ON THE RELATIVE PREDICTIVE VALUE OF THE NEW SPECTRAL BANDS IN THE WORLDVIEW-2 SENSOR

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1. INTRODUCTION

WorldView-2 (WV2), launched on October 8, 2009, is the first commercial satellite to carry a very high spatial resolution 8-band multi-spectral sensor. Focal planes on the WV2 sensors are enhancements over those used on QuickBird (QB). In addition to overall increased agility, the WV110 focal plane carried by WV2 (Figure 1) has a total of one panchromatic and eight multi-spectral bands (C=Coastal Blue, B=Blue, G=Green, Y=Yellow, R=Red, RE=Red Edge, NIR1, and NIR2, with center wavelengths at 425, 480, 545, 605, 660, 725, 835, and 950 nm respectively). By comparison, QB's four spectral bands (B, G, R ,NIR1) are centered at 485, 560, 660 and 830 nm. The added spectral dimensions (C, Y, RE, NIR2) target costal and vegetation land cover types with potential applications in environmental monitoring, resource management, disaster management, urban planning, growth and agriculture.

This study applies a rigorous data mining framework to some of the very first WV2 images to validate the application of the new spectral bands for improved land cover classification. The new imagery is from various locations around the world for which we already have ground survey data.

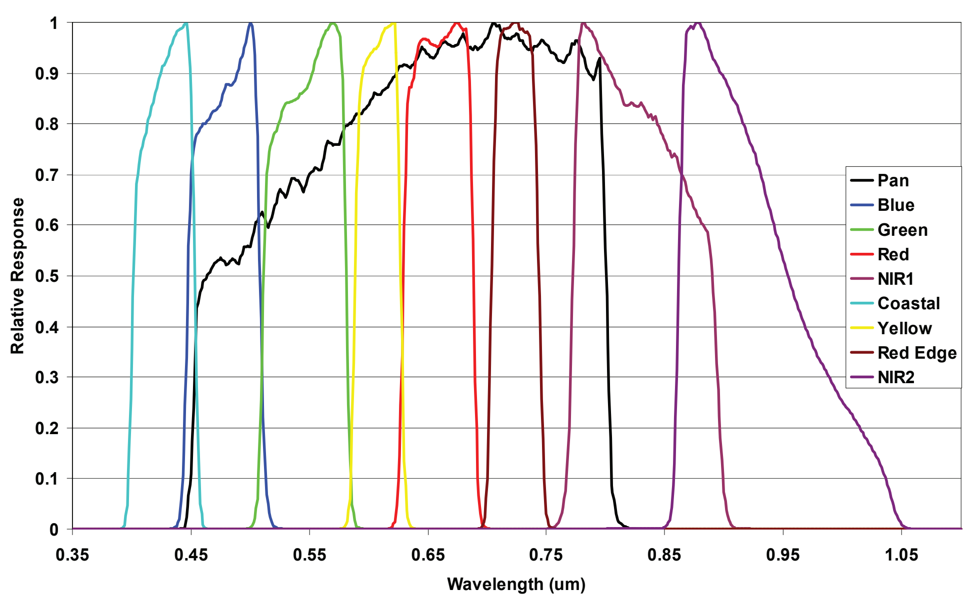

Fig. 1: WV100 relative spectral radiance response.

Our aim is to assess: (1) the incremental improvement in classification accuracy attributable to the new spectral bands vs. the traditional VNIR bands for a wide range of land cover types; and (2) the predictive power of each of the new spectral bands for each land cover type. Applied problem areas include plant species identification, mapping of vegetation phenomenology, crop stress, forest fires, benthic habitats, wetlands, coast water quality, bathymetry, and improved discrimination between spectral end members such as water and shadow. In the long term, we intend to assess the portability of all classification models in function of the new spectral bands for the creation of land cover maps on a large scale.

2. EXPERIMENTAL METHODOLOGY AND PRELIMINARY RESULTS

We restrict our study to spectral attributes of an image and their derivatives. Given a set of m land cover types for which we have ground truths, for each pixel sample we generate dual sets of $nb(nb+1)/2$ spectral attributes (where nb is the number of bands in a multi-spectral sensor). The attributes consist of the reflectance value in each of the original bands, plus all possible band ratios involving pairs of bands in the WV2 and traditional VNIR bands. This leads to a stack of 36 and 10 independent spectral predictors for each of the two sensors, respectively. Note that the spectral ratios are non-linear combinations of the original band responses.

