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Showcasing the Future
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Application of Image Processing and LiDAR Data in Stormwater Management

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Why is urban land classification necessary?

Impervious vs. pervious surfaces

Water quality issues

http://ga.water.usgs.gov/

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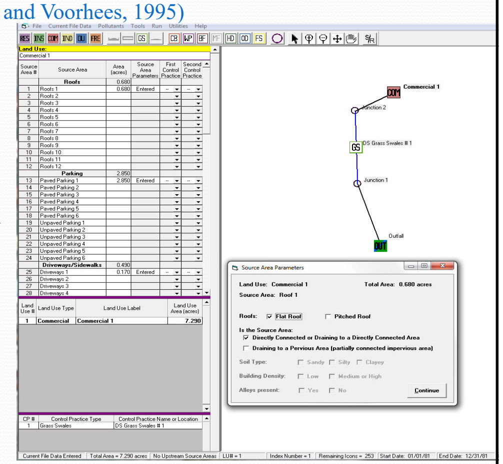
WinSLAMM (Pitt and Voorhees, 1995)

- WinSLAMM: Source Loading and Management Model for Windows
- Estimate runoff quantity and quality
- Design stormwater controls



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Objective

- Create a tool to facilitate urban surface classification, while maintaining reasonable accuracy and decreasing required analysis time.
- ArcGIS tool creation (ModelBuilder)
- Outcome Urban Classifications:
  - Roofs
  - Parking lots
  - Streets
  - Pervious areas

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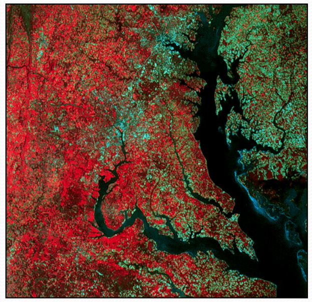
Image Types

- Satellite images at high (1-4 m) and low resolution
  - Landsat TM/ETM/ETM+, IKONOS, SPOT, Quickbird
- Aerial photos



Landsat
Chesapeake Bay area
Photo Credit: NASA

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Digital Image Processing

- Per-pixel classifiers
  - Maximum likelihood classifier
  - Nearest neighbor classification
  - Object-based algorithms
- Artificial neural networks (ANN)
- Classification and regression tree (CART) algorithms/decision tree learning
- Normalized Difference Vegetation Index (NDVI)
- Support Vector Machines (SVM)

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Color Variables

- Combine RGB, YC_bC_r, and HSI models
- In addition to RGB, use:
  - Luminance: Y
  - Hue: H
  - Saturation: S
  - Intensity: I
- Advantage: more variables available for image processing → more accurate result

$$Y = 65.481R + 128.553G + 24.966B + 16 \quad (1)$$

$$C_b = -37.797R - 74.203G + 112.000B + 128 \quad (2)$$

$$C_r = 112.000R - 93.786G - 18.214B + 128 \quad (3)$$

$$H = \begin{cases} \theta & , if \quad B \le G \\ 360 - \theta & , otherwise \end{cases} \text{, with}$$

$$\theta = \cos^{-1}\left\{ \frac{0.5[(R-G)+(R-B)]}{\sqrt{(R-G)^2 + (R-B)(G-B)}} \right\} \quad (4)$$

$$\boxed{S = 1 - \frac{3}{(R+G+B)}[MIN(R,G,B)]} \quad (5)$$

$$I = \frac{R+G+B}{3} \quad (6)$$

(Rottensteiner et al., 2002)

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Image Processing Problems

- Similar spectral responses:
  - Roof and pavement
  - Soil and concrete or asphalt
- Tree coverage
- Shadows
- Viewing angles

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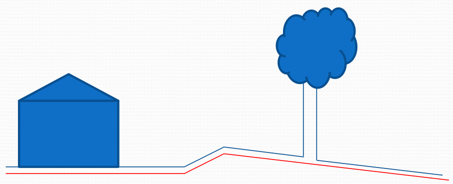
LiDAR

- Digital Surface Model (DSM): generated directly from reflective LiDAR points (blue color in the Figure)
- Digital Terrain Model (DTM): depicts the pure terrain surface, filtering functions are applied to remove surface objects (red color in the Figure)



NDSM = DSM – DTM

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Methodology

- Data:
  - Aerial photo
  - LiDAR
  - Centerline of streets
  - Solution shapefiles for UA campus
    - Streets, parking, buildings
- Approach
  - ArcGIS 10.0 tools
  - Partially automated image processing of nDSM and color band rasters

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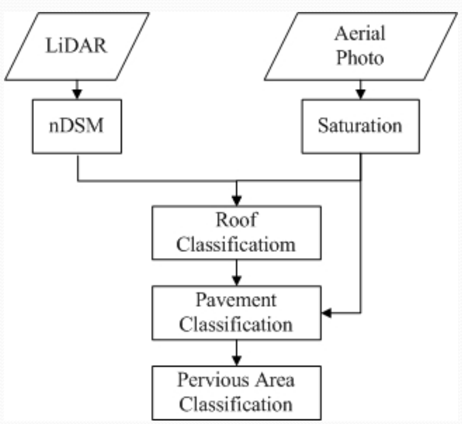
Process



