**NASA DEVELOP National Program**



University of Georgia

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**Ocmulgee Ecological Forecasting II**

*Utilizing NASA’s Earth Observations for Forecasting Land Use Change and Wildlife Disturbances Along the Ocmulgee River Corridor*

 **Technical Report**

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# I. Abstract

[Placeholder - do not put anything here until the final draft submission. The abstract in the project summary is where the working draft of the abstract should “live”]

**Keywords**

Conservation, Land Cover Change, Ecological Forecasting, Ocmulgee River, Endangered Species

# II. Introduction

**Objectives:**

The objective of this project was to utilize NASA Earth observations to support wildlife resource management with a focus on endangered species and increasing urbanization trends in the Ocmulgee River valley of central Georgia. The team utilized the results of a time series analysis for the years 2001 to 2014 to analyze the effects of changing environmental conditions on wildlife in the Ocmulgee River valley. The time series analysis combined with historic land cover datasets were used to forecast future ecological conditions within the corridor. These ecological forecasts will inform state conservation plans regarding threats to endangered species and at-risk habitats from urban encroachment.

**Background:**

The Ocmulgee River provides services such as ecological habitats, recreational resources, and a supply of fresh water for drinking and irrigation. The Ocmulgee River valley is also home to many historical sites. In the Georgia 2005 Wildlife Action Plan, the Ocmulgee corridor was defined as a high-priority landscape feature. The corridor was also identified as one of six priority land conservation areas by the Department of Natural Resources due to increasing urbanization pressure. The Ocmulgee River corridor consists of bottomland hardwood swamps and other natural communities that support important plant and animal populations. The corridor also serves as an important flyway habitat to millions of migratory birds, is home to the Central Georgia black bear, and contains several archeological sites of pre-contact Native American history.

**Study Area:**

Located in the heart of Georgia’s Coastal Plain region, the head waters of the Ocmulgee River begin near the Lake Jackson reservoir (south of Atlanta). The river flows southeast for nearly 290 kilometers before joining the Oconee River to form the Altamaha River, which feeds directly into the Atlantic Ocean (Figure 1). Macon, located on Georgia’s fall line, is the primary urban center near the Ocmulgee River. This study focused on the portions of the Ocmulgee watershed (as defined by the United States Geological Survey (USGS) Hydrologic Unit Code (HUC) system) which fall within 40 kilometers of the river itself, resulting in a total study area of approximately 11468 km2,with 5444 km2 corresponding to the Upper Ocmulgee and 6024 km2 corresponding to the Lower Ocmulgee.

**Study Period:**

This project used historical data from the National Land Cover Dataset (NLCD) for the years 2001, 2006, and 2011, and data from the United States Department of Agriculture (USDA) CropScape Cropland Data Layer (CDL) service for the years 2008 to 2014. The year 2001 was chosen as the starting date for this project due to the NLCD using a different classification system prior to that time (Homer, 2007). Through the use of recent Landsat 8 imagery, the timeline for this study was extended to 2014.

**National Application Area Addressed:**

This project addressed the Ecological Forecasting and Water Resources application areas. The team’s goal was to provide reliable ecological forecasts that will allow decision makers at the Georgia Department of Natural Resources (GA DNR) access to science-based tools in order to predict the impacts of environmental change on the Ocmulgee River Valley.

**Project Partners:**

The Ocmulgee Ecological Forecasting team partnered with the Georgia Department of Natural Resources to support their wildlife management and conservation goals. The GA DNR uses numerous decision-making tools to conserve state-owned and operated properties. Some of the GA DNR’s management techniques include the use of statistical and spatial analysis, fish stocking, and prescribed burns. The GA DNR combines field-based assessments with remotely- sensed data to support management decisions. Currently utilized datasets include: *in situ* water quality measurements, rare species inventories, digital aerial photography, Light Detection And Ranging (LiDAR), side imaging SOund Navigation And Ranging (SONAR), and digital elevation models (DEMs). Integrating their current resources with this study’s results served to update and enhance the GA DNR’s assessments of the Ocmulgee region. The GA DNR has personnel trained in GIS and remote sensing who will be able to utilize the tools and products resulting from this DEVELOP project.

# III. Methodology

**Land Cover Classification**

**Data Acquisition:**

Landsat images were acquired from the USGS Global Visualization Viewer website. The 2014 satellite imagery was collected by the Operational Land Imager (OLI) on-board Landsat 8 during April, May, and November. The historical data used for the 2001, 2006, and 2011 NLCD were derived from Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+).