Successively, we exploit a rigorous comparative data mining framework to generate classification models for each of the land cover types from the stacks of spectral attributes corresponding to each of the two multi-spectral sensors. Methods exploited include classification trees and tree ensembles, logistic regression, non-linear regression models, support vector machines, neural networks and Bayesian classifiers. The aim is dual: (1) to show the improvement in classification agreement for each of the land cover types due to the added spectral dimensionality, and (2) to stack rank the input spectral attributes in function of their predictive power for each land cover type. For instance, we may find that a previously unavailable band ratio, such the Coastal Blue/Yellow ratio is consistently among the top three predictor variables in resolving shadow across multiple classifiers (e.g. classification trees, tree ensembles, logistic regression), but has little or no predictive power when it comes to sand. Consistency in ranking of the spectral predictors across modeling methods is the key in discovering an optimal subset or combination of predictors for each land cover type.

Figure 2a shows the data mining framework used for classification and predictor analysis for two of the classification methodologies exploited in this study (classification trees and tree ensembles). Input ground truths are random partitioned (node 1) into training, test and validation samples. Within the single tree model (node 2), we perform in turn cross-validation by dividing the training pixels into k equally-sized groups. For each group, the remaining ($k-1$) groups are used to fit a tree, which is used to predict the left-out group. This gives a robust, cross-validated estimate of prediction error. In the tree ensemble model (nodes 10-12), we first apply stratified sampling (with optional replacement) to ensure equal representation from all pixel classes, then we fit an ensemble of randomly seeded trees. Predictions are based on the average from the ensemble. In the data mining literature, the sampling and ensemble modeling strategies we use here are often referred to as "bagging" and "boosting" [1][2]. The decision tree implementation underlying all of our tree-based classifiers is recursive partitioning trees after [3]. In the case of tree classifiers, the training and testing procedures involve adjusting parameters, such as entropy splitting criteria, tree complexity and number of trees. We compare classifiers by generating confusion matrices for all land cover classes (node 23), and lift charts showing precision recall curves across all classifiers (node 24). Finally, we validate all models (nodes 42-43 and 50-53) against the optimal set of predictors we derived from the calibration process, and we export them in PMML (Predictive Modeling Markup Language) format [4]. The adoption of PMML makes all our models portable, and leads to efficient implementations of the classification process outside of our design platform for large images. Figure 2b shows details of one of the first classification maps produced from a WV2 image taken over Dallas, TX.

Our analyses will validate which spectral bands or band ratios are the most effective predictors for each land cover type. Predictor diagnostics vary with each methodology. For instance, in the case of trees and tree ensembles, we compute individual entropy reduction for any given spectral variable by summing entropies over all tree splits involving that variable. In the case of regression based techniques, we infer predictor importance from t-statistics or ANOVA (ANalysis Of VAriance) tables [5].

