Capstone Final Report: Documenting Damage and Recovery across Bolivar Peninsula, Texas after Hurricane Ike using Object Based Image Analysis (OBIA*)*

Suzanne Zick, April 29, 2016

Introduction

Natural disasters are a formidable global problem. The UN estimates that since 1970, these disasters have killed more than 1.5 million persons, affected 7 billion persons, and caused economic losses totaling $1.68 trillion dollars (UNESCAP, 2015).

Disaster stakeholders around the world work hard to prepare for, mitigate against, and cope in the aftermath of these events. They need support tools that are flexible enough to work on a broad array of disaster types, as well as capable of monitoring change through time. A relatively new approach, called object based image analysis (OBIA) may be of help.

The goal of this project was to evaluate OBIA as a tool to support disaster stakeholders. A case study testing this approach was conducted across Bolivar Peninsula, Texas with a focus on the 2008 Hurricane Ike disaster event. OBIA software was used to classify six object types (buildings, water, roads, and three kinds of vegetation) for three separate time periods – before and after the storm to document damage, and a later period to document recovery.

Object based image analysis

Object-based image analysis is a semi-automated method to classify objects from high resolution, remotely sensed data. OBIA software fuses the disparate data sets, segments fused data into objects and then classifies objects based on a wide assortment of object properties. An example OBIA classification is shown in Figure 1.

Figure 1: The image shows the OBIA classification of the six object types indicated in the legend. Classified objects are overlaid on a high resolution aerial image.

Figure 2 displays an example rule set. Each line in the rule set represents one or more algorithms, which make use of parameter settings specified by the analyst. Algorithms may guide the computer to generate new data values using mathematical formulae, segment data prior to classification, classify objects of interest, and/or save and export the results in vector or raster format. The process is semi-automated because an OBIA analyst first develops the rule set that guides the computer, then the rule set is applied by the computer in a more automated fashion to the data.

Figure 2: Example rule set showing the sequence of rules used to segment and classify objects.

OBIA advantages

The object-based approach offers several important advantages over pixel-based approaches. First, OBIA exploits a range of characteristics to classify objects, not just spectral properties as pixel-based approaches do, but also the object's shape, size, texture, and context (Hay and Castilla, 2008). Consequently, OBIA is closer to the way in which humans make classification decisions (Blaschke et al, 2014).

Another advantage is that extracted objects are more intuitively meaningful than classes generated by pixel-based approaches (Blaschke et al., 2014), and are easier to confirm visually. Almost everyone can compare a classified building object to buildings in the imagery; and they will quickly grasp the implications if buildings are no longer present after a disaster event. This is a huge advantage for disaster applications, since it is critical that decision-makers clearly understand the quality and meaning of products generated for their use.

In addition, OBIA incorporates expert knowledge. The extraction relies on a rule set developed by the analyst and analysts are free to choose whatever objects are most germane to their project as long as the size of the object is appropriate to the resolution of the data. Further, analysts determine which object properties and parameter settings are most suitable to perform the classification. This flexibility permits analyses tailored to specific disaster events and particular stakeholder needs.

OBIA also offers potential advantages relative to human interpreters. Once the rule set is built, OBIA can be faster and more consistent than manual interpretation, especially for larger areas, as the rule set may be reused. Note however, that reuse requires a similar suite of data and a similar setting.

OBIA limitations

OBIA offers many advantages, but the approach does have limitations. Analysts should select target objects that are distinct from other phenomena, e.g. individual features such as a lakes or groupings of individual features like a forest (Bian, 2007). A continuous phenomenon or features on a continuum make poor or more problematic objects. It is possible to extract an object based on an arbitrary cutoff value, such as an elevation ≥ 5000 feet in topographic data. However, this would not represent a distinct object in the real-world, and thus could foster confusion among later users (Bian, 2007). In the disaster field, clarity is critical.

Other potential limitations are the availability of high resolution data and trained analysts. Since classified objects represent distinct features, OBIA works best with high resolution data. Moderate to coarse resolution data provide values averaged across a range of phenomena which limits their potential use in OBIA (Blaschke, 2010). In addition, advanced training is required for personnel to develop the rule set, including knowledge of the OBIA software and remotely sensed data.

Case Study: Bolivar Peninsula and Hurricane Ike - Setting and study questions

To investigate the usefulness of OBIA for disaster applications, a case study focusing on the Hurricane Ike event and Bolivar Peninsula, Texas was performed. Hurricane Ike made landfall on the western end of Bolivar in September, 2008 (see red hurricane track in Figure 3). Bolivar Peninsula (yellow outline) is a narrow spit of land located on the Texas Gulf Coast, southeast of the city of Houston.

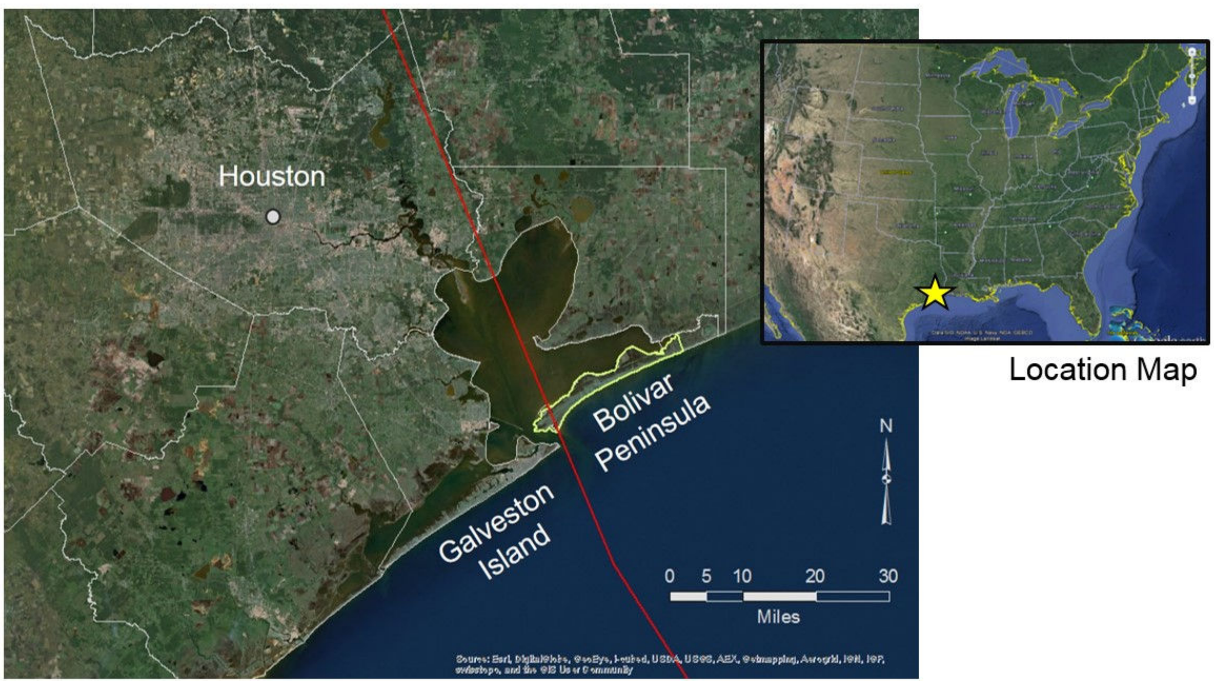

Figure 3: Map showing Bolivar Peninsula, Texas (yellow outline), as well as the track of Hurricane Ike (red line). The inset map highlights the study area (yellow star) on the U.S. Texas Gulf Coast.

Ike devastated Bolivar. In addition to hurricane force winds, the peninsula was inundated by storm surge, with water depths reaching at least 15' across parts of Bolivar (NOAA, n.d.). Before and after photos from the USGS illustrate some of the damage (Figure 4). FEMA (2009) reported that approximately 65% of the buildings on Bolivar were destroyed. In addition, roads were covered with sand and storm debris, a bridge was partly collapsed and the coastline and coastal dune system was badly eroded. Bolivar was chosen for the case study because it was hard-hit by Hurricane Ike and high resolution data for multiple time periods were publically available from state or national repositories. The perspective from the ground is shown in Figure 5.

Figure 4: Photos illustrating conditions on Bolivar Peninsula shortly before and after Hurricane Ike. Arrows highlight identical buildings in both photos. (Image credit: USGS)

Figure 5: Ground level view of Hurricane Ike damage on Bolivar. Note the storm debris, stripped vegetation, water-filled scour holes, and remnant building pilings. (Image credit: Jocelyn Augustino, FEMA)

Three study questions were of primary interest.

1. <u>Can OBIA accurately classify the types of objects likely to be of interest to disaster stakeholders?</u> Stakeholders were envisioned as local, state and federal government officials, insurance companies, engineering and construction firms, conservation organizations, and researchers interested in social vulnerability or social justice questions. Based on these stakeholder types, six test objects were chosen: buildings, roads, water and three vegetation classes. These objects were classified across Bolivar for three different time periods - before the storm, approximately six months after the storm, and roughly a year and a half after the storm.
2. <u>Can rule sets be reused, either for the same data set in adjacent areas, or for different data sets acquired at different time periods?</u> To save time, disaster analysts may wish to re-use a rule set in order to expand an area of interest or evaluate new data sets as they become available. Analysts may need to update preparedness plans, respond in the aftermath of a disaster event, or report on the state of recovery. Consequently, geographic reuse was tested, as well as reuse on data from different time periods.
3. <u>Can OBIA clearly document change through time?</u> Evidence of changing conditions is crucial to disaster stakeholders as they work to understand the immediate and long-term disaster effects on communities (Cutter et al., 2014), and on the natural environment. In addition, disaster events themselves may unfold gradually over years or even decades, such as extreme drought or rising sea level. Recognizing and mitigating such changes can reduce costs and save lives. To investigate this question, OBIA output for each of the three time periods was compared.

Data

Data included Lidar point clouds, high resolution aerial imagery, and vector data. **Appendix 1** shows a summarized metadata table.

Lidar point clouds: Portions of two point clouds were downloaded from NOAA's Digital Coast website: 1) *2006 Texas Water Development Board (TWDB) Lidar: Galveston County* and 2) *2009 U.S. Army Corps of Engineers (USACE) Topobathy Lidar: Post Hurricanes Gustav and Ike*. Both were discrete return lidar acquired using fixed wing aircraft. They were selected because they offered complete or near-complete coverage across Bolivar, provided a before and after perspective, and were free to the public.

