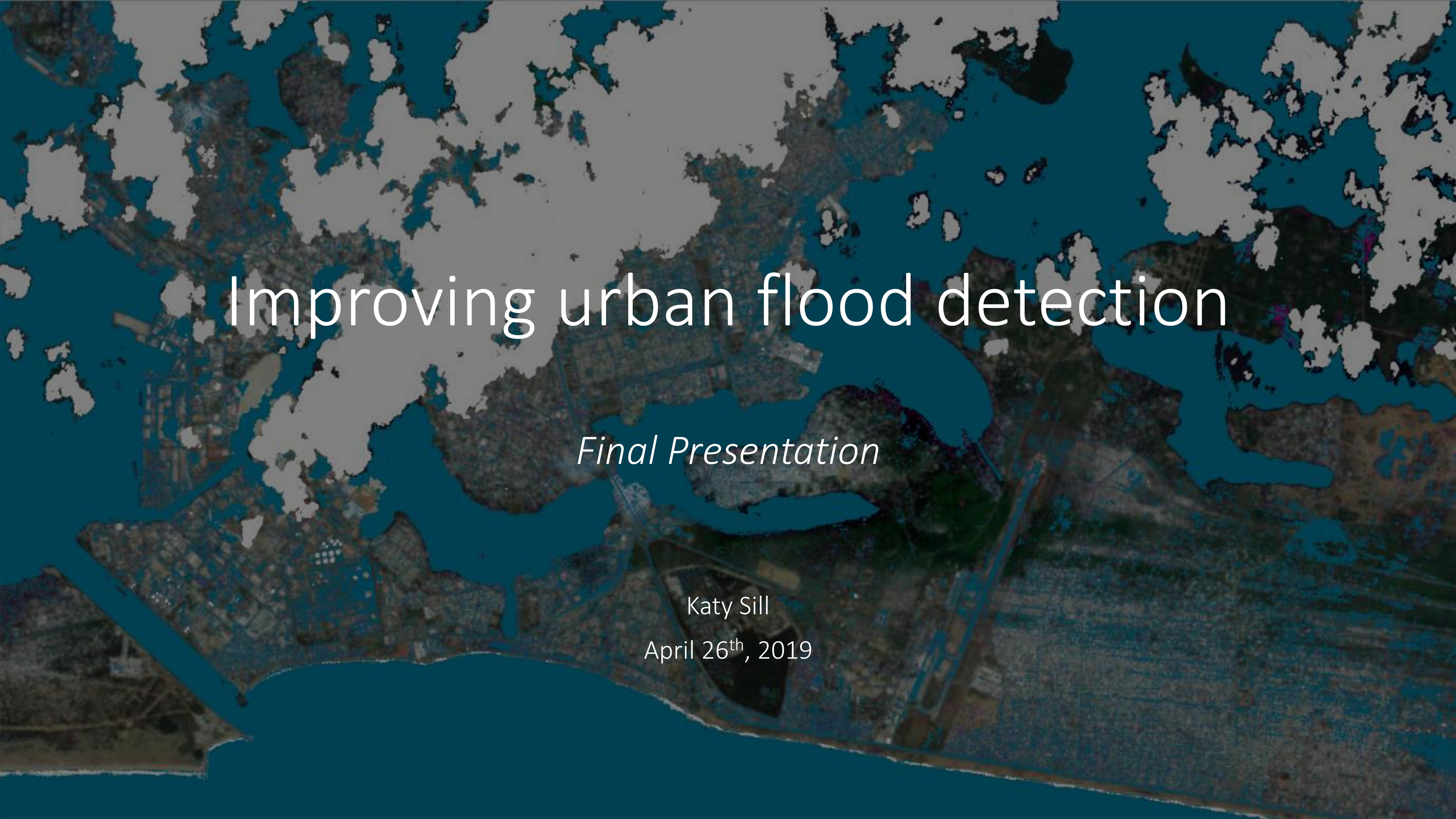


Improving urban flood detection

Final Presentation

Katy Sill

April 26th, 2019

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, with 90% of this growth is predicted to take place in Africa and Asia

Accurate flood maps build resilience

- Traditional flood mapping is resource intensive
- Out-of-date flood maps mean that residences and buildings are left out of flood mitigation and insurance plans
- Use of satellite imagery for developing flood maps allows for affordable rapid historical assessments and near real-time monitoring
- More up-to-date information can lead to improved preparation and disaster management responses
- Cloud to Street is a company working to provide improved flood maps to low and middle income communities

Urban flood map challenges

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

Modified water index requires spectral band not always available with high resolution imagery

Attempts at using a combination of indices and bands may fall short of mapping the true flooding extent

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

Current flood map issues

Areas of flood not captured by flood map

Building shadow misidentified as flood

Project goals

Improve urban flood detection

Focused on differentiating building shadow and flood waters

Explore open source Python-based tools

Cloud to Street currently uses Google Earth Engine

Geographic focus

Abidjan, Ivory Coast

Flooding event from June 2016

Final products

A report of the different potential options explored

A final workflow to create an improved flood extent map for Abidjan

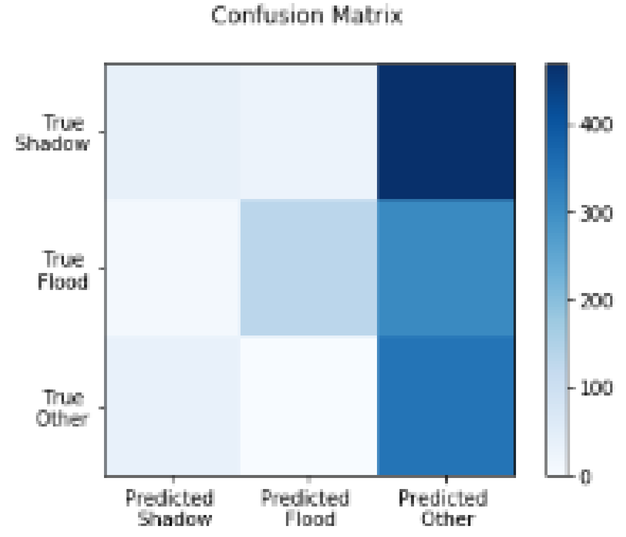
Study Approach

- Study image: Pan-sharpened DigitalGlobe WorldView-2 image of flooding event in Abidjan, Ivory Coast
  - Focused on two areas of interest: Koumassi and "Southeast"
- Three methods explored:
  - Thresholding spectral indices
  - Unsupervised machine learning
    - K-means
    - Gaussian mixture modeling (GMM)
    - Segmentation
  - Supervised machine learning
    - Support Vector Machine (SVM)
    - Random Forest (RF)
- Validated using reference dataset created in ArcGIS

Cloud to Street Koumassi Map

- Non-pan-sharpened imagery
- 37.9% accuracy score

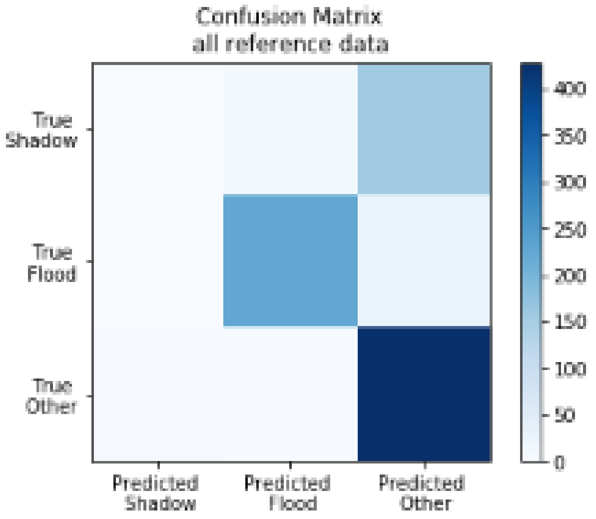
```
[[ 38  26 469]
 [ 10 133 307]
 [ 33   0 345]]
```

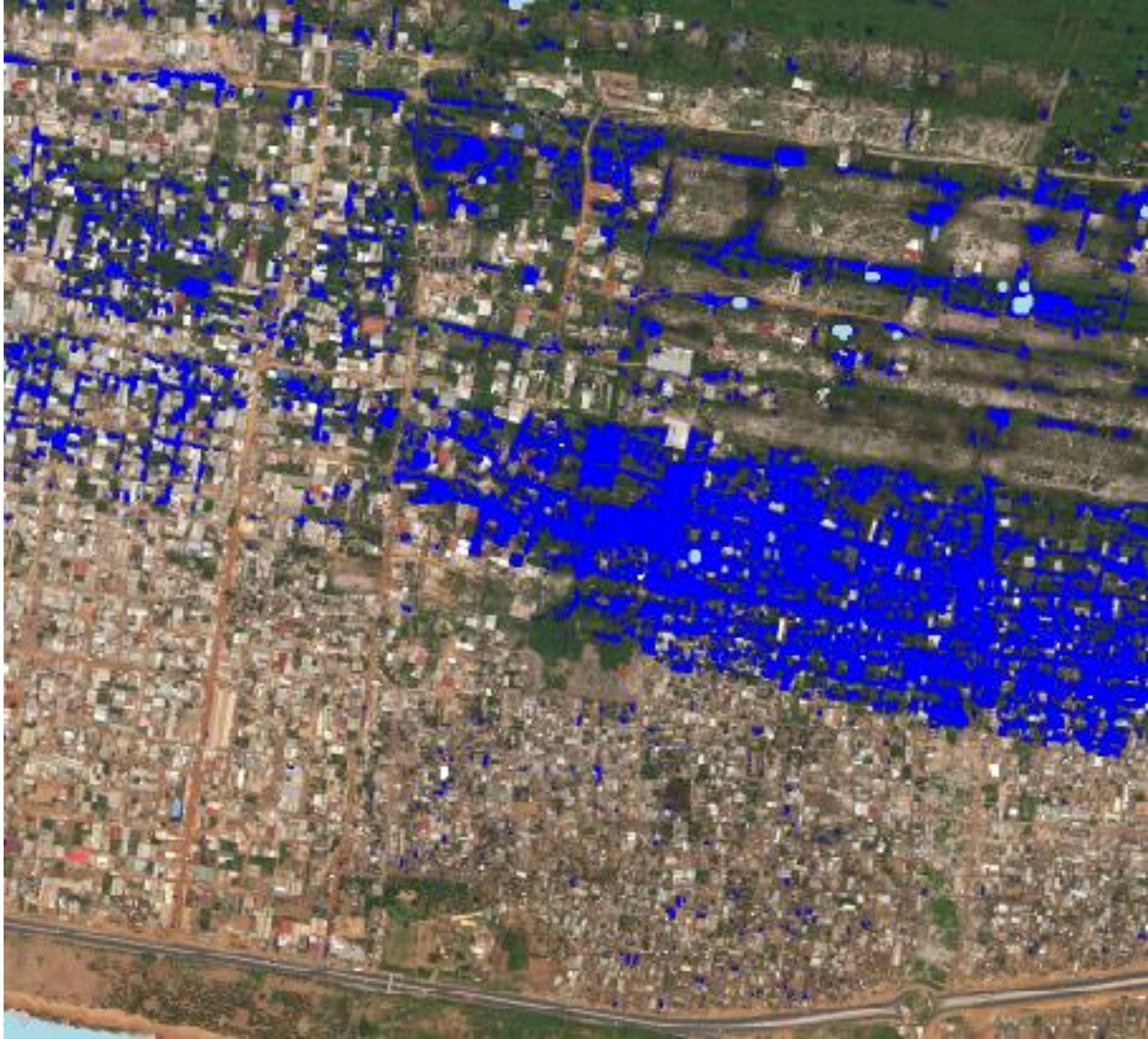


Cloud to Street Southeast Map

- Non-pan-sharpened imagery
- Accuracy score of 77.1%

```
[[  0  10 156]
 [  0 227  23]
 [  4   2 428]]
```





