Nonpoint Source Pollution Risk Mapping for Alabama’s Big Creek Lake

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ABSTRACT

Big Creek Lake is the primary water supply for Mobile, Alabama. Management of the watershed is important because nonpoint source (NPS) pollution can introduce contaminants into the lake. After the Mobile Area Water and Sewer System (MAWSS) expressed a need for a land suitability assessment to aid in mitigating NPS pollution in the watershed, we worked to assist them in mapping potential sources of NPS pollution there. First, we created a system for rating the relative contributions of various land cover and soil types to NPS pollution in the watershed. Then, we utilized land use/land cover information generated from ASTER satellite imagery along with GIS soil erodibility/organic content data to perform ordinal combinations and derive relative NPS pollution risk maps. The final map indicated that the majority of the watershed has low potential for NPS pollution, but several areas (predominantly agriculture and urban) have much higher potential and should receive priority for mitigation.

Key Words: GIS, ASTER, remote sensing, nonpoint source pollution, watershed

INTRODUCTION

According to the U.S. Environmental Protection Agency (EPA), our country’s largest source of water quality problems continues to be nonpoint source (NPS) pollution (EPA 2012a). Defined as any source of water pollution not meeting the legal definition of a point source within the Clean Water Act, NPS pollution is a broadly descriptive category that includes many diffuse sources of aquatic contaminants carried by rainfall or snowmelt runoff (EPA 2012b). Although sediment and nutrients are the most common NPS pollutants, pesticides, pathogens, salts, oil, grease, toxic chemicals, and heavy metals are also widespread (EPA 2012b). Many sources exist for NPS pollutants, but
the most recent National Water Quality Inventory found agriculture to be the leading contributor to water quality impairments, particularly within rivers and lakes. The inventory also reported urban area runoff to be the largest pollutant source for estuaries (EPA 2012a). These findings agree with Basnyat et al. (2000), Ribaudo et al. (2001), Tang et al. (2005), and Dowd, Press, and Huertos (2008) which identified agricultural activities and highly impervious urban areas as major sources of NPS pollution. Agriculture produces high amounts of NPS pollutants because the associated fertilizer, pesticide, and sediment (loosened by tilling) easily run off into streams (Dowd, Press, and Huertos 2008). Urban areas, on the other hand, generate high amounts of NPS pollution because their expanded coverage of impervious surfaces hampers the absorption of rainfall (Basnyat et al. 2000; Esen and Uslu 2008). The result is excessive stormwater discharge that can easily transport pollutants into nearby waterways. Although elimination of NPS pollution sources may not always be feasible, mitigation strategies can be greatly enhanced by gaining increased understanding of NPS pollution sources and transport processes. Fortunately, remote sensing technologies, computer models, and geographic information systems (GIS) provide the tools necessary to achieve that understanding.

In our study, we focused on analyzing and mapping NPS pollution risk in the watershed of Big Creek Lake (also known as J.B. Converse Reservoir) in Mobile County, Alabama (Fig. 1 and Fig. 2). Formed by the damming of Big Creek, a tributary of the Escatawpa River, the reservoir now serves as the drinking water source for the city of Mobile and its surrounding communities. The Mobile Area Water and Sewer System (MAWSS) manages the lake and operates a pumping station and two filtration facilities.
that provide treated water to Mobile (Journey and Gill 2001). Although the lake itself is only 3,600 acres, the watershed draining into it covers approximately 65,920 acres or 103 square miles (MAWSS 2011; Journey and Gill 2001). The lake is fed by seven major tributaries with the greatest inflow coming from Big Creek, which flows into the northernmost inlet of the lake (Fig. 3). Other lesser tributaries either feed into Big Creek before it reaches the reservoir or directly into other inlets of the lake (Journey and Gill 2001). The watershed flowing into these tributaries is predominantly forested but also has substantial acreage of scrub/shrub (young or stunted trees), pasture, developed, and cultivated land (Fig. 3 and Fig. 4). The majority of developed land within the watershed is residential (Journey and Gill 2001). Local topography within the watershed results generally in gentle slopes less than one degree facing southwest toward the coast, although steeper slopes of four degrees also exist in many areas (Journey and Gill 2001).

The four major soil associations within the watershed are Troup-Heidel-Bama, Troup-Smithton-Bibb, Notcher-Saucier-Malbis, and Esto-Troup-Benndale, with the first two covering 77.8% and 21.3% of the watershed respectively (Journey and Gill 2001).

In recent years, a great deal of controversy has surrounded the lake, primarily regarding a three-year court battle between MAWSS and the Alabama Department of Transportation (ALDOT) over a new eight mile stretch of U.S. Highway 98 currently under construction near the northern end of the lake to relieve traffic congestion (Fig. 3). MAWSS sued ALDOT in 2007, claiming that the construction project was contributing to increased erosion and transport of sediment runoff that would enter the reservoir and compromise drinking water quality. Due to the lawsuit, further construction of the highway was halted until the two parties reached a settlement in May 2010. The resolution included stipulations that ALDOT pay a monetary settlement to

Figure 2: Aerial photograph of Big Creek Lake, Alabama, looking north from the southern end of the lake. Pilot: Jason Jones. Photographer: Marco Allain. Photo taken in June 2009.
Figure 3: Big Creek Lake watershed land use/land cover derived from NOAA 2006 Coastal Change Analysis Program (CCAP) data. Note the location of the controversial addition to U.S. Hwy 98.
MAWSS and implement mitigation measures such as storm water containment systems and bridge design improvements (ALDOT 2010; MAWSS 2010). The controversy served to raise public awareness regarding the importance of responsible land use management within the watershed.

