to algae. Turbidity, which is measured by the intensity of light passing through a water sample, can be used as an indicator determining the effectiveness of the treatment resulting from different chemicals and the dosage needed in wastewater treatment plants (Sawyer and McCarty, 1986). In general, turbid water is considered to be highly related to the concentrations of inorganic suspended solids, dissolved organic materials, and the excessive growth of algae. These sources play a dominant role in determining the water color. In laboratories, an instrument
method is commonly used that makes use of nephelometry to measure the intensity of light scattered by the turbidity particles and is expressed in nephelometric turbidity units (NTU). For field sampling, there is one simple device to estimate the transparency of water called "Secchi disk", which is a black-and-white disk of a specified diameter. By recording the depth through water body which the Secchi disk can be seen — Secchi depth, engineers are able to easily, economically, and directly get an on-site estimation of turbidity. Water with low turbidity or high Secchi depth usually represents a high quality water.

Based on observation at Lake Michigan (Lathrop, 1985), a regression model between TM data and water quality parameters of Secchi depth, chlorophyll a, and turbidity was established. A simple power model, \( y = ax^b \), or transformed as \( \ln y = \ln a + b \ln x \), was employed. A final regression model for Secchi depth (SD), chlorophyll a (CHLA), turbidity (TURB), and temperature (TEMP) was defined as:

\[
\ln SD = -5.36 - 4.75 \ln TM2 \\
\ln CHLA = 6.18 + 3.79 \ln TM2 \\
\ln TURB = 13.53 + 5.74 \ln TM3 \\
TEMP = -38.33 + 0.463 TM6
\]

where TM2, TM3 and TM6 refer to the digital count values recorded for TM band 2, 3 and 6, respectively. This regression model is statistically significant with a
very high correlation ($R^2 = 91.2\%$ through 98.7%). The coefficients in the above equations would vary for different weather and illumination conditions.

Band ratio, another empirical approach, can also be employed to illustrate the correlation between multispectral bands. Band ratio usually consists of two or more reflectance measurements in separate portions of the spectrum. If two objects have similar spectral characteristics, a band ratio provides little extra information. If there is a big difference of spectral behaviors between them, the ratio could magnify the contrast. A typical application is vegetation indices, which involve ratios between various combinations of digital values from individual spectral bands (Campbell, 1987). Chlorophyll has a significant absorption in the red band (R) and a strong reflection in the near infrared band (NIR). The NIR/R ratio can effectively enhance the difference of a measurement on vegetation because of the inverse spectral relationship between living vegetation in red and near infrared light. However, the disadvantage of band ratio is that the ratio could be impacted by unknown external factors, such as atmospheric degradation. Other aspects of remote sensing analysis, such as principal components, also could be employed in the interpretation of remote sensing data for specific research (Jensen et al., 1989).
2.3 Geographic Information Systems

2.3.1 GIS Background

The concept of GIS was developed in the 1960s, but the use of GIS has been growing dramatically since the 1980s (Smith et al., 1987). The main reason for the two-decade hibernation is the limitation of computer hardware development, because GIS operations rely extremely heavily on computer power. The functionality of geographic information systems is defined as data collection, transformation and editing, storage and data structures, manipulation, analysis, and presentation operations (Fabbri, 1992). Basically, GIS is a convenient tool to handle a variety of data sets, to provide an effective assessment of environmental controls, and to derive an analysis in a decision-making process. In short, the view of GIS as an integrated system incorporating data, equipment, procedures, and users involves a more complete understanding of information. The scientific community can benefit considerably from adopting this integrated system in such fields as the physical, biological, and chemical sciences.

For water resources management, GIS is a bridge function linking data sources, e.g. remote sensing, through environmental understanding to strategy
planning. While considering water quality, a wide range of information is included, such as algal growth, nutrient concentrations, chemical reaction coefficients, temperature, water depth, flow velocity, and pollutant sources. Almost all the information mentioned above varies spatially and temporally. These numerical data could be tied to a georeferenced map so that any result of water quality analysis can be identified at the correct location. GIS not only stores this data within the context of a georeferenced map, but also records all attributes of every crucial point and pollution source. In addition, there are many functions provided in GIS, including statistical programs, coverage transformation, drafting packages, and map presentation, which are helpful for water resources management and water pollution control plan design.

Usually GIS data is stored in two data structure formats — raster and vector. A raster data structure stores information in cell-based maps; for example, the pixels of satellite images are in raster format. This data format provides an easy way to store and manipulate data, especially for a wide-area watershed. Moreover, its similarity to the structure of remotely sensed data benefits the integration of the two systems.

On the other hand, the vector format records objects using the coordinates of the vertices of a polygon, providing an accurate presentation of distances,
shapes and sizes. It is helpful to locate points and delineate lines, such as the outline of crooked rivers and the shape of watersheds. But it costs more to encode data and causes a problem when superimposing data layers.

While considering GIS as a tool to help in decision-making and management, a vector approach is adopted because it can support the needs of the particular application by using a compact data structure. However, the remote sensing community has relied on the raster format, through which spatial data is partitioned into a regular tessellation, to process and analyze data. The integrated system must be able to process data from both raster and vector data structures. It is possible to use these two different data formats in projects, if the errors produced in the format transformation can be reduced.

On the market, there are several GIS commercial software packages, including ERDAS IMAGINE, MAP, MIPS, Intergraph MicroStation, and Arc/Info. Map Analysis Package (MAP) is a raster-based system that presents digital cartographic information. MAP provides most basic GIS operations such as encoding, reclassification, statistical analysis, terrain analysis, shape analysis, distance analysis, local operation, and output display.

Arc/Info, a powerful GIS software package, was developed by the Environmental Systems Research Institute Inc. (ESRI). Arc/Info's versatility meets
the wide needs for a variety of applications, such as system design and implementation, business and marketing, recreation management, cultural resource management, ecosystem assessment, natural resources management, military applications, natural and technological disaster management, environmental management, geoscience research, telecommunications, transportation, and GIS education and training (ESRI, 1995). Arc/Info versions have been released to run on VAX/VMS, UNIX, and PC platforms. However, an IBM PC/AT version has certain limitations for handling data processing and image display. In addition, Arc/Info provides a programming language — ARC Macro Language (AML) to organize Arc/Info commands into sophisticated performances such as branching, variable manipulation and argument transfer (ESRI, 1993). In short, AML has functions of combining Arc/Info tools to create specialized functions, building interactive menus, creating new commands, enhancing native ARC capabilities, implementing complex applications, and performing modeling.

ERDAS IMAGINE is an easy-to-use image processing and GIS package. ERDAS IMAGINE is especially good at operating on raster data, such as satellite imagery, and allows users to view, analyze, and query the data base. Also, the functions of statistics, attribute tables, and analysis graphics are included. An ERDAS IMAGINE version 8.2 for UNIX was adopted in this research. For GIS
operations, ERDAS IMAGINE provides users with three means of access, including 1) script models created with the Spatial Modeler Language, 2) graphic models created with Model Maker, and 3) pre-packaged functions in Image Interpreter. Spatial Modeler Language is the basis for all GIS functions in a text format (ERDAS, 1995). Model Maker is essentially the Spatial Modeler Language with a graphic interface that makes it easy to create a new model, which can be edited, run, and saved in graphic symbols. In IMAGINE Interpreter, many GIS functions were previously created and can be used with a dialog box interface. There are over 200 functions and operators to manipulate raster layers, matrices, tables, and scalars provided in Model Maker, including analysis, Boolean, conditional, focal scan, and matrix. All GIS functions used in this research were tested through Image Interpreter and later were collected in graphic models generated by the Model Maker.

2.3.2 GIS Applications in Water Resource Management and Research

A water pollution problem usually relates to the amount and location of pollutant sources. With a quantitative relationship between the water quality condition and the pollutant sources, environmental engineers can simulate the
changes of water quality. The simulated results are not easily understood because
the simulated results are only numerical values. Since the water quality impact is
strongly associated with the distribution of pollutant sources, it is obviously better
to display the simulated results on a georeferenced map. For example, the water
resources system for metropolitan areas always has a complex and large
distribution. A GIS accommodating a great deal of polygons and lines,
as well as their attributes, can be very helpful for management and maintenance.

GIS is developed to store and analyze raw data, via analytical techniques,
into meaningful information that supports a decision-making process. For a basic
level of applications, GIS is a convenient tool for supplying inventory information
of water resources. Including water quantity and quality, there are many water
variables that can be shown as layers in GIS, such as flow, water temperature,
dissolved oxygen, nutrient concentrations, phytoplankton, suspended solids
concentration, and pH. At a higher level of application, GIS can be incorporated
with a water modeling and expert system that provides a sophisticated prediction
and management tool for water resources. The computer database in water quality
models is in a raster format, which is compatible with the grid image of the remote
sensing and cell-based GIS software packages. There are a number of applications
demonstrated, including the evaluation of suspended sediments in freshwater and
coastal ecosystems, temperature of water bodies, crop residue and tillage practices for evaluation of non-point pollution, concentrations of chlorophyll in water and in plants, and other various applications (Lyon and McCarthy, 1995). Hamlett et al. (1993) established a water ranking model to estimate the potential non-point source pollution problems for 104 major watersheds in Pennsylvania using ARC/INFO and ERDAS GIS software. All factors concerned with the potential production and transport of sediment, nutrients, and pesticides from agriculture were recorded into an 100-m resolution digital database. These layers include precipitation, hydrogeology, soils, topography, geology, animal type and distribution, land cover, groundwater subbasin, pesticide use, minor civil subdivisions, depth of water, and average net recharge areas. Attribute data for soils, geology, groundwater quality, chemical-nutrient use, and cropping are all also retrievable. This is a typical GIS application in water quality management.

In short, GIS techniques enhance water quality modeling in the following ways: (1) displaying numerical modeling results in color and on a geo-referenced map that can be rescaled by request; and (2) clearly distinguishing the change of water bodies and land use. Moreover, there is a close relationship between GIS and remote sensing (Campbell, 1987). First, the remote sensing system is the main source from where digital data in a GIS comes from. Second, remote sensing
systems and GIS share the same equipment and computer software. Third, GIS data from other sources than remote sensing systems act as an ancillary frame to reduce the errors while processing remote sensing images. The integration of remote sensing and GIS has a high potential to benefit water quality monitoring, forecast, and management.
CHAPTER 3

CALIBRATION OF WATER QUALITY MODEL PARAMETERS
WITH REMOTELY SENSED DATA

If environmental engineers have a timely forecast of the water quality of the inflow to water treatment plants, water treatment companies can operate treatment processes more efficiently. An appropriate prediction of water quality also significantly influences the desirable uses of water for recreation and fisheries. However, conventional manual field investigations of water quality take a long time to collect water samples and then go through many laboratory procedures. Besides the time factor, financial constraints and physical limitations also hamper field sampling, especially in water quality monitoring of non-point source pollution. Therefore, field water quality sampling is scheduled with limited frequency. Remote sensing overcomes these difficulties and enhances water quality modeling for use in a forecasting system. The contribution of remote
sensing is more evident when water quality undergoes a significant change, e.g., after a severe storm or an excessive pollutant input. Remotely sensed data can fill the gap between two low-frequency field samplings and calibrate a model by offering an real-time initial water condition for a more accurate water quality simulation. In addition, remote sensing provides for superior spatial coverage for water quality monitoring.

3.1 Literature Review of Model Parameter Calibration

Various mathematical models for water quality modeling have been developed and applied to streams, lakes, and estuaries (e.g. Lung, 1986; Thomann and Mueller, 1987; Kuo and Wu, 1991; Kuo et al., 1994; Cole, 1994). All water quality models simulate the principal interactions among various components of water quality variables. For example, the most important factors in algal growth include algal maximum growth rate, nutrients, light, temperature, and respiration rate. A complex model includes more processes and, hopefully, will result in a better fit of simulation data. However, even though every aquatic system has individual characteristics, most model parameters can only be assigned typical values found in the literature due to the lack of a field water quality investigation.
Consequently, the error caused by coefficient uncertainty decreases the model’s reliability (Canale and Seo, 1996). Therefore, it is important to calibrate the values of those model parameters before the model can be implemented on a real system.

Shastry et al. (1973) first introduced a nonlinear parameter estimation procedure to determine the values of the various parameters or coefficients appearing in dissolved oxygen (DO) and biochemical oxygen demand (BOD) models. Taylor series expansions were used to linearize the nonlinear equations in these models. By minimizing a selected criterion function, which is the difference between the predicted values and the measured values in their study, model parameters can be resolved. The maximum likelihood method and the least squares method were tested to derive the minimization. The maximum likelihood estimate is restricted by the premise of an identical variance of the errors in the observations, while the least squares method provides unequal error observations using weighting factors. The least squares method was shown to be a better approach for the parameter calibration of a nonlinear model. Also, their results concluded that when several parameters are estimated simultaneously, there may be several sets of parameter values that result from the least squares estimation.
There is usually no way to decide whether the results from the calibration model are unimodal.

Recently, a one-dimensional DO model was calibrated with six sets of measured DO profiles on the basis of root mean square error (Stefan et al., 1993). Another calibration of a one-dimensional DO model was conducted by achieving the optimal fit between simulations and measurements (Stefan and Fan, 1994). A zero-dimensional model, a modified WASP4 (Water Quality Analysis Program version 4), was used to simulate phosphorus and chlorophyll concentration for Lake Okeechobee, Florida. Some of the model parameters were calibrated by graphically comparing simulation and field data on a monthly averaged basis (James and Bierman, 1995). To determine model coefficient values in several popular phosphorus models (zero- or one-dimensional), calibration was achieved by minimizing the average difference between observed and simulated values using a trial-and-error method (Seo and Canale, 1996).

All previous research includes a zero- or one-dimensional (depth) model and multi-temporal (monthly or yearly) water quality data for parameter estimates. However, some model parameters change seasonally, such as algal growth rate and respiration rate. This is because the values of algal biological parameters depend on algal species and the dominant algal species can vary seasonally. Therefore, a
multi-spatial calibration model was developed in this research. Water quality parameters were calibrated using a one-dimensional (channel length) water quality simulation and two-dimensional (watershed plan) spatially distributed water quality data, which was derived from SPOT satellite data for the Te-Chi Reservoir, Taiwan.

Calibration of a water quality model requires a set of spatially and temporally distributed water quality data, in addition to a set of initial conditions. To overcome the lack of calibration data, remote sensing provides an alternative for water quality monitoring for a range of temporal and spatial scales. A number of studies have shown that satellite imagery, such as Landsat and SPOT, has a capability of meeting the demand for a large sample area to provide a spatial and temporal view of water quality (Scarpace et al., 1979; Lillesand et al., 1983; Verdin, 1985; Lathrop and Lillesand, 1989; Ritchie et al., 1991; Harding et al., 1995; Ruiz-Azuara, 1995). In this study, SPOT imagery is adopted as the calibration data, because of its high spatial resolution (20 m by 20 m), to determine the best values of biological parameters for algal growth in the Te-Chi Reservoir. Also, the least squares method is adopted because of an unequal variance of the errors in satellite derived chlorophyll a concentration calculated in the parameter calibration. To avoid the error source from mixed pixels and the
effect from trees on the river banks, the satellite-derived chlorophyll data were not used for computation elements of less than 100 m (5 pixels) width in the calibration data set because of satellite resolution (1 pixel = 20 m). Therefore, those elements with a width less than 100 m were ignored by assigning “0” to the weight factor for those narrow river sections and “1” for the rest of the computational elements. This problem will be discussed in more detail later in Chapter 5.

3.2 Integration of Remote Sensing And Water Quality Modeling

In water quality models, a water body is subdivided into many finite segments, as shown in Figure 3.1. All variables are represented as averaged values within a cell, much like the brightness of a pixel on digital imagery. To apply remote sensing in a water quality monitoring system, the first fundamental task is to establish a bridge connecting remotely sensed data with water quality variables. As mentioned previously, deterministic radiometric models and empirical regression models are two ways to reach this goal. For the situation where comprehensive observations are lacking for spectral physical phenomena, an empirical regression model is the most practical approach.
Figure 3.1 A stream network example for QUAL2E
(after Brown and Barnwell, 1985)
Once the remotely sensed data are converted to water quality variables, one has a set of estimated water quality data for the entire water body. This set of water quality data can be used as an initial data to simulate and predict the water quality conditions, and can be served as calibration data for the biological and environmental parameters used in the model, such as the maximum growth rate of phytoplankton, affinity constants, and the algal growth rate.

There are two major advantages of integrating remote sensing with water quality modeling. First, both systems store data in a compatible format, which is a raster basis. Pixels on digital imagery are similar to computational elements in water quality modeling. Generally, the size of the computational elements is larger than the spatial resolution of remotely sensed images. Therefore, there is no problem with transferring finer pixels to coarser elements. Secondly, remote sensing imagery helps identify the geographic characteristics of water bodies for water quality models. Remotely sensed images cover an area that is large enough to cover the whole watershed for a given water body of interest. Since water quality is sensitive to geographic characteristics and must be registered on a reference coordinate system, it becomes easier to interpret the variation of water quality and to locate the pollution sources. Moreover, digital remotely sensed data
are compatible with a numerical simulation without a transformation of data format.

3.3 Literature Review of Water Quality Modeling

Since a study on the Ohio River in 1914, water quality modeling has attracted a great deal of attention from environmental engineers (Thomann and Mueller, 1987). Di Toro et al. (1971) and Thomann et al. (1975) developed mathematical modeling of eutrophication in lakes and reservoirs more than two decades ago. A comprehensive description of water quality modeling based on biochemical interactions is addressed by Thomann and Mueller (1987). Currently, there are various mathematical models and numerous application cases on streams, lakes, and estuaries. For example, Lung (1986) used an averaged stream water quality model that was modified from QUAL2E to illustrate the limiting factors of phytoplankton growth in the James River Estuary, Virginia. The study employed two sets of water sampling data collected in 1983 to calibrate the model. Their study provided a good understanding of the cause-and-effect relationship between nutrient loads and phytoplankton growth.
Recently, a new release of QUAL-W2 with many improved capabilities has been demonstrated on DeGray Lake, a U.S. Army Corps of Engineers reservoir located on the Caddo River, Arkansas (Cole, 1994). QUAL2E was also modified to simulate the hydraulics and water quality routines for Lake Okeechobee watershed, Florida (Wagner et al., 1996). Other related research for using water quality models to simulate eutrophication in multi-dimensions can be found in Kuo and Thomann (1983), Ambrose et al. (1986), Bird et al. (1986), Kuo et al. (1994), and Wang et al. (1994).

3.3.1 Introduction to Water Quality Modeling

The problem of eutrophication occurs when the nutrient enrichment exceeds the self-purification capacity of streams and lakes. How to accurately delineate and appropriately predict the impact of pollution on an ecosystem are the most important issues in dealing with water quality problems. Environmental engineers have expended a great deal of progress on the development of water chemistry and mathematical modeling techniques. There are a number of different types of water quality models for different specific situations. QUAL2E is a typical water quality model for a stream system. It uses a comprehensive
description of various non-conservative and conservative substances in an advective and dispersive flow.

QUAL2E, a versatile modified stream water quality model based on QUAL-II, was developed by the National Council for Air and Stream Improvement, Inc. (NCASI) and the Environmental Research Laboratory at the Center for Water Quality Modeling (CWQM) of the United States Environmental Protection Agency (EPA) (Brown and Barnwell, 1985). QUAL-II is an extension of the stream water model QUAL-I developed by F. D. Masch and Associates and the Texas Water Development Board (1971). There were several different releases of QUAL-II to meet specific needs. Subsequently, in 1976 the Southeast Michigan Council of Government (SEMCOG) combined the best part of existing versions of QUAL-II into a widely applicable model. Eventually, a new release model, named QUAL2E, was developed in 1985 after several enhanced revisions.

QUAL2E is designed to simulate the spatial and temporal variations of contaminants in rivers, including dissolved oxygen (DO), bio-chemical oxygen demand (BOD), water temperature, algae as chlorophyll a, organic nitrogen, ammonia, nitrite, nitrate, organic phosphorus, dissolved phosphorus, coliforms, arbitrary non-conservative constituents, and three conservative constituents. Once the initial conditions and environmental parameters are given, QUAL2E can
simulate the transport and interactions of pollutants, and eventually result in a prediction about when and where an algae bloom may occur. QUAL2E users are allowed to choose a steady state or dynamic simulation, and subdivide the stream system into many different reaches (up to 50 reaches), depending on their hydraulic characteristics. In addition, each reach can consist of many elements (total maximum of 500 elements) of seven different types: the headwater element, the standard element, the element just upstream from a junction, the junction element, the last element in the system, the input element, and the withdraw element. Figure 3.2 shows the general structure of QUAL2E. QUAL2E can run on an IBM compatible personal computer systems with at least 256K bytes of memory.