Thresholding

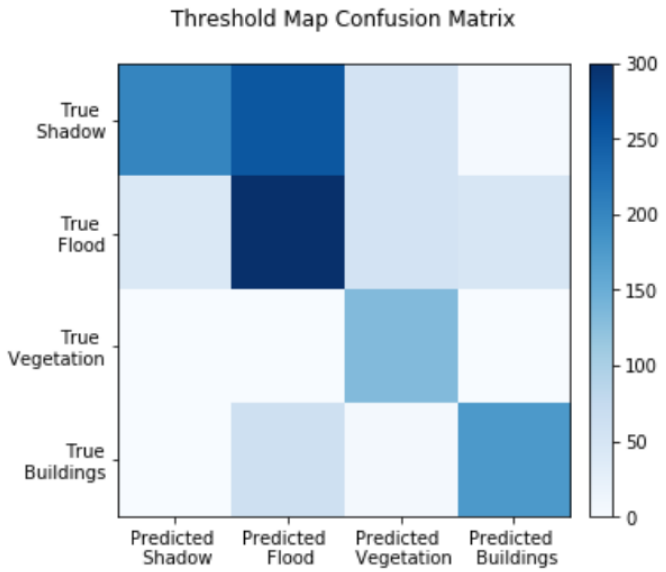
Thresholds were developed for:

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

Koumassi Thresholding Map

- Accuracy score of 59.5%

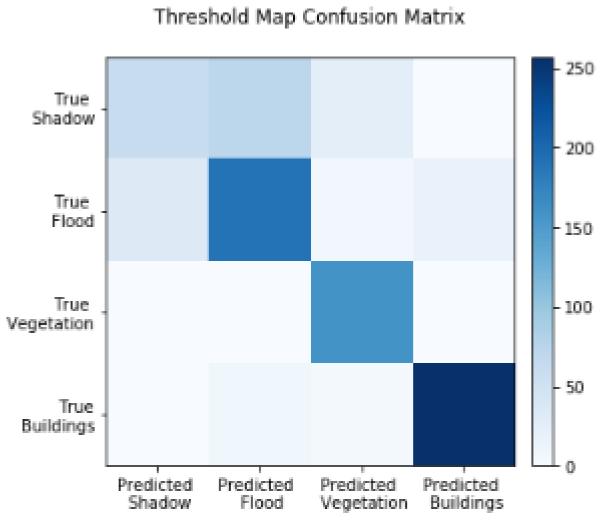
```
[[201 255  55   4]
 [ 43 300  54  49]
 [  0   0 133   0]
 [  0  62   6 177]]
```



Southeast Thresholding Map

- Accuracy score of 78.5%

```
[[ 61  72  25   0]
 [ 34 190   8  18]
 [  0   1 159   0]
 [  1  10   6 257]]
```



Key Findings for Thresholding

- Some confusion between flood, shadow and buildings/roads
- Works better for less built up environments
- Time intensive and somewhat of a guessing game

Unsupervised Machine Learning (k-means)

k-means Inputs

- 8-band raster image
- Spectral indices
- Various combinations

Number of Clusters

- Less than seven led to substantial confusion among land types
- More than seven resulted in more building and vegetation clusters

Validation

- Validated using entire reference data set for each site

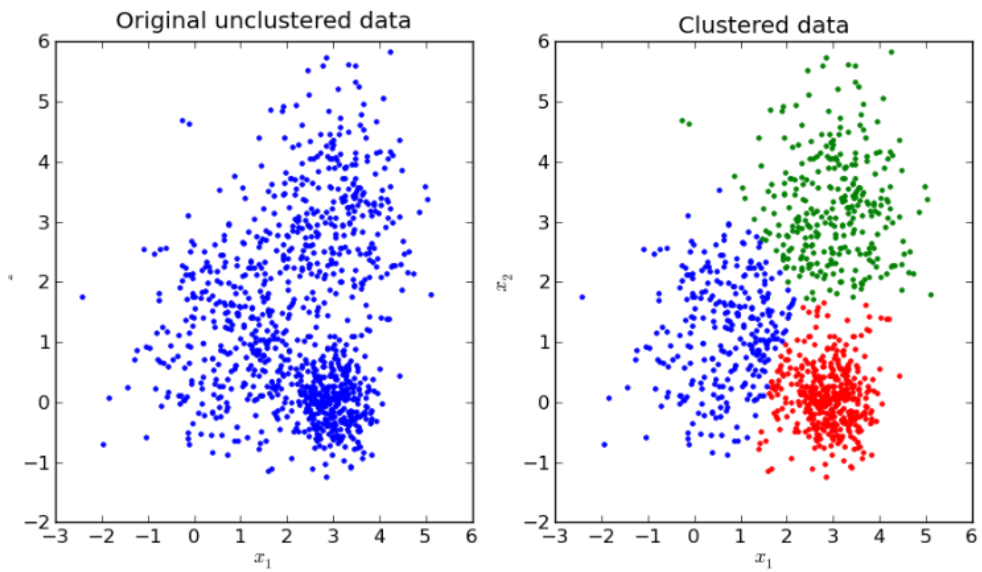
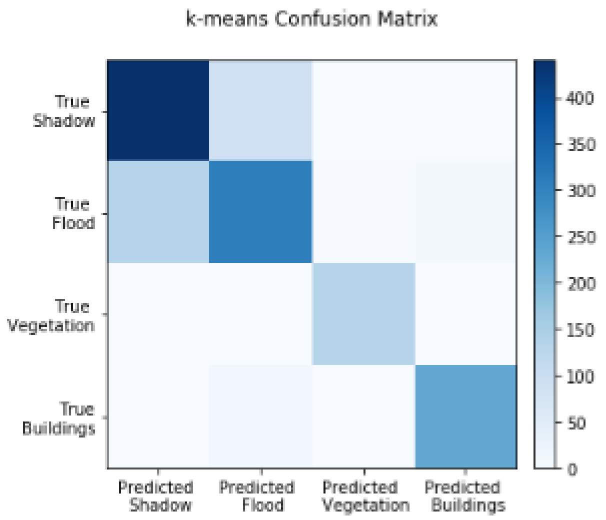


Image source: https://mubaris.com/posts/kmeans-clustering/

Koumassi
k-means

- Accuracy score of 82.8%
- Confusion between shadow and ocean and deep puddles

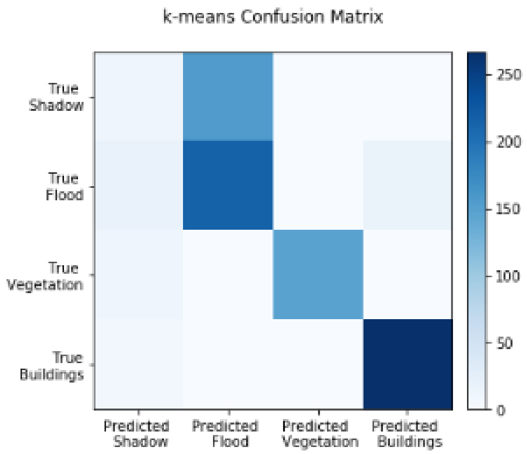
```
[[441  92   0   0]
 [132 308   2   8]
 [  0   0 133   0]
 [  0  12   0 233]]
```

