5-2012

# Sub-Pixel Classification of Forest Cover Types in East Texas

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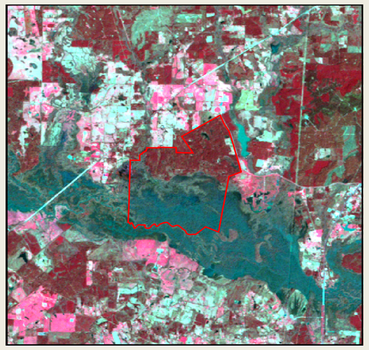
## Summary

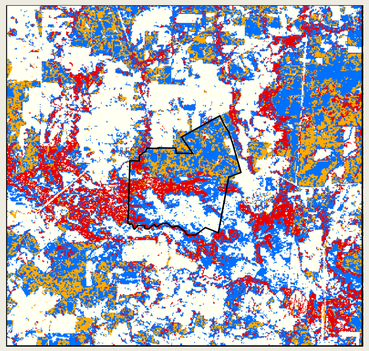
Sub-pixel classification is the extraction of information about the proportion of individual materials of interest within a pixel. Landcover classification at the sub-pixel scale provides more discrimination than traditional per-pixel multispectral classifiers for pixels where the material of interest is mixed with other materials. It allows for the un-mixing of pixels to show the proportion of each material of interest. The materials of interest for this study are pine, hardwood, mixed forest and non-forest. The goal of this project was to perform a sub-pixel classification, which allows a pixel to have multiple labels, and compare the result to a traditional supervised classification, which allows a pixel to have only one label. The satellite image used was a Landsat 5 Thematic Mapper (TM) scene of the Stephen F. Austin Experimental Forest in Nacogdoches County, Texas and the four cover type classes are pine, hardwood, mixed forest and non-forest. Once classified, a multi-layer raster datasets was created that comprised four raster layers where each layer showed the percentage of that cover type within the pixel area. Percentage cover type maps were then produced and the accuracy of each was assessed using a fuzzy error matrix for the sub-pixel classifications, and the results were compared to the supervised classification in which a traditional error matrix was used. The overall accuracy of the sub-pixel classification using the aerial photo for both training and reference data had the highest (65% overall) out of the three sub-pixel classifications. This was understandable because the analyst can visually observe the cover types actually on the ground for training data and reference data, whereas using the FIA (Forest Inventory and Analysis) plot data, the analyst must assume that an entire pixel contains the exact percentage of a cover type found in a plot. When compared to the supervised classification which has a satisfactory overall accuracy of 90%, non of the sub-pixel classification achieved the same level. However, since traditional per-pixel classifiers assign only one label to pixels throughout the landscape while sub-pixel classifications assign multiple labels to each pixel, the traditional 85% accuracy of acceptance for pixel-based classifications should not apply to sub-pixel classifications. More research is needed in order to define the level of accuracy that is deem acceptable for sub-pixel classifications.

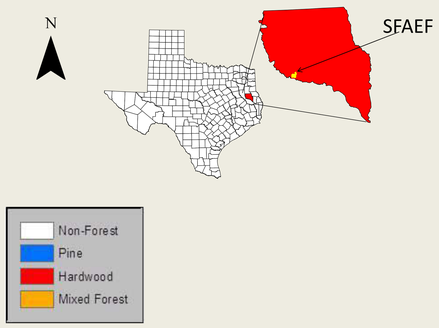
## Study Area

Landsat 5 TM image of the Stephen F. Austin Experimental Forest



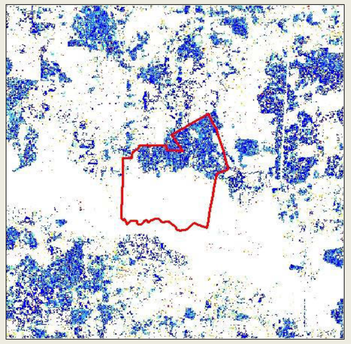
Traditional "Hard" Supervised Classification