We initiated our study based on MAWSS’ interest in identifying areas within the watershed that are potential sources of NPS pollution. Using satellite imagery and GIS soil data, our goal was to provide them with map products identifying locations with the highest potential for being NPS pollution sources. MAWSS can use these maps to focus mitigation efforts on areas with the highest risk.

**LITERATURE REVIEW**

Soil erosion is one of the primary sources of NPS pollution. Although aerial photography was historically used in erosion studies, now satellite imagery is widely used. Both optical sensors such as the Landsat and SPOT (Système Pour l’Observation de la Terre) systems and synthetic aperture radar (SAR) platforms like RADARSAT and ENVISAT have been used. Due to the typical small size of erosion features and the limited spatial resolution of satellite data, many studies have focused on assessment of eroded areas rather than detection of individual erosion features (Vrieling 2005). Methods used have included visual image interpretation, spectral data classification, correlation of field observations with spectral reflectance values, and change detection of surface soil conditions. Efforts have also been made to use remote sensing for detecting the downstream consequences of erosion, and several studies have found a significant relationship between in situ observations of suspended sediment in inland water bodies and atmospherically corrected satellite measurements of spectral reflectance (Vrieling 2005). Unfortunately, however, these relationships cannot be easily transferred to other geographic regions due to the way that variations in sediment characteristics influence water reflection (Vrieling 2005).

Other studies have focused on remote sensing assessments of erosion controlling factors such as topography, soil, and vegetation. With regard to topography, some studies have relied on visual interpretation of landforms evident from satellite imagery, but most spatial erosion models require a digital elevation model (DEM) as input. However, even though DEMs can be derived from
stereo optical imagery (e.g. SPOT), few researchers have actually used satellite-derived DEMs for erosion studies (Vrieling 2005). Regarding soil, optical imagery has been used to map and classify soil patterns so that a relationship between soil classes and their erodibility (susceptibility to erosion agents) could be established with published equations, but a limiting factor to this approach is the interference of vegetation with measuring the soil's spectral reflectance (Vrieling 2005).

While soil types and erodibility have been studied with optical data, SAR data has been used to analyze soil moisture, texture, and surface roughness (Vrieling 2005).

In addition to topography and soil, vegetation is another erosion controlling factor that can be studied with remote sensing. In fact, in the majority of published remote sensing/modeling studies related to soil erosion, vegetation was the only parameter measured through remote sensing. Data on additional factors is typically obtained through other sources such as soil maps, DEMs, and field measurements (Vrieling 2005). Mapping vegetation types that differ in their ability to limit soil erosion is commonly achieved through the classification of satellite imagery, and this classification is typically performed through visual image interpretation or through an automated approach such as unsupervised classification (Vrieling 2005). Additionally, a cover and management factor (C-factor) has often been used when accounting for the influence of vegetation on erosion. Wischmeier and Smith (1978) defined C-factor as the “ratio of soil loss from land cropped under specified conditions to the corresponding clean-tilled continuous fallow” (Vrieling 2005, 8). Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) or various improved derivations of it adjusted for soil reflectance have also been frequently used in vegetation studies (Vrieling 2005). After data on erosion controlling factors have been collected through remote sensing or other sources, they often are integrated and evaluated through the use of computer simulation models (Vrieling 2005). Our review of the literature found both modeling and GIS to be primary components in the majority of NPS pollution studies. Here, we provide a synopsis of literature involving usage of models alone as well as studies where models and GIS were integrated.

Corbett et al. (1997) used the agricultural nonpoint source runoff (AGNPS) model to compare runoff volumes, flow rates, and sediment loads between a forested watershed and an urban watershed that had similar soil and slope characteristics in South Carolina. Developed by the USDA, AGNPS is a tool for analyzing single-event rainfall scenarios and evaluating how management decisions impact a watershed (Bhuyan et al. 2003; He 2003). It uses a modified version of the universal soil loss equation and a runoff equation from the Soil Conservation Service (Corbett et al. 1997). Their simulations showed that the runoff ratio (the percentage of rainfall volume which becomes runoff) was on average 14.5% higher in the urban watershed than in the forested watershed, and runoff volumes increased linearly with impervious surface area (Corbett et al. 1997). Approaching the topic of NPS pollution from a policy perspective, Ribaudo et al. (2001) used the U.S. Agricultural Sector Mathematical Programming (USMP) model to compare the effectiveness of reducing fertilizer usage and restoring wetland acreage for reducing cropland nutrient loads. Fertilizer reduction was found to be a more cost-effective reduction strategy than wetland restoration (Ribaudo et al. 2001). Besides the ones just described, numerous other models have also been used in NPS pollution studies. An extensive overview of NPS pollution models currently being used in China (many of which were developed in the U.S.) is provided by Shen et al. (2012). These include the AGNPS, AnnAGNPS (Annualized AGNPS), ANSWERS (Areal Non-point Source Watershed Environment Response Simulation, CREAMS (Chemicals, Runoff, and Erosion from Agricultural Management Systems), HSPF (Hydrological Simulation Program-FORTRAN), SWAT (Soil
and Water Assessment Tool), and IMPULSE (Integrated Model of Non-point Source Pollution Processes) models as well as the export coefficient modeling and hydrograph separation statistical methods (Shen et al. 2012). Another model found in the literature is the Erosion Model for Mediterranean Regions (SEMMED), which is the only soil erosion model developed specifically to be used with satellite remote sensing data (Vrieling 2005).

