5-1-2020

Assessment of coastal watershed erosion potential using geographic information systems and expert input for decision support

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A Dissertation
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy
in Earth and Atmospheric Sciences
in the Department of Geosciences

Mississippi State, Mississippi

May 2020

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Title of Study: Assessment of coastal watershed erosion potential using geographic information systems and expert input for decision support

Pages in Study: 91

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Sediment is a major impairment in many streams and rivers in the drainage basins along the northern Gulf of Mexico. The use of geospatial technologies improves assessment and decision making for the management of environmental resources and conditions for coastal watersheds. This research focuses on the development of a conceptual qualitative model enhanced with expert input for the assessment of soil erosion potential in coastal watersheds. The conceptual model is built upon five layers (slope, precipitation, soil brightness or exposure, K-factor, and stream density) like those in a standard numerical soil loss model such as the Revised Universal Soil Loss Equation (RUSLE). The conceptual model produced a continuous surface to index erosion potential. Pearson's correlation coefficient was used to identify variable sensitivity. The model was most sensitive to K-factor variable, followed by soil brightness, stream density, and slope. The model was not sensitive to the precipitation variable due to the lack of variability across the watershed. Expert input was added to the conceptual model for erosion potential with the Analytical Hierarchy Process (AHP). The AHP is used to value the importance of criteria, providing a quantitative weight for the qualitative data. The expert input increased the overall importance of topographic features and this increased cell counts in the

upper erosion potential classes. The AHP weights were altered in 1% increments ranging from plus to minus 20% producing 201 unique runs. A quartile analysis of the runs was used to define areas of model agreement. The quartile analysis allowed for the application of an analysis mask to identify areas of increased erosion potential for improved management related decisions. The conceptual and AHP erosion potential output data, including watershed management priority rankings, were published as web mapping services for story map development as a transition to a decision support system. The limits of the story map to allow user interactions with model output rendered an unacceptable platform for decision support. The story map does offer an alternative to static reports and could serve to improve dissemination of spatial data as well as technical reports and plans like a watershed management plan.

DEDICATION

I dedicate this dissertation to my family for their constant support and encouragement. Dixie, Ethan, Alec, and Emily thank you so much for giving me more than I could ever give you. I love y'all.

ACKNOWLEDGEMENTS

I would like to express my gratitude and appreciation to my major advisor, Dr. John Rodgers, for his support and patience throughout this process. I would like to thank my outstanding committee members, Dr. Bill Cooke, Dr. Jamie Dyer, Dr. William McAnally, and Dr. Qingmin Meng. It has been a pleasure working with each of you during this process. This dissertation would not have been possible without the support of the Geosystems Research Institute at Mississippi State University, I am grateful to Dr. Robert Moorhead and my friends and co-workers at MSU. Finally, I would like to thank my family for all their love, support, and encouragement throughout this process.

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CHAPTER I

INTRODUCTION

1.1 Overview

Estuaries are a valuable resource and provide many beneficial ecosystem services. Estuaries and the coastal region of the southeastern United States are areas that are experiencing increased development from anthropogenic activities. This type of development causes disturbances that result in sediment erosion during precipitation events. These areas of (overland or watershed) erosion produce additional sediment that can impact the natural and environmental resources associated with the estuary. The interactions of general landscape characteristics (terrain, geomorphology, soils, land disturbance, and long-term precipitation) are often used by numerical soil loss models for quantification of erosion and sediment yield. The objective of this dissertation is to develop a qualitative conceptual model for the assessment of overland erosion potential by water at the watershed level. The focus on overland erosion provides additional watershed management resources that complement research on stream bank and channel erosion. Factors for the model are like those of the Universal Soil Loss Equation (USLE) and the Revised Universal Soil Loss Equation (RUSLE). USLE and RUSLE use factors for the assessment of soil erosion including topography, soil erodibility, land cover, and precipitation. The qualitative model is enhanced with expert input using the Analytic Hierarchy Process (AHP) to establish weights for the factors defining erosion potential. The approach used in this geospatial application will utilize those landscape characteristics (factors) to identify areas of increased erosion potential to aid resource and policy managers in making informed decisions about associated natural resources. The generalized project workflow will be to develop a qualitative geospatial model for erosion potential, add expert input to the model, and use web based geospatial technologies for data dissemination and technology transfer for decision support. This dissertation will contribute to the development of a geospatial application that allows a more simplistic approach to erosion modeling than the more complex numerical soil loss models that tend to be agricultural centric. Additionally, it will provide resource managers with tools to better understand erosion in their area of interest and focus it on issues more specific to the local area (i.e. urban development).

1.2 Research Objectives

The purpose of this research is to develop a novel approach to examine erosion potential for coastal watersheds with GIS. The research will focus on the development of a conceptual qualitative model with geospatial technologies for the assessment of soil erosion potential in coastal watersheds. The intent of such work is to expand research and technology that will improve the decision-making process based on the physical changes and drivers (e.g. landscape and climate) associated with increased erosion. This in turn will aid in the facilitation of planning, management, and conservation of natural resources at watershed and regional scales. The work will continue adding depth to the broad and numerous erosion assessments currently taking place in watersheds around the globe, thereby increasing information and knowledge of coastal systems as part of a changing planet. Typical soil loss models (RUSLE, SWAT, WEPP) are often complicated and not user friendly for natural resource managers. This research addresses the challenges resource managers are faced with by providing a process that will facilitate their input to model soil erosion potential. The general hypothesis of this research is that qualitative modeling and analysis of watershed erosion potential will simplify traditional soil loss models for improved decision support as it draws upon the experiences of resource managers. The primary objectives of this research are as follows:

- Project 1: Develop a conceptual geospatial model (qualitative) for the assessment of erosion potential for coastal watersheds with criteria similar to traditional soil loss models.
- Project 2: Apply expert input to the model with the analytic hierarchy process (AHP) to determine criteria/variable weights for multi-criteria-decision-support and analysis.
- Project 3: Evaluate recent geospatial technologies for data dissemination and technology transfer as a means of improved decision support.

1.3 Background Information

Estuaries and coastal environments provide valuable natural resources with complex and diverse ecosystem structure and function. In particular, the coastal zone of the United States is especially important because it is a major economic force and the most populated region of the country (NOAA NMFS, 2014; Shepard et al., 2013). However, the coastal areas of the United States are also one of most fragile natural environments with a wide range of sensitive habitats. The coastal zone includes various environments, from salt and freshwater marshes to barrier islands, beaches, bays, and estuaries. These environments are not only susceptible to the natural disturbances proximate to the coast (i.e. tropical storms, hurricanes, and other coastal hazards), but they are also susceptible to upland landscape alterations (urban development, agricultural, etc…) within the watershed or drainage area. The need to protect and preserve this area and the resources associated with it led to the development of the Coastal Zone Management Act (CZMA) of 1972. The CZMA states that resources within the coastal zone are of national importance and are worthy of protection. These resources of importance include any coastal wetland, beach, dune, barrier island, reef, estuary, or fish and wildlife habitat determined to be of substantial biological or storm protective value (CZMA, 1972). The CZMA goes on to state that the coastal zone is not only the areas immediately adjacent to the shore lands; the coastal zone also includes the tidelands and uplands to the extent necessary to control the shore lands.

The Gulf of Mexico's estuaries are critical for the survival of many species and provide habitat for numerous birds, fish, mammals and other wildlife. Estuaries are often termed as the 'nurseries of the sea' providing critical areas for many organisms during early life stages (Montagna et al., 2018; Turner, 2001; Turner and Rabalais, 2019). Estuaries and their associated wetlands provide not only important habitat for coastal ecosystems, but they also provide many valuable ecosystem services. For example, associated wetlands of coastal estuaries or salt marshes can serve as sites of retention for contaminates and sediment, they provide sources and sinks for carbon, and they serve as barriers for the protection of uplands against tropical storms, dissipation and absorption of flood waters, and other natural threats (Kennish, 2001; Kennish, 2002; Sheppard et al., 2011; Spalding et al., 2014). The services provided by estuaries (and the associated wetlands) are subject to impacts of tropical cyclones every year. During the last century areas such as south Florida, eastern North Carolina, and the northern Gulf Coast (specifically southeastern Louisiana, Mississippi, Alabama, and the western Florida panhandle) have experienced the highest frequency of land-falling tropical cyclones (Bilskie et al., 2019; Kish and Donoghue, 2013; Labosier and Quiring 2013; Muller and Stone, 2001). The interannual frequency of land falling tropical cyclones is highly variable with clusters of tropical landfalls being separated by several years. Tropical landfalls over the past five decades have been analyzed with El Niño-Southern Oscillation (ENSO) phases and it was shown that La Nina seasons produce more land falling tropical storms and hurricanes than during El Nino or neutral

ENSO seasons (Bilskie et al., 2019; Kish and Donoghue, 2013; Labosier and Quiring 2013; Muller and Stone, 2001).

In addition to the effects of landfalling tropical systems, estuaries are also impacted by human activities associated with increased development. Development, especially urban and suburban spread, proximate to estuaries can affect sediment and chemical loads causing poor water quality. This development can also change the overall watershed hydrology regime (Basnyat et al., 1999; Wang et al., 2011; Zhang et al., 2019). Upland freshwater inflow is one of the most influential landscape processes affecting functions of coastal estuaries. Landscape alterations affecting the timing and volume of fresh water inflow (including nutrient and sediment inputs) are one of the most common stresses on estuarine systems (Mickle et al., 2018; Sklar and Browder, 1998; Starr et al., 2018). Increases in the population of a watershed also increases the fluxes of nutrient inputs, sediments and nonpoint sources of pollution. The increase in nutrients, sediments, and pollution can result in reductions of the overall water quality and dissolved oxygen concentrations producing a degraded habitat impacting both flora and fauna at all community levels within the ecosystem (Boynton et al., 2018; D'elia et al., 2003). In addition to upland alterations, local channel modifications (i.e. channelization of tributaries) have shown relationships to degraded water quality when compared to natural, unaltered drainage (Lammers et al., 2013; Surge and Lohmann, 2002).

The building up and development of land in these watersheds generates large amounts of sediment that impairs estuarine systems (Wang et al., 2011; Wang et al., 2014; Zhang et al., 2019). The settlement of the Atlantic coast of North America increased soil erosion greatly (by a factor of at least 10) with the clearing of forest land for agriculture (Fryirs, 2013; Meade, 1982). It was estimated that 95% of the riverine sediment is trapped in estuaries and coastal wetlands.

Modern environmental policies and soil conservation have helped to decrease the erosion; however, areas provide a potential source of sediment for years to come. Anthropogenic activities and surface geology serve as strong indicators of sedimentation and erosion rates (as well as potential sources). Sedimentation and erosion rates are much greater in areas experiencing active land use changes due to expanding agriculture, industrialization, and urbanization (Jones et al., 2003; Reusser et al., 2015). It has been estimated that sedimentation rates of coastal waters have doubled since prehistoric times and this increase in sedimentation has been primarily due to anthropogenic activities such as crop farming, livestock grazing, logging, and urbanization increasing upland erosion (Cooper et al., 2013; Rooney and Smith, 1999).

The modeling of soil erosion in coastal watersheds is a complex task that involves a wide range of knowledge from several scientific and engineering disciplines. Erosion modeling in coastal watersheds requires several inputs, such as landscape characteristics (i.e. terrain, land cover, soil properties) and hydrologic models (Sivapalan and Kalma, 1995; Sanzana et al., 2017). Soil erosion across the landscape traditionally has been characterized with models such as the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1994; Patowary and Sarma, 2018) and the Water Erosion Prediction Program (WEPP) (Laflen et al., 1991; Laflen and Flanagan, 2013; Yousuf and Singh, 2016). The potential use of these type models can be beneficial in resource management; however, they are often beyond the skill set of decision makers and resource managers.

The quantitative nature of many of these models adds a level of complexity that often limits their use with resource managers. These models generate useful data for managers and utilization of the data can be increased with model optimization, for example a qualitative assessment versus numerical modeling, and technology transfer with web-based applications. Many of the models are discipline specific (primarily geared towards agriculture) and not applicable to the needs for all aspects of resource management. It is not only the models, some of the variables are complex and difficult to obtain. For example the RUSLE model uses the variables of C-Factor to represent land cover management and the P-Factor for supporting land practices so typical land use data is not adequate (Renard et al., 1997). The data utilized in models are not always readily available and typically require standardization and conversion.

The design of many soil erosion models allows them to work in conjunction with geographic information systems (GIS) and other geospatial applications. The coupling of these models with GIS (and subsequent spatial analysis) allows relationships to be established between sediment loading and spatial patterns on the landscape. This helps resource managers identify and control nonpoint source producing areas efficiently (Bel Hassen and Prou, 2001; Zhang et al., 2016). Additionally the combination of many of these models with GIS helps with transition from models (modeling) to decision-support and analysis.

1.4 Research Study Area

The basins draining to the Gulf of Mexico are not excluded from trends of increased urban and suburban development and the problems associated increases in nutrients, sediment, and pollutants as previously described. These basins encompass the majority of the continental United States and a small portion of Canada. In order to effectively study erosion potential in estuarine systems, it would be ideal to have a small, confined system with limited input; this removes variability and is a more manageable spatial scale. Smaller, confined systems help us understand overland erosion processes across the landscape in larger more complex systems. The Weeks Bay watershed located on the eastern shore of Mobile Bay is an ideal setting to use for an erosion potential model. It is an ideal basin for the assessment of erosion potential as it relatively small and confined from surrounding watersheds. The watershed has limited inputs from two major rivers (Fish and Magnolia) that both directly drain to Weeks Bay. The Weeks Bay watershed is a diverse natural and anthropogenically influenced landscape with natural, forested, agricultural, and developed areas that are reflective of the region's natural resources and demographics (MBNEP, 2017). The area is within the humid subtropical climate region, characterized by warm summers and relatively mild winters. Average annual precipitation averages near 165 centimeters due to winter storms (cold fronts), summer thunderstorms (including those from the sea breeze), and tropical systems. The abundant water resources in the area make for a range of very productive land uses from timber production, cash-grain crops, and forage production (USDA, 2008). The tourism industry is a significant and growing part of the local economy, which is increasing demand for developed land uses. The combination of the aforementioned leads to the hydrologic system having impairments due to an overabundance of sediment. Major resource concerns include overland water erosion, organic matter and soil productivity, surface water and run-off, and impervious surface areas (MBNEP, 2017).

The Weeks Bay watershed has two primary drainage systems, the Fish and Magnolia Rivers (Figure 1.1). The Fish River provides nearly 75% of the total discharge to the bay itself and is made up of three subwatersheds (Upper, Middle, and Lower Fish River). The Magnolia River provides the remaining discharge and consist of a single subwatershed or 12-digit hydrologic unit. Weeks Bay is a National Estuarine Research Reserve (NERR). There are data collection stations available for water quality and meteorological information from the NERR

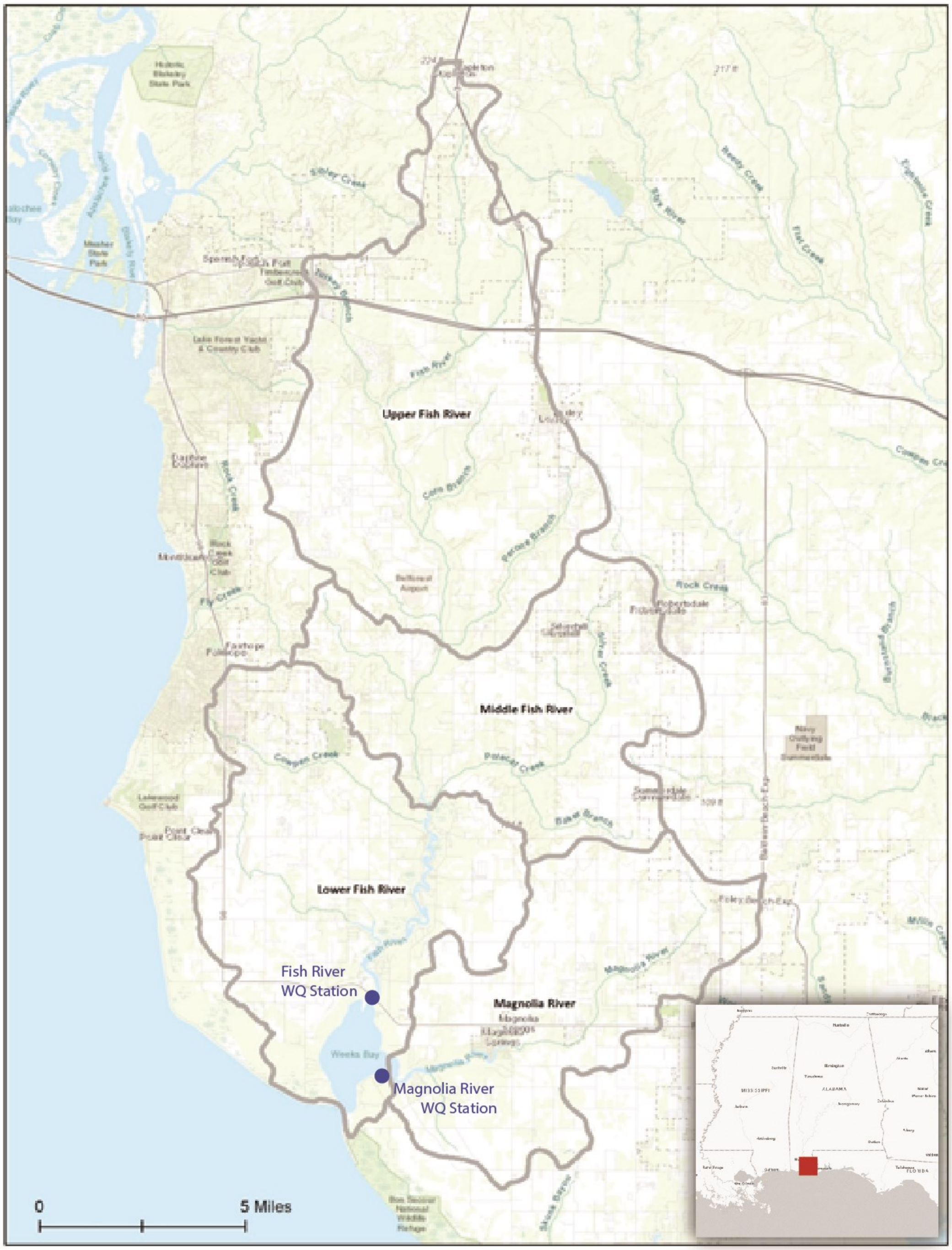

Figure 1.1 Weeks Bay Watershed Study Area

Weeks Bay watershed and subbasins on the eastern shore of Mobile Bay with System Wide Monitoring Program stations.

System-Wide Monitoring Program (SWMP), specifically of interest for this research is the turbidity data as it relates to suspended sediment loadings. Monitoring sites are located near the mouth of the Fish and Magnolia rivers. Figure 1.2 shows the 2015 turbidity and precipitation data from the System-Wide Monitoring Program stations for the Fish and Magnolia River data collection stations. Turbidity spikes align with precipitation events indicating increased concentrations of suspended sediment when compared to normal flow events.

Figure 1.2 SWMP Turbidity and Precipitation Data

Turbidity and precipitation data for 2015 from the SWMP data for A) Fish River and B) Magnolia River stations.

1.5 Merit and Impact

Soil erosion across the landscape traditionally has been characterized with models such as the Revised Universal Soil Loss Equation - RUSLE (Renard et al., 1994; Patowary and Sarma, 2018), Soil and Water Assessment Tool - SWAT (Arnold et al., 1998; Arnold and Fohrer, 2005; Kalin, 2017), and the Water Erosion Prediction Program - WEPP (Laflen et al., 1991; Laflen and Flanagan, 2013; Yousuf and Singh, 2016). Merit in this proposed work is the approach will utilize the analytic hierarchy process (AHP) coupled with geographic information systems (GIS) for multi-criteria decision analysis (MCDA) to gain spatial insight on erosion potential in coastal and estuarine drainage areas of the southeastern United States. The qualitative approach to erosion modeling will simplify watershed assessments and decision-making activities based on physical changes and drivers (e.g. landscape and development) associated with increased erosion. The broader impact of this research are improvements to decision making activities in coastal and estuarine drainage areas associated with the Gulf of Mexico. The improvements provide critical information for the management and policy development of Gulf of Mexico resources that account for nearly 20% of the United States Gross Domestic Product (NOAA NMFS, 2014). This approach will provide a pathway from science to operations that aid in the understanding and decision-making efforts related to erosion potential in coastal watersheds.