3.3.2 Modeling Algal Growth

In a water quality model for streams, especially for a eutrophic stream, the simulation of algal growth is the major concern. In most water quality investigations, chlorophyll \(a\) is reported. Chlorophyll \(a\) is a representative variable proportional to the concentration of phytoplankton biomass. For each water computational element, a mass balance equation for the phytoplankton \((P)\) in a
Figure 3.2 The general structure of QUAL2E
(after Brown and Barnwell, 1985)
homogeneous computational element is adopted as follows (from Thomann and Mueller, 1987):

\[
\frac{dP}{dt} = V(\mu - \rho)P - A \nu_p P + Q P_{in} - Q P
\]  

(3.1)

where

- \(P_{in}\): algal biomass concentration in incoming flow, M/L^3
- \(A\): area of a computational element, L^2
- \(V\): cell volume, L^3
- \(Q\): water flow, L^3/T
- \(\mu\): the specific growth rate of algae, 1/T
- \(\rho\): the death rate of algae, 1/T
- \(\nu_p\): the settling rate of algae, L/T

In general, water flow data can be obtained from hydrologic monitoring stations; the area and volume of each computational element are defined by users before a simulation; and death rate and settling rate of phytoplankton are set as constant or ignored because of their minor influences in the model. The
dominating factor of algal growth is the growth rate of algae and the respiration rate.

Under standard conditions, that is with sufficient nutrients and abundant sunlight, the maximum growth rate ($\mu_{\text{max}}$) at $20^\circ\text{C}$ for algae ranges from 1.5 to 2.5 d$^{-1}$, typically 1.8 d$^{-1}$ (Thomann and Mueller, 1987). However, in real water bodies there are several environmental factors limiting the growth rate of algae, including light intensity, nutrients, temperature, water velocity, pH value, and grazing pressure. Among those factors, light, nutrient concentration, as well as temperature are considered as the most important limiting factors. Thus, an approximate growth rate can be calculated by multiplying these effects as follows:

$$\mu_n = \mu_{\text{max}} G(I) G(N) G(T)$$

where $G(I)$ is the light factor, $G(N)$ is the nutrient factor, and $G(T)$ is the temperature factor. To compute the growth rate of algae under different circumstances, $G(I)$, $G(N)$, and $G(T)$ need to be acquired. These three principal environmental effects will be introduced in the following section.
**Light factor (G(I))**

The process of photosynthesis cannot occur without radiant energy. Light is a major form, which transfers energy from the sun to the earth. The penetration of sunlight into water is an important limiting factor for the rate of photosynthesis by aquatic plants. Light intensity varies with depth and depends on the light extinction coefficient of water bodies, as shown in Figure 3.3. The light extinction coefficient depends on suspended solids, organic matter, and living particulates in the water body. Beer's law describes the extinction coefficient ($K_e$) as a first order decay of the light ($I$) at a depth ($z$):

\[
\frac{dI}{dz} = -K_e I \quad (3.3)
\]

The value of $K_e$ can be calculated by measuring the Secchi depth ($Z_{sd}$) and ranges from 0.05 to 5 m$^{-1}$. The estimate of the extinction coefficient is based on Beer's Law. An assumption that the solar energy penetrates a water column to this Secchi disk depth is approximately 1/10 of the initial radiance on the water surface (Scherz et al., 1974). Therefore, the radiance at a Secchi depth ($I_{sd}$) can be calculated as follows:

\[
I_{sd} = I_0 e^{-K_eZ_{sd}} \quad (3.4)
\]
Solar radiation, $I$

(a) Decrease of light with depth. (b) Computation of extinction coefficient.

Figure 3.3 Light intensity varies with depth and light extinction coefficient of water bodies (after Thomann and Mueller, 1987)
where $I_0$ is the incoming solar radiation at the water surface. It follows that:

$$e^{-k_r Z_{SD}} = \frac{I_{SP}}{I_0} = \frac{1}{10} \quad (3.5)$$

or

$$K_r = \frac{2.3}{Z_{SD}} \quad (3.6)$$

There are several methods for computing the algal growth limitation factor for light, including Monod's half-saturation function, Smith's function, and Steel's function (QUAL2E, 1985). The first two methods state that algal growth increases when light intensity increases. Steel's function $F(I)$, which is popularly adopted in other related research, includes a photo-inhibition effect at high light intensities and is expressed as:

$$F(I) = \frac{I - I_{SP}}{K_L} e^{-(I - I_{SP})/K_L} \quad (3.7)$$
where \( K_c \) is a saturation light intensity when photosynthesis approaches a maximum value and \( I_z \) is the light intensity at a given depth \( Z \). Then, the light factor is estimated as the integration of the Steel's function with time and depth:

\[
G(I) = \int\int F(I) dtdz \tag{3.8}
\]

or

\[
G(I) = \frac{2.718}{K_c D} \left( e^{\frac{-I}{K_c}} - e^{\frac{-I}{K_c}} \right) \tag{3.9}
\]

where \( D \) is the water depth. A typical \( G(I) \) variation with light intensity is shown in Figure 3.4. The range of \( G(I) \) is from 0.10 to 0.50, which means the growth rate of algae decreases more than 50% due to the effect of light density (Thomann and Mueller, 1987).

**Nutrient factor \((G(N))\)**

Algae require from 17 to 18 kinds of nutrients for growth and maintenance (Darley, 1982). In natural water bodies, nitrogen and phosphorus are considered to be the fundamental nutrient that limits algal growth. Usually, only one nutrient is limiting the growth rate at a given time (Sykes, 1973; 1974). The growth rate
Figure 3.4 Effect of light $G(I)$ on algal growth rate (after Thomann and Mueller, 1987)

Figure 3.5 Effect of nutrient $G(N)$ on algal growth rate (after Thomann and Mueller, 1987)
increases as the limiting nutrient level is increased. But, the limiting nutrient can switch from one to another after one non-limiting nutrient is extensively consumed and remains deficient. The relationship between algal growth rate and the nutrient factor $G(N)$ is shown in Figure 3.5.

An empirically derived hyperbolic function, called the Monod function, is commonly adopted:

$$G(N) = \frac{N}{K_s + N} \quad (3.10)$$

The affinity constant, $K_s$, is the concentration of the nutrient when $G(N)$ is 0.5. It physically represents the affinity of the enzyme system for the ambient nutrient. A lower $K_s$ gives a higher ability to ingest nutrients at lower concentrations (Darley, 1982). A $K_s$ value of 10 - 20 $\mu$g/L for nitrogen and 1 - 5 $\mu$g/L for phosphorus is suggested (Thomann and Mueller, 1987).

Most of these nutrients are usually present in concentrations larger than $K$, and do not limit algal growth. Therefore, identifying can controlling the limiting nutrient is the most effective solution for eutrophic problems.
• Temperature factor \((G(T))\)

Compared with terrestrial life, aquatic organisms have no tolerance for wide temperature variations (Moran et al., 1989). As a result, a small change in water temperature could have a critical effect on an aquatic ecosystem. Temperature is closely related to biological activity and reaction, e.g., growth rate, feeding behavior and metabolism. The temperature adjusting value \((G(T))\) for algal growth rate is computed from the Streeter-Phelps formulation:

\[
G(T) = \theta^{(T-20)}
\]  

(3.11)

\(\theta\) is an empirical constant for the growth rate at different temperatures; and \(T\) is the water temperature. Since the maximum growth rate is defined as the growth rate at a standard temperature \((20^\circ C)\), \(G(T)\) makes an adjustment compensating for the temperature difference. The relationship between the temperature factor and temperature is illustrated in Figure 3.6. In addition, water temperature also has an effect on other aquatic species and water quality variables.
Figure 3.6 Effect of temperature $G(T)$ on algal growth rate (after Thomann and Mueller, 1987)
3.3.3 Finite Difference Solution in QUAL2E

The numerical solution of constituent concentrations in QUAL2E is solved by finite difference method. This section briefly illustrates the formulation of this numerical solution technique.

The governing equation is a one-dimensional advection-dispersion mass transport equation. This equation mathematically presents the interaction of each water quality constituent over space and time as (Brown and Barnwell, 1985):

\[
\frac{\partial C}{\partial t} = \frac{\partial (A_x D_L \frac{\partial C}{\partial X})}{A_x \partial X} - \frac{\partial (A_x \bar{u} C)}{A_x \partial X} + (rC + p) + \frac{s}{V} \tag{3.12}
\]

where,

\( C \) = the constituent concentration, \( M/L^3 \)

\( t \) = time, \( T \)

\( A_X \) = cross-sectional area, \( L^2 \)

\( D_L \) = dispersion coefficient, \( L^2/T \)

\( X \) = distance, \( L \)

\( \bar{u} \) = mean velocity, \( L/T \)
\( r \) = rate constant, 1/T

\( p \) = internal sources and sinks, M/T/L^3

\( s \) = external source or sinks, M/T

\( V \) = incremental volume, L^3

On the right-hand side of Eq 3.12, the terms represent dispersion, advection, constituent changes, external sources and/or sinks, respectively. \( r \) represents a first order growth/decay, such as the growth rate and respiration rate for algal simulation. \( p \) represents internal sources/sinks, such as nutrient loss from algal growth and benthos sources for phosphorus and nitrogen simulation. Considering chlorophyll concentration only in the calibration model, \( r \) is the sum of growth rate, respiration rate, and settling rate for algae, and \( p \) is zero because there is no internal sources/sinks for algal growth.

In water quality models, a water body is subdivided into many finite segments (Figure 3.1). All variables are represented as averaged values within an element, much like a pixel in digital imagery. The constituent concentrations in each computational element are calculated by a finite difference method. The implicit nodal scheme for the solution of constituent concentrations in QUAL2E is shown in Figure 3.7. With a superscript \( n \) as a time step and a subscript \( i \) as a
distance step, the derivative over time of a constituent concentration is estimated using finite difference, and the whole equation can be written as:

\[
\frac{\partial C_i}{\partial t} = \frac{(AD_{i} - \frac{\partial C}{\partial t})_{i} - (AD_{i} - \frac{\partial C}{\partial t})_{i-1}}{V_i} - \frac{(A\bar{u}C)_{i} - (A\bar{u}C)_{i-1} + r_i C_{i-1}^{t+1} + p_i + \frac{s_i}{V_i}}{V_i}
\]

(3.13)

In Eq 3.13, the incremental volume and the concentration change over time can be written as:

\[
\text{DOWNSTREAM} \leftarrow \text{UPSTREAM}
\]

<table>
<thead>
<tr>
<th>element i+1</th>
<th>element i</th>
</tr>
</thead>
<tbody>
<tr>
<td>i + 1</td>
<td>i</td>
</tr>
<tr>
<td>O</td>
<td>O</td>
</tr>
<tr>
<td>i</td>
<td>N: t-Δt/2</td>
</tr>
</tbody>
</table>

Figure 3.7 The implicit nodal scheme (after Brown and Barnwell, 1985)
Substituting Eq 3.14 into Eq 3.13 and applying finite difference to the temporal derivative of a constituent concentration, we have:

$$\frac{C_{i+1}^{n+1} - C_{i}^{n}}{\Delta t} = \frac{(AD_{t})_{i}C_{i+1}^{n+1} - (AD_{t})_{i}C_{i}^{n+1}}{V_{i}\Delta X_{i}} - \frac{(AD_{t})_{i-1}C_{i-1}^{n+1} - (AD_{t})_{i-1}C_{i}^{n+1}}{V_{i}\Delta X_{i}}$$

$$- \frac{Q_{i}C_{i}^{n+1} - Q_{i-1}C_{i-1}^{n+1}}{V_{i}} + r_{i}C_{i}^{n+1} + p_{i} + \frac{s_{i}}{V_{i}}$$

(3.15)

Furthermore, Eq 3.15 can be rearranged as:

$$a_{i}C_{i}^{n+1} + b_{i}C_{i+1}^{n+1} + c_{i}C_{i-1}^{n+1} = Z_{i}$$

(3.16)

where:

$$a_{i} = -[(AD_{t})_{i} - \frac{\Delta t}{V_{i}\Delta X_{i}} + \frac{Q_{i-1}\Delta t}{V_{i}}]$$

(3.17)

$$b_{i} = 1.0 + [(AD_{t})_{i} + (AD_{t})_{i-1} - \frac{\Delta t}{V_{i}\Delta X_{i}} + \frac{Q_{i}\Delta t}{V_{i}} - r_{i}\Delta t]$$

(3.18)

$$c_{i} = -[(AD_{t})_{i} - \frac{\Delta t}{V_{i}\Delta X_{i}}]$$

(3.19)

$$Z_{i} = C_{i}^{n} + \frac{s_{i}\Delta t}{V_{i}} + p_{i}\Delta t$$

(3.20)

For a river divided into a total of \(I\) elements, the finite difference equations in matrix form is:
The values of $a_i$, $b_i$, $c_i$, and $Z_i$ should be all known at time $n$, and $C_i$ at the time $n+1$ remains the only unknown. Initially $C_i^{n-1}$ can be solved by the $l$th equation. By processing a back substitution through the whole Eq 3.21, all $C_{r,i}$, $C_{r,2}$, $\cdots$, and $C_r$ at the next time step ($n+1$) can then be solved.

3.4 Development of Calibration Model Methodology

There are a number of environmental parameters in water quality models that influence the simulated results. In most water quality modeling, these parameters are set as customary constants because of limited field data. Calibration of those parameters in models requires a large sample size and long-term observations. Unfortunately, most water bodies lack intensive and continuous in situ sampling. However, those parameters, which greatly affect the
result of modeling, represent the characteristic of a local aquatic ecosystem. In a
eutrophication study, the most important parameters include the maximum growth
rate, affinity constant, light intensity constant, and temperature correction factor.
These parameters, which are essential parameters in the estimation of algal growth,
will improve the simulation by giving observed data rather than standard
customary values. In this section, the methodology of the parameter calibration by
multi-temporal and multi-dimensional remote sensing data is introduced.

3.4.1 Least Squares Estimates

The method of least squares is a general method of finding estimators. To
obtain the least squares estimators, the means of the least squares normal equations
are calculated by differentiating the criterion with respect to a regression
parameter and setting the derivatives equal to zero. The solution of the normal
equations yields the least squares estimates and the basic formulation appears as:

\[ V = AX - L \]  \hspace{1cm} (3.22)  

or
where $V$ is a residual vector, $A$ is a coefficient matrix, $X$ is a unknown parameter vector, and $L$ is an observation vector. $i$ represents the number of observations and $j$ represents the number of estimated unknowns. The solution of the unknown parameter vector is computed by:

$$X = (A^T PA)^{-1} A^T PL$$  \hspace{1cm} (3.24)
$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \end{bmatrix} = \begin{bmatrix} A_{11} & A_{21} & \cdots & A_{i1} \\ A_{12} & A_{22} & & A_{i2} \\ \vdots & \vdots & \ddots & \vdots \\ A_{1j} & A_{2j} & \cdots & A_{ij} \end{bmatrix}^{-1} \begin{bmatrix} A_{11} & A_{21} & \cdots & A_{i1} \\ A_{21} & A_{22} & & A_{i2} \\ \vdots & \vdots & \ddots & \vdots \\ A_{1j} & A_{2j} & \cdots & A_{ij} \end{bmatrix}$

where $P$ is the weight vector. Based on the root mean square, the estimated variance of unit weight is determined by:

$\sigma^2 = (AX - L)^TP(AX - L)/R$  \hspace{1cm} (3.26)
where $\sigma$ is variance and $R$ is redundancy. By minimizing the variance, the unknown parameters can be solved.

Using the method of least squares, a simple linear relationship can be established between the independent variables and predictor variables. By applying a Taylor series expansion,

$$f(x) = f(x_0) + \partial f/\partial x \, dx + \partial^2 f/\partial x^2 \, dx^2 + \cdots$$

all non-linear functions in the algal growth model (Eq 3.2 through Eq 3.7) can be linearized. Since all higher than first order terms are small enough to be neglected
compared with the first order term, eventually the Taylor expression consists of two principal components, which are the approximation value of the function \( f(x_0) \) and the sum of all first-order derivatives \( \partial f/\partial x \) multiplied by the linear corrections \( dx \). The initial approximation of the parameters can be assigned by a reasonable values within a range from literature. After several iterations, \( dx \) approaches a minimum and a set of suitable parameters are developed.

3.4.2 Algal Biological Parameters Calibration

With the incorporation of remote sensing, a more accurate initial condition can be obtained compared with the traditional estimation obtained from linear interpolation to the entire water body from several sampling points. Moreover, remotely sensed data will provide an opportunity to calibrate the environmental parameters used in a simulation by comparing the simulated results with another set of remotely sensed data. The water quality simulation and the calibration of environmental parameters is conceptually sketched in Figure 3.8. With two remotely sensed data sets and an iteration of least squares adjustment, a calibration model is established on top of the water quality model QUAL2E.
Figure 3.8 Flow chart of water quality modeling and remote sensing in the calibration model. $t_0$ is the initial time; $t_n$ is the time when the second satellite image was taken.
Since the most important water quality issue in this research is eutrophication, the calibration of algal parameters in modeling is necessary. To calibrate those biological parameters for algal growth, the difference between the concentrations of chlorophyll $a$ from the water quality simulation and remotely sensed data is calculated first. By minimizing this difference, a correction must be made to the approximate values of those biological parameters. To see how the biological parameters affect the difference between the difference of chlorophyll $a$, $\Delta b$, which is caused by differences of parameters, and $\Delta C$ are introduced into Eq 3.16 as follows:

$$a_i(C_{i-1} + \Delta C_{i-1}) + (b_i + \Delta b_i)(C_i + \Delta C_i) + c_i(C_{i+1} + \Delta C_{i+1}) = Z_i$$  \hspace{1cm} (3.29)$$

where $\Delta C_i$ is the difference between the concentrations of chlorophyll $a$ at the element $i$, and $\Delta b_i$ is the difference between the biological parameters at the element $i$. In Eq 3.29, $a_i$, $b_i$, and $c_i$ are constant, which are the same values in Eq 3.16. Substituting Eq 3.16 into Eq 3.29 and assuming $\Delta b_i \Delta C_i$ small enough to be ignored, we get:

$$a_i \Delta C_{i-1} + b_i \Delta C_i + \Delta b_i C_i + c_i \Delta C_{i+1} = 0$$  \hspace{1cm} (3.30)$$
In Eq 3.30, all terms are known, except for $\Delta C$ and $\Delta b_i$. For a steady flow, $\Delta b_i$ is only dependent upon the difference between the algal biological parameters ($\Delta r_i$). Since $r$ includes the growth rate, respiration rate, and settling rate as:

$$r = \mu - \rho - \frac{v_L}{D},$$

(3.31)

the difference between the biological parameters of algae can be written:

$$\frac{\Delta b}{\Delta t} = -\Delta r = -\Delta \mu + \Delta \rho + \frac{\Delta v_L}{D}.$$  

(3.32)

The specific growth rate of phytoplankton is limited by light, nutrient concentration, and temperature. An approximate growth rate can be calculated by multiplying these effects by the maximum growth rate of phytoplankton. Of more than two dozen biological parameters required in the simulation of algal growth, the maximum specific algal growth rate ($\mu_{max}$), the half saturation coefficient ($K_L$), and the Monod half saturation constant for nitrogen or phosphorus ($K_N$ or $K_P$) are the most dominant parameters. Applying Taylor series, which leads $\Delta f(x) = \partial f/\partial x$
dx, we can have linearized terms by adding the partial derivatives of μ with respect to μₘₐₓ, Kₐ, and Kₛ. Recalling Eq 3.2 through 3.8 for algal growth functions, the partial derivatives are:

\[
d\mu = A1 \times d\mu\text{ₘₐₓ} + A2 \times dkₐ + A3 \times dKₛ \tag{3.33}
\]

where:

\[
A1 = \frac{\partial r}{\partial \mu\text{ₘₐₓ}} = \frac{\partial r}{\partial \mu} \frac{\partial \mu}{\partial \mu\text{ₘₐₓ}} = G(I)G(N)G(T) = \frac{\mu}{\mu\text{ₘₐₓ}} \tag{3.34}
\]

\[
A2 = \frac{\partial r}{\partial Kₐ} = \frac{\partial r}{\partial \mu} \frac{\partial \mu}{\partial Kₐ} = \mu\text{ₘₐₓ}G(T)[\frac{2.718}{KₛD}\frac{I}{Kₐ}(e^{-\frac{I}{KₛD}} - e^{-\frac{I}{Kₛ}})]G(N)
\]

\[
= \frac{I}{Kₐ} \mu\text{ₘₐₓ}G(T)[2.718 - \frac{2.718}{KₛD}(1 - e^{-\frac{I}{KₛD}} - 2.718)]G(N)
\]

\[
= \mu \frac{I}{Kₐ} \frac{2.718}{KₛD}(1 - \frac{2.718}{KₛD}G(T)) \tag{3.35}
\]