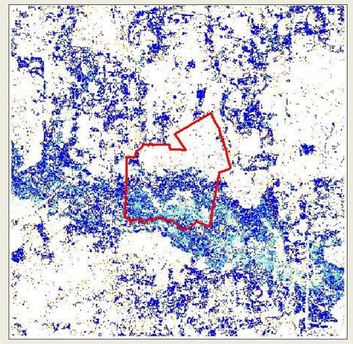



## Sub-pixel Classification Maps

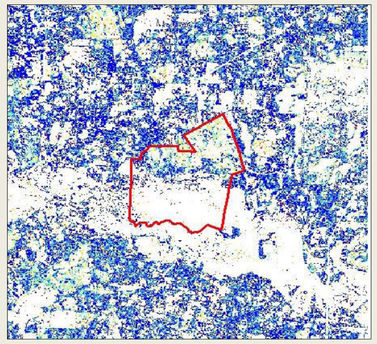
Pine



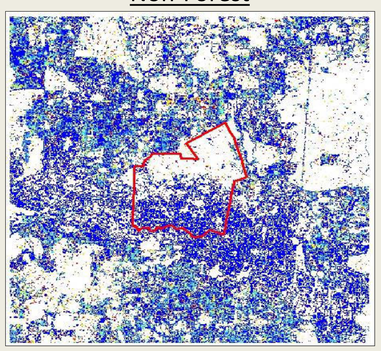
Hardwood



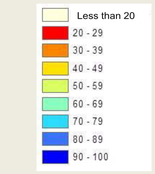
Mixed Forest



Non-Forest



Cover Type Percentage Classes

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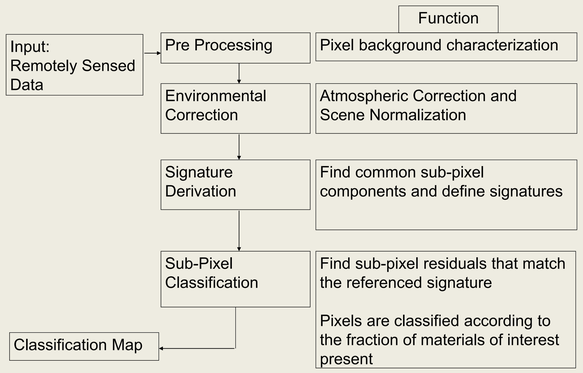
## Research Methods

Two sets of training and reference data were used; a high resolution color infrared aerial photograph and FIA (Forest Inventory and Analysis) tree crown plot data. Three sub-pixel classifications were conducted with the first one using the aerial photo for training and reference data, the second classification used the aerial photo for training data and the FIA plot data for reference data, and the third classification used the FIA plot data for training data and the aerial photo for reference data. Once the remotely sensed data are preprocessed and signatures are derived, the mixed pixel problem is solved by the following formula according to Huguenin et al. (1997).* It assumes each pixel $P_M$ contains some fraction $f_m$ of the material of interest $M$, (e.g., pine), and the remainder $1\text{-}f_m$ contains other background materials.

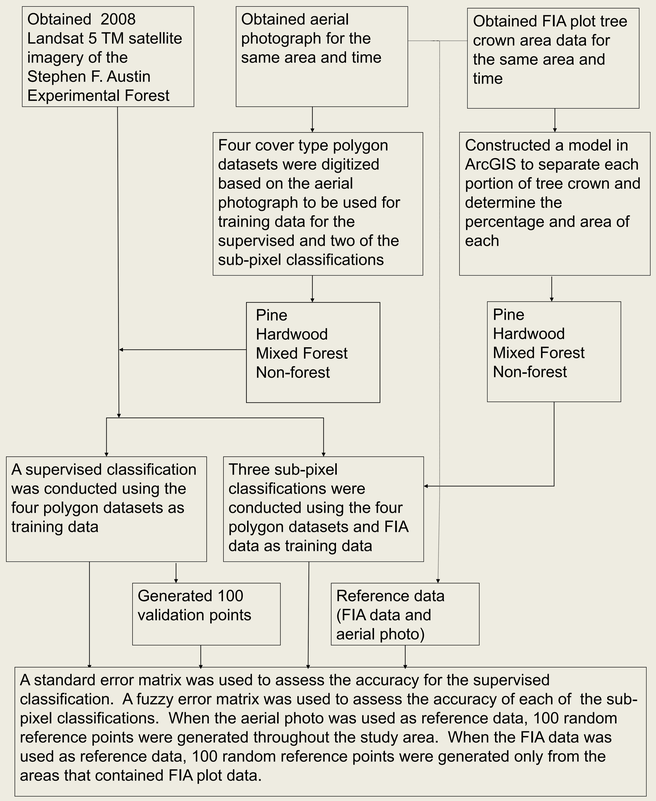
$$P_M = (f_m \times M) + [(1 - f_m) \times B_m]$$

*Huguenin, R. L,. M. A. Karaska,. D. Van Blaricom, and J. R. Jensen. 1997. Subpixel classification of bald cypress and tupelo gum trees in thematic mapper imagery. *Photogrammetric Engineering & Remote Sensing*. 63(6):717-725.

### Steps of Sub-pixel Classification




### Overall Flowchart




## Accuracy Assessment

| Classification | | Overall | Producer's | Users's | Kappa |
|---|---|---|---|---|---|
| **A** | **Overall** | **90%** | **88%** | **89%** | **0.86** |
| **B** | **Overall** | **65%** | **43%** | **49%** | **0.39** |
| | Pine | 82% | 41% | 47% | 0.56 |
| | Hardwood | 71% | 41% | 48% | 0.42 |
| | Mixed Forest | 62% | 54% | 45% | 0.34 |
| | Non-forest | 46% | 39% | 41% | 0.23 |
| **C** | **Overall** | **59%** | **28%** | **29%** | **0.18** |
| | Pine | 53% | 17% | 21% | 0.2 |
| | Hardwood | 67% | 28% | 29% | 0.35 |
| | Mixed Forest | 53% | 10% | 30% | 0.04 |
| | Non-forest | 29% | 29% | 24% | 0.21 |
| **D** | **Overall** | **48%** | **26%** | **31%** | **0.2** |
| | Pine | 64% | 25% | 31% | 0.44 |
| | Hardwood | 63% | 27% | 52% | 0.43 |
| | Mixed Forest | 49% | 14% | 13% | 0.09 |
| | Non-forest | 15% | 9% | 25% | 0.007 |

**A:** Supervised Classification

**B:** Sub-pixel Classification using the aerial photo for training and reference data

**C:** Sub-pixel classification using the aerial photo for training data and FIA data for reference data

**D:** Sub-pixel classification using FIA data for training data and the aerial photo for reference data