Although modeling is sometimes used as a standalone approach for studying NPS pollution, we have found that most studies combine modeling with the use of GIS and/or remote sensing for a more integrated approach. For example, one study used AVNPSM (ArcView nonpoint source pollution modeling), a Windows-based interface between ArcView GIS and AGNPS, to investigate the impacts of land use change on NPS pollution in a watershed located in southwestern Michigan (He 2003). GIS data inputs included soil, climate, a DEM, land use/land cover (LULC), hydrography, and management practices. Model outputs showed that urban growth will likely increase surface runoff, peak flow, and soil erosion within the watershed (He 2003). Similarly, another study used AGNPS along with an ArcInfo GIS interface to estimate nutrient loadings for sub-watersheds of the Cheney Reservoir in Kansas during selected storm events (Bhuyan et al. 2003).

Although AGNPS is likely the most common model used with GIS, other models are also sometimes utilized. For instance, one study employed the Land Transformation Model (LTM), which is built upon GIS and artificial neural networks, to predict land use changes within the Muskegon River watershed on the east coast of Lake Michigan (Tang et al. 2005). Predicted changes were then evaluated through a web-based version of the Long-Term Hydrologic Impact Assessment (L-THIA) GIS model to estimate their impact on surface runoff and NPS pollution. Results indicated that urbanization would increase runoff volume and nutrient losses in runoff and significantly increase the losses of oil, grease, and heavy metals (Tang et al. 2005). In another study focused on the Nif watershed in Turkey, the Simulator for Water Resources in Rural Basins (SWRRB-WQ) model was used along with ArcInfo GIS software and Landsat-derived LULC data to determine how NPS pollution loads would vary based on the application of different manage practices (Esen and Uslu 2008). In a study focused on the Lagoon of Venice in Italy, Giupponi, Eiselt, and Ghetti (1999) conducted a GIS-based multicriteria evaluation to determine the effectiveness of low input cultivation techniques versus standard farming techniques for reducing NPS pollution risks. The analysis used a mapping technique where agricultural impacts and land vulnerability were overlaid to produce a risk map. The impacts data for this analysis were generated from the Groundwater Loading Effects of Agricultural Management Systems (GLEAMS) model (Giupponi, Eiselt, and Ghetti 1999). Whereas the studies described above utilized existing computer models, Basnyat et al. (2000) developed their own model through implementation of a riparian buffer delineation equation. Focusing on the Fish River watershed in southeastern Alabama, they used geographic resource analysis system (GRASS) and ArcInfo software to produce LULC data from Landsat Thematic Mapper (TM) imagery and also obtained GIS soil data from the USDA Natural Resources Conservation Service (NRCS). Inputting these to their model, they found that forests act as nitrogen sinks and reduce nitrate levels downstream (Basnyat et al. 2000).

Drawing from methods and concepts in the literature, our approach was to conduct a GIS-based multi-criteria evaluation of factors affecting NPS pollution risk. Inputs to this analysis included soil erodibility, satellite-derived LULC, and soil organic content. Although we did not employ modeling software or evaluate a large number of NPS pollution variables, the simplicity of our analysis resulted in a methodology which can be easily replicated using no-cost data and typical GIS software.
METHODOLOGY

We conducted our research as part of a ten-week internship with NASA's DEVELOP National Program at John C. Stennis Space Center. We built upon previous student research focused on the reservoir and addressed a specific request by MAWSS for an additional analysis of potential NPS pollution sources in the watershed. MAWSS was interested in this analysis as a tool for aiding the decision upon which land to focus NPS pollution mitigation efforts (Brown and White, personal communication, 2008). In addition to the common NPS pollution constituents described in our literature review, MAWSS was also highly interested in identifying land areas that could contribute to increased total organic carbon (TOC) in the reservoir (Brown and White, personal communication, 2008). TOC is the total amount of all organic carbon compounds contained in water, including both dissolved and particulate matter (Journey and Gill 2001). It is a critical concern because chlorine used to disinfect the water can react with TOC to form trihalomethanes and haloacetic acids that pose a health risk. Moreover, trihalomethanes are known to be carcinogenic (Journey and Gill 2001; Lee, Ha, and Zoh 2009). Soil type is an important factor influencing TOC levels because different soils have varying organic contents and physical properties. For example, the adsorption properties of a soil influence whether organic carbon is slowly leached over time or quickly flushed during a rain event (Journey and Gill 2001). Although aquatic algae and microbes also can produce organic compounds, these products are not as reactive with chlorine as terrestrially-derived TOC (Journey and Gill 2001).