Ancillary datasets used for this project included: United States Department of Agriculture (USDA) CropScape land cover data, Environmental Protection Agency (EPA) 303d for impaired waters, EPA National Pollutant Discharge Elimination System (NPDES) for point-source pollution, GA DNR 2012 Side Scan SONAR for image data and Ocmulgee River substrate layers, GA DNR Index of Biotic Integrity for fish sample data, GA DNR long-term sport fish monitoring data for fish populations, GA DNR plant, animal, and fish survey data for rare and endangered species distributions, and GA DNR parcel data for land ownership.

**Data Processing:**

Landsat 8 satellite imagery was downloaded as Level 1 GeoTIFF Data Products and was processed using ArcGIS 10.2 and ENVI 5.0. To correct the images for interference from background values, a mask file was created using ArcGIS to eliminate the uneven overlap of bands along the edges of the image. Atmospheric correction of the Landsat 8 imagery was required to accurately extract pixel values and data. The team utilized the ENVI Quick Atmospheric Correction (QUAC) algorithm to process the satellite imagery. QUAC establishes parameters for correction directly from the observed pixel spectra within a scene without ancillary information. QUAC is based on empirical findings that the average reflectance of spectra is not dependent on each individual scene and it works for the visible near-infrared through shortwave infrared (VNIR-SWIR) wavelength range (Bernstein, 2005).

**Data Analysis:**

The 2014 Landsat images were classified using the NLCD’s 2011 land cover criteria. This method of land cover classification and designation is based on the Anderson Land Cover Classification System (Homer, 2012). The following 15 NLCD land cover classes apply to Central Georgia: Open Water, Developed Open Space, Developed Low Intensity, Developed Medium Intensity, Developed High Intensity, Barren Land, Deciduous Forest, Evergreen Forest, Mixed Forest, Scrub/Shrub, Grassland/Herbaceous, Pasture/Hay, Cultivated Crops, Woody Wetlands, and Emergent Herbaceous Wetland. The unsupervised classification used in the first term of this project proved too broad for the needs of our project partners, specifically with respect to projecting urban development and encroachment areas. The land cover classification was updated in ENVI 5.0 using a supervised classification method consisting of three main stages: training, classification, and output (Lillesand, 2008, p.547).

The training stage consists of the analyst identifying/defining homogeneous pixels or regions of interest (ROIs) in order to develop a numerical description of the spectral attributes of each land cover type of interest within the scene (Bhaskaran, 2010). Training samples from the same class category may possess different spectral characteristics and it is necessary to sample a wide variety of applicable pixels during the training stage. This project used 30-meter resolution Landsat imagery to develop training sets through visual interpretation of the land use and land cover characteristics. The NLCD maps from 2001, 2006, 2011, and USDA CDL maps from 2014 were used as reference when identifying ROIs to build the training sets.

During the classification stage each pixel in the image data set was categorized based on its comparison to the mean of the signatures derived from the training set. Classification in ENVI is specialized by using one or a combination of the following 4 algorithms: Maximum Likelihood, Minimum Distance, Mahalanobis Distance, and Spectral Angle Mapper (Lillesand, 2008, p.550-557). The Maximum Likelihood (MLC) and Minimum Distance (MDC) algorithms were primarily utilized in this study. Maximum Likelihood is the most widely used algorithm for per-pixel classification with remote sensing data (Harvey, 2002). Maximum likelihood classification is calculated using the following discriminant function below for each pixel in the image (Richards, 1999, p. 240; ENVI, 2015):

1. 

*Where:*

*i = the ith class*

*x = n-dimensional data (where n is the number of bands)*

*p(ωi) = probability that a class occurs in the image and is assumed the same for all classes*

*|Σi| = determinant of the covariance matrix of the data in a class*

*Σi-1 = the inverse of the covariance matrix of a class*

*mi = mean vector of a class*

Maximum Likelihood classification quantitatively evaluates both the variance and covariance of each class’s spectral response patterns. Lillesand notes that MLC assumes that the distribution of the groups of pixels forming the category within the training data is Gaussian (normally distributed). New pixel values are then assigned to the class with the highest probability of generating a given pixel (Lillesand, 2008, p.554-556).

The MDC technique computes the mean pixel vector of the “feature” class, and then assigns new pixels to the “feature” class based on the Euclidean distance from that pixel to the mean (Richards, 1999; ENVI, 2015). For the multiclass case, such as this study, pixels are assigned to the feature whose mean value is the minimum distance from the pixel (Harvey, 2002). Minimum distance classification is calculated using the following discriminant function below for each pixel in the image (Richards, 1999):

(2) 

*Where:*

*D = Euclidean distance*

*i=the ith class*

*x = n-dimensional data (where n is the number of bands)*

*mi = mean vector of a class*

**Ecological Modeling and Forecasting**

**Data Acquisition:**

The classification results were then mosaicked together in ArcGIS 10.2. A mosaic creates a single raster dataset from multiple raster datasets to optimize final product accuracy and minimize visual inconsistencies.

