

AUTOMATED SUPERVISED LAND USE CLASSIFICATION AND CHANGE DETECTION: AN IMAGE FUSION BASED APPROACH

Francis Padula, Julia MacDonough, Dan Bondy, Monica Cook

Integrity Applications Incorporated, 5160 Parkstone, Suite 230, Dr. Chantilly, VA

1. INTRODUCTION

The ability to rapidly identify and exploit large area land use change over time using high resolution multispectral data was investigated. This effort was part of a larger effort to support the United States Environmental Protection Agency (U.S. EPA) in the analysis of international land use change dynamics associated with agricultural expansion, in order to identify potential lifecycle impacts of domestic transportation fuel produced from vegetation. There are many approaches that rely on various schemes to perform large area land use classification and change detection using both supervised and unsupervised methods [1-3]. Key elements of all approaches are the utilized data set and its associated quality.

A multispectral image classification algorithm was constructed in which a Moderate Resolution Imaging Spectroradiometer (MODIS) land cover product provided a priori guidance to an automated supervised image classification algorithm. A Gaussian Maximum Likelihood (GML) classifier was developed and used to classify the high resolution image data provided by the quality controlled Global Landsat Survey (GLS) for the years of 2000 & 2005 [4].

The focus of this work is to illustrate the implementation of a novel approach to efficiently leverage the public availability and no-cost high quality global remote sensing data and data products to provide high quality land use change detection. This effort additionally demonstrates the potential of this technique with respect to rapid global and large area image classification and change detection analysis. Discussion spotlights the supporting methodology behind the automated process and the image processing techniques developed to assure product quality in the image fusion based approach.

2. METHODOLOGY

An image fusion based automated supervised land use classification and change detection algorithm was developed. The approach leverages the a priori scene knowledge derived from the well established 500 m spatial resolution MODIS (MCD12Q1 land cover type 1) International Geosphere Biosphere Programme (IGBP) Land Cover Product (17 land cover classes) to provide autonomous training data to a GML image classifier. Each Landsat scene was treated as an instantaneous sample, which provided a mutually exclusive result for each scene

processed. The overall quality and performance of any supervised classifier can be directly related to the quality of the training data. Training data was derived from vectors extracted based on a corresponding geo-registered Landsat image cube (i.e. 7 visible and near infrared bands) of interest and MODIS land cover product region mosaic, thus facilitating an automated process to acquire the training data. Because the training data is acquired from each scene uniquely, the need for scene calibration (i.e. digital number to radiance conversion), atmospheric correction, and other surfaces effects could be neglected under the assumption that the instrument noise is constant and the atmosphere uniform throughout the scene. This is a very powerful tool as it states that unique

spectral signatures can be defined regardless of time of day, “season”, and various illumination conditions, assuming the training pixels span a spatially diverse range in the image. This assumption is principally valid and developed to leverage the efforts of the rigorous pre-processing in the creation of the Landsat GLS archive.

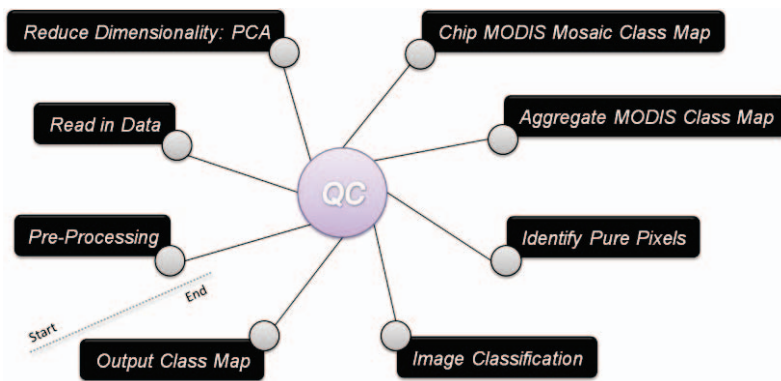


Figure 1: Automated image classification algorithm workflow.

Figure 1 illustrates the algorithm workflow. Data pre-processing steps involved identifying the Landsat images to process within the archive, building image mosaics from the MODIS land cover products for the region of interest (Ex. Brazil, India, etc.), and converting the two image data sets into a common referencing system. Principal Component Analysis (PCA) was performed on each Landsat image cube. PCA can significantly decrease computational time, while tending to improve classification results by maximizing the data’s variability. A chipped (i.e. subset) MODIS land cover product image was obtained over the corresponding Landsat image region. This image was used to recognize the classes to identify within the Landsat scene. The 17 classes of the MCD12Q1 land cover type 1 product were aggregated to 10 unique classes: water, wetlands, forest, shrubland, savanna, grassland, cropland, urban, cropland/natural vegetation mosaic and barren.