(due to \(e^{-\frac{I}{KₛD}} \to 0\) with \(Kₛ \approx 2.3\) and \(D \equiv 10\) m and \(G(T) = \frac{2.718}{KₛD}(1 - e^{-\frac{I}{Kₛ}})\))
\[ A3 = \frac{\partial r}{\partial K_s} = \frac{\partial r}{\partial \mu} \frac{\partial \mu}{\partial K_s} \]
\[ = \mu_{\text{max}} G(T) G(I) \left( -\frac{N}{(K_s + N)^2} \right) \]
\[ = \frac{\mu}{K_s + N} \quad (3.36) \]

For the calibration of the respiration rate and the settling rate, the correction factors are:

\[ A4 = d\rho = 1 \quad (3.37) \]

and

\[ A5 = dv_s = \frac{1}{D} \quad (3.38) \]

and the total difference of biological parameters is written as:

\[ dr = A1 \times d\mu_{\text{max}} + A2 \times dk_L + A3 \times dK_s - A4 \times d\rho - A5 \times dv_s \]
\[ \quad (3.39) \]

\( \Delta r \) can also be represented in matrix form and in terms of a correction coefficient matrix (A) multiplied with the correcting vector of those parameters (\( \Delta X \)):

\[ \Delta r = A \cdot \Delta X = -\Delta b / \Delta t \quad (3.40) \]
By including another set of water quality data from a remote sensing system, the difference between chlorophyll a in each element between the simulated results and the remotely sensed data is revealed. Recalling Eq 3.30, $\Delta b_i$ is left as the only unknown and can be estimated by making a correction to their approximation values. Eq 3.30 can be rearranged as:

\[
a_i \Delta C_{i-1} + b_i \Delta C_i + c_i \Delta C_{i+1} = -\Delta b_i C_i
\]

or

\[
(a_i \Delta C_{i-1} + b_i \Delta C_i + c_i \Delta C_{i+1}) / C_i = -\Delta b_i.
\]

Substituting $\Delta r$, $\Delta t$ for $-\Delta b_i$, Eq 3.40 is rewritten in matrix form:
where \( I \) is the \( I \times 1 \) unit matrix. All terms on the left-hand side are known and rely on an update water quality data derived from satellite imagery. On the right-hand side, the correction term for algal biological parameters are the unknowns. In Eq 3.43, all equations on the left-hand side equal to one value, \( \Delta r \). Revising Eq 3.24, we have a standard form for least squares estimate:
Eq 3.43 is in the standard least squares form as Eq 3.44. The residual vector \( \mathbf{V} \) (the left hand side of Eq 4.43) is the difference between the satellite-derived data and QUAL2E-simulated data for chlorophyll concentration. The coefficient matrix \( \mathbf{A} \) ([A.] on the right hand side of Eq 3.43) is the first derivatives of the calibrated parameters which can be calculated by using Eq 3.34 through 3.38, and becomes a vector due to the same values of parameters assigned to all computational elements. Initially, an approximation is given for each of these calibrated parameters in the first run of the water quality model. By applying least squares adjustment and minimizing the residual, the correction vector \( \mathbf{\Delta X} \) (column vector on the right hand side of Eq 3.43) can be solved. With a new set of parameters, the second run of water quality modeling starts and results in a new correction vector. After several iterations, these parameters approach stable conditions, which result in the final answer.
Usually the values of these biological and environmental parameters are not known and can only be found in general bio-chemical and aquatic ecological references. To calibrate these parameters for a specific water body, this calibration model is an economical and time-saving approach. The above equations are written as computer program code (presented in Appendix A) and will be run for the case study at the Te-Chi Reservoir. The results will be presented and discussed in Chapter 5.
CHAPTER 4

WATER QUALITY MONITORING SYSTEM AND
SHORT-TERM FORECASTING SYSTEM

This chapter focuses on how to use remote sensing data in a water quality model and operate the data in a GIS. A demonstration was performed to incorporate the water quality model QUAL2E and an image processing and GIS package, ERDAS IMAGINE, with a water quality monitoring system and forecasting system. The integrated system was applied to the Te-Chi Reservoir in Taiwan. The procedures include: 1) project data collection and study site analysis; 2) feature extraction and analysis of the SPOT satellite digital data; 3) GIS function operations, including data encoding, format transformation, image processing, data analysis, and map presentation; and 4) linking the QUAL2E model with IMAGINE via Matlab software. As a result, all water quality variables
from the simulations can be displayed in color on a geographically registered map to correspond to varying water quality conditions.

The two approaches used to integrate GIS and water quality models include a "linked-model" approach, which links models with GIS, and a "modeling-within" approach, which embraces models within the GIS (Poiani and Bedford, 1995). In a linked-model approach, models are separated from the GIS, but share the data set in the GIS and pass relevant information back and forth between the two systems. Therefore, stand-alone models can be fully stretched their advantage in simulation. However, to link existing models with GIS is difficult and specially developed programs are necessary to link these two systems. If a modeling-within approach is adopted, current GIS software is inadequate to provide complex numerical computations that are necessary for most water quality models. This deficiency results in two drawbacks, including (1) the loss of temporal resolution, and (2) a simplified mathematical expression. The modeling-within approach can be expected to be more efficient when two systems are incorporated, for example, the water quality monitoring system in this research. The linked-model approach is used in the forecasting system due to the complexity of water quality simulations and the necessity for temporal resolution.
4.1 Data Collection and Study Site

4.1.1 Data Collection

The data needed for the water quality parameter calibration and the water quality forecasting system include remote sensing images, *in situ* samples, and topographic maps. A lot of effort and time were spent to complete the data collection because of several strict requirements. The data were collected by considering the following requirements:

- **study site**: an inland water body, a river or lake, which has algal blooms, and satellite images taken at the same time as the field sampling;
- **surface sampling data**: water quality variables including nutrient concentration, water temperature, chlorophyll a, and Secchi depth;
- **satellite images**: two area- and date-matched satellite images that are cloud-free over the water body and are acquired in series.

After evaluation of these criteria and the accessibility of data sources, the Te-Chi Reservoir in Taiwan was selected as a study site.
4.1.2 The Study Site: Te-Chi Reservoir

Te-Chi Reservoir is located on the upstream part of Ta-Chia River within the Central Mountains in the middle of Taiwan with an elevation of about 1,200 m to 1,300 m above sea level. Figure 4.1 shows the location and watershed area of the Te-Chi Reservoir. The Te-Chi Reservoir is operated by the Taiwan Power Company and its main goal is to provide hydroelectric power for the Ta-Chia Basin. The major inflow (about 68%) to Te-Chi Reservoir is from the Ta-Chia River, which has backwater extending roughly about 14 km from the Te-Chi dam. The total watershed area is about 592 km², and is predominantly used for agriculture and tourism. In addition, there are nine other tributaries into the Te-Chi Reservoir, including Bi-Tan Creek, Da-Pan Creek, Jian-Shan Creek, Jian-yang Creek, Chen-Wu Creek, Chia-Yang Creek, Chin-Yuan Creek, Li-Shan Drainage, and Soong-Mao Creek. In this study, the Te-Chi Reservoir, referred to hereafter, is geographically a part of the Ta-Chia River. The river reach studied extends 9.3 km upstream from the dam. The Te-Chi Reservoir was chosen as a study site because of the following reasons:

- the accessibility of in situ water quality data and remote sensing images;
Figure 4.1 The location and watershed of the Te-Chi Reservoir
• high algal concentration during summer that would be visible on satellite imagery;

• much previous research related to the hydraulic characteristics and water quality modeling at the Te-Chi Reservoir;

• a controversial issue of how much agricultural activity should be reduced in the watershed of the Te-Chi Reservoir; and

• large body of water — a good test object for satellite imagery.

According to the investigation of the Te-Chi Reservoir Management Committee, a part (about 6.5%) of the Te-Chi Reservoir watershed was developed into an agricultural area for economic purposes (Te-Chi Reservoir Management Committee, 1994). Most of the agricultural area is located along the Te-Chi Reservoir. Since this uncontrolled development of orchards and vegetable farms, a large amount of nutrients from fertilizers and farm wastes has been entered the reservoir as point and non-point sources. The abundance of manmade nutrients has stimulated excessive growth of aquatic plants and has even caused an algal bloom. A brown film, caused by high concentration of Peridinium, which is a dominant algal species at the Te-Chi Reservoir during the summer time, covers a partial section of the water surface, especially in the upper Ta-Chia River. Eutrophication becomes a big concern on the Te-Chi Reservoir when a
chlorophyll a concentration more than 400 μg/L are observed in the summer season.

The R.O.C. Environmental Protection Administration supports many projects to evaluate the eutrophication problem in Te-Chi Reservoir and tries to clean up the water body. A long-term water quality monitoring program of the Ta-Chia River has been in process since 1983. A field investigation of water quality on the Te-Chi Reservoir has also been undertaken for 12 years. Field water quality sampling is carried out seven to nine times every year, depending on weather conditions. Most water samples are taken from the surface water, although several extra samples are taken from deep water for use in the analysis of stratification. The entire sampling program includes eight points inside the reservoir and another 18 points on the watershed and the tributaries. The data include temperature, DO, chlorophyll a, turbidity, BOD, total phosphorus, organic nitrogen, ammonia nitrogen, nitrate nitrogen, and pH.

In this study, five water quality samples taken on 30 and 31 August, 1994 that includes chlorophyll a measurements, were used to compare with SPOT satellite data. A SPOT image was acquired on August 31, 1994, taken within 24 hours of the time of in situ sampling. There was no significant climatological change during this 24-hour period. On 31 August, the Te-Chi Reservoir was at a
water elevation of 1402.57 m and was discharging at 37 cms. In addition, a 1:10,000 scale quadrangle map from the Department of Interior of R.O.C. was used for the purpose of geo-referencing.

The hydraulic characteristics of the Te-Chi Reservoir consist of stable water levels and a narrow, and deep water body (the maximum depth of 140 m occurring close to the dam). As a result, the reflectance recorded by remote sensors from bottom sediment can essentially be ignored, except along the immediate shoreline. Previous investigations and research showed that the Te-Chi Reservoir has a significant vertical thermal stratification during the summer (Figure 4.2) (Te-Chi Reservoir Management Committee, 1995). Therefore, a one-dimensional simulation that considers only the surface water is reasonable. Other hydrologic data, such as water temperature, daily flow, and precipitation, which were recorded by the Sung-Mao hydrologic station at the upstream of the Te-Chi Reservoir, are also included in Appendix B.

Researching the available satellite data over the Te-Chi Reservoir was the first task in image selection. Without a prior plan, it took an effort to obtain a cloud-free image taken on the period during the time of in situ sampling. The availability of remote sensing data was researched at the Center for Space and Remote Sensing Research, National Central University in Taiwan. The available
Figure 4.2 An *in situ* investigation shows a significant vertical thermal stratification at Te-Chi Reservoir during summer (from Te-Chi Reservoir Management Committee, 1995)
satellite images included Landsat (MSS & TM) and SPOT. In this study, SPOT images were adopted because of the short repetitive interval between images, when taking advantage of the off-nadir pointing capability, and the fine spatial resolution. SPOT multispectral (XS) image data include band 1 or XS1 (visible green), band 2 or XS2 (visible red), and band 3 or XS3 (near infrared). There are four SPOT images covering a part of the Te-Chi Reservoir watershed. Their paths (K) and rows (J) are (K299/J301), (K299/J302), (K300/J301), and (K300/J302), as shown in Figure 4.3. Matching the criteria, that a field sample and satellite image have to be taken on the same date, an image acquired on August 31, 1994 at local time 2:40:11 p.m. was selected. The image was recorded with a viewing angle of -0.76°, which means that the satellite was essentially vertical over the Te-Chi Reservoir. There was a time difference of 24 hours between the time of image acquisition and the time of the in situ water quality sampling, but there was no significant climatological change during this period. To acquire the best image coverage over the majority of the Te-Chi Reservoir water body, the SPOT images in this study were processed by shifting 20% south along the satellite’s longitudinal track on the nominal image (K299/J301), centering at longitude 121.21°E and latitude 24.50°N (Figure 4.4). The second SPOT image, which was
Figure 4.3 The SPOT paths and rows covering the Te-Chi Reservoir's watershed, including (K299/J301), (K299/J302), (K300/J301), and (K300/J302) (from Te-Chi Reservoir Management Committee, 1994)
Figure 4.4 False-color SPOT image (ID 2-299-301-940831-024011-1-x) acquired on 08/31/1994 centering at longitude 121.21° E and latitude 24.50° N which was shifted 20% south from the nominal image (K299/J301).
used for the calibration, was taken on September 5, 1994 (Figure 4.5). The subset area used in the study is obtained from both images.

The subset area used in the study is outlined on both images. Level 1B SPOT satellite data were acquired. Level 1B processing by the SPOT Image Corporation includes basic geometric and radiometric adjustments of the image data, sensor normalization, and several geometric corrections. The subset of the SPOT image of the Te-Chi Reservoir acquired on August 31, 1994 is shown in Figure 4.6. The second subset SPOT image, acquired on September 5, 1994, was used for the calibration and is shown in Figure 4.7.

A 1:10,000-scale quadrangle map from the Department of Interior of R.O.C. was used for the purpose of geo-referencing the images. The map is in the Universal Transverse Mercator (UTM) coordinate system. The central meridian is located at a longitude 121°E, which is in UTM zone number 51. The reference ellipsoid used is New International 1978.

4.2 Water Quality Monitoring System

To improve the ability to process the digital satellite data and to illustrate the results monitored by remote sensing, ERDAS IMAGINE was used in the water
Figure 4.5 False-color SPOT image (ID 2-299-301-940905-024011-1-x) acquired on 09/05/1994 centering at longitude 121.16° E and latitude 24.39° N which was shifted 20% south from the nominal image (K299/J301).
Figure 4.6 Subest false-color SPOT image of the Te-Chi Reservoir area acquired on 08/31/1994
Figure 4.7 Subset false-color SPOT image of the Te-Chi Reservoir area acquired on 09/05/1994
quality monitoring system. These GIS operations consist of illustrating the geographic information of the observation area, and storage and analysis of spatially referenced data. The general objective of the GIS application is to display remote sensing data on two or three dimensional maps and in a time series (Manfred et al., 1991). This section describes those GIS functions that were used in the water quality monitoring system.

4.2.1 A Regression Model Between Water Quality Variables And Remote Sensing Data

To improve the accuracy of the remotely sensed data, corrections of the remotely sensed data should be considered before a regression model is established. In general, there are two types of data corrections: geometric corrections and radiometric corrections. Geometric correction is applied to correct errors due to the earth’s curvature, the earth’s rotation, variations in viewing angle, and sensor motion. Radiometric correction is applied to correct errors due to differing sensitivities or malfunctioning of the detectors, topographic effects, and the scattering and absorbing effects of the atmosphere. Basic geometric and radiometric adjustments were made on the SPOT images with the level 1b
processing. Atmospheric effect could cause another error to the image. Considering the complexity of atmospheric modeling and the lack of comprehensive atmospheric profile data, such as pressure and water vapor, additional atmospheric corrections to the SPOT data were not made. In addition, the two SPOT scenes used in this study were cloud-free over the Te-Chi Reservoir and these conditions would minimize any atmospheric problems.

Moreover, the Te-Chi Reservoir has stable water levels and is more than 40 m deep, so the reflectance from the bottom sediment of the reservoir was ignored. The pixels close to the land are ignored when extracting data from the satellite images. Topographic effects are not significant in this case because a water body has a flat surface.

To transform the digital values recorded on satellite images to the water quality variables, the correlation between these two data sets has to be explored first. Water quality variables — chlorophyll a, Secchi depth, and phosphorus — are considered the most important indices of the eutrophic status of water bodies. These three variables were estimated from the SPOT image. The HRV sensor can be used to record concentrations of chlorophyll and suspended solids (low Secchi depth). Data from a single band is not adequate to estimate these water quality variables because suspended solids, due to their high reflectance, tend to mask the
chlorophyll content of the water. According to Lathrop and Lillesand (1985), a natural logarithmic transformation of the digital data to water quality variables can be expressed as:

\[ \ln Y_i = a_{i0} + a_{ij} \ln B_j \]  \hspace{1cm} (4.1)

where \( Y_i \) represents a specific water quality variable \( i \) from a field-test investigation, and \( B_j \) represents the value of band ratio \( j \). Through regression, \( a_{i0} \) and \( a_{ij} \) can be defined by a set of in situ data and a set of imagery brightness values.

The original sampling results, which were taken on 30 and 31 August, 1994, and a location map from Te-Chi Reservoir Management Committee are shown in Appendix C. Because of the sampling location is not recorded exactly, a window located over the water sample site may be selected as to represent the brightness of the water body. Basically, the digital values were selected at the center of the reservoir channel where the water sampling occurred. To relate the remote sensing data to the in situ sampling data, a mean value was calculated from the SPOT image data by using a 3 x 3 pixel window centered at each sample site. Chlorophyll \( a \) and Secchi depth were collected at five sampling sites and
phosphorus was collected at 18 sampling sites. The analysis of SPOT imagery related with the water quality parameters of Secchi depth (or turbidity), chlorophyll a, and inorganic matter (phosphorus) is shown in Table 4.1. A band ratio of XS2 (red) and XS3 (near infrared) was suggested to detect chlorophyll in water, due to a positive reflectivity of chlorophyll in the NIR and an inverse behavior in the red (Catts et al., 1985; Stumpf, 1988; Quibell, 1991; Mittenzwey, 1992; Rundquist et al., 1996). A high correlation between XS3/XS2 and chlorophyll a was also found in this research. Theoretically, the near infrared band is capable of directly detecting chlorophyll a, while the red band tends to represent the chlorophyll a in an inverse relationship.

