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Analysis of Aerial Multispectral Imagery to Assess Water Quality Parameters of Mississippi Water Bodies

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Analysis of aerial multispectral imagery to assess water quality parameters of Mississippi water bodies

By

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Analysis of aerial multispectral imagery to assess water quality parameters of Mississippi water bodies

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The goal of this study was to demonstrate the application of aerial imagery as a tool in detecting water quality indicators in a three mile segment of Tibbee Creek in, Clay County, Mississippi. Water samples from 10 transects were collected per sampling date over two periods in 2010 and 2011. Temperature and dissolved oxygen (DO) were measured at each point, and water samples were tested for turbidity and total suspended solids (TSS). Relative reflectance was extracted from high resolution (0.5 meter) multispectral aerial images. A regression model was developed for turbidity and TSS as a function of values for specific sampling dates. The best model was used to predict turbidity and TSS using datasets outside the original model date. The development of an appropriate predictive model for water quality assessment based on the relative reflectance of aerial imagery is affected by the quality of imagery and time of sampling.

DEDICATION

I would like to dedicate this research to the scientists and engineers that have come before me and for those many who will follow. I would also like to dedicate this research to my family and my fiancée, Molly McCann.

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NOMENCLATURE

ABE	*Agricultural and Biological Engineering*
ADEM	*Alabama Department of Environmental Management*
ANOVA	*Analysis of Variance*
CWA	*Clean Water Act*
R^2	*Coefficient of determination*
DO	*Dissolved oxygen*
GPS	*Global positioning system*
IRS	*Irradiance reflectance spectra*
km^2	*Square kilometer*
m	*Meter*
MDEQ	*Mississippi Department of Environmental Quality*
mg/l	*Milligram per liter*
MSU	*Mississippi State University*
NIR	*Near infrared*
nm	*Nanometer*
NOAA	*National Oceanic and Atmospheric Administration*
NRCS	*Natural Resources Conservation Service*
NTU	*Nephelometric Turbidity Units*

PRBDD	*Pearl River Basin Development District*
SPM	*Suspended particulate matter*
SSC	*Suspended sediment concentration*
TMDL	*Total maximum daily load*
TSS	*Total suspended solids*
TTWW	*Tennessee Tombigbee Waterway*
UPRW	*Upper Pearl River Watershed*
USEPA	*United States Environmental Protection Agency*
USACE	*United State Army Corp of Engineers*

CHAPTER I

INTRODUCTION

Water quality testing has been conducted on all regulated water bodies throughout the United States since the passage of the 1972 Clean Water Act (CWA) (EPA, 1972; MDEQ, 2007; MDEQ, 2009). The assessment of regulated water bodies allows researchers and environmental agencies to establish water quality criteria. The criteria for individual water bodies must follow federal standards implemented by Section 303(d) of the CWA. These federal standards require states to identify water bodies as impaired that do not meet the standards of a healthy water body (MDEQ, 2007; MDEQ, 2009). Since the implementation of Section 303(d), water quality parameters have been periodically collected mostly to determine if a water body is healthy or impaired. If the water body is considered impaired, the state must determine a total maximum daily load (TMDL) for that water body, which projects the maximum daily discharge of a pollutant that the water body can handle and still show recovery.

The assessment of water quality parameters like turbidity and suspended sediment requires a large amount of work from both an *in situ* and an *in vitro* sampling perspective (Ritchie et al., 2003). Sediment load, measured by turbidity and suspended solids testing, accounts for over eight percent of the list of pollutants in the CWA (Fangmeier et al., 2006; MDEQ, 2009; Ritchie et al., 1974). Unlike many of the pollutants on this list, sediment is rarely a point source pollutant (MDEQ, 2007; Wetzel, 2001). Sediment load is caused by other contributing factors such as erosion, due to land disturbances or unexpected flooding (Ponce, 1989). Sediment loads in water bodies have been shown to be statistically higher in the early spring and late fall (Wetzel, 2001). The understanding of the seasonal variations is linked to the unpredictable weather patterns generated during these times of year (Fangmeier et al., 2006; Ponce, 1989; Wetzel, 2001). These variations in sediment load require researchers and state agencies to often sample more than once a year to get an accurate assessment of the sampled water body (ADEM, 2006; MDEQ, 2007). Collecting samples and experimentation cost researchers and agencies a great percentage of water quality budgets. The cost is mainly in labor hours required to conduct the sampling and experimentation. This had led to a focus on remote sensing throughout the environmental field.

Remote sensing techniques for water quality assessment have been around since the early 1970s (Ritchie et al., 2003). Original sources of remote sensing used low resolution imagery from the Landsat program (Ritchie et al., 1974). From its conception the technique of remote sensing has depended on the change in spectral signature that is backscattered from the surface of the water body (Ritchie and Cooper, 1988). Most imagery analysis of water bodies has been done using multispectral and hyperspectral imagery from available satellites and high altitude aerial photography (Dekker et al., 2001; Doxaran et al., 2001; Lopez-Blanco and Zambrano, 2002).

While imagery analysis is expensive, it has proven to be a promising tool that can be used for water quality assessment. The recent integration of multispectral imagery has allowed the cost of remote sensing to drop by more than 30 percent (Lucieer, 2011). In some cases multispectral imagery can be less than a third of the cost of hyperspectral imagery. Multispectral imagery can be utilized in similar ways as hyperspectral imagery. Low altitude aerial multispectral remote sensing uses four bands, blue, green, red, and near infrared (NIR) which can be combined into simple band ratios. Aerial imagery also reduces the cost of the imagery while increasing the availability of the imagery. While the subject area is relatively new, finding ways to create a relationship between the multispectral imagery and water quality data will follow the same logic that was originally considered at the integration of imagery analysis of water quality parameters.

CHAPTER II

OBJECTIVE

The objective of this study was that through proper imagery analysis, a relationship could be established between the 8-bit values from the high resolution aerial imagery and water quality parameters. The objective of this study was to demonstrate the application of multispectral aerial imagery as a tool in detecting water quality indicators in a three mile segment of Tibbee Creek in Clay County, Mississippi. The specific objectives to this study were to:

1. Analyze water quality data collected from Tibbee Creek and relative reflectance extracted from aerial imagery, and
2. Independently validate, through sampling, a relationship between the imagery relative reflectance and water quality parameters that can be used for water quality assessment, and
3. Evaluate the relationship using independent data from different sampling dates.

CHAPTER III

LITERATURE REVIEW

3.1 Remote Sensing and Water Quality Parameters Studies

Remote sensing has been utilized across many disciplines including environmental and water quality using satellite and aerial remote sensing (Ritchie et al., 2003). Satellite remote sensing has proven to be costlier than some aerial remote sensing. As the remote sensing field grows, so does the need for lower cost analysis. Dekker et al. (2001) used methodology developed from an earlier study (Dekker et al., 1998) to estimate TSS in the southern Frisian Lakes in the Netherlands. The study presented an application of satellite-based remote sensing and water quality data. It also took into account a one-dimensional water quality model from Dekker et al. (1998). Using the relationship between the irradiance reflectance spectra (IRS) in comparison with the satellite's bands, a method was developed to link a specific reflectance to TSS. The geospatial data from Landsat Thematic Mapper (TM) provided a feature in establishing a relationship between each of the Landsat bands. Dekker et al. (2001) found that areas with higher TSS had higher IRS. Total suspended solids maps were generated with an algorithmic representation of the sediment compared to the IRS. The research provided an outlook to analytical optical modeling based on water quality and geospatial data. The research proved to be usable with different geospatial data but was sensitive for TSS levels above 40 milligrams per liter (mg/l) (Dekker et al., 2001). The authors stated that suspended sediment can cause saturation of reflectance, becoming a factor that would prevent a correlation between geospatial data and water quality data. This correlation could have barred the study from producing viable results simply due to the saturation of the geospatial data.

Doxaran et al. (2001) used an experimental methodology to interpret wavelengths seen from geospatial data provided by the SPOT-HRV satellite over the Gironde estuary in France. A relationship was established between the suspended particulate matter (SPM) and the remotely sensed reflectance values. In this experiment, the satellite data were corrected for atmospheric interference and false readings due to overexposure and/or clouds. The Gironde estuary was tested due to its SPM concentrations exceeding in some cases, 2000 mg/l. Unlike previous research, Doxaran et al. (2001) used both imagery and field measurements using a spectroradiometer. The authors measured upwelling radiance (reflectance from the water surface), down welling radiance (reflectance from the water surface through a spectralon plate), and sky radiance. Sky radiance was tested to eliminate the error caused from the geospatial data from satellite imagery. Saturation of the wavelength bands occurred at SPM concentrations above 250 mg/l. Saturation caused poor association making the outcomes less statistically significant. The bands had no association above 500 mg/l. This similarity in correlating saturated wavelengths and SPM concentrations was seen in Dekker et al. (2001) with TSS levels above 40 mg/l. The difference in concentration levels could be accredited to the makeup of the concentrations. Below a threshold of 250 mg/l, the bands showed correlation between green, red and NIR with the increase of SPM concentration. It was also presented that the cloud reflections and atmospheric scattering did not significantly affect the measurements. The study concluded that error from the satellite imagery was negligible. This claim helped support the authors' decision to ignore some solar radiance issues. The results provided information about sedimentary flow from the Gironde estuary by providing excellent current markers further proving that using geospatial data to identify sedimentation loads can help locate maximum turbidity and its causes (Doxaran et al., 2001). Doxaran et al. (2001) helped provide information on atmospheric correction and issues that are commonly faced with remote sensing interference. The procedure did not help in aerial remote sensing because the method used in that paper was already developed specifically for the SPOT-HRV satellite imagery. The authors described issues that could develop with correlation between water quality data and the satellite imagery, including saturation and false solar radiance. By providing examples where saturation occurred, similar to Dekker et al. (2001), where poor association occurred at specific TSS levels, the authors provided information on potential obstacles when studying a correlation between spectral values and water quality data.

Karabulut and Ceylan (2005) used close range remote sensing to determine the effects of increased suspended sediment concentration (SSC) containing different levels of organic matter on algal spectral patterns. The results determined that most remote sensing imagery equipment could measure spectral reflectance from 350 nanometers (nm) to 1100 nm, but only 400 nm to 900 nm was needed to determine spectral reflectance from turbid algae laden water (Knight et al., 2002). The research proved that as the SSC increased the red and NIR bands represented a more limited correlation. This was similar to results reported by Dekker et al. (2001) and Doxaran et al. (2001).

Karabulut and Ceylan (2005) cited that with less SSC more accurate results within the different bands were noticed. Overall, the research analyzed ten different levels of SSC and concluded that no matter the concentration, the spectral patterns caused by algae should be distinguishable from sediment concentrations. Karabulut and Ceylan proved a common similarity within all facets of remote sensing due to band wavelengths. This helped support the usage of low cost aerial imagery as the independent variable within the study. The authors' claim that lower sediment values could provide better correlation helped support research similar to Dekker et al. (2001) and Doxaran et al. (2001). This claim could provide reasons why irregular sampling data or saturated samples have low to no correlation to any spectral data.

Lopez-Blanco and Zambrano (2002) evaluated water quality parameters in ponds using digital imagery with relative reflectance. Shallow ponds were used for the study because of high evaporation rates and little to no stratification layer. Because of the specific parameters (e.g. high evaporation rates, little to no stratification layer) of the ponds, the study site resembled a large array of surface waters throughout the world with water quality values ranging from healthy to completely impaired. When the relative reflectance was extracted, the authors correlated those values with collected water quality parameters, including SSC and algae/chlorophyll-a. The authors used linear correlations for the analysis. This approach to using relative reflectance to correlate with water quality parameters helped support the differences between relative reflectance extraction and spectral wavelengths. The approach also supported the claim that these values could be used to assess water quality values as well as spectral values found in most remote sensing research.

Ritchie et al. (2003) incorporated the authors' former research that was conducted on suspended sediment, algae/chlorophyll-a, and plant growth in this collection of remote sensing and water quality parameters study. According to this research, the water quality parameters, suspended sediment, algae/chlorophyll-a, and plant growth in surface water affected the backscattering characteristics of surface water. Focusing on the SSC and using collected imagery, Ritchie et al. (2003) demonstrated a relationship between reflectance and band wavelength that was affected by the SSC. Landsat data provided the necessary geospatial data to interpret the backscattering effects caused by SSC. The relationship between the reflectance from the backscattering and the SSC could not form a curvilinear relationship to provide accurate interpretation at higher values. The relationship was due to the likelihood that the SSC would saturate as the reflectance peaked, similar to Dekker et al. (2001), Doxaran et al. (2001), and Karabulut and Ceylan (2005). In the lower ranges of SSC, the relationship between the concentration and reflectance was linear. The saturation of the wavelength bands, caused at higher values, was blamed on the current spatial resolution of satellite data. Ritchie and Schiebe (2000) claimed that as new satellites went into orbit, higher resolution would lead to better spectral data and more accurate assessment of the suspended sediments concentration. The geospatial data collected from sources like Landsat were inconclusive at higher SSC (Ritchie et al., 2003). Ritchie et al. (2003) confirmed that higher suspended concentration values could not be accurately linked to geospatial data. The authors also supported that in lower ranges a linear relationship could be formed. This relationship was supported by spectral values from Landsat imagery. Landsat imagery allowed the authors access to a wider red band that helped with the correlation between the spectral values and the water quality parameters. This correlation provided an answer to any issues that would arise when trying to correlate specific bands with water quality parameters (Bhargava and Mariam, 1991; Chen et al., 2004). If a specific band did not cover a known range, that band could provide false results.

Abd-Elrahman et al. (2011) utilized a ground hyperspectral sensor to determine the effects of using submerged reflective targets on chlorophyll-a estimations. The data was collected over changes in depth. Abd-Elrahman et al. (2011) did determine that better correlation was present at depth closer to the water surface. This was directly related to the spectral information collected by the sensor. The study results confirmed traditional information about absorption of specific bands with specific water columns. The information from the study helped provide one reason why a low correlation was present in the Tibbee Creek study.

3.2 Band Ratio Studies

The potential of spectral values captured by satellites and airplanes has led to an investigation of those values in situations such as shading and dense ecological populations. Band ratios allow researchers to separate similar values by determining different combinations of spectral bands. In the case of this study, the focus was on the specific relative reflectance range of each band. Kneubühler et al. (2005) utilized simple band ratios to conduct a study to correlate spectral reflectance to concentrations of total chlorophyll-content, total organic content, and dissolved organic content. The concept of the study was based around the water quality parameter chlorophyll-a as an indicator of algal growth and possible eutrophication. The authors took the approach toward the water quality parameter chlorophyll-a because agriculture played a specific role in the sample area. Runoff into the study area was noted by eutrophication. This focus on chlorophyll-a concentration from specific land usage supported the claim that TSS testing could prove to be too broad of a tested parameter. The spectral data were collected from a field spectroradiometer. The authors referenced research on simple band ratios by examining Dekker et al. (1998) and Koponen et al. (2002). The common band ratio through this research was a ratio centered around 675 to 705 nm. The authors developed an algorithm to investigate simple band ratios compared to continuum interpolated band ratios (Kneubühler et al., 2005). The research helped provide examples of the simple band ratio that needed to be investigated in the Tibbee Creek study. The research concluded that without specific spectroradiometer measurements or specific imagery, some band ratios are not possible due to the specific channels needed to complete the ratios. This discussion of simple band ratios using proved techniques of spectroradiometer data collection helped support the claim that the values could potentially be used in a correlation between the ratios formulated from imagery spectral values and water quality data (Dekker et al., 1998; Koponen et al., 2002).

Sudduth et al. (2005) utilized stepwise regression analysis to determine which band(s) correlated best with collected water quality parameters. Their study was closely related to the current research but one issue was the limited scope in their datasets. This issue helped support the Tibbee Creek study due to the increased sampling dates and points. With a broader sampling period, there is a potential for better correlation as well as a model that could be used outside the Tibbee Creek study area. The study was not able to provide a workable model outside its study area due to its limited scope. A difference that was noted in this study was the sampling on a lake instead of a uniform system such as a moving river. The study did provide a correlation between the NIR and red simple band ratio.

Lillesand et al. (2004) discussed the theoretical study of ratio images with the concept being focused on conveying characteristics of an image regardless of variations in illumination conditions within the image. The authors provided the example of shadowed values versus non-shadowed values. While the images must be layered properly to conduct this analysis, the images should show the same ratio value (Carroll et al., 1998). The authors discussed the different band ratios that were available for analysis from simple band ratios to more complex ratios involving more than three components. This study proved the importance of band ratios in imagery analysis by providing examples where band ratios can solve imagery issues such as solar radiance and shadows.

Song et al. (2009) used Landsat TM and *in situ* water quality samples collected concurrently with satellite overpass. Chlorophyll-a, turbidity, total dissolved organic matter, and total phosphorus was collected at the surface as the water quality parameters. The study area was selected because of the optical scattering due to the water quality parameters tested. Using regression models and neural networking, the authors were able to construct empirical models with strong statistical significance. Along with the imagery from the Landsat TM, field spectra were measured via a portable spectrometer. The authors concluded that in certain cases, individual bands provide a better correlation than a band ratio. Band ratios did not improve all water parameter accuracy in a stepwise regression (Song et al., 2009). The important factor of Song et al. (2009) was the mention of poor correlation with simple band ratios. In some cases of the authors' work, the band ratios did not provide a strong statistical significance when individual band spectral values did. This claim was important in the Tibbee Creek study to help support a stepwise regression test that included both individual band values and simple band ratios during each analysis. This research helped support individual band relationship not extensively discussed in other research (Dekker et al., 1996; Kneubühler et al., 2005). The authors' association between individual band data and water quality parameters helped bring focus to all bands and band ratios.

Teodoro et al. (2008) studied correlation between TSS and relative reflectance with multispectral data by approaching individual band relationships, multiple regression relationships, and neural networking. The authors' approach to the individual band relationships was a formation of a regression equation with only the individual band variables and the coefficients. By limiting the regression to the individual band models, specific bands could show more significance where previously the band would have been hidden by simple band ratios or multiple band regression. The method was considered a linear regression since the authors controlled the variables one by one. This study was similar to the previous Landsat TM research due to the easy correlation from the established spectral range for the imagery. The results were unique and supportive of a standardized equation that would be implemented on multiple datasets. The issue with this study falls within the discussion of established bands (Ritchie et al., 2003; Song et al., 2009). Most research support the use of the Landsat TM green band (520 nm to 600 nm) for sediment and suspended solids. The issues that must be addressed with this studies high resolution imagery is the lack of atmospheric correction which is found in Landsat TM imagery. The one advantage to high resolution imagery is the focus on smaller streams that Landsat TM would be to low resolution to analyze. As long as low cost aerial imagery can stay within the spectral bounds of the Landsat TM bands, the correlation could be similar in the Tibbee Creek study.

CHAPTER IV

METHODS AND MATERIALS

4.1 Study Area

4.1.1 Tibbee Creek

The study area is a section in Tibbee watershed is located approximately 20 miles west of Columbus Lake, in the southeastern part of Clay County, Mississippi. Tibbee Creek, a major stream in Tibbee watershed, was chosen for the project because it has historically suffered from ecological and environmental impairment (MDEQ, 2007; MDEQ, 2009; NRCS, 2009). The Tibbee watershed is 2,894 square kilometers (km^2) and west of the Tennessee-Tombigbee Waterway (TTWW) covering portions of seven counties in Mississippi, namely, Chickasaw, Clay, Lowndes, Monroe, Oktibbeha, Pontotoc, and Webster (McKee and McAnally, 2008;NRCS, 2009).

The predominant land use in the watershed is pasture and grassland, making up over 30 percent of the watershed land usage (ADEM, 2006; MDEQ, 2007; NRCS, 2009). The watershed contains 847 miles of major rivers/tributaries of which 440 miles are on the Mississippi Department of Environmental Quality (MDEQ) and United States Environmental Protection Agency (USEPA) Section 303(d) list of impaired streams and water bodies (EPA, 1972; MDEQ, 2009; NRCS, 2009). The tributaries include Goodfood Creek, Houlka Creek, Chuquatonchee Creek, Trim Cane Creek, Line Creek, and Catalpa Creek, all either biologically or sediment load impaired (Figures 4.1 and 4.2). Tibbee Creek flows for 24 miles in a southeast direction from the confluence of Chuquatonchee and Line Creeks to the confluence with the TTWW (MDEQ, 2007).

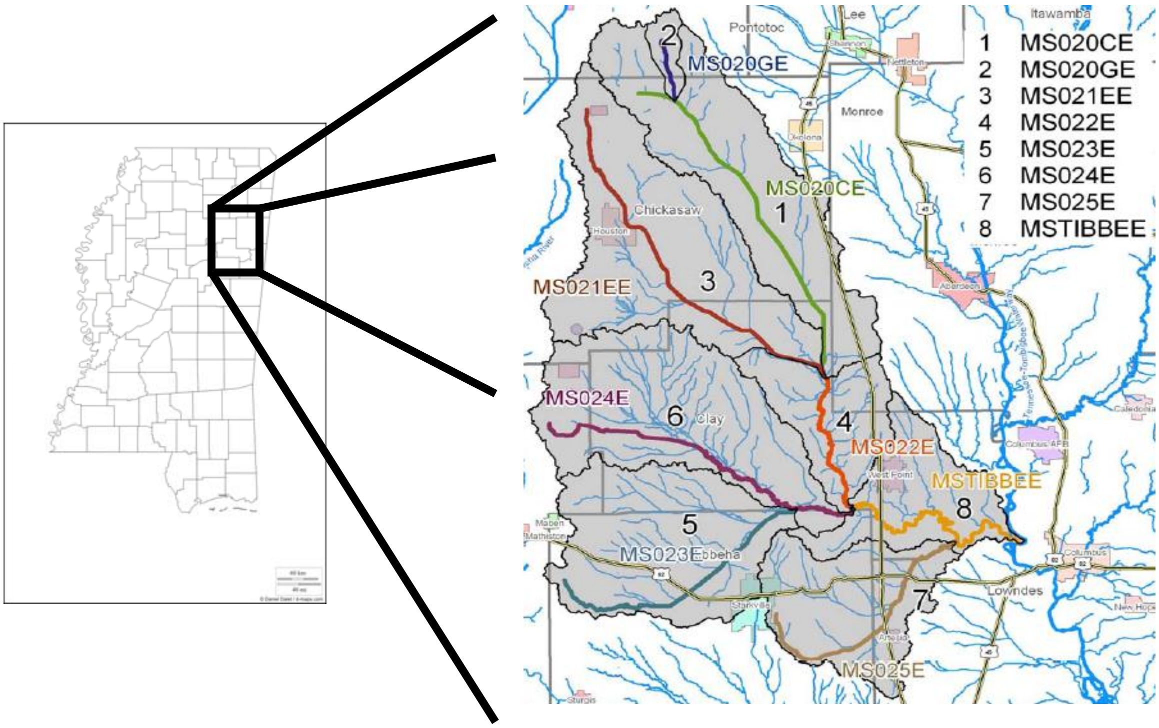

Figure 4.1 Tributary map of the Tibbee watershed with the State of Mississippi stream codes listed (Source: MDEQ, 2007).