High Resolution Imagery: Three high resolution image tile sets, acquired by fixed wing aircraft, were downloaded from the Texas Natural Resources Information System (TNRIS). These included Texas Orthophoto Program (TOP) natural color and color infrared image sets from 2008 and 2009, and 2010 4-band imagery from the National Agriculture Imagery Program (NAIP). TOP imagery had a spatial resolution of 0.5 m, while NAIP imagery had a spatial resolution of 1 m. These data were selected because they were high resolution, included near infrared (NIR) as well as red (R), green (G) and blue (B) bands, and they were freely available from the appropriate time periods.

Vector data: Census road vectors were downloaded that would have been available to an analyst pre-storm 2008 and post-storm 2009 and 2010. Based on data release dates, these were roads from 2007, 2008, and 2009, but as it turned out, Census roads across Bolivar Peninsula were identical in all three vector sets. Other vectors used in the study were the USGS "Best Resolution" National Hydrography Dataset (NHD) and manually digitized area of interest (AOI) outlines.

Figure 6 is a generalized timeline for the three time periods. Hurricane Ike is indicated by the dashed red line. In the pre-storm suite, Lidar was 20-24 months older than the imagery. As for post storm periods, the same 2009 lidar was used and was simply paired with different sets of imagery. For Post-storm 1, imagery was 1-3 months older than the lidar. For Post-storm 2, Lidar was 12-14 months older than the imagery. Since Census road vectors were identical, the same data (Census roads 2008) was used for all three time periods, which meant that road vectors became increasingly out-of-date over time.

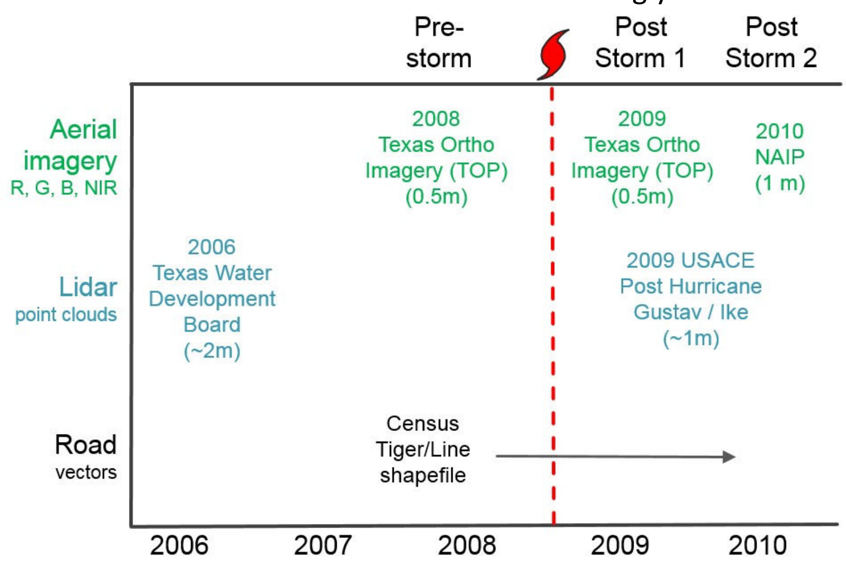

Figure 6: Primary data sets used in the capstone project.

Methods and Results

A simplified project workflow is provided in Figure 7 highlighting three project stages– data preprocessing, object based image analysis, and merging of OBIA output and review. Three technical software packages were utilized including 1) QCoherent LP360 Advanced (LP360 for ArcGIS version), 2) ESRI ArcGIS for Desktop 10.3, and 3) Trimble eCognition Developer 9.1.3. Summary descriptions of methods and results follow.

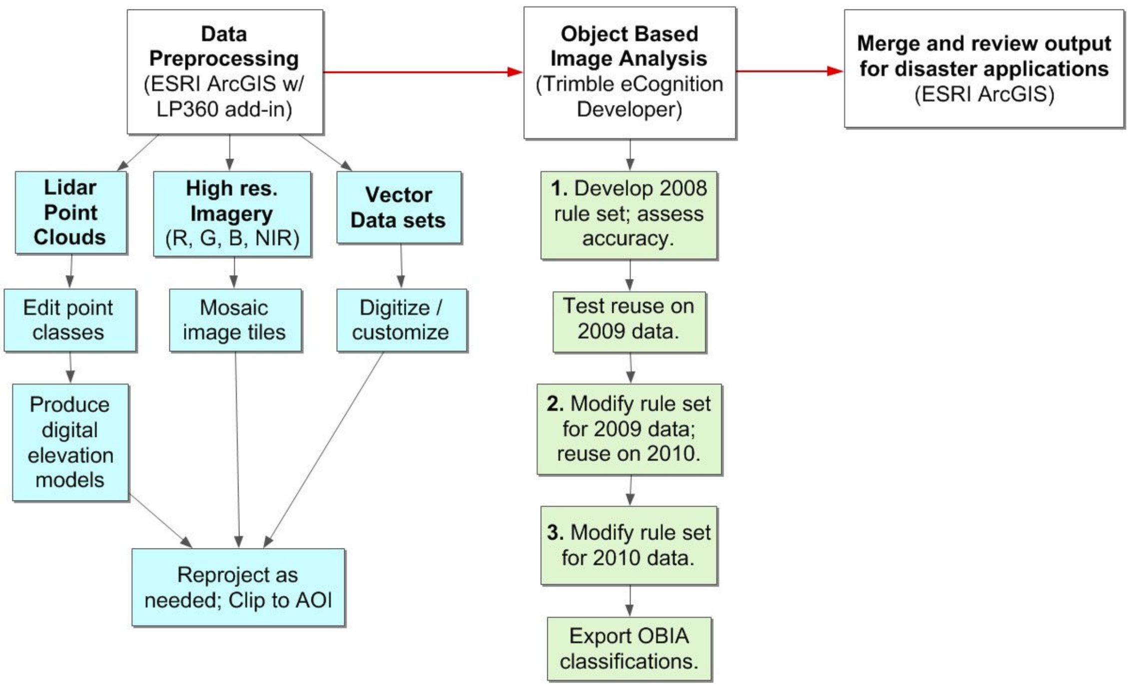

Figure 7: Simplified project workflow.

Data Preprocessing

Lidar: Downloaded lidar LAS files for both time periods were carefully reviewed at small and large (1:5000 or larger) scales; and the pre-existing point classes were edited as needed in LP360 software. Gross coverage for the 2006 lidar appeared complete, but two sizeable data voids were evident in the 2009 lidar. Notice the two narrow white rectangles in the center of Bolivar (Figure 8).

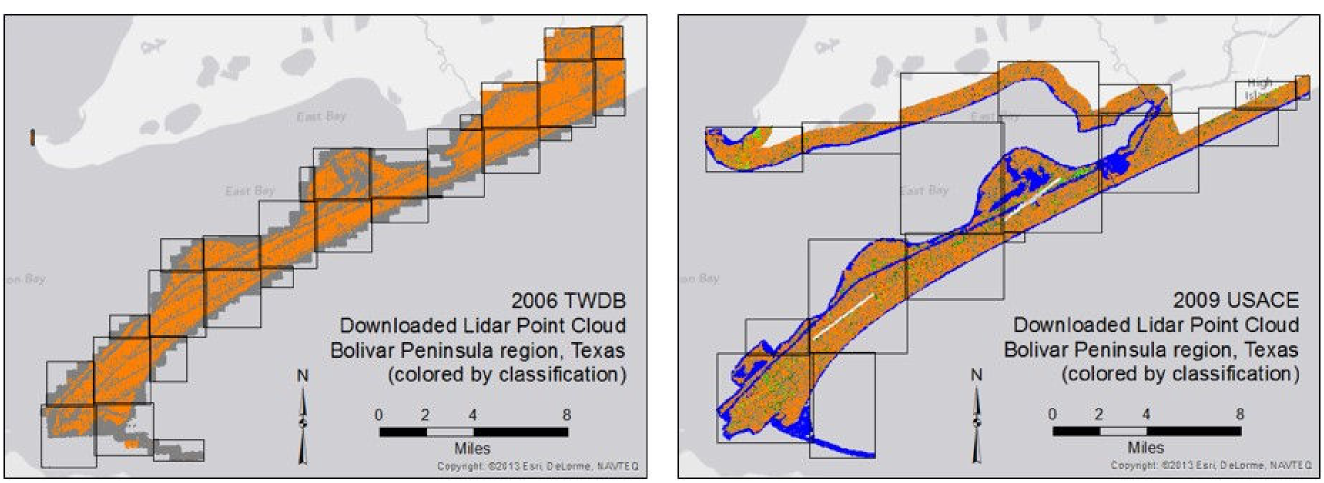

Figure 8: Lidar points colored by classification (unclassified=gray; ground=orange; water=blue; vegetation=green; buildings=red). Data from 2006 and 2009 are shown on the left and right, respectively, along with tile outlines.

Data voids appeared to be flightline gaps, but their specific cause was unknown. The vast majority of the terrain within these voids was low-lying marshland with areas of water, although a few isolated roadways, buildings, and a portion of a sand excavation/quarry were also observed. Derivative digital elevation models interpolated through these data gaps. No noteworthy large-scale (small) data voids were observed other than those positioned over water, or water likely at high tide. These were anticipated given the physical properties of the laser light (Pack, 2012).

The overall ground classification for 2006 appeared good, and TIN displays of the ground surface confirmed this assessment. However, several manual reclassifications were required including 1) reclassification of a few misclassified blocks of ground points to Class 1 - Unclassified; 2) reclassification of North Jetty ground points to Class 1 - Unclassified; 3) reclassification of high noise points to Class 18 - High noise.

Similarly for 2009, the overall ground classification was done well, again confirmed with the ground TIN. Some vegetation points more properly belong to the buildings class, e.g. scattered points on roofs. But since only ground and first returns were required for digital elevation surface models, edits were confined simply to reclassification of high noise points to Class 18 - High noise.

Once LAS files were edited, three derivative elevation products for each time period were generated in ArcGIS, specifically bare earth digital elevation models (DEMs) using ground points, digital surface models (DSMs) using first-return points, and normalized digital surface models (nDSMs) produced through subtraction of the DEMs from the DSMs. Associated hillshades were also created.

Elevation values for DEMs and DSMs were relative to the NAVD 88 vertical datum and units for all elevation models were in feet. Digital elevation models were projected to NAD 83 UTM Zone 15N and clipped to the AOI. Only the nDSMs were used in OBIA assessments.