To address the issues identified by MAWSS, we focused on analyzing sources of sediment run-off, total organic carbon, impervious surface run-off, and agricultural chemicals (i.e. pesticide/fertilizer). Our goals were to (1) conduct a spatial analysis of relative risk for NPS pollution, (2) demonstrate the usefulness of NASA satellite data products in decision support, and (3) create a series of maps showing potential sources of NPS pollution. Although we built upon principles and techniques found in the literature, our approach differed from previous studies in two ways. First, we wanted to employ methods that could be easily replicated by a local municipality using common GIS software and freely available data; therefore we chose to avoid the use of complex modeling software. Second, rather than modeling NPS loads under different land use or policy scenarios, we sought to map specific locations that posed a higher risk as potential sources for NPS pollution.

We used satellite imagery from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) to create a land use/land cover (LULC) map of the study area. ASTER is a pushbroom sensor onboard the Terra satellite platform and is a joint endeavor between NASA and the Japanese Ministry of Economy, Trade, and Industry (Parkinson et al. 2006). It has 14 bands operating on 3 sensor subsystems. The visible to near infrared (VNIR) subsystem acquires data in 3 bands from 0.52 μm to 0.86 μm at a 15 x 15 meter spatial resolution. The shortwave infrared (SWIR) subsystem acquires data in 6 bands from 1.6 μm to 2.43 μm at a 30 x 30 meter spatial resolution. The thermal infrared (TIR) subsystem captures data in five bands from 8.125 μm to 11.65 μm at a 90 x 90 meter spatial resolution. Data from the VNIR and SWIR subsystems have a quantization level (radiometric resolution) of 8 bits; while data from the TIR subsystem have a quantization level of 12 bits. ASTER's swath width is 60 kilometers, with varying temporal resolutions (Jensen 2007). We acquired our imagery from September 27, 2006, using the U.S. Geological Survey's (USGS's) online Global Visualization viewer.

Next, for accuracy assessment of the land cover map, we used aerial orthophotos from the USDA Farm Service Agency's National Agriculture Imagery Program (NAIP). The NAIP seeks to provide 1 meter spatial resolution true color and color infrared aerial
photos of the continental U.S. during typical agricultural growing seasons (USDA FSA APFO 2009). The photographs in our study were taken during the summer and fall of 2006, and we acquired them through the USGS’s online National Map server.

In addition to remotely-sensed imagery, we also utilized two forms of GIS data. One was Soil Survey Geographic Database (SSURGO) shapefile soil data from the NRCS, which was used to map the various soil types within the Big Creek Lake watershed. The other was shapefile property data that enabled identification of which property parcels may be at the highest levels of risk for NPS pollution. MAWSS provided both datasets.

Using ERDAS Imagine 8.7, we stacked the VNIR ASTER bands (excluding the backward-scanning band) and subset them to the watershed boundary. Then we projected the image to UTM Zone 16 North, WGS 84, with a 15 x 15 meter resolution and performed an ISODATA unsupervised classification on it. We chose the unsupervised, rather than the supervised, classification technique because the methodology could easily be recreated. Another reason for choosing the unsupervised classification method was that supervised classification requires a fair high level of familiarity with the study area (Jensen 2005). For maximum precision of cluster building, we used 100 iterations, a convergence threshold of 0.995, and twenty classes. With the initial classification complete, we used the National Oceanic and Atmospheric Administration’s (NOAA) Coastal Change Analysis Program (CCAP) data as a guide for merging the initial 20 classes into our 8 generalized classes of interest. These were deep water, shallow water, urban, shrub, forest, clear cut/grassland, agriculture, and gravel/quarry. The next step was to perform an accuracy assessment of the classification.

Accuracy assessments of LULC maps are performed by selecting a number of points in the classified image and checking them against reference data such as field survey results or aerial photographs of the region (Congalton 1991). We obtained NAIP aerial photos for this purpose and used the binomial probability theory equation to determine the number of points that should be selected for the accuracy assessment (Jensen 2005, 501):

$$N = \frac{Z^2 (p)(q)}{E^2}$$

The equation was computed where $N$ is the sample size, $Z = 2$ from the standard deviate of 1.96 for the 95% two-sided confidence level, $p$ is the expected accuracy for the entire map, $q = 100 - p$, and $E$ is the allowable error (Jensen 2005, 501). This amounted to 80 points with an expected accuracy of 85% and an 8% allowable error. Therefore, we chose a total of eighty points to evaluate for an accuracy assessment. Although accuracy assessments typically involve selecting much larger sets of sample points, it is often necessary to strike a balance between what is statistically sound and what is practically attainable (Congalton 1991). In our case, time constraints dictated use of a minimum number of points, but it should be noted that the resulting assessment is useful only for evaluating the general overall accuracy of the map. A more robust accuracy assessment would require far more sample points.

Using the Equalized Random point selection option in ERDAS Imagine 8.7, we randomly placed eighty points in the classified image to ensure that each class received exactly ten sample points. Then, so that these datasets could be referenced, these same points were also placed on a mosaic of fourteen NAIP photos. We checked each point on the classified image against the NAIP mosaic. Once the process was complete, we computed the accuracy statistics for each land cover class and for the overall classification (Table 1). The user’s accuracy indicates the probability that a pixel classified into a certain category actually is that category. It tells how likely a map user is to find the depicted land cover if they visit that location in the field. Producer’s accuracy, on the other hand, is a measure of how well a particular area can be classified, and the Kappa statistic
is an alternate means of evaluating the level of agreement between the reference data and the map. Finally, overall accuracy provides a single number representing the general accuracy of the entire map (Congalton 1991). Our overall classification accuracy was 78.75%, and the overall Kappa Statistic was 0.7571. According to Jensen (2005), these values represent a moderate level of accuracy.