CHAPTER II

THE CONCEPTUAL MODEL

2.1 Abstract

Sediment is a major impairment in many streams and rivers in the drainage basins along the northern Gulf of Mexico. The use of geospatial technologies for watershed erosion modeling improves assessment and decision making in terms of environmental resources and conditions. This conceptual model was built upon five layers (slope, precipitation, soil brightness or exposure, K-factor, and stream density) similar to those in a standard numerical soil loss model (USLE, RUSLE, etc…). The conceptual model produced a continuous surface to index erosion potential. Erosion potential tends to be lower in densely vegetated riparian and marsh areas and higher with the transitional type lands. The transitional lands are more agricultural and dynamic in terms of land practices. At the 12-digit HUC subbasin analysis level it was found that the southeastern most subbasin dominated by cultivated agricultural lands had the greatest erosion potential out of the four subbasins. Erosion potential cell distributions in this subbasin were estimated to be one and a half times that of the entire watershed and near twice that of two of the other basins. The conceptual model was sensitive to the variables of K-Factor, soil brightness, stream density, and slope. These variables are representative of land sensitivity and physical erodibility. The balance between of which qualitatively represents the natural erosion potential of the physical landscape and the alteration of erosional processes by anthropogenic activities.

2.2 Introduction

Many hydrologic systems have impairments from an overabundance of sediment due to in-stream and upland erosion. Sediment is the largest volumetric non-point source pollutant to surface waters (Basnyat et al., 1999; Wang et al., 2011; Zhang et al., 2019) and single most important water quality problem in the United States (Neary et al., 1988; Wang et al., 2014; Ward et al., 2017). An erosion potential assessment focused on watershed landscape characterizations provides a measure of assessment and aids in the identification of sediment sources contributing to degraded conditions within a watershed and the associated estuary. These characterizations are derived from land-use/land-cover changes and practices (i.e. land disturbance), terrain analyses, physical properties of soils, and other geomorphologic features such as surface drainage density

Coastal watersheds and their associated estuaries are important to the overall coastal environment and are very biologically productive (Sanger et al., 2015; Turner, 2001). The high level of productivity is in part due to the transition zone created by mixing of the upland drainage of fresh water with the saline seawater (Kennish, 2002). The influence of human population growth and unrestricted development in coastal watersheds is proving to be very detrimental to the overall integrity of the fragile, yet highly productive estuarine ecosystems. This growth has increased pollution inputs, loss of habitat, increased nutrients, and has led to degraded ecologic conditions (Basnyat et al., 1999; Wang et al., 2011; Zhang et al., 2019). These trends of degraded conditions due to human influence are indicating that impacts to estuaries will continue, creating higher instances of eutrophication, hypoxia, and anoxia. Other anthropogenic impacts are associated with overfishing and environmental demands from limited freshwater inputs due to human population growth and expansion (Kennish, 2002).

Modeling erosion in coastal watersheds is a complex task that involves a wide range of knowledge from several scientific and engineering disciplines. An effective understanding of coastal watersheds requires several inputs, such as landscape characteristics and hydrologic models (Sivapalan and Kalma, 1995; Sanzana et al., 2017). Developments in geographic information systems (GIS) and other geospatial technologies have greatly increased data quality available for hydrologic modeling (Briak et al., 2016; Maidment, 1993; Patino-Gomez, 2005; Sanzana et al., 2017). The coupling of GIS with other models is an approach that is apparent in the management resources of coastal watersheds. There are several hydrologic models, soil erosion models, and landscape erosion models coupled with geospatial technologies like GIS for improved data processing, anaylysis, and visualization (Briak et al., 2016; Hancock et al., 2011; Maidment, 1993; Patino-Gomez, 2005; Sanzana et al., 2017).

Geospatial technologies have provided several contributions to watershed modeling through their ability to utilize large temporal data sets from monitoring/sampling locations (e.g. hydrometric and climatic stations); (Patino-Gomez, 2005). Remote sensing has created a pathway for the classification of landuse/landcover changes in coastal watersheds which help to visualize landscape changes from increasing population and development (Yang and Liu, 2005). These types of classifications coupled with GIS and spatial analyses are allowing environmental decision makers to identify and rank landuse patterns for implementation of best management practices for nonpoint source pollutants (Abell et. al, 2019; Euan-Avila et. al., 2005). These GIS and spatial analysis allow relationships to be established between sediment loading and spatial patterns on the landscape to help identify and control nonpoint source producing areas efficiently (Bel Hassen and Prou, 2001; Zhang et al., 2016).

The design of many soil erosion models allow them to work in conjunction with GIS and other geospatial applications. Examples include the Water Erosion Prediction Project (WEPP), Soil and Water Assessment Tool (SWAT), and OpenNSPECT, the open source version of the Nonpoint Source Pollution and Erosion Comparison Tool. These models are often described as traditional soil loss models and are either mechanistic (i.e. SWAT) or empirical such as the revised universal soil loss equation (RUSLE) and modified soil loss equation (Coulthard et al., 2012). The RUSLE was developed to provide better estimates of soil loss over the earlier Universal Soil Loss Equation (USLE). The RUSLE may be expressed as

$$A = R \; x \; K \; x \; LS \; x \; C \; x \; P \qquad (2.1)$$

where 'A' is the average annual soil loss in tons/acre/year, 'R' is the average annual rainfall-runoff erosivity factor, 'K' is the soil erodibility factor, 'LS' is the slope length and steepness, 'C' is the land-cover management factor, and 'P' is the support practice factor (Renard et al., 1997). The use of these quantitative models is beneficial; however, the execution and data requirements of these models often limit updated assessments for specific management areas.

The primary effort of this project is to develop a conceptual geospatial model for the qualitative assessment of erosion potential in coastal watersheds. The model will serve as the base for multi-criteria-decision-analysis (MCDA) of erosion potential by decision makers and resource managers and will be based on criteria similar to traditional empirical soil loss models such as USLE and RUSLE. It is hypothesized that a less complicated qualitative model will produce comparable results to those of more complicated traditional soil loss modeling approaches. The primary objectives of this study effort are to:

- Develop a conceptual geospatial model based on criteria similar to that of existing soil loss models that less complicated qualitative assessment of erosion potential.

- Compare and summarize results across the basin and at the intra basin or subwatershed level to establish model variation based on landscape characteristics. It is hypothesized that erosion potential results will vary across the watershed based on landscape characteristics.

- Perform a sensitivity analysis (SA) of the model with each variable using the one at a time (OAT) method to identify the significance of each variable. It is hypothesized that all variables will be significant for the assessment of erosion potential.

2.3 Data and Methods

This project developed a geospatial tool for the assessment of surface erosion potential in coastal watersheds in Alabama. The model is conceptually based on existing numerical soil loss models such as RUSLE and SWAT. The model was developed with input from resource managers at the Weeks Bay National Estuarine Research Reserve to create a more simplistic method of erosion potential assessment. The geospatial application of the model provides a spatial context to assist with management and planning in watersheds. The model is based on principles of grid based (or raster) analysis utilizing basic map algebra techniques. The approach utilizes variables/criteria that target the physical landscape, built-up landscape, and climate. The criteria are similar to those typically used in soil loss models such as those previously mentioned.

Data layers utilized for the development of model variables are from national datasets and sources. These data layers represent features of terrain, geomorphology, soils, land disturbance, and long-term precipitation. Specific sources of data layers include the USGS National Elevation Dataset (NED), USGS National Hydrography Dataset (NHD), USDA Soil Survey Geographic Database (SSURGO), USGS Global Land Survey (GLS) datasets, and data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM). Table 2.1 provides a list of data layers, products and sources.

Table 2.1 Conceptual Model Data Sources

Data Layer	GIS Data Type	Raster Data Product	Data Source
Elevation	Grid (30 Meter)	Slope -30m	USGS National Elevation Dataset
Soils	Grid (30 Meter)	Erosion (K-Factor)-30m	USDA Soil Survey Geographic Database
Hydrology	Line	Stream Density-30m	USGS National Hydrography Dataset
Land Cover	Grid (30 Meter)	Soil Brightness-30m	USGS Global Land Survey Dataset
Precipitation	Grid (4 Kilometer)	Precipitation-30m	PRISM Climate Group

Data layer, data type, raster data analysis product, and data source used in conceptual model.

2.3.1 Workflow Development

The workflow development for the erosion potential analysis as previously mentioned is to follow that of a numerical soil loss model. In general the workflow system and model can be described with three high level data categories or components of variables. This includes physical erodibility, land sensitivity, and precipitation erosivity. The combination of these describe the total erosion potential (Kheir et al., 2008; Partowary et al., 2018; Wu et al., 2007; Yousuf et al., 2016). Breaking the components down yields the individual variables and data inputs for the analysis tool. The inputs include slope and stream density as measures of physical erodibility. Land sensitivity includes measures of soil K-factor and soil brightness (exposure). The final measure of precipitation erosivity consist of a single input from PRISM data for the 30-year rainfall averages (Figure 2.1).

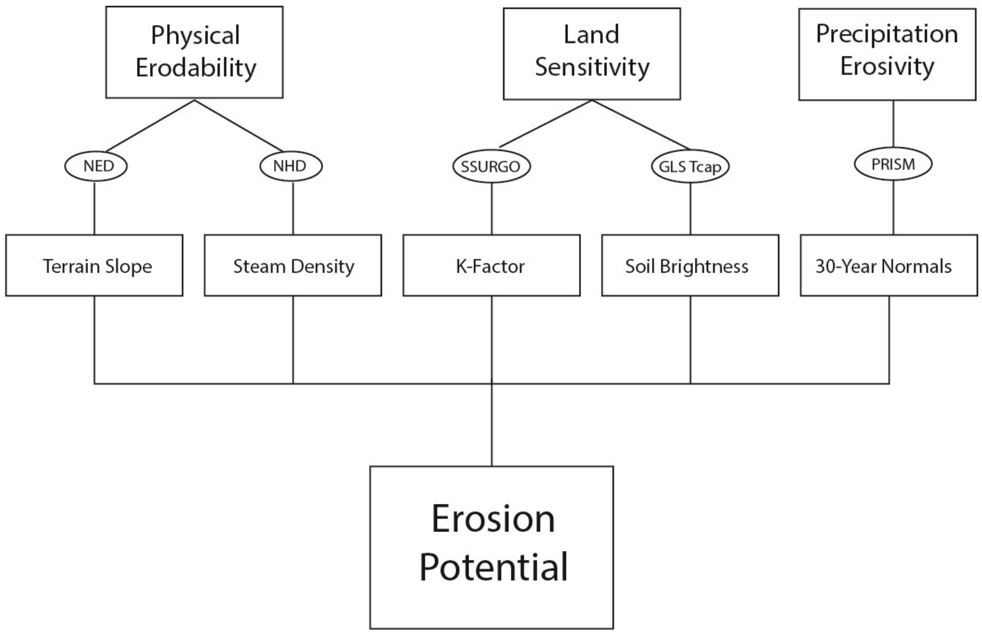

Figure 2.1 Conceptual Model Schematic

Model components with data source and model variables.

2.3.2 Data Inputs and Processing

Data layers used for input are selected from national datasets to ensure transferability between geographic areas within the United States for repeatability and comparisons across watersheds (i.e. Weeks Bay to Grand Bay to Apalachicola). Data sets were acquired and preprocessed for the Weeks Bay watershed within the Mobile Bay estuarine drainage area (EDA) by merging data tiles and sub-setting to the area or region of interest. The region of interest boundary was defined with vector based files for the four 12-digit hydrologic units that make up the Weeks Bay drainage area from the Watershed Boundary Dataset (WBD), see Figure 1.1. All data layers were set to the Universal Transverse Mercator (UTM) coordinate system for zone 16 north because this is the preferred projection of the Weeks Bay NERR resource managers. All data processing and workflow development were performed with a commercial GIS software.

Slope (slp): Base data for the derivation of slope was the USGS National Elevation Dataset (NED) which is a seamless data layer representing elevation for the United States. NED elevations are represented in a raster format with a horizontal resolution of 30 meters and a vertical accuracy of 2.5 meters for each grid cell. The slope calculation for a cell is based on the amount of descent between it and the surrounding eight cell neighborhood using Horn's 1981 algorithm (Esri, n.d.). The maximum value of descent is thus recorded as the cell's slope and can be calculated in percent or degrees, with the latter used in this work. Once slope values were calculated the data were normalized by the maximum value within the Weeks Bay watershed. The resulting data layer is a continuous index of slope with unitless values ranging from 0-1 (Figure 2.2).

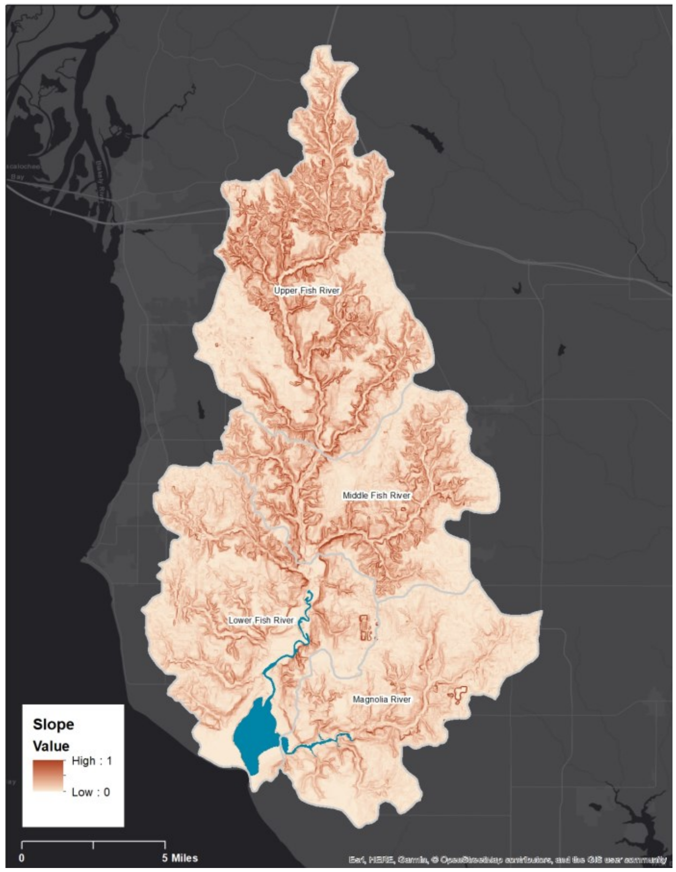

Figure 2.2 Terrain Slope

Stream Density (strdn): Stream network data were obtained from the USGS National Hydrography Dataset (NHD) for the four 12-Digit HUCS of the Weeks Bay drainage area in the Mobile Bay EDA. The NHD high resolution (1:24,000) data format was utilized in this study. Included in the NHD are vector spatial data representations for all surface water features, including manmade drainage, shore lines, and natural features with only relevant surface features (i.e. excluded shorelines, etc.) being used to generate the density layer. The generation of a stream density surface is used to spatially understand the dissection of the landscape, especially in combination with the derived slope. Higher instances of stream density are associated with increased erosion rates, specifically as they relate to the dissection of the landscape and the land-drainage system interactions (Clubb et al., 2016). Similar data layers are used in soil erosion analysis (Kheir et al., 2008) and are also used in numerous landscape evolution models that simulate erosion and deposition (Tucker et al., 2001).

The density function used for calculation utilized a neighborhood area with a specified search radius and all stream segments intersecting the area were counted and a continuous surface with the specified cell size was returned. The default search radius used in commercial GIS software is based on the minimal spatial dimension of the data set (Silverman, 1986). The default search radius for the NHD data set was 2257 meters based on the minimum spatial dimension measured by the GIS software. To confirm the validity of using the default value, multiple density analyses were run with varying search radii, and no appreciable changes in density occurred after approximately 2200 m, which suggests the default parameter is valid (Figure 2.3). The analysis cell size is set for 30 meters to match the other raster data products and density values were returned in length of stream per square kilometer. The derived density surface was normalized by the maximum value within the Weeks Bay Watershed. The resulting data layer is a continuous index of stream density with unitless values ranging from 0.055 – 1 (Figure 2.4).

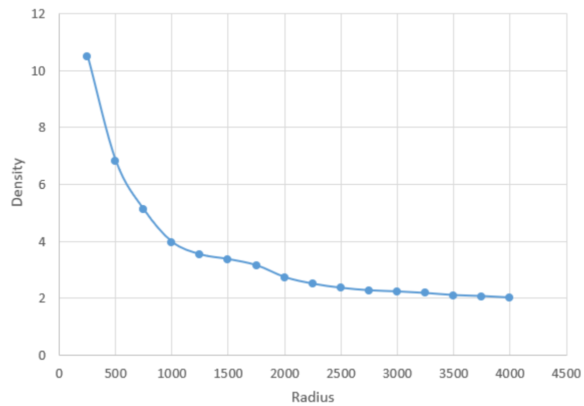

Figure 2.3 Stream Density Search Radius

Stream density values and search radius sizes used to confirm use of use of default value.

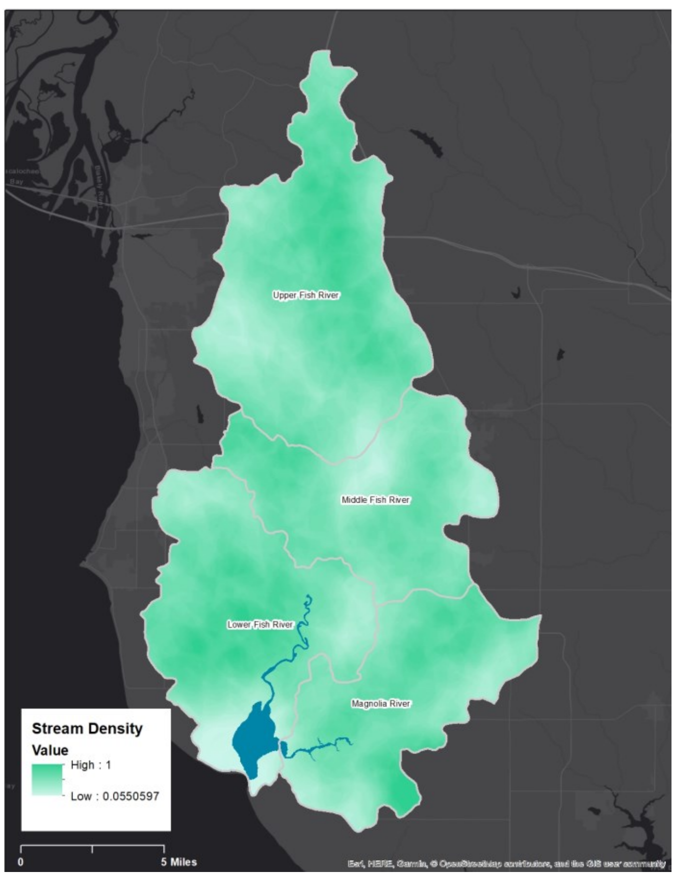

Figure 2.4 Stream Density

K-Factor (kfact): Soil data utilized were from the Soil Survey Geographic (SSURGO) database from the United States Department of Agriculture (USDA) Natural Resource Conservation Service (NRCS). The SSURGO database is the highest resolution database with survey data at the county level. The State Soil Geographic (STATSGO) database is the mid-level soil survey database available at the state level and the National Soil Geographic (NATSGO) database at the national level. The SSURGO database provides a wealth of information on the physical landscape with regards to soil properties and is available as gridded or vector data types. Soils data are provided in map units which are assembled by components with 60 properties and each component can have up to 6 layers with 28 properties. This study specifically used the K-factor property which is an erodibility factor that accounts for both the susceptibility or soil erosion based on soil texture and rate of runoff. Soil loss models such as USLE and RUSLE use soil K-factor to identify areas susceptible to erosion. Values of 0.20 or lower are described as having low potential with values greater than 0.20 and less than 0.40 having moderate potential and values over 0.40 having the most potential for erosion. These data were extracted from the database for the Weeks Bay Watershed and normalized by the maximum value. The resulting data layer is a continuous index of soil K-factor with unitless values ranging from 0.049 – 1 (Figure 2.5).

