Out of the Shadows: Improving urban flood detection

Katy Sill, Ph.D.
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Urban Flooding

- Floods account for 43% of recorded natural disasters over past 20 years
- Climate change is expected to result in increased flooding events
- In the next 30 years, the urban population is expected to grow by 2.5 billion people
  - 90% of this growth is expected in Africa and Asia

Accurate flood maps build resilience

- Satellite imagery-based flood maps are less resource intensive than traditional flood maps.
- Better information leads to less people and structures being left out of mitigation, disaster response and insurance plans.
- Cloud to Street is a start-up focused on tracking flooding in low- and middle-income communities.

Challenges with Urban Flood Mapping

Water index does not work well in urban settings due to interferences from the built environment

Building shadows look visually similar to flood waters and can be misidentified

Areas of flood not captured by flood map

Building shadow misidentified as flood

Thresholded Flood Map

Study Approach

- Study image: Pan-sharpened DigitalGlobe WorldView-2 image of flooding event
  - Abidjan, Ivory Coast
    - June 17, 2016
  - Focused on two areas of interest: Koumassi and “Southeast”
- Three methods explored:
  - Thresholding spectral indices
  - Unsupervised machine learning
  - Supervised machine learning
- Validated using reference dataset created in ArcGIS

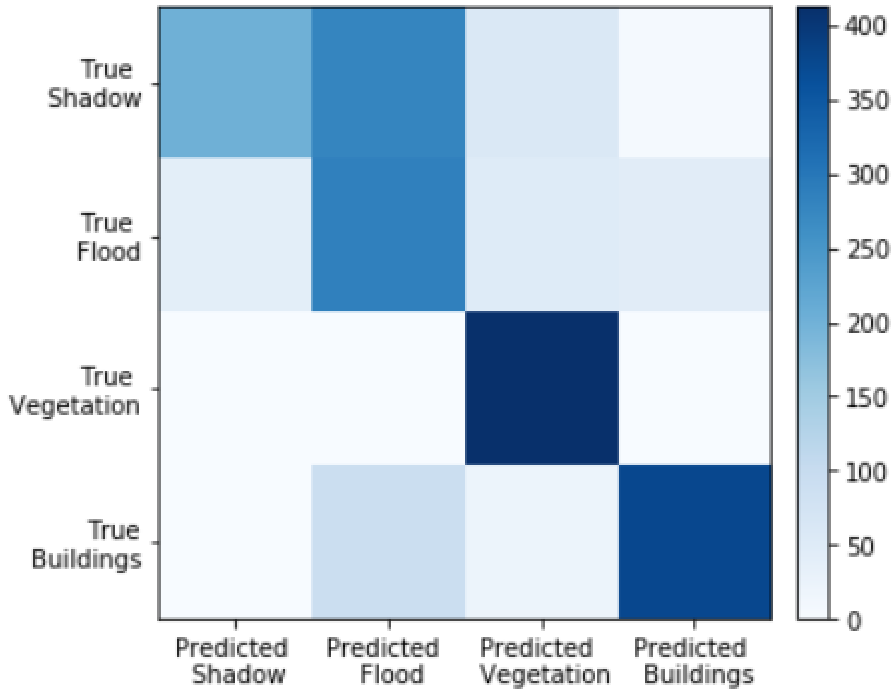
Thresholding

Thresholds were developed for:

Water	Norm Diff Water Index (NDWI)
Vegetation	Norm Diff Vegetation Index (NDVI)
Building shadow	Morphological Shadow Index (MSI)
Buildings	Morphological Building Index (MBI)

Koumassi Thresholding Map

- Koumassi accuracy score: 67%
- Southeast accuracy score: 79%



Supervised Machine Learning

- Support Vector Machine (SVM)
- Combined inputs from both sites: Koumassi and Southeast

Model Inputs Parameters:

- Dark parameter (sum of RE, NIR1, NIR2)
- Morphological Building Index (MBI)
- Morphological Shadow Index (MSI)
- Norm Diff Vegetation Index (NDVI)
- Norm Diff Water Index (NDWI)
- NDWI-MSI (difference)

60% of total combined reference points
n = 2049

40% of total combined reference points
n = 1367

Training data to develop model

Test data to internally validate model

External data to fully validate model

Internal testing accuracy score:

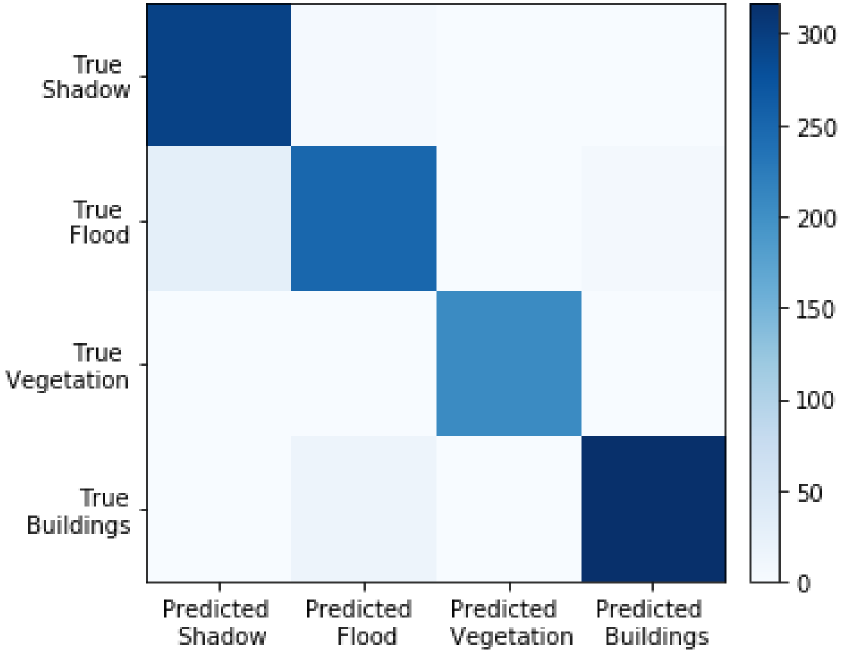
96%

External validation accuracy score:

93%

Koumassi SVM Result

- Overall accuracy score: 93%
- Minor confusion flood, shadow and buildings



Unsupervised Machine Learning (k-means)

k-means Inputs	Number of Clusters	Validation
• 8-band raster image • Spectral indices • Various combinations	• Less than seven led to substantial confusion among land types • More than seven resulted in more building and vegetation clusters	• Validated using entire reference data set for each site • $N_{Koumassi}$ = 1891 • $N_{Southeast}$ = 1525