Land use phenomena and land use change can occur at scales beyond the detectable limits of the 500 m MODIS product. An automated quality control process to identify pure training pixels from each MODIS-derived land cover class was developed to reduce errors in the

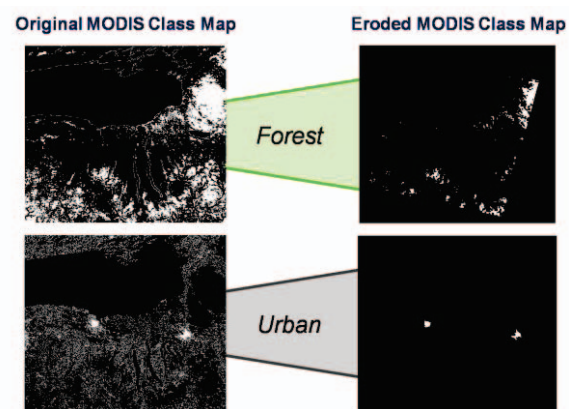


Figure 2: Schematic of the morphological erosion operators used in the spatial purity test; images of Western New York, USA.

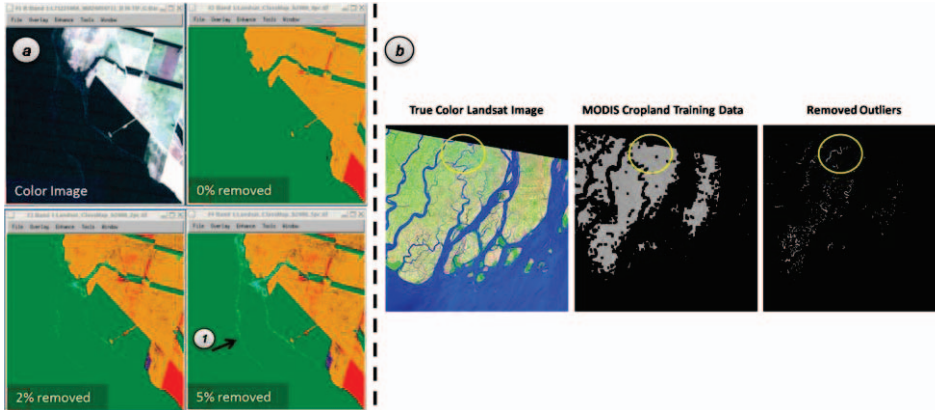


Figure 3: (a) Algorithm performance within an outlier removal trade space. (b) True color image of an India Landsat scene (left), MODIS derived cropland training data (center) and post spectral purity testing outlier identification (right).

are assumed to represent an entire pixel of a single land use type. Each set of subject training pixels was evaluated via two quality control steps investigating the spatial and spectral purity of the training data. Spatial purity was defined using an iterative morphological erosion approach on the identified MODIS class present. The ideal case (i.e. spatially purest pixels) would be those pixels that have eight “like” neighbors [Figure 2]; if a cluster of pixels was not identified for a given class, the entire set of MODIS derived pixels was considered.

The spectral purity test examined the covariance of the subject training pixels using an iterative process, by removing 5% (empirically derived [Figure 3 (a)]) of the training class outliers and statistically testing each classes covariance matrix (statistical metric defined in [5]) before and after outlier removal. This step ensured anomalous pixels, with respect to the class of interest, were not incorporated into the final training pixels for that class [Figure 3 (b)]. Each class mean and covariance of the quality controlled training pixels were then used as final class training pixels in the GML image classification algorithm.