**Data Processing:**

**Data Analysis:**

For the ecological forecasting and modeling of the Ocmulgee River valley, we utilized the Clark Labs geospatial software system called TerrSet. This program incorporates a variety of models for conservation planning such as: Land Change Modeler (LCM), Habitat and Biodiversity Modeler (HBM), Ecosystem Services Modeler (ESM), Earth Trends Modeler (ETM), and Climate Change Adaption Modeler (CCAM). Both the LCM and HBM models were used in this study. The LCM is a vertical application that maps and graphs land change scenarios, including net gains, net losses, net change, persistence, and provides a breakdown of contributors to each transition. The LCM calculates empirical information using historical changes to develop the mathematical model and GIS data to generate change potential maps (Perez, 2012). The HBM is also a vertical application used for modeling species distributions, habitat assessments, habitat changes, gap analyses, biodiversity analyses, and the planning of reserves and biological corridors (Clark Labs, 2015).

# IV. Results & Discussion

**Land Cover Classification:**

This project’s supervised classification results indicated several changes in land cover in the Ocmulgee River valley since 2011. The most apparent changes were summarized as area and percent land cover changes (Figures 2, 3, and 4).

Classification errors occurred from data limitations and possible misinterpretation of the imagery. The 30-meter resolution of the Landsat 8 imagery is coarse enough to represent the heterogeneous land cover, but not detailed enough to capture the desired classification in some areas. Additionally, accurate identification of specific vegetation types and urban intensity through visual and spectral analysis was difficult at this resolution. In both cases (vegetation and urban), overlapping pixel values for land cover classes was responsible and reduced the overall accuracy of the results. Hand-coding of suitable feature-detection algorithms becomes impractical when pixels/algorithm parameters overlap for multiple classes (Harvey, 2002). Urban land cover is difficult to classify due to the large number of classes present in such a small area (Ridd, 2006).

The supervised classification proved to have greater accuracy and correct feature detection over the unsupervised classification when compared to historical data. Using multitemporal imagery allowed for better classification of land classes (Yuan et al., 2005). However, the advantage of any technique over another with respect to classification accuracy depends upon the biophysical state of the study area (Eiumnoh, 2000). Several previous studies have confirmed the use of supervised classification by MLC for urban areas as the most appropriate method (Eiumnoh, 2000; Shalaby and Tateishi, 2007; Thapa and Murayama, 2009).

In the future, a combined spectral and spatial approach may be useful to map urban features, particularly those with low spectral distinction (Bhaskaran, 2010). Future work could focus on smaller portions of the study area with higher resolution imagery to get a more accurate classification of urban features. Although project partners provided useful ground truth data for verification, the final classification could benefit from a formal accuracy assessment.

**Ecological Forecasting:**

# V. Conclusions

# VI. Acknowledgments

The Ocmulgee Ecological Forecasting team would like to acknowledge project partners, Thom Litts and Melanie Riley, from the Georgia Department of Natural Resources who provided us with valuable onsite information and ancillary data for our study area. Special thanks to our science advisors Dr. Marguerite Madden, Dr. Thomas Jordan and Dr. David Cotton of The University of Georgia Center for Geospatial Research for their continual guidance, expertise, and support.

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# VIII. Content Innovation

# IV. Appendices

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Figure 1: Project Study Area.

|  |  |
| --- | --- |
|  | ***Area (km2)*** |
| **Land Cover Type** | **2001** | **2006** | **2011** | **2014** |
| *Barren Land* | 54.36 | 44.38 | 47.35 | 32.17 |
| *Cultivated Crops* | 997.31 | 982.96 | 958.11 | 775.86 |
| *Deciduous Forest* | 2262.98 | 2250.19 | 2066.55 | 1695.37 |
| *Developed, High Intensity* | 30.02 | 35.36 | 40.44 | 134.49 |
| *Developed, Low Intensity* | 243.48 | 281.53 | 291.42 | 665.73 |
| *Developed, Medium Intensity* | 68.01 | 83.76 | 95.26 | 270.21 |
| *Developed, Open Space* | 694.67 | 764.86 | 771.83 | 884.40 |
| *Emergent Herbaceous Wetlands* | 81.43 | 74.84 | 97.50 | 58.30 |
| *Evergreen Forest* | 2828.62 | 2728.67 | 2574.40 | 2716.79 |
| *Hay/Pasture* | 1133.06 | 1096.34 | 1070.86 | 588.45 |
| *Herbaceous* | 918.91 | 871.44 | 972.12 | 506.10 |
| *Mixed Forest* | 545.80 | 515.88 | 460.79 | 772.22 |
| *Open Water* | 132.75 | 134.94 | 139.64 | 178.81 |
| *Shrub/Scrub* | 180.09 | 309.66 | 598.75 | 1044.29 |
| *Woody Wetlands* | 1288.64 | 1285.32 | 1275.13 | 1154.29 |