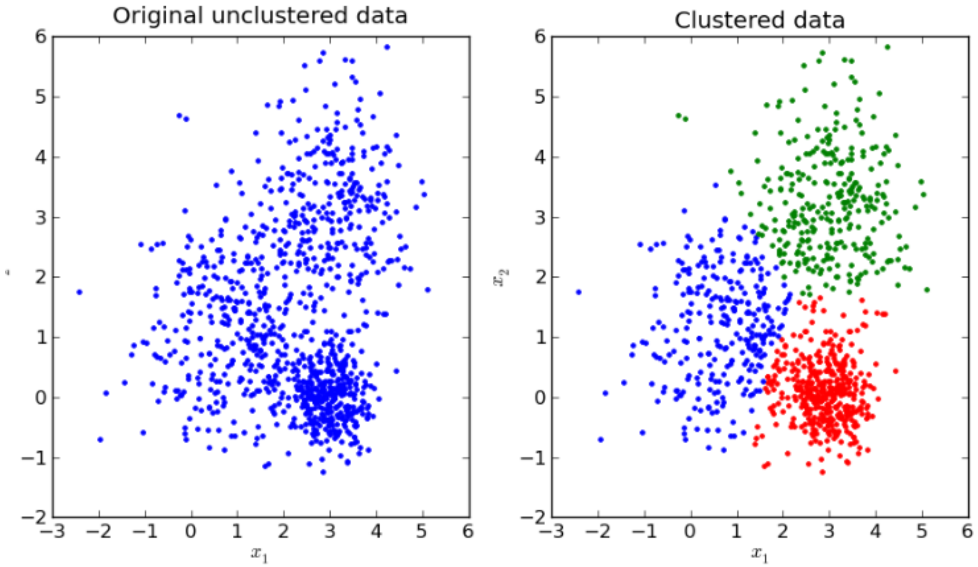
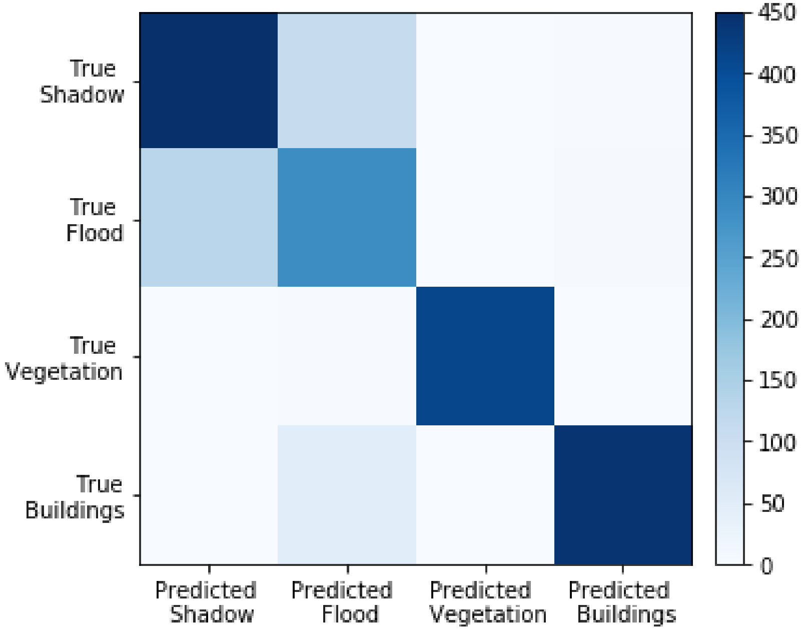