We then developed a system for rating NPS pollution risk variables and used these ratings to conduct a GIS-based multi-criteria evaluation (MCE). MCE is simply using multiple criteria to assess the capability and suitability of land for supporting a certain activity (Drobne 2009). It has been used for numerous applications such as determining suitability for agriculture, assessing landslide susceptibility, refining location-based services, prioritizing competing land uses, and mapping risks of agricultural pollution (Chen, Yú, and Khan 2010; Nandi and Shakoor 2009; Raubal and Rinner 2004; Bojórquez-Tapia, Díaz-Mondragón, and Ezcurra 2001; Giupponi, Eiselt, and Ghetti 1999). The first step in our MCE was to rate land cover types based on their relative contributions to NPS pollution. Using ArcMap 9.2, we recoded the eight land cover classes into five categories of erosion and runoff risk (Fig. 5 and Table 2). Our final five classes were nearly identical to the ones selected by Tang et al. (2005) and Basnyat et al. (2000).

In our rating scheme, a value of five indicates the highest risk; whereas a value of zero represents no risk (Table 2). Justification for these ratings is provided below. Before proceeding, however, it is interesting to note from Figure 4 and Table 2 that the highest risk categories of land cover comprise smaller percentages of the study area than the lowest risk categories, a fortunate occurrence from a watershed management perspective.

After comparing various types of land, Esen and Uslu (2008) found dry croplands to produce the highest runoff and be a major source of soil erosion. Similarly, Dowd, Press, and Huertos (2008) identified agriculture as being the single largest contributor to NPS pollution in the United States. Additionally, Basnyat et al. (2000) and Ribaudo et

<table>
<thead>
<tr>
<th>Class Name</th>
<th>Producer’s Accuracy</th>
<th>User’s Accuracy</th>
<th>Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deep water</td>
<td>100 %</td>
<td>90 %</td>
<td>0.8873</td>
</tr>
<tr>
<td>Shallow water</td>
<td>71 %</td>
<td>50 %</td>
<td>0.4521</td>
</tr>
<tr>
<td>Urban</td>
<td>53 %</td>
<td>90 %</td>
<td>0.8730</td>
</tr>
<tr>
<td>Shrub</td>
<td>88 %</td>
<td>70 %</td>
<td>0.6667</td>
</tr>
<tr>
<td>Forest</td>
<td>71 %</td>
<td>100 %</td>
<td>1.0</td>
</tr>
<tr>
<td>Clearcut/Grassland</td>
<td>80 %</td>
<td>80 %</td>
<td>0.7714</td>
</tr>
<tr>
<td>Agriculture</td>
<td>100 %</td>
<td>70 %</td>
<td>0.6712</td>
</tr>
<tr>
<td>Gravel/Quarry</td>
<td>100 %</td>
<td>80 %</td>
<td>0.7778</td>
</tr>
</tbody>
</table>

Table 1: Land use/land cover map accuracy report.

<table>
<thead>
<tr>
<th>Risk Rating</th>
<th>Land Cover Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Water/Shallow Water</td>
</tr>
<tr>
<td>1</td>
<td>Forest</td>
</tr>
<tr>
<td>2</td>
<td>Shrub (Young Forest)</td>
</tr>
<tr>
<td>3</td>
<td>Gravel/Quarry and Clearcut/Grassland</td>
</tr>
<tr>
<td>4</td>
<td>Urban</td>
</tr>
<tr>
<td>5</td>
<td>Agriculture</td>
</tr>
</tbody>
</table>

Table 2: Relative NPS pollution risk rating for each land cover type.
Figure 5: Big Creek Lake watershed land use/land cover rated for run-off risk. Source: NASA ASTER imagery from 2006.

Map created by Jason Jones and Marco Allain
al. (2001) also explained agriculture to be a major contributor to NPS pollution. This is because mechanized, intensive tillage farming systems can have adverse effects on environmental quality and soil health. For example, intensive farming causes a higher modulus of soil rupture and greater soil erosion. Because of conventional farming tillage methods, inadequate crop rotation, and fertilizer and pesticide usage, current agricultural practices pose a high risk of erosion and run-off (Dowd, Press, and Huertos 2008). Based on these facts, we assigned agriculture the highest risk value of five.

He (2003) created a watershed simulation model which showed that expansion of urban land is likely to lead to an increase in surface runoff, peak flow, and soil erosion. In another modeling study, Corbett et al. (1997) found that runoff from an urban watershed was on average much higher than from a forested one. Basnyat et al. (2000) explained that urban, residential, and built up land generate large volumes of NPS pollution due to storm water discharge, and Tang et al. (2005) found that urbanization will increase runoff volume. This is due to the fact that although water from rainfall will often percolate into the ground and be absorbed, in many cases, urban impervious surfaces such as roads, paved streets, and bridges, prevent water from penetrating the topsoil layer, thereby contributing to rainfall runoff. Impervious surfaces also collect pollutants such as heavy metals, oil, and grease. These pollutants are washed off and delivered to aquatic systems by storms (Gove et al. 2001). Consequently, we assigned urban land cover (including residential land) the second highest risk level, four.