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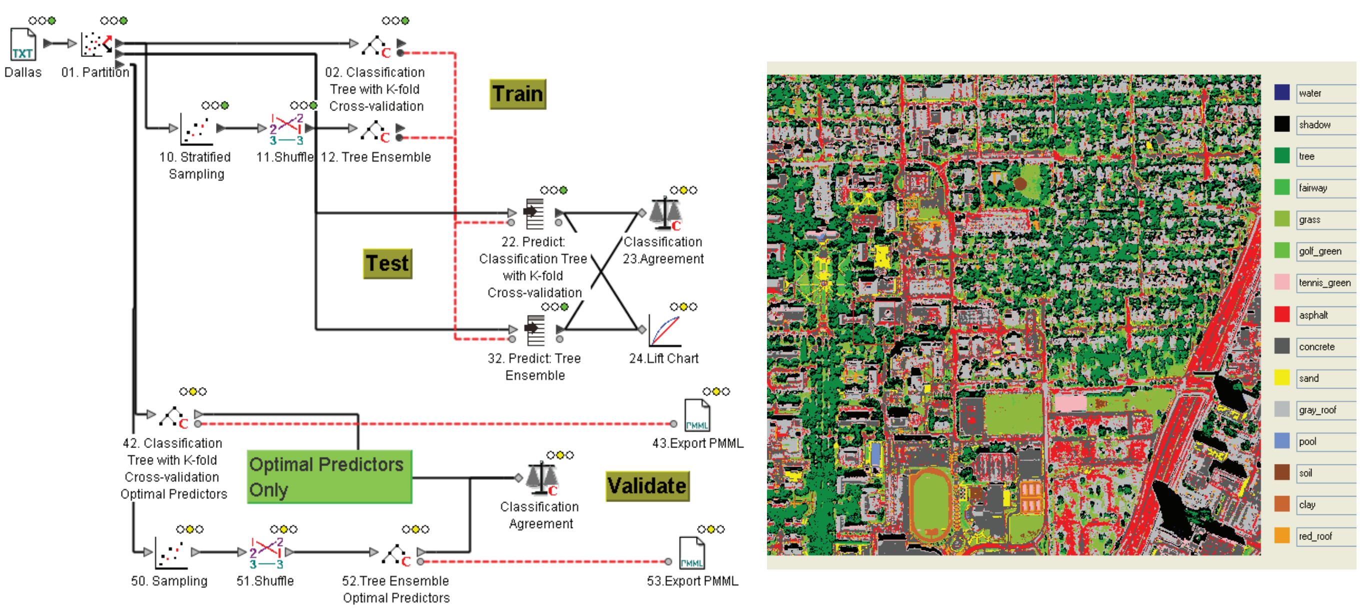
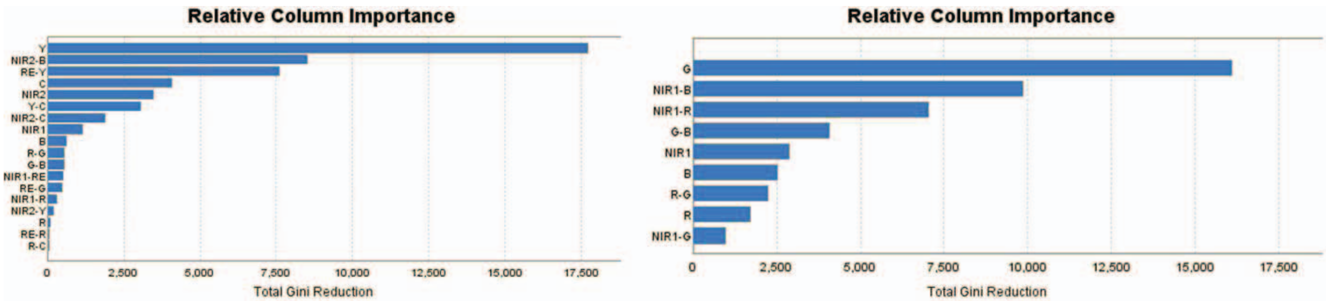


(a) (b)

Fig. 2: (a) Data mining framework, and (b) tree ensemble classification image based on WV2 spectral attributes.



(a) (b)

Fig. 3: Comparative (a) WV2 and (b) VNIR ranking of spectral predictors for a tree based classification of an image taken over Dallas, TX. We introduced abbreviations for spectral band names at the onset of the paper. NIR2-B in the vertical axis labels stands for the NIR2/B band ratio.

The end result in all cases is a comparison chart ranking the predictive power of each spectral variable. Figure 3 is an example of such a chart for tree models computed from the Dallas image using WV2 vs. VNIR spectral attributes. Over 50% of the top predictors are spectral variables unavailable in traditional VNIR imagery. We employ Trellis style graphics [6] to further break down the contribution of each spectral predictor to the classification accuracy of each land cover type.

3. CONCLUSION

In this paper, we discuss the results on a global experiment of the world first commercial very high spatial resolution 8-band multi-spectral sensor, with the goal of providing guidance in terms of application and problem areas where the new WV2 spectral bands can provide an advantage. Our goal is to generate a comprehensive atlas detailing the usefulness of each new spectral predictor in resolving selected land cover types. Preliminary results show that the added spectral dimensions in WV2 provide a significant percentage of the predictive power for certain land cover types. The data mining framework exploited also provides an ideal environment for selective integration of other non-spectral attributes, such as textural, morphological, and geometrical, in the classification process of very high spatial resolution imagery.

4. REFERENCES

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