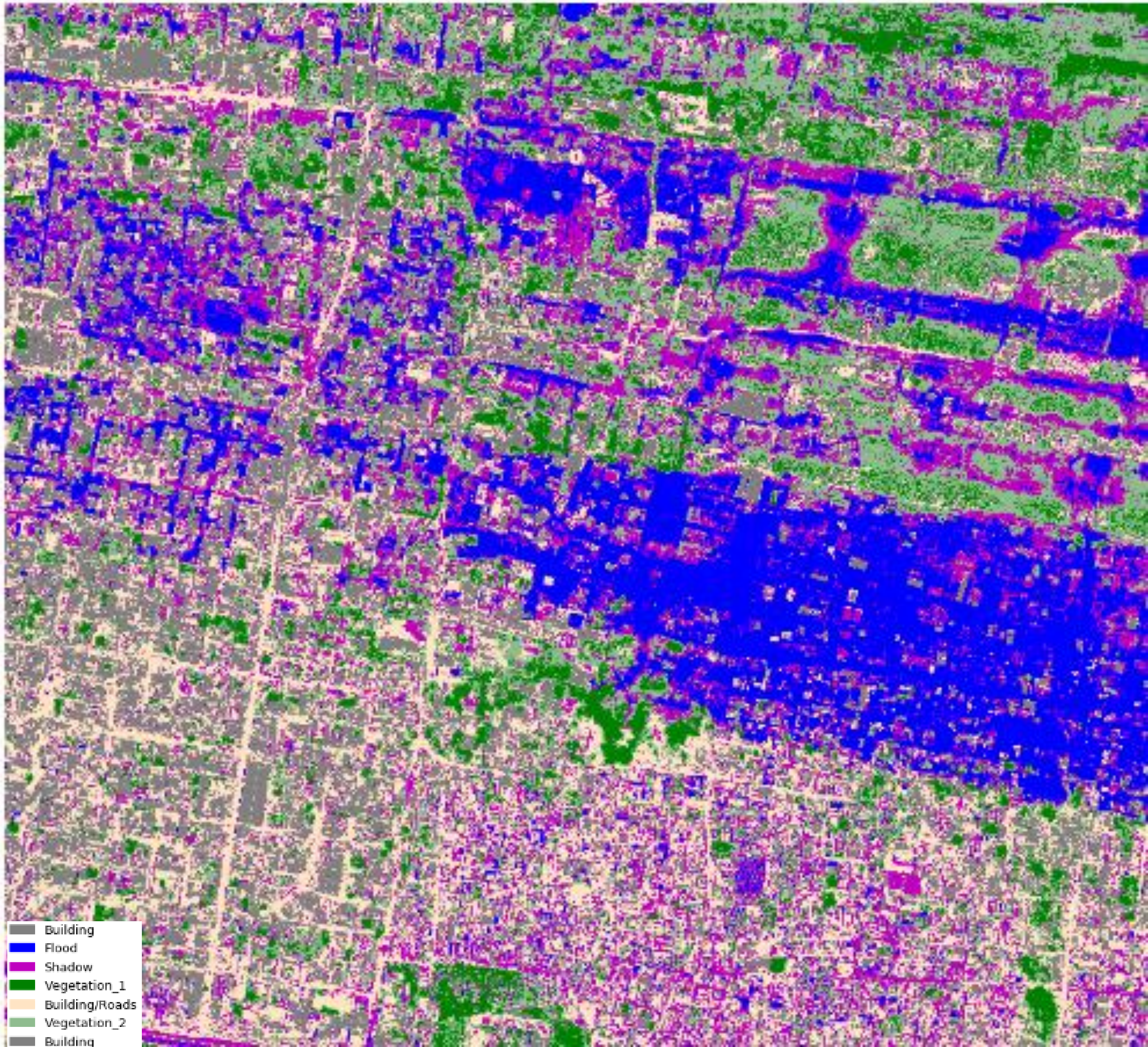


Southeast k-means

- Accuracy score of 75.4%
- Confusion between vegetation, shadow and flood

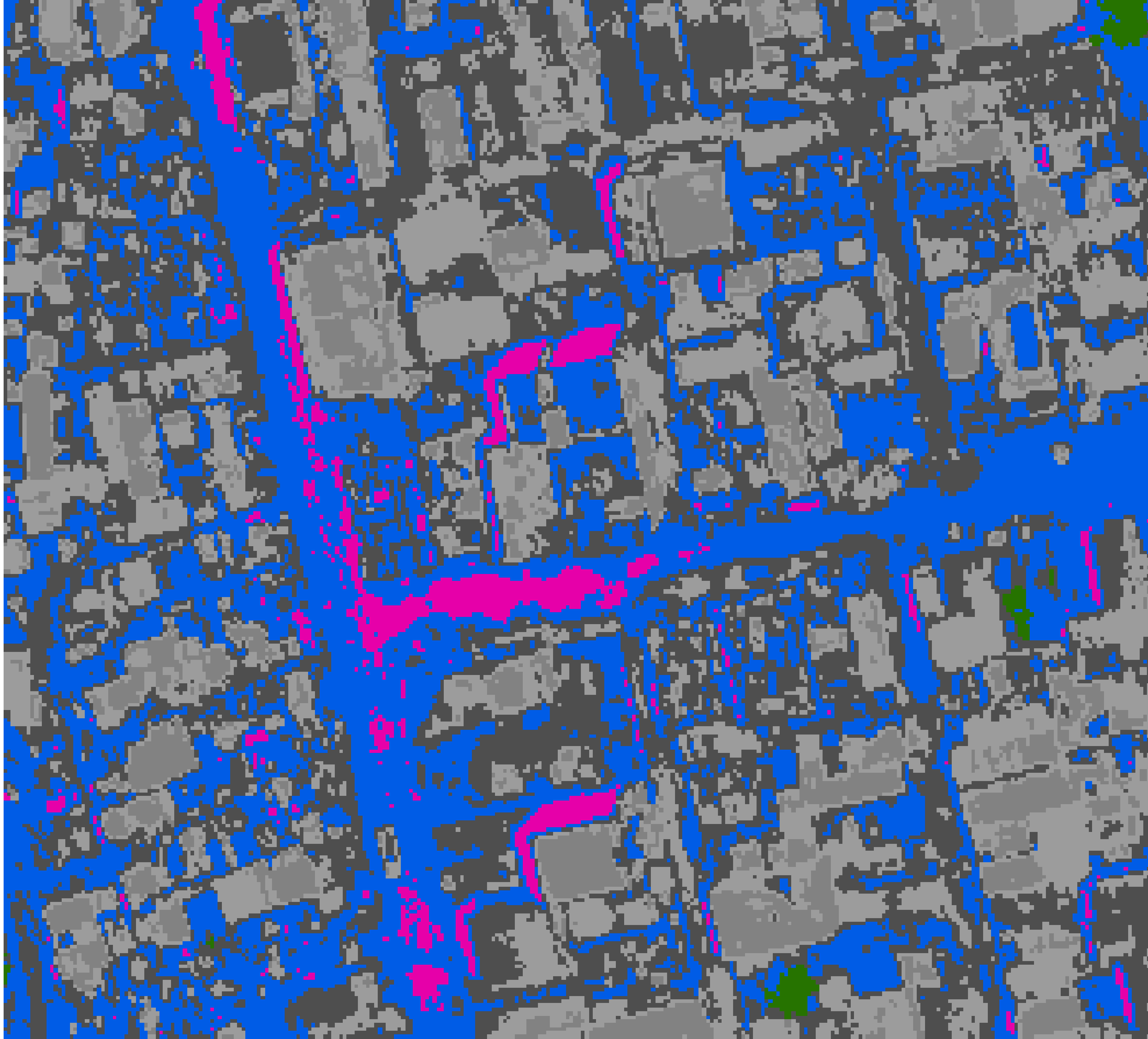
```
[[ 11 155   0   0]
 [ 18 215   0  17]
 [ 11   1 148   0]
 [  7   0   0 267]]
```





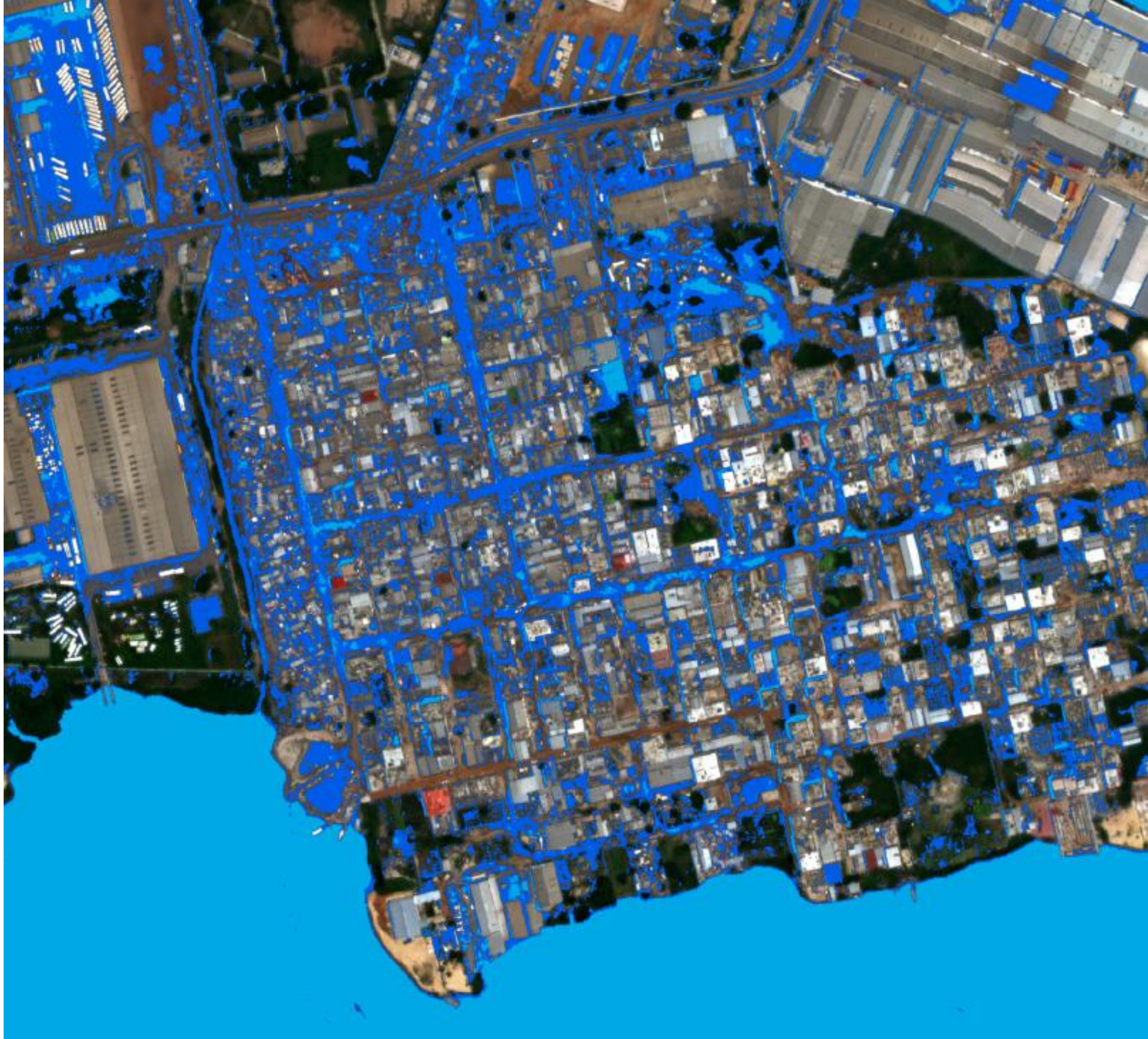
Challenges with k-means

- “Shadow” cluster contains a fair amount of flood
- Tried reassigning clusters based on object properties with mixed results
- Goal is to accurately identify flood..
    - Is it better to over- or under-estimate?
    - Which approach leads to better protection for residents?



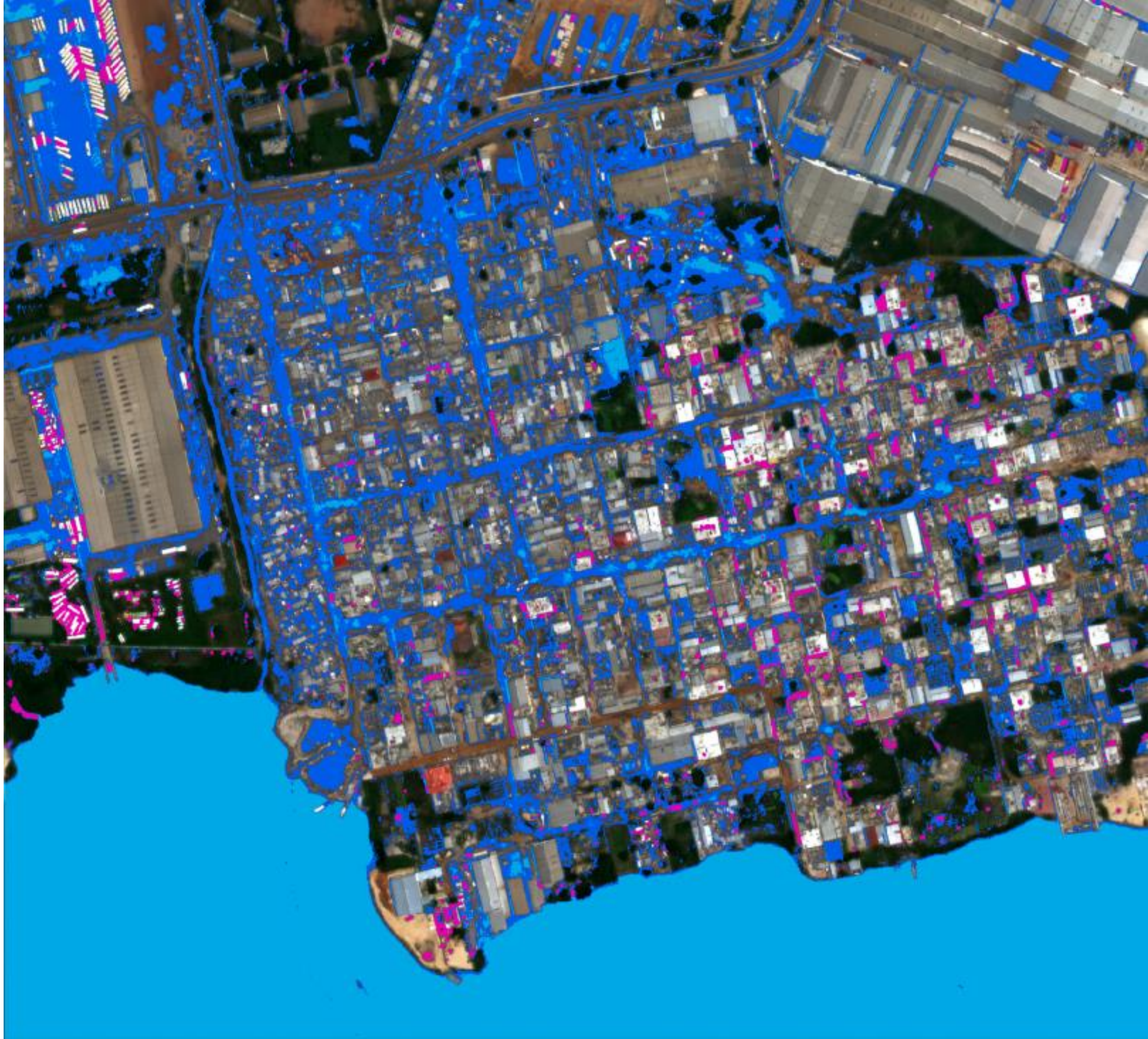
Focusing on flood detection Koumassi

- Change “shadow” cluster to be “flood” cluster
- Improves overall visualization
- Flood only accuracy score increased to 97.8%
- Southeast flood only accuracy score increased to 93.2%
- Accuracy score for shadow only decreases to 0%
- Overestimation of flooded areas



Focusing on flood detection Koumassi

- Change “shadow” cluster to be “flood” cluster
- Improves overall visualization
- Flood only accuracy score increased to 97.8%
- Southeast flood only accuracy score increased to 93.2%
- Accuracy score for shadow only decreases to 0%
- Overestimation of flooded areas
- Apply shadow mask from thresholding