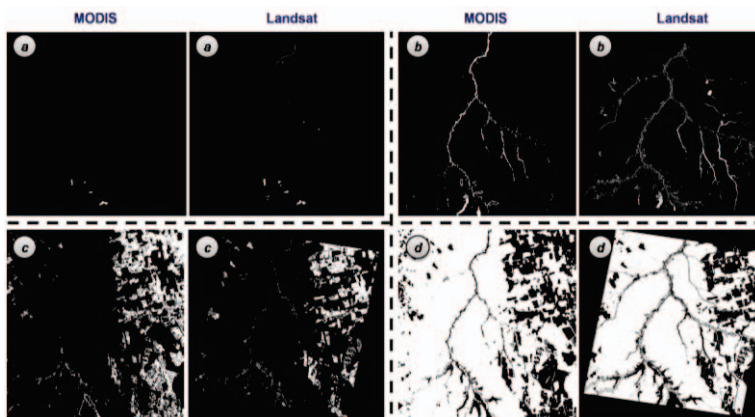


Figure 4: Comparison of water, wetland and forest classes of the MODIS derived and Landsat derived products (Correlation: 0.43, 0.27, 0.8 & Percent Different from MODIS: 235.3, 182.3, 2.8, water, wetland, forest respectively).

training process (largely due to the difference in resolution of the two images) and to ultimately enhance algorithm performance. Pure training pixels are those pixels that have passed quality control testing, to enhance quality and resulting stability of the image product, as they

3. RESULTS

The fusion of the higher resolution Landsat data with the MODIS Land Cover product facilitated an automated and quality controlled image classification process that could be used to rapidly assess landuse dynamics over larger areas. Figure 4 illustrates a class-to-class example of a common observation throughout this study. In the absence of ground truth, this initial effort relied on a direct image-to-image

comparison (correlation and percent difference) between the MODIS and Landsat derived products [Figure 4]. Note the automated algorithm was capable of utilizing the limited set of MODIS derived pixels to distinguish an expansive water system; similarly note the wetlands comparison. Due to the resolution constraints of the MODIS instrument, the classification of small scale terrain will be limited, as is evident in the percent differences in the water and wetlands classes [Figure 4(a-b)].

However, large scale features, such as forests in this example, illustrate results that are quite consistent [Figure 4(c)].

Processing the comprehensive GLS data archive for the effective years of 2000 and 2005 produced two land classification image mosaics. Change detection was then performed to identify the landuse changes (i.e. deforestation/cropland expansion) in various regions of the globe [Figure 5].

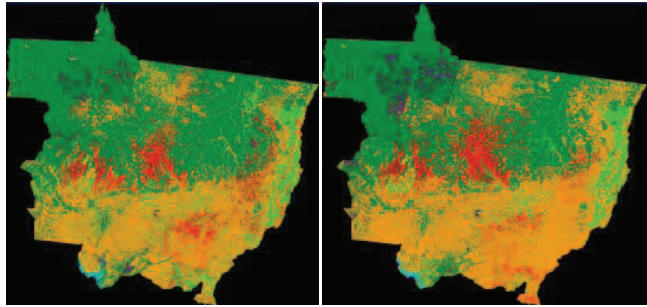


Figure 5: Land Classification results: Matto Grosso, Brazil 2000 (right) and 2005 (left).

4. CONCLUSIONS

An image fusion based land use classification and change detection algorithm was developed. This algorithm leverages the accuracy and stability of a coarser resolution MODIS product to achieve a quality automated higher resolution product that can be rapidly implemented to cover large regions of interest. Through the fusion of the two data sources, an accurate and quality controlled higher resolution land classification product was obtained providing valuable information into the classification of land use type and land use change over time. This initial effort focused on the proof of concept; future work can provide a deeper investigation of results verification. The focus of this effort was to inform the U.S. EPA analysis of international land use change dynamics associated with agricultural expansion on potential lifecycle impacts of domestic transportation fuel produced from vegetation.

5. REFERENCES

- [1] M.A. Friedl et. al., "Global land cover mapping from MODIS: algorithms and early results," *Remote Sensing of Environment*, vol. 83, pp. 287 – 302, 2002.
- [2] M. C. Hansen and B. Reed, "A Comparison of the IGBP DISCover and University of Maryland 1 km global land cover products," *Int. J. Remote Sensing*, vol. 21, no. 6 & 7, pp. 1365 – 1373, 2000.
- [3] R. Latifovic et. al., "Land cover mapping of North and Central America—Global Land Cover 2000," *Remote Sensing of Environment*, vol. 89, pp. 116 – 127, 2004.
- [4] Gutman, G., Byrnes, R., Masek, J., Covington, S., Justice, C., Franks, S., and R. Headley, Towards monitoring land cover and land-use changes at a global scale: The Global Land Survey 2005, *Photogrammetric Engineering and Remote Sensing*, 74, pp. 6-10, 2008.
- [5] R. Johnson & Dean Wichern, "Applied Multivariate Statistical Analysis", Prentice Hall, *fifth edition*, 2002.