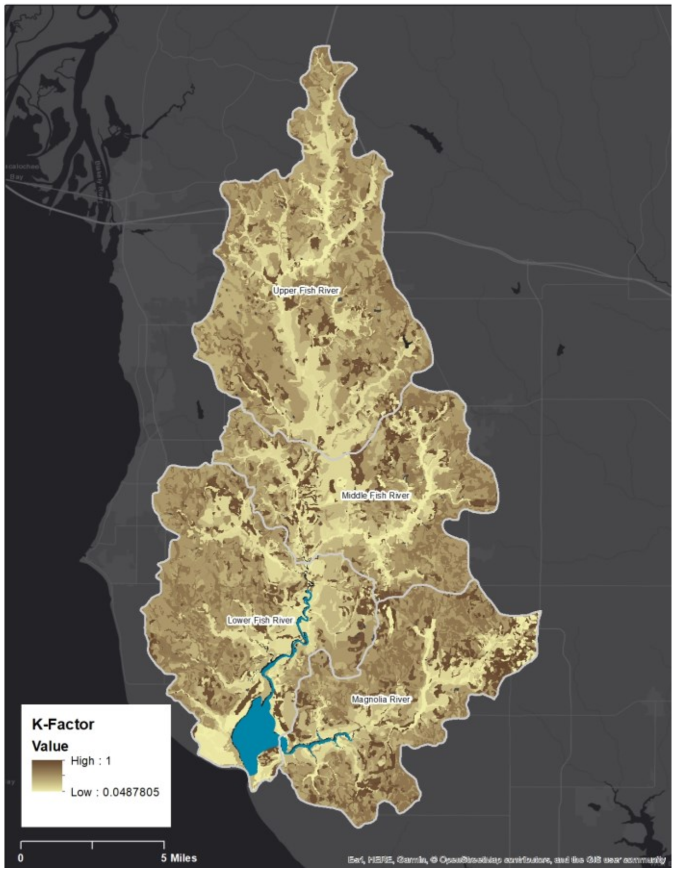

Figure 2.5 K-Factor

<u>*Soil Brightness (tcap):*</u> Global Land Survey (GLS) datasets, Landsat satellite imagery for specific time periods, are generated by the USGS and NASA. These datasets contain images with minimal cloud cover for assessments of land cover characterizations at national and global levels. Multiple images are available for areas to help normalize seasonal variations across the landscape for annual assessments. The imagery available for this study area was acquired during the 2010 – 2012 timeframe. The imagery is dynamically processed with the Tasseled Cap transformation which provides separate indices for greenness, wetness, and soil brightness. The soil brightness band of the Tasseled Cap transformation provides an index of measure for soil reflectance/exposure and not just the lack of vegetation (Kauth et al., 1979). The soil brightness

data from the GLS dataset were extracted and subset to the Weeks Bay Watershed and normalized by the maximum value. The resulting data layer is a continuous index of soil brightness with unitless values ranging from 0.018 – 1 (Figure 2.6).

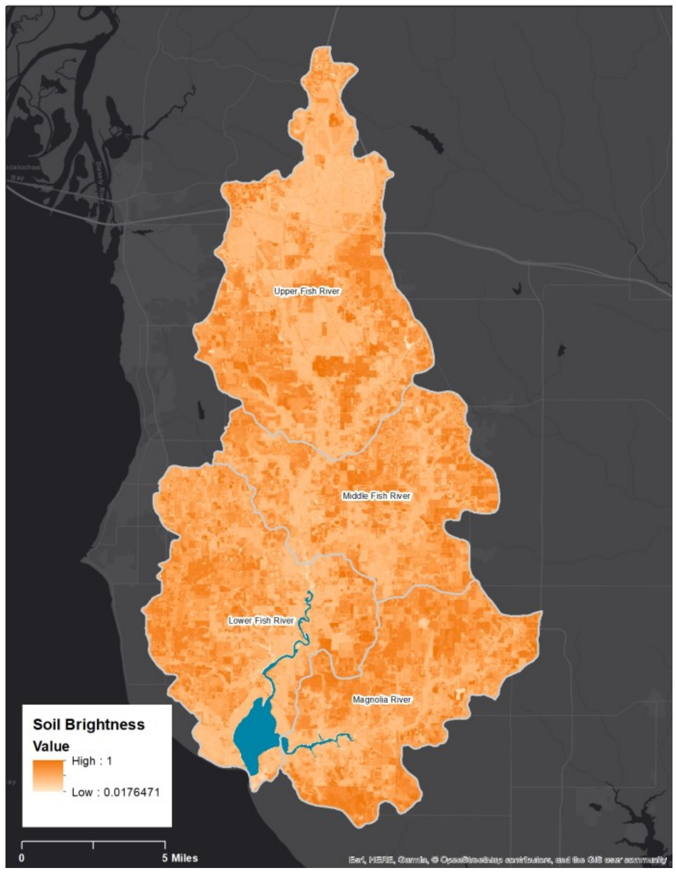

Figure 2.6 Soil Brightness

Precipitation Erosivity (prsm): 30-Year precipitation normals describing average monthly and annual conditions for the three most recent full decades were obtained from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) and processed for the study area. PRISM data are from a knowledge-based system which uses spot measurements and observations of precipitation, temperature, and other climate related factors to generate continual surface data for various temporal scales of climatic data (i.e. monthly, yearly, etc…) (Daly, 2002). The most recent PRISM annual precipitation climatology is based on data from 1981-2010 and was used for this study. These data were extracted from the database for the region of interest, normalized by the maximum value, and resampled to 30 meters (from 4 kilometers). The resulting data layer is a continuous index of annual precipitation climatology with unitless values ranging from 0.96 – 1 (Figure 2.7).

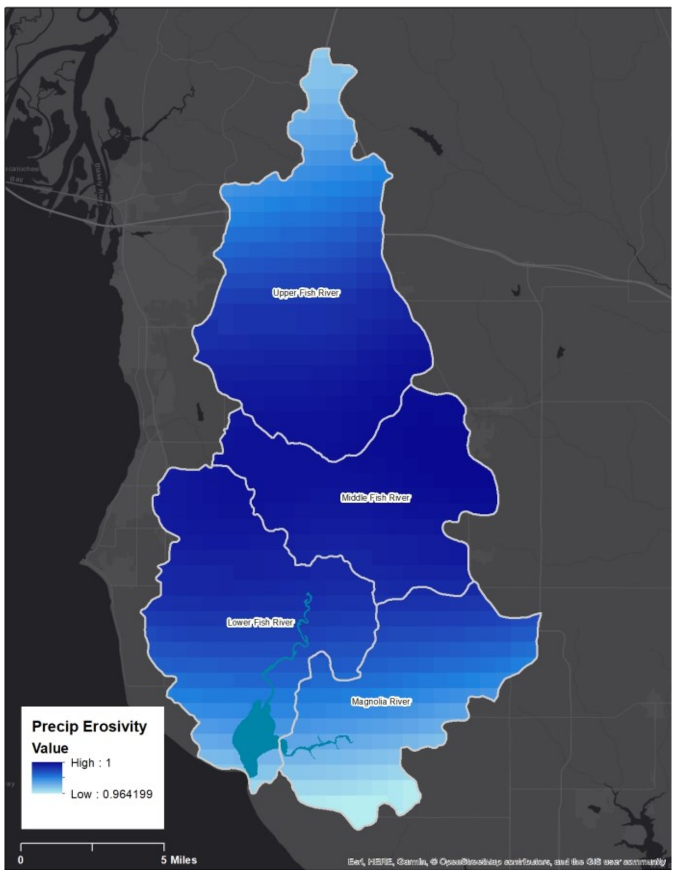

Figure 2.7 Precipitation Erosivity

2.3.3 Workflow Process

The workflow process was executed by utilizing a standard weighted linear combination (WLC) for the summation of the five raster data layers (Malczewski, 2000). Each of the layers were weighted equally (weight factor of .20) for the initial system run for erosion potential estimation. This approach allows for a final data product (or index) with values ranging between 0-1. This allows for data value alignment with the input of the individual variables. The simple combination is as follows:

$$Erosion\ Potential = Slope + Stream\ Density + K\ Factor + Soil\ Brightness + Precipitation\ Erosivity \quad (2.2)$$

After the initial run, five additional runs were completed with one variable omitted and the other four variables combined equally (weight factor of .25). This produced comparative data outputs to test the sensitivity of the conceptual model response to each of the variables following methods similar to that of Chen et al., (2010) and Rahmati et al., (2017). Comparisons of each model run were analyzed using the Pearson Correlation Coefficient. The comparison was performed using the values for the raster grids at each pixel or cell. Differences between each variable sensitivity model run and the conceptual model were calculated for each cell to identify areas of variable influence spatially.

2.4 Results

The output of the conceptual erosion model produced a continuous surface of erosion potential based on physical erodibility, land sensitivity, and precipitation erosivity for the Weeks Bay watershed (Figure 2.8). Erosion potential across the watershed averaged 0.529 based on the WLC mentioned previously. The four 12-digit subbasins had similar erosion potential averages across each subwatershed. Field observations during site visits showed that the upland, head water areas of the watershed and the areas dominated by cultivated agricultural areas are expected to have higher erosion potential. Lower erosion potential values are expected in the densely vegetated riparian and marsh areas. Table 2.2 provides general statistics for the developed measure of erosion potential at the basin and subbasin level.

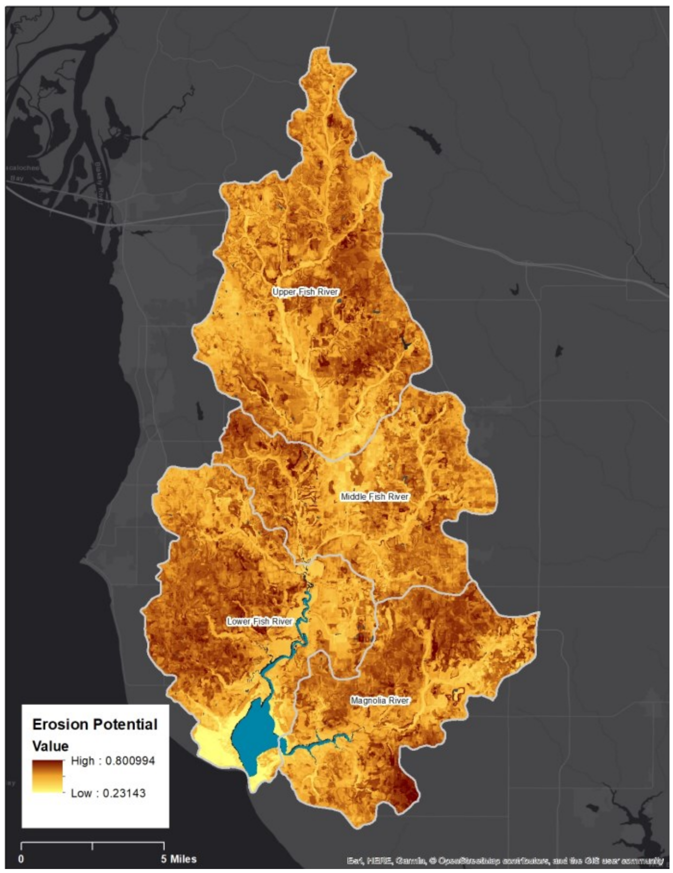

Figure 2.8 Watershed Erosion Potential

Conceptual model erosion potential for the Weeks Bay watershed.

2.4.1 Classified Erosion Potential

The erosion potential data were classified to better identify areas that may or may not be susceptible to erosion (Figure 2.9). The classes were based on standard deviations from the average basin erosion potential as the data are normally distributed (Figure 2.10). This produced a total of seven classes with class 1 representing lower erosion potential and class 7 representing higher erosion potential (Table 2.2). At the watershed (drainage basin) level 69% of the data are within one standard deviation of the mean. There are a total of 8515 cells (1.5%) in the upper most erosion potential ranks (classes 6 and 7). Approximately 80,000 cells (14%) are in the moderate erosion potential rank (class 5). The lower erosion potential ranks (classes 1-3) are similar in distribution to the upper ranks (classes 5-7).

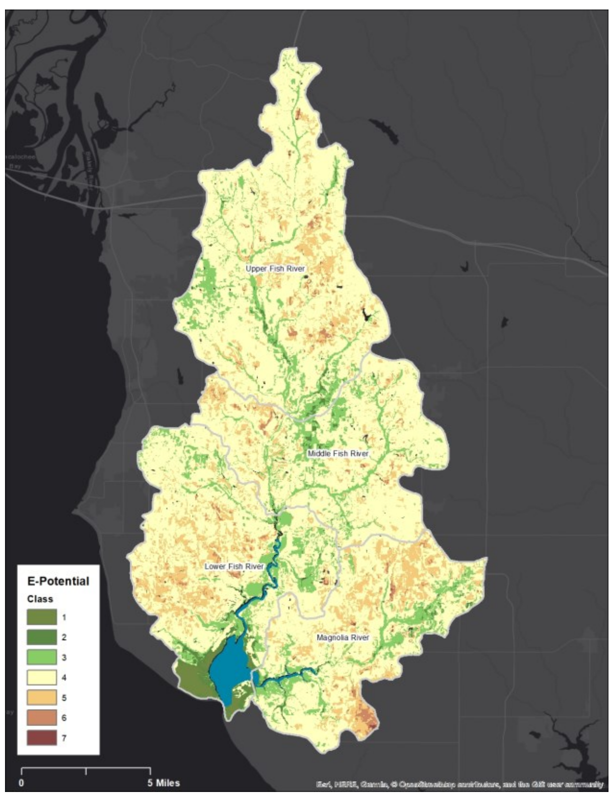

Figure 2.9 Classified Erosion Potential

Classified erosion potential at the subbasin level has some variations when compared to each other. The two downstream basins have decreased proportions of cells around the mean erosion potential and the two upstream basins have increased cell proportions around the mean of the given subbasin. In terms of increasing erosion potential, the Magnolia River subbasin has the largest count of cells in the upper erosion potential ranks (classes 5-7) at 23%. The Lower Fish has the next highest count with almost 17% of the subbasin in the upper erosion potential ranks, however it also has the largest cell count in the lower ranks (classes 1-3) at 21%. The Upper and Middle Fish subbasins both have about 75% of their cell count within one standard deviation of the mean and about 12% or less in the upper ranks. Table 2.2 and Figure 2.11 provides a complete description of cell counts (with upper and lower ranks) at the basin and subbasin level.

Table 2.2 Erosion Potential Cell Counts and Descriptive Statistics

	Upper Fish	Middle Fish	Lower Fish	Magnolia	Weeks Bay
Class 1	0	1	5,279	50	5,330
Class 2	1,436	825	5,225	1,335	8,821
Class 3	22,586	16,072	19,899	15,938	74,495
Class 4	141,679	89,391	90,602	71,948	393,620
Class 5	21,206	12,331	22,433	23,872	79,842
Class 6	2,287	1,147	1,908	2,788	8,130
Class 7	109	26	62	188	385
Minimum	0.356	0.353	0.231	0.294	0.231
Maximum	0.801	0.770	0.771	0.787	0.801
Range	0.445	0.417	0.540	0.493	0.570
Mean	0.527	0.526	0.520	0.537	0.527
Std. Dev.	0.050	0.050	0.069	0.059	0.057

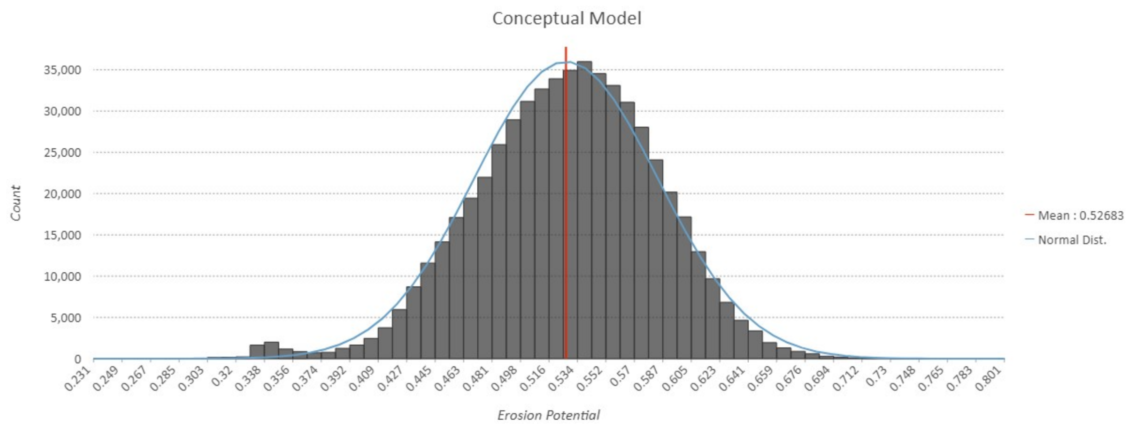

Figure 2.10 Conceptual Model Histogram

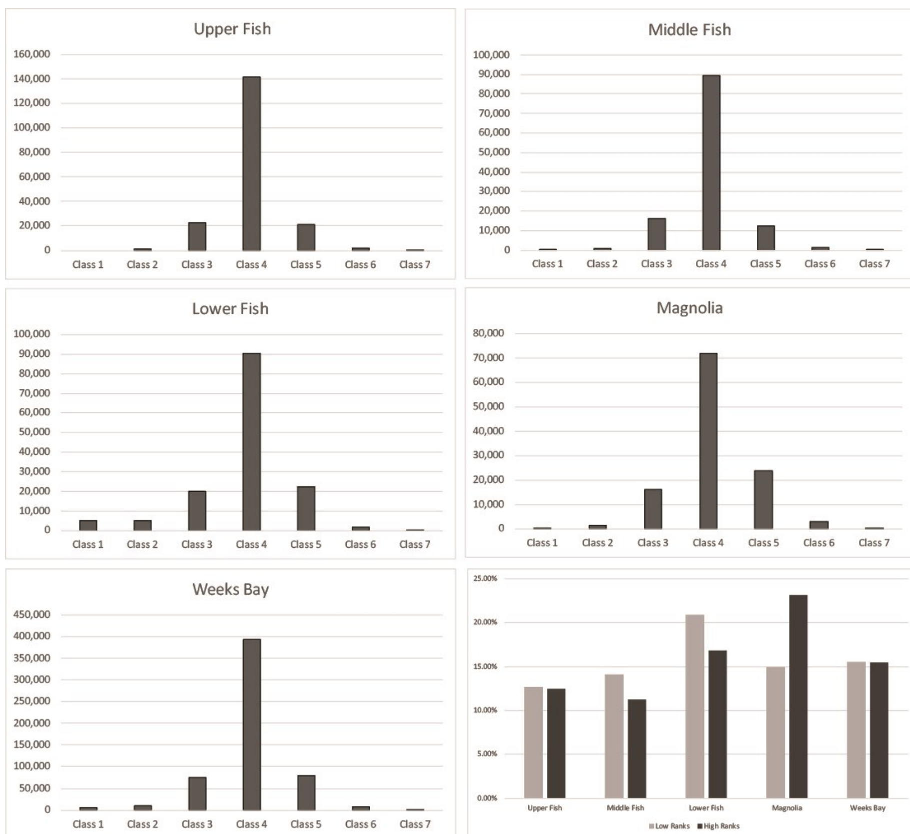

Figure 2.11 Classified Erosion Potential Distribution and Upper and Lower Ranks

2.4.2 Variable Sensitivity Assessment

To better understand the performance and sensitivity of the conceptual model each variable was removed one at a time (OAT) and the workflow processed again. This resulted in five additional outputs of erosion potential produced by equally weighting four of the five variables. Each of the five runs were compared to the conceptual model for assessment. The model runs without variables all had moderate to strong correlation with the conceptual model run. The model without the precipitation variable had the strongest correlation (R = 1.00) followed by the model run without slope input (R = 0.94). The runs without stream density and soil brightness were moderately correlated, R = 0.88. The run with the weakest correlation was the one without K-factor, R = 0.79. The correlation results showed that the conceptual model was most sensitive to the K-factor variable and moderately sensitive to the variables of stream density and soil brightness. The model was least sensitive to the precipitation and slope variables (Table 2.3 and Figure 2.12).