Key Findings for Unsupervised Machine Learning

- Clusters do not represent individual land cover types
- Requires interpretation for what clusters represent
- Potential overestimation of flood waters
- Diversity in building and vegetation types somewhat challenging
- However.. relatively low level of effort required for reasonable accuracy score

Supervised Machine Learning

- Support Vector Machine (SVM)
- Random Forest (RF)
- Combined inputs from 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=1326

40% of total combined reference points
n = 885

Training data to develop model (60%)

Test data to internally validate model (40%)

External data to fully validate model

Internal testing accuracy score:

95.3%

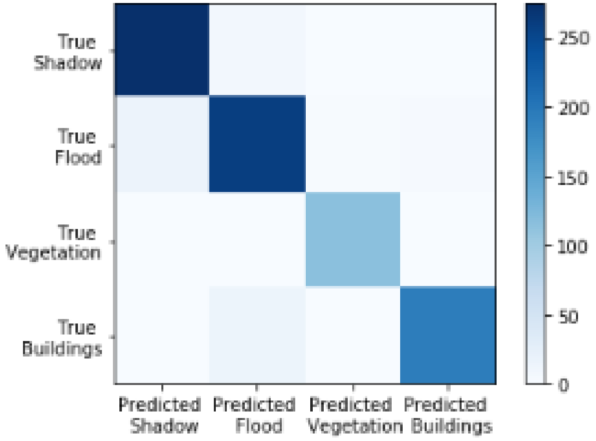
External validation accuracy score:

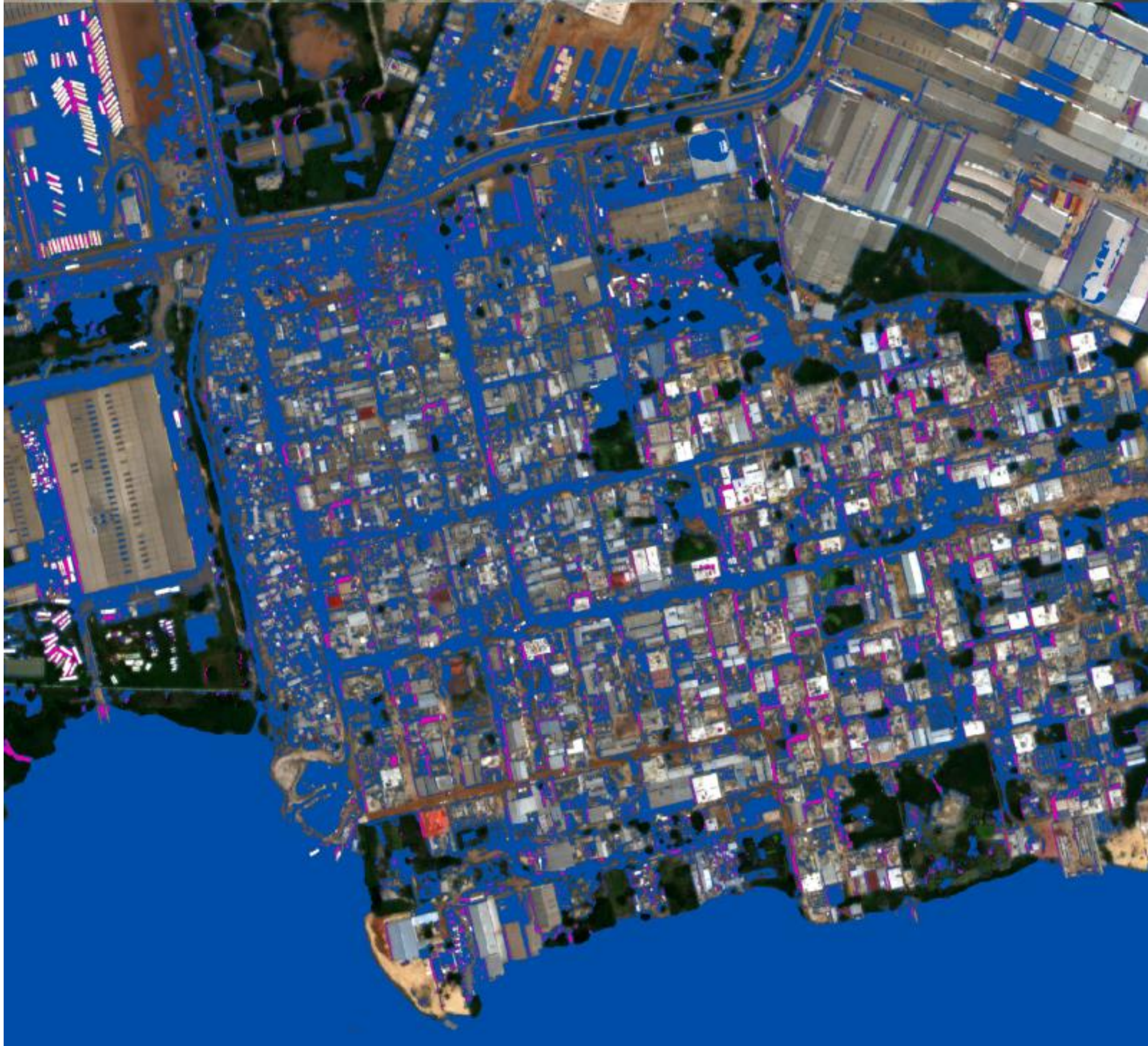
95.3%

Koumassi SVM Result

- 95.3% accuracy score
- Minor confusion flood, shadow and buildings

```
[[275   7   0   0]
 [ 16 259   2   3]
 [  0   0 116   0]
 [  0  14   0 193]]
```

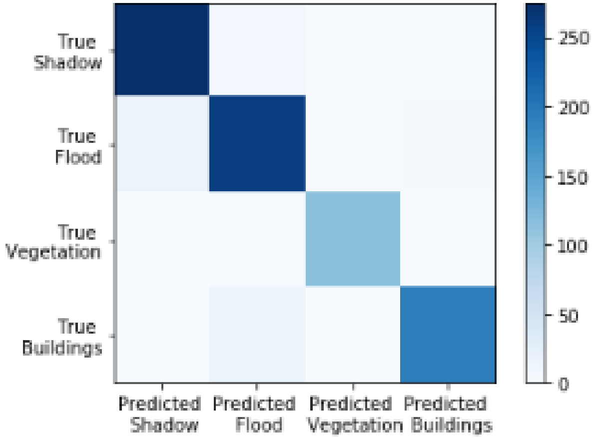


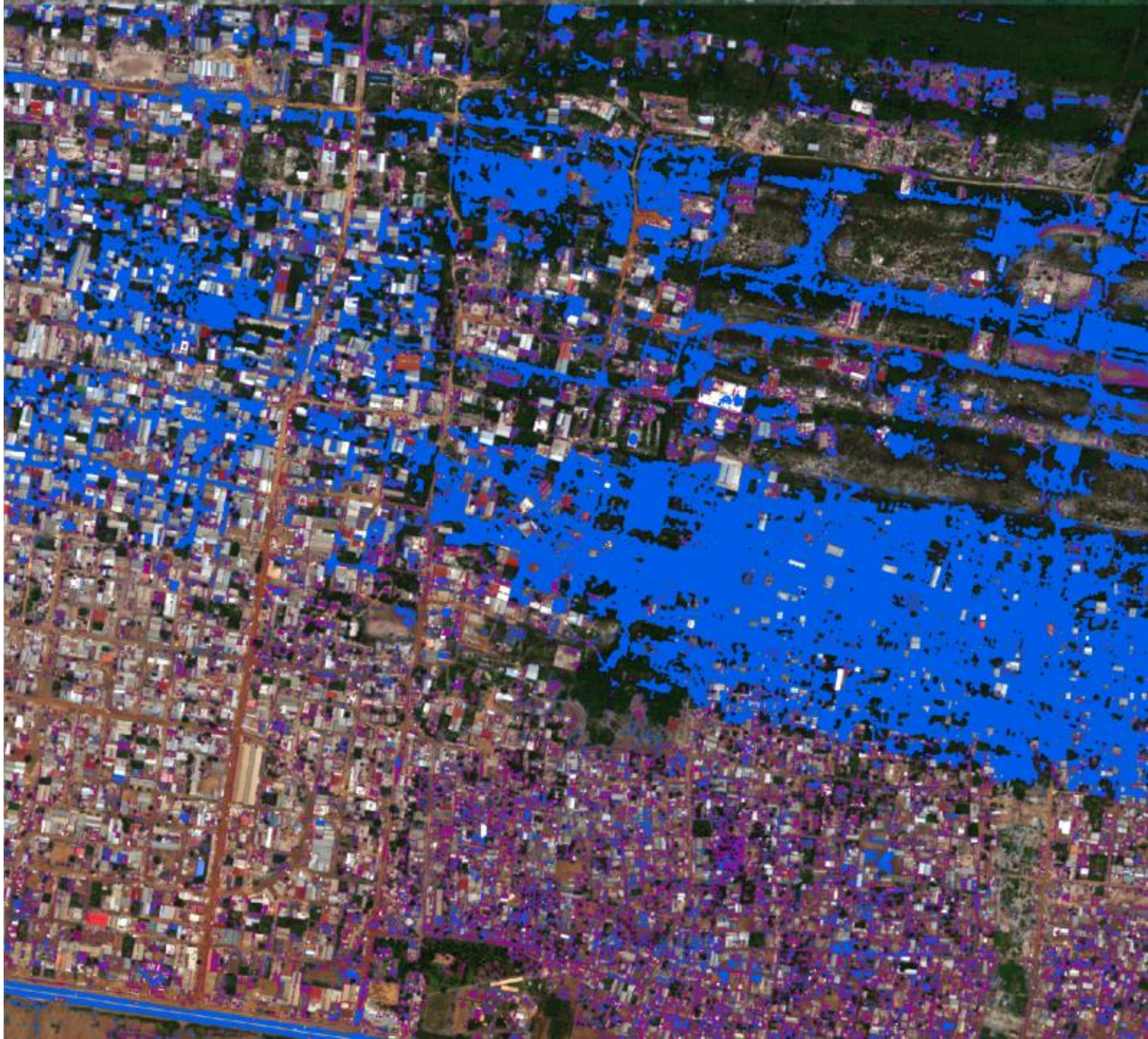


Southeast SVM Result

- 95.3% accuracy score
- Minor confusion flood, shadow and buildings

```
[[275   7   0   0]
 [ 16 259   2   3]
 [  0   0 116   0]
 [  0  14   0 193]]
```





Key Findings for Unsupervised Machine Learning

- Training data is key! But also a source of uncertainty
- Expanding training data set improves model results
- Best single method for reliably identifying building shadow
- Is the additional 15% accuracy score improvement worth the time?

Why is this project important?

Identified methods to better differentiate building shadow from flood waters. Increased extent of flood detection.

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

Potential to train classifier on small representative portions of city and apply to entire image.

Python-based open source tools appear to offer reasonable estimations of flooding extent.

More accurate information means that more people can be better prepared and protected from the potential damage from floods.

Future Work

Revisit training data set to see how “flood” points are defined

Expand training data set to develop a more robust classifier

Test expanded classifier and k-means approach to other locations and scale to larger geographic regions

Add Open Street Map building layer to more clearly delineate buildings from flood

Questions?