Although extensive literature was available regarding the relative risks of agricultural, urban, and forested land as NPS pollution sources, few studies provided explicit guidance related to our clear cut/grassland and gravel/quarry classes. However, logging operations associated with clear cutting are well-known to cause soil disturbance, reduce vegetation cover, and increase erosion rates (NOAA 2008b; EPA 2012c). Additionally, because gravel extraction is typically associated with streams or floodplains and results in hydrologic modification of the land, it is generally considered to be a source of NPS pollution. Improper gravel pit operation can result in both surface and ground water impairment (SEAGO n.d.; Alaska DEC 2011). Because the clear cut/grasslands and gravel/quarry land cover classes posed similar risks, we assigned them both to the middle run-off risk class, giving them a value of three.

The land use/land cover nutrient linkage model developed by Basnyat et al. (2000) showed that forests act as nitrate sinks, thereby lowering NPS pollution rates. Additionally, woodlands characterize the best protection of lands from sediment and pollutant losses. Woodlands have low hydrologic activity due to high surface storage in leaves and terrain roughness. Dense layers of forest canopy decrease the runoff potential of rainfall and accrue large amounts of biomass on the ground, which further decreases the chance of erosion (Esen and Uslu 2008). Based on these facts, we assigned the shrub class (young forest) a risk value of two and the forest class a value of one.

Lastly, we assigned the water and shallow water classes a risk value of zero. Once the rating system in Table 2 was complete, we used the ArcMap “Reclassify” function in Spatial Analyst to convert the LULC map into a raster dataset where each pixel represented an NPS pollution risk value from zero through five (Fig. 5). Using ASTER imagery to create this important LULC dataset achieved our goal of demonstrating the usefulness of NASA data for decision support.

The next step in the multi-criteria evaluation was to convert the SSURGO soil shapefile into a raster dataset where each pixel represented soil erodibility on a scale of zero to five. This was necessary because every soil type does not contribute equally to nutrient transport (Basnyat et al. 2000). To rate the soil types, we used the Soil Survey of Mobile County, Alabama to find the K-factor for each soil (Hickman and Owens 1980).
K-factor is the soil erodibility factor used in the Universal Soil Loss Equation (He 2003). It is a measure of a soil’s susceptibility to erosion and its estimated run-off rate under the conditions of a standard unit plot (MSU 2009). It is derived using this equation:

$$K = \frac{A}{R}$$

where $A$ is the mean annual soil loss, $R$ is the rainfall erosivity factor and $K$ is the soil erodibility factor (Zhang et al. 2007). The K factor is generally considered an inherent soil property with a constant value; thus these values can be readily referenced for each soil type (Vaezi et al. 2008). Possible K-factor values range from 0.10 to 0.43, with the lower values indicating lower susceptibility to erosion and the higher values indicating higher susceptibility to erosion (Hickman and Owens 1980).

We listed the K values for all soil types in the watershed and then rated each soil type on a scale of zero to five based on its corresponding K-factor (Table 3). In our rating scheme, zero denotes no risk of erodibility, and five indicates high risk. Use of the erodibility factor in such a manner is not new. For example, Nandi and Shakoor (2009) used the K-factor along with other instability factors to create landslide susceptibility maps from the input of rated raster layers.

Since a soil’s top layer is what will erode into a nearby lake or stream, we rated erodibility solely on the K value of the top layer of soil. The bottom layers of soil should not erode unless they are disturbed by deep cutting. Within the study area, K-factor values ranged from 0.10 to 0.37. Water does not have a K value; therefore, we assigned it a rating of 0. Using an equal interval classification scheme in ArcMap, we gave soils with K values ranging from 0.10–0.154 a rating of 1, those ranging from 0.154–0.208 a rating of 2, those ranging from 0.208–0.262 a rating of 3, those ranging from 0.262–0.316 a rating of 4, and those ranging from 0.316–0.37 a rating of 5. These ratings were created in}

ArcMap using the Spatial Analyst “Reclassify” function, where each group of K-factors was assigned ratings as described above, thereby generating a new raster file of soils rated based on erodibility (Fig. 6).

As previously discussed, carcinogens may be formed when organic carbon from soils mix with water treatment chemicals. Theorizing that soils higher in organic content are more likely to contribute to increased TOC levels in the reservoir, we chose soil organic content as the final factor of our multi-criteria analysis. Using the Soil Survey of Mobile County, Alabama and GIS soil data provided by MAWSS, we were able to determine the organic content of each soil type (Hickman and Owens 1980). The soils that were low in fertility and possessed a strong acidic reaction were generally low in organic content. Pactolus loamy sand had very little organic content, Johnston-Pamlico association had moderate organic content, and Pamlico-Bibb complex had high organic content. The rest of the soil types in the watershed had low organic content. Soils were rated on a scale of one to four in ascending order of organic content (Table 3) and generated a raster file representing these four classes (Fig. 7). A higher rating represents a higher organic content; whereas a lower rating represents a lower organic content.

After creating the three rated raster datasets, we performed an ordinal combination by adding the three files together with the Raster Calculator in ArcMap 9.2 Spatial Analyst. Because the rated land cover raster contained values 0–5, the rated erodibility raster contained values 0–5, and the rated organic content raster contained values 0–4, after we added them together, the resulting output raster could only contain values 0 – 14. A value of 14 would represent the highest relative NPS pollution risk based on our combination of factors; whereas a value of 0 would indicate no NPS pollution risk. In our combined dataset, however, the highest value was only 12. To aid in visual interpretation of this dataset, we converted it into a map of five equal interval classes (Fig.
Figure 6: Big Creek Lake watershed soil erodibility. Sources: USDA NRCS SSURGO shape-files and the soil survey of Mobile County, Alabama (Hickman and Owens 1980).
Table 3: Soil types present within the study area and their associated attributes.