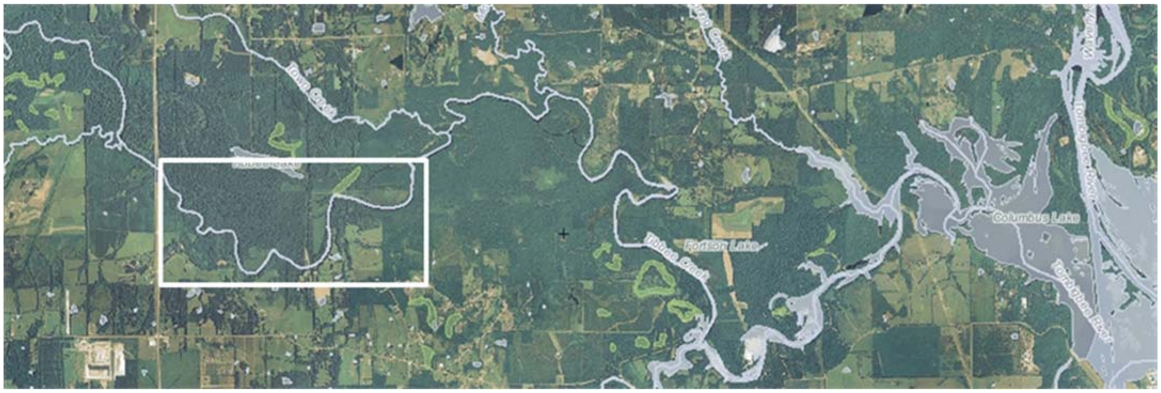

Figure 4.2 Location map of the study area in Tibbee Creek denoted by a box and Columbus Lake on the right (Source: MARIS, 2010).

4.1.2 Upper Pearl River

A secondary area monitored for supplementary study is located in the Upper Pearl River Watershed (UPRW). The UPRW located in East-Central Mississippi is a large watershed (7,588 km^2) dominated by forest (MDEQ, 2007). The Upper Pearl River originates from the headwaters in Choctaw and Winston counties in Mississippi and flows into the Ross Barnett Reservoir (Figure 4.3). The study area is 70 miles southwest of the Tibbee Creek in Edinburg, Mississippi. The portion of the Upper Pearl River established as the secondary sample area was a part of the Section 303(d) list of impaired streams for pesticide contamination and sediment load (MDEQ, 2007; MDEQ, 2009). The Upper Pearl River study area was chosen as a secondary testing site to confirm specific results from the original Tibbee Creek study area.

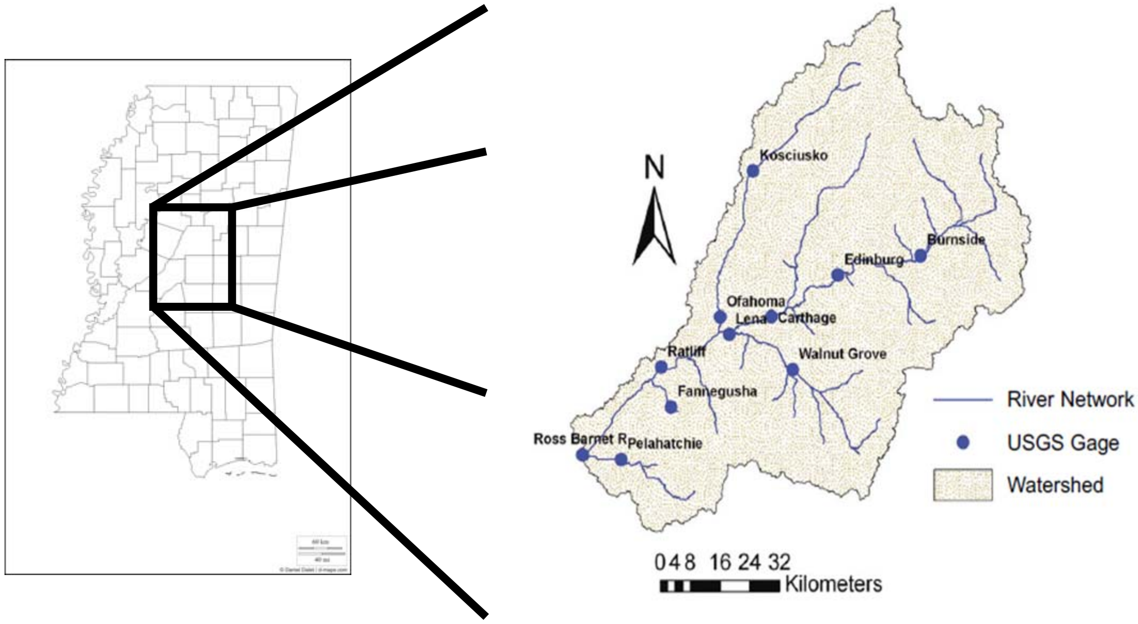

Figure 4.3 A map of the tributaries that drain into the Upper Pearl River watershed (Source: Parajuli et al., 2011).

4.2 Sampled Parameters and Techniques

4.2.1 Tibbee Creek

Samples were collected at different points along a three mile section of Tibbee Creek during two periods from May 2010 to October 2010 (14 sampling dates) and May 2011 to October 2011 (11 sampling dates). The DO and temperature levels were measured on-site. Ten major points were chosen at the beginning of the project and marked by a Delorme Earthmate PN-40 global positioning system (GPS) unit. A transect of five sample points was randomly set at each major point. Fifty water samples were collected along Tibbee Creek using the transect based sampling method. Aerial imagery of Tibbee Creek was captured concurrently during collection of water samples over the two periods. Figure 4.4 shows the United States Army Corps of Engineers (USACE) and

National Oceanic and Atmospheric Administration (NOAA) gauging station location and the sample points along Tibbee Creek.

Figure 4.4 The sample points, denoted by red dots, established along a three mile segment of Tibbee Creek. The USACE/NOAA stream gauging station is marked by a green dot. Imagery was captured on June 14, 2011 (Scale 1:15,196).

4.2.2 Upper Pearl River

Samples were collected at different points along a 1.5-mile section of the Upper Pearl River, near Edinburg, Mississippi, during one period from May 2010 to October 2010. Five major points were chosen at the beginning of the project and marked by the same GPS unit. For each major point along the river, five samples were collected within a transect, similar to the sampling procedure implemented on Tibbee Creek. Twenty five water samples were collected along the portion of the Upper Pearl River. Aerial imagery was captured concurrently with each collection period. Figure 4.5 shows the sample points along the Upper Pearl River in Edinburg, Mississippi.

Figure 4.5 The sample points, denoted by red dots, established along a 1.5 mile segment of the Upper Pearl River. Imagery was captured on June 24, 2010 (Scale 1:14,000).

4.2.3 In-stream Measurements

Dissolved oxygen (mg/l) and temperature (^{o}C) were measured using an Oakton DO 110 meter[1] at each sample point along the study areas in Tibbee Creek and the Upper Pearl River. The meter simultaneously collected the DO and temperature at each point. On-site measurements were made at the same time a sample was collected from one meter below the water surface as seen in a previous study (Doxaran et al, 2001). A 250 ml water sample was collected and stored in a polypropylene graduated bottle.

[1] Mention of company or product names is for information only and does not constitute endorsement by the author or Mississippi State University.

Dissolved oxygen is the physical parameter representing the amount of saturated oxygen that is dissolved in a liquid medium. The saturated oxygen allows for aerobic biological respiration in a medium. Temperature is the physical parameter that represents thermal conductivity in a medium. The State of Mississippi requires that DO concentrations shall be maintained at a daily average of no less than 5.0 mg/l with an instantaneous minimum of no less than 4.0 mg/l. Maximum temperature level shall not exceed 32 ^{o}C. These water quality parameter requirements are for all state water bodies and must be maintained per sampling period (EPA; 1972; MDEQ, 2007; MDEQ, 2009).

4.2.4 Gauge Height

Gauge data was collected by the USACE and NOAA gauging station during both of the sampling periods on Tibbee Creek. River stage (ft.) was recorded once per hour during the first sampling period from May 2010 to October 2010. River stage was recorded once per 15 minutes during the second sample period from May 2011 to October 2011. On average, the gauge height throughout the sample periods was 9.5 feet. Because of the inconsistencies of the data collection and the changes in depth throughout the sampling area, the hydrologic data were recorded for observation purposes and was not correlated to relative reflectance values.

4.2.5 Water Quality Parameters

The water samples were tested in the laboratory for turbidity and TSS. The samples were maintained at similar conditions as found in stream to eliminate errors. Turbidity is an optical property where light is scattered and absorbed rather than transmitted in straight lines through a water sample. The turbidity is caused by the molecules found in a water sample including, dissolved solids, organic matter, and inorganic matter (McCarthy et al, 1974; Thackston and Palermo, 2000). Turbidity measurements are done by emitting a light into a sample and capturing the scattered light. The amount of scatter is dependent on the size, shape, and reflectance of the particles in the water sample (Lillycrop et al., 1996). Turbidity, expressed in Nephelometric Turbidity Units (NTUs), was measured using a Hach 2100 series portable turbidimeter (Fangmeier et al., 2006). Prior to each testing cycle, the turbidimeter was calibrated using turbidity standards (Thackston and Palermo, 2000). While some states have a 50 NTUs maximum turbidity limit, the State of Mississippi has no turbidity standard requirement for surface water (EPA, 1988; MDEQ, 2009).

Total suspended solids include inorganic and organic particles suspended in water. Inorganic solids may be clay, silt, and sand while organic solids may be algae and detritus in water (Schmugge et al., 2002). The dry weight of suspended solids is reported in mg/l as in equation 4.1, where A is the weight of the filter with suspended solids in mg, B is the weight of the filter alone in mg, and C is the amount of water sample filtered in ml. The TSS content was tested using the USEPA standard methods and practices of suspended solids (ESS Method 340.2) (EPA, 1993; Fangmeier et al., 2006; Thackston and Palermo, 2000).

$$TSS, \frac{mg}{l} = \frac{(A - B) \times 1{,}000}{C} \tag{4.1}$$

Values for each turbidity and TSS were estimated from previous ranges found in TMDLs for the study areas. This provided the study with a suggested range of the water quality parameters. Turbidity and TSS was estimated in the range of 0 to 200 NTUs and

0 to 200 mg/l, respectively, for Tibbee Creek. The Upper Pearl River samples were estimated in the range of 0 to 50 NTUs for turbidity and 0 to 50 mg/l of TSS (MDEQ, 2007; MDEQ, 2009). All of the collected water quality parameters that were measured and tested were categorized by dates (Table 4.1 and 4.2). Water quality data and GPS coordinates of each sample point were saved in a spreadsheet and converted to ArcMap shapefiles (ESRI, 2010). If any dataset was missing water quality parameters more than one water quality parameter, it was not used for statistical analysis.

Table 4.1

Parameters tested and measured along Tibbee Creek at different sampling dates

Sampling Date	Stream Segment[1]		Water Quality Parameters			
	Downstream	Upstream	Dissolved Oxygen	Temperature	Turbidity	TSS
05/11/2010		•	•	•	•	
05/12/2010	•		•	•	•	
05/18/2010	•		•	•	•	
05/19/2010		•	•	•	•	
05/26/2010	•		•	•	•	
05/27/2010		•	•	•	•	
06/08/2010	•		•	•	•	
06/09/2010		•	•	•	•	
06/15/2010	•		•	•	•	
06/16/2010		•	•	•	•	
06/22/2010	•		•	•	•	
06/23/2010		•	•	•	•	
06/29/2010	•		•	•	•	•
06/30/2010		•	•	•	•	•
07/06/2010	•		•	•	•	
07/07/2010		•	•	•	•	
07/13/2010		•	•	•	•	
07/14/2010	•		•	•	•	
07/20/2010	•		•	•	•	
07/21/2010		•	•	•	•	
07/27/2010		•	•	•	•	
07/28/2010	•		•	•	•	
08/03/2010		•	•	•	•	•
08/04/2010	•		•	•	•	•
08/10/2010		•	•	•	•	•
08/11/2010	•		•	•	•	•
10/05/2010	•		•	•	•	•
10/06/2010		•	•	•	•	•
05/11/2011	•	•	•	•	•	•

Table 4.1 (continued)

05/24/2011	•	•	•	•	•	•
05/30/2011	•	•	•	•	•	•
06/07/2011	•	•	•	•	•	•
06/14/2011	•	•	•	•	•	•
06/24/2011	•	•	•	•	•	•
06/29/2011	•	•	•	•	•	•
07/07/2011	•	•	•	•	•	•
08/02/2011	•	•	•	•	•	•
09/10/2011	•	•	•	•	•	•

[1]Stream segment: downstream: major points 1-5 and upstream: major points 6-10

Table 4.2

Parameters tested and measured along the Upper Pearl River at different sampling dates

Sampling Date	Stream Segment[1]	Water Quality Parameters			
	All Points	Dissolved Oxygen	Temperature	Turbidity	TSS
06/24/2010	•	•	•	•	
07/01/2010	•	•	•	•	•
07/15/2010	•	•	•	•	
07/22/2010	•	•	•	•	
07/29/2010	•	•	•	•	
08/12/2010	•	•	•	•	

[1]Stream segment: major points 1-5

4.3 Image Acquisition and Analysis

4.3.1 Imagery Information

This study used low altitude aerial imagery consisting of four bands to determine a relationship between water quality parameters at the sample point locations marked by GPS on Tibbee Creek. The high resolution (0.5 m) multispectral aerial imagery was taken using a Geoscanner Sensory Pod unit designed by Geovantage of Peabody, Massachusetts and Simwright of Navarre, Florida. The imagery was acquired by GeoData Airborne Mapping and Measurement (GeoData Airborne) of Weir, Mississippi, within the hour of the water sample collection.

The multispectral camera recorded reflectance of four bands, producing 8-bit values for a blue, green, red, and NIR banded image (Table 4.3). The blue, green, and red bands can be layered to produce a regular color image. The green, red, and NIR bands can be layered to produce a false color image.

Table 4.3

Characteristics of bands found in the aerial imagery used in this study

Band	**Center**	**Width**
Blue	450 nm	+/- 40 nm
Green	550 nm	+/- 40 nm
Red	650 nm	+/- 40 nm
Near Infrared	850 nm	+/- 20 nm

The imagery provided by GeoData Airborne was supplied in a large mosaic bitmap image and 55 single bitmap images for faster data analysis. The mosaic image was formed by GeoData Airborne by overlapping the 55 single bitmap images. All of the images contained metadata and were georeferenced allowing easy correlation between the imagery and the collected water quality parameters. Mosaics were chosen for imagery analysis.

4.3.2 Image Selection

From the collection of acquired imagery, a visual test was conducted to select images suitable for statistical analysis. The process involved checking each sample point collected on each image for the presence of variations caused by sensor electronic noise and atmospheric effects caused by clouds or haze (Lucieer, 2011). Images that had the least visual variance were accepted and subsequently analyzed. Grids based off pixels were centered on each sample point for the analysis. A five x five (5 x 5) pixel grid established around each sample point was used for image interpretation (Figure 4.6).

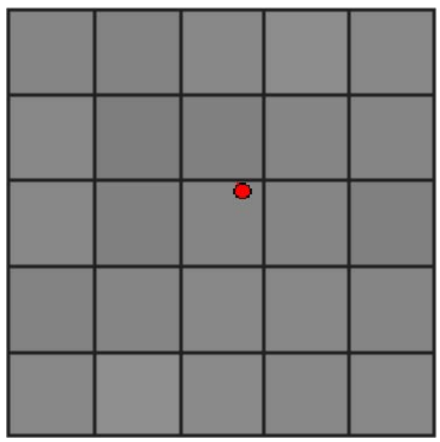

Figure 4.6 A 5 x 5 pixel grid surrounding a sample point for individual image selection. The red dot represents a sample point surrounded by 25 pixels.

Visual analysis of each sample grid accounted for the presence of tree shadows, cloud capture or reflectance, partial land collection, and camera gain issues. Tree shadows were caused by the sun angle at certain times of image capture. Cloud capture or reflectance was in the imagery either due to a ceiling low enough to capture actual clouds or the clouds casted a reflection on the water the image. Auto gain issues were represented by a saturation of the sensor response causing the uncorrected reflectance values of certain pixels in the imagery to be recorded at values past the sensors threshold for all bands (Figure 4.7). Partial land collection was an issue when the sample point fell onto the land. Shifting of the grid was proposed if land was collected, but in some cases the sample point was close to the stream bank and some land collection could not be avoided. If the sample grid showed less than 25 sample points with failed criteria, the image was used but those sample points that failed the criteria were marked as potential outlying data. Eleven out of 13 dates met the list of criteria. All dates were reviewed and formed into a summary (Tables 4.4 and 4.5).

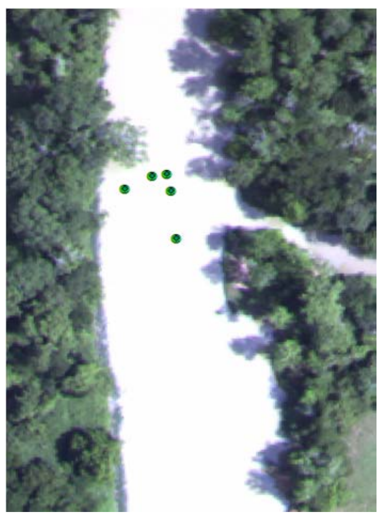

Figure 4.7 Auto gain issues at a sample point transect taken from June 23, 2010 imagery.

Table 4.4

A summary of acquired imagery by date of Tibbee Creek and subsequent statistical analysis

Sampling Date	Stream Segment[1]		Images			Statistical Analysis
	Downstream	Upstream	Acquired	Analyzed	Notes[2]	
05/10/2010		•				
05/11/2010	•					
05/18/2010	•		•	•	C,S	•
05/19/2010		•	•	•		•
05/26/2010	•					
05/27/2010		•				
06/08/2010	•					
06/09/2010		•				
06/15/2010	•					
06/16/2010		•				
06/22/2010	•					
06/23/2010		•	•	•	C,S	
06/29/2010	•					
06/30/2010		•				
07/06/2010	•		•	•	S,L	•
07/07/2010		•	•	•	C,S,L	•
07/13/2010		•				
07/14/2010	•					
07/20/2010	•					
07/21/2010		•				
07/27/2010		•				
07/28/2010	•					
08/03/2010		•				
08/04/2010	•					
08/10/2010		•				
08/11/2010	•					
10/05/2010	•					
10/06/2010		•				

Table 4.4 (continued)

05/11/2011	•	•	•	•	C,S,L	
05/18/2011	•	•	•	•	C,S	•
05/24/2011	•	•				
05/30/2011	•	•	•	•	C,S	•
06/07/2011	•	•	•	•		•
06/14/2011	•	•	•	•		•
06/24/2011	•	•				
06/29/2011	•	•				
07/07/2011	•	•				•
08/02/2011	•	•	•	•	S,H	•
09/10/2011	•	•	•	•	S,H	•

[1]Stream segment: downstream: major points 1-5 and upstream: major points 6-10
[2]C – heavy cloud cover; S – Shadows; L – Low ceiling; H – Haze

Table 4.5

A summary of acquired imagery by date of the Upper Pearl River and subsequent statistical analysis

Sampling Date	Stream Segment[1]	Images			Statistical Analysis
	All Points	Acquired	Analyzed	Notes[2]	
06/24/2010	•	•	•	C,S	•

[1]Stream segment: major points 1-5
[2]C – Cloud reflectance; S – Shadows; L – Low ceiling; H – Haze

4.3.3 Relative Reflectance Extraction

Relative reflectance are values that contain information about the intensity of each pixel that make up the image and can display a specific intensity to represent a visual color (Bilge et al., 2003). When multiple bands are stacked together, the values represent a specific collection of colors such as true color or false color. In this study, all images were in the 8 bit coding range. Three band color images are composed of three numbers 0 to 255. If all bands are represented as 255 the sensor at that moment was saturated by some factor. In this study, this was seen in the auto gain issues (Lopez-Blanco and Zambrano, 2002).

Relative reflectance extraction was conducted on all 11 of the image dates using the focal statistics tool in ArcMap. The tool performed a neighborhood operation that output a raster where the output values were the mean of the values of all of the input cells. The cells for the operation were the individual 0.5 meter resolution pixels. Neighborhoods utilized the individual bands and a 5 x 5 grid to average the 25 pixels into one number. This obtained one blue, one green, one red, and one NIR value per pixel grid. The output raster was then run through an extraction process with each of the spreadsheets containing the physical data from *in situ* and lab testing. These relative reflectance values were compared through ratios to the collected water quality parameter tested values from samples taken at flight time of the correlated imagery (Lopez-Blanco and Zambrano, 2002).

4.4 Simple Band Ratio Analysis

Simple band ratio is a technique that enhances an image by dividing the relative reflectance in one spectral band by the relative reflectance of another band. The advantage to this analysis is the conveyance of characteristics of the image regardless of illumination conditions (Lillesand et al., 2004). Simple band ratios help discriminate against spectral variations that could otherwise affect a relative reflectance in an image. Simple band ratio is calculated using equation 4.2:

$$SBR = \frac{\text{band}_x}{\text{band}_y} \tag{4.2}$$

where, *SBR* is simple band ratio, band_x is the blue, green, red, or NIR band, and band_y is the opposing blue, green, red, or NIR band. The simple band ratio required that band_x be different than band_y (Lilliesand et al., 2004; Song et al., 2009; Teodoro et al., 2008; Yang et al., 1999).

