Suitability of Sample Classification Schemes in a Sodden & Scrambled Setting

1. Overview

Classification of remote sensing Landsat Tile Edge study of a variety of phenomena ranging from urbanization to water and mineral exploration. Is the convenience of computer-automated (unsupervised) classification mechanisms such as k-Means worth any resulting trade-offs in accuracy? To

determine this, we compare and analyze the results of classifying Public Domain remote sensing imagery for MetroWest-Boston (depicted behind this text) with several common techniques.

Boston

2. Method

Given the established deficiencies of methods such as minimum distance and parallelpiped, they were not tested. Instead, the image was classified with four different mechanisms: Normalized Digital Vegetation Index (NDVI), k-Means (13 classes, 13 iterations), Maximum Likelihood & Spectral Angle Mapping (SAM). k-Means and Max. Likelihood were also performed on a Minimum Noise Fraction (MNF) image; its use is nonsensical for the other methods. The Max. Likelihood and SAM methods used training areas of 200–10,000 pixels each for: Grass+Golf Courses (Scrub), Trees, Wetlands, Shallow+Deep Water, Asphalt, and Urban areas. The NDVI image was classified via density slicing with the values at right.

3. Results

At first glance, the classified images in 3a seem very similar, however closer inspection of the smaller-scale images in 3b reveals a number of differences. Many can be attributed to relatively minor inter-related class swapping i.e; classifying "Urban (hi)" as "Urban (lo)" or "Asphalt." Other differences, such as NDVI's tendency to classify shallow water bodies as built-up land, are more problematic. Whereas SAM's conflation of "Asphalt" and null space around the image is a minor inconvenience.

How significant are all of these differences? One measure was obtained by calculating a "Confusion matrix" using ground truth with regions of interest (ROI). The resulting overall accuracy figures are shown in the last column of Table 4d. They imply that Maximum Likelihood is the most accurate technique, but is this really the case? After all, assessing ground truth with the initial training sites is rather tautological.

3b. Land Cover Classification Zoom J Null 🛹 Urban (lo) 🚅 Urban (hi) 📕 Asphalt P Water retland 🛹 Scrub Frees

10 km



NDVI	Clas
.4020	Water
.2016	Urban
.16-0.0	Aspha
0.016	Urban
.16–.25	Urban
.25–.47	Grass
.47–.615	Wetlaı
.615–.75	Trees







3a. MetroWest–Boston Land Cover Classification



4. Analysis

To further ascertain classification accuracy pared to independently



produced GIS data of comparable features e.g; the water class was compared to established hydrography vectors. The classes in the legend above, common to each of the accuracy analyses shown at far right, were produced in ArcMap with bitmap math similar to this expression: Not Null(known)+2×(classified=indicesOfInterest)

The resulting values indicate whether there is no feature pixel in either raster (0), an omitted feature (1), a committed pixel (2), or a correctly classified pixel (3).

4a. Unsurprisingly NDVI, a technique for distinguishing vegetation, was best at locating trees. The consistently high commission rates for this class are to be expected since the comparison data for "Prime Forests" does not include canopy in parks or residential areas. The higher omission rates for the Maximum Likelihood classifications would appear to result from user error and insufficient variety in training sites. At least two of the three polygons used in tree training are from wetland forest. The 3rd forest polygon, which is more than 300m from a water body and presumably upland forest, comprises only 8% of the ROI area. Yet with the same ROIs SAM's omission rate is half of Maximum Likelihood's.

4b. The "Asphalt", "Urban (hi)," and "Urban (lo)" classes were combined and compared to the National Land Cover Database imperviousness data where $\geq 50\%$ of land was built-up. This was deemed more accurate than the available land use data derived from parcels, which did not account for mixed coverage such as partially wooded lots. However the cut-off was chosen arbitrarily. As it is lowered commission decreases and omission increases e.g; at 33% impervious, k-Means commits 10% and omits 41%.

4c. The commission of pixels around Boston Harbor is due to the detection of beaches and tidal flats e.g; Lynn Shores Reservation in Nahant. This is to be expected for the methods using ROIs (SAM and Likelihood) given the use of a large training site in neighboring Broad Sound. Omission values in the low teens for all methods are acceptable given the mismatch between the spatial resolution of the source imagery (30m) and the presence of narrow, foliage flanked streams throughout the state. The k-Means classifications likely performed better here because they were able make adjustments for the resulting mixed-coverage pixels, whereas the water ROIs used were restricted to broader, uniform features like ponds.

4d. Statistical Accuracy

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	Canopy	Urban	Water		
k-Means	20.8% 25.3%	19.4% 26.7%	8.0% 16.6%	87.0%	
k-Means (MNF)	35.8% 32.1%	16.2% 33.1%	10.2% 15.3%	82.6%	
Max. Likelihood	12.2% 33.4%	32.8% 10.5%	6.4% 18.2%	95.2%	
Max. Like. (MNF)	26.4% 28.9%	16.8% 32.3%	7.8% 16.8%	89.2%	
NDVI	24.2% 15.4%	21.3% 35.1%	4.2% 38.3%	79.2%	
SAM	24.9% 15.3%	14.7% 38.9%	4.6% 23.4%	86.6%	

5. Conclusion

Of the examined methods, Maximum Likelihood is recommended as the best general-use/first-try classification scheme for medium-resolution, multi-spectral data such as that provided by the Landsat series of satellites. Even though tracing ROIs takes additional time, the higher accuracy is well worth the effort. The availability of the ROIs also allows for some assessment of ground truth, and the ability to run other classifications in the future e.g; reuse of existing ROIs with higher spectral resolution imagery, or determination of draft results with higher spatial resolution imagery.

SAM & MNF processing should be reserved for hyperspectral images. In special cases, NDVI may be useful with the high spatial-resolution aerial imagery such as that available from MassGIS.



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	NDVI Max. Likelihood	NDVI Max. Likelihood

Maps compiled April 2009 by Jerrad Pierce using data from: (1:25,000) (Polygons)". Polygons)"



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