- 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.
    - Huang, X., and Zhang, L. (2012) Morphological Building/Shadow Index for Building Extraction From High-Resolution Imagery Over Urban Areas. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 5, 161-172.
    - Xie, C., Huang, X., Zeng, W., & Fang, X. (2016). A novel water index for urban high-resolution eight-band WorldView-2 imagery. International Journal of Digital Earth, 9(10), 925–941.
    - Cloud to Street. Urban Flood Mapping Using Very-High Resolution Satellite Imagery. Available at: https://abidjan.cloudtostreet.info/info

- Acknowledgements:
    - Jenny Palomino, CU Earth Lab
    - Joe McGlinchy, CU Earth Lab
    - Jeff Ho, Cloud to Street

Extra slides

SVM Beira, Mozambique

- Applying Abidjan SVM model to Beira
- Doesn’t capture true shadow well
- Try adding more vegetation from Abidjan to SVM model
- And/or add verification points from Beira to create 2-city model

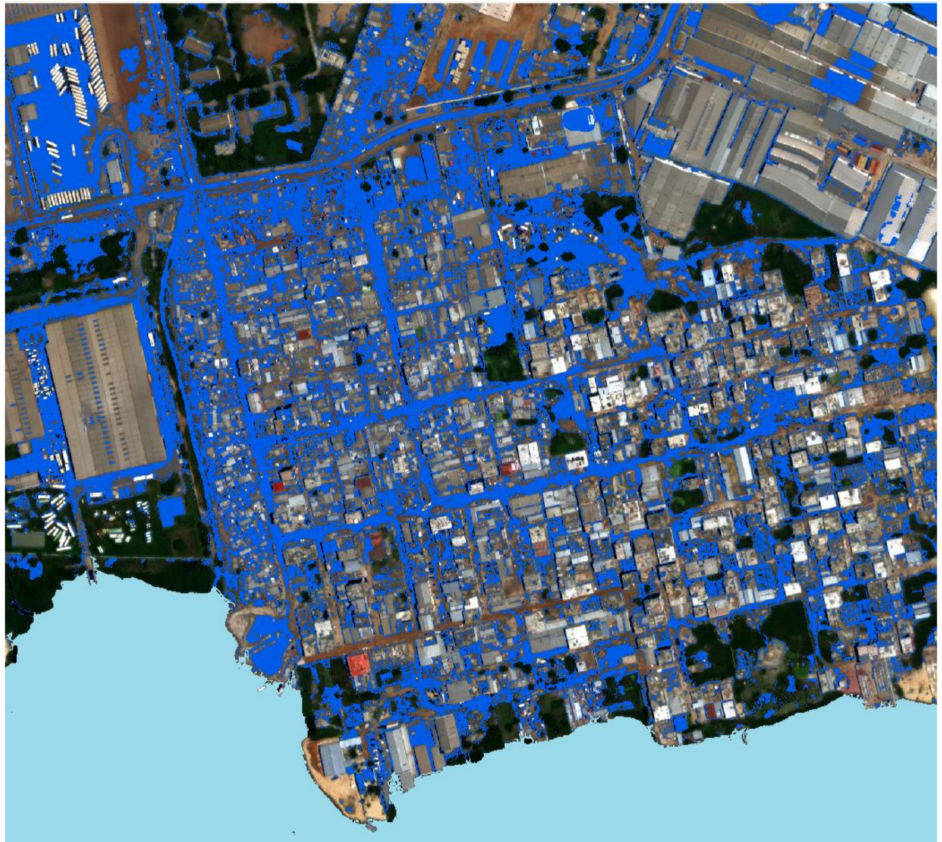
k-means Beira, Mozambique

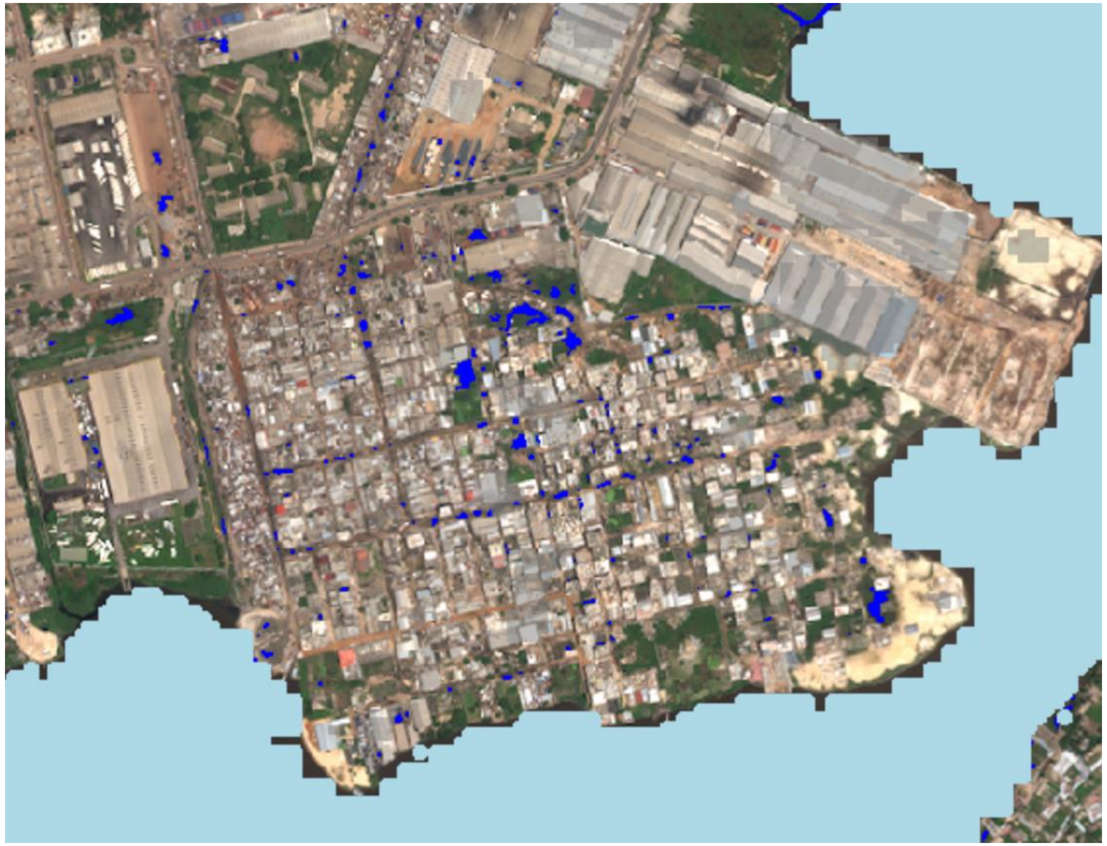
- Model does not appear to capture shadow well.. Swapped out “shadow” cluster for a vegetation cluster.
- No longer differentiates shadow, but visualization appears more accurate. Changed grey to tan.
- Try developing shadow mask to apply after k-means.

SVM Beira, Mozambique

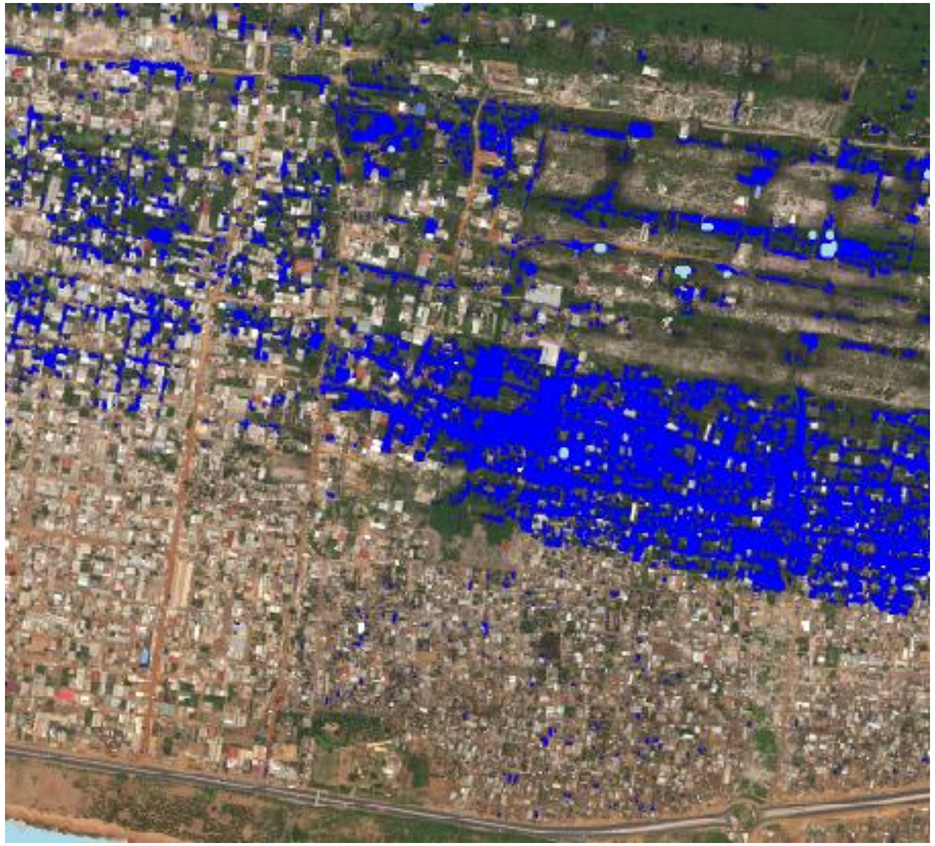
- Changed shadow to vegetation for SVM results
- Seems to over-estimate flood