<table>
<thead>
<tr>
<th>Water sample</th>
<th>SPOT on 08/31/96</th>
</tr>
</thead>
<tbody>
<tr>
<td>location</td>
<td>Chl (µg/L) SD (m) PO4 (µg/L) XS1 XS2 XS3</td>
</tr>
<tr>
<td>S-6</td>
<td>9 5.4 1.75 66 27 13</td>
</tr>
<tr>
<td>S-18</td>
<td>12 3.8 1.64 65 28 15</td>
</tr>
<tr>
<td>S-28</td>
<td>32 3.5 1.00 51 24 13</td>
</tr>
<tr>
<td>S-39</td>
<td>383 9.0 0.80 46 22 16</td>
</tr>
<tr>
<td>R-4</td>
<td>342 11.0 0.61 94 50 34</td>
</tr>
</tbody>
</table>

Table 4.1 SPOT image values and in situ water quality data at the five sample points.
<table>
<thead>
<tr>
<th>Regression type pattern</th>
<th>Statistical significance</th>
<th>Theoretical background</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 $\ln CHL = 9.37 + 10.10 \ln (XS3/XS2)$</td>
<td>$R^2$: good; $P$ value: good</td>
<td>good</td>
</tr>
<tr>
<td>2 $\ln CHL = 10.0 - 5.27 \ln (XS1/XS2) + 5.65 \ln (XS3/XS2) + 0.52 \ln (XS1/XS3)$</td>
<td>$R^2$: good; $P$ value: poor</td>
<td>poor</td>
</tr>
<tr>
<td>3 $\ln CHL = 12.3 - 4.97 \ln (XS1/XS2) + 2.93 \ln (XS2/XS3) + 7.79 \ln (XS3)$</td>
<td>$R^2$: good; $P$ value: poor</td>
<td>poor</td>
</tr>
<tr>
<td>4 $\ln (XS1/XS2) = 0.74 + 0.026 \ln CHL + 0.251 \ln SD - 0.030 \ln P04$</td>
<td>$R^2$: good; $P$ value: OK</td>
<td>poor</td>
</tr>
<tr>
<td>5 $\ln (XS1/XS2) = 2.12 + 0.053 \ln CHL + 0.54 \ln SD - 0.062 \ln P04$</td>
<td>$R^2$: good; $P$ value: OK</td>
<td>poor</td>
</tr>
<tr>
<td>6 $\ln (XS1) = 17.2 - 0.036 \ln CHL + 23.2 \ln SD + 0.72 \ln P04$</td>
<td>$R^2$: good; $P$ value: poor</td>
<td>OK</td>
</tr>
<tr>
<td>7 $\ln (XS1) = 61 - 11.1 \ln CHL - 20 \ln SD + 15.6 \ln P04$</td>
<td>$R^2$: good; $P$ value: poor</td>
<td>OK</td>
</tr>
<tr>
<td>8 $\ln (XS1) = 4.21 - 0.18 \ln CHL - 0.27 \ln SD + 1.23 \ln P04$</td>
<td>$R^2$: poor; $P$ value: poor</td>
<td>OK</td>
</tr>
</tbody>
</table>

Suggested model (type 1):

\[
\begin{align*}
\ln CHL &= 9.37 + 10.10 \ln (XS3/XS2) \\
\ln SD &= -3.32 + 4.39 \ln (XS1/XS2) \\
\ln P04 &= 10.85 - 10.01 \ln (XS1/XS2)
\end{align*}
\]

Table 4.2 The examination results of regression equations by evaluating statistical significance and physical explanation
A various of regression types were experimented, including taking logarithm and/or original values of imagery data and/or field data from a single band and a band ratio. After an examination of all types of regression equations for the correlation between water quality variables and the digital data, the results show that the band ratio exponential model is the best fit regression model. The results were evaluated from two points of view, statistical significance and theoretical explanation (see Table 4.2). A final regression model was searched for chlorophyll a (CHLA), Secchi depth (SD), and phosphorus (PO4) for the Te-Chi Reservoir as:

\[ \ln CHLA = 9.373 + 10.080 \ln(XS3/XS2) \]  
\[ (R^2 = 0.951, P = 0.005) \]

\[ \ln SD = -3.32 + 4.39 \ln(XS1/XS2) \]  
\[ (R^2 = 0.953, P = 0.004) \]

\[ \ln PO4 = 10.851 - 10.015 \ln(XS1/XS2) \]  
\[ (R^2 = 0.827, P = 0.032) \]

Several statistical parameters were presented as indicators of the significance of the regression model. The square of the correlation coefficient (R^2)
represents the level of relationship between the two sets of data. The correlation matrix shows that the band ratio of XS1 (green) to XS2 (red) has a significant correlation with turbidity, similar to what was found by Lathrop and Lillesand (1989). Table 4.3 shows a strong positive relationship between the band ratios and the water quality variables. The standard error of the dependent variable is an indicator evaluating the fit between the two systems. If the P-value is greater than a critical value taken from the probability distribution table, the regression model is acceptable. In general, the level of significance of 0.05 is adopted as a critical value. These statistical analyses reveal that the predictive capability of the regression model is good without consideration of a bias. Digital values from the SPOT data were converted to water quality variables using this regression model. The regression model is statistically significant (based on the $R^2$ and $P$ values) between the band ratios of chlorophyll $a$ and Secchi depth. A lower correlation value was found for the phosphorus variable. The coefficients in the above equations could vary under different weather and illumination conditions. Because chlorophyll was examined for only 5 of 23 samples, the regression model could have a bias due to the small sampling size.
Table 4.3 SPOT image values and water quality variables correlation matrix. All values are shown using a natural logarithmic operation.
To accurately record the sampling locations, a GPS (Global Positioning System) device should be used while taking samples from a water body. Due to the limited sample size (= 5), which could cause a high bias, the regression model should be applied with caution. Moreover, error could be introduced by the time difference between satellite image acquisition and water sampling. However, the Te-Chi Reservoir is a slow-moving river, moving about 500 m/day, and bio-chemical reactions have only a slight variation within 24 hours. Also, the weather was stable during this time period (see Appendix B). For the water quality monitoring system, the time delay between imagery and water sample collection could introduce some error, but should not reduce the contribution that the remote sensing system offers in terms of monitoring. Moreover, this problem cannot be completely avoided in any case because in situ sampling is time-consuming, particularly for a large water body. Overall, the general relationship between the image data and water quality data matches the theoretical model and other research literature.
4.2.2 GIS Operation in The Water Quality Monitoring System

After a regression model was established, image processing is conducted to convert the satellite image into water quality variables. The GIS and image processing functions used included (also see Figure 4.8):

1. Subset image for the area of interest from the full scene image.
2. Resample images into a standard coordinate system.
3. Feature extraction of water body from the image.
4. Generation of a mask layer using GIS showing only the water area.
5. Statistical analysis of image data for histogram standardization.
6. Converting remote sensing data to water quality variables through use of the regression model
7. Data geo-referenced with a SPOT topographic image for processing final thematic maps.
Figure 4.8 Flow chart of GIS and image processing functions used in the water quality monitoring system
In the water quality monitoring system, converting the remote sensing data to water quality variables is the essential process. A model was established to extract water bodies from SPOT images, calculate band ratios, process the data through regression models, and illustrate chlorophyll, Secchi Depth, and phosphorus data on maps. This "modeling-within" approach was conducted using the Spatial Modeler part of ERDAS IMAGINE version 8.2. By defining functions represented as circles) in the model, mathematical operations can be executed on input images that result in output images. The general procedures were used and are briefly described in the following sections.

**Image Subset for the area of interest from the full scene image**

Subsetting an image is to cut out the area of interest from the full sized image. This smaller image speeds up processing and saves computer memory due to the smaller amount of data to process and store. A full scene of SPOT image data includes 3000 columns and 3000 rows (or 9 Mbytes of data) for each band. All three bands take about 29 Mbytes of storage. A small portion of the image, which covers the Te-Chi Reservoir and a part of the watershed, was subset from the entire image. For this study site, 500 columns and 350 rows (or 175,000 pixels) were used in the model. As shown in Figures 4.6 and 4.7, the result from
this process was a false-color image of the Te-Chi Reservoir area with band 1 (green) in blue, band 2 (red) in green, and band 3 (near infrared) in red.

**Resampling images into the standard coordinate system**

For use in the water quality monitoring system, the satellite images should be resampled into a standard coordinate system. In this format, the images can be used with the mask layer, water boundary layer, and the computational element map, which will be explained later.

A suitable area, which is larger than 500 columns by 350 rows, was subset from the second image. This image needed be georeferenced to match with the original image. The image was resampled by the nearest-neighbor transformation into the same coordinate system as the system used by the original image. By specifying the upper left and lower right coordinates, the corresponding 500 columns by 350 rows subset can be produced in the correct georeferenced coordinate system. In ERDAS IMAGINE, a “link” function can used to achieve the best match between two images.
Feature extraction

The main purpose of this task is to extract the feature of interest. In this study, the water body was subset into a pre-defined length for modeling purposes. To achieve this goal, some general procedures are briefly described. The first step is to determine the suitable bands to use from the full satellite images. For example, the near IR or middle IR wavelength are useful for land-water delineation. Unsupervised classification, which identifies natural groups or structure within the multispectral data, can be employed to extract the water body from an image. Unsupervised classification is more suitable than supervised classification for creating a mask layer because no extensive prior knowledge of the region is required, the classified groups are more uniform, the opportunity for human error is minimized, and unique classes are recognized as distinctive units (Campbell, 1987). The drawback of unsupervised classification is that those classes may not correspond one-to-one to the informational categories. To overcome this problem, the analyst has to assign a large number of classes that will be generated by the classification algorithm. Then, a comparison of several potential classes to a reference map can correctly delineate the outline of categories of interest.
By classifying the image into several cluster categories and eventually resulting in two categories — water and non-water pixels, the reservoir area can be identified. An unsupervised classification with a total of 150 categories and 6 iterations was applied on the SPOT XS3 (near infrared) image. Technically, the result from this process can be obtained by slicing the histogram because only one band of data is used in the unsupervised classification. Only the first class was recognized as water. By renumbering those pixels included in the first class to “1” and the rest of the pixels to “0”, a mask layer was created. Afterward, the reservoir pixels can be extracted from any image layer by “multiplying” the satellite image data with this mask layer of 0’s and 1’s.

The spectral characteristic of water has significantly less reflectance in the near infrared wavelengths than in the visible wavelengths. SPOT band 3 represents the digital brightness data in the near infrared region. The mask layer resulting from the extraction process is shown in Figure 4.9. The water extraction process is essential for generating the mask layer because ground reference maps such as standard quadrangle maps and ground control points are limited for this area. Even though a small error was introduced into the coordinate transformation of the sample site locations, the accuracy is acceptable compared with the size of
Figure 4.9 Water body which was extracted by using unsupervised classification on the SPOT image. White (brightness value = 1) presents water and black (brightness value = 0) presents land.
the computational elements (mostly more than 25 pixels or 10,000 m²) used in the water quality model.

**Histogram analysis of image data for normalization**

The image data were examined by a statistical histogram analysis. The histograms for all three bands of the second SPOT image were compared with the brightness histograms of the original SPOT image to ensure that the two images have a similar distribution shape. In other words, data from all three bands are examined to detect those that are brighter or darker than the original SPOT images, and are adjusted to a standard histogram. This process is known as normalization (Campbell, 1987).

A group of pixels located next to the Te-Chi Dam, which represent a shadowed area adjacent to the dam, was chosen as a standard reference point. Pixel values of this standard area for all three bands should remain the same on multi-date images, because the pixel area represents the least reflectance area adjacent to the 180 m high and 290 m wide dam. Before the implementation of the regression model, all pixel values on the second image were adjusted by the difference in the reflectance between the two images. In other words, the histogram was shifted by a ± amount so that the darkest area recorded by the
SPOT sensors was the same for both dates. This process is known as dark body subtraction.

Remote sensing data conversion

The regression model, which was established previously to convert SPOT digital values into water quality variables, was included in the water quality monitoring system. First, the band ratios are calculated and then used in the regression model. The chlorophyll a, Secchi depth, and phosphorus maps are the result of this process. This "modeling-within" approach was conducted by using the Spatial Modeler in ERDAS IMAGINE. The approach is illustrated as a graphic model in Figure 4.10. Basically, Figure 4.10 shows a procedure operated in IMAGINE to process steps shown in Figure 4.8. By placing and defining functions (represented as circles) with Model Maker, one can execute the model and turn input images into output images. Once the model is established, it is easy to use and is fast. For example, to transform the digital data of the SPOT images (500 columns by 350 lines) into water quality variables took only one minute and 45 seconds on a Silicon graphics UNIX system.
Figure 4.10 The water quality monitoring system conducted by Spatial Modeler in ERDAS IMAGINE to assess chlorophyll, Secchi depth, and phosphorus.
Topographic image overlay and final production

Each water quality variable was displayed as an individual layer. The water quality variables were represented in various colors related to concentration levels and each pixel was associated with geographic location. The water-only thematic layers were overlaid on one band of the gray-scale SPOT image. This display presents water quality variables in a map format with detailed geographic information. The output images were georeferenced in IMAGINE according to a 1:10,000-scale R.O.C. Interior quadrangle map. Four ground control points (GCPs), which can easily be identified on both the images and the reference map, were selected (see Table 4.4 and Figure 4.11). A transformation matrix, which is a set of transformation coefficients in a polynomial equation, is presented in Table 4.5. These linear polynomial equations were used to transform images from the image coordinate system into a UTM coordinate system. The residuals, RMS (root mean square) error of the GCPs, had a total RMS of 0.2339 pixel (0.1809 pixel for X and 0.1482 pixel for Y, respectively). By resampling the original images using a nearest-neighbor transformation, which preserves the original grid better than a cubic convolution transformation, the final images were transformed into UTM coordinates, as shown in Figure 4.12.
<table>
<thead>
<tr>
<th>GCP</th>
<th>Image coordinate (pixel)</th>
<th>UTM coordinate (m)</th>
<th>Location description</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>X</td>
<td>Y</td>
<td>X</td>
</tr>
<tr>
<td>1</td>
<td>1676.97</td>
<td>746.97</td>
<td>266200</td>
</tr>
<tr>
<td>2</td>
<td>1826.03</td>
<td>852.84</td>
<td>269500</td>
</tr>
<tr>
<td>3</td>
<td>1917.97</td>
<td>863.03</td>
<td>271350</td>
</tr>
<tr>
<td>4</td>
<td>1958.03</td>
<td>815.09</td>
<td>271960</td>
</tr>
</tbody>
</table>

Table 4.4 The locations of four ground control points (GCPs) which were identified on both images to reference maps

<table>
<thead>
<tr>
<th>constant</th>
<th>X coefficient</th>
<th>Y coefficient</th>
<th>RMS Error (pixel)</th>
</tr>
</thead>
<tbody>
<tr>
<td>X (pixel)</td>
<td>15236</td>
<td>0.049680</td>
<td>-0.009981</td>
</tr>
<tr>
<td>Y (pixel)</td>
<td>-148853</td>
<td>0.006784</td>
<td>0.055070</td>
</tr>
</tbody>
</table>

Table 4.5 The linear transformation equations and its RMS
Figure 4.11 Ground control points (GCPs) identified on a SPOT image
Figure 4.12 Geo-referenced SPOT image in UTM coordinate system by resampling the original images using nearest-neighbor transformation.
4.3 Water Quality Forecasting System

Even though QUAL2E model is not an extremely complex water quality model, all current commercial GIS software packages are not able to handle the numerical operation in QUAL2E. Consequently, a "linked-model" approach was chosen, which links water quality models to a GIS with specific software as shown in Figure 4.13. For this research, Matlab (Matrix Laboratory) (version 4.2c) was used as a bridge to transfer remote sensing data to QUAL2E for water quality modeling and the simulated results from QUAL2E were transferred to ERDAS IMAGINE for display. Moreover, the computational elements for QUAL2E were defined in Matlab. Matlab is a technical computing software package that provides versatile functions for numeric computation and visualization.

In water quality models, a water body is subdivided into many finite segments. All variables are represented as averaged values within a cell, much like a pixel of digital imagery. In QUAL2E, chlorophyll a is a representative variable proportional to the concentration of phytoplankton biomass. For each water cell in QUAL2E, a mass balance equation for chlorophyll a is calculated between the changes of inflow, outflow, growth, death, and settling.
Figure 4.13 Sketch of water quality forecasting system
4.3.1 Defining Computational Elements for QUAL2E

To run the one-dimensional water quality model, the Te-Chi Reservoir is divided into 93 computational elements. Each element belongs to one of 22 reaches where the computational elements have the same hydrogeometric properties, such as stream slope, cross section, flow, and velocity, and the same biological rate constants, such as algal growth rate, algae settling rate, nutrient decay rates, light and extinction rate. Each element has a length of about 100 m (5 pixels on the SPOT image) and the same width as the real river width, ranging from 80 to 600 m. Each element was identified as a specific type, depending upon its position and function in the model. There are seven element types allowed in QUAL2E, as listed in Table 4.6.

All data processes were operated in Matlab. Matlab reads the mask image as a matrix, which is an output in a generic binary format from IMAGINE. The water boundary was defined in an X and Y map coordinate system through an edge detection procedure, which scans the values of pixels ('0' or '1') on the mask image. After the edge was identified, every water pixel was assigned to a computational number (from upstream to downstream). The map of computational element designation is shown in Figure 4.14. Each element is about 5 pixels on
Figure 4.14 Computational element of the Te-Chi Reservoir defined in the water quality model QUAL2E.
the SPOT image and 100 m on the ground. Data can be imported back into IMAGINE in a generic binary format. The area of each computational element was tabulated as an attribute element within IMAGINE. The digital numbers can be extracted from and recorded for these water cells. All Matlab computer codes are listed in Appendix D, including the functions of data reading, elevation designation, element designation, data extraction, and data writing.

<table>
<thead>
<tr>
<th>Code</th>
<th>Function type of computational elements</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>headwater source element</td>
</tr>
<tr>
<td>2</td>
<td>standard element, incremental inflow/outflow only</td>
</tr>
<tr>
<td>3</td>
<td>element on mainstream immediately upstream of a junction</td>
</tr>
<tr>
<td>4</td>
<td>junction element</td>
</tr>
<tr>
<td>5</td>
<td>most downstream element</td>
</tr>
<tr>
<td>6</td>
<td>input element</td>
</tr>
<tr>
<td>7</td>
<td>withdrawal element</td>
</tr>
</tbody>
</table>

Table 4.6 Typical types of computational elements in QUAL2E.
4.3.2 Running Water Quality Model QUAL2E

QUAL2E simulates the spatial and temporal variations of water quality variables, including dissolved oxygen (DO), biochemical oxygen demand (BOD), water temperature, algae as chlorophyll a, organic nitrogen, ammonia, nitrite, nitrate, organic phosphorus, and dissolved phosphorus (Broen and Barnwell, 1985). Once the initial conditions and environmental parameters are given, QUAL2E calculates the transport and interactions of pollutants, and consequently predicts the sequential change of algae, nutrients, and temperature for a given time interval. Among the variety of initial water quality variables, the chlorophyll a and phosphorus concentrations are the most important concern and these two variables were derived from the SPOT image.

Because a significant stratification occurs in the Te-Chi Reservoir during the summer and the light penetration available for algal growth, only a 10-m-deep water level from the surface was used in the one-dimensional dynamic simulations. Each of 93 computational elements is represented by a lateral average of all water quality variables. In the study, QUAL2E required meteorological, hydrological, and biological data inputs. Water flow data were obtained from hydrologic monitoring stations; cell area and volume are defined in advance for the
simulation; and death rate and settling rate of phytoplankton are set as constant values or ignored because of their minor influence in the model. Thus, the factor dominating algal growth is the growth rate of algae. Under standard conditions, that is with sufficient nutrients and abundant sunlight, the maximum growth rate ($\mu_{max}$) at 20°C for algae ranges from 1.5 to 2.5 l/day, typically 1.8 l/day (Thomann and Mueller, 1987). In natural water bodies there are several environmental factors limiting the growth rate of algae, including light intensity, nutrients, temperature, water velocity, pH value, and grazing pressure. Of these factors, light, limiting nutrient concentration, as well as temperature, are considered the most important limiting factors. The meteorological data from the Te-Chi Reservoir area, including temperature, wind, atmospheric pressure, and precipitation, which was recorded by the Taiwan Power Company, were input to QUAL2E.

The upstream section of the Ta-Chia River above the Soong-Mao Creek was treated as a headwater source element because of its major contribution of flow. The remaining seven tributaries were treated as point sources to the input elements. Those biological parameters in QUAL2E were obtained from the unpublished technical reports of Dr. Kuo who calibrated those parameters by using in situ sequential water quality data. A six-day water quality forecast was made
based on a steady pollution source with a chlorophyll $a$ value of 340 $\mu g/L$ and phosphorus of 35 $\mu g/L$ which was the water quality condition at the upper stream derived from the SPOT image.

4.3.3 Displaying Simulate Results

The simulated results were converted to pixels and displayed as images in IMAGINE. The images were smoothed by a 7x7 low pass filter to remove any sharp differences between computational elements. In other words, the water quality condition at every pixel was presented following a linear interpolation of two computational element centers. Then, the smoothed images were merged with the land-only image. As in previous overlay procedures, georeferenced data were applied to these images using the UTM coordinate system using the nearest-neighbor transformation. Consequently, geo-registered thematic images of water quality variables were created for Te-Chi Reservoir. In addition to these thematic maps, the final product from the study also includes an animated sequence of images. All thematic maps for each individual water quality variable were arranged by time sequence and presented successively on the computer monitor screen. This process makes it easier to visualize the progression of the water
quality condition, by transforming the data into a dynamic sequence rather from viewing individual static images.
CHAPTER 5

RESULTS AND DISCUSSION

The water quality monitoring and forecasting systems developed in Chapter IV were implemented in the Te-Chi Reservoir, Taiwan. A combination of techniques — remote sensing, water quality modeling, and GIS, yielded a series of water quality thematic maps for various water quality variables, such as chlorophyll a, Secchi depth, and phosphorus. The daily simulation of chlorophyll a was also recorded on video tape and displayed sequentially over time. The calibration model developed in Chapter 3 was tested and implemented on the Te-Chi Reservoir. The results from the modeling and calibration efforts are presented and discussed in this chapter.
5.1 The Water Quality Monitoring System

5.1.1 Verification of The Regression Model

To convert digital values of SPOT images to recognizable water quality indices, a regression model was developed and included in the water quality monitoring system. The band ratios in Eqs 4.1 through 4.3 were found to be the best fit with the ground truth information on water quality. According to the correlation matrix, band ratios and water quality variables are highly correlated, even though a significant bias could arise due to the small sample size (see Table 4.3). Several types of regression analyses were conducted. The summary of regression model analysis shows that a band ratio has the best result (see Table 4.2). Based on both the statistical significance and theoretical background, the band ratio of XS3/XS2 was adopted for chlorophyll, and the band ratio of XS1/XS2 was selected for Secchi depth and phosphorus (see Eqs 4.1 through 4.3). The Secchi depth and chlorophyll a are highly correlated with the satellite data while the total phosphorus was not correlated with the satellite data. This finding was also found by Lillesand et al. (1983). They found that for Minnesota lakes the total phosphorus variable could not be accurately fitted by Landsat MSS data (with
low $R^2$ of about 0.70), while the regression equations for chlorophyll and Secchi depth have high correlation coefficients (up to 0.95).