The band ratios were designed to eliminate issues found in individual bands that were affected by specific criteria found in visual analysis like auto gain issues. Simple band ratios were chosen based on several studies that concluded simple band ratios provide enough information that statistically correlate with physical water quality parameters (Kneubühler et al., 2005; Lillesand et al., 2004; Lopez-Blanco and Zambrano, 2002; Song et al., 2009). Studies noted that ratios with a combination of the green and red bands had the best correlation with specific water quality parameters such as turbidity and TSS (Ritchie et al., 1974; Ritchie and Cooper, 1988; Thomas et al., 2006). Similar to the four band values, all of the ratios were correlated with specific sample points. No matter the effect of the band ratio on the specific point, if the point was marked as a potential outlier during visual analysis, the mark stayed. Case studies claimed that marking potential outliers was not necessary after simple band ratios analysis. For this study, the points were still considered potential outliers.

4.5 Imagery Issues

Misregistration of bands caused by the physical misalignment can cause an issue in imagery interpretation and analysis. The physical misalignment caused by metadata errors prevent a clean image and can produce artifacts during imagery analysis (Carroll et al., 1998). In the case for this study, misregistration was potentially caused by interruptions during imagery capture. Turbulence could have caused one of the camera sensors to have a specific view of the target while causing the other sensors to not have the same view (Casey and Kerekes, 2009). Misregistration, while only seen when the bands are layered, can affect any finished imagery processing, including simple band ratios and principle component analysis. The biggest issue found with misregistered bands was the potential to affect the data collection when simple band ratios were applied (Figure 4.8).

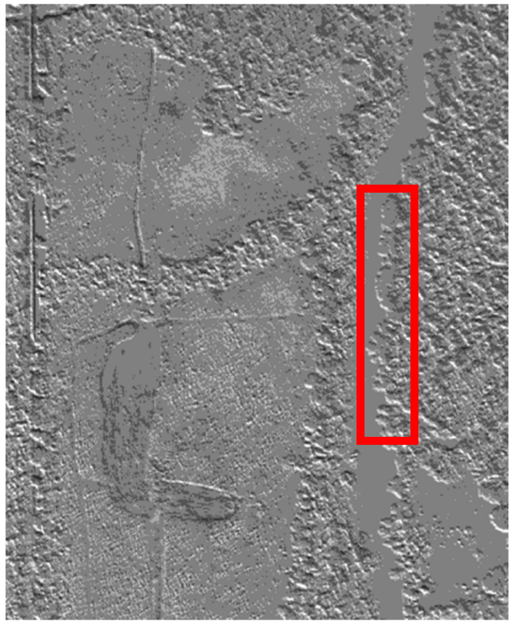

Figure 4.8 Misregistered red/green simple band ratios from a downstream section of Tibbee Creek. The red box emphasizes the affected shadowed areas and the unaffected non-shadowed areas of the creek.

Band ratios were found to be potentially affected by the misregistered bands outside of visual inspection. When viewing the output of simple band ratios, non-shadowed portions of Tibbee Creek remained unaffected by the misregistration. This further supported the flagging of points in shadowed areas. The misregistered band ratios did correct for the solar radiance issues and the overlapping issues previously discussed.

The most common tool for correcting misregistered bands was to use a geocorrection tool in imagery software (Carroll et al., 1998; Casey and Kerekes, 2009; ERDAS, 2011). For this study, no geocorrection was completed due to the assumption that the misregistration did not affect the creek itself. This assumption was based off the creek being a uniform water body. It was also assumed that if a point was located within the misregistration area it was already marked as a potential outlier.

4.6 Statistical Analysis

The objective of this study was to use stepwise regression equations that were represented by an elevated R^2 value to prove if the equation and its components formed a relationship between water quality parameters and relative reflectance from the aerial imagery. The statistical analysis supplied a two to four variable stepwise regression equation that was utilized to test multiple water quality parameter datasets and determine an elevated R^2.

Datasets consisted of water quality parameters along with relative reflectance band values and simple band ratios. Datasets were tested only if the contained values had passed visual analysis requirements and had completed water quality parameter sets. Stepwise regression analysis was conducted using SAS software (SAS Institute Inc., 2011). Water quality parameters were set as the dependent variables while each individual band and band ratios were designated as independent variables (Bilge et al., 2003). The selection criterion was based on the highest R^2 values and the lowest Mallows' Cp value from the entire collection of models generated by stepwise regression. The final step provided each individual component for the regression equation and its coefficients. With this information a regression equation was built for each sample date and water quality parameter.

4.6.1 Analysis of Individual Sample Points

Each sample point was cataloged with date Relative reflectance reflectance and corresponding simple band ratios. Each dataset, based off of dates, consisted of a statistical sample size of 50. The method for statistical analysis for the original sample points was a stepwise regression procedure using SAS that considered all bands and simple band ratios as independent variables while turbidity and total suspended solids were the dependent variables. The 2010 datasets that did not have TSS were excluded in the analysis. The output presented what independent variable correlated the best with the dependent variables for each of the 50 sample points (SAS Institute Inc., 2011). The output from the SAS computation provided an analysis of variance (ANOVA) table with correlated independent variables, variable coefficients, R^2 values, Mallows Cp, and statistical significance. These values were utilized to generate a regression equation with correlated independent variables to a specific dependent variable (Ott and Longnecker, 2010; SAS Institute Inc., 2011).

4.6.2 Analysis of Transect Values

All 50 sample points were averaged into 10 major points by the original five sample point transects. Stepwise regression analysis of the smaller sample size was implemented by turbidity and TSS as the dependent variables. The analysis considered all bands and simple band ratios as independent variables (Ott and Longnecker, 2010; Song et al., 2009; Teodoro et al., 2008). SAS model output, provided an ANOVA table with correlated independent variables, variable coefficients, R^2 values, Mallows Cp, and statistical significance. These values were utilized to generate a regression equation with correlated independent variables to a specific dependent variable.

Transect value analyses were conducted on the dependent variables, turbidity and TSS. The 2010 datasets did not have TSS testing results. Those datasets were not tested for a correlation and were noted as being skipped. Each dataset that met the requirements of the imagery analysis and water quality parameter criteria was analyzed to determine what Relative reflectance and simple band ratios correlated with the water quality parameters. Some of the datasets did conclude to be not statistically significant when the stepwise regression was conducted. These datasets were noted as being not statistically significant (Ott and Longnecker, 2010; SAS Institute Inc., 2011).

4.6.3 Regression Models

Correlated independent variables from the previous analyses were placed into regression equations consisting of no more than four variables. The equations were utilized based on the R^2 values found in the ANOVA tables. Each utilized equation was tested on all sample dates to provide a correlation outside of the equation's specific date. The intentions of the regression equations were to determine the inconsistencies between sampling dates (Ott and Longnecker, 2010). The dates were marked inconsistent if the R^2 value dropped below 0.5. Testing was done in SAS using equations from previously tested variables. If any dates did not have specific parameters, those dates were skipped. The output displayed how the independent variables correlated with the dependent variable using values from different datasets. The output from the SAS computation provided an ANOVA table with variable coefficients, R^2 values, and statistical significance. These values were utilized to generate a regression equation with correlated independent variables to a specific dependent variable (SAS Institute Inc., 2011). The test was completed on both the individual sample points and the transect values. This analysis helped determine if the original goal of correlating one equation into other datasets was statistically probable.

The goal for this experiment was to provide one or more equations that could prove to be statistically significant outside the specific dataset range where the equation was generated. Equations with an R^2 value above 0.50 were considered probable components to test against other data sets. Some regression analyses were found to have a probability value (p-value) greater than the tested alpha level (0.05). If the p-value was greater than the alpha level, the null hypothesis (statistical significance) was rejected (Ott and Longnecker, 2010; SAS Institute Inc., 2011). Figure 4.9 shows a process diagram for the regression modeling.

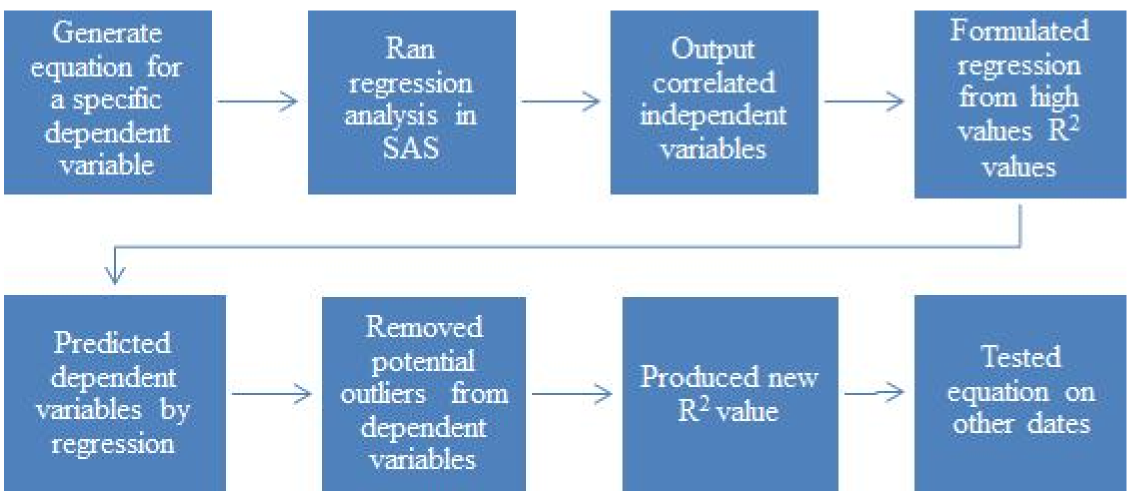

Figure 4.9 Process for the regression modeling from stepwise regression to the full scale model.

4.6.4 Removal of Potential Outliers

This secondary testing confirmed the statistical parameters by providing a similar ANOVA table. When the independent variables were confirmed, the equations were applied to the individual imagery and water quality values in Excel. Relative reflectance values and simple band ratios, depending on the independent variables needed, were input into the equations, as seen in equation 4.3, where Y is the predicted dependent variable, X_n are the independent variables, b_0 is the equation coefficient, and b_n are the independent variable coefficients.

$$Y = b_0 + b_n(X_n) \tag{4.3}$$

The resulting model predicted turbidity or TSS values which were plotted against the original measured turbidity or TSS values (Wass et al., 1997). Once these values were plotted, all of the values that were originally marked as potential outliers for any imagery issues were removed from the test as anomalous data. The new plot was analyzed to determine if removing the potential outliers affected the R^2 values. This analysis was computed on equations that produced strong R^2 values and were statistically significant.

The transect regression equations were not tested to keep sample sizes (n) above 25 or half of the original sample size. The values using the regression equations were called predicted water quality values and were plotted against the original measured water quality values.

CHAPTER V

RESULTS

5.1 Tibbee Creek Water Quality Parameters

5.1.1 Dissolved Oxygen

Dissolved oxygen values on Tibbee Creek ranged from 3.0 mg/l to 11.0 mg/l (Figure 5.1). The average DO value throughout all sample dates was 6.25 mg/l, above the State of Mississippi requirement of 5.0 mg/l for daily average. Fifteen percent of the DO samples were below the instantaneous minimum of 4.0 mg/l (MDEQ, 2009). No specific location of the creek was defined as low values since 10 of the dates had low DO values downstream (5.74 mg/l), and nine dates had low DO values upstream (5.97 mg/l). Dissolved oxygen values were relatively the same (6.54 mg/l) at both upstream and downstream segments in six sampling dates (May 10-11, 2010, May 11, 2011, May 18, 2011, June 14, 2011, June 29, 2011, and September 10, 2011.

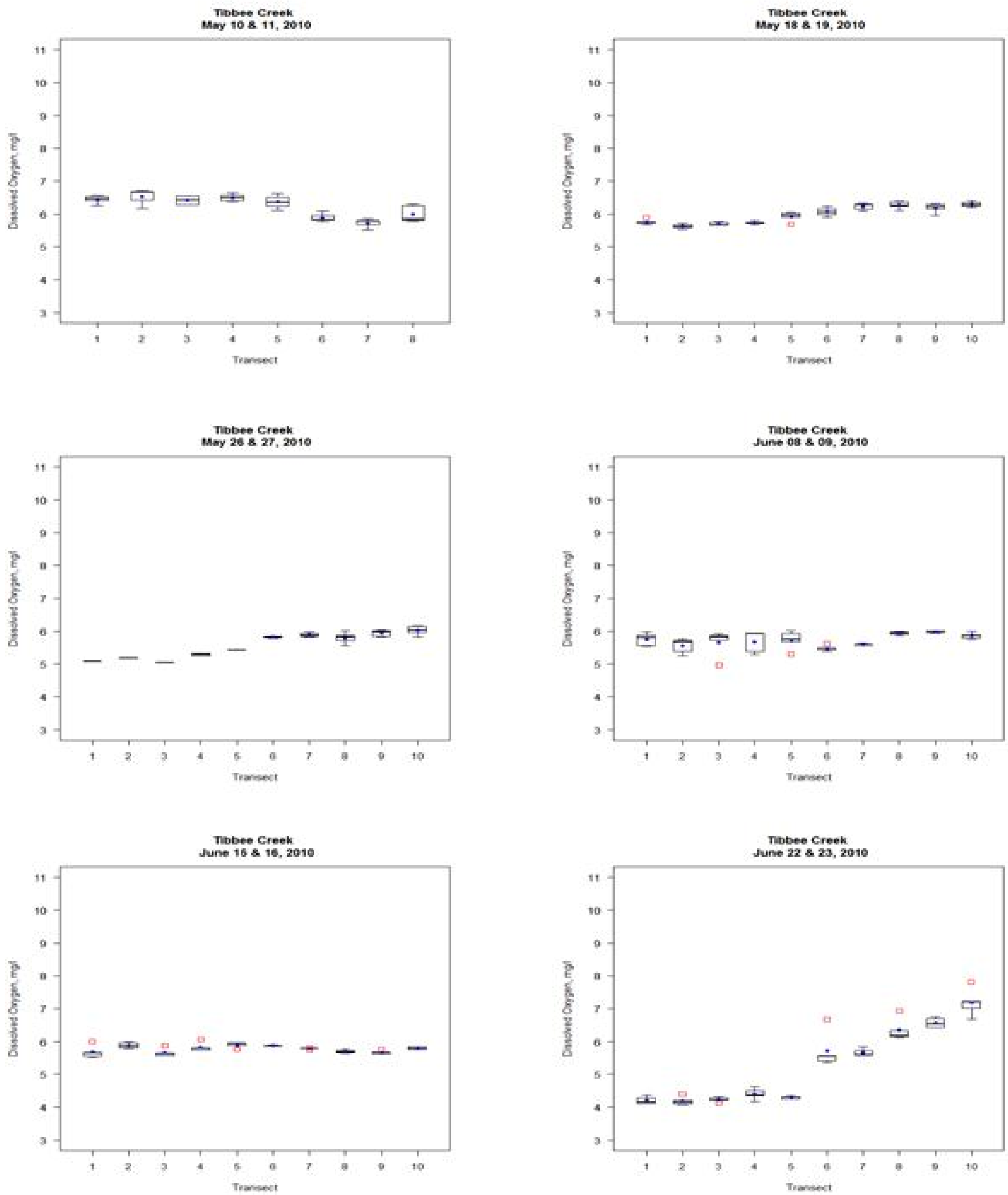

Figure 5.1 Dissolved Oxygen levels of water samples collected from Tibbee Creek at different sampling dates.

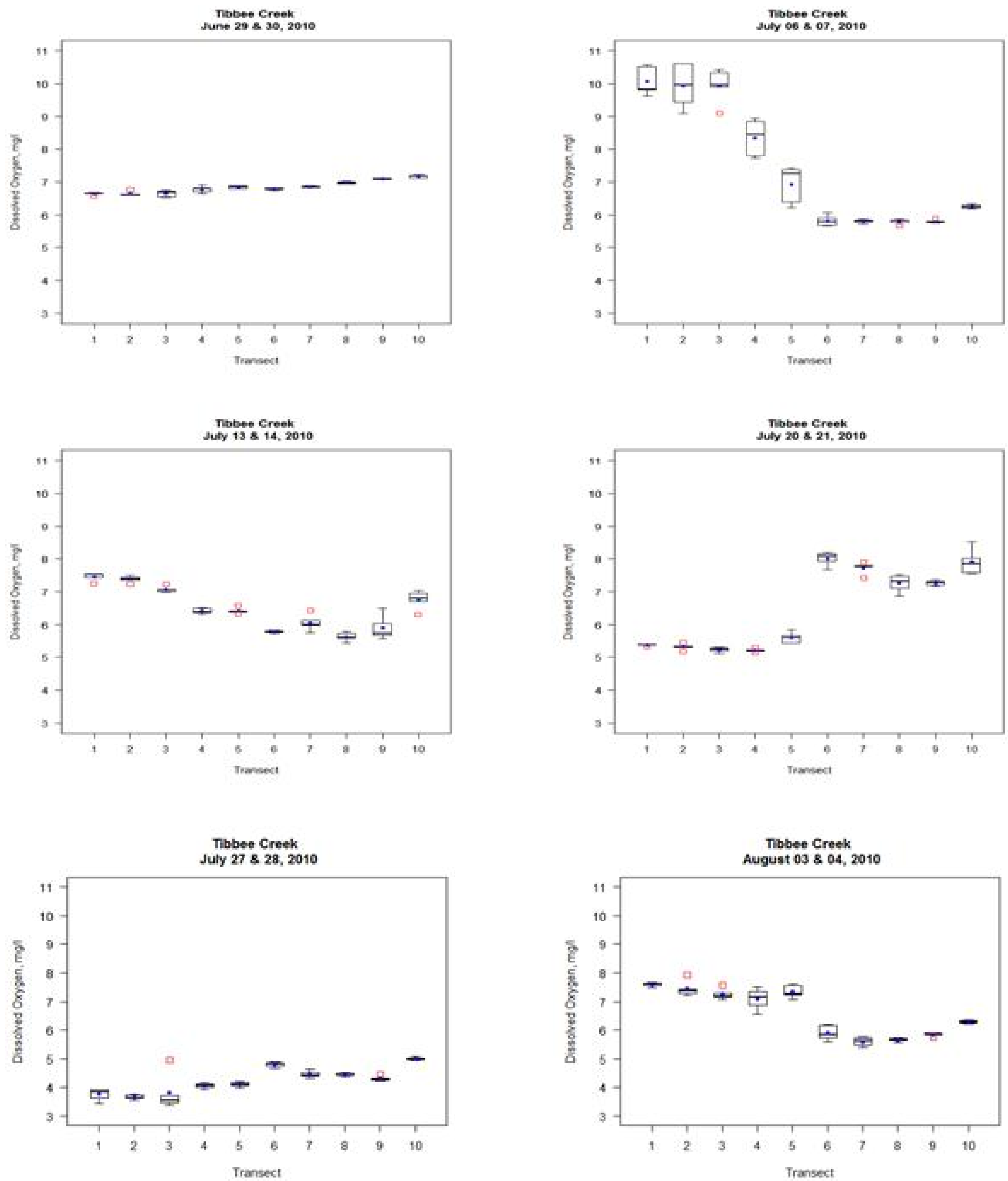

Figure 5.1 (continued).

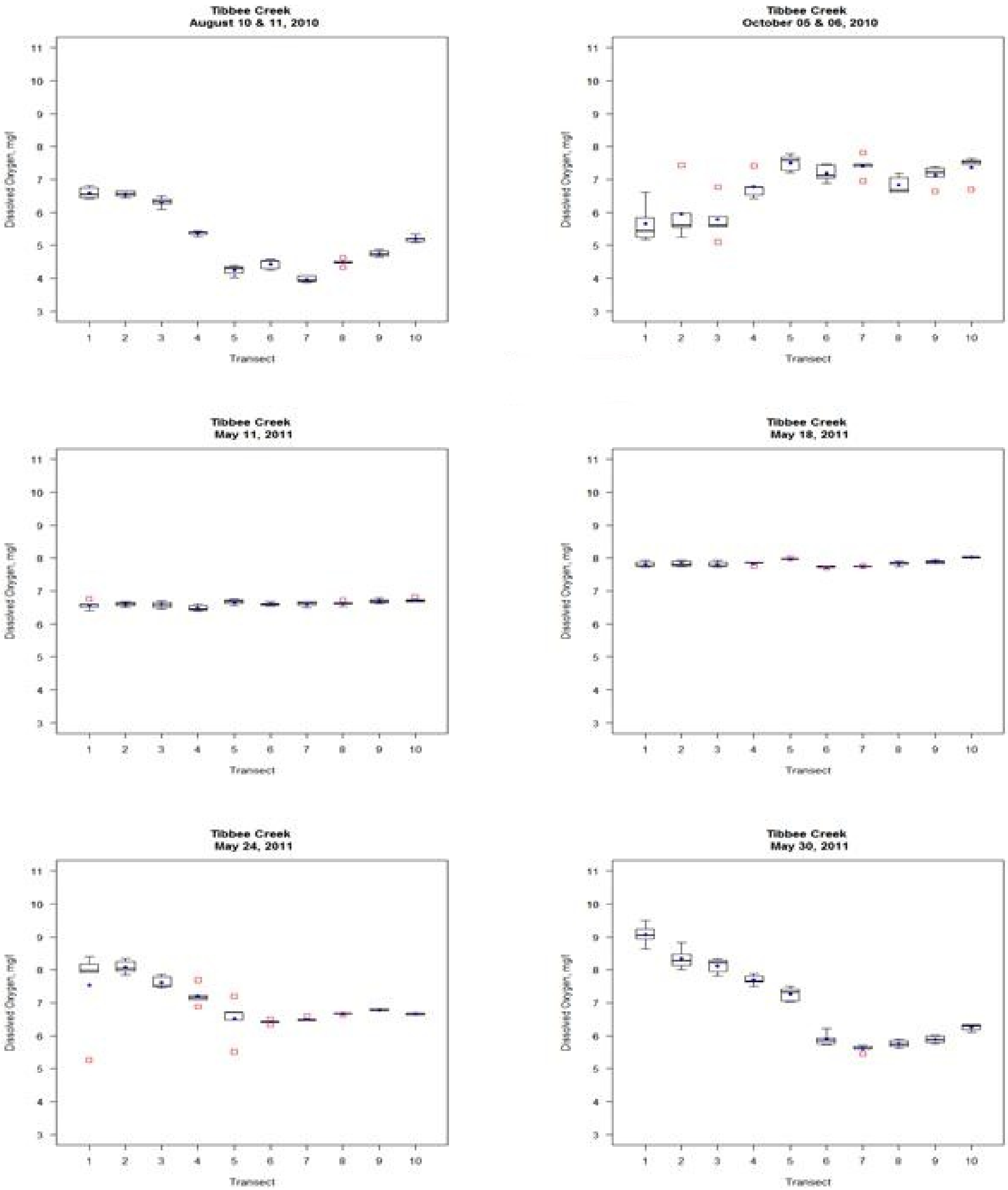

Figure 5.1 (continued).