Koumassi – Side by Side - SVM

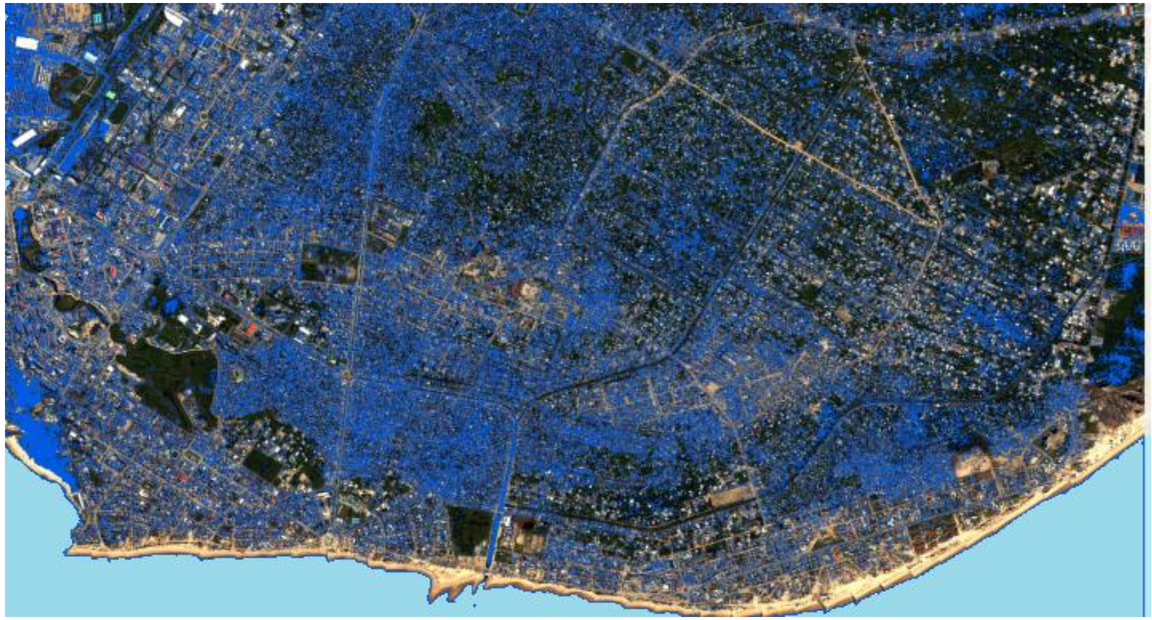


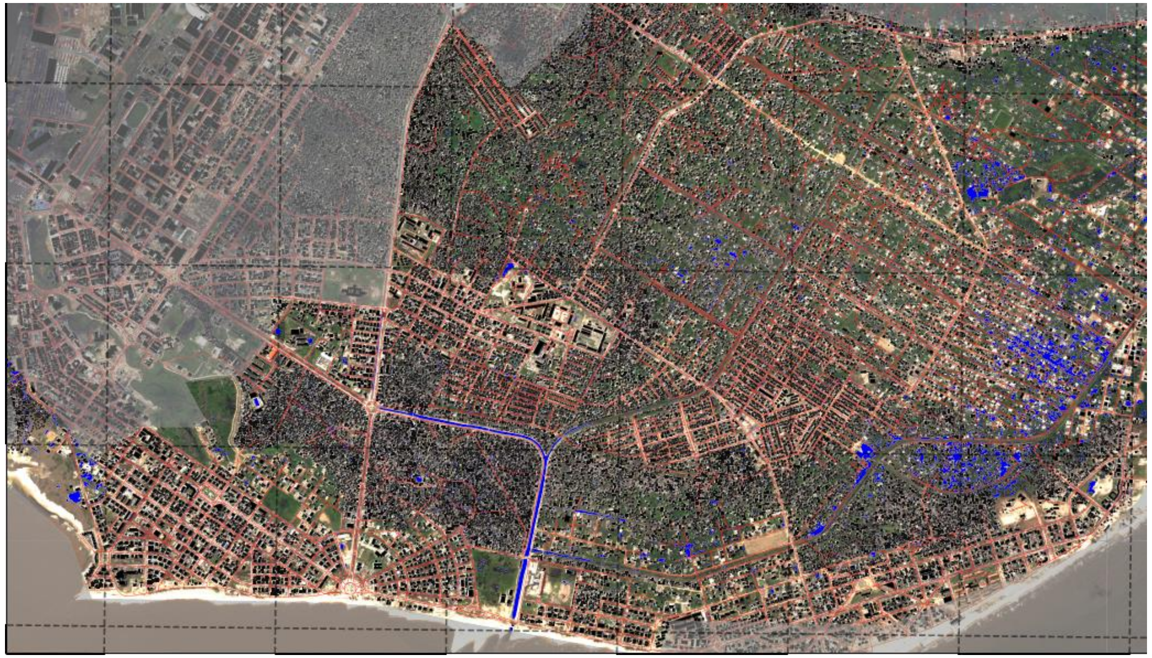


Southeast Side-by-Side - SVM

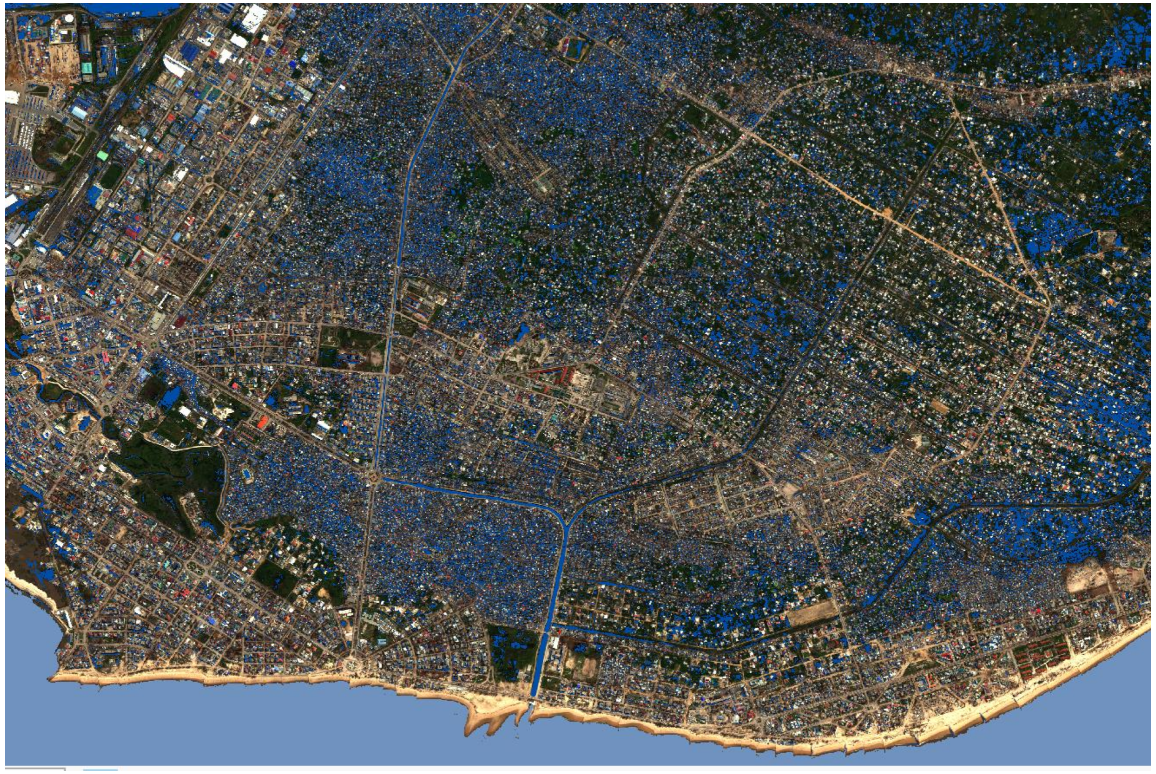


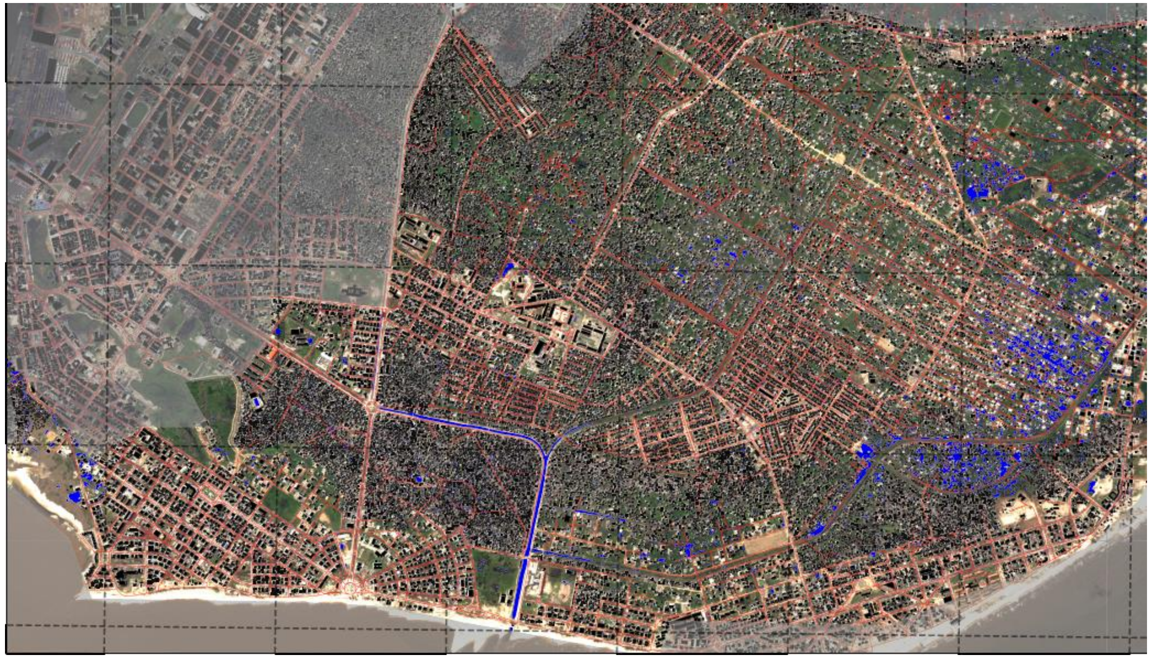
Beira Side-by-Side – SVM





Beira Side-by-Side – k-means





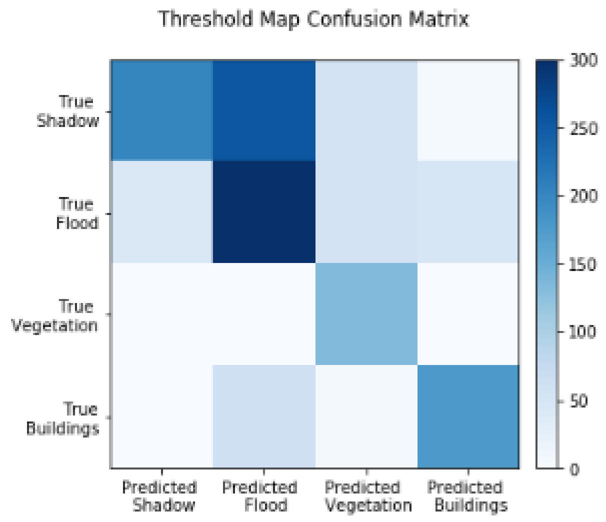
Refined SVM Model (in-progress)

- Increased numbers of vegetation reference points.
- Reviewed and eliminated some flood points that were questionable
- Visualization has improved.
- Accuracy score is similar (95%)

Koumassi Thresholding Map

- Accuracy score of 59.5%

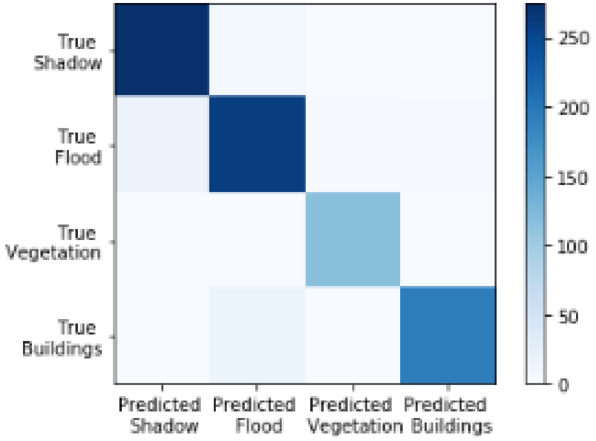
```
[[201 255  55   4  18]
 [ 43 300  54  49   4]
 [  0   0 133   0   0]
 [  0  62   6 177   0]
 [  0   0   0   0   0]]
```



Koumassi SVM Result

- 95.3% accuracy score
- Minor confusion flood, shadow and buildings

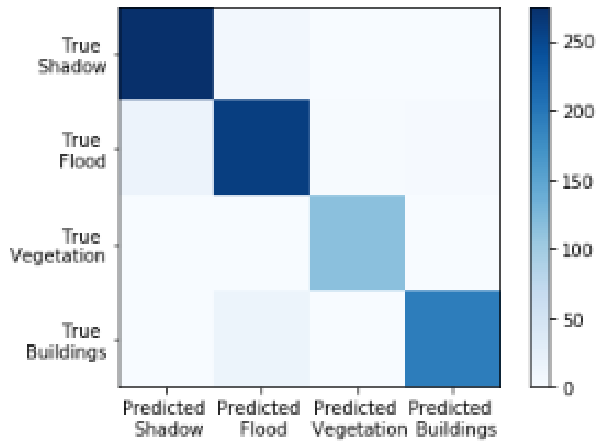
```
[[275   7   0   0]
 [ 16 259   2   3]
 [  0   0 116   0]
 [  0  14   0 193]]
```