<u>Imagery:</u> Imagery was reviewed and pre-processed in ArcGIS software. Image quality for the 2008 and 2009 TOP imagery appeared good, however spectral variation between tiles for the 2010 NAIP imagery was pronounced. This was particularly noticeable over water. No spectral corrections were applied over concern that stretched values might impact later OBIA analyses. In addition, the accuracy of the NAIP data was lower than the TOP data, so much so that TNRIS recommended that the NAIP imagery be used only for base maps.

Since image data was already in the proper projection, no re-projection was needed. However, as all sets were downloaded as tiles, image mosaics across Bolivar Peninsula were created. Separate natural color and color infrared mosaics were generated for the TOP 2008 and 2009 image sets, while only one mosaic was produced for the 4-band NAIP 2010 imagery. These mosaics were subsequently clipped to the AOI outline.

<u>Vector data:</u> The final AOI outline over Bolivar Peninsula was manually digitized in ArcGIS, and included only the areas having full data coverage. Note: Exceptions were the two large voids in the 2009 lidar discussed previously. A small portion of land visible in the imagery was not included in the AOI (see arrow in Figure 9) because it was absent from the 2006 lidar data set. In addition, most of the North Jetty, extending off the SE tip of Bolivar, was excluded because it was not pertinent to the study. The final AOI was approximately 49 sq. miles (127 sq. km) in area.

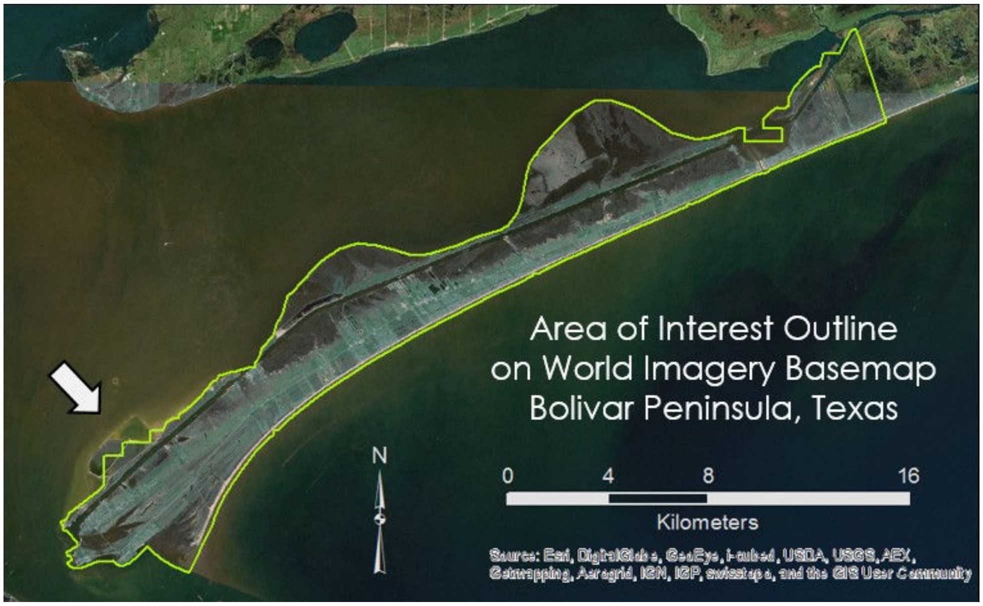

Figure 9: Final outline of project AOI. The arrow highlights the portion of Bolivar that was not included because one lidar set did not cover that region. Also, most of the North Jetty was also excluded.

Road vectors over Bolivar were selected from the Census road vector set for Galveston County, based on their location. These were later projected to NAD83 UTM zone 15N and clipped to the AOI in ArcGIS.

2008 OBIA evaluation (pre-storm)

OBIA classifications were generated for each time period in eCognition software using rule sets alone. No manual editing, which is possible in eCognition, was performed. Each period presented a unique set of challenges. A major challenge during the 2008 assessment was learning which OBIA algorithms worked most effectively for each object type. To test various algorithms during rule set development, several small area subsets were created for distinctive locales across Bolivar, for example marshland, shoreline, commercial areas, or various residential settings such as wooded neighborhoods, beach-front communities or marina developments. Creation of the rule set was a highly iterative process involving much trial and error. The interim rule set was applied repeatedly to these small subsets to evaluate the efficacy of individual rules as they were considered.

Once the rule set was complete, it was applied in sequence to 18 larger overlapping subsets that covered all of Bolivar Peninsula. Object shapefiles from each of the 18 subsets were exported and later merged into composited shapefiles in ArcGIS. The same process was followed for the post storm time periods as well. It should be noted that the final rule set for 2008 was initially applied to entire AOI. After three days of processing with no end in sight, the job was killed. Apparently this was too large an area for the available computing resources, which was why the area was subdivided into 18 regions. Final composited OBIA objects for the pre-storm 2008 assessment is shown in Figure 10, while larger scale views of the 2008 OBIA classification are provided in Appendix 2.

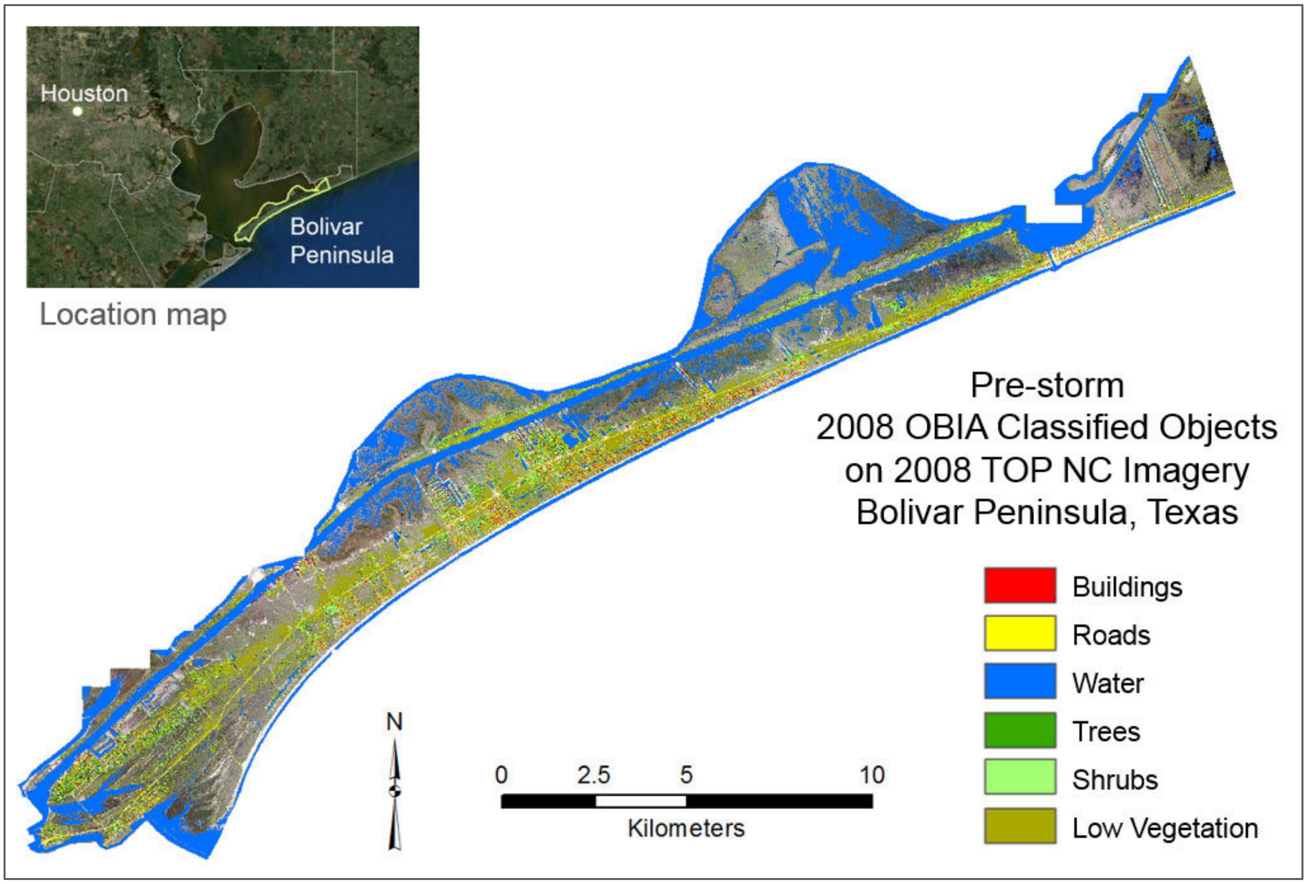

Figure 10: Pre-storm (2008) OBIA classified objects on natural color imagery.

<u>2008 thematic accuracy</u>

Due to time constraints, detailed accuracy assessments were only conducted on the 2008 OBIA classification. This evaluation was performed across a 4.2 sq. mile region in the center of Bolivar Peninsula. Figure 11 shows the location of the assessment AOI (red box) along with a more detailed view of the area. This AOI was chosen because it contained an assortment of settings and features, including marshland, a variety of housing and commercial developments, local roads and a state highway, and a range of vegetation and water body types.

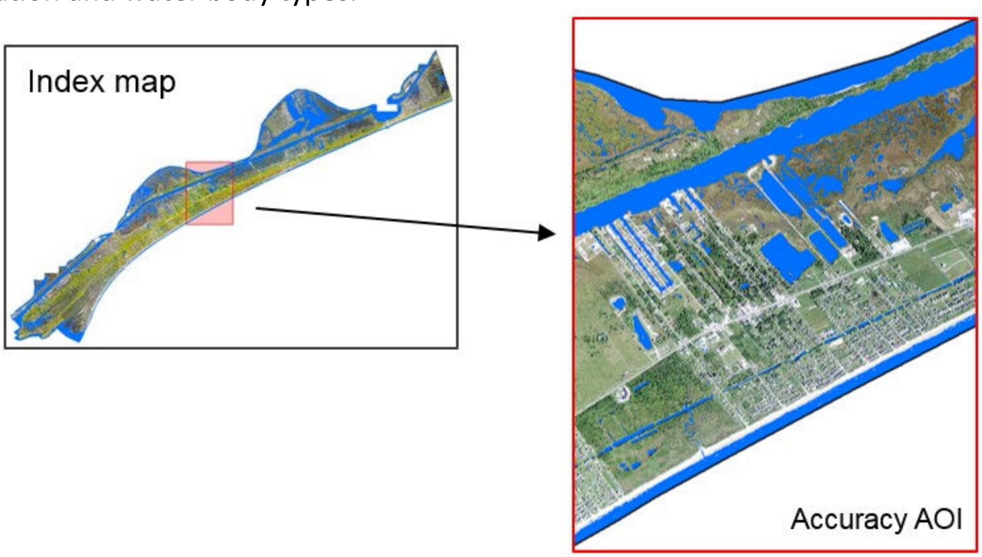

Figure 11: Location maps showing the AOI selected for thematic accuracy assessments.