Table 2.3 Descriptive Statistics and Pearson Correlation for Sensitivity Analysis

	Conceptual	**Variable Removed from the Conceptual Model** *Slope*	*Stream Density*	*K-Factor*	*Soil Brightness*	*Precipitation*
Mean	0.527	0.634	0.539	0.511	0.540	0.411
Median	0.529	0.635	0.542	0.513	0.542	0.414
Mode	0.518	0.573	0.398	0.520	0.552	0.444
Std. Dev.	0.057	0.072	0.061	0.052	0.061	0.072
Variance	0.003	0.005	0.004	0.003	0.004	0.005
Kurtosis	0.467	-0.033	-0.103	0.724	0.418	0.416
Skewness	-0.328	-0.152	-0.103	-0.292	-0.184	-0.304
Range	0.570	0.632	0.611	0.560	0.544	0.711
Minimum	0.231	0.288	0.269	0.277	0.270	0.046
Maximum	0.801	0.920	0.881	0.837	0.814	0.757
Count	570,623	570,623	570,623	570,623	570,623	570,623
Pearson Correlation	-	0.940	0.882	0.788	0.881	1.000

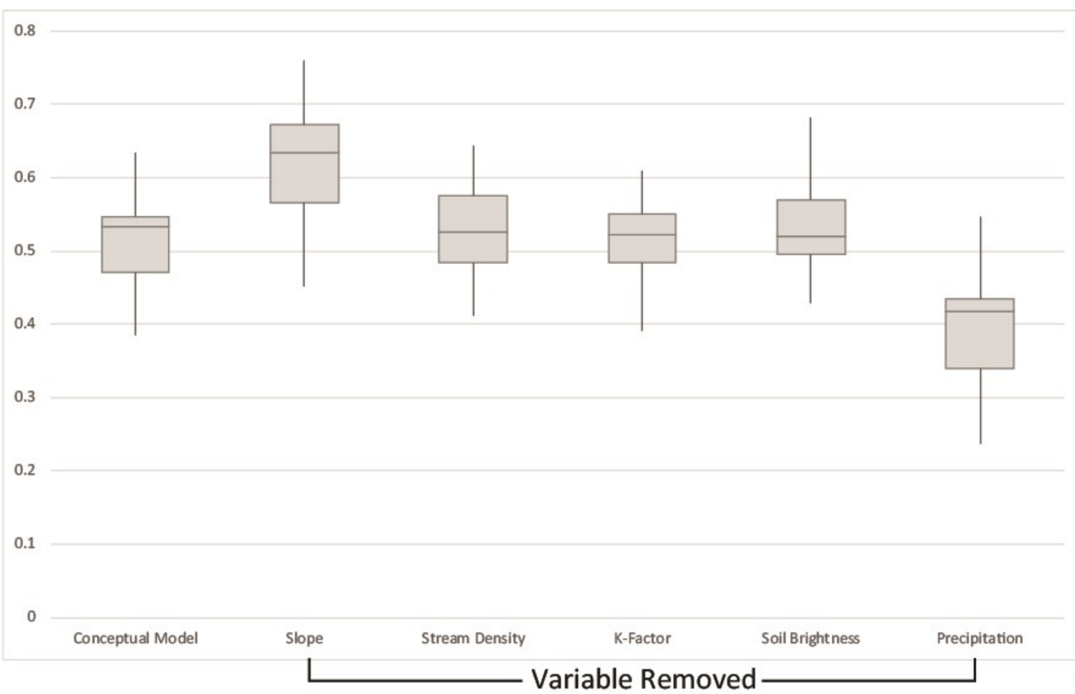

Figure 2.12 Data Spread of Model Sensitivity Runs

2.5 Discussion

The developed model included variables for slope, precipitation, soil brightness or exposure, K-factor, and stream density. The approach is similar to RUSLE (Renard et al., 1994) but differs by using normalized data sets that are more generalized in terms of application, for example not centric to agriculture. This approach helped to develop a model that allows resources managers to execute it for the assessment of erosion potential as it relates to their specific location without on emphasis on a specific land practice. The sensitivity assessment of the variables used in the model indicated that the qualitative erosion potential model was most sensitive to the K-factor variable, followed by soil brightness and stream density. The model was least sensitive to the precipitation erosivity variable and slightly more sensitive to the slope variable.

2.5.1 Erosion Potential Assessment

The conceptual model showed the variability that was expected across the watershed and the four subbasins. The agricultural dominated southern subbasin (Magnolia River) had the highest erosion potential as compared to each of the other subbasins and the entire watershed. The headland area of the watershed (Upper Fish River) was the second highest and has the most topographic variation of the subbasins. The middle areas of the watershed (Middle and Lower Fish) had the lowest erosion potential assessment. The results for the Magnolia River subbasin are in line with what is expected with higher erosion along stream reaches in agricultural areas (Basnyat et al., 1999; Bel Hassen and Prou, 2001).

Overall erosion potential in the Weeks Bay watershed tends to be lower in densely vegetated riparian and marsh areas. Many of these areas, especially in the southern area near the bay, are part of the Weeks Bay National Estuarine Research Reserve. Areas in the watershed with higher erosion potential are associated more with transitional type lands that appear to be more agricultural or dynamic in terms of land practices. The southeast region of the watershed reflects this as it is an area dominated by agricultural practices such as cultivated crops and turf grass farms (Figure 2.13). The classified erosion data provide a better perspective of the erosion potential in the watershed. Overall the watershed appears to be somewhat balanced when we look at the general distribution of the erosion potential data. The upper and lower ranks are near equal with each making up about 15.5% (31% total) of the watershed. This can be used to prioritize management decisions for specific areas within the four 12-digit subbasins of the Weeks Bay watershed.

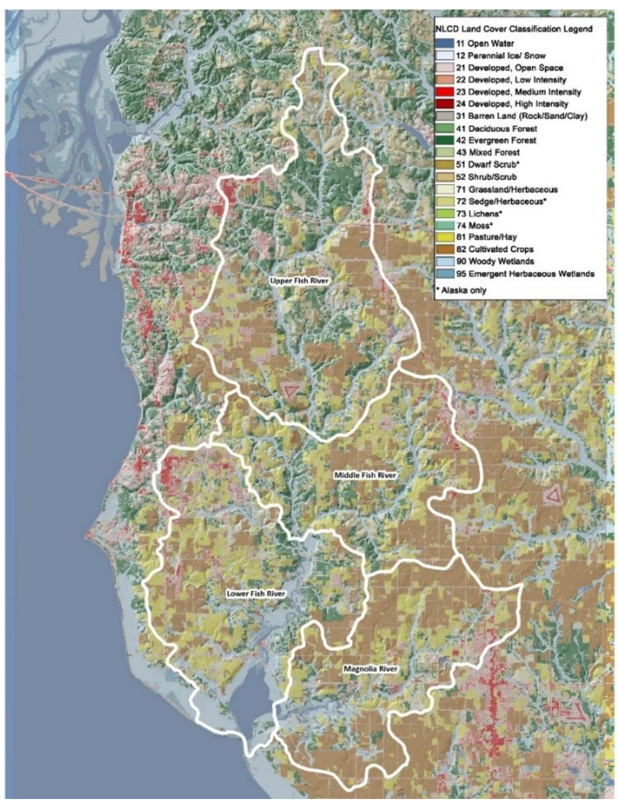

Figure 2.13 NLCD 2011 Land Cover

The southern portion of the watershed has a larger portion of cells within the upper erosion potential ranks (classes 5-7). This includes both the Lower Fish River and Magnolia River subbasins. The Magnolia subbasin has the highest count of higher erosion potential ranks and when the higher ranks cells are normalized by the lower ranks has a ratio 1.5 times that of the entire watershed which is approximately 1.0. The Upper Fish River subbasin has a ratio of .99 and the Middle and Lower Fish River subbasins both have ratios of .80. The ratio of upper ranks/lower ranks offers a bit more insight or ranking as to how the subbasins compare to each other as well as the overall watershed. The ratio of the subbasin indicates that the Magnolia subbasin is the most susceptible in terms of erosion potential and would make it a higher priority in terms of resource management needs.

2.5.2 Model Sensitivity Assessment

The model sensitivity analysis used comparisons of Pearson correlations to evaluate the variability of the model for all the factors used in the conceptual model. Difference grids were produced to help visualize areas where each of model variables were changing the classified erosion potential output within the Weeks Bay watershed (Figure 2.14). Grid cells sensitive to the variable are highlighted, areas of increase are highlighted in orange and areas of decrease in green. The strongest correlation was between the conceptual model and the run without the precipitation variable ($R = 1.00$). The precipitation variable had minimal variation across the Weeks Bay watershed and the lack of influence of this variable is homogeneous with the smallest amount of erosion potential class changes in the northern and southern most regions of the watershed (Figure 2.14F).

Model runs without the physical erodibility (topographic) factors, slope and stream density, had moderately strong correlations with the conceptual model. The slope variable has the stronger correlation of the two and the areas influencing increased erosion potential of the classified model data are visible in near active stream and river channels (Figure 2.14B). The model run without the stream density had was moderately correlated (R = 0.88) and exhibited more influence on the conceptual model. Stream density influence on increased erosion potential occurred in similar areas when compared to that of the slope influence, along the stream and river channels. The overall stronger influence of the stream density variable is visible in the intensity of grid cells in areas of both increasing and decreasing erosion potential (Figure 2.14C). These areas of increased potential are indicative of higher concentrations of stream reaches with more surface interaction with runoff waters and lower soil infiltration rates (EPA, 2015; Kheir et al., 2008; Kheir et al., 2006).

Model runs that omitted the land sensitivity factors of soil brightness and K-factor were moderately correlated with the conceptual model. The correlation of model run without the soil brightness variable was the stronger of the two (R = 0.88). This matches the correlation value of model run without stream density indicating similar levels (not type) of influence with these two variables on the conceptual model. Soil brightness is indicative of disruptive land uses and increases in erosion potential from this variable are apparent in agricultural dominated areas of the watershed (Figure 2.14E). The weakest correlation of the conceptual model was with the run without the K-factor variable (R = 0.79). K-factor is used in USLE and RUSLE applications that represents soil texture and composition (Renard et al., 1994; Patowary and Sarma, 2018; Terranova et al., 2009). Areas of influence are similar to those of soil brightness (Figure 2.14D)

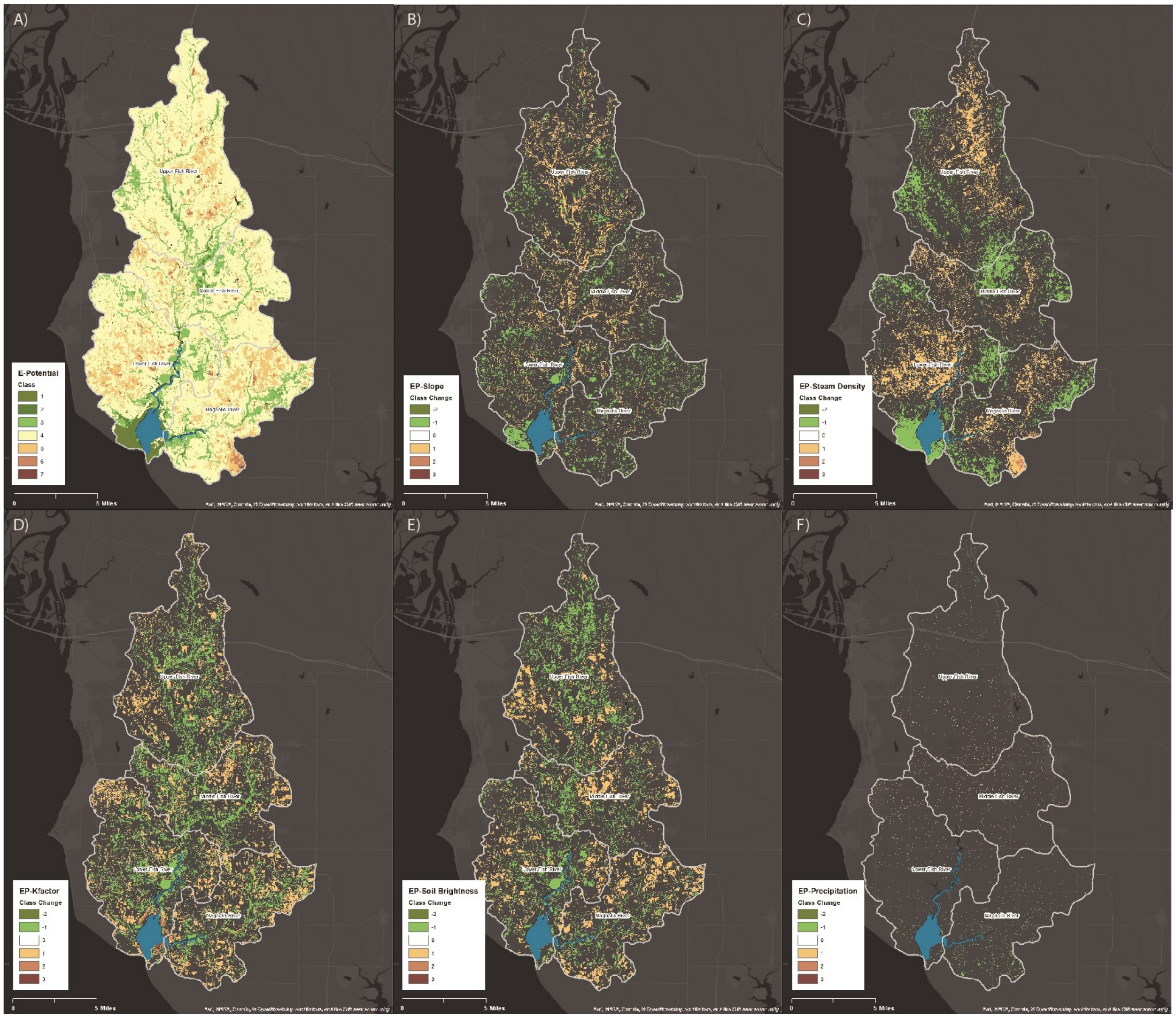

Figure 2.14 Classified Model Output and Variable Difference Grids

A) Classified erosion potential, B) slope influence, C) stream density influence, D) K-Factor influence, E) Soil brightness influence, and F) precipitation influence.

2.6 Conclusions

The conceptual model developed for this project produced an erosion potential surface that aligns with the erosion trends described in the Weeks Bay watershed management plan (MBNEP, 2017). The general trend described has more erosion occurring in areas associated with agricultural practices and areas of increasing urban and suburban development (MBNEP, 2017). The 12-digit HUC (subbasin analysis) found that the subbasin with the higher ranks of erosion potential cells was in the southeast portion of the watershed which is dominated by cultivated crops and turf-grass related agriculture. The conceptual model had various levels of sensitivity to the variables of K-Factor, soil brightness, stream density, and slope. The model had minimal sensitivity to the precipitation variable as it showed little variation across the watershed. The variables of K-factor and soil brightness identified areas of land disturbance and development. Slope and stream density identified areas associated with stream networks and headland areas of the watershed. The balance between these two groups of variables qualitatively represents the natural erosion potential of the physical landscape and the alteration of erosional processes by anthropogenic activities. Limits in this phase of the research include the lack of exact validation data for watershed erosion. The following chapter will build upon the conceptual model with the addition of expert input to prescribed weights on variables for the WLC. Additionally, erosion potential output from the conceptual model and the expert input will be compared to the output of a standard numerical soil loss model to identify alignment in a later chapter.

CHAPTER III

THE ANALYTIC HIERARCHY PROCESS

3.1 Abstract

Evaluating soil erosion is often assessed with traditional soil loss models like the Revised Universal Soil Loss Equation and similar models. These models are often integrated with Geographic Information Systems (GIS) to assist with execution and utilization. This chapter is focused on moving from the models towards a Multi-Criteria Decision Analysis (MCDA) approach to transition from model to decision support. The base effort of this work is to add expert input to the previously developed conceptual model for generalized watershed erosion potential and to establish a foundation for improved decision support. The Analytical Hierarchy Process (AHP) is used to value the importance of criteria based on expert input, providing a quantitative metric (weight) for qualitative data. The expert input increased the overall importance of topographic features, with topographic related criteria carrying half of the weight in the AHP run. The results show that the AHP input to the conceptual model statistically changes to overall erosion potential. The AHP run of erosion potential was classified (7 classes) based on standard deviations to compare to the conceptual model. The AHP run changed class cell counts most noticeably by decreasing counts in low erosion potential classes (classes 1, 2, and 3) and the moderate erosion potential class (5). The upper ranks (class 6 and 7) had increased cell counts, as did the base of cells around the mean erosion potential. The increase in the upper ranks was most evident in areas along the drainage areas of the rivers and streams of

the watershed. The AHP weights were altered in 1% increments ranging from plus to minus 20% producing 41 runs per criteria or 201 unique runs. A quartile analysis was used to define areas of model agreement (or alignment) using a threshold of less than 25% outlier generation for each cell in the analysis. This allowed for an analysis mask to be applied to identify areas of increased erosion potential as a means for improved management related decisions.

3.2 Introduction

Soil erosion across the landscape traditionally has been characterized with models such as the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1994; Patowary and Sarma, 2018) and the Water Erosion Prediction Program (WEPP) (Laflen et al., 1991; Laflen and Flanagan, 2013; Yousuf and Singh, 2016). The combination of many of these models with geographic information systems (GIS) helps with transition from models (modeling) to decision-support and analysis. GIS coupled with the analytical hierarchy process (AHP) (Yalew et al., 2016) is proving to be an important tool for multi-criteria-decision-analysis (MCDA) (Jankowski, 1995; Jankowski, et al., 2001). GIS utilizing AHP is an established and credited approach for MCDA for land resource management decisions (Malczewski and Rinner 2005; Akinci, et al., 2013) and is an important part of sustainable land planning approaches (Tudes and Yigiter, 2010; Mosadeghi, et al., 2015).

Erosion assessments have been conducted at locations around the globe from regions down to catchments. Regional soil erosion assessments in Mediterranean karst landscapes were developed by looking at two sets of factors, endogenous and exogenous parameters. Endogenous parameters were those associated with geologic/physical characteristics of the landscape; a) rock infiltration, established from lithology, lineament density, karstification and drainage density, b) soil erodibility and c) morphology. Exogenous parameters are those acting upon the landscape surface; a) land cover/use and b) rainfall erosivity (Kheir et al., 2008). The model used AHP techniques to determine the importance of each of the factors that made up both the endogenous and exogenous parameters. This was building upon previous work looking at regional erosion risk in the same area (Kheir et al., 2006).

Modeling approaches for soil erosion are typically either classified as qualitative or quantitative (Terranova et al., 2009). Qualitative modeling approaches are often driven by an expert input. This makes them very useful in the decision making process, specifically for tasks like vulnerability assessments and other methods (Kachouri et al., 2014). The combination of GIS and AHP is useful for MCDA in natural resource assessments like soil erosion mapping (Wu and Wang, 2007). While models and tools of this type do not allow for the quantification of sediment yields or soil loss rates due to erosion, they do offer resource managers and decision makers with information to better manage watersheds and the related water resources.