From a eutrophication point of view, this exponential regression model was also compared with empirical data. Since both the Secchi depth and phosphorus are derived from the same band ratio (XS2/XS1), this suggests that a high correlation exists between these two water quality variables. From Eqs 4.2 and 4.3, the relationship between the Secchi depth and phosphorus can be derived as follows:

$$\ln SD = 1.44 - 0.44 \ln PO4$$  \hspace{1cm} (5.1)

or

$$\log SD = 0.63 - 0.44 \log PO4$$  \hspace{1cm} (5.2)

Based on field sampling of several northeastern U.S. lakes and reservoirs, Thomann and Mueller (1987) developed two empirical equations that relate chlorophyll with the total phosphorus (TP) and Secchi depth (SD) as:

$$\log CHL = -0.194 + 0.81 \log TP$$  \hspace{1cm} (5.3)

$$\log SD = 0.803 - 0.473 \log CHL$$  \hspace{1cm} (5.4)
Combining these two equations, a mathematical relationship between the Secchi depth and phosphorus can be written as:

\[ \log SD = 0.90 - 0.38 \log TP \]  

Comparing Eqs 5.2 and 5.5, we see a significant similarity between these two equations that represent the relationship between Secchi depth and phosphorus, even though these two equations were derived from different observation sources. Note that the constant in Eq 5.2 is smaller than that in Eq 5.5, probably because dissolved phosphorus (PO$_4$ or orthophosphorus) is only a part of the total phosphorus content.

5.1.2 Error Sources in The Regression Model

There are several potential error sources existing in the regression model, including statistical bias, time discrepancy between satellite images acquired and water samples taken, water-and-land mixed pixels, and distortion from the satellite system.
Because of the small sample size of chlorophyll, the coefficients in the regression model could have a bias. One could take more water samples to avoid this error. A time discrepancy between satellite detection and concurrent surface reference sampling can cause some error, too. This problem cannot be completely avoided because in situ sampling takes a relatively long time, particularly for a large water body. However, the Te-Chi Reservoir is a slow-moving river (velocity ranging from 0.01 to 0.005 m/s). Stable meteorological conditions occurred between image acquisition and water quality sampling (see Appendix A). Therefore, bio-chemical reactions could have only a slight variation within a 24-hour period.

The error caused by water-and-land mixed pixels is due to the resolution of the satellite image. A 20 m x 20 m area that could cover both water and land is represented as a single value of brightness. Thus, the pixels at the edges of the water should be neglected in the data set used in the regression model. This error causes only a problem to those narrow water sections in the river, but will become less significant as the spatial resolution of satellite data improves in the future. For geometric and radiometric distortions, some initial corrections have been made before the images were purchased. Such corrections include sensor normalization and several geometric corrections. Other error sources, such as relief replacement
and illumination angle, do not cause a significant influence to the regression model for this research and can be corrected by mathematical models, if necessary.

5.1.3 Products from The Water Quality Monitoring System

Besides the regression model, other GIS operations, such as feature extraction, band ratio calculation, and image creation were developed in ERDAS IMAGINE. This system is known as the water quality monitoring system. The system, which is an automatic data transformation program from satellite data to water quality conditions, was executed on a IRIX 5.3 (UNIX for Silicon Graphics) work station. The processing took only 1 minute and 45 seconds for the 500 by 350 subset area, compared with several days of laboratory work for traditional water quality monitoring. During the feature extraction process, the first class of 150 classes was identified as water and totaled an area of 4,154,800 m². Compared with an estimation of $4.20 \times 10^6$ m² from the elevation-area curve of the Te-Chi Reservoir (see Appendix C), there is about a 0.8% difference. The error could be caused by excluding pixels with high brightness values due to high turbidity in the upper reaches. Only 3,925,600 m² (9814 pixels) were used in the
study, because the upper stream was masked out from this study due to its narrow width.

The remote sensing-derived water quality thematic layers were overlaid onto a single band SPOT image to serve as a geographic background. The remote sensing-derived water quality data show the finest spatial resolution of water quality conditions in the Te-Chi Reservoir than ever recorded before. Figure 5.1 was derived from the SPOT image acquired on August 31, 1996. Figure 5.2 was derived from the second SPOT image acquired on September 5, 1996. Blue — Green — Red represents chlorophyll concentration 0 μg/L — 250 μg/L. Both thematic maps show a high chlorophyll concentration in the upper stream and a reduced concentration in the down stream. This was due to a large amount of nutrients being released from the watershed because of intense farming activity and a strong settlement effect of particulates when moving downstream.

Figures 5.3 and 5.4 show the thematic maps of Secchi depth derived from the SPOT image acquired on August 31, 1996 and September 5, 1996, respectively. Blue — Green — Red represents Secchi depth 2.5 m — 0 m. Apparently, Secchi depth was reduced by about 1 m on September 5, because a large amount of suspended solids were introduced into the Te-Chi Reservoir by a severe storm occurring on September 1 (see Appendix B). The large amount of
Figure 5.1 SPOT-derived thematic map of chlorophyll a at the Te-Chi Reservoir on August 31, 1994.
Figure 5.2 SPOT-derived thematic map of chlorophyll a at the Te-Chi Reservoir on September 5, 1994.
Figure 5.3 SPOT-derived thematic map of Secchi depth at the Te-Chi Reservoir on August 31, 1994.
Figure 5.4 SPOT-derived thematic map of Secchi depth at the Te-Chi Reservoir on September 5, 1994.
runoff eroded the agricultural land in the watershed and carried sediments, nutrients, and pesticides to the water body. The band ratio of red/green (XS2/XS1) shows a great sensitivity to changes in turbidity, as represented by Secchi depth in this study. Figure 5.5, which is a thematic map of phosphorus concentration on August 31, 1996, shows that the distribution of the phosphorus concentration was related to the chlorophyll a content. Blue — Green — Red represents phosphorus concentration 0 μg/L — 100 μg/L. The result of phosphorus distribution derived from the second SPOT image was not adopted because the low correlation coefficient of the regression equation converting satellite data to phosphorus concentrations.

Comparing all of the thematic maps of chlorophyll a and Secchi depth, I found a consistent information about the distribution of water quality conditions at the Te-Chi Reservoir. A worse water quality condition occurred at the upper stream, and the water quality became better while the water moved down to the Te-Chi Dam. Also, an opposite relationship was found between the distributions of the Secchi depth and the chlorophyll that agrees with the explanation from a eutrophication theory. From the eutrophication point of view, a high concentration of nutrient is usually accompanied with a low Secchi depth and a high chlorophyll a content. The consistent eutrophic status of the Te-Chi Reservoir is clearly
Figure 5.5 SPOT-derived thematic map of phosphorus at the Te-Chi Reservoir on August 31, 1994.
revealed from these three thematic maps — chlorophyll a, Secchi depth, and phosphorus — products from the water quality monitoring system.

There is a question remaining unsolved in the thematic maps of chlorophyll a. In Figures 5.1 and 5.2, a high chlorophyll a content appears along the edge of the Ta-Chia River. From a biological point of view, an algae bloom could occur close to the river banks due to a better growing environment. On the other hand, this could also be caused by the spectral characteristics of shallow water. A comparatively high spectral reflectance could be recorded in the red band from the bottom sediment for the pixels located at the edges of the water adjacent to land. To explain this anomaly demands more in situ water samples from the center of the river to both river banks. In this study, the mixed-pixels along the river bank were ignored when processing chlorophyll a data from the images for use in the water quality modeling and calibration.

5.2 The Implementation of The Water Quality Forecasting System

The water quality model QUAL2E is linked with the monitoring system through a data conversion routine Matlab — this contribution serves as the water quality forecasting system. The system is a “linked-model” due to the complexity
of numerical computations in water quality modeling. Water quality variables were transferred from IMAGINE to QUAL2E as initial conditions and simulated results were transferred back for display in IMAGINE. Every single water quality variable was presented in an individual thematic layer and displayed in color to represent varying levels. The initial conditions for several computational elements located at the upper stream reaches with a narrow cross sectional area were calculated by interpolating field data instead of SPOT-derived values, due to the mixed pixel problem. Figure 5.6 shows the algae variation during the second, fourth, and sixth days following August 31, 1994. These figures show the results of the simulation and are the products of the water forecasting system. In the fourth and sixth-day images, the high chlorophyll a concentration area extended to the downstream reaches under a steady pollution source. Figure 5.7 shows contour maps for the forecasts of chlorophyll a concentration. Contour maps were made in an interval of 5 μg/L, but not every 5 μg/L level line is shown in Figure 5.7. Numbers on the contour maps indicate the chlorophyll a concentration level. Because of a steady pollutant input at the head water and point sources, the chlorophyll a concentration did not change very much in the upper reaches, but was significantly increased in the middle reaches. For example, those computational elements nearby Chin-Yuan Creek (see Figure 4.1) or around the
Figure 5.6 Sequential pictures of chlorophyll $a$ forecast at the Te-Chi Reservoir since August 31, 1994
Figure 5.7 Contour maps in an interval of 5 µg/L for the forecasts of chlorophyll a. Selected level lines are shown for clarity in the areas of large concentrations (>65 µg/L).

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38th computational element number showed a two-fold increase of chlorophyll \( a \) concentration within one week. Comparing the SPOT-derived thematic maps of chlorophyll \( a \) concentration, a significant increase occurred at most of reaches on September 5 since August 31 at the Te-Chi Reservoir (see Figures 5.1 and 5.2). Calibration of the water quality model is another critical factor affecting the simulation results. Before this forecasting system is available to make an accurate forecast, model parameters must be calibrated by sufficient field data. Furthermore, these sequential images were recorded on a video tape to display water quality changes dynamically as movie-like pictures for a given time step. This visualization technique helps users to easily visualize the progression of water quality.

5.3 Calibration of Algal Biological Parameters

Since most model parameters are not usually available to simulate a water body, the model calibration is an essential procedure before the forecasting system can be used for accurate predictions. Model calibration and parameter estimation require a set of field data, which is difficult to acquire in most cases. Since a data
set of high spatial resolution water quality data were derived from satellite images, we have enough calibration data available to examine the model parameters.

The calibration model established in Chapter 3 was transformed into a FORTRAN computer program, which is listed in Appendix A. Figure 5.8 is the flow chart showing how this calibration model works. The main computer program for the calibration model connects to a modified QUAL2E program, which provides all model parameters needed in Eqs 3.2 through 3.21. Also, the SPOT-derived chlorophyll a concentration and weight factors were placed in an input file. The output file includes starting parameter values, average difference of chlorophyll a, parameter correction values, variance, and new parameter values for each iteration. The biological parameters calibrated in this study include the maximum algal growth rate and nutrient affinity constant. These were found in this study to have the most profound influence on algal growth. By giving the initial approximation of the parameters and comparing the simulated results with the satellite-derived data, which serves as a set of calibration data, the calibration model results in a set of correction values for the input parameters. A new set of parameters was calculated by adjusting the correction values on the old values, and was input into QUAL2E again. A new set of correction values for the model parameters was estimated by comparing the new simulated result with the
Figure 5.8 Flow chart of the calibration model
calibration data. By minimizing the difference between simulated and satellite-derived chlorophyll a concentration, the most suitable parameters are identified. The calibration model was implemented for a hypothetical case to test its performance and was applied later to the Te-Chi Reservoir. This procedure is described below.

5.3.1 Analysis of Results and Sensitivity Analysis

The biological parameters in Eq 3.2 include the algal respiration rate (ρ), the algal settling velocity (V_p), the algal maximum growth rate (μ_max), the nutrient affinity constant (or PO_4 half-saturation constant) (K_s), the light saturation constant (K_l), and temperature coefficient (θ_t). Table 5.1 shows the result of the sensitivity analysis. When a value of parameter is doubled, the change of algal growth rate is calculated in percentage that represents the sensitivity of algal growth to the parameter. The respiration rate and the algal maximum growth rate have the most significant influence on the algal growth when compared with other model parameters. Thus, only the maximum growth rate and respiration rate parameters are included in the calibration model.
<table>
<thead>
<tr>
<th>Parameters</th>
<th>Notation</th>
<th>Values</th>
<th>Unit</th>
<th>Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Respiration rate</td>
<td>$\rho$</td>
<td>0.05 - 0.5</td>
<td>1/day</td>
<td>-100%</td>
</tr>
<tr>
<td>Algal settling velocity</td>
<td>$V_p$</td>
<td>0.1 - 0.3</td>
<td>m/day</td>
<td>-10%</td>
</tr>
<tr>
<td>Algal maximum growth rate</td>
<td>$\mu_{\text{max}}$</td>
<td>1.0 - 3.0</td>
<td>1/day</td>
<td>100%</td>
</tr>
<tr>
<td>PO$_4$ half-saturation constant</td>
<td>$K_s$</td>
<td>0.001 - 0.005*</td>
<td>$\mu$g/L</td>
<td>-6%</td>
</tr>
<tr>
<td>Light saturation constant</td>
<td>$K_L$</td>
<td>100 - 400*</td>
<td>ly/day</td>
<td>-5%</td>
</tr>
</tbody>
</table>

*reference from Thomann and Mueller (1987); others from Brown and Barnwell (1985).

Table 5.1 Sensitivity analysis of algal model parameters

5.3.2 Implementation of the Calibration Model

To evaluate the utility of the calibration model, a hypothesis test was formulated. In the beginning, one set of known biological parameters ($\mu_{\text{max}} = 2.50$ d$^{-1}$ and $\rho = 0.20$ d$^{-1}$) was used as the input data to QUAL2E and the water quality data derived from the first SPOT satellite imagery served as initial conditions. Other parameters related to algal growth are listed in Table 5.2. The chlorophyll a concentration from this simulation was used as the set of calibration data. Subsequently, the calibration model was run for several cases by giving a different
combination of parameter values for the initial approximation. By observing the trajectory of the calibration, we know how the initial approximation is corrected until the original "true" values is resulted. This procedure of can test the utility of the calibration model.

The test runs were carried out by giving four sets of initial approximations for a set of low and/or high algal maximum growth rates and respiration rates, including \((\mu_{\text{max}}, \rho) = (1.0, 0.3), (4.0, 0.3), (1.0, 0.1)\) and \((4.0, 0.3)\). The parameter estimates were determined by minimizing the difference between the predicted values and the measured values. The results from the four test runs are shown in Figure 5.9. The sequence of iteration runs is listed in Table 5.3, including initial values, difference of chlorophyll a between the predicted values and the measured \(\mu_{\text{max}}\) and \(\rho\) values, the variance, and the correction for the next iteration. In Figure 5.9, all iterations have a spiral trajectory, regardless of whether a low or high parameter was given as the approximation. In all four cases, the calibration model tracked the maximum growth rate and respiration rate back to the hypothetical values with errors within 0.5% of the original values. Evidently, this calibration model is successful to estimate the set of biological parameters which are used to generate a set of calibration data.
Figure 5.9 Results of parameter calibration from test runs
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Affinity constant ((K_a))</td>
<td>0.005</td>
<td>mg/L</td>
</tr>
<tr>
<td>Light saturation constant ((K_d))</td>
<td>0.323</td>
<td>ly/min</td>
</tr>
<tr>
<td>Temperature effect constant for (\mu) ((\theta))</td>
<td>1.068</td>
<td>—</td>
</tr>
<tr>
<td>Temperature effect constant for (\rho)</td>
<td>1.080</td>
<td>—</td>
</tr>
<tr>
<td>Temperature effect constant for (V_p)</td>
<td>1.024</td>
<td>—</td>
</tr>
<tr>
<td>Algal (O_2) uptake</td>
<td>2.67</td>
<td>g (O_2)/g algae</td>
</tr>
<tr>
<td>Algal (O_2) production</td>
<td>1.60</td>
<td>g algae/g (O_2)</td>
</tr>
<tr>
<td>Algal extinction coefficient</td>
<td>0.006</td>
<td>(\mu g/ft)</td>
</tr>
<tr>
<td>Algal preference for (NH_3-N)</td>
<td>0.5</td>
<td>—</td>
</tr>
<tr>
<td>Algal (N) content</td>
<td>0.120</td>
<td>mg N/mg algae</td>
</tr>
<tr>
<td>Algal (P) content</td>
<td>0.005</td>
<td>mg P/mg algae</td>
</tr>
<tr>
<td>Algal solar radiation factor</td>
<td>0.65</td>
<td>—</td>
</tr>
<tr>
<td>Phosphorus input in headwater</td>
<td>0.03</td>
<td>mg/L</td>
</tr>
</tbody>
</table>

Table 5.2 The values of other model parameters used for the calibration of algal growth simulation in QUAL2E.
Case I: Given initial approximation $\mu_{\max} = 1.00 \ \text{d}^{-1}$ and $\rho = 0.10 \ \text{d}^{-1}$

<table>
<thead>
<tr>
<th>Iteration</th>
<th>$\mu_{\max}$</th>
<th>$\rho$</th>
<th>Ave. diff.</th>
<th>$\mu_{\max}$ correct.</th>
<th>$\rho$ correct.</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.000</td>
<td>0.100</td>
<td>-1.03 x $10^0$</td>
<td>0.512</td>
<td>0.044</td>
<td>1.39 x $10^{-1}$</td>
</tr>
<tr>
<td>2</td>
<td>1.512</td>
<td>0.144</td>
<td>-3.63 x $10^{-1}$</td>
<td>0.391</td>
<td>0.027</td>
<td>8.15 x $10^{-2}$</td>
</tr>
<tr>
<td>3</td>
<td>1.903</td>
<td>0.171</td>
<td>-8.60 x $10^{-2}$</td>
<td>0.265</td>
<td>0.015</td>
<td>4.58 x $10^{-2}$</td>
</tr>
<tr>
<td>4</td>
<td>2.168</td>
<td>0.186</td>
<td>6.93 x $10^{-3}$</td>
<td>0.036</td>
<td>0.008</td>
<td>2.46 x $10^{-2}$</td>
</tr>
<tr>
<td>5</td>
<td>2.330</td>
<td>0.194</td>
<td>3.28 x $10^{-1}$</td>
<td>0.093</td>
<td>0.004</td>
<td>1.27 x $10^{-2}$</td>
</tr>
<tr>
<td>6</td>
<td>2.423</td>
<td>0.198</td>
<td>3.28 x $10^{-2}$</td>
<td>0.048</td>
<td>0.002</td>
<td>5.97 x $10^{-3}$</td>
</tr>
<tr>
<td>7</td>
<td>2.471</td>
<td>0.200</td>
<td>3.12 x $10^{-2}$</td>
<td>0.040</td>
<td>0.001</td>
<td>2.94 x $10^{-3}$</td>
</tr>
<tr>
<td>8</td>
<td>2.495</td>
<td>0.201</td>
<td>3.04 x $10^{-3}$</td>
<td>0.024</td>
<td>0.000</td>
<td>2.37 x $10^{-3}$</td>
</tr>
<tr>
<td>9</td>
<td>2.503</td>
<td>0.201</td>
<td>2.18 x $10^{-2}$</td>
<td>0.008</td>
<td>0.000</td>
<td>1.86 x $10^{-3}$</td>
</tr>
</tbody>
</table>

Case II: Given initial approximation $\mu_{\max} = 4.00 \ \text{d}^{-1}$ and $\rho = 0.10 \ \text{d}^{-1}$