Water: Water objects from 2008 were visually assessed relative to the 2008 imagery and later compared to the 2016 “best resolution” National Hydrography Dataset (at right in yellow) (Figure 12). Along the margin of the Gulf Intracoastal Waterway (red arrow), the NHD was more accurate than the OBIA water object. The OBIA object incorporated some of the sandy (wet?) margins of the waterway, which the NHD did not. However, when the two sets were compared relative to inland water bodies, the OBIA object set was both more comprehensive and more detailed. Notice that the NHD water bodies were simpler in shape and simply ignored “islands” found within them. Island-like features were properly excluded by the OBIA water objects. In the marshland setting, the detail captured by the OBIA water classification was remarkable.

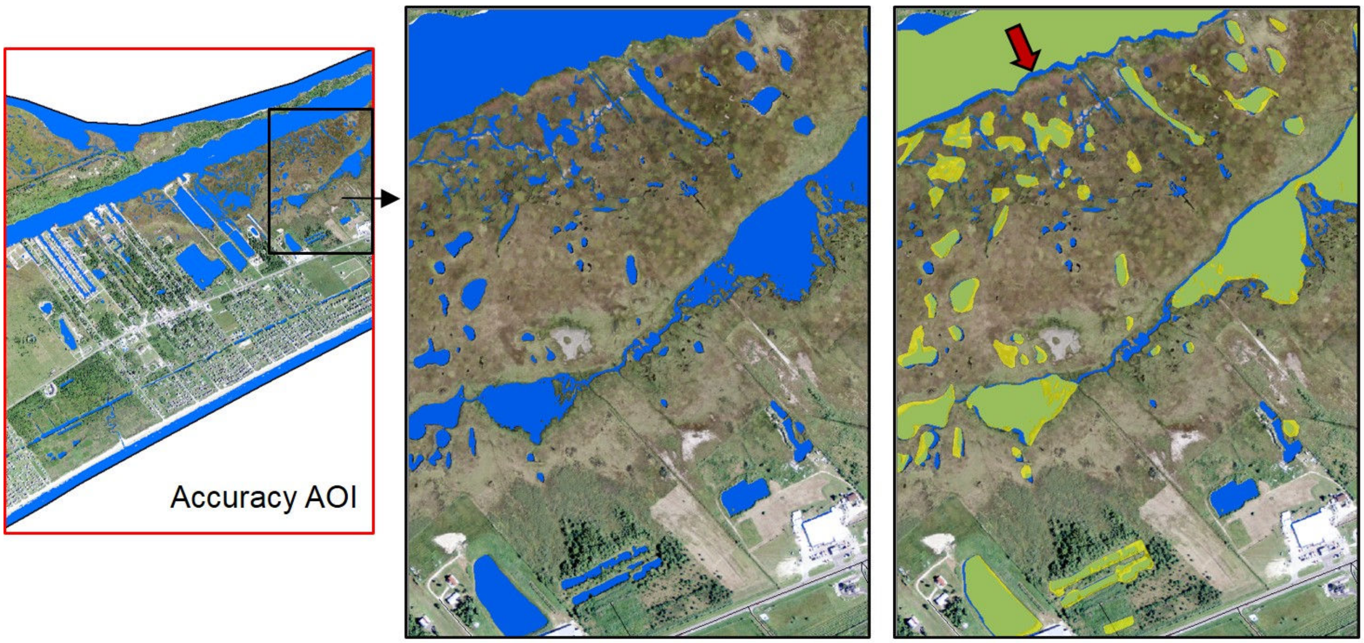

Figure 12: Water object accuracy relative to imagery (center) and 2016 National Hydrography Dataset (NHD) (right).

Not shown were water objects located outboard of the beach on the peninsula’s Gulf of Mexico side. There, saltwater was well classified except for narrow bands of turbulent water where ocean waves were breaking. These linear zones were typified by substantially different spectra, and thus were left unclassified. In the future, if the need arises, these frothy water zones could be incorporated into the water class via contextual algorithms. To summarize, the OBIA water object classification appeared quite good based on qualitative visual inspection.

Buildings: Visual comparisons were made of all buildings and classified building objects within the assessment area. Buildings were classified primarily on a height above ground of 10 feet or more to exclude small structures like sheds, and a negative NDVI value to exclude tall vegetation. 1446 buildings were located in the assessment area based on imagery. OBIA classified 1463 objects as buildings, of which 1388 were correctly classified. Therefore, provisional building accuracy was 96%. Accuracies were provisional because the same data used in OBIA were also used in accuracy assessment; plus the same person doing the analysis also evaluated the accuracy (Congalton and Green, 2009). Appendix 3 contains a more detailed discussion of the buildings accuracy.

Building omission errors were of two types. First were data inconsistency omissions resulting from differing acquisition dates (lidar-2006; imagery-2008). This omission type was most often exemplified by buildings misclassified as water. This occurred because their height above ground was less than 10 feet since the building had not been built at the time lidar was acquired. All other omissions were labeled as “basic”. Forty-nine data inconsistency and nine basic omissions were observed. The provisional total omission error percentage was 4%.

Commission errors or “false buildings” numbered 75. These were mostly bits of tree canopy (50), boats (12), water slides (2), microwave tower (1), windmill (1), water tower (1) and unknown (8). The occurrence of commission errors increased in areas where buildings were nestled amongst trees, for example homes in wooded neighborhoods; and in marina areas where boats were occasionally misclassified as buildings. The provisional commission error was 5%. Overall the Buildings classification looked quite good, but it could be improved in the future by manual editing.

Roads: Early attempts to classify roads using imagery and elevation data alone resulted in significant amounts of non-road pavement, such as parking lots and driveways, being included in the Roads class. Repeated attempts to remove non-road features improved the classification, but overall it was still insufficiently accurate. Consequently, the rule set was modified to include proximity to Census road vectors as part of the road classification scheme.

To assess OBIA roads accuracy, the actual (true), omitted and false road segments were digitized on-screen in ArcGIS based on imagery, and their lengths were compared (Figure 13). Actual road length was 45,580 meters. OBIA classified road length was 44,532 meters; correctly classified OBIA road length was 43,674 meters; omitted road length was 1,906 meters and false road length was 858 meters. Therefore, provisional roads accuracy was 96%, omission error was 4% and commission error was 2%. In summary, the roads classification was quite good, but could be improved by using a more accurate road vector file.

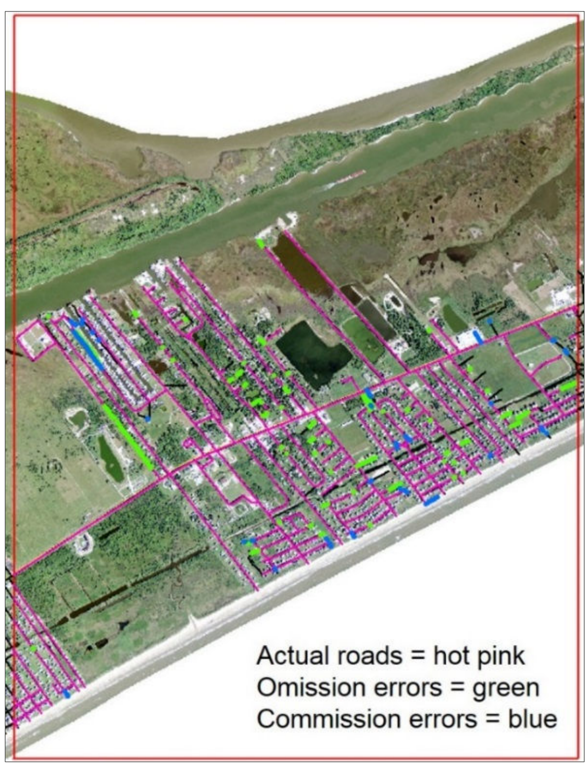

Figure 13: Digitized road segments within the accuracy assessment AOI.

Vegetation: Vegetation classes (trees, shrubs and low vegetation) were visually spot checked against imagery and lidar. Based on qualitative visual inspection, classification of vegetation in general looked good (Figure 14), as unclassified impervious surfaces and other objects types were nicely excluded. But subdivided low vegetation, shrub, and tree classes appeared less meaningful than anticipated. In particular, the height cutoff values appeared arbitrary. For example in the figure, notice that the tops of shrubs were classified as trees, while lower branches of trees were classified as shrubs. As discussed in the OBIA limitations section above, this a good example of how features on a continuum, in this case a height continuum, are more problematic for OBIA techniques.