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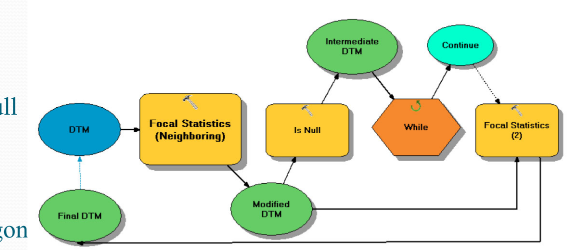
ArcGIS Tools

- Raster Calculator
- Slope thresholds
- Curvature
- SetNull and IsNull
- ZonalGeometry
- Buffer
- Generalize Polygon
- Aggregate Polygon
- While/For loops



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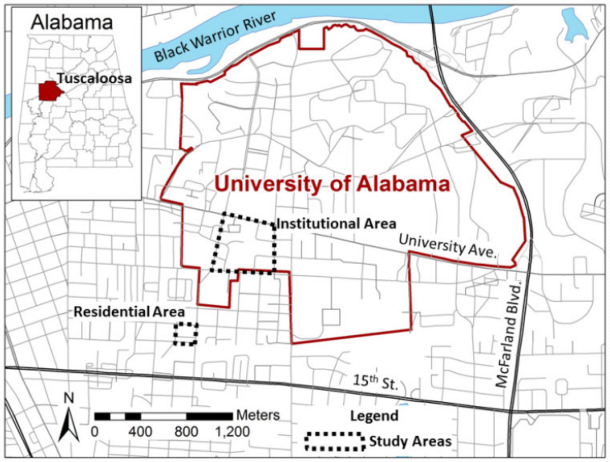
Case Study



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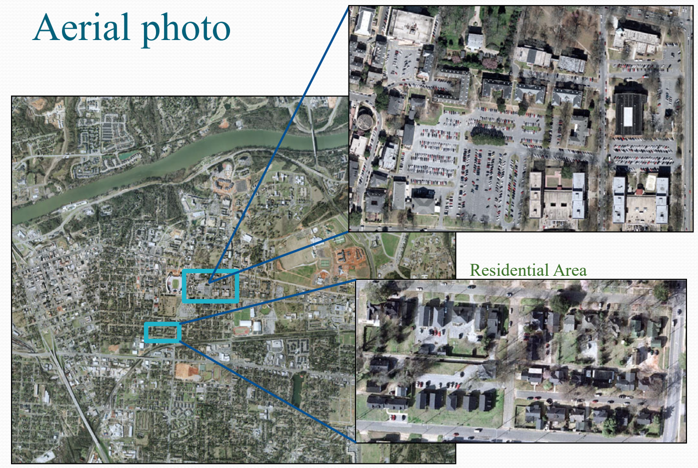
Aerial photo



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Model Parameters

Threshold	Institutional	Residential
Saturation	20	18
Slope	70	40
Curvature	120	30
Area	100	70
Thickness	4	3
Buffer	3	4

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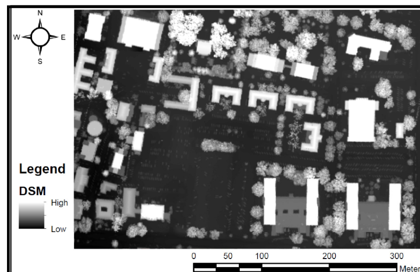
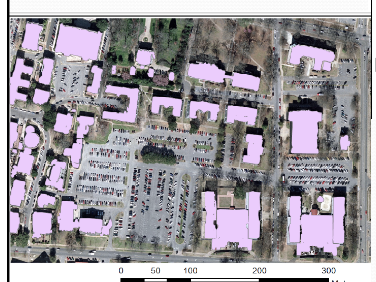
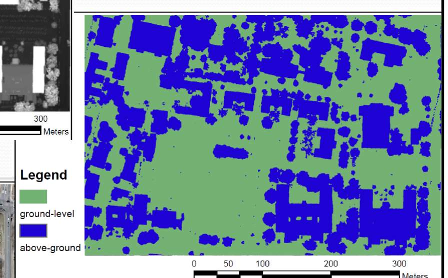
Roof Classification







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Pavement Classification

- At the end of roof classification, the roof polygon feature class is converted back into a raster for further analysis.
- Pavement areas were obtained by adding the darker saturation raster areas to the buffered centerline areas and subtracting the previously defined roof areas.
- Note that by using the freely available TIGER centerline feature class as an input data source, tree coverage of streets is not a source of error as in the case of sole image processing.