<table>
<thead>
<tr>
<th>Soil Type</th>
<th>K factor</th>
<th>MUSYM</th>
<th>Erodibility Rating</th>
<th>TOC Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benndale sandy loam</td>
<td>0.2</td>
<td>10</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Escambia sandy loam</td>
<td>0.24</td>
<td>16</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Grady loam</td>
<td>0.1</td>
<td>19</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Harleston sandy loam</td>
<td>0.2</td>
<td>20</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Heidel sandy loam</td>
<td>0.2</td>
<td>22</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Johnston-Pamlico association</td>
<td>0.17</td>
<td>27</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Lucedale sandy loam</td>
<td>0.24</td>
<td>29</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Malbis sandy loam</td>
<td>0.28</td>
<td>30</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Notcher sandy loam</td>
<td>0.28</td>
<td>32</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Pactolus loamy sand</td>
<td>0.1</td>
<td>36</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Pamlico-Bibb complex</td>
<td>0.1</td>
<td>37</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>Pits</td>
<td>0.2</td>
<td>38</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Poarch sandy loam</td>
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<td>39</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Saucier sandy loam</td>
<td>0.24</td>
<td>42</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Shubuta sandy loam</td>
<td>0.37</td>
<td>43</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>Smithton sandy loam</td>
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<td>45</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>Smithton-Urban land complex</td>
<td>0.32</td>
<td>46</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>Bama sandy loam</td>
<td>0.24</td>
<td>4</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Troup loamy sand</td>
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<td>50</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Troup-Benndale association</td>
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<td>55</td>
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<td>2</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>W</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

In addition to combining all three rated factor raster datasets, we also experimented with combining two at a time similar to the way that Gomes and Lin (2002) used various combinations. Due to page limitations, the results of each combination are not shown here. For an overview of all data processing steps, refer to Figure 9.

RESULTS AND DISCUSSION

We generated two series of maps, which comprise the main physical results of our research. The first series contained three maps: one of LULC, one of soil erodibility, and one of organic content, with each rated based on its likely contributions to NPS pollution (Figs. 5, 6, and 7). The second map series contained combinations of the three previous maps: a combined LULC/erodibility map (not shown), a combined LULC/TOC map (not shown), and a map with all three factors combined (Fig. 8). When using these map products, it should be noted that they are meant to be used as tools for evaluating NPS pollution mitigation options and
Figure 7: Big Creek Lake watershed soils rated for relative total organic carbon (TOC) risk. Sources: USDA NRCS SSURGO shapefiles and the soil survey of Mobile County, Alabama (Hickman and Owens 1980).
Figure 8: Relative nonpoint source pollution risk map for the Big Creek Lake watershed.
are based on the best available information; however, they may not depict local conditions accurately.

Each of the initial input risk maps displays informative spatial patterns of runoff and erosion risk. For example, Figures 3 and 5 show that the majority of the land in the watershed is forested, thereby posing a low risk. However, the agricultural and developed land most common in the northeast and southeast portions of the watershed poses a much higher risk. A possible explanation for the close spatial proximity between the developed and agricultural land use is that agriculture requires the logistical support of laborers who may live in the nearby residential areas. Figures 6 and 7 pertain to soil erodibility and organic content respectively. Although soils in the tributaries feeding the lake have low erodibility factors, they have the highest organic contents. The majority of these tributaries are forested, meaning that the land cover poses a low erosion risk (Fig. 3 and Fig. 5). Consequently, the risk value depicted along many of these tributaries when all three factors are combined is only moderate (Fig. 8). However, the moderate rating of these areas should not be quickly dismissed. The soils in these locations are highly organic and are also located next to tributaries; therefore if a disturbance is introduced (e.g., timber harvesting), erosion would cause highly organic runoff into the lake. This illustrates the complexity and limitations of our analysis. A similar limitation is also evident when the effect of land cover on soil erosion is considered. For instance, because the land cover is impervious, urban land might not contribute eroded soil and organic matter to runoff even though the soil underneath might have high erodibility and high organic content. In such overlapping areas, land cover alone is the primary risk to runoff.

In the final risk map (Fig. 8), the majority of the watershed has a low NPS pollu-
tion risk. This is not surprising, since forest dominates the study area and was assigned the lowest risk rating on the LULC input layer (Fig. 5 and Fig. 8). The areas of moderate to high risk are of much greater concern from a mitigation standpoint. As discussed above, most of the major tributaries are rated as a moderate risk due to the high organic content of the underlying soils (Fig. 7 and Fig. 8). The next higher risk category occurs primarily in agricultural areas and developed urban areas where soil erodibility was typically moderate to high (Fig. 3, Fig. 6 and Fig. 8). Frequency of this risk class was highest in the northeastern and southeastern portions of the watershed (Fig. 8). Finally, it should be noted that the highest risk class covers such a small area (3.7 acres) that it is not even visible on the map (Fig. 8). This is because very few locations possessed the highest risk rating in all three input categories. These findings regarding the relative NPS pollution risk of various portions of the watershed provide an enhanced means for MAWSS to prioritize which land parcels require the most mitigation. Areas identified as higher risk require the most extensive mitigation measures and should be addressed before areas identified as lower risk.