Expanding GIS utilization for MCDA has improved decision support models for land based suitability evaluations. These expanding efforts have increased the need for ways to evaluate the performance of the models and tools utilized as well as the sensitivity of the variables or layers used (Chen et al., 2010; Rahmati, et. al., 2017). There are numerous procedures that are used with GIS for MCDA, examples include Boolean overlay, weighted linear combination (WLC), ordered weighted Averaging (OWA), and analytical hierarchy process (AHP) (Romano et al., 2015). The WLC is one of the most commonly used decision support tools in the GIS environment (Malczewki, 2000; Malczewki, 2006). The AHP is a robust method for determining criteria weights (Saaty, 1980) and works well with MCDA in the GIS environment.

The qualitative nature of MCDA often requires nontraditional methods of uncertainty assessment. Sensitivity analysis of the variable weights can assist with identifying stability in model performance with changing criteria weights (Chen et al., 2010). Sensitivity analysis with GIS based MCDA should offer insights to the spatial aspects of the changing criteria weights. Feick and Hall (2004) suggested that efforts to analyze criteria weight sensitivity should result in geographic visualization of the sensitivity.

The general objective of the second phase of this research is to build on the conceptual model and migrate it towards a multi-criteria-decision-analysis application based on expert user input. It is hypothesized that the addition of the expert input will influence erosion potential values based on the conceptual model output. The primary objectives of this second phase are to:

- Add expert user based inputs to the conceptual model by developing criteria weights with AHP methodologies at the watershed level.
- Compare the erosion potential results of the conceptual model with AHP based results. It is hypothesized that the expert input will influence the erosion potential as compared to the conceptual model.
- Perform a modified sensitivity analysis based on the changing criteria weights for each of the five variables or layers to establish alignment in the model runs. It is hypothesized that this will identify areas within the watershed that return consistent results to focus management efforts.

3.3 Data and Methods

This project will expand on the conceptual erosion potential model that was developed and described in the previous chapter. The conceptual model was designed to simplify traditional numerical soil loss models with a quantitative approach. The conceptual approach was built around data layers from nationally available data sets. These data sets include elevation, soils, hydrology, land cover, and precipitation. The expansion in this chapter comes by the addition of expert input to weight each of the data layers used in the erosion potential assessment. Expert input was obtained from the resource mangers of the Weeks Bay NERR, the managers prioritized each layer relative to the other layers used in the conceptual model. The weights of the data layers were determined with the AHP. The AHP uses a pairwise comparison to generate criteria weights based on an expert rating of the criteria.

The data layers utilized included slope, stream density, K-factor, soil brightness, and precipitation. Slope was derived from the USGS National Elevation Dataset (NED). The surface slope was calculated with ArcGIS surface tools and values normalized for standardization. Stream density was calculated from the USGS National Hydrography Dataset (NHD). The stream density was calculated with the ArcGIS line density tool and values normalized. K-factor is a measure of soil erodibility from the Soil Survey Geographic (SSURGO) database. The K-factor data was obtained from the gridded SSURGO database and values normalized. Soil brightness is obtained from Global Land Survey (GLS) dataset. GLS data are derived from Landsat imagery which are dynamically processed with the Tasseled Cap transformation (and other processes). Tasseled Cap data provides information on soil brightness. Soil brightness is an index of measure for soil reflectance. These data were extracted for the Weeks Bay watershed and normalized for standardization with the other layers. Precipitation data were obtained from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM). The data utilized represented the 30-year precipitation normals. PRISM data have a 4 kilometer resolution (all the other layers are 30 meters) and were resampled to 30 meter and then normalized to match the other data.

The combination of slope and stream density represent the physical erodibility. K-Factor and soil brightness represent land sensitivity, and the 30-year precipitation normal represents the precipitation erosivity. The combination of all five layers provides the base for erosion potential in the conceptual model. Chapter two provides a more detailed narrative on the data inputs and the conceptual model.

3.3.1 Analytical Hierarchy Process Methods

The AHP method was executed in three phases or steps. Step one was the standardization of data layers, this was accomplished with the normalization of each data layer. The second step was criterion weight assignment for each of the layers based on scores in Table 3.1. Criterion weight assignment used Saaty's method of a continuous rating scale for pairwise comparison (Saaty 1980). The third step was the weighted linear combination (WLC) of standardized data layers with the weights generated from the pairwise comparison. This output defines the erosion potential based on the expert input of the relative importance between data layers to establish variable weights.

Table 3.1 Scale for AHP Comparisons

Scale	Definition	
9	Extremely	More Important
7	Very Strongly	
5	Strongly	
3	Moderately	
1	Equally Important	
1/3	Moderately	Less Important
1/5	Strongly	
1/7	Very Strongly	
1/9	Extremely	

The data standardization for each data layer was accomplished by normalizing each data set by the global maximum value in the data set. This procedure set each data layer with a possible data range of zero to one for a common scale of assessment. Zero would be a minimal impact on erosion potential and values of one having the greatest impact. Each data layer was then compared individually with the other data layers as they relate to erosion potential. For example, slope would be ranked to provide input as to whether it was more or less important than soil brightness based on the definitions in Table 3.1. Weights for each data layer were assigned based on results from the pairwise comparison matrix. With all layers standardized and weighted the WLC was used to apply the weights from the expert input for the assessment of erosion potential. This allows each data layer to multiplied by the expert defined weight and then summed for a continuous surface of overall erosion potential.

3.3.2 Weighted Criteria Variations

A basic sensitivity assessment was performed for the conceptual model in the previous chapter. The assessment was a simplistic one-at-a-time (OAT) procedure were a single variable or layer was removed and the erosion potential analysis was processed again. For the AHP method the sensitivity assessment focused on the variation of weights. The procedure used follows that of Chen, Yu, and Khan (2010) and Romano, Dal Sasso, Trisorio Liuzzi, and Gentile (2015). The procedure changes the weight of each variable in 1% increments of the initial variable weight for the range of -20% to 20% (Table 3.2). This resulted in 41 runs for each of the five variables for a total of 205 runs with 201 being unique. The 201 runs were summarized for each of the 570,623 analysis or grid cells used in the erosion potential assessment. Data summaries were based on a quartile analysis of the erosion potential runs and used a guide to determine the alignment of model runs.

Table 3.2 Criteria Weight Variation Example

Run	**Slope**	Stream Density	K-factor	Soil Brightness	Precipitation
-20	**0.270**	0.184	0.166	0.158	0.222
-19	**0.274**	0.183	0.165	0.157	0.221
-18	**0.277**	0.182	0.164	0.156	0.220
-17	**0.281**	0.181	0.164	0.155	0.219
-16	**0.284**	0.180	0.163	0.154	0.219
-15	**0.287**	0.180	0.162	0.154	0.218
-14	**0.291**	0.179	0.161	0.153	0.217
-13	**0.294**	0.178	0.160	0.152	0.216
-12	**0.297**	0.177	0.159	0.151	0.215
-11	**0.301**	0.176	0.158	0.150	0.214
-10	**0.304**	0.175	0.158	0.149	0.213
-9	**0.308**	0.175	0.157	0.148	0.213
-8	**0.311**	0.174	0.156	0.148	0.212
-7	**0.314**	0.173	0.155	0.147	0.211
-6	**0.318**	0.172	0.154	0.146	0.210
-5	**0.321**	0.171	0.153	0.145	0.209
-4	**0.324**	0.170	0.153	0.144	0.208
-3	**0.328**	0.169	0.152	0.143	0.208
-2	**0.331**	0.169	0.151	0.143	0.207
-1	**0.335**	0.168	0.150	0.142	0.206
0	***0.338***	*0.167*	*0.149*	*0.141*	*0.205*
1	**0.341**	0.166	0.148	0.140	0.204
2	**0.345**	0.165	0.147	0.139	0.203
3	**0.348**	0.164	0.147	0.138	0.202
4	**0.352**	0.164	0.146	0.137	0.202
5	**0.355**	0.163	0.145	0.137	0.201
6	**0.358**	0.162	0.144	0.136	0.200
7	**0.362**	0.161	0.143	0.135	0.199
8	**0.365**	0.160	0.142	0.134	0.198
9	**0.368**	0.159	0.142	0.133	0.197
10	**0.372**	0.158	0.141	0.132	0.197
11	**0.375**	0.158	0.140	0.132	0.196
12	**0.379**	0.157	0.139	0.131	0.195
13	**0.382**	0.156	0.138	0.130	0.194
14	**0.385**	0.155	0.137	0.129	0.193
15	**0.389**	0.154	0.137	0.128	0.192
16	**0.392**	0.153	0.136	0.127	0.191
17	**0.395**	0.153	0.135	0.127	0.191
18	**0.399**	0.152	0.134	0.126	0.190
19	**0.402**	0.151	0.133	0.125	0.189
20	**0.406**	0.150	0.132	0.124	0.188

Variations of weight for slope criteria at a 1% increment rate of change for plus/minus 20 steps**.**

3.4 Results

The output from the AHP erosion potential surface is similar to that of the conceptual model. Expert input was applied to the individual layers that define the physical erodibility, land sensitivity, and precipitation erosivity for the Weeks Bay watershed. Expert defined layer weights were varied (1% rate of change for 20 increase and decreasing steps). This helped to create an analysis mask to identify alignment within the model runs to create focus (or priority) areas of higher ranks of erosion potential.

3.4.1 Analytical Hierarchy Process Applied

The conceptual model was adjusted based on the expert input via the pairwise comparison of data layers. The input of multiple experts was averaged to determine the updated weights for the assessment of watershed erosion potential. The expert averaged weight for slope was 33.8%, 16.7% for stream density, 14.9% for K-factor, 14.1% for soil brightness (tasseled cap), and 20.5% for precipitation. The output produced a new erosion potential surface for the study area watershed (Figure 3.1). The updated (AHP) average erosion potential for the watershed is 0.472 (S.D.=0.051), the conceptual model average was 0.527 (S.D.= 0.057). The maximum erosion potential value is 0.808 and the minimum erosion potential value is 0.229, providing a slight increase in the range of data (Table 3.3). The AHP model was strongly correlated with the conceptual model with a Pearson's R value of 0.923.

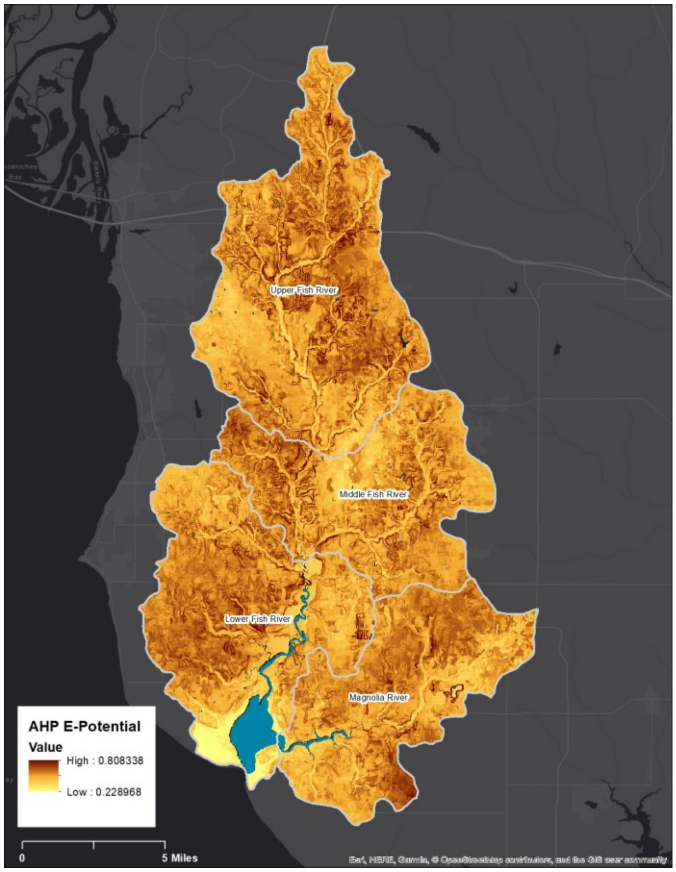

Figure 3.1 AHP Erosion Potential

Table 3.3 Descriptive Statistics for Conceptual and AHP Models

	Conceptual Model	*AHP Model*
Mean	0.527	0.472
Median	0.529	0.473
Mode	0.518	0.499
Standard Deviation	0.057	0.051
Sample Variance	0.003	0.003
Kurtosis	0.467	0.965
Skewness	-0.328	-0.101
Range	0.570	0.579
Minimum	0.231	0.229
Maximum	0.801	0.808
Pearson Correlation	-	0.923

Cell counts were compared at the watershed level of the AHP run by categorizing the erosion potential values. The same reclassification methods are used for the AHP data that were used for the conceptual erosion potential model in the previous chapter. The approach defined the classes based on standard deviations from the mean watershed erosion potential as the data are normally distributed (Figure 3.2). The classified erosion potential for the AHP output was binned in seven classes. At the watershed level 71% of the data are within one standard deviation of the mean, similar to that of the conceptual model at 69%. In the upper ranks (class 6 and 7) of the classes there are a total of 12,389 cells (2.17%) and 68,674 (12.03%) cells in the moderate erosion potential rank of class 5. The lower erosion potential ranks (classes 1 and 2) are similar to the upper ranks (classes 6 and 7) with a total of 12,939 cells (2.27%). The moderately low class of erosion potential (class 3) has 72,206 cells. The AHP run produces slightly more cells (4082) in the lower ranks than the upper ranks (Table 3.4 and Figure 3.3). Differences between the AHP model and the conceptual model were calculated for each cell to identify these areas of change spatially (Figure 3.4).

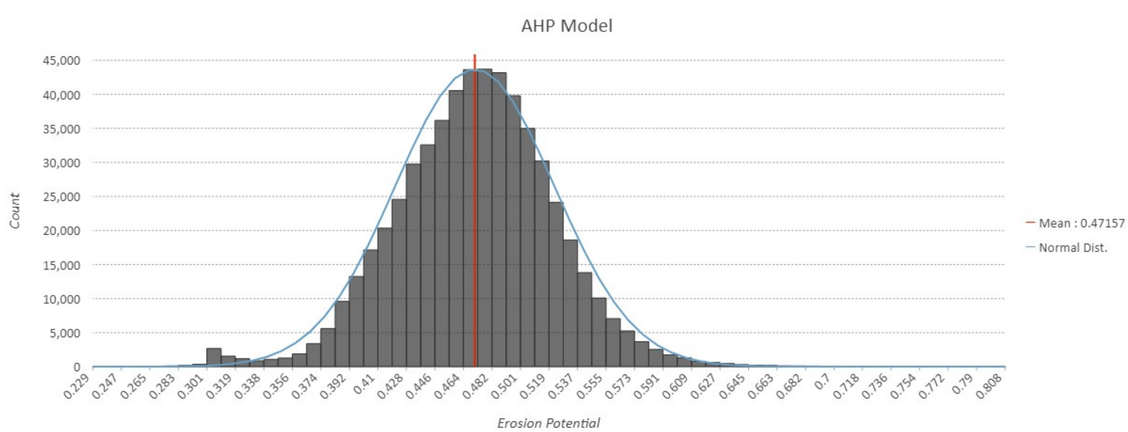

Figure 3.2 AHP Model Histogram

Table 3.4	Erosion Potential Cell Counts

	Conceptual Model	AHP Model	Change
Class 1	5,330	4,927	-403
Class 2	8,821	8,012	-809
Class 3	74,495	72,206	-2,289
Class 4	393,620	404,415	10,795
Class 5	79,842	68,674	-11,168
Class 6	8,130	10,482	2,352
Class 7	385	1,907	1,522

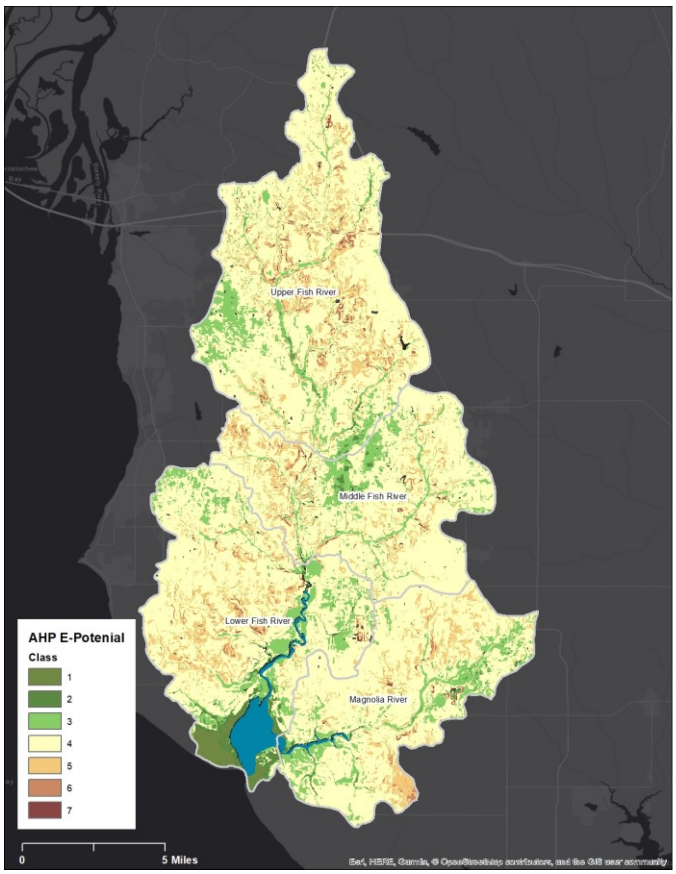

Figure 3.3	Classified AHP Erosion Potential

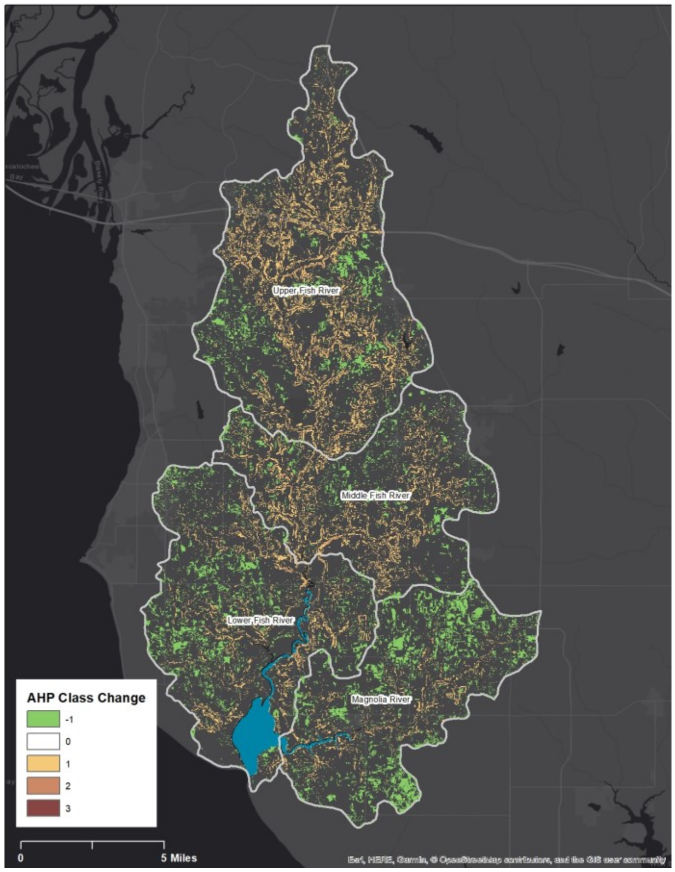

Figure 3.4 AHP Model Difference Grid

3.4.2 Weighted Criteria Data Runs

The 201 runs with varying weights were summarized for a quartile analysis with upper and lower fences to determine variations in the erosion potential output based on the changing of layer weights. At each grid cell to total of runs producing outliers were counted and mapped to look at variations spatially (Figure 3.5). The extreme end showed that there were grid cells that produced outliers up to 40% of the time with the changing weights (about 1% of the watershed). Using an outlier threshold of 25% it found was that 37.5% of the watershed was producing inconsistent or varying erosion potential results. The inverse 62.5% of the watershed was then looked at based on the classified AHP output. This region of the watershed is where the AHP runs aligned for both low and high erosion potential. Cells count in this region for the moderate and upper ranks (classes5, 6, and 7) decreased proportionally. In the upper ranks (classes 6 and 7) cell counts total 7471 (1.31%) and 43,148 (7.56%) in the moderate rank (class 5). The proportional decrease shows that the higher instances of outliers are not clumped within the lower or upper ranks of erosion potential. This provides the definition or identification of focus areas (an analysis mask) for increased erosion potential in the Weeks Bay watershed Figure 3.6)

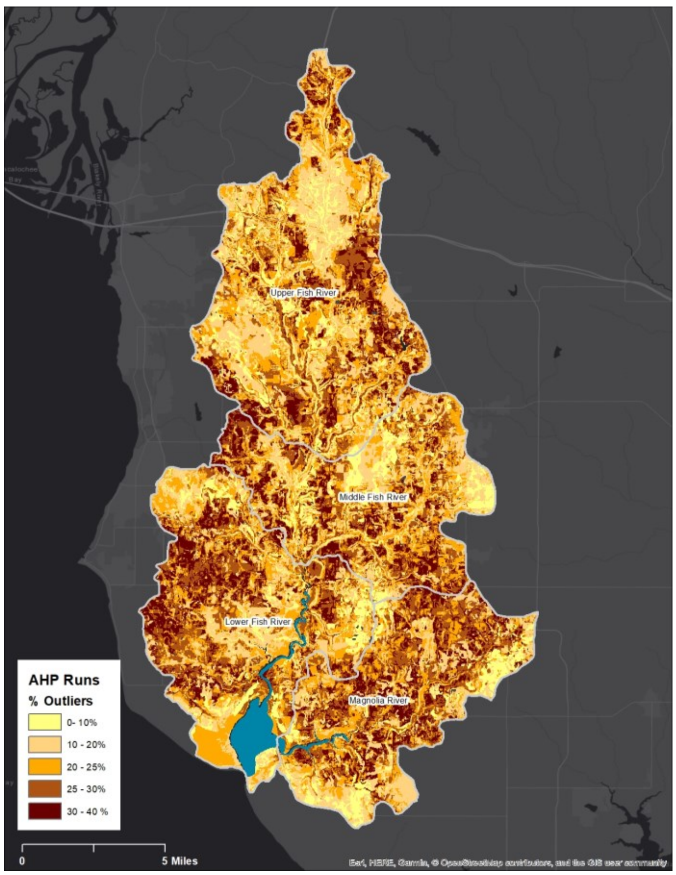

Figure 3.5 Percent Outliers Weighted Data Variations

2017).

