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TEST OF AN OBJECT-ORIENTED EMPIRICAL DISTRIBUTION-BASED STRATEGY FOR HIGH-RESOLUTION LANDCOVER CLASSIFICATION

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ABSTRACT:

There are many approaches for classifying high-resolution imagery to general land cover classes. One of the most promising new approaches is the Object-Oriented Empirical Distribution (OOED) approach as described by Sridharan and Qiu (2014). This approach relies on the assumption that within segments, different classes of features have characteristic distributions. These differences in distribution within a segment can be used to distinguish between general land cover types to a high level of accuracy. In order improve accuracy results in a supervised land cover classification, it may be helpful to use independent variables based on the distribution of values within a segment. In this study, this concept is tested against more traditional object-oriented techniques by classifying a RapidEye image three different ways. First, a more traditional approach to object-oriented classification is performed which involves segmenting the imagery into an object layer, then creating a set of statistical variables derived by intersecting the imagery with the segments derived from the imagery. These statistical variables include the mean, range, standard deviation, sum, min, max, and a shape variable. These statistical layers are then classified. Second, another traditional method tested is to simply classify the raw image pixels with no segmentation approach. The third method tested is the OOED approach. This approach is implemented by using the same segmentation layer created in the first step to intersect with the image to create independent variables based on the distribution of brightness values in each band individually within each segment. To represent the distribution for each band, ranges of the distribution are broken into individual variables. Each layer of the variables dataset represents approximately a 100 value range for one band. All of the variables together should represent sufficiently the within segment distribution for the entire dataset. No other independent variables are used. In order to isolate the effects of just the independent variables on the classification accuracy, a supervised approach is run, in this case a decision tree regression classifier, on each set of independent variables. The same parameters are used for each approach. The dependent variable, or training dataset are collected in the area covered by the satellite image. Around 600 points are collected in a stratified random distribution. An effort is made to collect a reasonable number of points for every class being mapped. The classification scheme used is the standard NLCD classification scheme. Half of these points are withheld for validation by randomly selecting 50% of points from each class. The accuracy results are calculated by Kappa coefficient and reported in a table for comparison. Each method uses the same image base, a RapidEye satellite image covering the Washington DC area. This area has a diversity of different land cover types and if there is a confusion over an area of classification results, a short drive resolves any dispute. The same field collected training dataset is used for each approach. No ancillary datasets is used as independent variables in any of the approaches, with the aim of testing the effectiveness of each approach as purely as possible. The OOED approach to image classification should be tested as the concept holds promise for increasing classification accuracies.