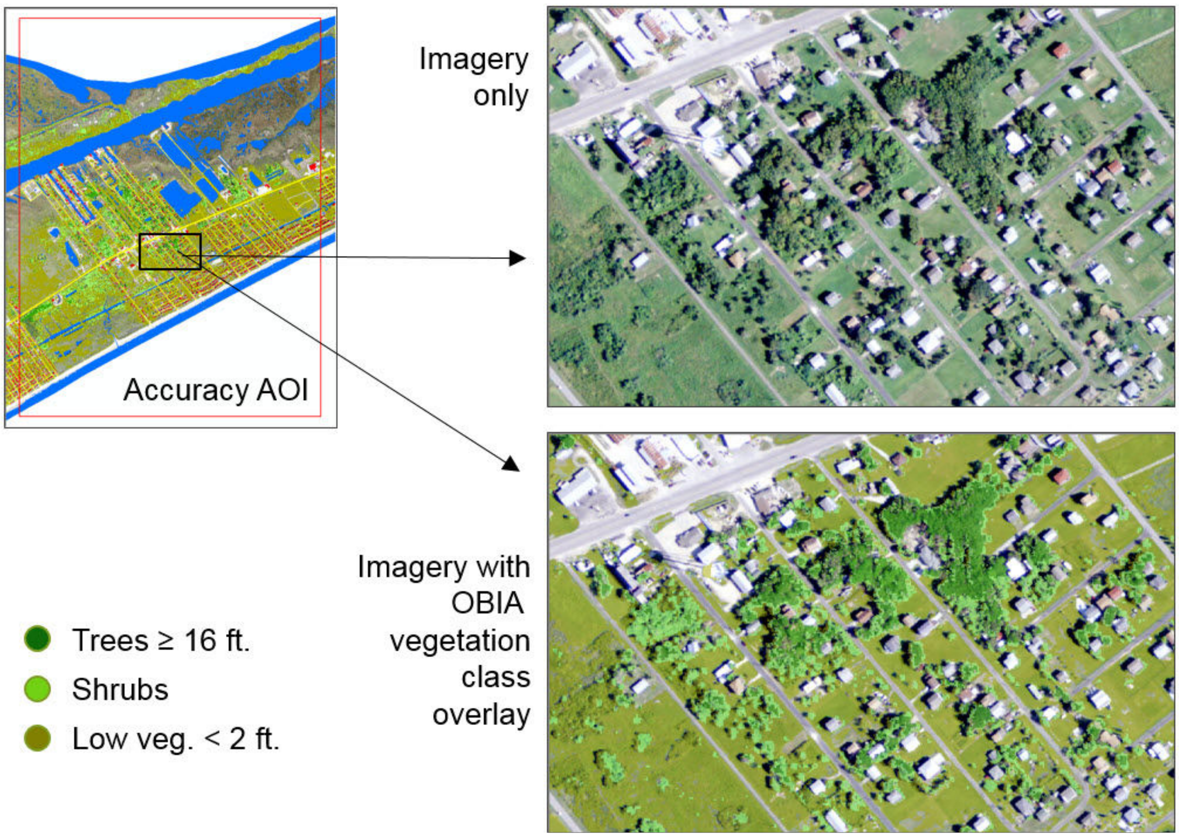

Figure 14 – Close-up view of the vegetation classifications.

Therefore, a more simplified classification scheme is suggested for the future that has lower and taller vegetation classes only. While vegetation remains on a height continuum, the logic is that grasses and other short vegetation are different than trees/shrubs for disaster purposes. Key stakeholders should be consulted to determine whether this scheme is appropriate and what cutoff value would best suit their needs.

2009 OBIA evaluation (post storm 1)

Turning to the 2009 OBIA evaluation. OBIA classifications overall were good (see Figure 15, with more detailed views in Appendix 4.). But to obtain these results, some of the 2008 classification strategies were altered due to extensive hurricane damage. For one example, roofs damaged by the storm were commonly covered by blue FEMA tarps. These tarps had a slightly positive NDVI signature that caused them to be misclassified as vegetation. New rules were added to properly classify them as buildings.

The 2009 classification was not quite as accurate as the 2008 one. Stripping of vegetation by the storm (note the exposed light colored sand across approximately ¾ of the length of the peninsula) reduced 2009 road accuracy relative to 2008. In 2008, roads that were abandoned or never developed were covered by vegetation and thus were not classified as roads. However, in 2009 the absence of vegetation allowed inactive roads to be included. Fortunately, by 2010, this problem was largely mitigated by vegetation regrowth. On the positive side for roads in 2009, tree/canopy loss reduced the amount of shaded roadway, which had previously diminished road accuracy in the 2008 data.

One other issue that diminished accuracy were the lidar voids (note orange rectangles). Within these areas, nine buildings were left unclassified and several clusters of shrubs and trees were misclassified as low vegetation. Water, roads, and true areas of low vegetation appeared accurate. In the future, boats misclassified as buildings can be removed from the Buildings class using contextual rules.

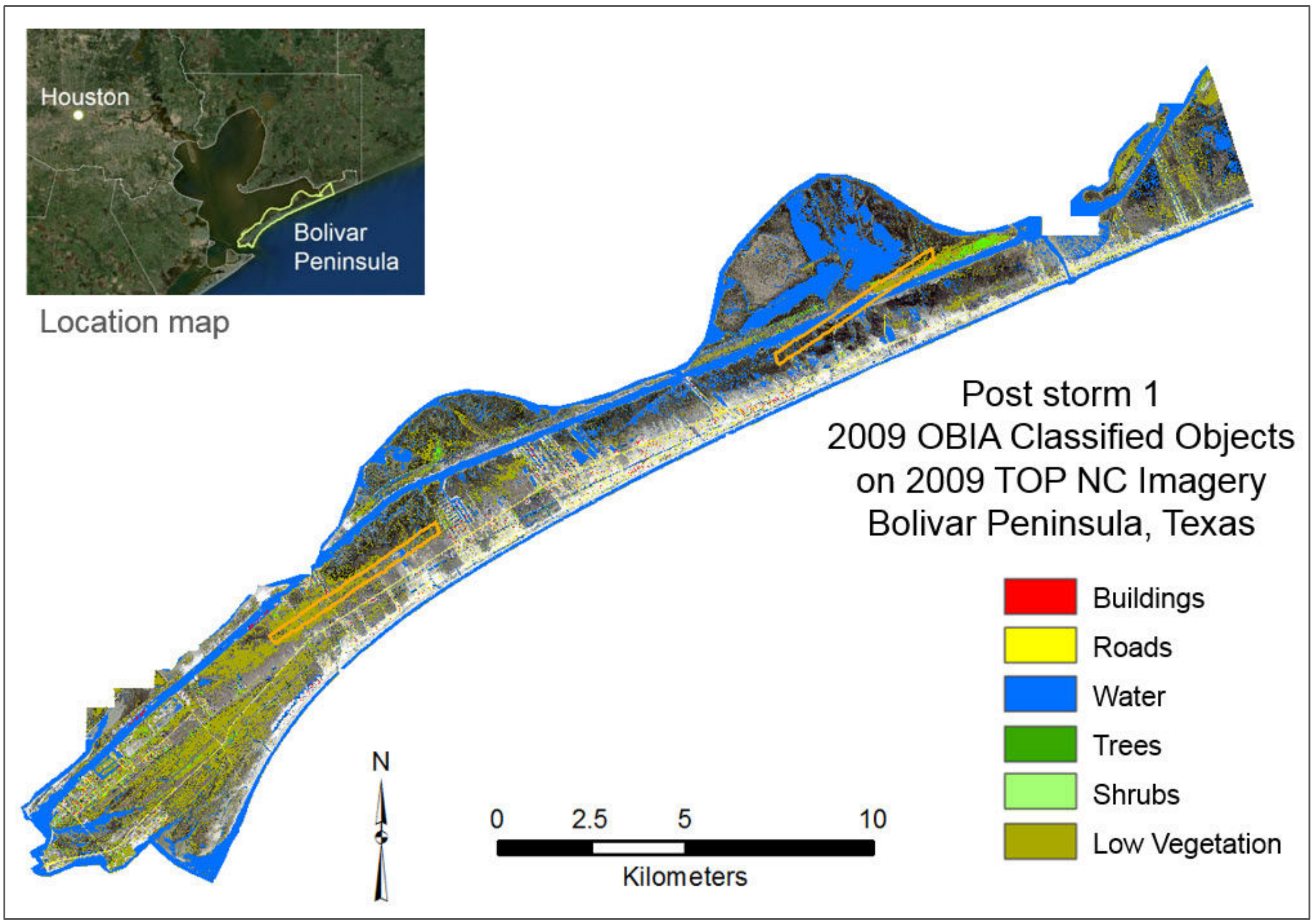

Figure 15: Post storm (2009) OBIA classified objects on 2009 TOP natural color imagery.

2010 OBIA evaluation (post storm 2)

Recall that that TNRIS recommended use of NAIP imagery for base map purposes. Since NAIP data are systematically acquired every few years across the United States, it was important to learn whether these data could be used as primary input for OBIA studies. Overall, the 2010 OBIA classifications looked reasonably good as can be seen in Figure 16 and in larger scale views in Appendix 5. However, marked spectral variations between image tiles and data inconsistencies made rule set development challenging.

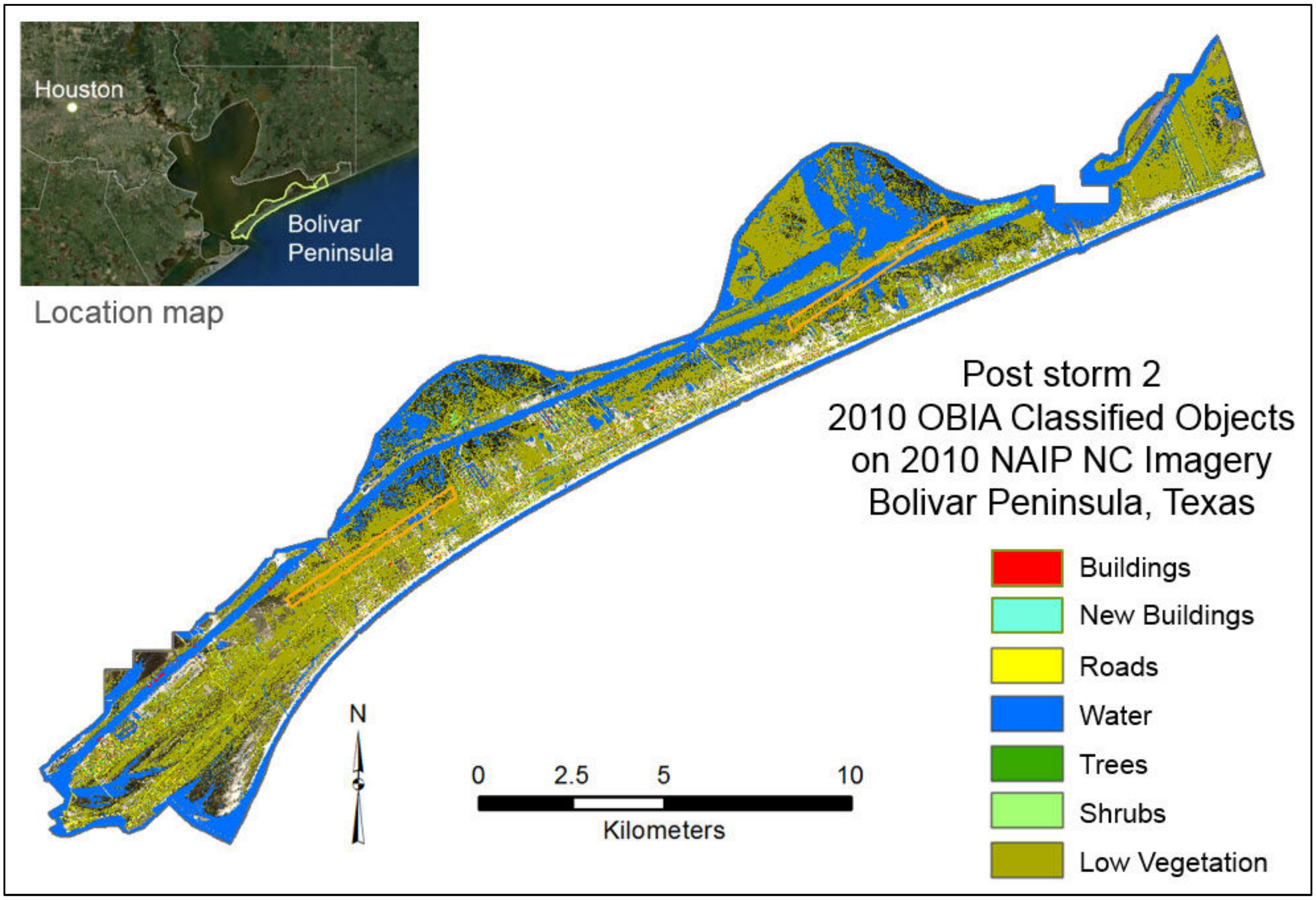

Figure 16: Post storm (2010) OBIA classified objects on 2010 NAIP natural color imagery.