<table>
<thead>
<tr>
<th>Iteration</th>
<th>$\mu_{\max}$</th>
<th>$\rho$</th>
<th>Ave. diff.</th>
<th>$\mu_{\max}$ correct.</th>
<th>$\rho$ correct.</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.000</td>
<td>0.100</td>
<td>-3.96 x $10^0$</td>
<td>-0.163</td>
<td>-0.063</td>
<td>3.01 x $10^{-1}$</td>
</tr>
<tr>
<td>2</td>
<td>3.837</td>
<td>0.163</td>
<td>-2.00 x $10^0$</td>
<td>-1.357</td>
<td>-0.023</td>
<td>1.54 x $10^{-1}$</td>
</tr>
<tr>
<td>3</td>
<td>2.480</td>
<td>0.140</td>
<td>-1.24 x $10^0$</td>
<td>-0.320</td>
<td>0.013</td>
<td>7.46 x $10^{-2}$</td>
</tr>
<tr>
<td>4</td>
<td>2.160</td>
<td>0.153</td>
<td>-6.27 x $10^{-1}$</td>
<td>0.010</td>
<td>0.017</td>
<td>4.83 x $10^{-2}$</td>
</tr>
<tr>
<td>5</td>
<td>2.170</td>
<td>0.170</td>
<td>-2.71 x $10^{-1}$</td>
<td>0.106</td>
<td>0.014</td>
<td>3.21 x $10^{-2}$</td>
</tr>
<tr>
<td>6</td>
<td>2.276</td>
<td>0.184</td>
<td>-1.02 x $10^{-1}$</td>
<td>0.098</td>
<td>0.009</td>
<td>1.92 x $10^{-2}$</td>
</tr>
<tr>
<td>7</td>
<td>2.374</td>
<td>0.193</td>
<td>-2.12 x $10^{-2}$</td>
<td>0.067</td>
<td>0.005</td>
<td>1.01 x $10^{-2}$</td>
</tr>
<tr>
<td>8</td>
<td>2.441</td>
<td>0.198</td>
<td>9.32 x $10^{-3}$</td>
<td>0.040</td>
<td>0.002</td>
<td>4.72 x $10^{-3}$</td>
</tr>
<tr>
<td>9</td>
<td>2.480</td>
<td>0.200</td>
<td>1.99 x $10^{-2}$</td>
<td>0.020</td>
<td>0.001</td>
<td>1.91 x $10^{-3}$</td>
</tr>
<tr>
<td>10</td>
<td>2.501</td>
<td>0.201</td>
<td>1.09 x $10^{-2}$</td>
<td>0.004</td>
<td>0.000</td>
<td>8.84 x $10^{-4}$</td>
</tr>
</tbody>
</table>

Table 5.3 Sequence of the iteration for the test runs of parameter calibration. A QUAL2E-generated result was used as the calibration data.
Table 5.3 (continued)

Case III: Given initial approximation $\mu_{\text{max}} = 1.00 \, d^4$ and $\rho = 0.30 \, d^4$

<table>
<thead>
<tr>
<th>Iteration</th>
<th>$\mu_{\text{max}}$</th>
<th>$\rho$</th>
<th>Ave. diff.</th>
<th>$\mu_{\text{max}}$ correct.</th>
<th>$\rho$ correct.</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.000</td>
<td>0.300</td>
<td>$2.46 \times 10^0$</td>
<td>2.462</td>
<td>0.065</td>
<td>$1.92 \times 10^1$</td>
</tr>
<tr>
<td>2</td>
<td>3.461</td>
<td>0.365</td>
<td>$1.72 \times 10^0$</td>
<td>0.477</td>
<td>-0.036</td>
<td>$1.37 \times 10^1$</td>
</tr>
<tr>
<td>3</td>
<td>3.939</td>
<td>0.329</td>
<td>$9.96 \times 10^{-1}$</td>
<td>-0.417</td>
<td>-0.060</td>
<td>$1.39 \times 10^1$</td>
</tr>
<tr>
<td>4</td>
<td>3.522</td>
<td>0.269</td>
<td>$3.86 \times 10^{-1}$</td>
<td>-0.501</td>
<td>-0.042</td>
<td>$8.90 \times 10^2$</td>
</tr>
<tr>
<td>5</td>
<td>3.021</td>
<td>0.227</td>
<td>$5.20 \times 10^{-2}$</td>
<td>-0.311</td>
<td>-0.020</td>
<td>$4.19 \times 10^2$</td>
</tr>
<tr>
<td>6</td>
<td>2.710</td>
<td>0.207</td>
<td>$-5.45 \times 10^{-2}$</td>
<td>-0.150</td>
<td>-0.007</td>
<td>$1.64 \times 10^2$</td>
</tr>
<tr>
<td>7</td>
<td>2.560</td>
<td>0.198</td>
<td>$-6.04 \times 10^{-2}$</td>
<td>0.060</td>
<td>-0.002</td>
<td>$5.70 \times 10^3$</td>
</tr>
<tr>
<td>8</td>
<td>2.500</td>
<td>0.198</td>
<td>$-3.44 \times 10^{-2}$</td>
<td>-0.013</td>
<td>0.000</td>
<td>$2.17 \times 10^3$</td>
</tr>
</tbody>
</table>

Case IV: Given initial approximation $\mu_{\text{max}} = 4.00 \, d^4$ and $\rho = 0.30 \, d^4$

<table>
<thead>
<tr>
<th>Iteration</th>
<th>$\mu_{\text{max}}$</th>
<th>$\rho$</th>
<th>Ave. diff.</th>
<th>$\mu_{\text{max}}$ correct.</th>
<th>$\rho$ correct.</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.000</td>
<td>0.300</td>
<td>$3.45 \times 10^1$</td>
<td>-0.795</td>
<td>-0.063</td>
<td>$1.32 \times 10^1$</td>
</tr>
<tr>
<td>2</td>
<td>3.241</td>
<td>0.237</td>
<td>$6.07 \times 10^1$</td>
<td>-0.456</td>
<td>-0.029</td>
<td>$5.98 \times 10^2$</td>
</tr>
<tr>
<td>3</td>
<td>3.785</td>
<td>0.208</td>
<td>$-9.47 \times 10^2$</td>
<td>-0.212</td>
<td>-0.010</td>
<td>$2.23 \times 10^3$</td>
</tr>
<tr>
<td>4</td>
<td>2.573</td>
<td>0.198</td>
<td>$-1.00 \times 10^1$</td>
<td>-0.081</td>
<td>-0.002</td>
<td>$7.83 \times 10^3$</td>
</tr>
<tr>
<td>5</td>
<td>2.492</td>
<td>0.196</td>
<td>$-6.75 \times 10^2$</td>
<td>-0.021</td>
<td>0.001</td>
<td>$4.30 \times 10^3$</td>
</tr>
<tr>
<td>6</td>
<td>2.471</td>
<td>0.197</td>
<td>$-3.64 \times 10^2$</td>
<td>0.005</td>
<td>0.001</td>
<td>$3.44 \times 10^3$</td>
</tr>
<tr>
<td>7</td>
<td>2.476</td>
<td>0.198</td>
<td>$-9.32 \times 10^3$</td>
<td>0.012</td>
<td>0.001</td>
<td>$2.14 \times 10^3$</td>
</tr>
<tr>
<td>8</td>
<td>2.488</td>
<td>0.199</td>
<td>$-7.97 \times 10^3$</td>
<td>0.004</td>
<td>0.000</td>
<td>$1.26 \times 10^3$</td>
</tr>
<tr>
<td>9</td>
<td>2.492</td>
<td>0.200</td>
<td>$-2.42 \times 10^3$</td>
<td>0.005</td>
<td>0.000</td>
<td>$9.94 \times 10^4$</td>
</tr>
</tbody>
</table>
5.3.3 The Maximum Growth Rate and Respiration Rate of The Te-Chi Reservoir

The calibration model was used on the Te-Chi Reservoir. The calibration data were extracted from the second SPOT satellite image, which was taken on September 5, 1994. Chlorophyll a concentration was calculated for each computational element by taking an average value for all pixels within a computational element. To avoid the errors from mixed pixels and the effect from trees on the river banks, water quality data in computational elements of less than 100 m (5 pixels) width were eliminated from the calibration data set, since the satellite resolution was 1 pixel (20 m).

The calibration model was executed 25 times by giving an initial approximation with an interval of 0.5 d⁻¹ of maximum growth rate and 0.05 d⁻¹ respiration rate. A linear equation for the algal maximum growth rate ($\mu_{\text{max}}$) and respiration rate ($\rho$) was found for the Te-Chi Reservoir using the calibration model. The results of the iteration of the calibration are shown in Table 5.4. After drawing an imaginary 45° line in Figure 5.10 (from the lower left corner to the upper right corner), the calibration results show that the initial approximation points at the lower right have a trajectory ending on this 45° line, whereas the
Figure 5.10 Results of parameter calibration for the Te-Chi Reservoir.

- o: iteration starting point
- x: irrational iteration ending point;
- *: rational iteration ending point.
initial approximation points at the upper left of this figure have divergent results. Those test runs with a respiration rate less than 0.1 d\(^{-1}\) show negative values for the parameters and are, therefore, not physically exist. Instead of a single point in the test runs, the calibration model generated a series of values from the convergent approximations. The final values for the maximum growth rate and respiration rate from the convergent points are plotted in Figure 5.11. Thus, the best-fit values of the maximum growth rate and the respiration rate can be expressed in term of a linear equation through a statistical regression as:

\[
p = 0.0576 \mu_{\text{max}} + 0.134, \quad R^2 = 0.965, \ n = 14 \quad \text{(5.1)}
\]

The regression equation with a high correlation coefficient (\(R^2\) of 0.965) presents a set of parameter values that yield a best fit for chlorophyll a distribution in the Te-Chi Reservoir.
<table>
<thead>
<tr>
<th>Initial approximation</th>
<th>First iteration</th>
<th>Second iteration</th>
<th>Third iteration</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1.0, .10)</td>
<td>X</td>
<td></td>
<td></td>
<td>negative</td>
</tr>
<tr>
<td>(1.5, .10)</td>
<td>X</td>
<td></td>
<td></td>
<td>negative</td>
</tr>
<tr>
<td>(2.0, .10)</td>
<td>X</td>
<td></td>
<td></td>
<td>negative</td>
</tr>
<tr>
<td>(2.5, .10)</td>
<td>X</td>
<td></td>
<td></td>
<td>negative</td>
</tr>
<tr>
<td>(3.0, .10)</td>
<td>X</td>
<td></td>
<td></td>
<td>negative</td>
</tr>
<tr>
<td>(1.0, .15)</td>
<td>(.682, .172)</td>
<td>(.829, .195)</td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(1.5, .15)</td>
<td>(.886, .165)</td>
<td>(.749, .178)</td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(2.0, .15)</td>
<td>(1.022, .154)</td>
<td>(.532, .152)</td>
<td>(.492, .178)</td>
<td>convergent</td>
</tr>
<tr>
<td>(2.5, .15)</td>
<td>(1.058, .137)</td>
<td>(.316, .128)</td>
<td>(.086, .145)</td>
<td>convergent</td>
</tr>
<tr>
<td>(3.0, .15)</td>
<td>(1.058, .137)</td>
<td>(.829, .195)</td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(1.0, .20)</td>
<td></td>
<td>(.829, .195)</td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(1.5, .20)</td>
<td>(1.573, .242)</td>
<td></td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(2.0, .20)</td>
<td>(1.817, .237)</td>
<td></td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(2.5, .20)</td>
<td>(2.219, .281)</td>
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<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(3.0, .20)</td>
<td>(2.223, .219)</td>
<td>(2.199, .265)</td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(1.0, .25)</td>
<td></td>
<td>(.829, .195)</td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(1.5, .25)</td>
<td></td>
<td>(.829, .195)</td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(2.0, .25)</td>
<td></td>
<td>(.829, .195)</td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(2.5, .25)</td>
<td>(2.786, .313)</td>
<td></td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(3.0, .25)</td>
<td>(3.099, .310)</td>
<td></td>
<td></td>
<td>convergent</td>
</tr>
<tr>
<td>(1.0, .30)</td>
<td>X</td>
<td></td>
<td></td>
<td>divergent</td>
</tr>
<tr>
<td>(1.5, .30)</td>
<td>X</td>
<td></td>
<td></td>
<td>divergent</td>
</tr>
<tr>
<td>(2.0, .30)</td>
<td>X</td>
<td></td>
<td></td>
<td>divergent</td>
</tr>
<tr>
<td>(2.5, .30)</td>
<td>X</td>
<td></td>
<td></td>
<td>divergent</td>
</tr>
<tr>
<td>(3.0, .30)</td>
<td>X</td>
<td></td>
<td></td>
<td>divergent</td>
</tr>
</tbody>
</table>

Table 5.4 Iteration of the parameter calibration for the Te-Chi Reservoir. Values in parenthesis stand for $(\mu, \rho)$ with a unit of d$^1$. All iterations end with a convergent result, except for the those followed by an X.
Figure 5.11 The best-fit line from parameter calibration for the Te-Chi Reservoir

\[ \rho = 0.0576 \mu_{\text{max}} + 0.143 \]

\[ R^2 = 0.965 \]

\[ n = 14 \]
According to Thomann and Mueller’s (1987) suggestion, the maximum growth rate ranges from 1.5 to 2.5 day\(^{-1}\) and has an average of 1.8 day\(^{-1}\) \((\mu_{\text{max}} = 1.8\) and \(\rho = 0.25\) as a set of typical parameters). QUAL2E user’s guide (Brown and Barnwell, 1985) suggests values of 1.0 - 3.0 day\(^{-1}\) for the maximum growth rate and 0.05 day\(^{-1}\) for respiration rate for clean streams or 0.2 day\(^{-1}\) for streams with greater than twice the nutrient affinity constant \(K_s\). From Eq 5.1, the respiration rate ranges from 0.2 to 0.3 day\(^{-1}\), while the maximum growth rate ranges from 1.0 to 3.0 day\(^{-1}\). Compared with the nutrient affinity constant assigned in this simulation \(K_s = 4 \ \mu g/L\), the concentration of phosphorus in the Te-Chi Reservoir is more than twice and even 10 times more than the nutrient affinity constant in some locations. Therefore, a respiration rate greater than 0.2 day\(^{-1}\) is reasonable. For a typical value of maximum growth rate of 1.8 day\(^{-1}\), the respiration rate is about 0.25 day\(^{-1}\) for the algal growth during the late August/early September time period for the Te-Chi Reservoir.

The results from the Te-Chi Reservoir calibration are not as clear as the results from the hypothesis test. The major reason for the different results from the same calibration model could be the characteristics of the calibration data set. Figure 5.12 shows the final result from the simulation and satellite-derived chlorophyll \(a\) concentration. The SPOT data present a higher variability of water
Figure 5.12 Comparison of chlorophyll a concentration from calibrated simulation and SPOT-derived data on September 5, 1994 at the Te-Chi Reservoir.
quality, while the chlorophyll a concentration from the QUAL2E simulation has a more homogeneous decrease along the Ta-Chia River, moving downstream. In QUAL2E, each element has a significant relationship with its adjacent elements, and almost no concentration spike could occur in elements, except for those elements with an extremely high amount of pollutant input. However, a comparatively high chlorophyll a concentration could occur in an element that has a high unknown pollution source. In other words, the distribution of chlorophyll a in practical cases may not have such a strong decreasing pattern, as seen in the simulation of any water quality model. Since QUAL2E is a one-dimensional stream water quality model, there could also be some unknown non-point sources that cause a minor variation of algal growth. However, this level of uncertainty is still acceptable for most water resources applications.

After the parameters with a major effect on the algal growth rate are resulted, we can fix the major parameters and run the calibration model for the second major parameters. Overall, the calibration model performed effectively to calibrate algal maximum growth rate and respiration rate. The calibration model provides a mathematical approach to estimate biological parameters of algae instead of using trial-and error or random guesses.
CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 The Water Quality Monitoring and Forecasting System

Even though water quality modeling techniques have been developed for more than three quarters of a century, there have limited to the study of trends instead of making accurate short-term forecasts. A major barrier to water quality forecasting is the lack of an efficient system for water quality monitoring. In this study, the SPOT satellite data provide to be an efficient tool to fill the gap between sampling dates, maintain periodic water quality monitoring, and make real-time water quality forecasts.

The first achievement in this research was to develop a water quality monitoring system using SPOT satellite imagery. This system provides not only an instant water quality report, but also more accurate initial conditions for water quality modeling. The procedure of how to convert the digital values from
satellite images into water quality variables through a regression model was demonstrated for the Te-Chi reservoir. Thematic maps of chlorophyll $a$, Secchi depth, and phosphorus show high spatial resolution for water quality assessment. The final products presented in Chapter 5 (Figure 5.1 through Figure 5.5) reveal that the empirical approach for applying remote sensing techniques to water quality monitoring is valid and efficient. The system takes a comparatively short amount of time to resolve the water quality condition compared with traditional *in situ* sampling. This advantage makes an instantaneous forecast become more feasible. Even though the remote sensing water quality system is still restricted to the accessibility of satellite images, which is restricted by the weather conditions and image acquisition times, remote sensing is relatively less prohibitive traditional approaches. However, since the core of the water quality monitoring system is the regression model, which is established based on ground truth, the verification of the coefficients in the regression equations by *in situ* sampling on a seasonal or yearly basis is critical.

The second achievement was to integrate the monitoring system with a quality model, QUAL2E, as a forecasting system, and to display the prediction in a GIS image processing system, ERDAS IMAGINE. Because of the high spatial and temporal resolution, water quality detection by satellites make a short-term forecast possible. Furthermore, the visualization techniques provided in a GIS and
image processing system were undertaken to enhance the display of prediction maps from the water quality forecasting system. The simulated results were presented in two-dimensional thematic maps and in dynamic sequential images that provide a easier way to understand and visualize water quality variations in a large reservoir system. As shown in the Te-Chi Reservoir study case (see Figure 5.6), all water quality variables from the simulations were displayed on a geographically registered map and in color to correspond with varying water quality levels. Moreover, these sequential images were also recorded on a video tape to display water quality changes dynamically as animations. These visualization techniques help inexperienced users to understand the progression of water quality conditions.

The complete integrated system being developed is designed to be economical and efficient and can be used to answer “what-if” questions whenever pollutant sources change in the system. A timely monitoring and forecasting system for water quality could result in an effective strategy plan for water resources. Thus, water quality problems can be predicted and dealt with before they become serious and damage the aquatic ecosystem.
6.2 The Water Quality Calibration

The traditional approaches for water quality assessment cannot always provide enough water quality data to satisfy the demands of model parameter calibration. SPOT imagery provides a set of calibration data with a high reliability due to its high spatial resolution and wide coverage over a water body. Parameter estimation is made possible by using remote sensing data. A calibration model for those parameters affecting algal growth was established based on a least squares adjustment. After a sensitivity analysis, algal maximum growth rate and respiration rate were chosen as the most important parameters growth to be calibrated for algal in the Te-Chi reservoir. The results from the Te-Chi Reservoir case were quite different from the results from the hypothetical test run. The Te-Chi Reservoir case resulted in a set of linear combinations of parameters, while the test run had spiral trajectories and ended in a single point, disregarding different given initial approximations. This inconsistency can be explained by analyzing the characteristics of data patterns. The satellite-derived data presented water quality with a higher resolution (or higher spatial diversity). In contrast, water quality data from the QUAL2E simulation appears as a strong decreasing pattern along the Ta-Chia River. Therefore, there is only one set of best-fitting parameters when using the simulation result as the calibration data, but an unlimited set of
best-fitting parameters by using satellite-derived data as the calibration data. Overall, the automated calibration model performed effectively to calibrate algal maximum growth rate and respiration rate, and is highly recommended to be expanded for other model parameters, such as affinity constant and light saturation intensity, and for different water bodies.

6.3 Recommendations and Further Study

The water quality system can be expected to be used for other lakes and water quality variables. When the system is used for different water bodies, a regression model has to be established in the beginning. Therefore, in situ sampling must be available to serve as ground truth. When in situ sampling is conducted, it is suggested to use a GPS (Global Positioning System) receiver to record accurate coordinates of each water sample location. For remote detection of different water quality variables, the major concern is the suitable spectral channels to use in deriving various characteristics of water quality variables. Regarding any further improvement on a water quality forecasting system, a more complex water quality model should be used, such as the three-dimensional water quality model WASP5 (Water Quality Analysis Simulation Program version 5) (Ambrose et al., 1991). However, the model still depends on the hydrological
characteristics of the watershed, available field data, and the water quality variables of interest.

