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Object-based forest classification to facilitate landscape-scale conservation in the Mississippi Alluvial Valley

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ABSTRACT

The Mississippi Alluvial Valley is a floodplain along the southern extent of the Mississippi River extending from southern Missouri to the Gulf of Mexico. This area once encompassed nearly 10 million ha of floodplain forests, most of which has been converted to agriculture over the past two centuries. Conservation programs in this region revolve around protection of existing forest and reforestation of converted lands. Therefore, an accurate and up to date classification of forest cover is essential for conservation planning, including efforts that prioritize areas for conservation activities. We used object-based image analysis with Random Forest classification to quickly and accurately classify forest cover. We used Landsat band, band ratio, and band index statistics to identify and define similar objects as our training sets instead of selecting individual training points. This provided a single rule-set that was used to classify each of the 11 Landsat 5 Thematic Mapper scenes that encompassed the Mississippi Alluvial Valley. We classified 3,307,910 ± 85,344 ha (32% of this region) as forest. Our overall classification accuracy was 96.9% with Kappa statistic of 0.96. Because this method of forest classification is rapid and accurate, assessment of forest cover can be regularly updated and progress toward forest habitat goals identified in conservation plans can be periodically evaluated.

1. Introduction

Before European settlement, approximately 9.7 million ha within the Mississippi Alluvial Valley were forested (King et al., 2006). By the 1930s the area of bottomland forest in this region had declined to about 4.2 million ha and suffered an additional 45% decline through the 1980s (Oswalt, 2013). Since then, conservation partners in the Mississippi Alluvial Valley have implemented strategic habitat conservation for wildlife via a landscape-scale approach to forest conservation and restoration (U.S. Fish and Wildlife Service, 2008). This approach relies upon: (1) the development of species-habitat models to define sustainable landscapes; (2) implementation of conservation actions in accordance with these landscape-designs; and (3) the ability to monitor and evaluate progress towards meeting conservation objectives. Specifically, the Lower Mississippi Valley Joint Venture partnership exists for the purpose of facilitating landscape-scale conservation and restoration of bottomland hardwood forest ecosystems with an emphasis on supporting healthy populations of avian species and other forest dependent wildlife species in this region (Twedt et al., 1999; LMVJV Operational Plan, 2013). Therefore, the ability to characterize the forest landscape (e.g., amount and spatial arrangement) is necessary to facilitate planning and evaluation of conservation goals.

To characterize the forest landscape of the Mississippi Alluvial Valley, conservation partners have historically used: (1) traditional analytical methods using 30 m resolution Landsat TM imagery and aerial photography in a supervised classification (Twedt and Loesch, 1999); (2) data from the U.S. Forest Service's Forest Inventory and Analysis Program (Bechtold and Patterson, 2005) in conjunction with aerial or satellite photography (Rudis and Birdsey, 1986; Oswalt, 2013); and (3) publicly available National Land Cover Data (NLCD; Fry et al. 2011).

Although these approaches provided useful and accurate estimates of forest area and distribution, advances in remote sensing software and analysis now permit classification of remotely sensed imagery that is more economical, efficient, and has improved accuracy compared to previously used pixel-based classification methods. For example, relatively inexpensive medium and high-resolution imagery is available that allows analysis at improved spatial and temporal scales. Geographic Information System (GIS) software has incorporated object-based image analyses as an alternative to pixel-based methods. Additionally, decision tree

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creation in software supports analysis and classification of landscapes with improved repeatability (Friedl and Brodley, 1997; Pal and Mather, 2003; Immitzer et al., 2012; Mellor et al., 2013). This combination of object-based image analysis and decision tree classification has the potential to facilitate and enhance landscape-scale conservation efforts through use of more effective, transparent, and repeatable analytical processes.

Object-based image analysis allows for segmentation, attribution, classification, and establishment of relationships among defined objects that are not possible in pixel-based analyses (Cufi et al., 2002). This image analysis method takes digital input (e.g., Landsat 5 Thematic Mapper [TM] imagery) in the form of spectral bands, as well as spectral indices created from these bands, and creates multiple sets of similar pixels (i.e., objects) that may be more meaningful and easier to analyze than individual pixels (Blaschke and Strobl, 2001). Each identified object assumes the attributes of all the pixels that comprise it, as well as contextual information such as its relationship to surrounding objects.