These between-tile spectral variations were a particular issue for water, as bright sparkling water required different types of classification rules than darker water. Specifically, the more expansive NIR and brightness cutoffs required for bright water objects was paired with the requirement that that these objects also share borders with previously classified water. This is one example of how contextual algorithms give OBIA the edge over pixel-based approaches.

Data set inconsistency was also a consideration for the 2010 time period. Recall that the 2009 lidar point cloud was used in both 2009 and 2010. By 2010, this lidar was older by a year or more than the imagery; and during that time, rapid changes were underway. In regard to buildings, the older lidar documented building loss, while the newer imagery documented new construction. To address this disparity, an additional object type called “New Buildings” was created just for the final time period to distinguish “Buildings” - classified using both imagery and lidar, from new buildings based primarily on spectral properties and proximity to road vectors and building shadows.

Not surprisingly, the New Buildings class was less accurate and complete than the Buildings class that drew on elevation information. Nonetheless, this new class did provide a general understanding of the magnitude of the rebuilding effort and where these efforts were taking place (principally in beach front developments). Note new buildings (blue-green/teal) in Figure 16, Figure 18 and Appendix 5. As with 2009, misclassification of boats as buildings could be corrected by contextual rules relating to water.

Also observed were narrow bands of vegetation classification errors at the edges of some buildings. Differences in spatial accuracy, or perhaps spatial resolution between imagery and lidar, may have been responsible. The combination of positive NDVI from low vegetation in the imagery and elevated nDSM heights from buildings caused some building edges to be misclassified as trees or shrubs. Finally lidar data voids were again areas of lower confidence. Rule sets for all time periods are located in Appendix 6.

Rule Set Reuse

Two different reuse scenarios were tested. First, a rule set developed using small test areas was applied across a much larger geographic area. The whole area used the same base data sets. This reuse approach was successfully tested for all three time periods. Just to clarify, each period had its own suite of data and its own specific rule set that exploited that suite.

The other scenario was reuse between time periods. This was tested twice, first when the 2008 rule set was applied to 2009 data and second, when the 2009 rule set was applied to 2010 data. In both cases, the rule set was not useful when applied blindly to data from different time periods. An example is shown in Figure 17, which shows the blind application of the 2009 rule set on 2010 data.

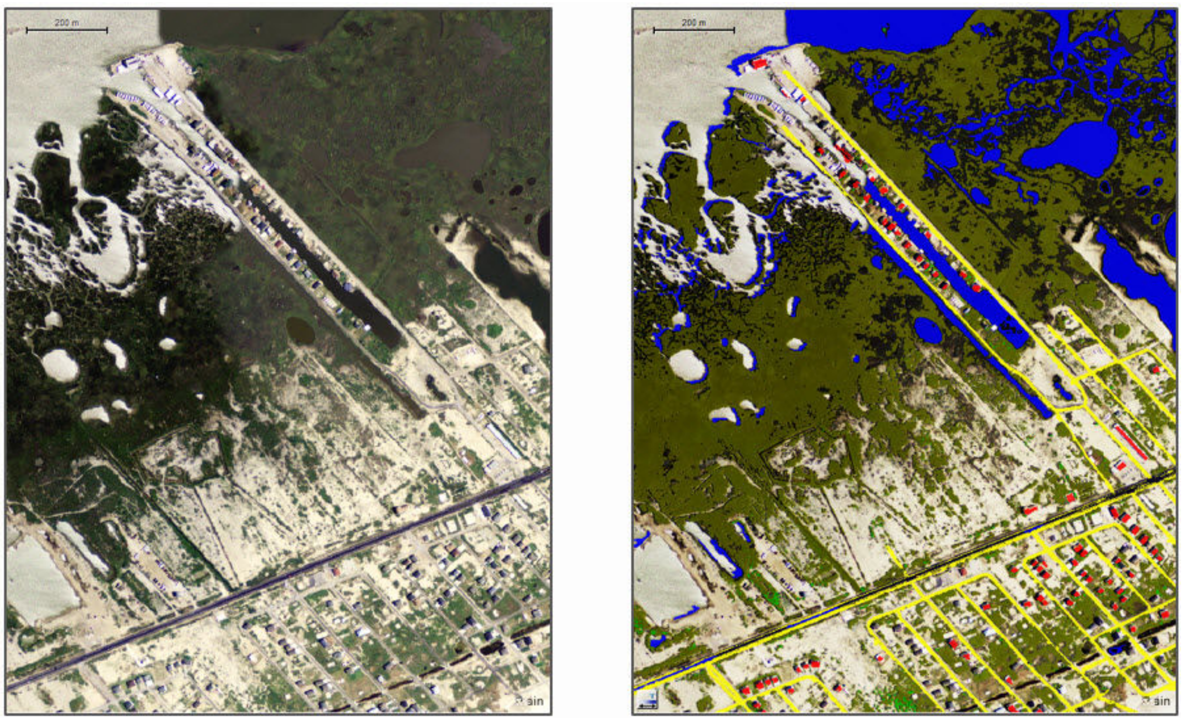

Figure 17: Close-up views - Imagery alone (left), imagery with OBIA overlay (right).

In the figure, notice that water and buildings were poorly classified, roads were fair and vegetation appeared good. Here, dramatic spectral differences between image tiles complicated the water classification. Buildings were omitted because of data inconsistencies between image and elevation data due to differing acquisition dates. As discussed above, new rules had to be added to solve these and other issues. Therefore, based on the results of this study, reuse of rule sets between time periods is not recommended.

Change Through Time

Final composited OBIA output from each time period was visually compared to output from other time periods. Figure 18 highlights the same set of beach-front communities for all three time periods.

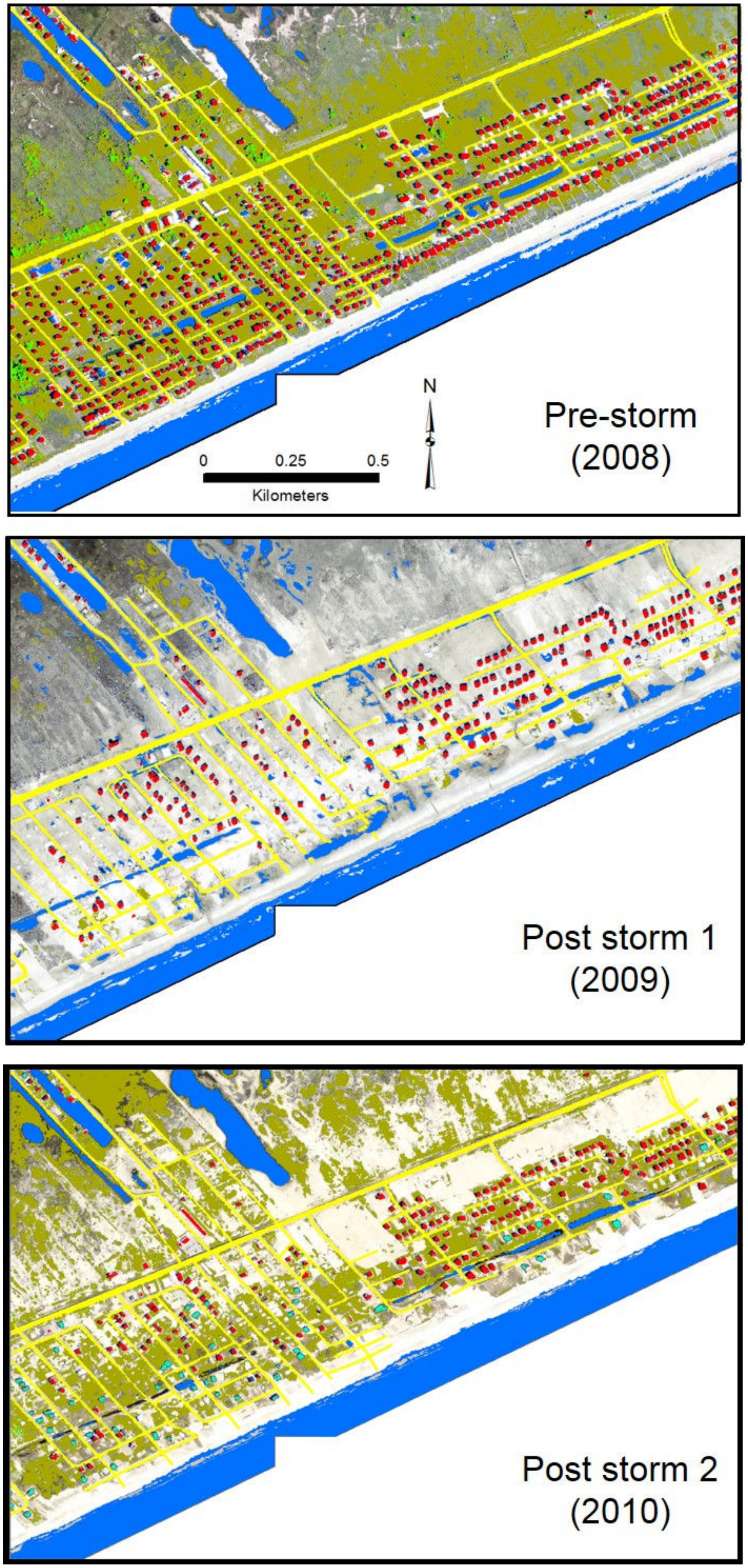

Figure 18: OBIA classifications overlaid on imagery for pre-storm 2008, and post-storm 2009 and 2010.