Figure 2: Land cover area for study years- adapted from NLCD class names.

|  |  |  |
| --- | --- | --- |
|  |  | **Change in Area (km2)** |
| **Land Cover Type** |  | **2001-06** | **2006-11** | **2011-14** | **2001-11** | **2001-14** |
| *Barren Land* | -9.98 | 2.96 | -15.18 | -7.02 | -22.20 |
| *Cultivated Crops* | -14.35 | -24.85 | -182.25 | -39.20 | -221.45 |
| *Deciduous Forest* | -12.79 | -183.64 | -371.18 | -196.43 | -567.61 |
| *Developed, High Intensity* | 5.35 | 5.07 | 94.05 | 10.42 | 104.47 |
| *Developed, Low Intensity* | 38.05 | 9.89 | 374.31 | 47.94 | 422.25 |
| *Developed, Medium Intensity* | 15.75 | 11.50 | 174.95 | 27.25 | 202.20 |
| *Developed, Open Space* | 70.20 | 6.97 | 112.57 | 77.16 | 189.73 |
| *Emergent Herbaceous Wetlands* | -6.60 | 22.67 | -39.21 | 16.07 | -23.14 |
| *Evergreen Forest* | -99.95 | -154.27 | 142.39 | -254.22 | -111.83 |
| *Hay/Pasture* | -36.72 | -25.49 | -482.41 | -62.20 | -544.61 |
| *Herbaceous* | -47.47 | 100.68 | -466.02 | 53.21 | -412.81 |
| *Mixed Forest* | -29.92 | -55.09 | 311.43 | -85.01 | 226.42 |
| *Open Water* | 2.19 | 4.70 | 39.17 | 6.89 | 46.06 |
| *Shrub/Scrub* | 129.56 | 289.09 | 445.54 | 418.66 | 864.20 |
| *Woody Wetlands* |  | -3.32 | -10.20 | -120.84 | -13.52 | -134.35 |

Figure 3: Area changes for study years- adapted from NLCD class names.

|  |  |
| --- | --- |
|  | **Land Cover Change (%)** |
| **Land Cover Type** | **2001-06** | **2006-11** | **2011-14** | **2001-11** | **2001-14** |
| *Barren Land* | -18.36 | 6.67 | -32.06 | -12.91 | -40.83 |
| *Cultivated Crops* | -1.44 | -2.53 | -19.02 | -3.93 | -22.20 |
| *Deciduous Forest* | -0.57 | -8.16 | -17.96 | -8.68 | -25.08 |
| *Developed, High Intensity* | 17.81 | 14.34 | 232.59 | 34.71 | 348.03 |
| *Developed, Low Intensity* | 15.63 | 3.51 | 128.44 | 19.69 | 173.42 |
| *Developed, Medium Intensity* | 23.15 | 13.73 | 183.65 | 40.07 | 297.30 |
| *Developed, Open Space* | 10.11 | 0.91 | 14.58 | 11.11 | 27.31 |
| *Emergent Herbaceous Wetlands* | -8.10 | 30.29 | -40.21 | 19.73 | -28.41 |
| *Evergreen Forest* | -3.53 | -5.65 | 5.53 | -8.99 | -3.95 |
| *Hay/Pasture* | -3.24 | -2.32 | -45.05 | -5.49 | -48.07 |
| *Herbaceous* | -5.17 | 11.55 | -47.94 | 5.79 | -44.92 |
| *Mixed Forest* | -5.48 | -10.68 | 67.58 | -15.57 | 41.48 |
| *Open Water* | 1.65 | 3.48 | 28.05 | 5.19 | 34.70 |
| *Shrub/Scrub* | 71.94 | 93.36 | 74.41 | 232.47 | 479.86 |
| *Woody Wetlands* | -0.26 | -0.79 | -9.48 | -1.05 | -10.43 |

Figure 4: Percent changes in land cover- adapted from NLCD class names.