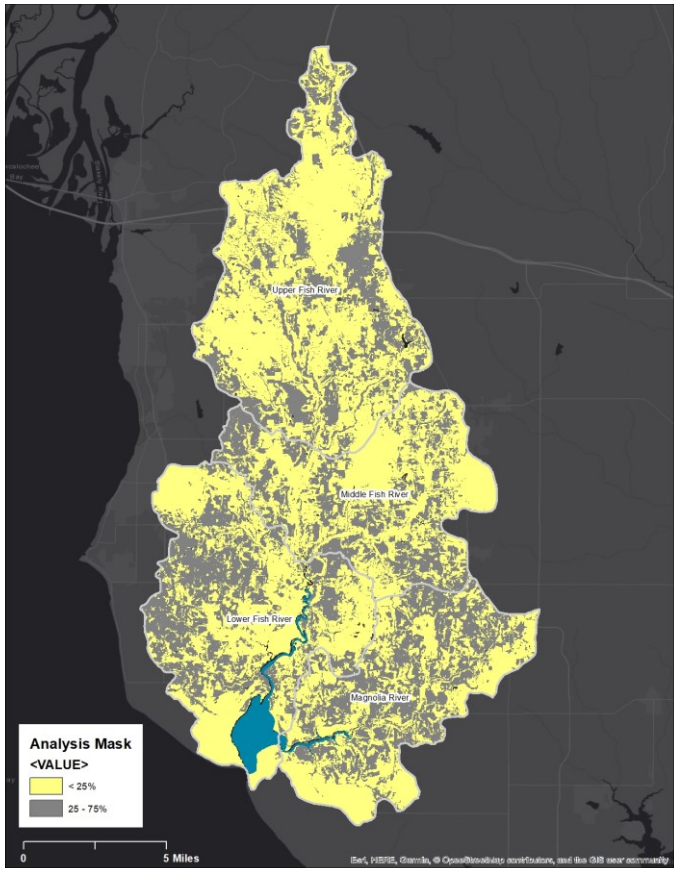

Figure 3.6 Analysis Mask

3.5 Discussion

The experts identified slope (first) and precipitation (second) as the two most important criteria for erosion potential assessment. The other criteria were deemed less important than what was proposed in the conceptual model (Chapter 2). Weighted emphasis for K-factor and Tasseled Cap (a proxy measure of land cover) at the bottom. It was surprising that an emphasis of land cover was not included by the experts because most soil erosion models include land cover (Arnold et al., 1998; Laflen et al., 1991; Renard et al., 1994;). This is interesting as many of the concerns with erosion are from increasing development in coastal watersheds (MBNEP, 2017).

Expert input to the conceptual model was beneficial in identifying areas with increased erosion potential in the upper ranks of classification. There were shifts increasing the cell counts in the upper ranks (classes 6 and 7) by 18% or about 1500 cells. The shift in classes matches what others have reported with similar approaches (Chen et al., 2013 and Kheir et al., 2008). Given that the developed conceptual model and subsequent variation with expert input are not typical numerical models they are more suited for qualitative geospatial assessment of possible erosion potential. Variations of the weighted data runs defined areas of alignment of in erosion potential output for all ranks and classes. The areas of alignment offer a management resource that can guide processes for improved decision support.

3.5.1 Erosion Potential Overview

There was a significant difference in the erosion potential values of between the AHP and conceptual model. The experts focused on slope, which coupled with stream density, has the majority of the model weighted on terrain characteristics. This shifted the concentration of erosion cells to areas close to the active stream channel, were the slope breaks on the landscape. This proved to show limited areas where erosion potential was related to land cover. In addition to the sloped areas near the active channel the lower southeast quadrant had a concentration of cells with increased erosion potential. This area is dominated by agriculture and has a high stream density due to irrigation channels on a relatively flat landscape. The expert input and opinions about the weights of the variables did not perfectly align with what would be expected using the conceptual model. However, it is interesting that the expert's opinion about weights conforms to the research of Rameriz-Aliva (2011) that showed erosion was primarily dominated by stream banks processes for the Town Creek Watershed (a headland watershed of the Mobile Bay basin). The utilization of the AHP for expert input is considered successful as results were similar to other AHP studies (Akinci et al., 2013; Kheir et al., 2008; Tudes and Yigiter, 2010). Despite the ease of use, trustworthiness, and precision the AHP does have limitations and is often criticized for limits with larger numbers of comparisons and obscurity in importance between variables (Jankowski, 1995).

The expert input put more of an emphasis on watershed topography by weighting the slope variable at 0.338, an increase of over 1.5 times that of the conceptual model. This increase came with decreases in the emphasis of stream density, k-factor, and soil brightness. The latter two are both metrics of land sensitivity that were near equal weights, 0.149 and 0.141 respectively. Steam density, a topographical related measure was decreased to 0.167. That leaves precipitation being essentially unchanged at a weight of 0.205. Thus, the experts put a large emphasis on topography-related variables by weighting the combination of them at slightly more than 50%. This can be observed in Figure 3.7 as areas of increased slope near stream banks show values of higher erosion potential.

The classified data give more insight on how the expert input changes the erosion potential and better characterizes the watershed. Within the watershed the upper and lower ranks remained somewhat balanced (near equal percentages outside the upper and lower bounds of one standard deviation above and below the mean), similar to the conceptual model. The overall shift of cells with AHP run was largest on the moderate erosion potential rank (class 4) with a 14% decrease in the cell count of that class when compared to the conceptual model. This cell count is similar to the number of cells shifted to within one standard deviation of the mean. As previously mentioned, the most noticeable observation was that the all erosion potential ranks (classes 1, 2, 3, and 5) lost cells and the upper ranks (class 6 and 7) gained cells. This lends to the idea that the input of the experts, while not changing the overall erosion potential of the watershed, is helping to identify areas that are more susceptible to erosion. The refined identification of these areas can help resource managers establish priority areas for management.

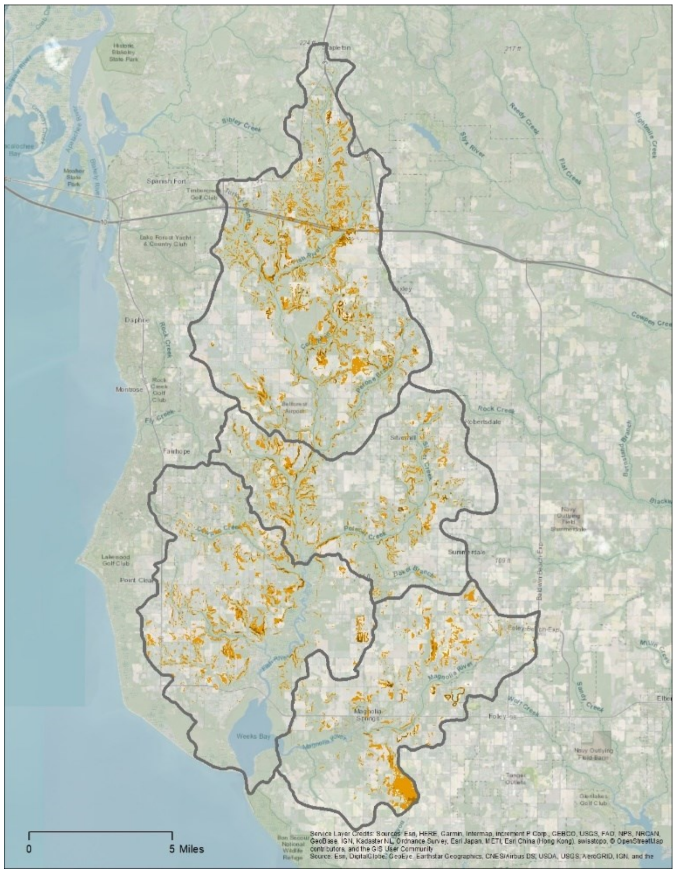

Figure 3.7 High Ranks of Erosion Potential

Areas of increased erosion potential (classes 5, 6, and 7) from the AHP run based on weighted criteria data run agreement

3.5.2 Weighted Variations of Data Runs

The variations of the expert input are normally used to look at shifts between classes to identify areas of increasing or decreasing potential. This project used an outlier approach to focus on the identification of areas of model alignment for high ranks of erosion potential. This approach allowed for an analysis (management) mask to be generated for these areas that are consistently high irrespective of the variation in criteria weights. The areas identified were generally associated with higher slopes associated with stream and channel networks. This is expected as the experts placed increasing importance on slope and terrain characteristics as previously stated. The outlier mask was successful to help identify management areas however a more typical suitably model approach would allow for the quantification shift between ranks of erosion potential (Chen et al., 2013; Mosadghi et al., 2015; Yalew et al., 2016).

The approach of using multiple AHP runs with varying weights appears to be an effective way of finding areas where model runs are in alignment. This alignment is defined by the areas that had minimal outliers, minimal being defined as less than 25% of the runs. Since the effort was focused on area of increasing potential only the moderate and upper ranks (classes 5, 6, and 7) were looked at with the analysis mask produced by the 201 AHP runs. The cells identified with the mask appear primarily in association the hydrologic features (rivers and streams) of the watershed. Given that the experts increased the weight of slope this makes sense. The focus of the variables towards topography by the experts highlighted erosion cells that are connected to topography breaks near the drainage areas (features) of the watershed.

The analysis mask produced from the weighted variations of the AHP runs creates a tool that can be used by resource managers and/or decision makers to focus management efforts. This concept can be folded into a decision support tool that provides added dynamics to management decisions by fine tuning efforts or helping to compare different modeling scenarios. Caution should be used as the variations of criteria weights should not be thought of as a mechanism of calibration, rather just a means of identify areas with minimal variance as the criteria are altered.

3.6 Conclusion

The addition of expert input appears to help identify the cells that are most susceptible to erosion, as evident by shifts of cells in the upper ranks. This coupled with the analysis mask generated by the criteria weighting variations provides areas that may more sensitive to erosion. Given the importance the experts put on slope (topography) the output is somewhat focused to areas where there appears a topographic break point adjacent to the rivers and streams in the watershed. It is my thoughts that the impact of land cover may be somewhat minimalized based on the expert input.

Limits in this phase of the research are similar to those associated with the conceptual model, the lack of exact validation data. This phase of the research helps to establish a path to move the concept to more of a decision support approach by allowing expert input. The AHP methodology offers users a way to add quantitative metrics based on qualitative input. This effort offers to provide a mechanism to for generalized landscape assessments of multiple criteria when a standard suitably analysis is not available. The AHP generation of weights on continuous data variables and their subsequent combination instead of a standard suitability classification of grouped criteria.

CHAPTER IV

EROSION POTENTIAL MANAGEMENT PRIORITIES AND DATA DISSEMINATION

4.1 Abstract

Many approaches have been used to model soil loss and erosion at the watershed level. In 2017 an updated watershed management plan was developed for the Weeks Bay watershed and a SWAT (Soil & Water Assessment Tool) model was used to calculate sediment yield for the watershed. The previously developed conceptual and AHP erosion potential model results were compared to the SWAT sediment yields. The comparisons were limited to basic observations between the qualitative and quantitative output of the data. The comparisons did show a general visual alignment in subbasins of increasing development and headland drainage areas. Areas of discrepancy were visible with expert influenced AHP output due to the increased emphasis on topographic features. The data were summarized for 18 management areas of the Weeks Bay watershed and ranked to determine management priority. There were few direct matches in ranks between the three datasets, however there were some observational trends. In the upper third of the SWAT ranks the conceptual erosion potential model had four similar ranks (66%) and the AHP model run had three similar ranks (50%). In the mid third of the SWAT ranks the conceptual erosion potential model again had four similar ranks (66%) and the AHP model run had two (33%). In the lower third of the SWAT ranks the conceptual erosion model had three similar ranks (50%) and the AHP model run again had two (33%). The conceptual and AHP erosion potential output data, including management priority rankings were published as

web mapping services and used to develop a story map as a transition to a decision support system. The limits of the story map to allow user interactions with model output data rendered an unacceptable platform for decision support development. The story map does offer a dynamic alternative to static reports and could serve to improve dissemination of spatial data as well as technical reports and plans like a watershed management plan.

4.2 Introduction

The previous chapters of this work focused on the development of a conceptual erosion potential model. The model utilized similar criteria to standard numerical soil loss models for a qualitative assessment of erosion potential across the landscape. Expert input was added to the conceptual model with the Analytic Hierarchy Process (AHP) as a transition for Multi-Criteria Decision Analysis (MCDA) decision support. This chapter takes the erosion potential surface and compares it with the results of traditional soil loss model at the subbasin scale. The comparison is against the output of Soil and Water Assessment Tool (SWAT) model that was developed for the Weeks Bay Watershed Management plan.

The general objective of the third phase of this work is to develop a proof of concept that would show the transition of this type of data for a management or decision-making approach. This would allow for resource managers to look at scenarios or management priorities without understanding of more complex soil loss models. The idea being that the developed conceptual model would not replace the SWAT model in a watershed management plan. This would continue to migrate the overall project towards a multi-criteria-decision-analysis application for improved resource management. The general hypothesis is that data dissemination would improve comprehension and transition outcomes to facilitate decision support. The primary objectives of this third phase are to:

- Compare the conceptual model with a numerical soil loss model for the identification of potential erosion areas. It is hypothesized that qualitative erosion potential model will align with areas of high sediment yield in a numerical soil loss model.
- Look at all model output to prioritize and/or rank management areas for the Weeks Bay watershed. It is hypothesized that each model will identify common management areas based on erosion potential and sediment yield.
- Incorporate the output data into a system for data dissemination for improved decision making, education, and outreach. It is hypothesized that the utilization of improved online GIS technologies will enhance data dissemination.

4.2.1 Weeks Bay Watershed Management Plan

The Mobile Bay National Estuary Program (MBNEP) publish an updated watershed management plan for the Weeks Bay Watershed in November 2017. The development of the management plan was in response to concerns about degraded water quality conditions due to increased stormwater runoff and land use practices. Included in these concerns is the increased erosion and the resultant sedimentation in the rivers and streams of the Weeks Bay watershed. The management plan listed half of the steams in the watershed as an area of concern due to increased sediment and turbidity. The sediment and erosion data used by the plan were derived from a SWAT model (Kalin, 2017). In the future there are hopes to refine the SWAT model to identify areas of instream erosion and to define/map source areas within the higher sediment yielding subwatersheds (MBNEP, 2017).

The SWAT model used for the Weeks Bay watershed management plan was created by Dr. Latif Kalin specifically with funding from the MBNEP. Data used in the model consisted of topography, soils, hydrography, land use and cover, climate, point sources, crop types, atmospheric deposition, daily stream flow, and water quality data (Kalin, 2017). The model delineated the weeks bay watershed into 237 subwatersheds (197 for the Fish River and 40 for the Magnolia River), these are used to produce the computational hydrologic response units

(HRU's) in SWAT. Sediment yield results from the model were based on 2011 land use/cover and it was reported that over half of the sediment yield produced from about one-third of Weeks Bay watershed (MBNEP, 2017).

4.2.2 Story Maps for Data Dissemination

Data dissemination of geospatial data has evolved rapidly over the past decade due to improvements in web-based GIS solutions (Dalton, 2017; Dawidowicz and Kulawiak, 2017). These developments have carried geospatial technologies beyond basic data archives and warehouses to a host of web-mapping services that provide near real-time data. Web services go beyond just data, these services also offer geoprocessing and query request that allow for geospatial analysis that were once limited to desktop GIS systems and locally stored data. These advances in data dissemination (as well as processing, storage, etc.) facilitate improved decision making with improved data and technology transfer (Otten et al., 2015; Evangelidis, Agrianidis et al., 2018).

Web-based GIS solutions have transitioned from basic to dynamic viewers, offering both 2-dimensional as well as 3-dimensional capabilities, as well as temporal (time aware data) capabilities (Kulawiak et al., 2019). These viewers are now not just stand-alone applications (web, mobile, etc.) as they now can be embedded and presented in tandem with textual, graphical, and pictorial information with Story Maps. Story Maps are interactive, web-based applications that combine geographic information with text and multimedia content. Utilization of Story Maps improves data accessibility across multiple platforms, improving data management and information transfer (Cope et al., 2018; Groshans et al., 2019). The incorporation of these types of data into a single package (like a Story Map) is building a foundation that will provide a seamless transition from research to education and outreach to improve the decision-making process for all users.

4.3 Data and Methods

This project takes the results from the previously developed conceptual model for erosion potential and compares it with results from a numerical soil loss model (SWAT). Additionally, the project incorporates the output data and results to a web-based GIS for data dissemination and transition to a decision-support tool. By incorporating the output data in this manner, an alternative to traditional reporting and management plans is offered to facilitate use of the data and derived information for improved decision making.

4.3.1 Model Comparison

The comparison of the conceptual model with the numerical SWAT model is a comparison between qualitative (erosion potential) and quantitative (sediment yield) data. To make the comparison the data of each had to be summarized to establish if there was any alignment between the two. The conceptual model was previously summarized or classified by standard deviations into seven classes as described in the previous chapters, with the upper most classes showing moderate to high erosion potential (areas of most concern). The SWAT model was presented in five sediment yield classes in the Weeks Bay management plan, with the upper most class having yields ranging from 1.71 – 5.96 tonnes per hectare. The SWAT defined subwatersheds with sediment yield values in this range are stated of those with most need for management efforts.