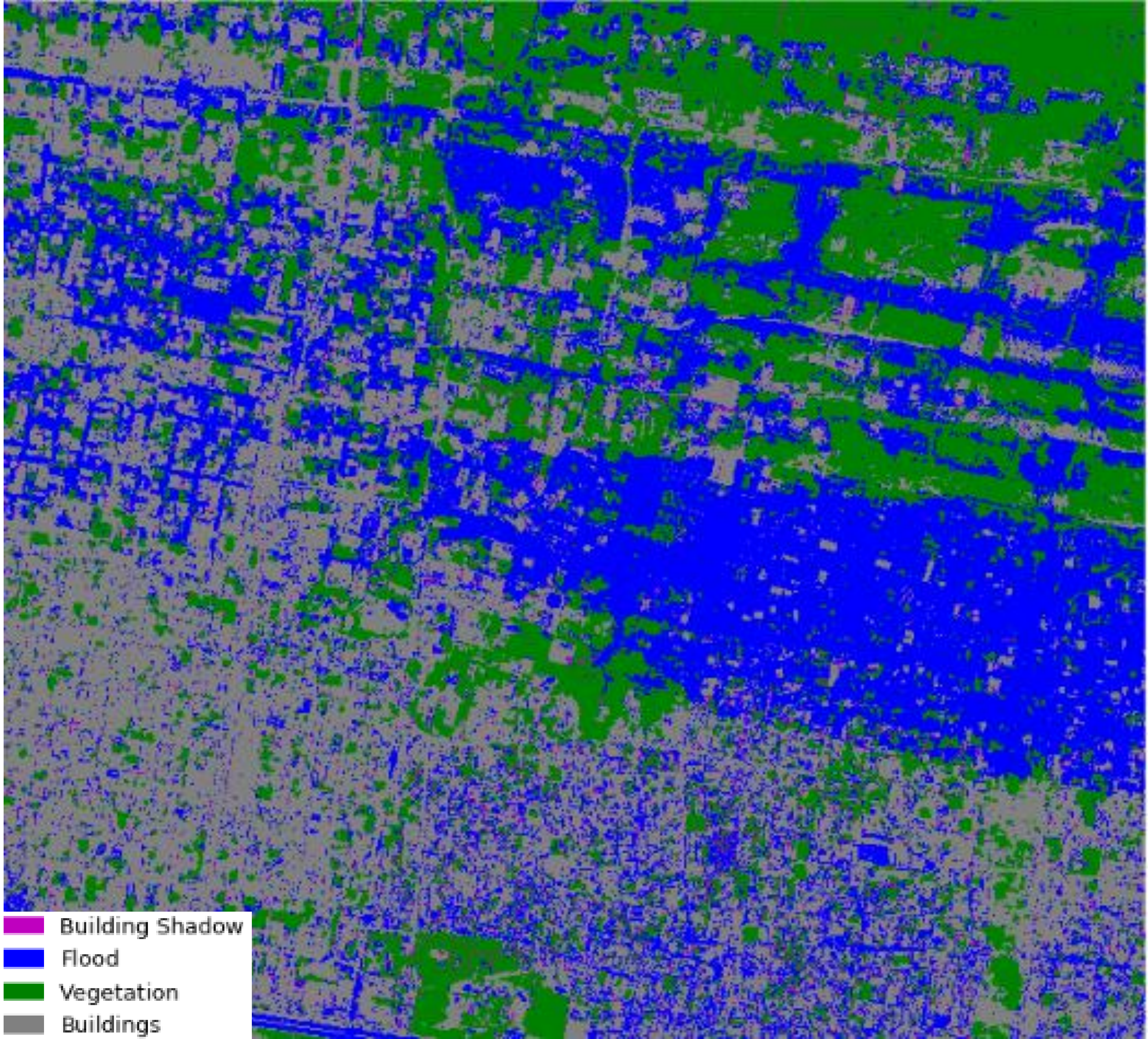


Southeast SVM Result

- 95.3% accuracy score
- Minor confusion flood, shadow and buildings

```
[[275   7   0   0]
 [ 16 259   2   3]
 [  0   0 116   0]
 [  0  14   0 193]]
```

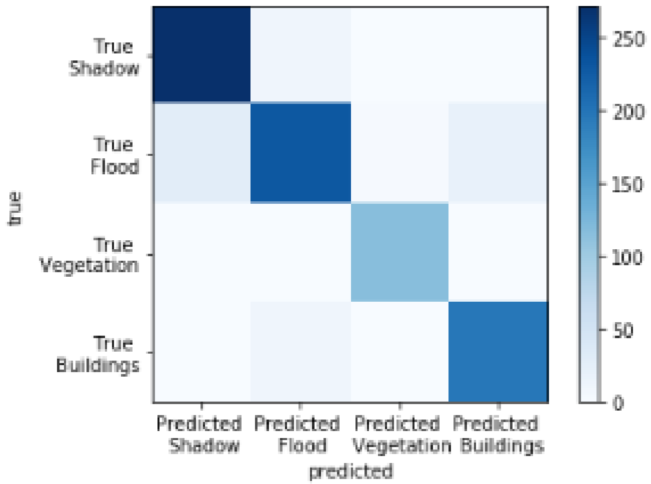




Koumassi Random Forest

- Pansharpened imagery
- 91.8% accuracy score

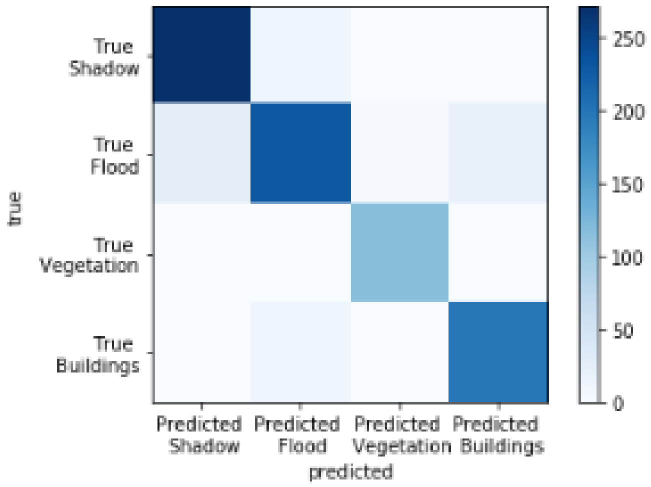
```
[[271  11   0   0]
 [ 28 229   3  20]
 [  0   0 116   0]
 [  0  11   0 196]]
```

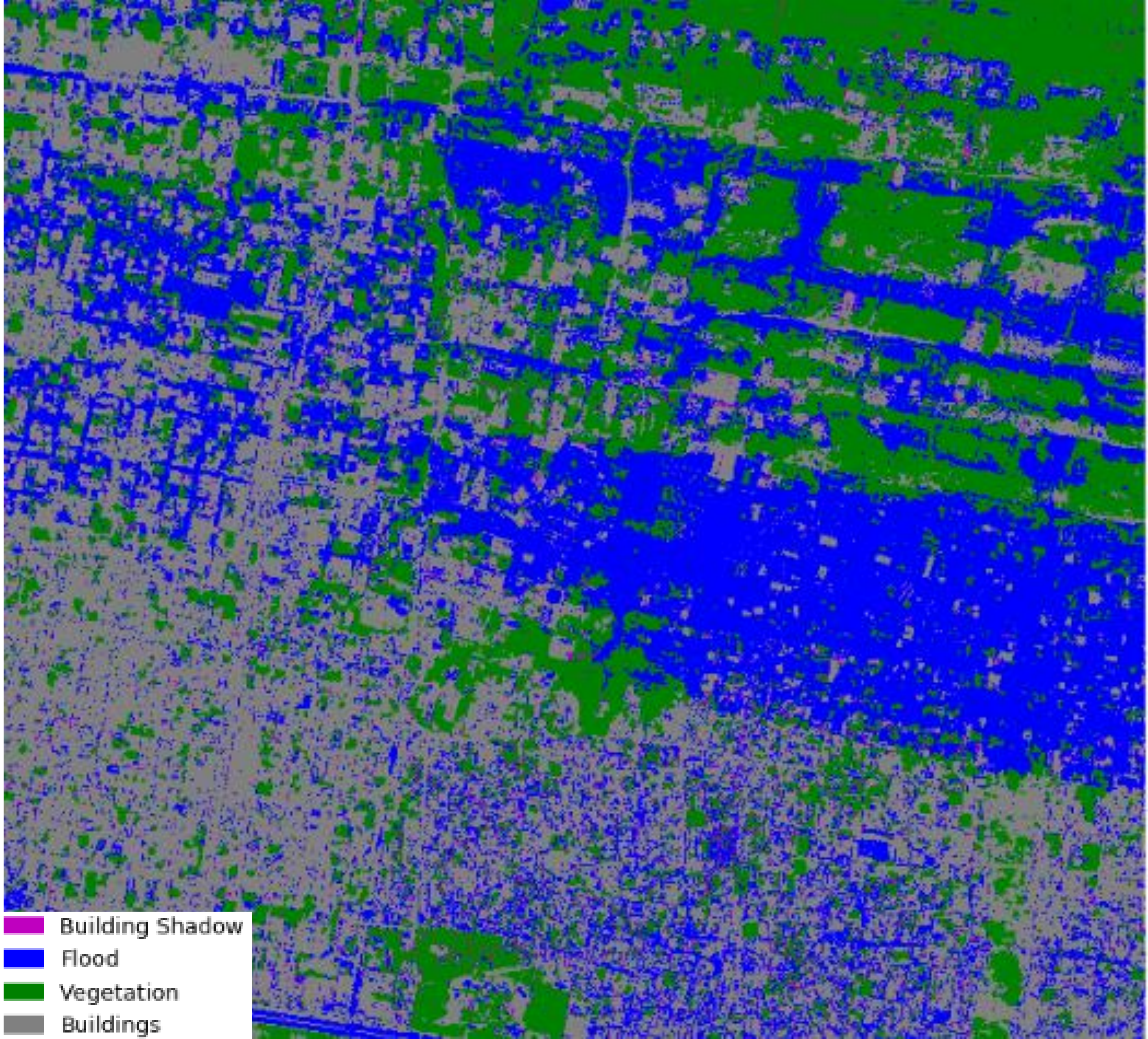


Southeast Random Forest

- Pansharpened imagery
- 91.8% accuracy score

```
[[271  11   0   0]
 [ 28 229   3  20]
 [  0   0 116   0]
 [  0  11   0 196]]
```





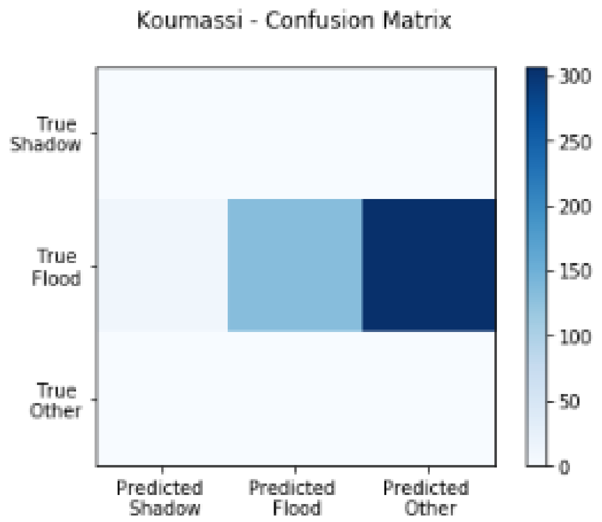
Focusing on flood detection Southeast k-means

- Change “shadow” cluster to be “flood” cluster
- Improves overall visualization
- Accuracy score for flood only increases to 93.2%
- Accuracy score for shadow only decreases to 0%
- Overestimation of flooded areas

Cloud to Street maps: Focusing on flood detection

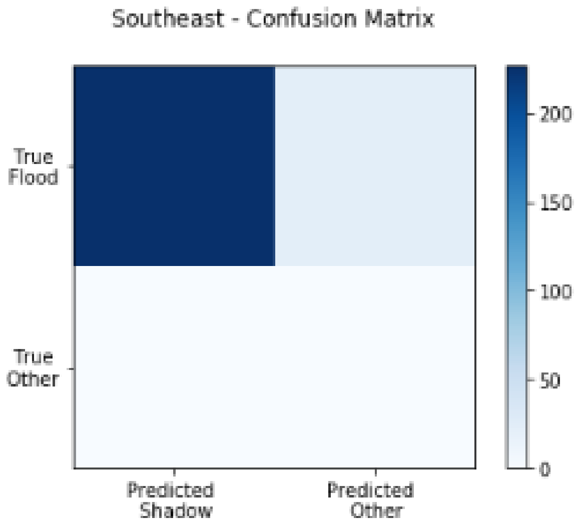
- Goal is to find flood.. not shadow or other land cover types
- Ran accuracy scores with just flood reference data

```
[[  0   0   0]
 [ 10 133 307]
 [  0   0   0]]
```



Accuracy score 29.6%

```
[[227  23]
 [  0   0]]
```



Accuracy score 90.8%

Open Street Map: Building layer

Validation Process

- For the development of the SVM map, the reference data set was divided:
  - 60% for training and testing
    - 40% for testing
    - 60% for training
  - 40% for external validation
  - SVM map was created based the entire image
- The Kmeans and thresholding maps were created based on the entire image.
  - Accuracy scores were calculated for the 60% training/testing dataset, the 40% external dataset and the entire reference dataset.