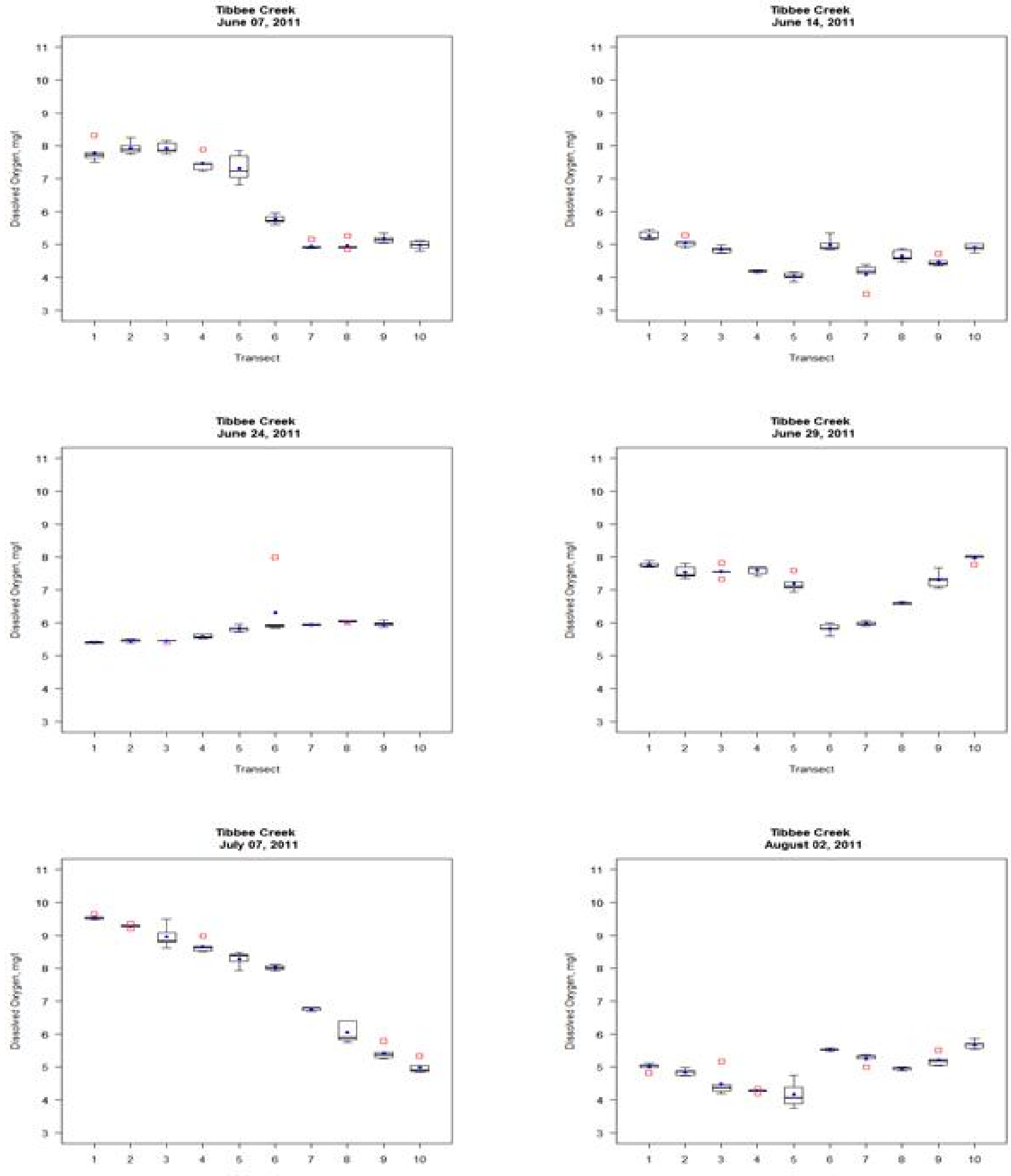

Figure 5.1 (continued).

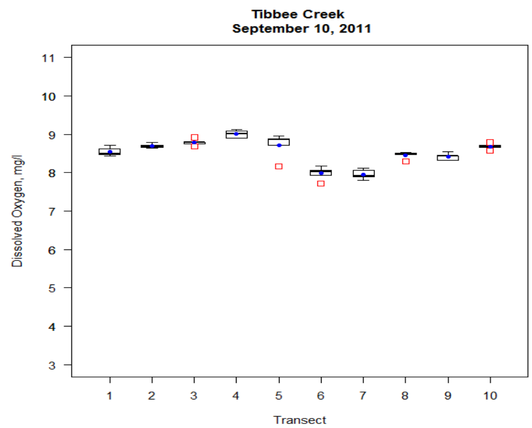

Figure 5.1 (continued).

5.1.2 Temperature

Temperature on Tibbee Creek ranged from 17 °C to 34 °C (Figure 5.2). The average value throughout all sample dates was 28 °C, below the State of Mississippi requirement of 32 °C for daily maximum. Temperature rises to the greatest value in June through August during both periods. Twenty four percent of samples were above the 32 °C for daily average (MDEQ, 2009). No specific location of the creek was defined as high temperature since 10 of the dates were equal in temperature both upstream and downstream. Temperature in the upstream segment (29.3 °C) was higher than the downstream portion (25.6 °C) in nine sampling dates (May 26-27, 2010, June 15-16, 2010, June 22-23, 2010, June 29-30, 2010, July 20-21, 2010, July 27-28, 2010, June 14, 2011, June 24, 2011, and August 02, 2011). Temperatures in six dates were higher downstream than the upstream segment (June 8-9, 2010, July 13-14, 2010, October 5-6, 2010, May 11, 2011, May 18, 2011, and May 30, 2011).

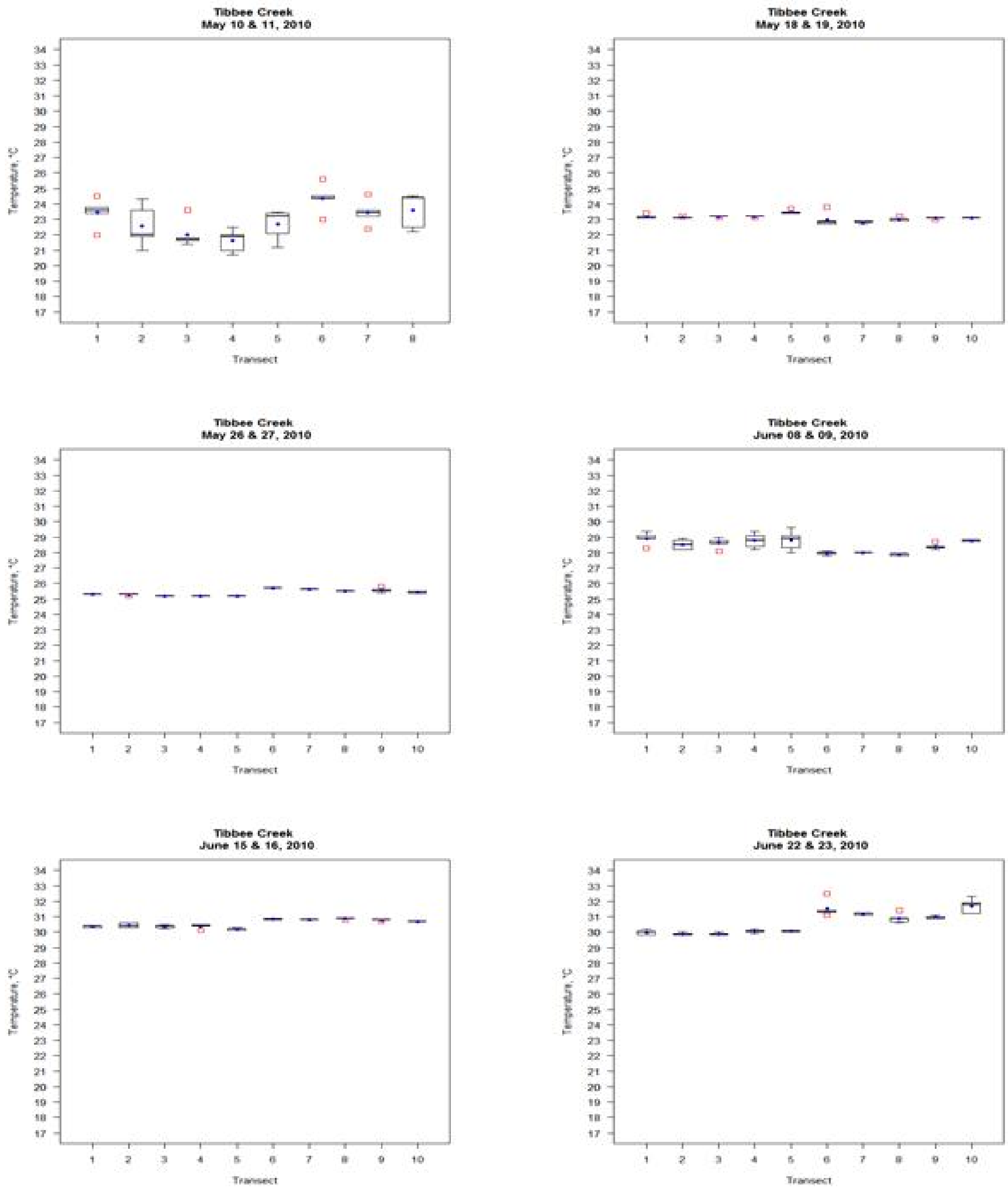

Figure 5.2 Temperature levels of water samples collected from Tibbee Creek at different sampling dates.

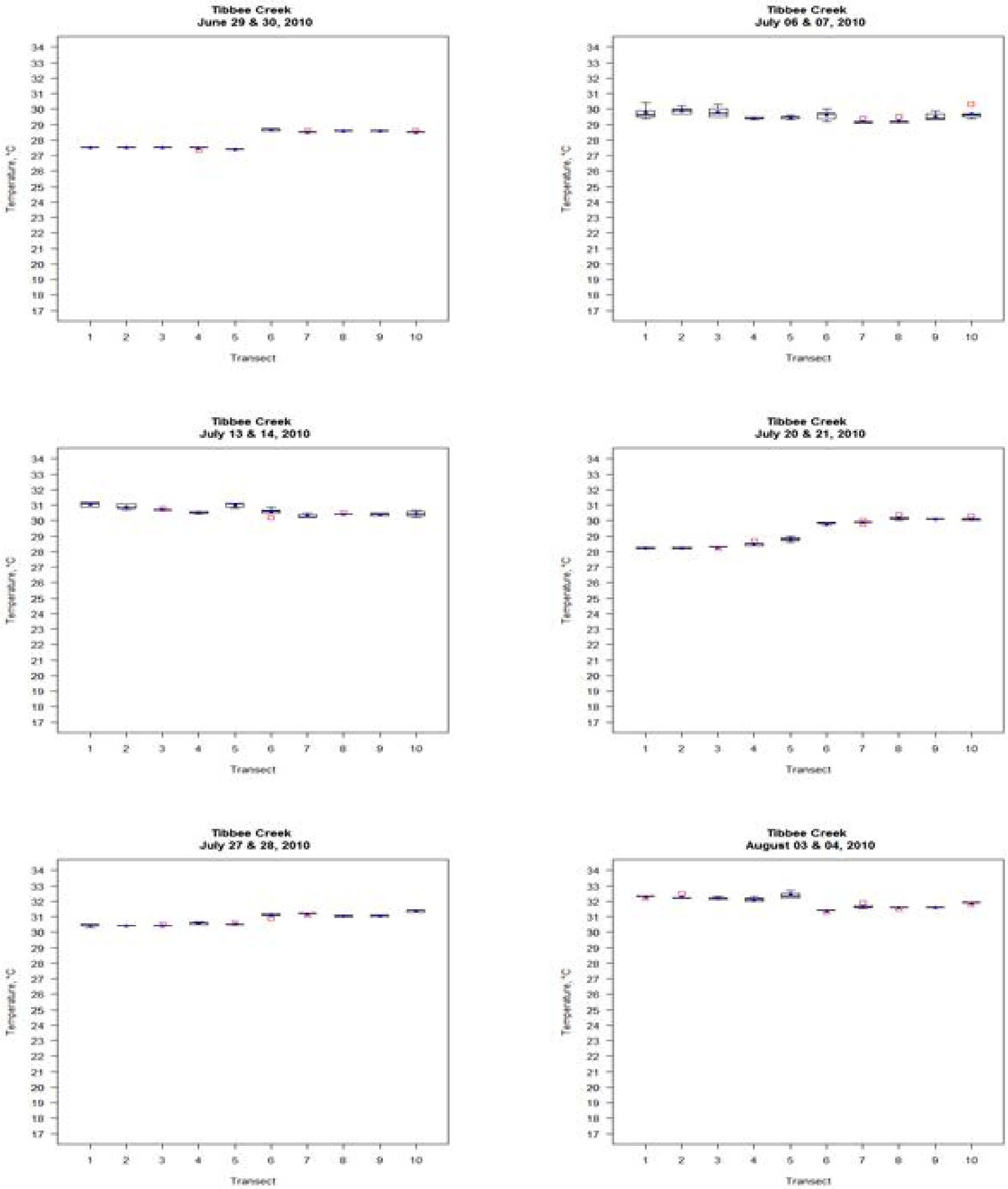

Figure 5.2 (continued).

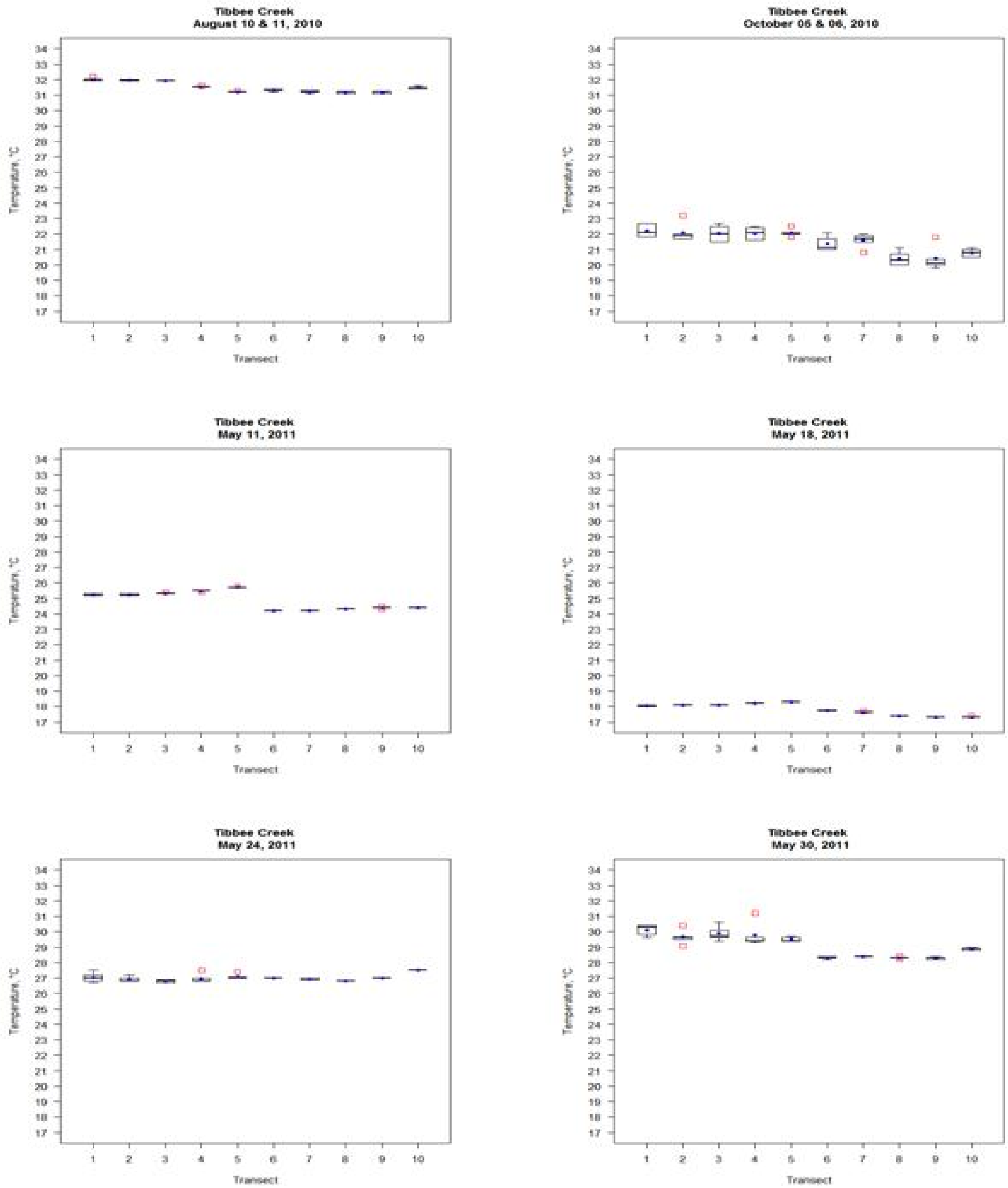

Figure 5.2 (continued).

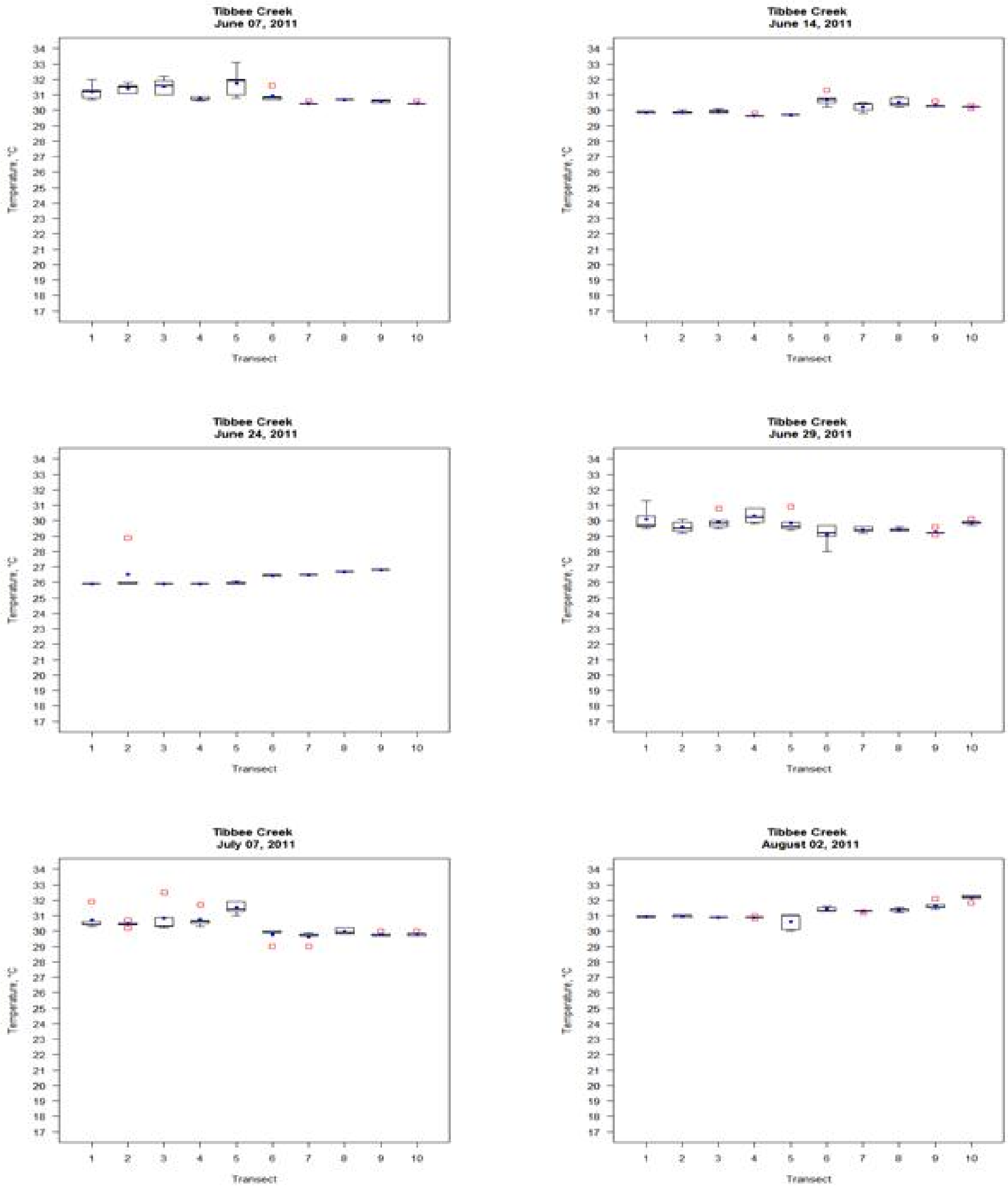

Figure 5.2 (continued).

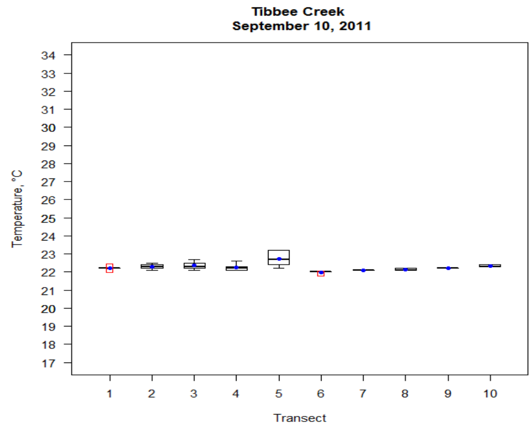

Figure 5.2 (continued).