The comparison between the grid based conceptual model (a distributed type of output) to the subwatershed SWAT model (a lumped or semi-distributed type of data output) used aggregated data of each at the subbasin level. The subbasin data layer used for the aggregation was provided by Weeks Bay resource managers and divides the watershed into management areas at a smaller scale than the 12-digit HUCS from the USGS cataloging units. The aggregation of each of the datasets provides a visual for a prioritization (or rank) of the erosion potential and sediment yield that allows for areas of similar results to be identified. The aggregation was an average of all values for a specific management area.

4.3.2 Data Dissemination with a Story Map

Transitioning this type of data to a web-based GIS environment includes minimal steps. The basic requirements of developing a proper functioning GIS covers the data preparation needs for the transfer and dissemination of these types of data. The effectiveness of a Story Map requires textual information beyond that of the spatial data and the application it is to disseminate. Textual information for this application was taken from sections of the projects associated with the development of the conceptual model, as well as the expert input with the AHP, and the comparison to the SWAT model. The Story Map was published using ArcGIS Online, which is subscription based online GIS platform offering a wide range of templates and resources for sharing GIS data and applications. The Story Map offered a proof of concept that provides alternatives for reporting and presenting data similar to that of a management plan with a more multimedia rich experience.

4.4 Results

4.4.1 Model Comparison

The first comparison between the SWAT and conceptual erosion potential effort was a visual comparison of the map output of the model and the two erosion surfaces (conceptual model and AHP). The SWAT model for all comparisons is displayed based on the sediment yield categories defined in the management plan. The erosion potential output from the conceptual and AHP model was displayed with a stretch (based on standard deviations, the default for raster data types). Figure 4.1 displays the maps of each surface, areas of similar output are visible (higher SWAT yields and greater erosion potential). The darker reddish-brown areas (higher potential) of the erosion potential map align with the darker brown subwatersheds (higher yield) of the SWAT output. This is evident in southwestern area of watershed (Lower Fish River subbasin) and the northeastern area of the watershed (southeast part of the Upper Fish River subbasin) for the conceptual model. This alignment is similar with the AHP model erosion potential map, except in the Upper Fish River subbasin where areas of higher erosion potential are visible in the northern portion.

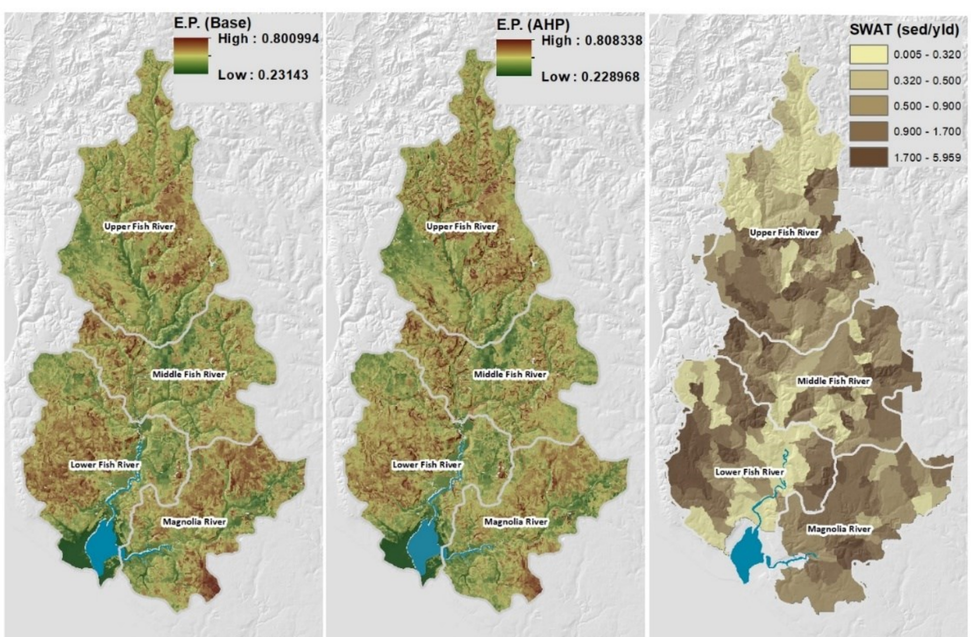

Figure 4.1 Erosion Potential Comparison with SWAT Sediment Yield

The second comparison was between the SWAT model, as previously described, and the reclassified erosion potential data for the conceptual and AHP model. The reclassified data were binned to 7 classes based on standard deviations beyond the mean (see previous chapters). The moderate and upper classes (class 5, 6, and 7) were used for the comparison as they are the areas of highest erosion potential. Figure 4.2 displays the maps of conceptual and AHP classified erosion potential next to the SWAT model sediment yield classes for the subwatersheds. This visualization shows areas where the higher erosion potential aligns with the subwatersheds with higher sediment yields. The observed visual results are similar to that of the unclassified data. The alignment with SWAT model is again apparent in the southwestern area of watershed (Lower Fish River subbasin) and the northeastern area of the watershed (southeast part of the Upper Fish River subbasin) for the conceptual model. The results of the AHP model comparison can again be summarized as similar, with the exception of Upper Fish River subbasin showing higher erosion potential trends, due to the expert input emphasizing topography (slope) more than the conceptual base model. Figure 4.3 displays the maps of conceptual and AHP erosion potential high ranks (in red) overlaid on the SWAT model sediment yield classes for each subwatersheds, providing more visual alignment due to the focus on the moderate and upper classified ranks.

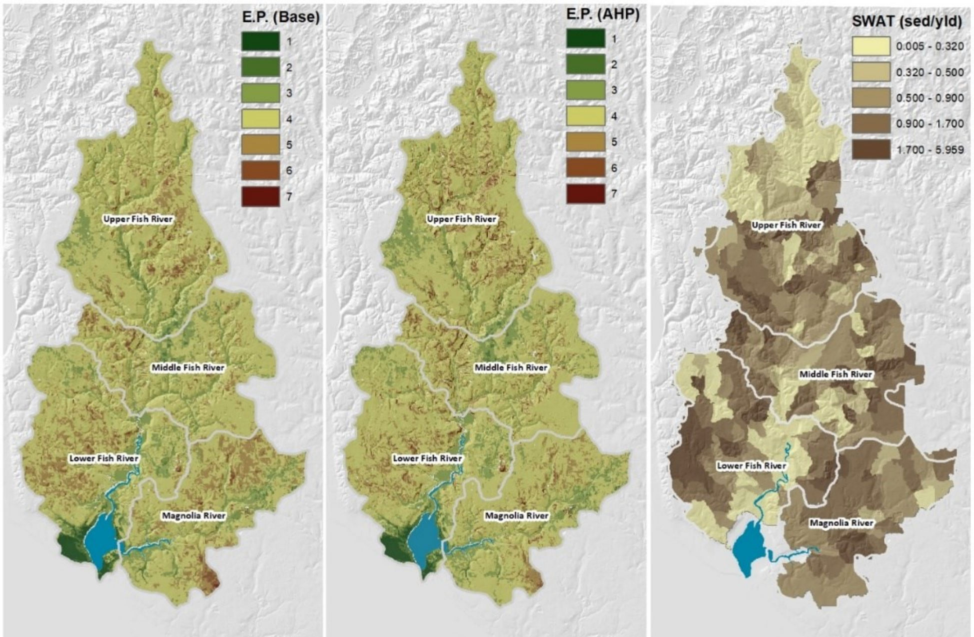

Figure 4.2 Classified Erosion Potential Comparison with SWAT Sediment Yield

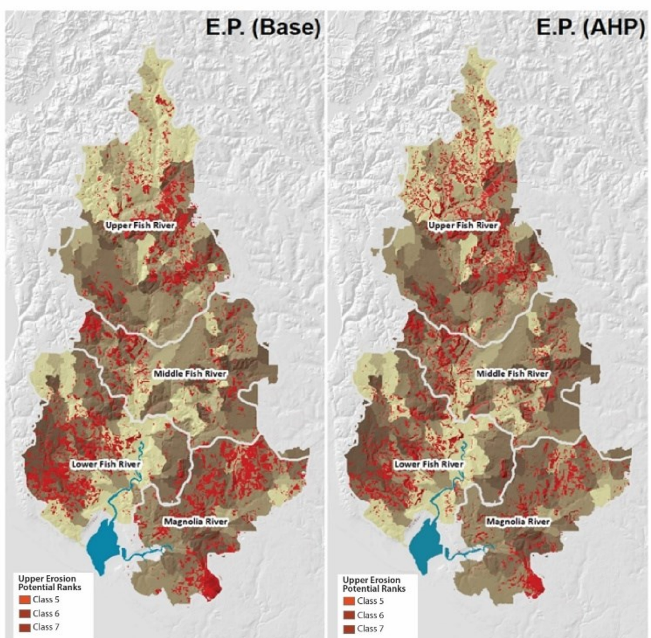

Figure 4.3 Erosion Potential High Ranks with SWAT Sediment Yield

The final comparison was an aggregate of the erosion potential (conceptual and AHP) and the SWAT model data to the management areas provided by the Weeks Bay resource managers. This was accomplished by averaging the erosion potential and SWAT sediment yield data individually for each of the management areas. The management areas were ranked or prioritized based the average value. Table 4.1 provides the rankings for each management area for the three erosion datasets. The table is sorted based on the SWAT data as it what is used to define areas of need by the Weeks Bay management plan. There are 18 management areas based on smaller streams in the watershed, except for Weeks Bay which is the bay proper (Figure 4.4). There were few direct matches in ranks between the three datasets, however there were some observational trends. In the upper third of the SWAT ranks the conceptual erosion potential model had four similar ranks (66%) and the AHP model run had three similar ranks (50%). In the mid third of the SWAT ranks the conceptual erosion potential model again had four similar (66%) and the AHP model run had two (33%). In the lower third of the SWAT ranks the conceptual erosion model had three similar ranks (50%) and the AHP model run again had two (33%). Two management areas in the upper third of SWAT ranks stand out in terms of the conceptual and AHP model runs, Perone and Picard Branch. The ranks of these were somewhat displaced. The same can be said for Three Mile and Green Creek in the lower third of the SWAT ranks.

Table 4.1 Weeks Bay Watershed Management Area Rankings

Management Area	*Sub-Basin*	*EP*	*AHP*	*SWAT*
Pensacola Branch	Middle Fish	2	1	1
Perone Branch	Upper Fish	12	10	2
Waterhole Branch	Lower Fish	1	2	3
Turkey Branch	Lower Fish	3	8	4
Picard Branch	Upper Fish	15	15	5
Corn Branch	Upper Fish	5	3	6
Barner	Lower Fish	16	16	7
Magnolia River	Magnolia	7	12	8
Polecat Creek	Middle Fish	14	14	9
Cowpen Creek	Lower Fish	11	13	10
Baker Branch	Middle Fish	9	11	11
Unknown	Middle Fish	8	5	12
Three Mile Creek	Upper Fish	6	4	13
Green Creek	Lower Fish	4	6	14
Bay Branch	Upper Fish	13	9	15
Weeks Branch	Lower Fish	17	17	16
Upper Fish River	Upper Fish	10	7	17
Weeks Bay	Lower Fish	18	18	18

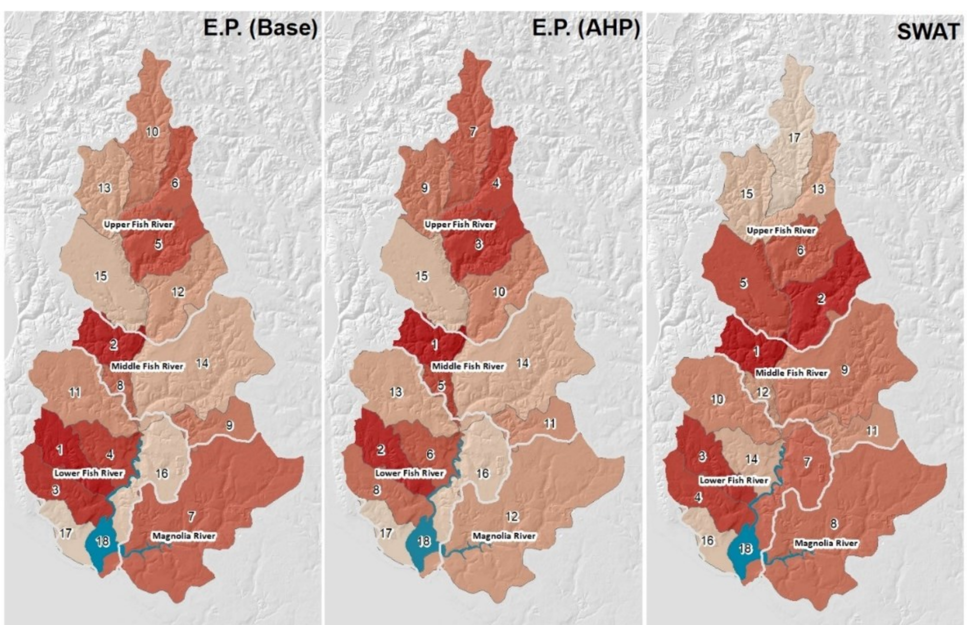

Figure 4.4 Weeks Bay Watershed Management Rankings

4.4.2 Data Dissemination with a Story Map

The spatial data output for the model variables, model output (floating and classified), and management area prioritizations were published as a web distributed mapping service. Web mapping services were created using an ArcGIS Online Organization account, which utilizes cloud-based infrastructure via a subscription service. The mapping services for all the variables and model output were based on image tiles due to the raster data types. The management area prioritization area data were able to be published as mapping services with feature access due to the vector data file type. This allows for query and data extraction, which is not an option with the tile-based data services. The services were used to build a generic web-based map (Figure 4.5) that would basically provide a container (or staging area) for the data to be disseminated. From this web map a map series style story map was generated to help develop a multimedia enhanced experience for data dissemination. The story map that was developed utilized a series of tabs or panels to showcase the data. The story map utilized five tabs to provide a brief introduction, explain the variables, visualize the model data (conceptual and AHP), and identify management areas. The results of this effort are focused on the application of working with this type of data in a web-based mapping environment. There are no results to discuss or explore the usability of the story map product from an end user's perspective, rather just a general exploration of transitioning these types of data to this type of platform for dissemination, decision making, and reporting.

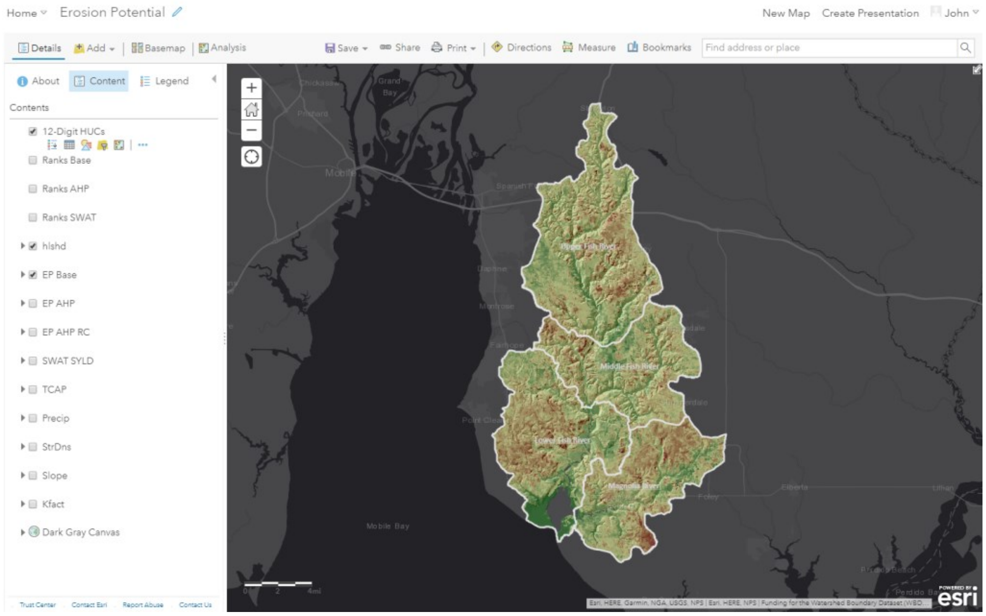

Figure 4.5 ArcGIS Online Web Map

ArcGIS Online generic web map for model variables, output, and management prioritization areas

The map tabs provided a means for simple visualization of the data with textual and pictorial information to provide an informative narrative. The application seems to be better suited for vector-based data as it allows for more user interactions with interactive windows for data inquiry and query. Interactions with the model data is limited to visualization only with no means of extracting values or altering symbology. This limitation prevents user derived simulations or layer visualizations for a true user defined experience. Several graphics are provided as samples (Figure 4.6) of the interface with data layers. A well-defined story map offers a dynamic alternative to static reports and could serve to improve dissemination of spatial data as well as technical reports and plans like a watershed management plan.

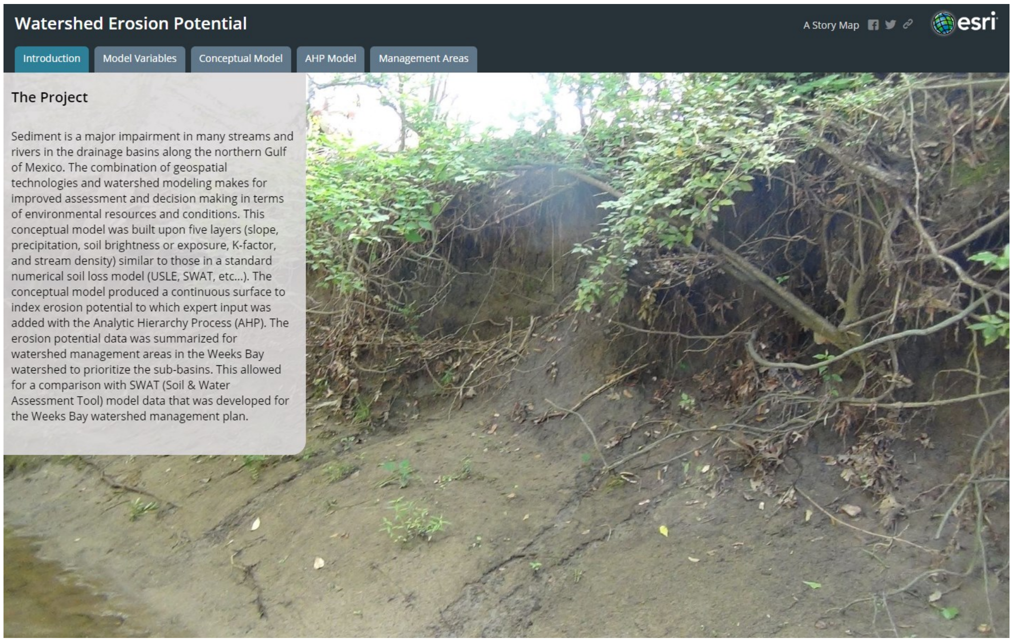

Figure 4.6 Story Map Frames

Introduction story map series tab.

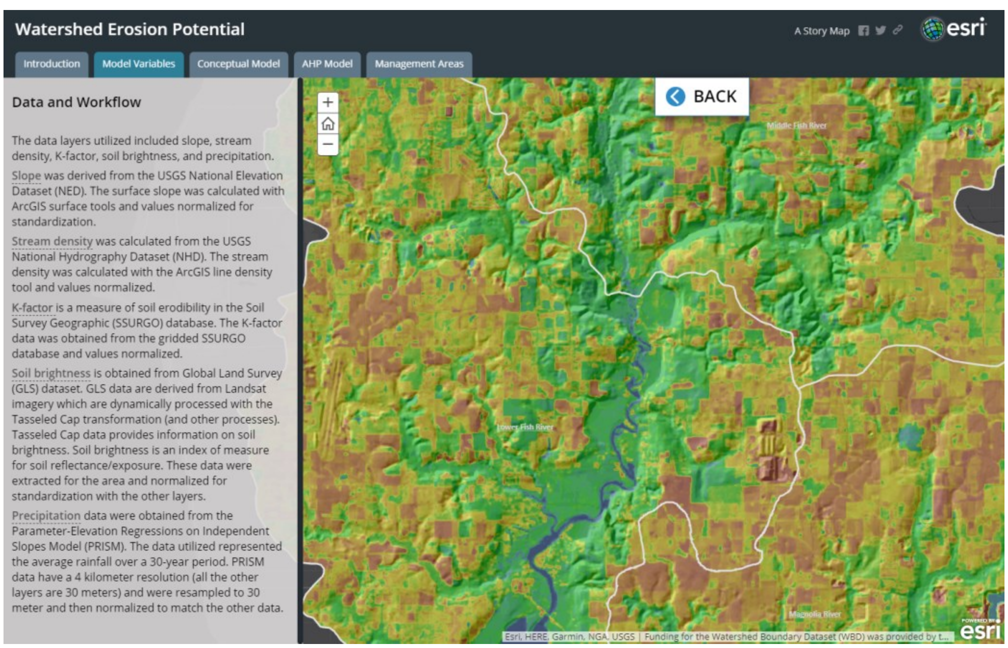

Figure 4.6 (continued)

Interactive model variable map series tab with selectable layers in the text to toggle visibility.