When used in conjunction with classification and regression tree (CART) methods, object-based image analysis allows for the creation of dynamic decision tree rule-sets that can be applied to separate datasets (Breiman et al., 1984). This method uses training objects to predict the class of other objects. As a binary classification tree, a test and output decision is applied at each node within CART analysis until reaching a final prediction. The Random Forest algorithm is analogous with CART methodology but builds multiple decision trees and compares the outcome of all these trees to make a decision. Even so, Random Forest is fast, accurate, and is capable of forming as many trees as the user specifies without over fitting the data being analyzed (Breiman and Cutler, 2005). In many cases, Random Forest classification produces higher accuracies than other classification approaches and has been successfully used to separate imagery classes that are spectrally similar (Akar and Güngör 2012).

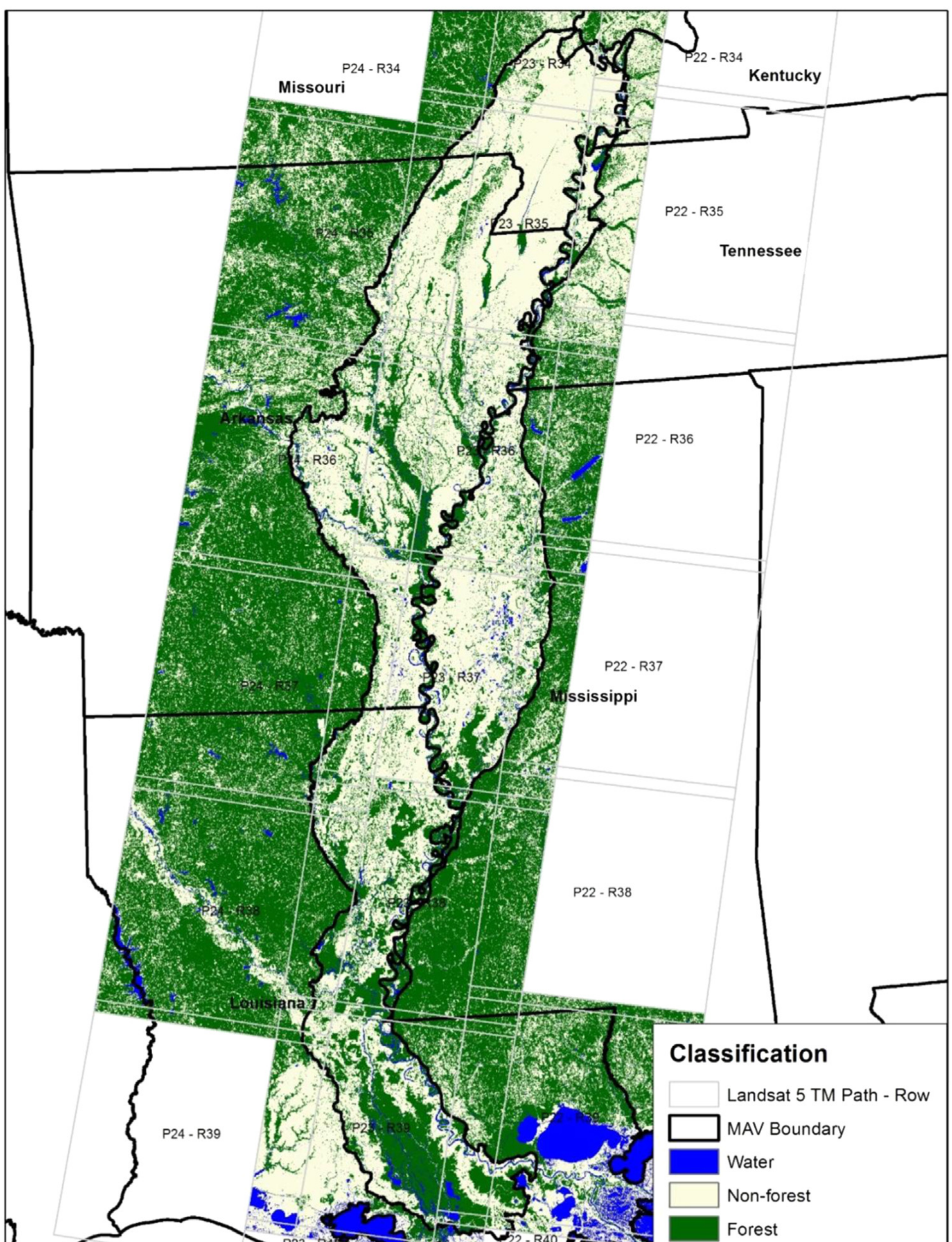

Fig. 1. Boundaries of the Mississippi Alluvial Valley and Landsat 5 Thematic Mapper (TM) scenes (path-rows) as well as the final classification.