Abidjan, Cote D'lvoire

- 5 million people
- Francophone West Africa's largest economy
- 21 people killed by flash flood in June 2018
- X mm of rain fell
- 136 people rescued
- Authorities intend to demolish structures and compensate owners

Unique algorithms for each image

Final algorithms for Dar es Salaam and Kinshasa flood maps

Because of present issues with flood mapping algorithms determined here (see Table 5), we recommend that these maps in particular should be validated with local information where possible.

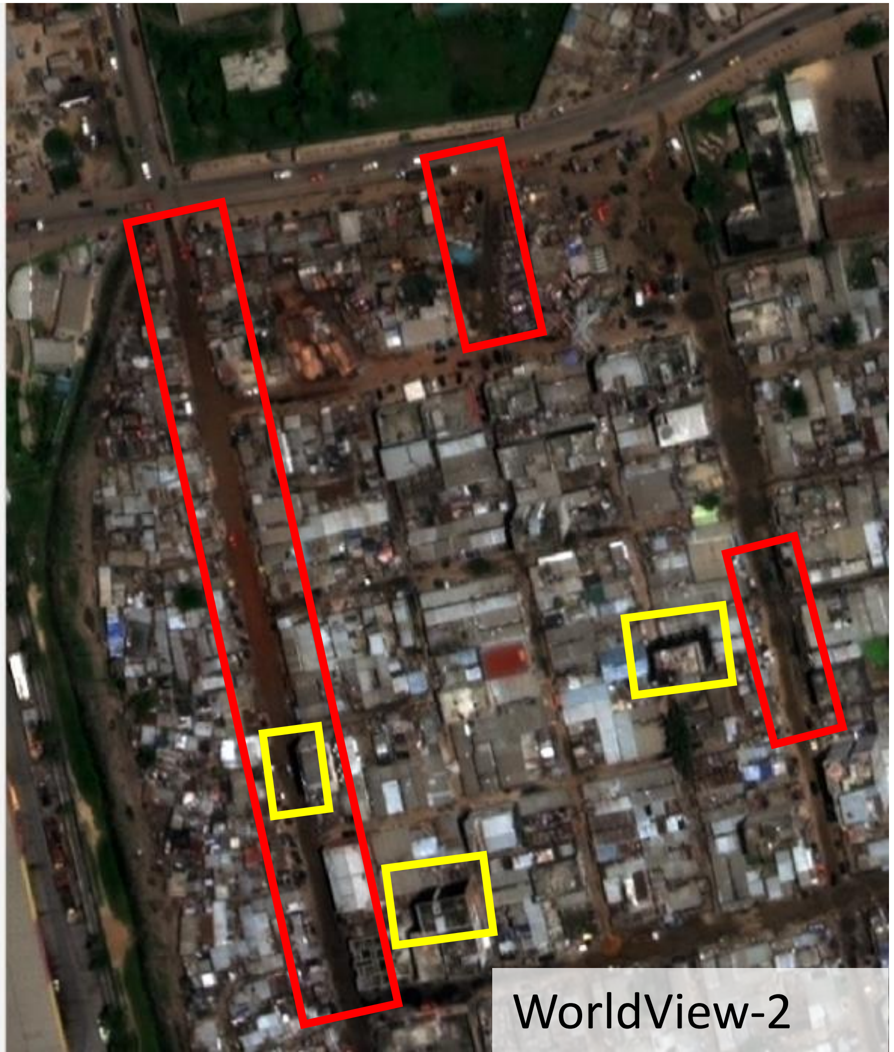
City	Image Date	Algorithm*	Cloud to Street assessment	Present Issues
Dar es Salaam	2011-12-24	Clouds: $C \geq 0.26$ and $RE \geq 0.26$ Flood: $(G + Y + R) / NIR2 \geq 7$ and $R \leq 0.05$	Moderate to High quality	Some under prediction of flooded areas and overprediction of floods in building shadow areas
Dar es Salaam	2017-10-30	Clouds: $C \geq 0.25$ and $RE \geq 0.25$ Flood: $(G + Y + R) / NIR2 \geq 5.5$, $R \leq 0.05$, and G texture < 25,000	Low quality due to high cloud cover	Small percentage of the image was cloud free and mappable, some overprediction of floods in cloud shadow areas
Kinshasa	2015-12-15	Clouds: $C \geq 0.0875$ and $RE \geq 0.0875$ Flood**: $(G + Y + R) / NIR2 \geq 3$, $NDWI > -0.05$, $C + B + G < 0.2$, and G texture < 1,500	Low to Moderate quality	Minimal overprediction of floods in cloud shadow areas but some underprediction of floods with no sedimented water (typically in wetland areas)
Kinshasa	2016-01-12	Clouds: $B \geq 0.07$ and $NIR \geq 0.06$ Flood***: $NIR \leq 0.038$, $PCA2 \geq 0.9$, $NDVI < 0.05$, and $NDWI > 0.05$	Low quality, but still can provide useful information	Overprediction of floods outside of regions identified manually****
Abidjan	2016-06-17	Clouds: $C \geq 0.25$ and $RE \geq 0.25$ Flood*****: ($NDWI1 \geq -0.35$, $DARK \leq 5$, $C \leq 1$, and $R \leq 0.85$) or ($NDWI2 \geq 0.03$, $DARK \leq 5.8$, $C \leq 1$)	High quality	Dark spots near agricultural areas may be underestimated, but ground truth necessary to know

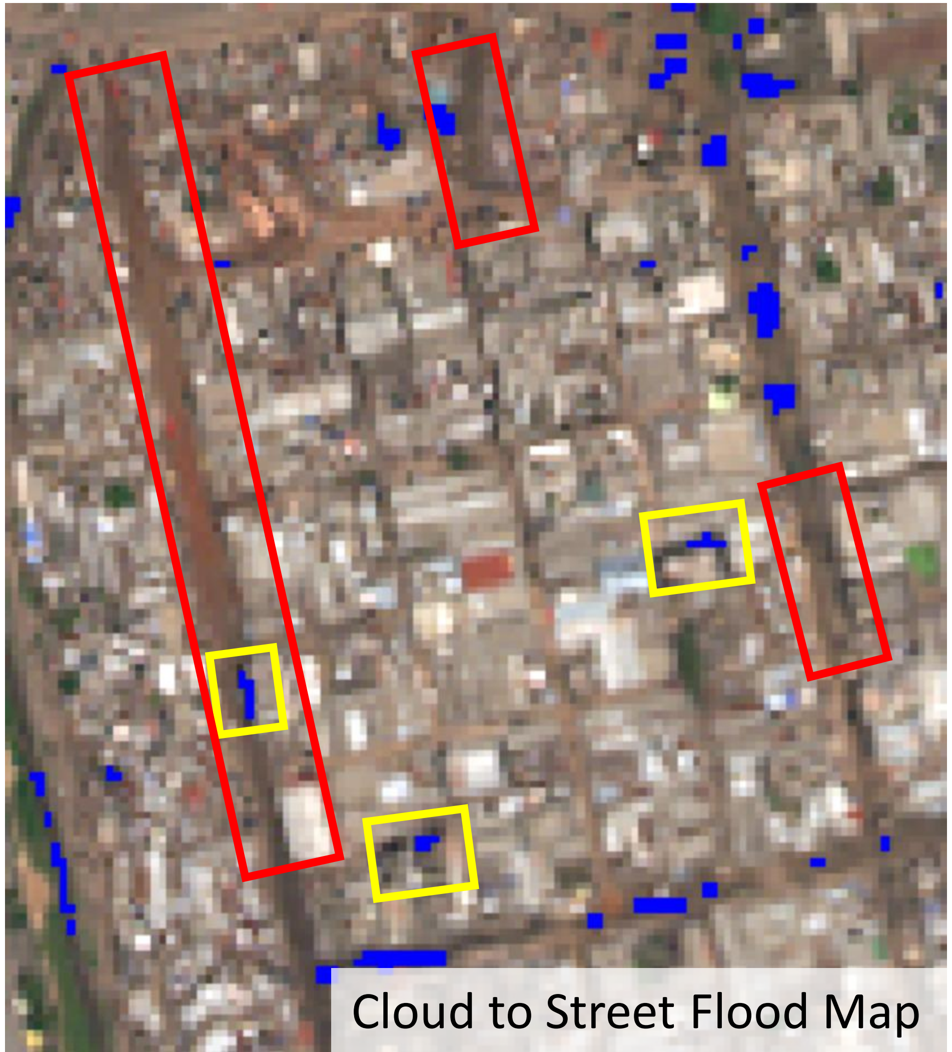
Table 5: Final algorithms identified for each image, with qualitative assessment based on its quality for use in decision-making.
* Band acronyms as described in Table 2 (e.g., C = coastal aerosol)
**$NDWI = (G - NIR2)/(G + NIR2)$. Note that bands are different for WorldView sensors versus GeoEye (see Table 2) and so NDWI is calculated using different bands for the two Kinshasa images.
***$PCA2 = -0.20(B) + 0.48(G) + 0.51(R) - 0.68(NIR)$; $NDVI = (NIR - R)/(NIR + R)$; $NDWI = (G - NIR)/(G + NIR)$
****Regions were drawn manually around areas of visible flooding due to overall poor image quality. Flooding may have occurred in areas outside of hand-drawn region, but the image quality is too poor there to robustly map floods.
*****$NDWI1 = (C - NIR2)/(C + NIR2)$; $NDWI2 = (Y - NIR2) / (Y + NIR2)$; $DARK = RE+NIR1+NIR2$

Current flood map issues

Areas of flood not captured by flood map

Building shadow misidentified as flood





Cloud to Street

- High-resolution maps of flood-prone areas for:
  - planners
  - insurers
  - disaster response agencies
- To better:
  - prepare for floods
  - respond to flood events in near real-time
  - understand and price flood risk
  - insure vulnerable populations

Thresholding Explorations

Determining which spectral indices to use

Methods to reduce noise in the image

- Labeling objects to remove pixels below a set size
- Morphological smoothing to reduce noise

Combined thresholded indices into single image

Validated using entire reference data set for each site

K-means Explorations

- Different inputs into k-means
  - 8-band raster image
  - Index stack (NDWI, NDVI, MSI, MBI)
  - Masks (flood, shadow, vegetation, buildings)
  - Various combinations
- Different number of output clusters
  - Less than seven led to substantial confusion with buildings and water and shadow
  - Diverse types of buildings is a challenge
- Labeling k-means outputs to try and reassign clusters based on region props

SVM Explorations

- Different inputs into SVM
  - Spectral indices
  - Raw spectral bands
  - Various combinations
- Combined Koumassi and Southeast points to build more robust model
  - Attempt to improve shadow/flood confusion