Even though water quality assessment using remote sensing is less expensive than *in situ* sampling, the imagery cost is still substantial. In the future, it can be expected that the cost of satellite imagery will be significantly reduced, the spatial and spectral resolution will improve, and the data transmission will become more efficient. With advancements in electronic and computer technologies, the monitoring and forecasting system should be more economical and practical in the future. For the next several years, we can expect more data and higher quality global land data from satellite systems. Based on the current schedule, at least 17 satellites will be launched within the coming five years. Those satellite sensors will provide remote observation of the earth at spatial resolutions of ranging from 1 to 3 m in panchromatic images and 4 to 15 m in multispectral bands (Fritz, 1996). In addition to high spatial resolutions, temporal coverage will be enhanced as well. Delivery time from acquisition to users can be shortened to 15 minutes or 48 hours, which makes real-time monitoring and forecasting feasible. With more satellite data available, this increases the accessibility of images. And a better spatial resolution improves the accuracy of reflectance from a water element without the effect from surrounding land.
Water quality monitoring, water quality modeling, and water quality management (3WQMs) are sequential techniques used in water resources engineering. In this study, the first two goals have been achieved and a data base management system has been established. This study demonstrates that use of remote sensing data for assisting in real-time water quality monitoring and forecast is promising, as long as remote sensing data can be accessible from satellite systems. The integration of a strategy-designing model with a forecasting system could be the subject of future work for a complete management system for water quality.
BIBLIOGRAPHY


Yang, Ming-Der. 1993. Trophic Cascade in Shallow River Systems. (unpublished Master thesis). The Ohio State University, Columbus, OH.
APPENDIX A

THE CALIBRATION MODEL
C MAIN PROGRAM
DIMENSION A(93), B(93), C(93), S(93), E(93,4), ETRANS(4,93),
+ EINV(4,4), TEMP(4,1), ALGAE(93), PHOS(93), delta(93),
+ DALGAE(93), GROWTH(93), DEPTH(93), EXTC(93), dal(93),
+ X(4,1), Y(4,1), Z(4,1), DUM(93,4), AGFL(93), AGFP(93),
+ COEF(93,1), SPOT(93), T(93), ALGSET(93), ALG(93),
+ WEIGHT(93), WW(93)
REAL DALL
WRITE(*,*)'CALIBRATING DATA IS INCLUDED SINCE ELEMENT # ?
+ (eg. 1 OR 20)'
READ(*,*)MM
CALL QUAL2E
OPEN(UNIT=2, FILE='PARAM1.DAY')
OPEN(UNIT=5, FILE='SP0T2')
OPEN(UNIT=6, FILE='RESULT')
M=93
C MM=20 OR 1
L=4
N=1
DAY=6.0
J=0
TF=12./24.
CCC READ INPUT CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
DO 106 I=1,M
READ(5,*) SPOT(I), WEIGHT(I)
106 READ(2,107) A(I), B(I), C(I), S(I), ALG(I), ALGSET(I)
C READ(4,*) GROWTH(I), ALGSET(I), PHOS(I)
1999 J=J+1
WRITE(*,*) 'ITERATION #', J
WRITE(6,*) 'ITERATION #', J
OPEN(UNIT=3, FILE='PARAM1')
OPEN(UNIT=7, FILE='PARAM3')
DO 118 I=1,M
READ(3,107) (DUM(I,K), K=1,4), ALGAE(I)
READ(7,117) PHOS(I), AGFL(I), AGFP(I), GROWTH(I), T(I),
+ DEPTH(I), EXTC(I)
118 CONTINUE
107 FORMAT(6F7.3)
117 FORMAT(7F10.6)
READ(7,127) SUM1, XF, RF, EF, PKS, GRWMAX, CPRATIO
127 FORMAT(7F8.3)
READ(7,*) (Y(K,1), K=1,L)
DO 119 I=1,L
119 Z(I,1)=Y(I,1)
A(I)=0.
C(93)=0.
WEI=0.
DALL=0.
IF(J.GT.1) GO TO 109
DO 108 I=1,M
ALG(I)=ALG(I)/CPRATIO
108 SPOT(I)=SPOT(I)/CPRATIO
109 DO 120 I=1,M
DALGAE(I)=(SPOT(I)-ALGAE(I))
T(I)=((T(I)-32)*5.0/9.0-20)*1
120 END
DEPTH(I)=DEPTH(I)/3.2808

DO 121 I= 1,M
   DALL=DALGAE(I)*WEIGHT(I)+DALL
121 WEI=WEIGHT(I)+WEI
   DALL=DALL/WEI
   WRITE(6,*)DALL,'----------------AVERAGE DIFFERENCE'
   WRITE(*,*)DALL,'----------------AVERAGE DIFFERENCE'

CKL=Y(2,1)*24*60
PKS=Y(3,1)
GRWMAX=Y(1,1)
WRITE(*,107)(Y(K,1) ,K=1,L)
WRITE(*,*)'-OLD PARAMETERS'
WRITE(6,107)(Y(K,1) ,K=1,L)
WRITE(6,*)'-OLD PARAMETERS'

C RFOLD
RF=429.6/CKL
DO 110 I= 1,M
   GROWTH(I)=GRWMAX*((1.047)**T(I))
   AGFL(I)=2.718*TF/DEPTH(I)/EXTC(I)*(1-EXP(-RF/TF))
   GROWTH(I)=GROWTH(I)*AGFL(I)
   GROWTH(I)=GROWTH(I)*PHOS(I)/(PKS+PHOS(I))
110 DELTA(I)  =LOG(SPOT(I)/ALGAE(I)  )/DAY
C GROWTH(I)=GROWTH(I)*Y(1,1)/Z(1,1)
C GROWTH(I)=GROWTH(I)*(1-EXP(-RF/TF))/(1-EXP(-RFOLD/TF))
C 110 GROWTH(I)=GROWTH(I)*(Z(3,1)+PHOS(I))/(Y(3,l)+PHOS(I))

CCCC CALCULATE NORMAL MATRIX E CCCCCCCCCCCCCCCCCC
ZZ=RF/CKL/TF*(1-1/(1-EXP(-RF/TF))
DO 128 1= 1,M
   E(  1 ,1)=GROWTH(I)/GRWMAX
   E(I,2)=GROWTH(I)*ZZ
   E(I,2)=RF/CKL/TF*(1-2.718*TF/DEPTH(I)/EXTC(I)/AGFL(I))
   E(I,3)=-GROWTH(I)/(PKS+PHOS(I))
128 CONTINUE

CCCC LEAST SQUARES ADJUSTMENT CCCCCCCCCCCCCCCCCC
R=1/DAY
DO 777 1=1,M
   DAL{I)=DALGAE(I)/day
777 CONTINUE

DO 777 I=1,M
   COEF(I,1)=A(I)*DAL(I-1)+(B(I)-0.0)*DAL(I)
   +C(I)*DAL(I+1)
1 CONTINUE

CCCCC SKIP THE FIRST 19=MM ELEMENTS
MMM=M-MM+1
DO 773 I=1,MMM
   COEF(I,1)=COEF((I+MMM-1),1)
   ALGAE(I)=ALGAE(I+MMM-1)
   DAL(I)=DAL(I+MMM-1)
   WW(I)=WEIGHT(I+MMM-1)
   E(I,1)=E((I+MMM-1),1)*ALGAE(I)
773 E(I,2)=E((I+MMM-1),2)*ALGAE(I)

C THE FINAL COEF(1,1) IS THE OBSERVATION VECTOR CCCCCCCCCCCCC
L=2

C MUL ETRANS*WEIGHT=ETRAN (L,MMM,MMM) CCCCCCCCCCCCCCCCCCCCCC
DO 2 K=1,MMM
DO 2 I=1,L
ETRANS(I,K)=E(K,I)
2 ETRANS(I,K)=ETRANS(I,K)*WW(K)

C 235 FORMAT(25F2.1)
C 177 FORMAT(4F7.3)
CALL MUL(ETRANS,E,EINV,L,MMM,L)
CALL MUL(ETRANS,COEF,TEMP,L,MMM,N)
CALL INV(EINV,EINV,L)
CALL MUL(EINV,TEMP,X,L,L,N)

C 187 FORMAT(6F7.3)
C CALL MUL(TEMP,COEF,X,L,M,N)
CCC ESTIMATE VARIANCE OF UNIT WEIGHT CCCCCCCCCCCCCCCCCC
CALL MUL(E,X,DUM,MMM,L,N)
CALL SUB(DUM,COEF,DUM,MMM,N)
SIGMAOLD=0.0
SIGMA=0.0
DO 5 K=1,MMM
SIGMA=SIGMA+SIGMAOLD+COEF(K,1)*COEF(K,1)*WW(K)
5 SIGMA=SIGMA+DUM(K,1)*DUM(K,1)*WW(K)
SIGMA=SQRT(SIGMAOLD/(MMM-L))
SIGMA=SQRT(SIGMA/(MMM-L))
L=4
X(4,1)=X(2,1)
X(3,1)=0.
X(2,1)=0.

C X(2,1)=X(2,1)/60./24.
WRITE(*,*)'*','PARAMETER CORRECTIONS'
WRITE(6,*)'(X(K,1),K=1,L)
WRITE(6,*)' PARAMETER CORRECTIONS'
WRITE(*,')'SIGMAOLD =',SIGMAOLD,' SIGMA =',SIGMA
WRITE(6,')'SIGMAOLD =',SIGMAOLD,' SIGMA =',SIGMA
C WRITE(*,')'DIFFERENCES IN % OF OLD PARAMETERS'
C WRITE(*,*)'Z(K,1),K=1,L)
DO 52 K=1,L
Z(K,1)=Y(K,1)
52 Y(K,1)=X(K,1)+Y(K,1)
WRITE(*,107)(Y(K,1),K=1,L)
WRITE(*,'') NEW PARAMETERS'
WRITE(6,107)(Y(K,1),K=1,L)
WRITE(6,')' NEW PARAMETERS'
WRITE(*,')'NEED ANOTHER ITERATION? YES(l) OR NO(2)'
READ(*,*)K
IF(K.GT.1) GO TO 9999
CLOSE(3)
CLOSE(7)
CALL QUAL2F(Y(1,1),Y(4,1))
GO TO 1999
9999 STOP
END
SUBROUTINE ADD(A,B,C,L,M)
C ADD MATRIX A AND B INTO MATRIX C
C IMPLICIT REAL*8(A-H,O-Z)
DIMENSION A(L,M),B(L,M),C(L,M)
DO 2 J=1,M  
   DO 2 I=1,L  
   2  C(I,J)=A(I,J)+B(I,J)
RETURN  
END

SUBROUTINE SUB(A,B,C,L,M)
C SUBTRACT MATRIX A AND B INTO MATRIX C
C IMPLICIT REAL*8(A-H,O-Z)
DIMENSION A(L,M),B(L,M),C(L,M)
DO 2 J=1,M  
   DO 2 I=1,L  
   2  C(I,J)=A(I,J)-B(I,J)
RETURN  
END

SUBROUTINE MUL(A,B,C,L,M,N)
C MULTIPLY MATRIX A BY B EQUAL MATRIX C
C IMPLICIT REAL*8(A-H,O-Z)
DIMENSION A(L,M),B(M,N),C(L,N)
DO 5 J=1,N  
   DO 5 I=1,L  
      C(I,J)=0.  
      DO 5 K=1,M  
      5  C(I,J)=A(I,K)*B(K,J)+C(I,J)
RETURN  
END

SUBROUTINE TRA(A,C,L,M)
C TRANSPOSE MATRIX A INTO MATRIX C
C IMPLICIT REAL*8(A-H,O-Z)
DIMENSION A(L,M),C(M,L)
DO 2 J=1,M  
   DO 2 I=1,L  
   2  C(I,J)=A(J,I)
RETURN  
END

SUBROUTINE INV(A,C,I)
C INVERT MATRIX A INTO MATRIX C
C IMPLICIT REAL*8(A-H,O-Z)
DIMENSION A(I,I),C(I,I),D(100)
DO 10 K=1,I  
   DO 10 J=1,I  
      10  C(K,J)=A(K,J)
IM=I-1  
   DO 5 K=1,I  
   DO 2 J=1,IM  
      2  C(K,J)=A(K,J)
RETURN  
END
2 \text{D(J)} = \frac{C(1,J+1)}{C(1,1)}
D(I) = 1.0 / C(1,1)
DO 4 L = 1, IM
DO 3 J = 1, IM
3 \text{C(L,J)} = C(L+1,J+1) - C(L+1,1) \times D(J)
4 \text{C(L,I)} = -C(L+1,1) \times D(I)
DO 5 J = 1, I
C(I,J) = D(J)
5 \text{CONTINUE}
RETURN
END
APPENDIX B

HYDROLOGIC AND METEOROLOGICAL DATA RECORDED AT THE
SUNG-MAO STATION FOR AUGUST AND SEPTEMBER, 1994
Daily Average Temperature at Station Sung-Mao

- Water temperature
- Air temperature

Temperature (°C)

Date (1994):
- 1-Aug
- 11-Aug
- 21-Aug
- 31-Aug
- 10-Sep
- 20-Sep
- 30-Sep
Wind Speed at Station Sung-Mao

Date (1994)

Speed (m/s)

0 5 10 15 20 25

1-Aug 11-Aug 21-Aug 31-Aug 10-Sep 20-Sep 30-Sep
Daily Precipitation at Station Sung-Mao

Date (1994)

Precipitation (mm)
APPENDIX C

WATER SAMPLING FOR THE TE-CHI RESERVOIR
The original report for the sampling on August 30, and 31, 1994 from the Te-Chi Reservoir Committee

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<th>Sample ID</th>
<th>Temp (°C)</th>
<th>Soluble Oxygen (mg/L)</th>
<th>pH</th>
<th>DO (mg/L)</th>
<th>Calcium (mg/L)</th>
<th>Magnesium (mg/L)</th>
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196
The sampling locations for the Te-Chi Reservoir Sampling Program
APPENDIX D

COMPUTER CODES IN MATLAB FOR DATA PROCESSING
%READ.M -------------- read a binary file
function [img] = read(fname)
% [img]: image matrix
fid = fopen(fname, 'r');
fread(fid,3,'char'); %Read P5
size = fscanf(fid,'%d',3);
fread(fid,1,'char');
height = size(1);
width = size(2);
height = 500;
width = 350;
img = zeros(width,height);
for i=1:height
    img(i,:) = fread(fid,width,'uchar');
end
imgl = fread(fid,[height, width],'uchar');
img = imgl';
fclose(fid);
for i=1:width
    for j=1:height
        img(i,j) = imgl(j,i);
    end
end
subplot(1,1,1);
colormap(gray(80));
image(img);
return
%WRITE.M --------- write a binary file
function [img1] = write(boundr, bound2, bound4, img, fname, variable)
% e.g. [day1] = write(boundr, bound2, bound4, img,'day1',2);
% [img]: image matrix; fname: input image file;
% variable: water quality variable in the image from QUAL2E
% define elements and put in water quality variable from QUAL2E
% Read element numbers and water quality variables
% row: #, chlorophyll, phosphorus ***** from water.dat
total=94;
load water.dat;
%load bound2;
%load bound4;
%load boundr;
% the 2nd section element definition (5-13)
adjunct1=5;%the 1st element at the 2nd section
for i=121:166
    k=ceil((i-120)/5);
    L=i-120;
    for j=bound2(1,L):bound2(2,L)
        img(i,j)=water((adjunct1+k-1),variable);
    end
end
% extra element for #13 (j=166)
for j=bound2(1,L):bound2(2,L)
    img(i,j)=water(13,variable);
end
% the 4th section element definition (31-35)
adjunct2=31;%the 1st element at the 2nd section
for i=173:197
    k=ceil((i-172)/5);
    L=i-166;
    for j=bound4(1,L):bound4(2,L)
        img(i,j)=water((adjunct2+k-1),variable);
    end
end
% extra element for #31 (j=167-172)
for i=167:172
    L=i-166;
    for j=bound4(1,L):bound4(2,L)
        img(i,j)=water(adjunct2, variable);
    end
end
%BOUNDARY.M ------- define boundary

function [boundr, bound2, bound4] = boundry(img)
% define section 1, 3, and 5 (boundr)
for j=1:490
    count=1;
k=1;
    for i=1:350
        if count==1
            if img(i,j)>0
                boundr(k,j)=i;
                count=0;
                k=k+1;
            end
        else
            if img(i,j)==0
                boundr(k, j)=i-1;
                k=k+1;
                count=1;
            end
        end
    end
end
% define section 2 (bound2)
for i=121:166
    count=1;
k=i-120;
    bound2(2,k)=425;
    for j=409:428
        if count==1
            if img(i,j)>0
                bound2(l,k)=j;
                count=0;
            end
        else
            if img(i,j)==0
                bound2(2, k)= j-1;
                count=1;
            end
        end
    end
end
bound2(2,3)=bound2(2,1);
% define section 4 (bound4)
for i=167:224
    count=1;
k=i-166;
    bound4(2,k)=323;
    for j=309:334
        if count==1
            if img(i,j)>0
                bound4(1,k)=j;
                count=0;
            end
        elseif count==2
            else
                end
        end
end
bound2(2,3)=bound2(2,1);
if img(i,j)==0
    bound4(2,k)=j-1;
    count=2;
end
end
end
bound4(2,3)=bound4(2,2);

% writing boundary matrices into binary files in Matlab
%fid = fopen('bound2', 'w');
%fwrite(fid,bound2,'uchar');
%fclose(fid);
%fid = fopen('bound4', 'w');
%fwrite(fid,bound4,'uchar');
%fclose(fid);
%fid = fopen('boundr', 'w');
%fwrite(fid,boundr,'uchar');
%fclose(fid);
%save bndry boundry -ascii;
return

*******************************************************************************
%define new boundary and extract data from images
b1=boundr;
b2=bound2;
b3=bound4;
%----------------------------------------------------------
%remove outline from the boundary
def1= write(boundr, bound2, bound4, img, 'def1',1);
def=def1';
%element 1
for k=2:40
    i=k+120;
def(i, bound2(1,k))=0;
end
for k=4:46
    i=k+120;
def(i, bound2(2,k))=0;
end
%element 2
for k=2:27
    i=k+166;
def(i, bound4(1,k))=0;
end
for k=12:58
    i=k+166;
def(i, bound4(2,k))=0;
end
%element 1, 3, 5
for k=18:444
    def(boundr(1,k), k)=0;
def(boundr(2,k), k)=0;
end
%renumber 1st and last outline as 0
for i=boundr(l,17):boundr(2,17)
def(i, 17)=0;
end
for i=boundr(l,445):boundr(2,445)
def(i, 445)=0;
end
%fix problem pixels
def(149,418)=0;
def(226,309)=0;
def(226,310)=0;
def(226,311)=0;
def(225,311)=0;
%----------------------------------------------------------
%calculating average digital values by extracting remotely sensed data from SPOT

t3=read('te3');
t2=read('te2');
t1=read('tel');
for k=1:94
    % spot3(k)=0;
    % spot2(k)=0;
    % spotl(k)=0;
    count(k)=0;
end
for i=115:326
    for j=17:445
        if def(i,j)==k
            spot3(k)=spot3(k)+te3(i,j);
            spot2(k)=spot2(k)+te2(i,j);
            spot1(k)=spot1(k)+te1(i,j);
            count(k)=1+count(k);
        end
    end
end
% spot3(k)=spot3(k)/count(k);
% spot2(k)=spot2(k)/count(k);
% spot1(k)=spot1(k)/count(k);
end
% band ratio and water quality variable calculation
% band2--spot2; band3--spot3
for k=1:94
    br(k)=spot3(k)/spot2(k);
    chi(k)=exp(9.37)*exp(10*log(br(k)));
end
APPENDIX E