Image source: https://mubaris.com/posts/kmeans-clustering/

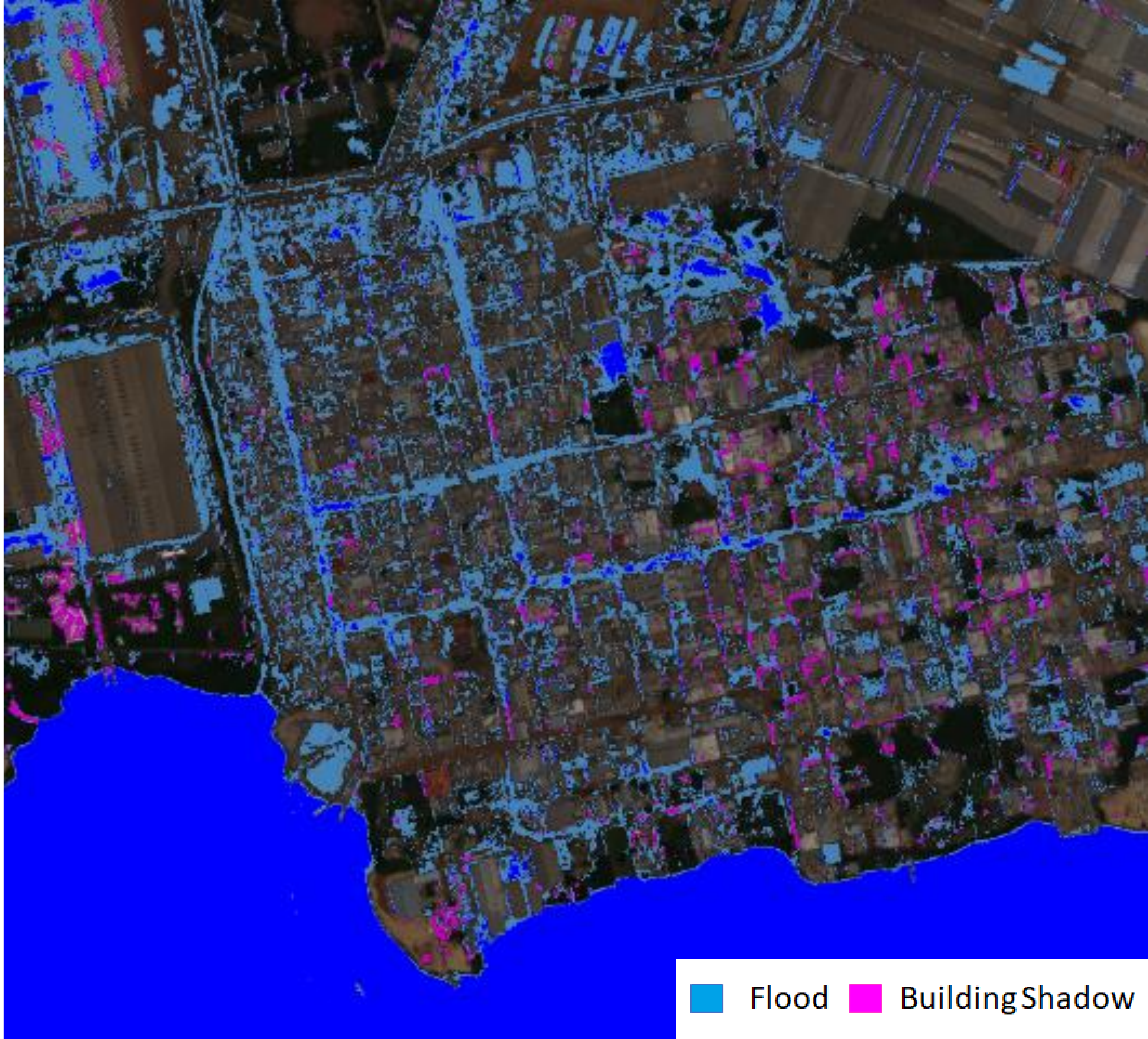
Koumassi
k-means result

- Koumassi accuracy score: 84%
- Southeast accuracy score: 79%



Koumassi Combining Methods

- Change “shadow” cluster to be “flood” cluster
- Apply shadow mask from thresholding approach
- Flood only accuracy score increased to 98%
- Southeast flood only accuracy score increased to 93%
- Accuracy score for shadow only decreases to 0%



The Takeaway

Machine learning methods appear to offer additional and more accurate information for developing flood maps compared with the thresholding result, with a similar (or lesser!) level of effort.

Supervised machine learning was the best method for specifically differentiating building shadow from flood waters.. but requires development of a detailed training data set.

Unsupervised machine learning provides a relatively low-level of effort approach, but requires some interpretation after clusters are defined.

Potential to use multiple methods together to present minimum and maximum scenarios. More accurate information means that people can be better prepared and protected from the potential damage from floods.

Questions?

katysill@colorado.edu

www.github.com/
katysill/flood-detection

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  - Joe McGlinchy, CU Earth Lab
  - Jeff Ho, Cloud to Street

- References:
  - Huang, X., Xie, C., Fang, X., Zhang, L. (2015) Combining Pixel-and Object-Based Machine Learning for Identification of Water-Body Types from Urban High-Resolution Remote-Sensing Imagery. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 8, 2097–2110.
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  - Cloud to Street. Urban Flood Mapping Using Very-High Resolution Satellite Imagery. Available at: https://abidjan.cloudtostreet.info/info