5.1.3 Turbidity

Turbidity values on Tibbee Creek ranged from 4 NTUs to 198 NTUs (Figure 5.3). The average value throughout all sample dates was 41 NTUs. Turbidity values were higher upstream (27.8 NTUs) throughout 15 of the datasets. These datasets make up the majority (60 percent) of turbidity sample dates of all dataset collected on Tibbee Creek over the two sampling periods. Downstream values were higher (94 NTUs) during three of the datasets (May 10-11, 2010, June 22-23, 2010, and June 29-30, 2010). The turbidity values followed closely with the gauge data. Turbidity rose to an average of 75 NTUs after a rainstorm or the beginning of a sampling period (May—June), while dropping to an average of 20 NTUs during the dry summer months (July—August). Analysis showed that turbidity readings were higher in the downstream segment of the creek during the first sampling period from May through June. In 2011, turbidity never reached above 50 NTUs except for June 24, 2011 (100 NTUs). The high turbidity values may be linked to the increase in gauge height (3 feet) around that sampling date.

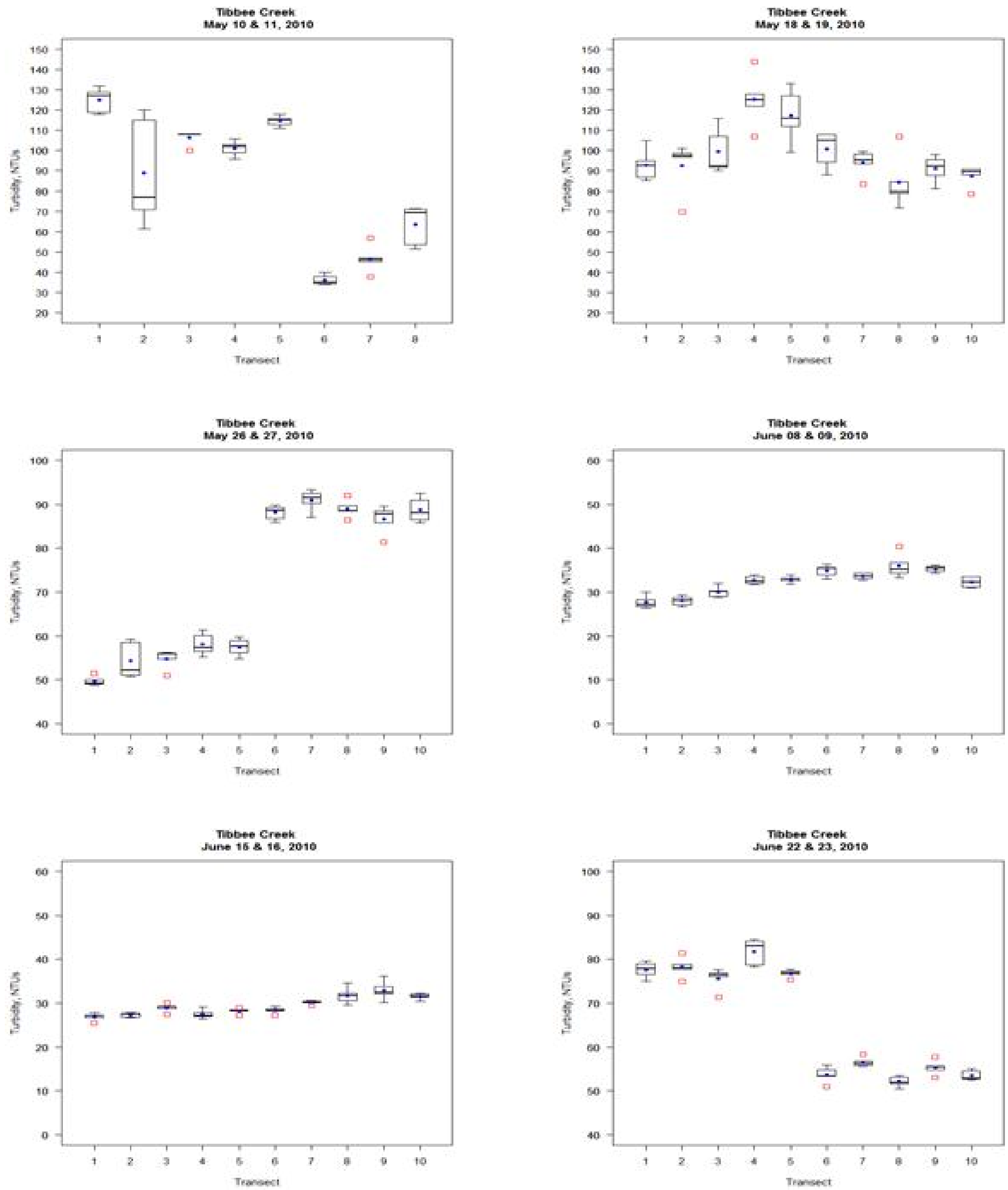

Figure 5.3 Turbidity levels of water samples collected from Tibbee Creek at different sampling dates.

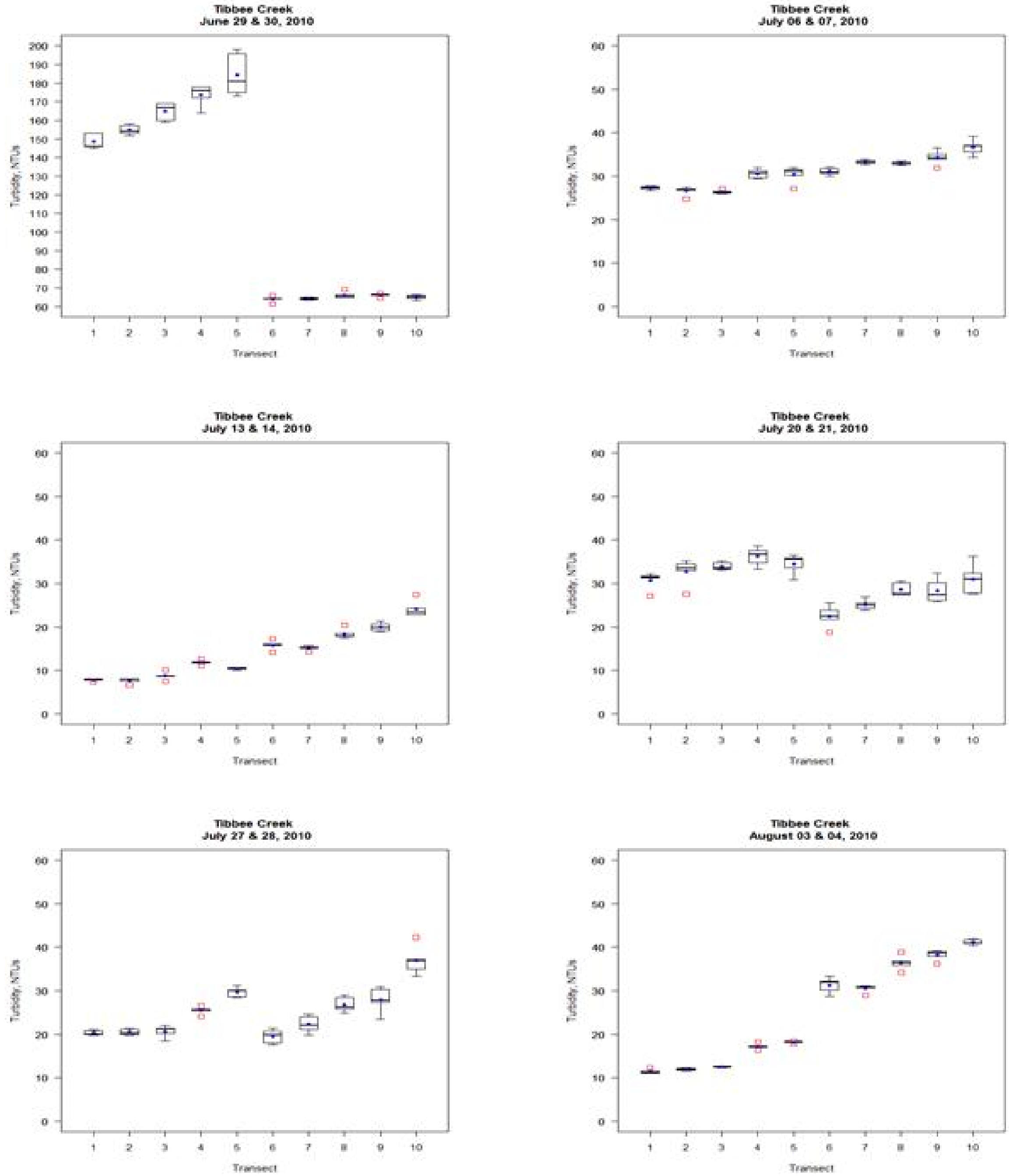

Figure 5.3 (continued).

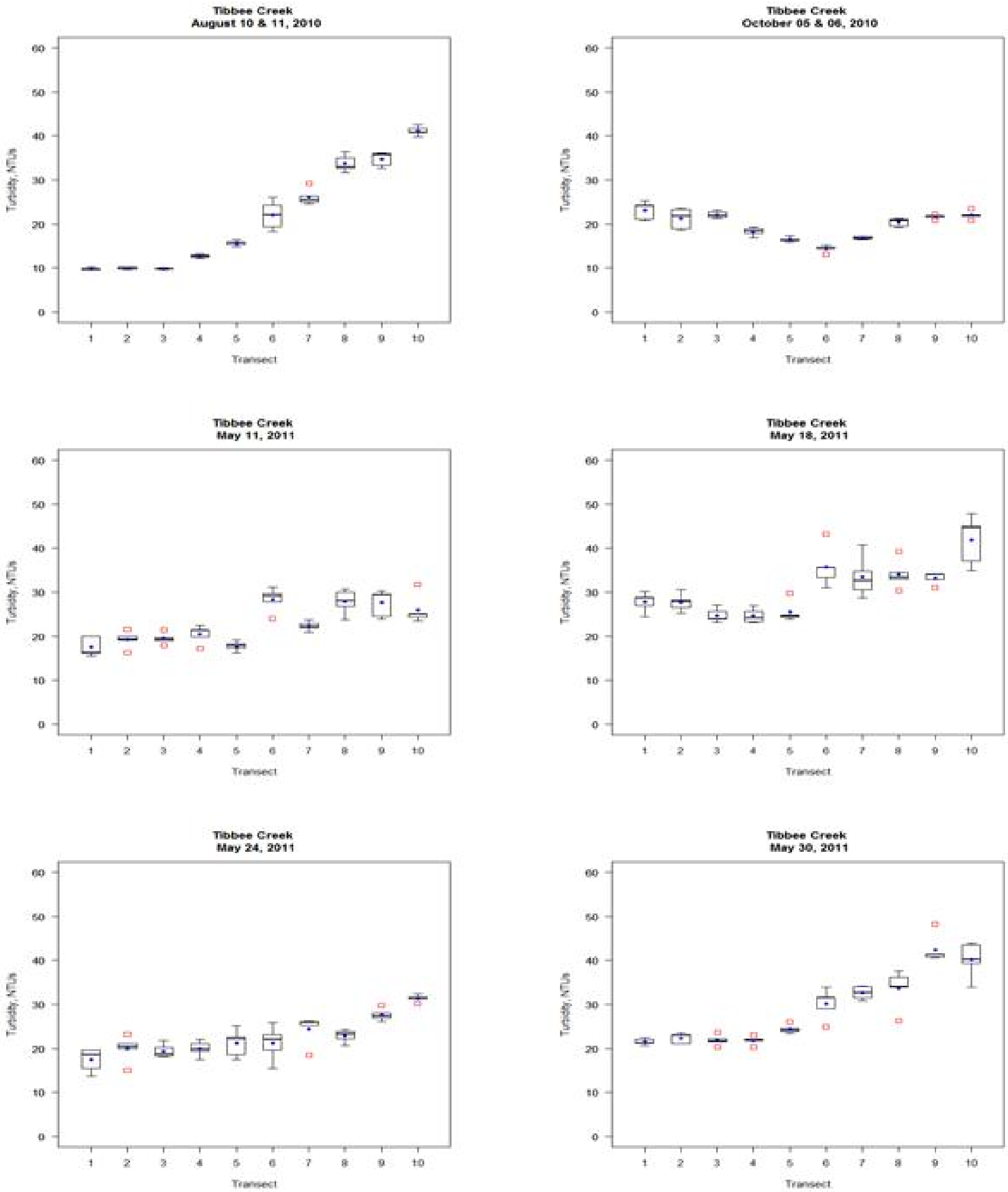

Figure 5.3 (continued).

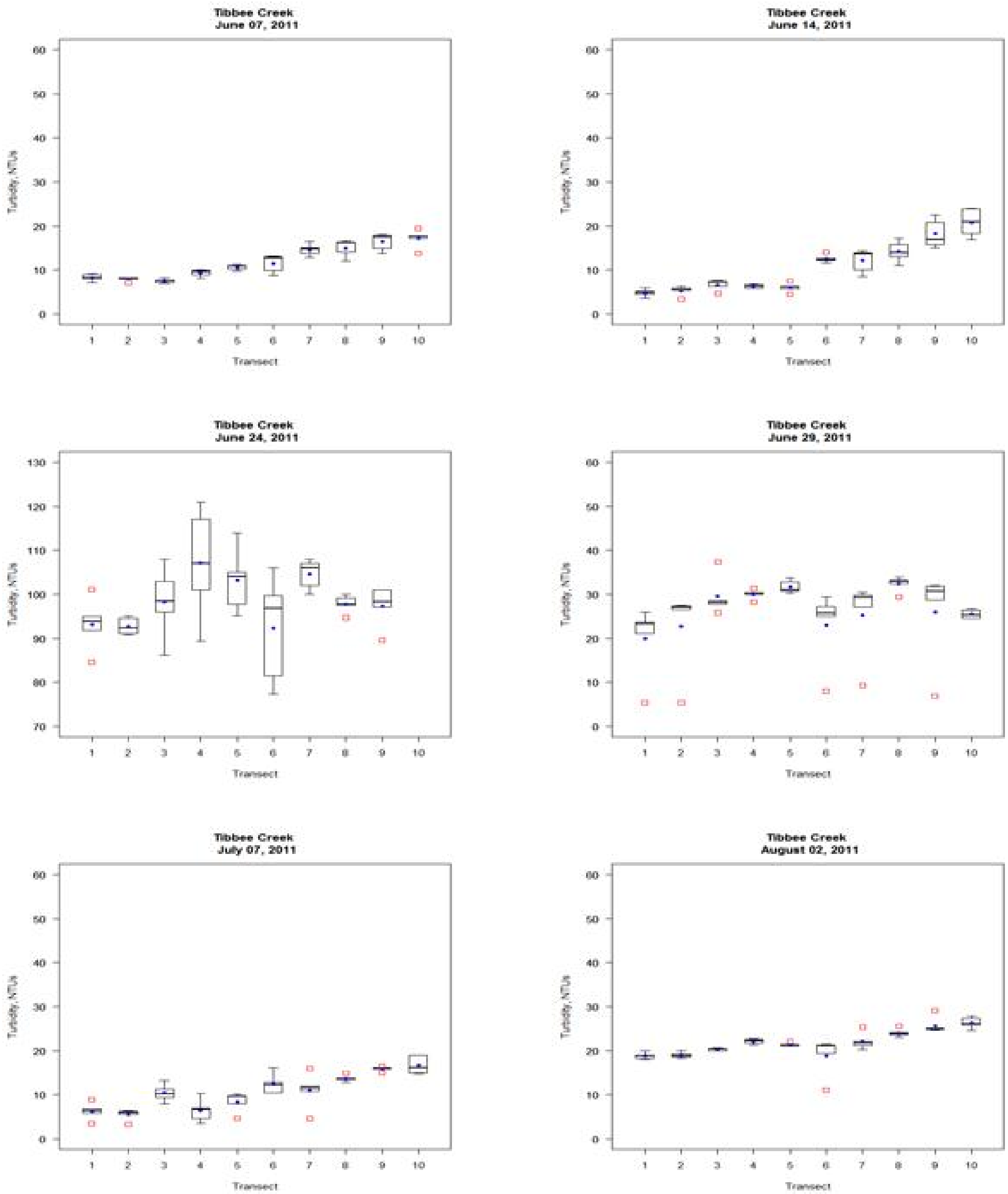

Figure 5.3 (continued).

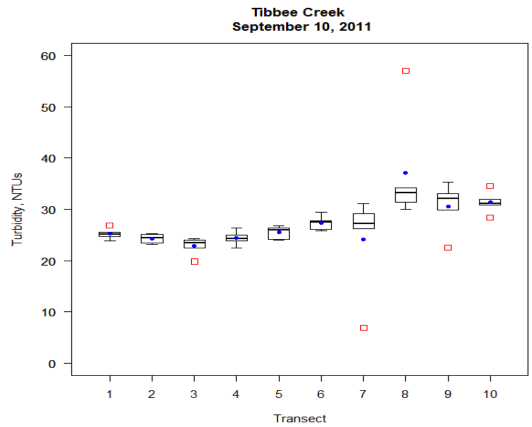

Figure 5.3 (continued).

5.1.4 Total Suspended Solids

Total suspended solids of water samples collected from Tibbee Creek ranged from less than 1 mg/l to 200 mg/l (Figure 5.4). The average value throughout all sample dates was 38 mg/l. The four TSS datasets from the first sampling period (June 29-30, 2010, August 3-4, 2010, August 10-11, 2011, and October 5-6, 2010) were higher (47.5 mg/l) than the values from the 2011 period (32 mg/l) collected over 11 sample dates from May 2011 to September 2011. Analysis showed that TSS values were equal throughout the creek but scaled closely to turbidity (Thackston and Palermo, 2000). June 29-30, 2010 provided the only TSS values that were higher downstream (120 mg/l). Unlike turbidity, no relationship was established between higher TSS values and increases in gauge height. Values fluctuated throughout the sampling periods with two of the highest sample datasets occurring at the end of June during the dryer portion of the summer.

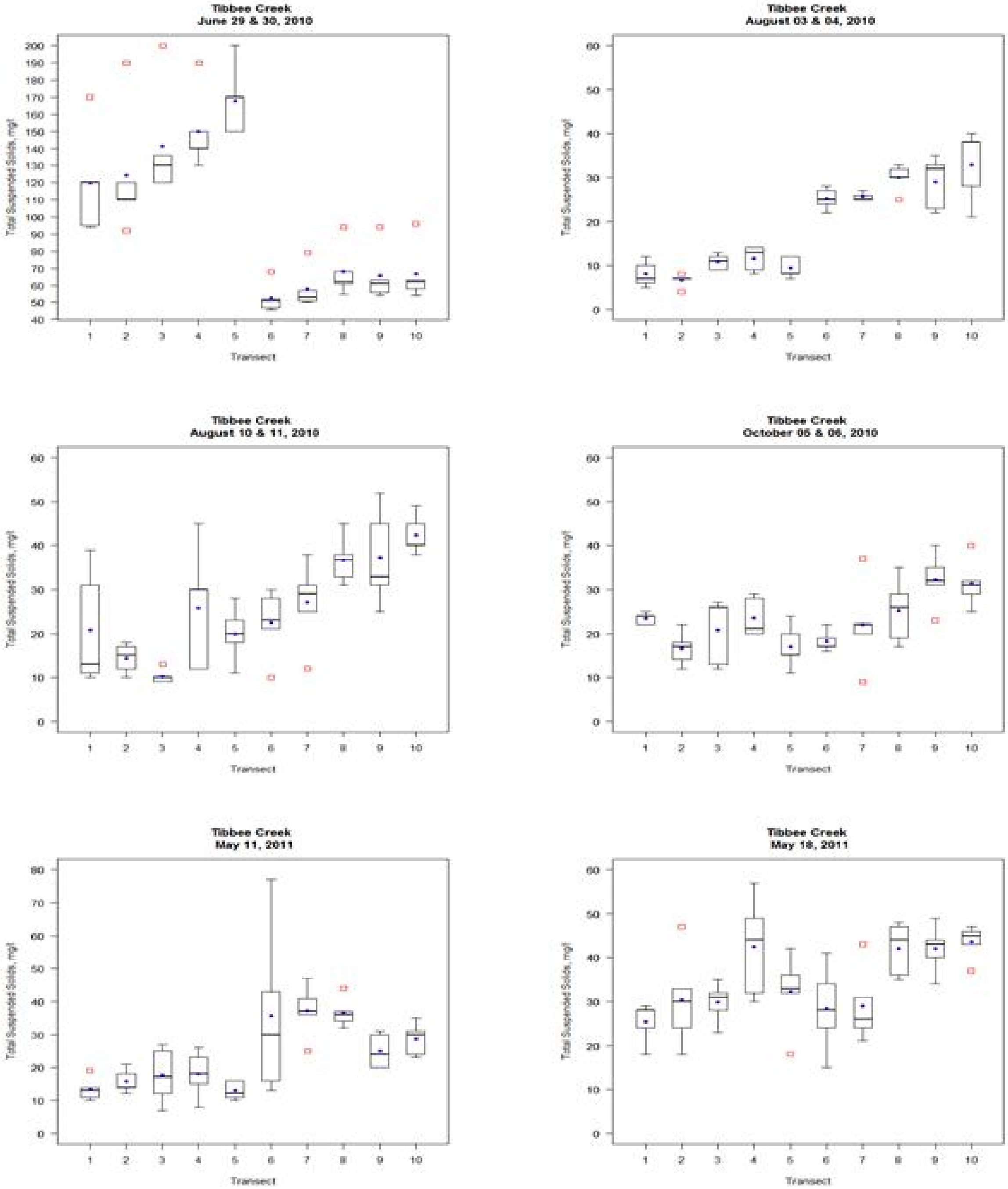

Figure 5.4 Total suspended solids levels of water samples collected from Tibbee Creek at different sampling dates.