AN EXAMPLE OF AN INPUT FILE FOR QUAL2E
TITLE01  QUAL-2E; DATA SET Te-Chi reservoir 8/31/94-9/05/94
TITLE02  SEMCOG DATA SOURCE - MODIFIED ROUGE RIVER REACHES
TITLE03  NO  CONSERVATIVE MINERAL I  TDS  MG/L
TITLE04  NO  CONSERVATIVE MINERAL II
TITLE05  NO  CONSERVATIVE MINERAL III
TITLE06  YES  TEMPERATURE
TITLE07  YES  5-DAY BIOCHEMICAL OXYGEN DEMAND IN MG/L
TITLE08  YES  ALGAE AS CHL-A IN UG/L
TITLE09  YES  PHOSPHORUS CYCLE AS P IN MG/L
TITLE10  (ORGANIC-P; DISSOLVED-P)
TITLE11  YES  NITROGEN CYCLE AS N IN MG/L
TITLE12  (ORGANIC-N; AMMONIA-N; NITRITE-N; NITRATE-N)
TITLE13  YES  DISSOLVED OXYGEN IN MG/L
TITLE14  NO  FECAL COLIFORMS IN NO./100 ML
TITLE15  NO  ARBITRARY NON-CONSERVATIVE BOD  MG/L
ENDTITLE
NO LIST DATA INPUT
NO WRITE OPTIONAL SUMMARY
NO FLOW AUGMENTATION
NO STEADY STATE
TRAP
NO PRINT LCD/SOLAR DATA
NO Plot DO AND BOD
FIXED DNSTM CONC (YES-1)= 0  5D-ULT BOD CONV RATE COEF  0.00
INPUT METRIC (YES-1) = 1  OUTPUT METRIC (YES-1) = 1
NUMBER OF REACHES = 22  NUMBER OF JUNCTIONS = 0
NUM OF HEADWATERS = 1  NUMBER OF POINT LOADS = 8
TIME STEP (HOURS) = 1  LNGTH COMP ELEMENT (DX)= .1
MAXIMUM ITERATIONS = 132  TIME INC. FOR RPT2 (HRS)= 132
LATITUDE OF BASIN (DEG) = 23.8  LONGITUDE OF BASIN (DEG)= 121.1
STANDARD MERIDIAN (DEG) = 63.2  DAY OF YEAR START TIME = 243.0
EVAP. COEFF. (AE) = .0000062  EVAP. COEF. (BE) = .0000055
ELEV OF BASIN (ELEV) = 1300.  DUST ATTENUATION COEF. = 0.13
ENDATAA
O UPTAKE BY NH3 OXID(MG O/MG N)= 3.5  O UPTAKE BY NO2 OXID(MG O/MG N)= 1.20
O PROD BY ALGAE (MG O/MG A) = 1.6  O UPTAKE BY ALGAE (MG O/MG A) = 2.67
N CONTENT OF ALGAE (MG N/MG A) = .120  P CONTENT OF ALGAE (MG P/MG A) = 0.005
ALG MAX SPEC GROWTH RATE(1/DAY)= 4.000  ALGAE RESPIRATION RATE (1/DAY) = 0.100
N HALF SATURATION CONST (MG/L) = .02  P HALF SATURATION CONST (MG/L) = 0.004
LIN ALG EXCO (1/FT)/(UG-CHLA/L) = .0060  NLINCO(1/FT)/(UG-CHLA/L)**(2/3) = 0.0
LIGHT FUNCTION OPTION (LFNOPT) = 3  LIGHT SATURATION COEF(LNGY/MIN) = 0.196
DAILY AVERAGING OPTION (LAVOPT)= 3  LIGHT AVERAGING FACTOR (AFAPT) = 1.0
NUMBER OF DAYLIGHT HOURS (DLH) = 12  TOTAL DAILY SOLAR RADTN (LNGYS) = 600
ALG/GROW CALC OPTION(GROPT)= 1  ALGAL PREF FOR NH3-N (PREFN) = 0.5
ALG/TEMP SOLR RAD FACTOR(TFACT)= .65  NITRIFICATION INHIBITION COEF = 0.6
ENDATAA
THETA  BOD SETT  1.024
THETA  NH3 DECA  1.047
THETA  OXY TRAN  1.060
THETA  ORGN SET  1.000
THETA  NH3 SRCE  1.000
THETA  PORG SET  1.000
THETA  DISP SRC  1.000
THETA  ALG GROW  1.068
THETA  ALG RESP  1.080
THETA  ALG SETT  1.024
THETA  ANC DECA  1.047
THETA  ANC SETT  1.000
ENDATAA
STREAM REACH  1.0RCH= #1 - #2  FROM  9.3 TO  9.1
STREAM REACH  2.0RCH= #3 - #4  FROM  9.1 TO  8.9
STREAM REACH  3.0RCH= #5 - #9  FROM  8.9 TO  8.4
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| HYDRAULICS RCH | 4.0 | 0.35 | 0.02 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 5.0 | 0.35 | 0.02 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 6.0 | 0.35 | 0.02 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 7.0 | 0.35 | 0.02 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 8.0 | 0.35 | 0.02 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 9.0 | 0.35 | 0.02 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 10.0 | 0.35 | 0.02 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 11.0 | 0.35 | 0.03 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 12.0 | 0.35 | 0.03 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 13.0 | 0.35 | 0.03 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 14.0 | 0.35 | 0.03 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 15.0 | 0.35 | 0.03 | 0. | 2.0 | 1.50 |
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| HYDRAULICS RCH | 17.0 | 0.35 | 0.04 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 18.0 | 0.35 | 0.04 | 0. | 2.0 | 1.50 |
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| HYDRAULICS RCH | 20.0 | 0.35 | 0.06 | 0. | 2.0 | 1.50 |
| HYDRAULICS RCH | 21.0 | 0.35 | 0.06 | 0. | 2.0 | 1.50 |
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| N AND P COEF RCH | 1.0 | 0.11 | 0.0 | .80 | 0.0 | 1.0 | 0.07 | 0.01 |
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| N AND P COEF RCH | 17.0 | 0.11 | 0.0 | .80 | 0.0 | 1.0 | 0.07 | 0.01 |
| N AND P COEF RCH | 18.0 | 0.11 | 0.0 | .80 | 0.0 | 1.0 | 0.07 | 0.01 |
| N AND P COEF RCH | 19.0 | 0.11 | 0.0 | .80 | 0.0 | 1.0 | 0.07 | 0.01 |
| N AND P COEF RCH | 20.0 | 0.11 | 0.0 | .80 | 0.0 | 1.0 | 0.07 | 0.01 |
| N AND P COEF RCH | 21.0 | 0.11 | 0.0 | .80 | 0.0 | 1.0 | 0.07 | 0.01 |
| N AND P COEF RCH | 22.0 | 0.11 | 0.0 | .80 | 0.0 | 1.0 | 0.07 | 0.01 |

| ALG/OFFER COEF RCH | 1.0 | 25. | 0.05 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OFFER COEF RCH | 2.0 | 25. | 0.05 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OFFER COEF RCH | 3.0 | 25. | 0.05 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
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| ALG/OFFER COEF RCH | 9.0 | 25. | 0.05 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OFFER COEF RCH | 10.0 | 25. | 0.05 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OFFER COEF RCH | 11.0 | 25. | 0.05 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OFFER COEF RCH | 12.0 | 25. | 0.05 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OFFER COEF RCH | 13.0 | 25. | 0.05 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |

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| ALG/OTHER COEF | RCH= 14.0 | 25. | 0.05 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OTHER COEF | RCH= 15.0 | 25. | 0.20 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OTHER COEF | RCH= 16.0 | 25. | 0.15 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OTHER COEF | RCH= 17.0 | 25. | 0.10 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OTHER COEF | RCH= 18.0 | 25. | 0.10 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OTHER COEF | RCH= 19.0 | 25. | 0.10 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OTHER COEF | RCH= 20.0 | 25. | 0.10 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OTHER COEF | RCH= 21.0 | 25. | 0.25 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |
| ALG/OTHER COEF | RCH= 22.0 | 25. | 0.45 | 1.0 | 1.5 | 0.6 | 0.1 | 0.0 |

ENDATA6B

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| INITIAL COND-1 | RCH= 2.0 | 23.0 | 16.0 | 17.0 |
| INITIAL COND-1 | RCH= 3.0 | 23.0 | 16.0 | 10.0 |
| INITIAL COND-1 | RCH= 4.0 | 23.0 | 15.6 | 7.25 |
| INITIAL COND-1 | RCH= 5.0 | 23.0 | 15.2 | 5.00 |
| INITIAL COND-1 | RCH= 6.0 | 23.0 | 14.7 | 3.50 |
| INITIAL COND-1 | RCH= 7.0 | 23.0 | 14.3 | 2.00 |
| INITIAL COND-1 | RCH= 8.0 | 23.0 | 14.0 | 1.60 |
| INITIAL COND-1 | RCH= 9.0 | 23.0 | 13.7 | 1.50 |
| INITIAL COND-1 | RCH= 10.0 | 22.5 | 13.3 | 1.40 |
| INITIAL COND-1 | RCH= 11.0 | 22.0 | 12.8 | 1.30 |
| INITIAL COND-1 | RCH= 12.0 | 21.5 | 12.4 | 1.25 |
| INITIAL COND-1 | RCH= 13.0 | 21.5 | 10.8 | 1.20 |
| INITIAL COND-1 | RCH= 14.0 | 21.5 | 10.6 | 1.50 |
| INITIAL COND-1 | RCH= 15.0 | 21.4 | 10.4 | 1.70 |
| INITIAL COND-1 | RCH= 16.0 | 21.3 | 10.2 | 1.90 |
| INITIAL COND-1 | RCH= 17.0 | 21.1 | 10.0 | 2.10 |
| INITIAL COND-1 | RCH= 18.0 | 21.0 | 9.8 | 2.30 |
| INITIAL COND-1 | RCH= 19.0 | 21.0 | 9.6 | 2.50 |
| INITIAL COND-1 | RCH= 20.0 | 21.0 | 9.3 | 2.10 |
| INITIAL COND-1 | RCH= 21.0 | 21.0 | 9.0 | 1.80 |

ENDATA7

| INITIAL COND-2 | RCH= 1.0 | 340. | 0.19 | 0.19 | .01 | 0.97 | .300 | .035 |
| INITIAL COND-2 | RCH= 2.0 | 300. | 0.19 | 0.19 | .01 | 0.97 | .300 | .035 |
| INITIAL COND-2 | RCH= 3.0 | 280. | 0.19 | 0.19 | .01 | 0.97 | .350 | .035 |
| INITIAL COND-2 | RCH= 4.0 | 200. | 0.25 | 0.25 | .01 | 0.97 | .330 | .035 |
| INITIAL COND-2 | RCH= 5.0 | 230. | 0.32 | 0.32 | .01 | 0.97 | .320 | .035 |
| INITIAL COND-2 | RCH= 6.0 | 70. | 0.39 | 0.39 | .01 | 0.97 | .310 | .035 |
| INITIAL COND-2 | RCH= 7.0 | 80. | 0.45 | 0.45 | .01 | 0.97 | .300 | .035 |
| INITIAL COND-2 | RCH= 8.0 | 60. | 0.52 | 0.52 | .01 | 0.97 | .240 | .016 |
| INITIAL COND-2 | RCH= 9.0 | 36. | 0.45 | 0.45 | .01 | 0.97 | .200 | .020 |
| INITIAL COND-2 | RCH= 10.0 | 52. | 0.38 | 0.38 | .01 | 0.98 | .160 | .020 |
| INITIAL COND-2 | RCH= 11.0 | 32. | 0.29 | 0.29 | .01 | 0.99 | .120 | .020 |
| INITIAL COND-2 | RCH= 12.0 | 50. | 0.19 | 0.19 | .01 | 0.99 | .080 | .015 |
| INITIAL COND-2 | RCH= 13.0 | 27. | 0.11 | 0.11 | .01 | 1.00 | .045 | .015 |
| INITIAL COND-2 | RCH= 14.0 | 32. | 0.11 | 0.11 | .01 | 0.99 | .045 | .020 |
| INITIAL COND-2 | RCH= 15.0 | 12.0 | 0.10 | 0.10 | .01 | 0.99 | .045 | .020 |
| INITIAL COND-2 | RCH= 16.0 | 11.0 | 0.09 | 0.09 | .01 | 0.98 | .045 | .010 |
| INITIAL COND-2 | RCH= 17.0 | 9.0 | 0.08 | 0.08 | .01 | 0.97 | .050 | .010 |
| INITIAL COND-2 | RCH= 18.0 | 15.0 | 0.07 | 0.07 | .01 | 0.97 | .050 | .035 |
| INITIAL COND-2 | RCH= 19.0 | 20.0 | 0.06 | 0.06 | .01 | 0.96 | .050 | .035 |
| INITIAL COND-2 | RCH= 20.0 | 16.0 | 0.05 | 0.05 | .01 | 0.97 | .050 | .035 |
| INITIAL COND-2 | RCH= 21.0 | 10.0 | 0.05 | 0.05 | .01 | 0.97 | .045 | .020 |
| INITIAL COND-2 | RCH= 22.0 | 5.0 | 0.04 | 0.04 | .01 | 0.97 | .040 | .003 |

ENDATA7A

| INCR INFLOW-1 | RCH= 1.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= 2.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= 3.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= 4.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= 5.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= 6.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= 7.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 |

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| INCR INFLOW-1 | RCH= | 8.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 9.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 10.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 11.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 12.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 13.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 14.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 15.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 16.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 17.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 18.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 19.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 20.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 21.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-1 | RCH= | 22.0 | 0.0 | 18.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

| INCR INFLOW-2 | RCH= | 1.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 2.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 3.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 4.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 5.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 6.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 7.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 8.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 9.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 10.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 11.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 12.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 13.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 14.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 15.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 16.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 17.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 18.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 19.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 20.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 21.0 | 0.0 | 0.0 | 0.0 |
| INCR INFLOW-2 | RCH= | 22.0 | 0.0 | 0.0 | 0.0 |
| LOCAL CLIMATOLOGY | 8 | 31 | 94 | 0 | 0.00 | 0.1 | 15.0 | 13.0 | 620.0 | 2.0 |
| LOCAL CLIMATOLOGY | 8 | 31 | 94 | 3 | 0.00 | 0.1 | 14.0 | 12.0 | 620.0 | 2.0 |
| LOCAL CLIMATOLOGY | 8 | 31 | 94 | 6 | 20.40 | 0.6 | 16.0 | 12.5 | 623.0 | 2.0 |
| LOCAL CLIMATOLOGY | 8 | 31 | 94 | 9 | 41.20 | 0.1 | 24.0 | 20.0 | 623.0 | 2.0 |
| LOCAL CLIMATOLOGY | 8 | 31 | 94 | 12 | 54.00 | 0.0 | 26.5 | 22.0 | 623.0 | 4.0 |
| LOCAL CLIMATOLOGY | 8 | 31 | 94 | 15 | 40.00 | 0.2 | 24.0 | 21.0 | 623.0 | 5.0 |
| LOCAL CLIMATOLOGY | 8 | 31 | 94 | 18 | 9.20 | 0.5 | 22.0 | 19.0 | 623.0 | 4.0 |
| LOCAL CLIMATOLOGY | 9 | 1 | 94 | 0 | 0.00 | 0.1 | 18.0 | 16.0 | 623.0 | 2.0 |
| LOCAL CLIMATOLOGY | 9 | 1 | 94 | 3 | 0.00 | 0.1 | 14.0 | 12.0 | 620.0 | 2.0 |
| LOCAL CLIMATOLOGY | 9 | 1 | 94 | 6 | 8.40 | 0.6 | 16.0 | 12.5 | 617.0 | 4.0 |
| LOCAL CLIMATOLOGY | 9 | 1 | 94 | 9 | 29.20 | 0.8 | 17.0 | 13.0 | 617.0 | 10.0 |
| LOCAL CLIMATOLOGY | 9 | 1 | 94 | 12 | 54.00 | 0.6 | 19.0 | 15.0 | 617.0 | 7.0 |
| LOCAL CLIMATOLOGY | 9 | 1 | 94 | 15 | 40.00 | 0.5 | 18.0 | 15.0 | 617.0 | 5.0 |
| LOCAL CLIMATOLOGY | 9 | 1 | 94 | 18 | 8.00 | 0.3 | 18.0 | 15.0 | 617.0 | 2.0 |
| LOCAL CLIMATOLOGY | 9 | 1 | 94 | 21 | 0.00 | 0.1 | 17.0 | 14.0 | 617.0 | 1.0 |
| LOCAL CLIMATOLOGY | 9 | 2 | 94 | 0 | 0.00 | 0.1 | 16.0 | 13.0 | 620.0 | 0.5 |
| LOCAL CLIMATOLOGY | 9 | 2 | 94 | 3 | 0.00 | 0.1 | 18.0 | 15.0 | 622.0 | 0.0 |
| LOCAL CLIMATOLOGY | 9 | 2 | 94 | 6 | 10.00 | 0.1 | 20.0 | 17.0 | 623.0 | 0.0 |
| LOCAL CLIMATOLOGY | 9 | 2 | 94 | 9 | 28.60 | 0.0 | 22.0 | 19.0 | 623.0 | 3.3 |
| LOCAL CLIMATOLOGY | 9 | 2 | 94 | 12 | 54.00 | 0.0 | 25.5 | 22.0 | 623.0 | 1.0 |
| LOCAL CLIMATOLOGY | 9 | 2 | 94 | 15 | 40.00 | 0.1 | 23.0 | 21.0 | 623.0 | 0.5 |
| LOCAL CLIMATOLOGY | 9 | 2 | 94 | 18 | 10.00 | 0.3 | 19.0 | 16.0 | 623.0 | 0.2 |
| LOCAL CLIMATOLOGY | 9 | 2 | 94 | 21 | 0.00 | 0.1 | 17.0 | 14.0 | 623.0 | 0.1 |
| LOCAL CLIMATOLOGY | 9 | 3 | 94 | 0 | 0.00 | 0.1 | 15.0 | 13.0 | 623.0 | 0.0 |
| LOCAL CLIMATOLOGY | 9 | 3 | 94 | 3 | 0.00 | 0.1 | 18.0 | 15.0 | 622.0 | 0.0 |
| LOCAL CLIMATOLOGY | 9 | 3 | 94 | 6 | 10.00 | 0.1 | 20.0 | 17.0 | 623.0 | 0.5 |
| LOCAL CLIMATOLOGY | 9 | 3 | 94 | 9 | 29.20 | 0.0 | 25.0 | 22.0 | 623.0 | 0.7 |
| LOCAL CLIMATOLOGY | 9 | 3 | 94 | 12 | 54.00 | 0.0 | 30.0 | 27.0 | 623.0 | 2.0 |
| LOCAL CLIMATOLOGY | 9 | 3 | 94 | 15 | 40.00 | 0.3 | 26.0 | 23.0 | 623.0 | 1.5 |
| LOCAL CLIMATOLOGY | 9 | 3 | 94 | 18 | 10.00 | 0.5 | 19.0 | 16.0 | 623.0 | 0.2 |
| LOCAL CLIMATOLOGY | 9 | 3 | 94 | 21 | 0.00 | 0.1 | 17.0 | 14.0 | 623.0 | 0.1 |
| LOCAL CLIMATOLOGY | 9 | 4 | 94 | 0 | 0.00 | 0.1 | 15.0 | 13.0 | 623.0 | 0.0 |
| LOCAL CLIMATOLOGY | 9 | 4 | 94 | 3 | 0.00 | 0.1 | 18.0 | 15.0 | 622.0 | 0.0 |
| LOCAL CLIMATOLOGY | 9 | 4 | 94 | 6 | 10.00 | 0.1 | 20.0 | 17.0 | 623.0 | 0.5 |
| LOCAL CLIMATOLOGY | 9 | 4 | 94 | 9 | 29.20 | 0.0 | 25.0 | 21.0 | 623.0 | 0.5 |
| LOCAL CLIMATOLOGY | 9 | 4 | 94 | 12 | 54.00 | 0.0 | 28.5 | 25.0 | 623.0 | 3.5 |
| LOCAL CLIMATOLOGY | 9 | 4 | 94 | 15 | 40.00 | 0.3 | 23.0 | 20.0 | 623.0 | 1.5 |
| LOCAL CLIMATOLOGY | 9 | 4 | 94 | 18 | 10.00 | 0.5 | 19.0 | 16.0 | 623.0 | 0.2 |
| LOCAL CLIMATOLOGY | 9 | 4 | 94 | 21 | 0.00 | 0.1 | 17.0 | 14.0 | 623.0 | 0.1 |
| LOCAL CLIMATOLOGY | 9 | 5 | 94 | 0 | 0.00 | 0.1 | 15.0 | 13.0 | 623.0 | 0.0 |
| LOCAL CLIMATOLOGY | 9 | 5 | 94 | 3 | 0.00 | 0.1 | 18.0 | 15.0 | 622.0 | 0.0 |
| LOCAL CLIMATOLOGY | 9 | 5 | 94 | 6 | 10.00 | 0.1 | 20.0 | 17.0 | 623.0 | 0.5 |
| LOCAL CLIMATOLOGY | 9 | 5 | 94 | 9 | 29.20 | 0.0 | 22.0 | 19.0 | 623.0 | 0.5 |
| LOCAL CLIMATOLOGY | 9 | 5 | 94 | 12 | 54.00 | 0.0 | 26.0 | 23.0 | 623.0 | 3.5 |
| LOCAL CLIMATOLOGY | 9 | 5 | 94 | 15 | 40.00 | 0.3 | 23.0 | 21.0 | 623.0 | 1.5 |
| LOCAL CLIMATOLOGY | 9 | 5 | 94 | 18 | 10.00 | 0.5 | 19.0 | 16.0 | 623.0 | 0.2 |
| LOCAL CLIMATOLOGY | 9 | 5 | 94 | 21 | 0.00 | 0.1 | 17.0 | 14.0 | 623.0 | 0.1 |
| LOCAL CLIMATOLOGY | 9 | 6 | 94 | 0 | 0.00 | 0.1 | 15.0 | 13.0 | 623.0 | 0.0 |
| LOCAL CLIMATOLOGY | 9 | 6 | 94 | 3 | 0.00 | 0.1 | 18.0 | 15.0 | 622.0 | 0.0 |
| LOCAL CLIMATOLOGY | 9 | 6 | 94 | 6 | 10.00 | 0.1 | 20.0 | 17.0 | 623.0 | 0.5 |

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