Prior to the storm, vegetation was widely distributed; many buildings were evident; and an array of water bodies and roads were clearly visible. By 2009, 4-7 months after Hurricane Ike, the picture had changed dramatically. Vegetation and sediment had been stripped from many areas by storm surge. This was particularly pronounced closer to the Gulf shore. In the back beach, scoured lows where sand and dunes had been eroded were now filled with water. In addition, many buildings present in 2008 were absent, particularly in communities west of center in this figure. Roads looked similar to 2008, but by this time, storm transported sand and debris similar to that shown in Figure 5 had already been cleared. However, the partly collapsed bridge along State Highway 87 was still not repaired (Figure 19).

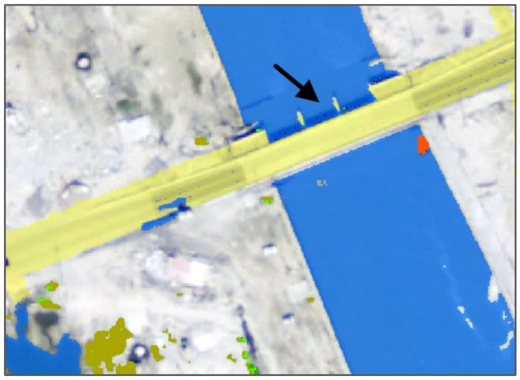

Figure 19: Partly collapsed bridge along State Highway 87 was still not repaired in the 2009 analysis.

By 2010, approximately a year and half after Ike, the picture had changed again. Vegetation was recovering, re-development was occurring (note blue-green/teal rectangles), and the beach had been restored. Again, the road network looked similar to previous time periods.

Reconstruction was not evenly distributed. Beach front developments in particular began active recovery, while other areas remained derelict or appeared abandoned altogether. Figure 20 shows an all but abandoned inland residential development as of January 2016, more than seven years after the disaster. In summary, clear evidence of change was observable between all time periods.

Figure 20: Photo shows part of an inland residential development, eastern Bolivar Peninsula, that remained all but abandoned more than seven years after Hurricane Ike. (Image credit: S. Zick; photo captured January 2016).

Discussion and Conclusions

Based on this case study, OBIA analysis of remotely sensed data appears to be a good tool to support disaster stakeholders, especially to plan for events and to monitor recovery. Because of the time required to develop rule sets, OBIA is probably not the best option for the earliest response stage.

Objects likely to be of interest to the disaster community were classified with a high degree of accuracy. Recall that rule sets alone were used for classification, with no manual editing. Clearly, appropriate manual editing would improve accuracies and are recommended if higher accuracies are needed.

Rule sets were reused successfully over a wide geographic region when the same base data were input. However reuse across time periods, using different data, was not successful. This was disappointing as reuse between periods would have made OBIA more practical for the shortened time frames inherent to disaster response.

Since the choice of OBIA objects is flexible as long as the size of the object is appropriate to the resolution of the data, and since expert knowledge is directly incorporated into the analysis, OBIA offers powerful advantages to the disaster community relative to more traditional pixel-based approaches. But the selection of appropriate objects, as well as key object properties and cutoffs, is critical to the process. This requires well trained analysts and a clear understanding of stakeholder needs.

Red, green, blue and near-infrared image bands, normalized digital elevation models (height above ground) and road vectors were utilized for this project. Classifications using NAIP imagery were reasonably good, but the higher quality TOP imagery resulted in superior object classification. For regions undergoing rapid change as these were, coincident acquisition of image and lidar data is highly recommended.

Finally, OBIA can document change through time. Both damage and recovery were clearly evident, which fostered additional questions. Why were some communities more badly damaged than others? Was this was due to differences in building construction, the height or shape of the protective dune line, focused storm intensity? Why was recovery progressing unevenly? Beach front communities were undergoing rapid re-development, while some of the inland developments were languishing. Perhaps this disparity was driven by economic factors or administrative ones, or perhaps something else entirely.

Potential Uses and Future work

So how specifically, can OBIA-derived objects offer value to disaster stakeholders? Beyond the displays already shown, OBIA objects can be used again and again in a GIS in combination with other types of data. For example, objects could be integrated with parcel or demographic data, with storm surge models, or with nesting bird populations. While potential uses are far too numerous to list exhaustively, Table 1 provides a partial listing of disaster applications where OBIA objects would be beneficial.

Table 1: Partial listing of disaster applications that could benefit from OBIA objects.

Disaster Preparation

- Documenting pre-disaster baseline conditions - built and natural environments
- Evacuation zone and route planning
- Site selection: emergency equipment/supply staging areas, emergency shelters, recovery centers.
- What-if scenario testing, e.g. storm surge flood modeling; impermeable surface mapping; economic forecasting.
- Understanding persons at risk: Demographics and composite social vulnerability

Disaster Response / Recovery / Mitigation

- Pre-disaster base maps for first responders
- Documenting disaster damage and damage patterns - structures, transportation, the natural environment.
- Researching causes for damage patterns, e.g. poor construction, location
- Needs assessments for housing and economic assistance
- Identifying areas for federally-financed buyouts
- Business recovery planning
- Understanding the impact to the tax base for government budget planning
- Planning for sustainable re-development
- Planning wetland / natural area restoration projects
- Monitoring the pace and places of recovery for social justice research
- Evaluating costs and benefits of protection structures, e.g. coastal storm barriers
- Developing best practices for disaster planning, mitigation and recovery

Work for the future:

1. Compare OBIA analyses from other hurricane-impacted areas, or areas impacted by different types of disasters, e.g. tornado, stream flood, landslide.
2. Evaluate OBIA techniques using very high resolution UAS imagery and lidar data.
3. Investigate the best methods to evaluate classification accuracy. Considerations are likely to be the size of individual objects and the percentage of the total area that each object type occupies. Rare or uncommonly small objects may require different approaches than very large individual objects (like merged ocean water) or object classes that cover a lot of territory.

To summarize, project results provided strong support for OBIA in disaster analysis. OBIA classified objects were highly detailed and of good accuracy. Rule set reuse proved successful using the same data across a larger area, but was not effective with data from different time periods. OBIA was capable of documenting change through time.

Acknowledgements

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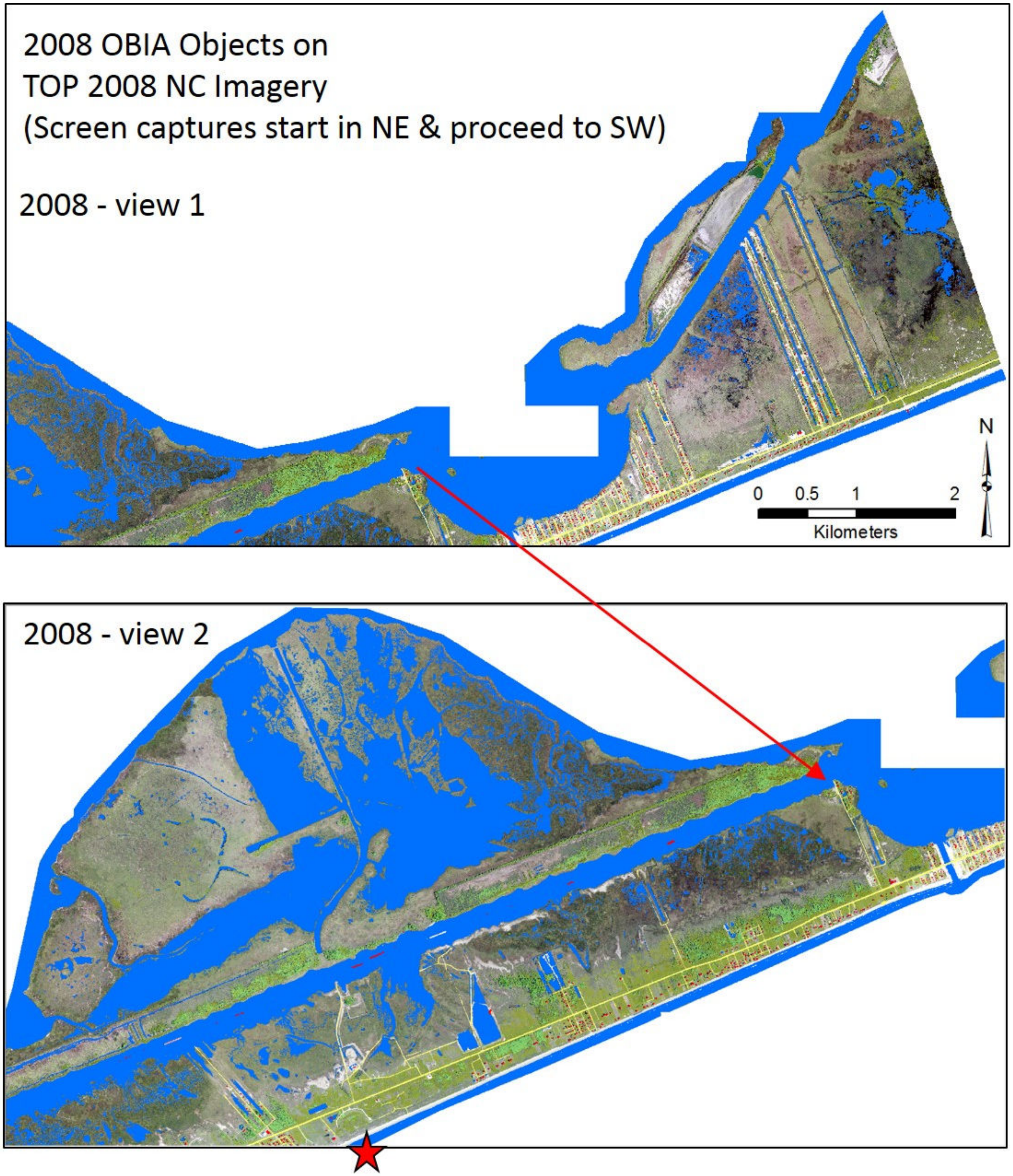
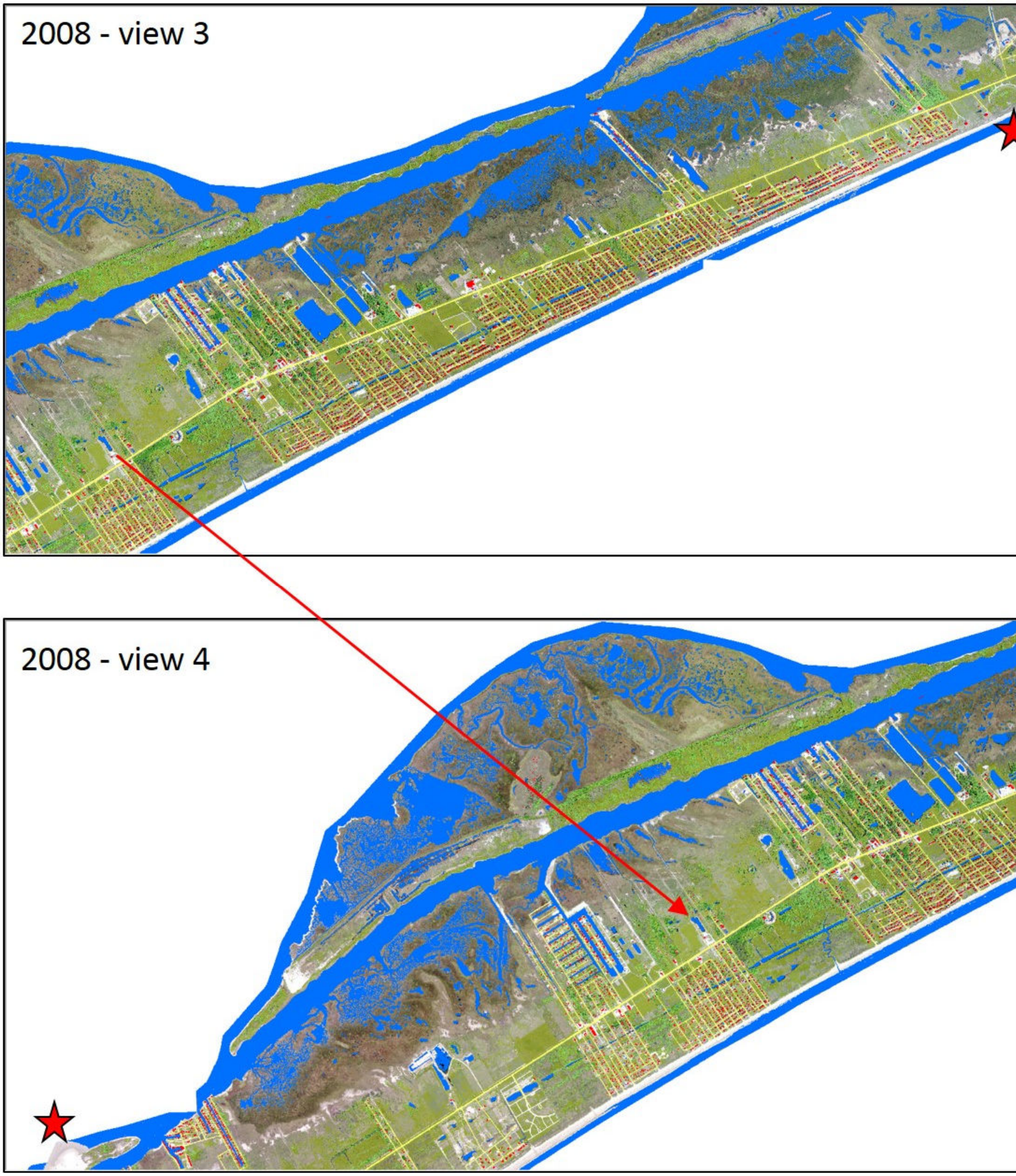
Appendix 1: Summarized metadata for project.