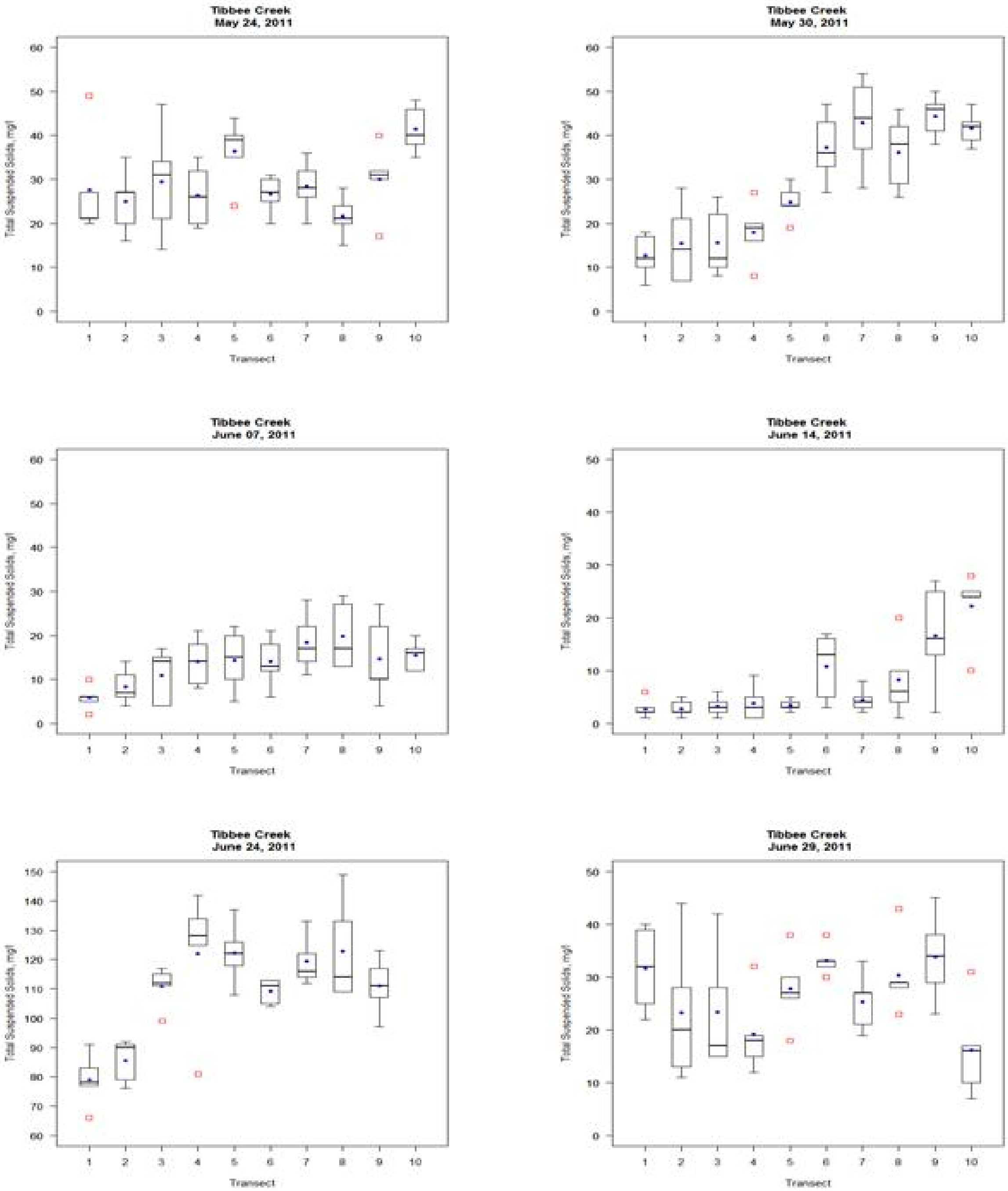

Figure 5.4 (continued).

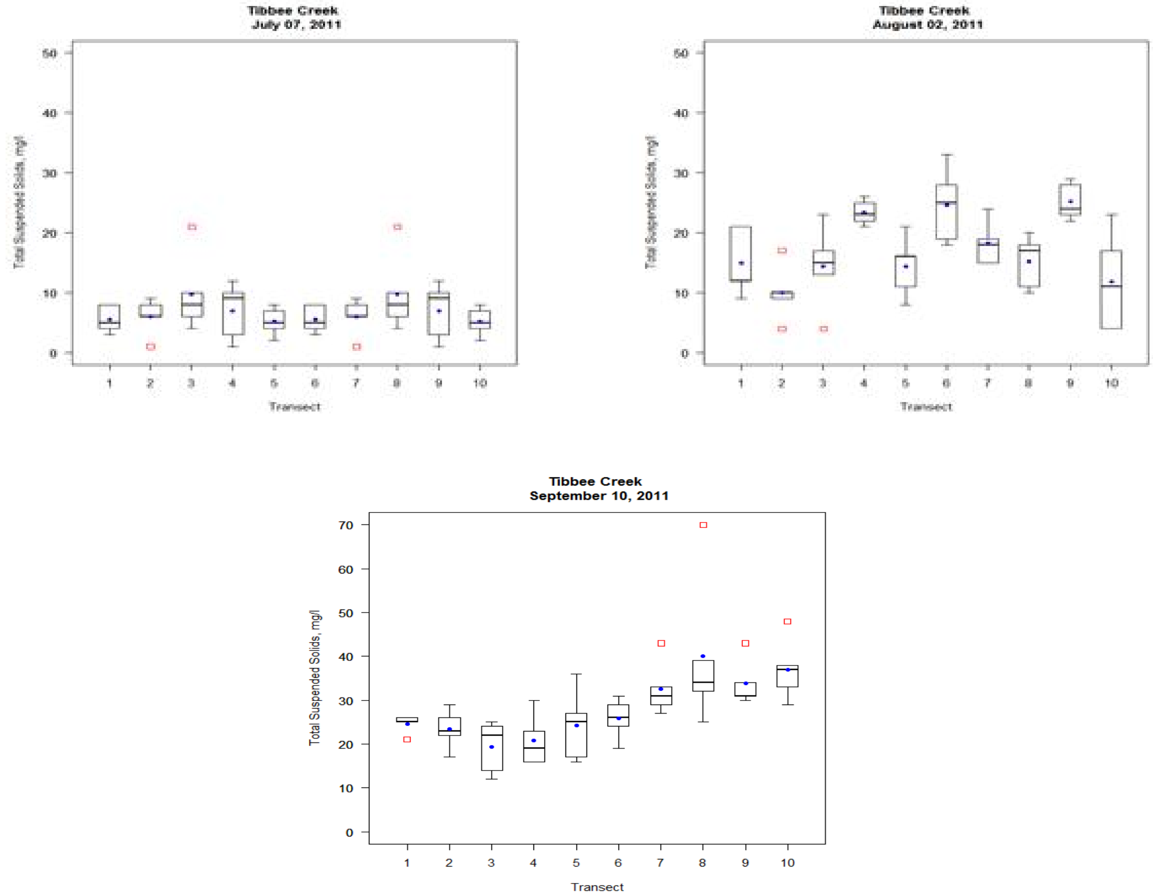

Figure 5.4 (continued).

5.2 Upper Pearl River Water Quality Parameters

5.2.1 Dissolved Oxygen and Temperature

Dissolved oxygen values on the Upper Pearl River ranged from 5.0 mg/l to 7.5 mg/l (Figure 5.5). The average DO value throughout all sample dates was 6.3 mg/l, above the State of Mississippi requirement of 5.0 mg/l for daily average. None of the DO samples were below the instantaneous minimum of 4.0 mg/l (MDEQ, 2009). No specific location of the river was defined as low or high values given that the river contained five transects.

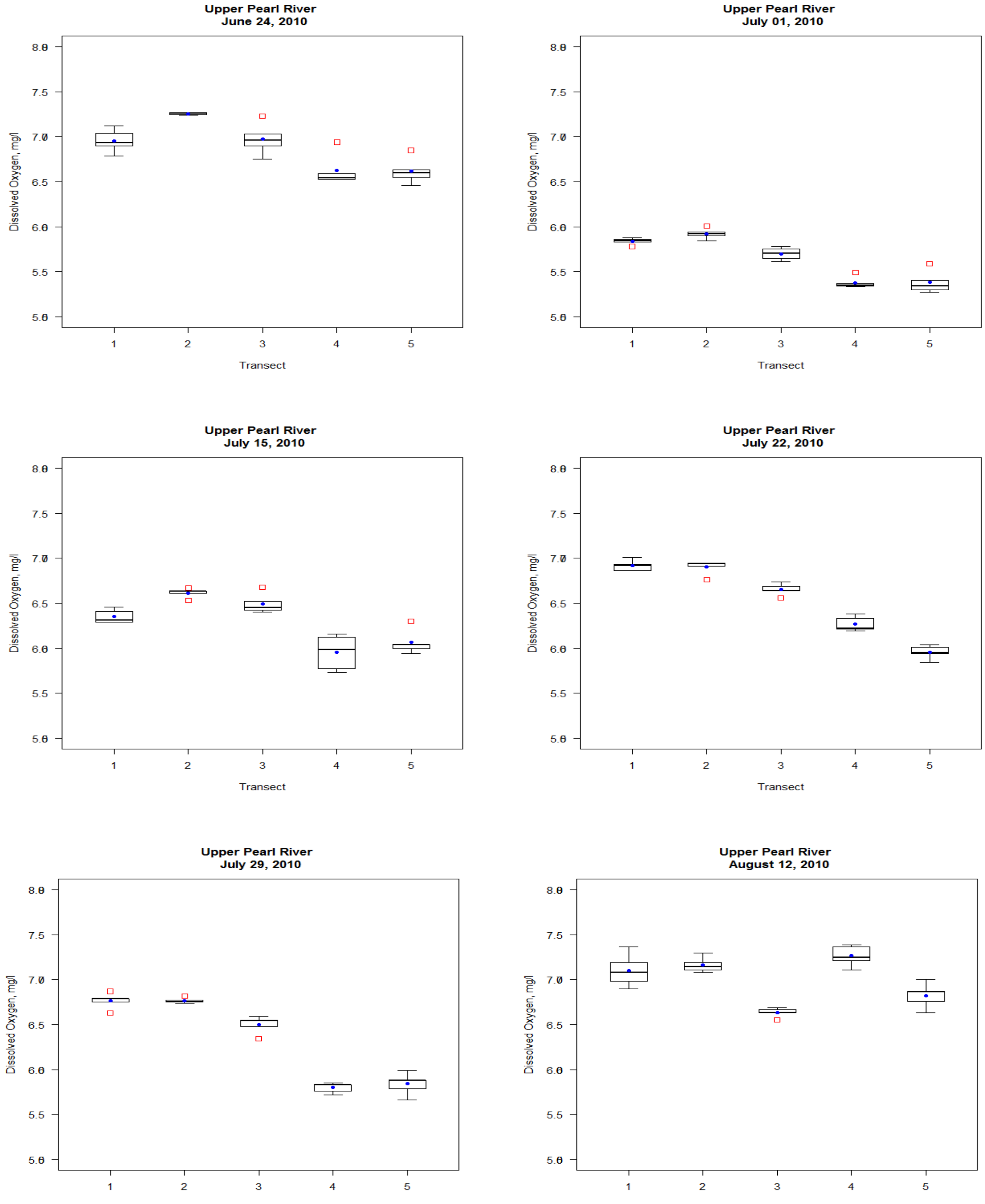

Figure 5.5 Dissolved oxygen levels of water samples collected from Upper Pearl River at different sampling dates.

In-stream temperature measurements along the Upper Pearl River, in Edinburg, Mississippi ranged from 27.5 °C to 32 °C (Figure 5.6). The average temperature throughout all sample dates was 29.4 °C, below the State of Mississippi requirement of 32 °C for daily average. No samples were above the 32 °C for daily average (MDEQ, 2009). No specific location of the river was defined as low or high values given that the river contained five transects.

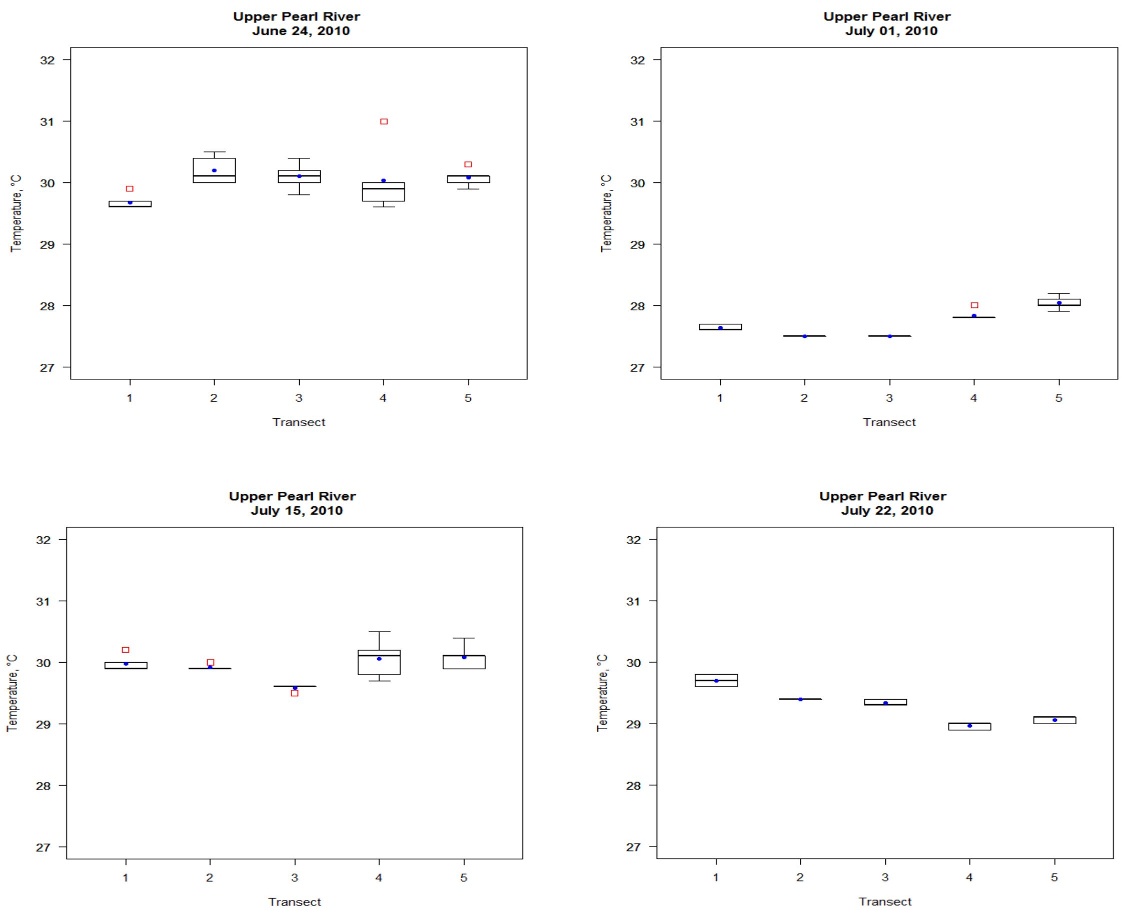

Figure 5.6 Temperature levels of water samples collected from the Upper Pearl River At different sample dates.

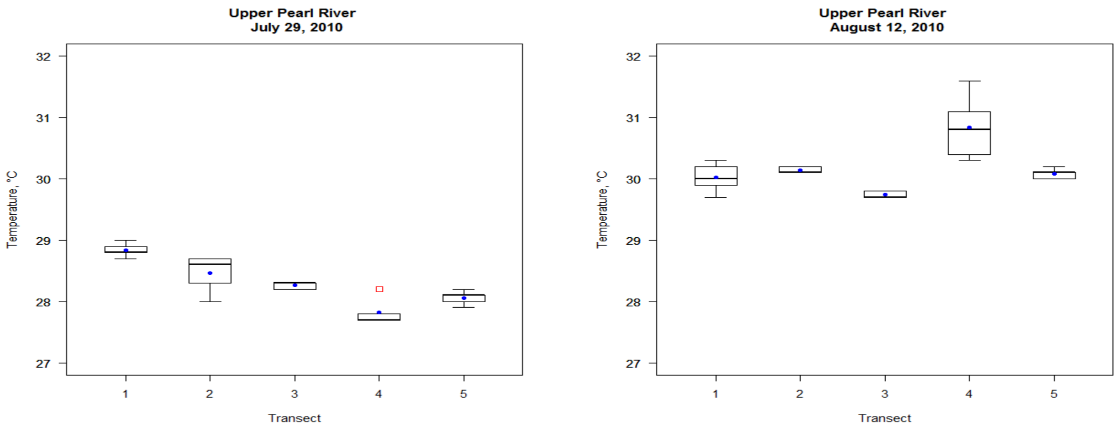

Figure 5.6 (continued).

5.2.2 Turbidity and Total Suspended Solids

Turbidity values on the Upper Pearl River ranged from 12 NTUs to 52.5 NTUs (Figure 5.7). The average value throughout all sample dates was 23.1 NTUs. Turbidity values were low (22 NTUs) throughout 60 percent of the sampling period (June—August). Two dates, July 22, 2010 and July 29, 2010 were above 30 NTUs. No specific location of the river was defined as low or high values given that the river contained five transects.

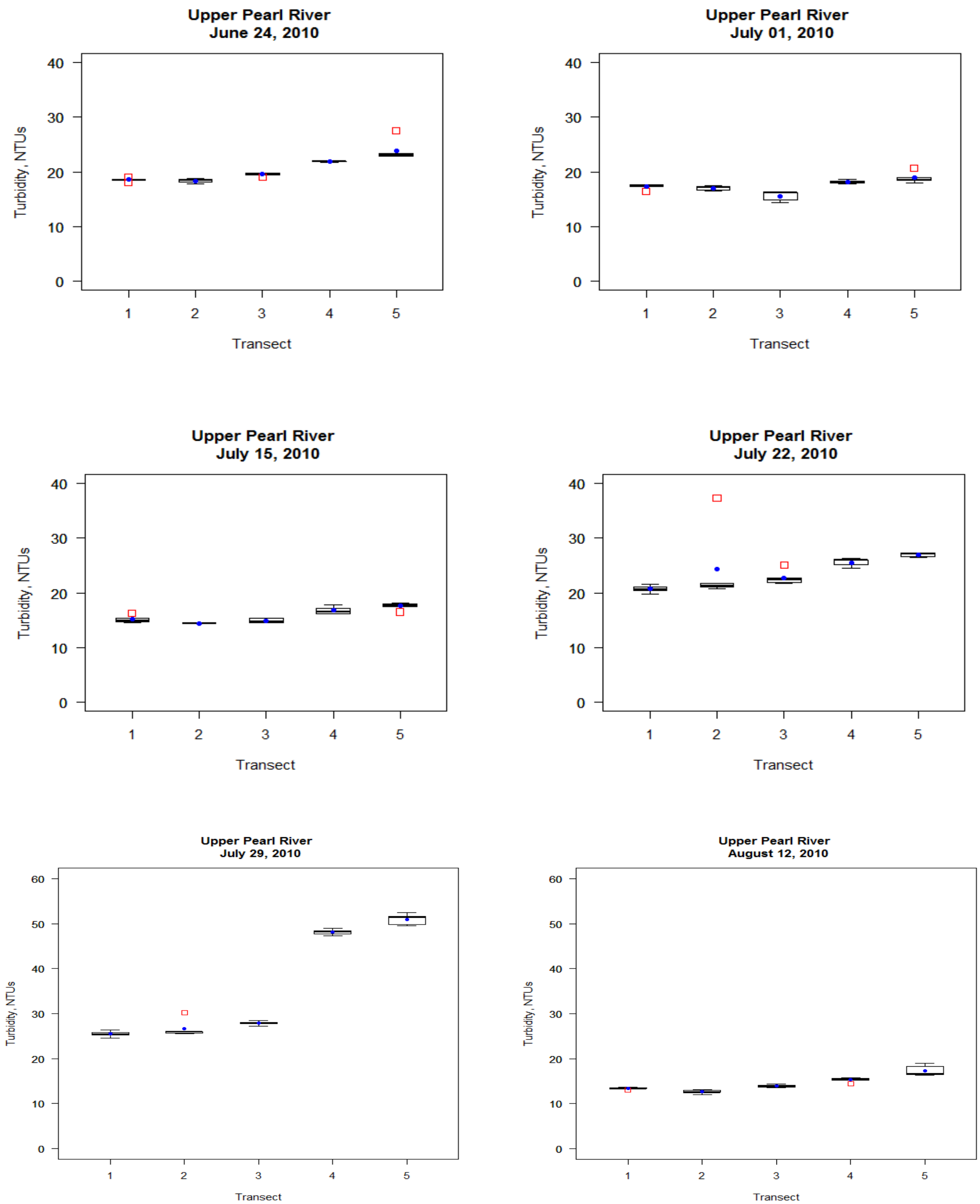

Figure 5.7 Turbidity levels of water samples collected from the Upper Pearl River at different sampling dates.

There was one TSS sample value on the Upper Pearl River ranging from 4 mg/l to17 mg/l (Figure 5.8). The average value of the sample was 10.5 mg/l. The one TSS dataset for the Upper Pearl River could not conclude any significant information about the Upper Pearl River. No specific location of the river was defined as low or high values given that the river contained five transects.

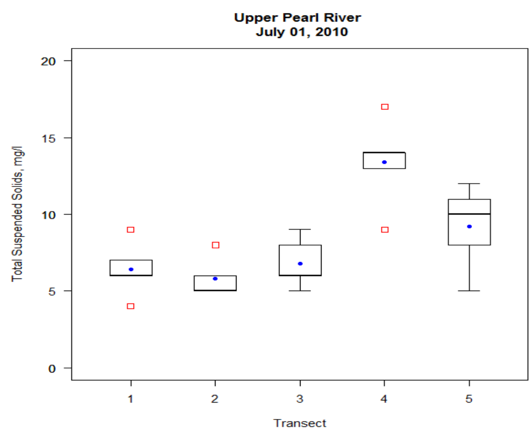

Figure 5.8 Total suspended solid levels of water samples collected from the Upper Pearl River at different sampling dates.

5.3 Statistical Results

Statistical analysis for this study were conducted using SAS software and techniques from similar case studies (Dekker et al., 2001; Doxaran et al., 2001; Lopez-Blanc and Zambrano, 2002; Ott and Longnecker, 2010; SAS Institute Inc., 2011; Teodoro et al., 2008).

5.3.1 Analysis of Tibbee Creek Data

The regression analysis for the large datasets of turbidity and Relative reflectance yielded eight stepwise equations that were statistically significant. Three out of eight equations that had R^2 values above 0.5 were periods from May 30, 2011, June 7, 2011, and June 14, 2011 (Table 5.1). The regression models featured one to four variables. Green/red and red/green band ratios were the common independent variables linked with the R^2 values. Case studies have linked the green/red and red/green band ratio to inorganic suspended matter (Kneubühler et al., 2005; Song et al, 2009). The studies utilized the band ratios because of the broad spectral range that can be found from each ratio (Lillisand et al., 2004). The regression analysis for the large datasets of TSS and Relative reflectance yielded four stepwise equations that were statistically significant. One out of the four stepwise equations, May 30, 2011, had an R^2 value above 0.5 (Table 5.2). The regression models featured two to four variables. The blue band and red/blue band ratio were the common independent variables linked with the R^2 value. There was no defined study for the provided variables. Explanation for the outputs could have been linked to potential sky reflectance (Doxaran et al. 2001; Karabulut and Ceylan, 2005).