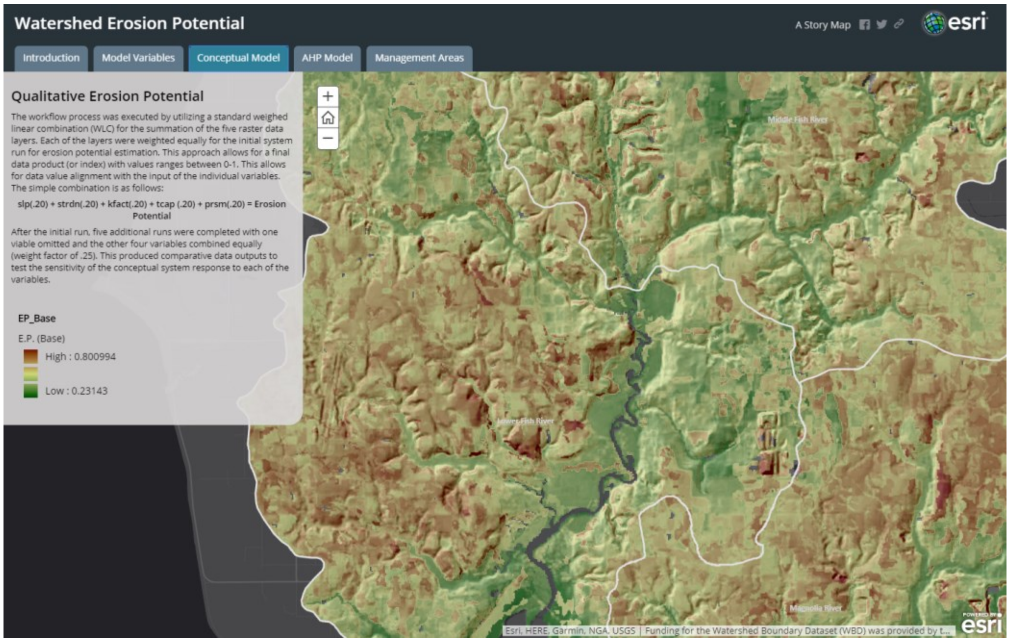

Figure 4.6 (continued)

Conceptual erosion potential (BASE) map series tab.

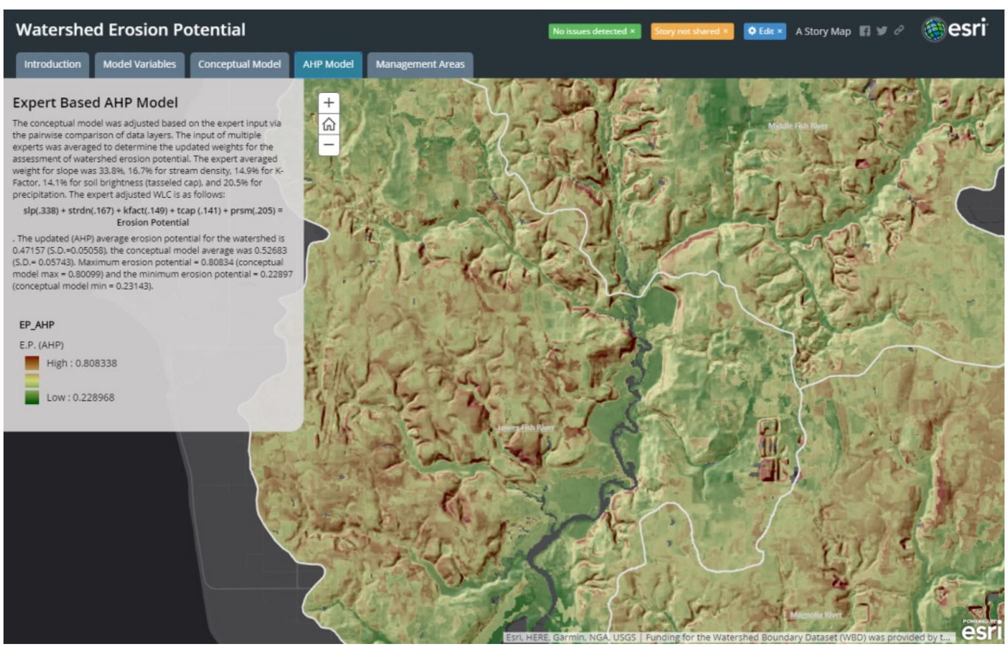

Figure 4.6 (continued)

Analytic Hierarchy Process (AHP) map series tab.

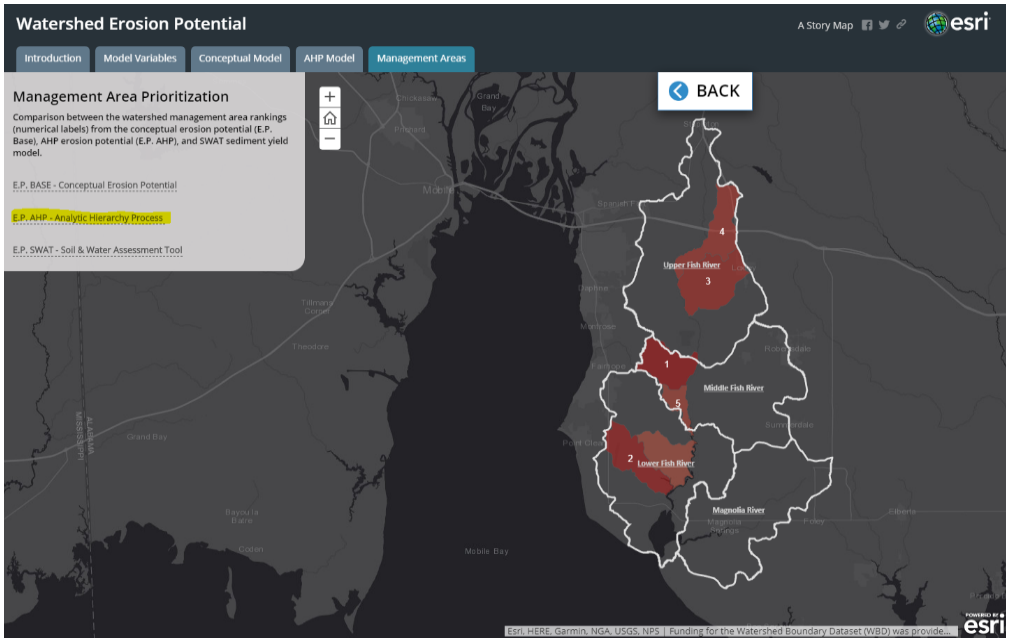

Figure 4.6 (continued)

Management area prioritization for Analytic Hierarchy Process (AHP) erosion potential summaries for Weeks Bay sub-basins.

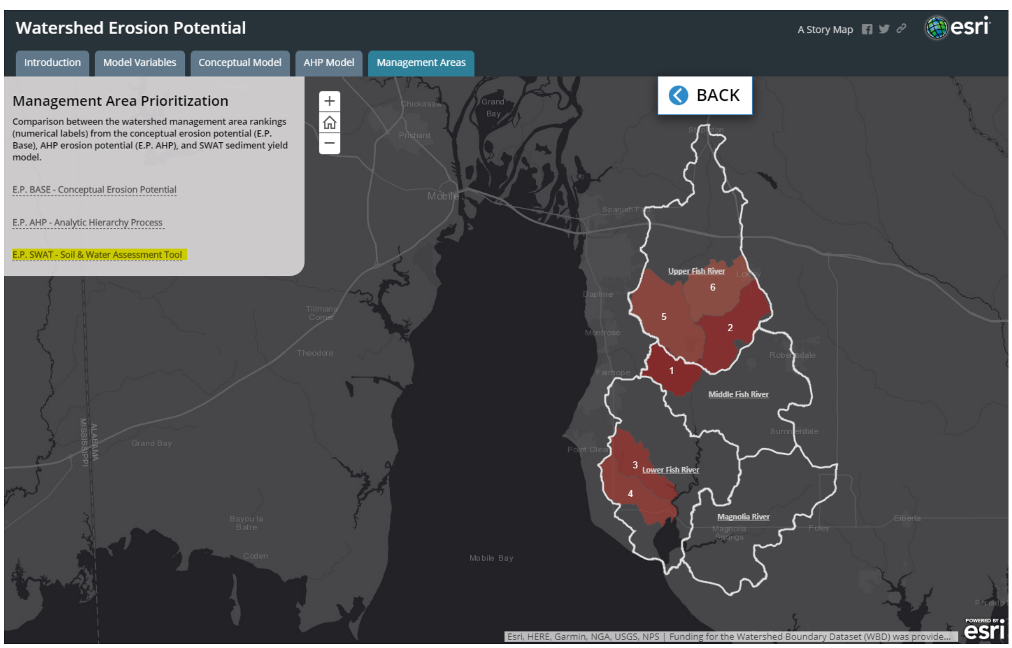

Figure 4.6 (continued)

Management area prioritization for Soil & Water Assessment Tool (SWAT) sediment yield summaries for Weeks Bay sub-basins.

4.5 Discussion

The comparisons of the conceptual and AHP erosion potential model output with that with the SWAT sediment yield were used to help identify if there was any visual alignment or trends between the qualitative and quantitative output. The first two comparisons were very similar with the primary difference being the focus of higher erosion potential values in the conceptual and AHP model runs. Focus in this context is referring to the binning or grouping of the higher erosion potential values in the output data (natural breaks vs. standard deviations). The alignment of the data is most apparent in the Lower Fish River subbasin, this area is one of transition with expanding development and agricultural land practices. As noted earlier the AHP output produces some areas that are more focused on topographic features because of the expert input placing more emphasis on slope and other terrain measures (stream density). This was most apparent in the Upper Fish River, the headland area of the watershed. The SWAT subwatershed with the highest sediment yield showed strong visual alignment with the conceptual and AHP output. The areas with the strongest visual alignment all appeared to be focused on increasing development and agricultural practices. The most notable area of over estimation of erosion potential by both the conceptual and AHP model runs occurs in Magnolia River subbasin in the southern most part of the watershed. This appears to be due to extremely high stream density calculations from man-made irrigation canals associated with agricultural practices that produce high measures of bare soil (turf/sod farms).

The final comparison of the data was a prioritization or ranking for the management watersheds obtained from the Weeks Bay National Estuarine Research Reserve. As stated earlier there were few direct matches between each of the three prioritizations from the model output. The only alignment that is apparent is in those management watersheds that ranked near the top in the prioritization. Specifically the Pensacola and Waterhole Branch watershed management areas which are heavily impacted by increasing development. Referring to Table 4.1 it can be observed that these areas have rankings of 1 to 3 in terms of erosion potential or sediment loading. The same is true for the Weeks Bay and Weeks Branch watershed management areas in terms of lower ranks. These two areas had the lowest rankings ranging from 16 to 18. The only areas of overlap between the erosion potential (conceptual and AHP) model with the SWAT sediment yield model rankings for management areas is toward the extremes of the upper and lower rankings. This tends to indicate that there is a lack of alignment between the qualitative (erosion potential) and quantitative (SWAT). Other exploratory analysis further indicated that there was a lack of alignment at the management area scale. This is not unexpected as the process or workflow between the two approaches, while similar, are different and not equally tasked.

The web-based story map approach for data dissemination is very visually appealing and offers an efficient means for reporting with dynamic multimedia rich content. The lack of true geographic system information functionality makes it not suitable for a true decision support system, especially with raster data types. The story map approach for data dissemination with dynamic or interactive reporting does seem advantageous. Typical watershed management plans can be hundreds of pages, the Weeks Bay watershed management plan is 480 pages with an additional 692 pages of appendices. Many sections of the report could be concisely presented with a series of story maps to help disseminate the large amounts of data. Conversations with other geospatial scientist have resulted in similar conclusions, specifically in terms of disseminating geospatial research and project outcomes, whether to operational programs, resource managers, decision/policy makers, or the general public.

The limits of interactive processes with raster data types renders story maps less than ideal in terms of an immersive user experience system. Vector data is only interactive to extent of simple identification with multimedia style information windows. While the story platform offers many benefits for data dissemination and reporting it does not provide a utility for migration to a decision support system type of approach. The lack of being able to create scenarios or generate user defined data analysis is the major factor in limiting the transition towards this type of system. The story map experience for the user is really determined by the developer, as their design of the story map guides the path of user through data and ancillary information. Other resources, such as Esri's Web App Developer, would be much more suited for applications related to decision support.

4.6 Conclusion

The comparisons of the conceptual and AHP model runs displayed a visual alignment with the SWAT sediment yield data from the Weeks Bay watershed management plan. The comparisons however were not a direct correlation between the two data sets. General observations appeared to offer similar results between the qualitative and numerical erosion modeling approaches. The data summaries provided results that aligned in the upper and lower ranks of erosion potential and sediment yield. The mid ranks appeared random with minimal alignment for the management areas in the Weeks Bay watershed. While both approaches use similar variables, they are not equal in the way they are applied. Land use is used by SWAT and the equivalent in the conceptual and AHP models was soil brightness (TCAP). Both are used to measure land areas on the landscape, but soil brightness is not indicative of use or physical disturbance, just exposure of bare soil areas. SWAT, like many other soil loss models, focuses on agricultural land use practices with little or no consideration for transitioning and developed lands.

The transition of this data to a story map did not offer the desired result. The limits of interactions with raster data types restricts the use of story maps to visualization and multimedia enhanced reporting. The story map approach would serve as an ancillary type of info to a technical project report for generalized data and research dissemination. The story map does not offer a means to transition efforts to a decision support type system. There are other technologies available for geospatial web application development that would provide work for decision support system development. These types of applications could be directed to potential users via a story map, offering a narrative with a means to interact and manipulate data for geospatial based applications.

CHAPTER V

SUMMARY AND FUTURE RESEARCH

5.1 Summary

In 1972 the United States Congress passed the Coastal Zone Management Act (CZMA). Through the CZMA, and subsequent amendments, Congress officially stated that resources within the coastal zone should be protected and are of national importance. The CZMA states that any coastal wetland, beach, dune, barrier island, reef, estuary, or fish and wildlife habitat determined to be of substantial biological or storm protective value is of national significance (CZMA, 1972). The CZMA goes on to establish that the coastal zone is not only the areas immediately adjacent to the shore lands, it includes all tidelands and uplands to the extent necessary to control the shore lands. That definition provides the clarification of the connectedness of the coastal zone to the landscape via hydrologic networks and watersheds. The individuals (resource managers, decision makers, stakeholders, etc.) dealing with protecting these resources are often faced with numerous challenges in gaining needed information. Geospatial technologies have lessened these challenges with improved data acquisition, analysis, and reporting.

The overall general objective of this research was to develop a geospatial based alternative to describe landscape erosion potential in coastal watersheds. The alternative was developed based on nationally available data for repeatability and transfer across coastal watersheds in a given region. This allows resource managers to compare and evaluate management priorities across a common landscape region. The alternative was developed as a geospatial model based on data characterizing terrain, geomorphology, soils, land disturbance, and long-term precipitation. Specific data sources include the National Elevation Dataset (NED), National Hydrography Dataset (NHD), Soil Survey Geographic Database (SSURGO), Global Land Survey (GLS) datasets, and data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM).

The specific data layers included slope (NED), stream density (NHD), K-factor (SURCGO), soil brightness (GLS – TCAP), and precipitation (PRISM). These data layers were used to represent physical erodibility (slope and stream density), land sensitivity (K-factor and soil brightness), and precipitation erosivity (30-year precipitation). The layers were combined using a standard weighted linear combination (WLC) for the conceptual model and expert input was added with the Analytic Hierarchy Process (AHP) to develop a measure of erosion potential. The output was compared to Soil and Water Assessment Tool (SWAT) sediment yield output from the Weeks Bay watershed management plan. This allowed for data summaries at defined management areas and the establishment of prioritization ranking. The model output and management area prioritizations were published as web mapping services and used to develop a story map for transition to a decision support system as means of operational research.

This dissertation, through the efforts previously described, was an attempt to utilize geospatial modeling and analysis of watershed erosion potential for improved decision support. The conceptual model produced a visual assessment of erosion potential that aligns with what resource managers are seeing in the area. The expert input with the AHP model placed the most emphasis on topography with terrain slope weighted at 34%. Rainfall was weighted the same as the conceptual model at 20% and the variables for K-factor, stream density, and soil exposure were decreased slightly. Variations of the AHP weights at 1% (+/-) increments allowed for an areas of model alignment to be defined. This can be used to assist resource managers with the identification of areas that could be more sensitive to erosion.

The conceptual and AHP model output were both compared to a SWAT model that was developed for the Weeks Bay watershed management plan. Similarities were apparent between the them, however there was not a direct correlation. The alignment between the numerical SWAT model and the geospatial conceptual models was best in the upper and lower ranks of erosion potential. The model results and comparisons were incorporated and shared with story maps as means of data dissemination for improved decision support. The web-based story map approach was a robust and simple method for data dissemination. By not utilizing them with an enterprise system (a standard subscription-based system was used) the GIS functionality was limited due to the complexity of the raster data sets. However, the story map offers simplistic visualization of geo-data types with ancillary info for technical reporting and public awareness offers an advantageous approach for concise data dissemination with dynamic and interactive capabilities.

5.2 Future Research

The advances in geospatial technology and software over the past few years have been moving at pace that is a challenge to keep up with in many academic settings. Many complex and computationally intensive data analysis and manipulation processes are now cloud based subscription services. These services extend beyond data processing and analysis to include data services that are packaged and ready to be utilized. For example, this project used tasseled cap transformation brightness indexes that were obtained from a data service that was ingested directly into the GIS for modeling and analysis. Many data layers, that were once a significant portion of the labor and processing to set-up a research project, are now packaged and ready to be used (with proper metadata and documentation). This is especially true at regional and larger scales, no longer is there the need to download, exact, convert, merge, and inspect digital elevation model data for terrain analysis. These tasks have been completed, documented, and the data served out and readily transferred to the end-user.

These advances create an avenue to fully incorporate traditional numerical soil loss models with decision support systems, especially at the regional level (for example an estuarine drainage area that is typically numerous 8-digit HUCs). The idea of adding on-the-fly expert input to multicriteria decision-based analysis in geospatial modeling is now attainable with current technologies and does not require expensive enterprise systems or specialized programing expertise. This is providing a means to carry typical research workflows to operations at a faster pace with more ease than just a few years ago. In terms of natural resource management this is enabling the subject matter experts to directly apply their research outputs with management tools.

In addition to numerical soil loss models, which tend to be focused on erosion related to agricultural practices, there are landscape evolution models. These models are used to simulate erosion and deposition within a drainage system at much larger time scales, tens of thousands of years. This has changed in recent years and numerous landscape evolution models are now capable of simulating erosion with much shorter period (i.e. decades). Just like soil loss models these landscape evolution models use data focus around terrain, soil characteristics, ground cover (disturbance), and rainfall. The advancing geospatial technologies could be a mechanism to couple these models to better model erosion and ultimately link them to management practices for improved decision support of related resources in coastal environments.

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