Based on this logic and the results shown in Figure 8, MAWSS should focus most of its NPS pollution prevention efforts on cultivated agricultural land and developed urban locales within the watershed. Because streams transport NPS pollution, the most rigorous pollution control measures should be applied to agricultural and urban lands immediately adjacent to the reservoir’s tributaries. Some methods that MAWSS could pursue in agricultural areas to reduce runoff include planting cover crops when primary crops are not growing, establishing buffer strips of vegetation along field boundaries, practicing reduced tillage between planting dates, using contour plowing across slopes, and erecting sediment fences (NOAA 2008a). Similarly, control measures for urban runoff include implementing buffer strips, creating retention ponds, constructing wetlands, using porous paving materials, planting grass around construction sites, and employing sediment fences (NOAA 2008a). Before deciding on an NPS pollution strategy, however, watershed managers should work with local land owners to ensure that the mitigation strategy is sustainable and mutually beneficial.

Although the areas identified as relatively high risk in Figure 8 (mostly agricultural and urban) should receive the highest priority for mitigation, our analysis suggests that many locations assessed as only a moderate risk should also be addressed. This is because of their immediate proximity to tributaries which can easily transport pollutants into the reservoir (Fig. 8 and Fig. 3). Additionally, many of the underlying soils along the tributaries in these locations contain high organic content (Fig. 7) and, if eroded, could therefore contribute to increased TOC levels in Big Creek Lake. Fortunately, the soil erodibility along many of these tributaries is typically low (Fig. 6), and the land cover is often forested (Fig. 3). While this suggests that erosion of the organic material is unlikely, the possibility of soil disturbance still exists (e.g. logging); therefore an effective mitigation strategy must involve protecting these areas from disturbance.

Since errors in any of the input data layers would propagate throughout subsequent processing steps, results of the land cover map accuracy assessment should be considered when interpreting the final results (Table 1). The overall classification accuracy was 78.75%, and the Kappa Statistic was 0.7571. According to Jensen (2005), this indicates only a moderate level of accuracy. A possible explanation for this somewhat low reported accuracy is that while conducting the accuracy assessment, there appeared to be a minor rectification error of about one or two pixel’s width between the classified ASTER image and the reference aerial photos. This minor error could have affected the accuracy assessment negatively. Furthermore, accuracy assessment on the quality of the soil data from the SSURGO database or on the
information from the hard copy soil survey was not conducted. If these data were inaccurate, the accuracy of our results would be further affected.

LIMITATIONS AND FUTURE WORK

Although our simple methodology offered several advantages, it unfortunately, also possessed several inherent limitations, and further refinement is necessary. As explained in the literature review, most spatial erosion models require a DEM as input (Vrieling 2005). This is because slope is an important variable in the Universal Soil Loss Equation (MSU 2009; He 2003). The addition of slope to our analysis would therefore greatly improve the accuracy of our results. A one-meter spatial resolution digital DEM produced from aerial LiDAR data could be used for this purpose. Such a high-resolution DEM would allow a more intrinsic examination of subtle changes in the slope of local terrain. Alternatively, basic slope information provided by Hickman and Owens (1980) could also be used to derive a relative slope rating system.

The further a body of water is located from a potential polluting source, the lower the risk of pollution is; however, our analysis did not take this into consideration (Giupponi, Eiselt, and Ghetti 1999). Consequently, the utility of our mapping products could be improved by adding a geospatial analysis of the distance between NPS pollution sources and the tributaries of Big Creek Lake. Such an analysis could be accomplished by generating a distance grid with the Spatial Analyst extension of ArcGIS and developing a rating system based on a pixel’s distance to tributaries or the lake.

Finally, the use of different weights for each of our input factors should also be explored. Changing the weight of an input factor will impact the results of any multi-criteria decision making model, and the use of weighting has been an important component of many studies using multi-criteria evaluation techniques (Chen, Yu, and Khan 2010; Nandi and Shakoor 2009; Raubal and Rinner 2004; Bojórquez-Tapia, Díaz-Mondragón, and Ezcurre 2001). Following their methodology, further research needs to be completed to determine suitable weights for each of our input layers.

CONCLUSIONS

Our goals of analyzing potential NPS pollution sources, demonstrating the usefulness of NASA remote sensing data for decision support, and mapping the results were all met. The map products generated from our study can be used to better understand potential sources of NPS pollution within the watershed and to plan mitigation efforts. As explained in the Results section above, MAWSS can begin implementing NPS pollution control measures in areas with the highest risk. Additionally, using individual components of the analysis (i.e. LULC, soil erodibility, and soil organic content), they can gain a better understanding of potential risks for specific locations, regardless of what the combined factor rating is. For example, even though the overall risk rating of an area may be low, it is possible that individual factors such as soil organic content make the location a higher priority for mitigation.

Beyond the specific context of our study area, we have also demonstrated a GIS approach that can be easily implemented using freely available data and without the use of complex computer models. As a simplified multi-criteria evaluation technique, our methodology can be used in other watersheds as a decision support tool to identify relative NPS pollution risks. Furthermore, it can be modified to meet specific users’ needs through the edition of other data inputs.

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