5.3.2 Analysis of Upper Pearl River Data

The dataset for the Upper Pearl River contained one dataset from June 24, 2010. The 2010 dataset did not have TSS. The regression analysis for the large dataset of turbidity yielded one dataset, June 24, 2010, that was statistically significant had an R^2 value above 0.5 (Table 5.3). Three variables featured by the regression model are green, red, and simple band ratio green/NIR. Studies have linked the green and red bands to inorganic suspended matter (Dekker et al. 2001; Doxaran et al., 2001). The correlation between the green and red bands and the dataset supported the water quality parameters found in the Upper Pearl River, including TSS.

Table 5.1

Tibbee Creek individual sample points turbidity regression analysis

Date	Components	Coefficients	R^2	C(p)	F Value	Pr > F	*Sig*
05/18/2010 05/19/2010	Blue/Red	$b_0 = 73.71$ $b_1 = 20.10$	0.31	10.07	21.41	<0.0001	**
07/06/2010 07/07/2010	Green	$b_0 = 34.94$ $b_1 = -0.03$	0.16	28.09	9.16	0.0040	**
05/18/2011	Red NIR/Green	$b_0 = 10.98$ $b_1 = 0.10$ $b_2 = 30.26$	0.47	10.62	20.47	<0.0001	**
05/30/2011	Blue Green NIR Red/Blue	$b_0 = -20.63$ $b_1 = -0.26$ $b_2 = -0.14$ $b_3 = -0.43$ $b_4 = 172.21$	0.60	28.82	17.06	<0.0001	**
06/07/2011	Blue Green/Red Red/Green NIR/Red	$b_0 = -212.69$ $b_1 = -0.04$ $b_2 = 74.21$ $b_3 = 166.98$ $b_4 = 2.95$	0.70	34.09	26.44	<0.0001	**
06/14/2011	Green/Red Red/Green	$b_0 = -531.72$ $b_1 = 183.57$ $b_2 = 391.85$	0.67	25.63	46.64	<0.0001	**
08/02/2011	Blue/NIR NIR/Red	$b_0 = 34.18$ $b_1 = -1.76$ $b_2 = -6.93$	0.36	12.58	13.30	<0.0001	**
09/10/2011	Red NIR/Green NIR/Red	$b_0 = 7.35$ $b_1 = 0.09$ $b_2 = -327.90$ $b_3 = 373.94$	0.37	0.49	9.05	<0.0001	**

** Statistically significant

Table 5.2

Tibbee Creek individual sample points total suspended solids regression analysis[1, 3]

Date	Components	Coefficients	R^2	C(p)	F Value	Pr > F	*Sig*
05/30/2011	Blue NIR Red/Blue NIR/Red	$b_0 = -80.32$ $b_1 = -0.49$ $b_2 = -1.47$ $b_3 = 288.49$ $b_4 = 84.00$	0.58	12.12	15.55	<0.0001	**
06/07/2011	Green Red/Blue	$b_0 = -3.02$ $b_1 = -0.07$ $b_2 = 24.26$	0.28	5.96	9.28	0.0004	**
06/14/2011	Blue Green/Red Red/Green	$b_0 = -693.33$ $b_1 = -0.24$ $b_2 = 231.36$ $b_3 = 568.50$	0.49	-1.38	14.67	<0.0001	**
09/10/2011	Blue Red/NIR	$b_0 = 28.62$ $b_1 = 0.18$ $b_2 = -3.06$	0.29	9.17	9.73	0.0003	**

[1] 05/18-19/2010 and 07/06-07/2010 no sample
[3] 05/18/2011 and 08/02/2011 not statistically significant
** Statistically significant

Table 5.3

Upper Pearl River individual sample points turbidity regression analysis

Date	Components	Coefficients	R^2	C(p)	F Value	Pr > F	*Sig*
06/24/2010	Green Red Green/NIR	$b_0 = 19.75$ $b_1 = -0.14$ $b_2 = 0.16$ $b_3 = -0.43$	0.84	-1.12	28.24	<0.0001	**

** Statistically significant

5.3.3 Analysis of Tibbee Creek Transects

Regression analysis of transect turbidity data and Relative reflectance yielded four stepwise equations that were statistically significant. Three out of four equations, May 18-19, 2010, May 18, 2011, and June 14, 2011, had R^2 values above 0.5 (Table 5.4), and all regression models featured one variable. In all three stepwise equations, the red band was a common variable in the regression models, either as a distinct factor or as part of a simple band ratio. Other studies linked the red band to organic suspended matter (Dekker et al., 2001; Doxaran et al. 2001; Ritchie et al, 2003). It is possible that the water at Tibbee Creek contained significant amounts of organic suspended matter. However, the organic suspended matter content was not determined for this study. Regression analysis of averaged TSS and Relative reflectance yielded three stepwise equations that were statistically significant. One out of three dataset, June 14, 2011, had an R^2 value above 0.5 (Table 5.5). NIR and NIR/red were the common variables in the regression equation. Some case studies found that leaves or fresh suspended organics were revealed in the red edge that occurs at the NIR band (Ritchie et al., 2003). Fresh suspended organics solids were not determined for this study.

5.3.4 Analysis of Upper Pearl River Transects

Regression analysis of a turbidity and Relative reflectance produced one dataset that was statistically significant. The dataset June 24, 2010 had an R^2 value above 0.5 (Table 5.6). The red band was the one variable included in the regression equation. Similar to the individual sample point analysis, the red band has been correlated to inorganic suspended matter (Dekker et al. 2001; Doxaran et al., 2001). The correlation between red band and the dataset supported the water quality parameters found in the Upper Pearl River, including TSS (Ritchie et al., 2003).

Table 5.4

Tibbee Creek transect turbidity regression analysis[1]

Date	Components	Coefficients	R^2	C(p)	F Value	Pr > F	*Sig*
05/30/2011	Blue/Red	$b_0 = 92.96$ $b_1 = -46.18$	0.46	0.00	6.69	0.0323	**
06/14/2011	NIR NIR/Red	$b_0 = 4.97$ $b_1 = 2.27$ $b_2 = -219.73$	0.83	0.00	17.17	0.0020	**
09/10/2011	Red/NIR	$b_0 = 41.48$ $b_1 = -2.08$	0.44	0.00	6.35	0.0358	**

1 07/06-07/2010, 05/30/2011, 06/07/2011, and 08/02/2011 not statistically significant
** Statistically significant

Table 5.5

Tibbee Creek transect total suspended solids regression analysis[1, 3]

Date	Components	Coefficients	R^2	C(p)	F Value	Pr > F	*Sig*
05/18/2010 05/19/2010	Blue/Red	$b_0 = 62.20$ $b_1 = 29.98$	0.66	0.00	15.15	0.0043	**
05/18/2011	Red	$b_0 = 5.83$ $b_1 = 0.15$	0.63	0.00	13.55	0.0062	**
06/14/2011	Red/Green	$b_0 = -63.22$ $b_1 = 94.41$	0.75	0.00	24.50	0.0011	**
09/10/2011	Red/NIR	$b_0 = 35.92$ $b_1 = -1.35$	0.47	0.00	7.20	0.0278	**

1 05/18-19/2010 and 07/06-07/2010 no sample
3 05/18/2011, 06/07/2011, and 08/02/2011 not statistically significant
** Statistically significant

Table 5.6

Upper Pearl River transect turbidity regression analysis

Date	Components	Coefficients	R^2	C(p)	F Value	Pr > F	*Sig*
06/24/2010	Red	$b_0 = 14.95$ $b_1 = 0.07$	0.88	0.00	22.00	0.0183	**

** Statistically significant

5.3.5 Regression Models

The stepwise equations and the statistical analysis were designed to determine association between a collection of water quality parameters data, Relative reflectance, and simple band ratios. Correlated independent variables from Tibbee Creek and Upper Pearl River were output into regression equations consisting of no more than four variables in tables 5.1 through 5.6. The output from the Upper Pearl River dataset was not used as an equation because of its smaller sample size and lack of general information. The Upper Pearl River dataset was used to test the Tibbee Creek equations outside of the original parameters. The outputs from the statistical analysis were variable coefficients, R^2 values, and the statistical significance. These values were utilized to generate a linear equation with correlated independent variables to a specific dependent variable.

The May 30, 2011 turbidity model yielded eight regression equations that were statistically significant (Tables 5.7 and 5.8). One out of eight equations, June 14, 2011 from Tibbee Creek, had an R^2 value above 0.5. The variables from the May 30, 2011 model were blue, green, NIR, and red/blue. Two regression equations, June 24, 2010 from the Upper Pearl River dataset and August 02, 2011 from Tibbee Creek were not statistically significant. The correlation between May 30, 2011 and June 14, 2011 from Tibbee Creek was established with the R^2 value above 0.5. The equation was tested successfully outside the original dataset it was generated. Testing the equation outside of Tibbee Creek using the Upper Pearl River dataset did not establish the same correlation. The turbidity regression model May 30, 2011 was considered to be usable within Tibbee Creek for this study.

The June 7, 2011 turbidity model yielded eight regression equations that were statistically significant. Two out of eight equations, June 24, 2010 from the Upper Pearl River and June 14, 2011 from Tibbee Creek, had R^2 values above 0.5 (Tables 5.9 and 5.10). The variables from the June 7, 2011 model were blue, green/red, red/green, and NIR/red. One regression equations, August 2, 2011, was not statistically significant. The correlation between June 24, 2010 from the Upper Pearl River, June 7, 2011 from Tibbee Creek, and June 14, 2011 from Tibbee Creek was established with R^2 values above 0.5. The equation was tested successfully outside the original dataset it was generated. Testing the equation outside of Tibbee Creek using the Upper Pearl River dataset established the same correlation. The June 7, 2011 equation passed both Tibbee Creek and the Upper Pearl River datasets, establishing a tested correlation that the equation can be utilized to determine turbidity for this study outside Tibbee Creek.

The June 14, 2011 turbidity model yielded eight regression equations that were statistically significant. No equations had R^2 values above 0.5 (Tables 5.11 and 5.12). The variables from the June 14, 2011 model were green/red and red/green. Three regression equations, July 6-7, 2010, August 2, 2011, and September 10, 2011 were not statistically significant. The equation did not produce R^2 values above 0.5 for either

Tibbee Creek or the Upper Pearl River. The June 14, 2011 equation was not statistically validated to determine turbidity for this study. The June 14, 2011 equation was not statistically validated to determine turbidity for this study outside of Tibbee Creek.

Table 5.7

Tibbee Creek turbidity analysis using equation from 05/30/2011

Date	Coefficients	R^2	F Value	Pr > F	*Significance*
05/18-19/2010	b_0 = 188.00 b_1 = -0.91 b_2 = 0.81 b_3 = 0.31 b_4 = -76.01	0.41	7.72	<0.0001	**
07/06-07/2010	b_0 = 28.26 b_1 = 0.00 b_2 = -0.04 b_3 = 0.01 b_4 = 9.16	0.22	3.10	0.0246	**
05/18/2011	b_0 = 15.30 b_1 = -0.05 b_2 = 0.13 b_3 = 0.24 b_4 = 1.25	0.45	9.30	<0.0001	**
06/07/2011	b_0 = -10.30 b_1 = 0.35 b_2 = -0.34 b_3 = 0.04 b_4 = 27.81	0.45	9.20	<0.0001	**
06/14/2011	b_0 = -4.56 b_1 = -0.07 b_2 = 0.01 b_3 = 0.30 b_4 = 38.35	0.60	17.09	<0.0001	**
08/02/2011	b_0 = 12.03 b_1 = 0.08 b_2 = -0.08 b_3 = 0.02 b_4 = 9.21	0.06	0.68	0.6114	+
09/10/2011	b_0 = 57.04 b_1 = -0.31 b_2 = 0.31 b_3 = 0.62 b_4 = -42.25	0.24	3.49	0.0145	**

** Statistically significant
+ Reject null hypothesis

Table 5.8

Upper Pearl River turbidity analysis using equation from 05/30/2011

Date	**Coefficients**	**R^2**	**F Value**	**Pr > F**	***Significance***
06/24/2010	$b_0 = 15.56$ $b_1 = 0.06$ $b_2 = -0.03$ $b_3 = 0.01$ $b_4 = 2.33$	0.33	2.57	0.0692	+

\+ Reject null hypothesis

Table 5.9

Tibbee Creek turbidity analysis using equation from 06/07/2011

Date	Coefficients	R^2	F Value	Pr > F	*Significance*
05/18-19/2010	$b_0 = 19.21$ $b_1 = -0.14$ $b_2 = 61.70$ $b_3 = 45.35$ $b_4 = -35.41$	0.36	6.18	0.0005	**
07/06-07/2010	$b_0 = 53.85$ $b_1 = -0.04$ $b_2 = -12.17$ $b_3 = -5.23$ $b_4 = -1.94$	0.21	3.07	0.0254	**
05/18/2011	$b_0 = -141.49$ $b_1 = 0.16$ $b_2 = 73.10$ $b_3 = 67.80$ $b_4 = 32.10$	0.45	9.20	<0.0001	**
05/30/2011	$b_0 = -87.09$ $b_1 = -0.03$ $b_2 = 29.29$ $b_3 = 103.55$ $b_4 = -5.73$	0.25	3.79	0.0097	**
06/14/2011	$b_0 = -498.37$ $b_1 = -0.04$ $b_2 = 169.53$ $b_3 = 380.53$ $b_4 = 6.85$	0.67	23.13	<0.0001	**
08/02/2011	$b_0 = -13.14$ $b_1 = 0.02$ $b_2 = 9.74$ $b_3 = 23.58$ $b_4 = 1.47$	0.07	0.86	0.4936	+
09/10/2011	$b_0 = 803.02$ $b_1 = 0.07$ $b_2 = -365.61$ $b_3 = -427.54$ $b_4 = 45.37$	0.27	4.15	0.0061	**

** Statistically significant
+ Reject null hypothesis

Table 5.10

Upper Pearl River turbidity analysis using equation from 06/07/2011

Date	Coefficients	R^2	F Value	Pr > F	*Significance*
06/24/2010	b_0 = -122.39 b_1 = 0.05 b_2 = 67.59 b_3 = 69.58 b_4 = -0/15	0.54	5.91	0.0026	**

** Statistically significant

Table 5.11

Tibbee Creek turbidity analysis using equation 06/14/2011

Date	Coefficients	R^2	F Value	Pr > F	*Significance*
05/18-19/2010	b_0 = 63.18 b_1 = 38.50 b_2 = -6.46	0.26	8.14	0.0009	**
07/06-07/2010	b_0 = 42.33 b_1 = -8.27 b_2 = -4.80	0.04	0.92	0.4049	+
05/18/2011	b_0 = 310.00 b_1 = -173.17 b_2 = -108.76	0.21	6.28	0.0038	**
05/30/2011	b_0 = -83.90 b_1 = 27.72 b_2 = 94.93	0.24	7.60	0.0014	**
06/07/2011	b_0 = -235.20 b_1 = 87.14 b_2 = 171.30	0.35	12.74	<0.0001	**
08/02/2011	b_0 = 1.21 b_1 = 5.85 b_2 = 15.85	0.06	1.37	0.2644	+
09/10/2011	b_0 = 641.44 b_1 = -289.58 b_2 = -325.09	0.01	0.25	0.7814	+

* Statistically significant
\+ Reject null hypothesis

Table 5.12

Upper Pearl River turbidity analysis using equation from 06/14/2011

Date	**Coefficients**	**R^2**	**F Value**	**Pr > F**	***Significance***
06/24/2010	b_0 = -77.07 b_1 = 43.95 b_2 = 51.60	0.38	6.65	0.0055	**

** Statistically significant

The May 30, 2011 TSS model yielded three regression equations that were statistically significant. No equations had R^2 values above 0.5 (Table 5.13). The variables from the May 30, 2011 regression equation were blue, NIR, red/blue, and NIR/red. The TSS regression equation did not produce R^2 values above 0.5 for Tibbee Creek, and the parameter was not tested on the Upper Pearl River dataset. The May 30, 2011 equation was not statistically validated to determine TSS for this study.

The June 14, 2011 TSS model yielded three regression equations that were statistically significant. No dataset had R^2 values above 0.5 (Table 5.14). The variables from the June 14, 2011 regression equation were blue, green/red, and red/green. One regression equation, September 10, 2011, was not statistically significant. The TSS regression equation did not produce R^2 values above 0.5 for Tibbee Creek, and the parameter was not tested on the Upper Pearl River dataset. The June 14, 2011 equation was not statistically validated to determine TSS for this study.

Table 5.13

Tibbee Creek total suspended solids analysis using equation 05/30/2011[1, 3]

Date	**Coefficients**	**R^2**	**F Value**	**Pr > F**	***Significance***
06/07/2011	b_0 = -0.36 b_1 = -0.08 b_2 = -0.04 b_3 = 21.42 b_4 = 0.54	0.28	4.36	0.0046	**
06/14/2011	b_0 = 13.75 b_1 = -0.26 b_2 = 1.90 b_3 = 53.79 b_4 = -185.22	0.47	9.83	<0.0001	**
09/10/2011	b_0 = -6.50 b_1 = 0.12 b_2 = 0.11 b_3 = 5.85 b_4 = 78.39	0.27	4.17	0.0059	**

[1] 5/18-19/2010 and 07/06-07/2010 no sample
[3] 05/18/2011 and 08/02/2011 not statistically significant
** Statistically significant

Table 5.14

Tibbee Creek total suspended solids analysis using equation 06/14/2011[1, 3]

Date	Coefficients	R^2	F Value	Pr > F	*Significance*
05/30/2011	b_0 = -42.16 b_1 = 0.06 b_2 = 3.40 b_3 = 66.17	0.18	3.37	0.0262	**
06/07/2011	b_0 = -227.24 b_1 = -0.10 b_2 = 82.80 b_3 = 182.16	0.20	3.91	0.0143	**
09/10/2011	b_0 = -23.24 b_1 = -0.03 b_2 = 3.12 b_3 = 54.65	0.06	0.91	0.45	+

1 05/18-19/2010 and 07/06-07/2010 no sample
3 05/18/2011 and 08/02/2011 not statistically significant
** Statistically significant
+ Reject null hypothesis

The May 18-19, 2010 turbidity transect model yielded four regression equations that were statistically significant. Three out of four equations, June 24, 2010 from the Upper Pearl River, May 18, 2011, and June 14, 2011 from Tibbee Creek, had R^2 values above 0.5 (Table 5.15). The variable from the May 18-19, 2010 regression equation was blue/red. Two of the regression equations, June 24, 2010 from the Upper Pearl River and September 10, 2011 from Tibbee Creek, were not statistically significant. The correlation between May 18-19, 2010, June 24, 2010, May 18, 2011, and June 14, 2011 was established with R^2 values above 0.5. The equation was tested successfully outside the original dataset. Testing the equation using the Upper Pearl River dataset established the same correlation. Even with the correlation, the average turbidity regression equation from May 18-19, 2010 was not considered to be usable outside of Tibbee Creek for this study due to the rejected significance of the Upper Pearl River dataset.

The May 18, 2011 turbidity transect model yielded four regression equations that were statistically significant. Three out of four equations, May 18-19, 2010 from Tibbee Creek, June 24, 2010 from the Upper Pearl River, and June 14, 2011 from Tibbee Creek, had R^2 values above 0.5 (Table 5.16). The variable from the May 18, 2011 regression equation was red. One of the regression equations, September 10, 2011 from Tibbee Creek, was not statistically significant. The correlation between May 18-19, 2010, June 24, 2010, May 18, 2011, and June 14, 2011 was established with R^2 values above 0.5. The equation was tested successfully outside the original dataset. Testing the equation using the Upper Pearl River dataset established a stronger correlation. The equation passed both Tibbee Creek and the Upper Pearl River datasets, establishing a tested correlation that the equation can be utilized to determine average turbidity for this study outside Tibbee Creek.

The June 14, 2011 turbidity transect model yielded three regression equations that were statistically significant. One out of three equations, June 24, 2010 from the Upper Pearl River, had an R^2 value above 0.5 (Table 5.17). The variable from the June 14, 2011 regression equation was red/green. Two of the regression equations, June 24, 2010 from the Upper Pearl River and May 18, 2011 from Tibbee Creek, were not statistically significant. The correlation between June 24, 2010 and June 14, 2011 was established with R^2 values above 0.5. The equation was tested unsuccessfully using the Tibbee Creek dataset, where the original dataset was generated, yet when tested using the Upper Pearl River dataset, the equation established correlation. Even with the correlation, the averaged turbidity regression equation from June 14, 2011 was not considered because it failed to test inside Tibbee Creek parameters, and it was rejected as statistically significant.

The June 14, 2011 TSS transect model yielded two regression equations that were statistically significant. One out of the two equations, September 10, 2011 had an R^2 value above 0.5 (Table 5.18). The variables from June 14, 2011 regression equation were NIR and NIR/red. One of the regression equations, May 30, 2011, was not statistically significant. The correlation between June 14, 2011 and September 10, 2011 was established with R^2 values above 0.5. The equation was tested successfully outside the equation's original dataset. The TSS parameter was not tested on the Upper Pearl River dataset. The June 14, 2011 equation was not statistically validated to determine TSS for this study outside of Tibbee Creek.