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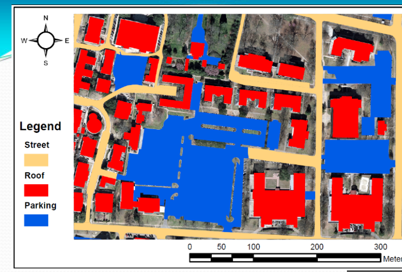
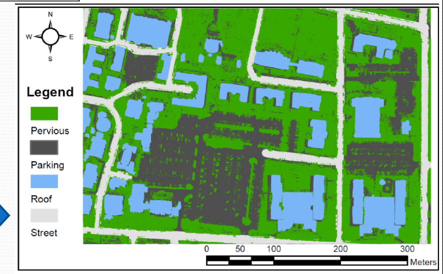


Institutional Area

Solution by
Manual Delineation

Model
Output



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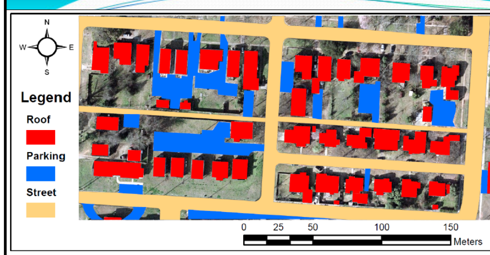
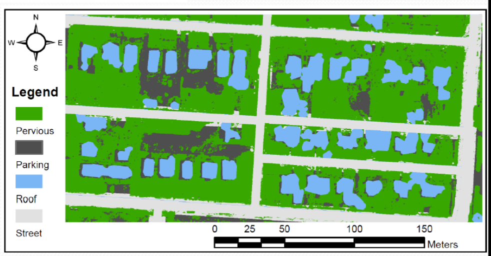


Residential Area

Solution by
Manual Delineation

Model
Output



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Accuracy Assessment

- Overall accuracy : dividing the total number of correct pixels (the sum of the major diagonal) by the total number of pixels in the error matrix (Congalton, 1991).
- User's accuracy : is a "measure of commission error" which is the probability that a pixel classified on the map correctly corresponds to the same category on the reference
- Producer's accuracy : is a "measure of emission" which represents the probability that a reference pixel is being correctly classified (Story and Congalton, 1986).

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Error Matrix and Accuracy Assessment for Institutional Area

		Classification from manual delineation					User's accuracy (%)
		Roof	Street	Parking	Pervious	Total	
Classification from model	Roof	1,384,123	109	6,228	134,441	1,524,900	90.8
	Street	4,356	820,779	17,435	70,199	912,768	89.9
	Parking	56,473	47,385	16,95,687	170,218	1,969,764	86.1
	Pervious	83,173	49,703	280,406	3,221,886	3,635,168	88.6
	Total	1,528,124	917,976	1,999,756	3,596,744	8,042,600	
Producer's accuracy (%)		90.6	89.4	84.8	89.6		

Overall accuracy: 88.6%

Matrix entries represent number of pixels.

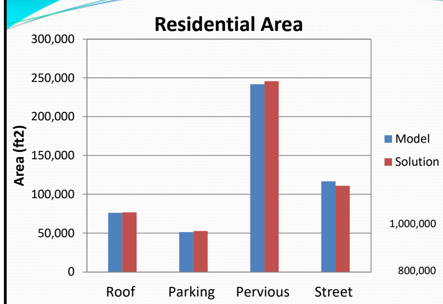
Error Matrix and Accuracy Assessment for the Residential Area

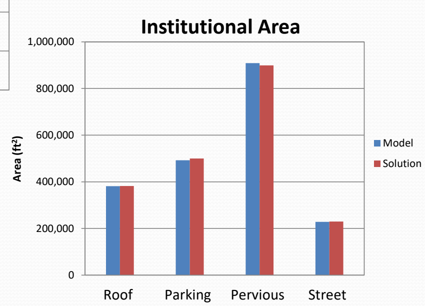
		Classification from manual delineation					User's accuracy (%)
		Roof	Street	Parking	Pervious	Total	
Classification from model	Roof	245,942	2,870	2,112	53,927	304,852	80.7
	Street	0	359,605	14,825	92,066	466,496	77.1
	Parking	33,428	4,013	146,311	21,719	205,472	71.2
	Pervious	27,850	76,980	47,488	815,143	967,460	84.3
	Total	307,220	443,468	210,736	982,856	1,944,280	
Producer's accuracy (%)		80.1	81.1	69.4	82.9		

Overall accuracy: 80.6%

Matrix entries represent number of pixels.

Results





Conclusions

- Land use classification is necessary to accurately calculate water quality and runoff volumes.
- This work presented an approach to classify land use as roofs, streets, parking lots, and pervious areas based on analysis of LiDAR data, aerial photographs, and TIGER line data using ArcGIS 10.0 tools in a ModelBuilder program.
- Two case studies in Tuscaloosa, Alabama, including an institutional land use, and a residential land use.
- The accuracy assessment shows high value of overall accuracy for both land uses; 89% and 81% for the institutional and residential land use test areas respectively.

Conclusions

- The comparison of output areas for each category (roofs, streets, parking lots, pervious areas) to known areas (manually delineated) showed highest result accuracy for roof areas.
- Therefore, this model is very suitable for determining roof areas for designing cisterns and drywells for roof runoff stormwater harvesting systems.
- Although the other three area estimates are less accurate than the roof result, they are sufficiently accurate (< 6% error) for most preliminary design purposes.