The two successful models, June 7, 2011 for turbidity, and May 30, 2011 for TSS provided an equation that was used to output values of either water quality parameter (Equation 5.1 and Equation 5.2). The equations provide turbidity and TSS with specific components and component coefficients.

$$\text{Turbidity} = -498.37 - 0.04(\text{BLUE}) + 169.53\left(\frac{\text{GREEN}}{\text{RED}}\right) + 380.53\left(\frac{\text{RED}}{\text{GREEN}}\right) + 6.85\left(\frac{\text{NIR}}{\text{RED}}\right) \tag{5.1}$$

$$\text{TSS} = 13.75 - 0.26(\text{BLUE}) + 1.90(\text{NIR}) + 53.79\left(\frac{\text{RED}}{\text{BLUE}}\right) - 185.22\left(\frac{\text{NIR}}{\text{RED}}\right) \tag{5.2}$$

Table 5.15

Turbidity analysis using the transect equation from 05/18-19/2010[1]

Date	Coefficients	R^2	F Value	Pr > F	***Significance***
05/18/2011	$b_0 = 73.92$ $b_1 = -41.00$	0.51	8.17	0.0212	**
06/14/2011	$b_0 = 29.82$ $b_1 = -11.91$	0.50	8.10	0.0216	**
09/10/2011	$b_0 = 21.69$ $b_1 = 4.10$	0.22	2.28	0.1696	+
06/24/2010[3]	$b_0 = 27.70$ $b_1 = -6.01$	0.66	5.86	0.0941	+

1 07/06-07/2010, 05/30/2011, 06/07/2011, and 08/02/2011 not statistically significant
3 Upper Pearl River dataset
** Statistically significant
+ Reject null hypothesis

Table 5.16

Turbidity analysis using the transect equation from 05/18/2011[1]

Date	Coefficients	R^2	F Value	Pr > F	***Significance***
05/18-19/2010	$b_0 = 128.42$ $b_1 = -0.16$	0.53	9.25	0.0160	**
06/14/2011	$b_0 = -5.21$ $b_1 = 0.14$	0.63	13.66	0.0061	**
09/10/2011	$b_0 = 35.92$ $b_1 = -1.35$	0.12	1.05	0.3362	+
06/24/2010[3]	$b_0 = 14.95$ $b_1 = 0.07$	0.88	22.00	0.0183	**

1 07/06-07/2010, 05/30/2011, and 08/02/2011 not statistically significant
3 Upper Pearl River dataset
** Statistically significant
+ Reject null hypothesis

Table 5.17

Turbidity analysis using the transect equation from 06/14/2011[1]

Date	Coefficients	R^2	F Value	Pr > F	*Significance*
05/18-19/2010	$b_0 = 158.16$ $b_1 = -62.20$	0.47	7.13	0.0284	**
05/18/2011	$b_0 = -62.90$ $b_1 = 87.61$	0.26	2.79	0.1331	+
06/24/2010[3]	$b_0 = 5.63$ $b_1 = 13.66$	0.61	4.72	0.1182	+

[1] 07/06-07/2010, 05/30/2011, 06/07/2011, 08/02/2011, and 09/10/2011 not statistically significant
[3] Upper Pearl River dataset
** Statistically significant
+ Reject null hypothesis

Table 5.18

Total suspended solids analysis using the transect equation from 06/14/2011[1, 3]

Date	Coefficients	R^2	F Value	Pr > F	*Significance*
05/30/2011	$b_0 = 33.60$ $b_1 = 0.85$ $b_2 = -135.23$	0.35	1.86	0.2250	+
09/10/2011	$b_0 = 9.53$ $b_1 = 0.67$ $b_2 = 46.10$	0.58	4.83	0.0480	**

[1] 05/18-19/2010 and 07/06-07/2010 no sample
[3] 05/18/2011, 06/07/2011, and 08/02/2011 not statistically significant
** Statistically significant
+ Reject null hypothesis

5.3.6 Removal of Potential Outliers

Removal of potential outliers from turbidity analysis caused R^2 values to increase up to 0.5 of the original R^2 values collected from statistical analysis. Removal of potential outliers from TSS analysis caused R^2 values to decrease during the individual sample point analysis, but to increase during the regression modeling (Figure 5.9 and Figure 5.10).

Turbidity equations observed an increase in R^2 values when marked potential outlying sample points were removed. The June 7, 2011 equation using its own dataset increased by 0.15. The June 14, 2011 equation using the June 7, 2011 dataset increased by 0.51. June 7, 2011 equation using the June 14, 2011 dataset increased by 0.15. Total suspended solids equations observed no increase in an R^2 value from the May 30, 2011 equation. The R^2 dropped 0.01, essentially not changing. However, the May 30, 2011 equation using the June 14, 2011 dataset saw an increase 0.10 (Table 5.19).

The results of the tests confirmed that the anomalous data affected the turbidity regression equations but did not confirm the same for TSS. Studies have shown the optical reflectance properties of turbidity to correlate with remote sensing data in a regression analysis (Dekker et al., 2003). Research has linked the correlation with specific suspended solids such as organic suspend solids (Doxaran et al. 2001; Ritchie et al, 2003).

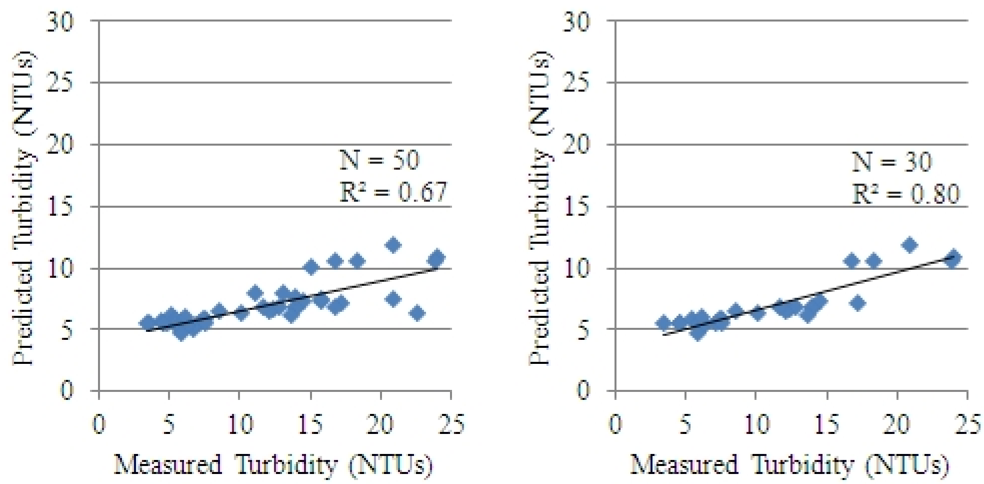

Figure 5.9 Measured and predicted turbidity values on a regression line of June 14, 2011 samples being tested with the June 7, 2011 stepwise equation before (left) with an $R^2 = 0.67$ and after (right) potential outliers were removed with an $R^2 = 0.80$

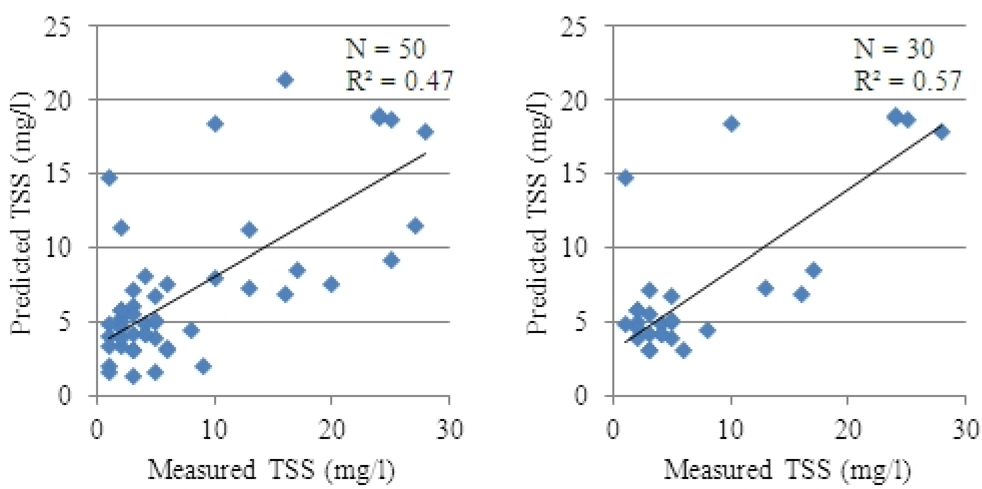

Figure 5.10 Measured and predicted TSS values on a regression line of June 14, 2011 samples being tested with the May 30, 2011 stepwise equation before (left) with an $R^2 = 0.47$ and after (right) potential outliers were removed with an $R^2 = 0.57$

Table 5.19

Removal of potential outliers found in visual analysis from turbidity and TSS regression models that used all 50 sample points

Tested Parameter	Before Removal	After Removal
06/07/2011 turbidity equation using 06/14/2011 dataset	$R^2 = 0.67$ N = 50	$R^2 = 0.80$ N = 30
05/30/2011 TSS equation using 06/14/2011 dataset	$R^2 = 0.47$ N = 50	$R^2 = 0.57$ N = 30

[1]R^2 is the coefficient of determination
N is the sample size

5.4 Effect of Stream Flow Conditions

Gauge height data, typically considered a surrogate for stream flow data, was used to examine the effect on turbidity and TSS data, and to some extent, on the interpretation of imagery data. Figure 5.11 shows the gauge height in Tibbee Creek between May 1 and September 30, 2011, along with water quality parameters and R^2 values of the regression models for three sampling dates. Turbidity and TSS values on May 18 and September 10 were higher than on June 7. The height of the stream was higher prior to sampling on May 18 (10.6 ft.) and September 10 (14.75 ft.) than on June 7 (9.8 ft.). Gauge height was fairly stable several days before the sample collection on June 7, possibly contributing to low suspended solids. On the other hand, significant decrease in gauge height several days prior to sample collection on May 18 (-0.8 ft.) and September 10 (-4.95 ft.) may have contributed to mixing of sediment in the stream, and consequently higher turbidity and TSS. Studies have concluded that suspended sediment discharge increases as flow rate increases potentially due to the movement of sediment load in the creek (Fangmeier et al., 2006; Ponce, 1989; Wetzel, 2001). The movement of sediment in the creek can cause suspension of the sediment leading to higher TSS and turbidity values in collected water samples (Fangmeier et al., 2006). Regression models for May 18 and September 10 had R^2 values of 0.47 and 0.37, respectively, while June 7 had a relatively high R^2 value 0.70. The results suggest that the timing of sample collection can affect water quality parameter measurements and the corresponding model developed using imagery data.

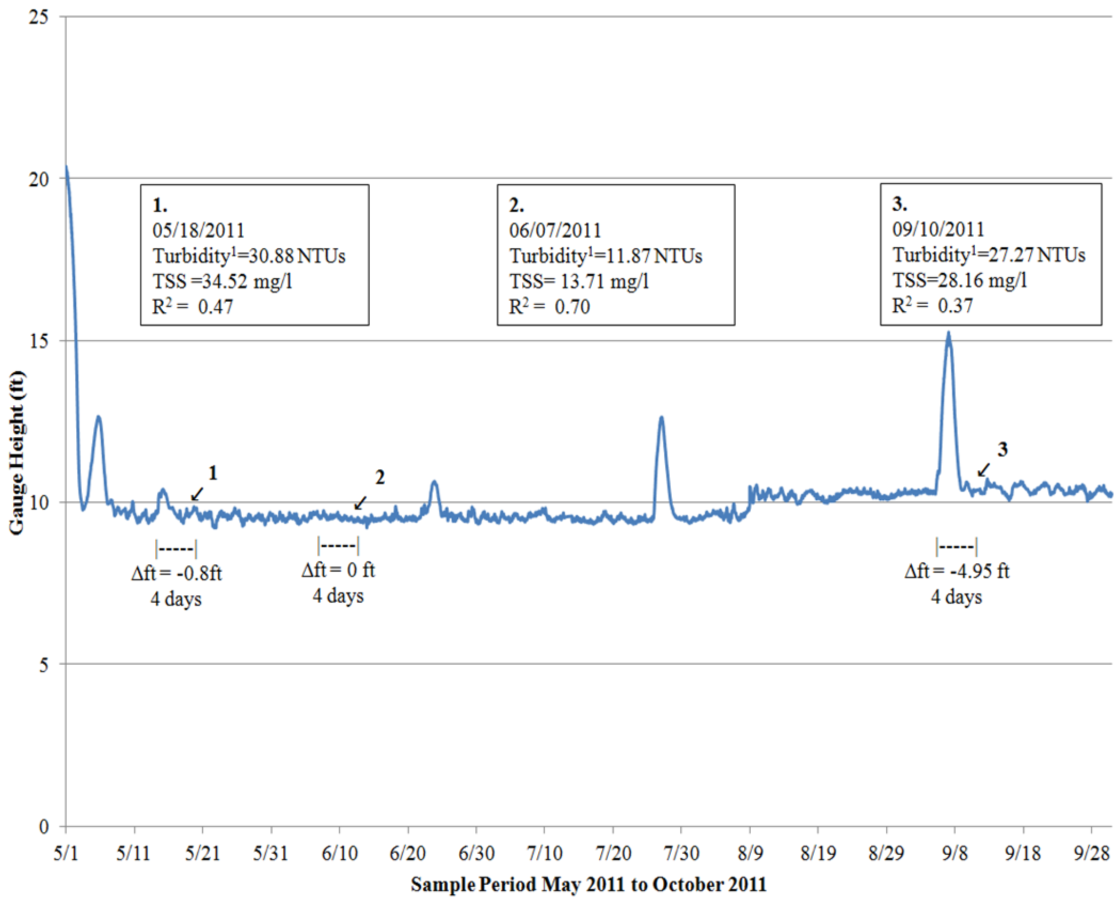

Figure 5.11 The association between gauge height and decrease in correlation between the statistical parameters of this study over three dates, May 18, 2011, June 7, 2011, and September 10, 2011.
[1]Averaged turbidity and TSS at the specified date.

CHAPTER VI

DISCUSSION

6.1 Discussion of the Results

6.1.1 Regression Models

Regression models of remotely sensed areas can provide a quick and efficient way to determine the healthiness of water body. The regression models showed the predicted levels of turbidity and TSS throughout a segment of a water body, based on specific bands and band ratios. Modeling required a closer look into former case studies dealing with specific bands and band ratios. The use of aerial imagery and application of regression models allows the study area to be much larger than conventional grab sampling could ever provide. Although there were notable variations and sometimes weak correlation in the models observed in this study, the progression to map a moving water body was successful by the means of the given study parameters. The bands and band ratios that made up the components of the turbidity model were explained through former case studies. The blue band in both models was potentially linked to the lack of atmospheric correction in the imagery (Bhargava et al., 1991; Sudduth et al., 2005). The NIR band in the TSS model was linked to organics suspended solids in the sample columns. The band ratios, which were found in case studies to remove eccentricities and normalize the data, allowed potentially affected bands to be utilized. These bands have been found to be linked to both organic and inorganic suspended solids (Dekker et al., 2001; Doxaran et al., 2001). The use of band ratios proved to be successful when considering the output of the model and the percentage of the model containing the ratios (Curran et al., 1988; Koponen et al., 2002; Wass et al., 1997). The turbidity model provided a relatively accurate portrait of the study area with a scale between 5 NTUs to 25 NTUs (Figure 6.1). To be able to visually analyze turbidity over a large area is considered a powerful tool in the regulatory and environmental science fields (Ritchie et al., 2003).

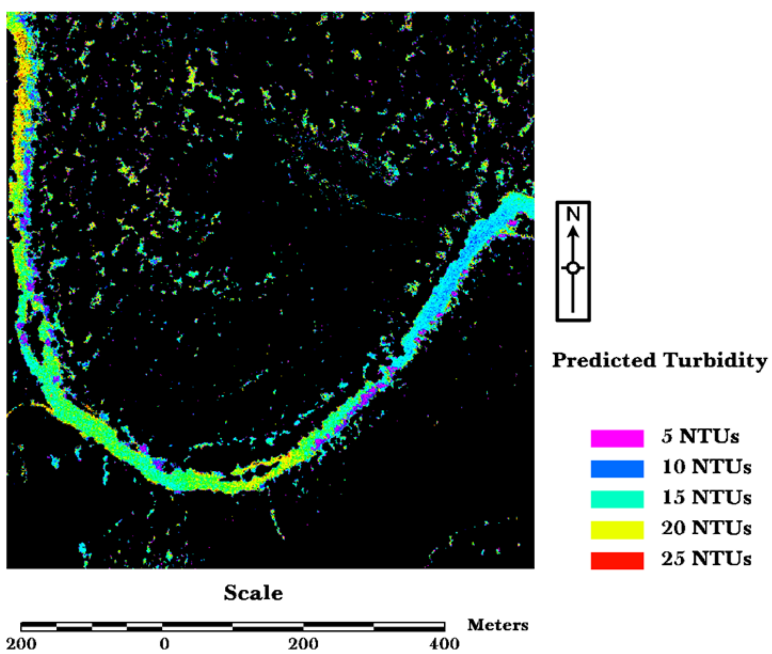

Figure 6.1 The predicted turbidity levels of the study are based on June 7, 2011 regression model and June 14, 2011 imagery (Scale: 1:2,500).

Similar to the turbidity model, the TSS model although it exhibited high variability also provided a successful look at a large area. The TSS model provided a relatively accurate portrait of the study area with a scale between 10 mg/l to 60 mg/l (Figure 6.2). Both turbidity and TSS models are prime examples of how imagery and subsequent regression models could potentially help provide agencies and companies with a quick and efficient way to sample water bodies.

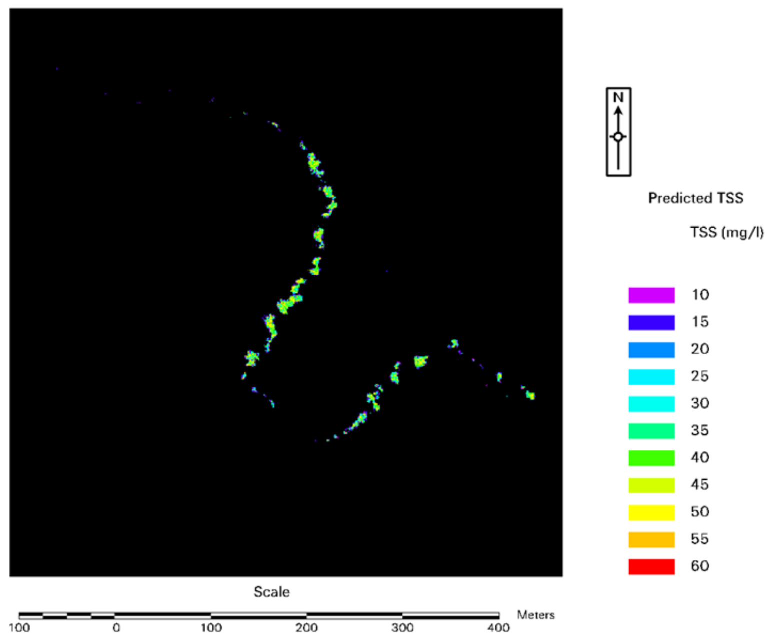

Figure 6.2 The predicted TSS levels based on May 30, 2011 regression model and June 14, 2011 imagery (Scale: 1:5,500).

6.1.2 Removal of Potential Outliers

There was an increase in R^2 values by removing the outliers. This further supported the visual analysis aspect of this study prior to statistical analysis. In some case studies, areas of water bodies were assumed constant. Due to Tibbee Creek always being in motion, no areas could have been assumed. In some studies, the authors removed some samples as outliers based on parameters, such as R^2, generated after statistical modeling (Karabulut and Ceylan, 2005; Song et al., 2011). No other case studies showed a removal of potential outliers within water bodies during visual analysis, before modeling. The removal of potential outliers was cited in research to improve environmental anomalies (Ott and Longnecker, 2010). While it did lower the sample number and can potentially be viewed as biased, the removal of any points that failed visual criteria, helped with any potential problems that were present in the imagery.

6.1.3 Gauge Height Comparison

Consideration of gauge height in this study was an approach commonly found in water quality analysis (Wetzel, 2001). The issue with inconsistent records prevented this study to characterize models around that type of data. It was noted that the sample of results did show some links between lower correlation of relative reflectance and water quality parameters when the creek was disturbed beyond normal circumstances, such as a rain events.

6.2 Uniqueness of the Study and Results

This study was unique compared to all other similar research in that it provided low cost high resolution imagery over multiple dates. The high resolution aerial imagery provided a better assessment of the area. Most available low cost imagery could not be used for smaller creeks and streams due to its low resolution.

Multiple dates with multiple images and multiple parameters proved an unbiased way to create a predictive model. The large collection of sampled data determined the ability to develop an appropriate predictive model, and multiple dates allowed for consideration of the removal of potential outliers. Without the large sample datasets, the removal of the outliers could have prevented a correlation between the relative reflectance values and the water quality parameters.

CHAPTER VII

CONCLUSION

7.1 General Conclusion

The main goal of this study was to demonstrate the application of aerial imagery as a tool in detecting water quality indicators in a three mile segment of Tibbee Creek in Clay County, Mississippi. Water samples from 10 transects were collected per sampling date over two periods from May 2010 to October 2010 (14 sampling dates), and from May 2011 to October 2011 (11 sampling dates). Temperature and DO levels were measured at each point, and water samples were tested for turbidity and TSS. High resolution multispectral aerial images that covered the study area were obtained to capture spatial differences. Stepwise regression analysis was used to select a model that relates Relative reflectance extracted from aerial images and specific water quality parameters. A regression model developed for turbidity as a function of Relative reflectance using June 7, 2011 data had an R^2 equal to 0.70, and it was used to predict turbidity for other dates. The best model for predicting turbidity from the June 7, 2011 equation was June 14, 2011 which had an R^2 of 0.67. A model developed for TSS using May 30, 2011 data had an R^2 of 0.58, and it was used to predict TSS for other dates. The best model for predicted TSS from the May 30, 2011 equation was June 14, 2011 which had an R^2 of 0.47. The removal of anomalous data points from imagery issues such as shadows, improved the accuracy of the regression models. Turbidity data showed increased accuracy of the regression models by as much as 0.5, while TSS showed improved accuracy of the regression model by only 0.1.

High resolution multispectral aerial imagery can be very useful in the development of predictive models for water quality assessment over a large area. This study shows that a regression model developed for a sampling date can be used to predict specific water quality parameters on a different date. However, the development of an appropriate predictive model for water quality assessment based on the relative reflectance of aerial imagery are affected by two major factors, namely, quality of imagery and time of sampling. The factors listed also have important implications on the development of TMDLs for nutrient and biological impairment because these are typically based on one or two sampling dates. If all aspects of this study are considered and implemented, the sampling data needed for TMDLs could potentially be completed by a remote sensing source rather than by typical *in situ* measurements.

7.2 Recommendations for Future Research

This study highlighted the importance of good quality image data and physical parameters that can be used for water quality assessment. Researchers must be cognizant of the impact of the time of water sample collection as well as the limitations of using imagery, and problems introduced during image acquisition. Recommendations for future water quality and remote sensing studies include refinement of sampling through imagery and water quality data collection. Stream flow velocity must be considered in determining when to collect water sample, and sampling should be avoided after a storm event. Acquisition of aerial imagery should be made concurrent with the collection of water quality parameters. Caution must be exercised in using a regression model developed for a particular location and set of conditions, and applying it to a different set of conditions.

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