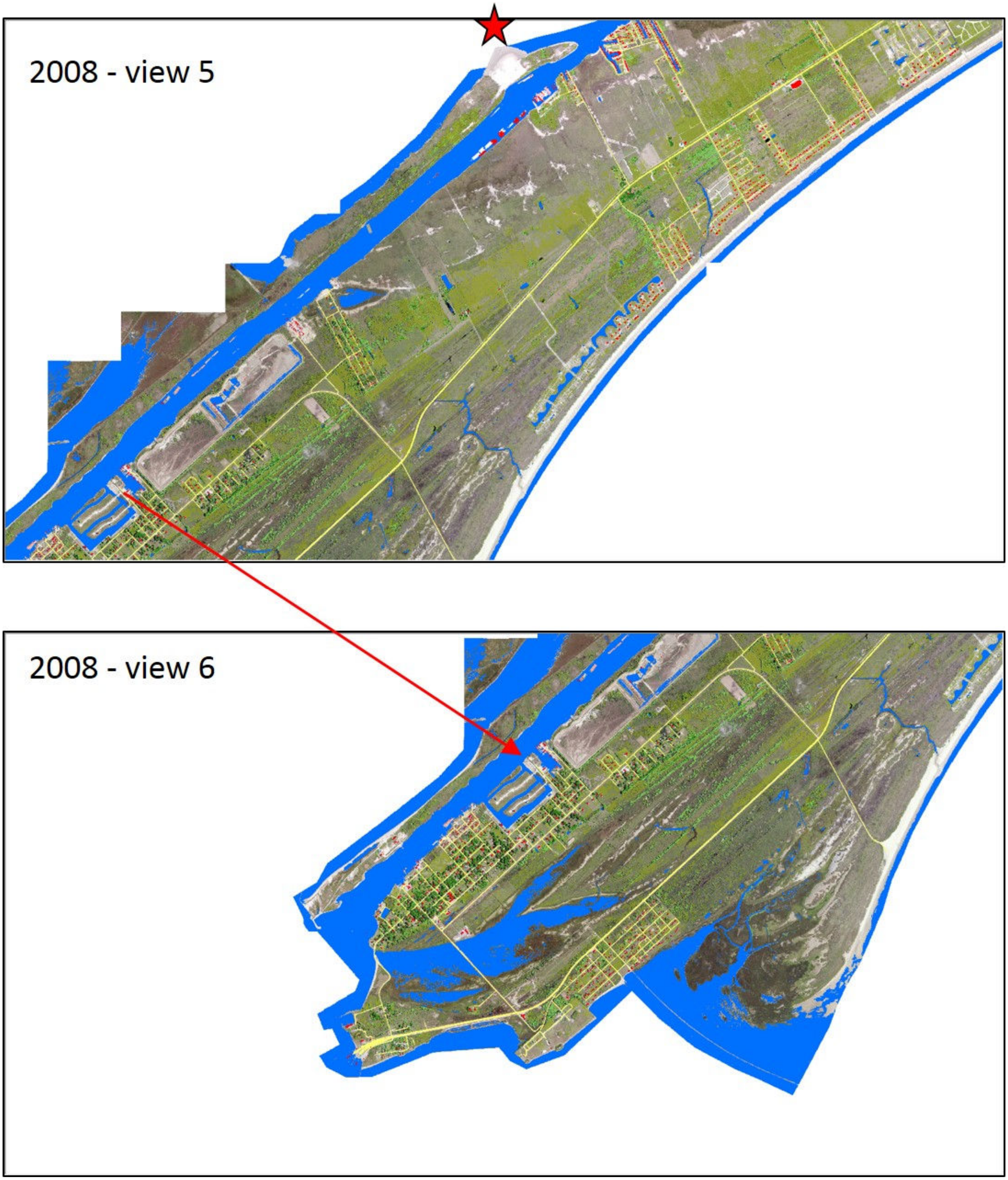
Data Set Name / Format	Coordinate System	Date of Coverage / Creation (Year or Range)	Scale (1:x or cell size) or Resolution	Description (What each provides for analysis)
2006 Texas Water Development Board (TWDB) Lidar: Galveston Co. (Elevation Point Cloud) **Platform:** Fixed wing aircraft **Source:** NOAA Digital Coast **Format:** LAS	**Horizontal Datum:** NAD83 **Projection:** State Plane 1983, Zone: Zone 4204 Texas South Central **Units** = U.S. feet **Vertical Datum:** NAVD88 **Units:** feet	**Collected By:** Sanborn Mapping Co. **Acknowledgement:** Texas Natural Resources Information system **Collection:** Sept. 1-30, 2006 **Publication Date:** Aug. 2007	**Nominal point spacing:** 1.4m (NOAA rpt.: 1.5-2 m.) **Est. horiz. accuracy:** 1m **Est. vert. accuracy:** RMSE 18.5 cm (open, bare terrain)	Extracted from larger data set. Data acquired using a LH Systems ALS 50 Light Detection And Ranging (LiDAR) system. Multiple returns and intensity. Lidar classifications included: Unclassified and Ground.
2009 U.S. Army Corps of Engineers (USACE) Topobathy Lidar: Post Hurricanes Gustav and Ike (Elevation Point Cloud) **Platform:** Fixed wing aircraft **Source:** NOAA Digital Coast **Format:** LAS	**Horizontal Datum:** NAD83 **Projection:** State Plane 1983, Zone: Zone 4204 Texas South Central **Units** = U.S. feet **Vertical Datum:** NAVD88 **Units:** feet	**Collected By:** 3001 International Inc. **Collection:** Feb. 3 - April 23, 2009 **Processing:** May 2009; Aug. 2011; May, 2014	**Nominal point spacing:** 0.67 m **Flown for max. final post spacing:** 1.5 points/m **Horiz. Accuracy:** RMSE = 1m **Vert. accuracy:** RMSE = 0.15m	Multiple discrete returns per pulse and intensity. Data were tide controlled and were classified as: 1 - Unclassified, 2 - Ground, 3 - Low Vegetation, 4 - Medium Vegetation, 5 -High Vegetation, 6 - Buildings, 7 - Low Point (Noise), and 9 - Water.
2008/2009 Texas Orthoimagery Program (TOP) **Platform:** Fixed wing aircraft **Source:** TNRIS **Raster Format:** JPEG2000	**Horizontal Datum:** NAD83 **Projection:** UTM zone 15 N **Units** = meters	**Collection:** Leaf-on: May or Sept. 2008 Leaf-off: Jan. 2009	**GSD:** 0.5 m **Horiz. accuracy:** within 3-5 m or better	Natural color & color infrared images collected with a Leica ADS40 SH52 digital camera. **Natural color:** Band 1 = Red; Band 2 = Green; Band 3 = Blue. **Color infrared:** Band 1 = Near infrared; Band 2 = Red; Band 3 = Green.
2010 NAIP 1m 4-Band Imagery **Platform:** Fixed wing aircraft **Source:** TNRIS **Raster Format:** JPEG2000	**Horizontal Datum:** NAD83 **Projection:** UTM zone 15 N **Units** = meters	**Collection:** April, 2010. **Published:** Aug. 30, 2010.	**Nominal GSD:** 1 m **Pixel size** = 1 m x 1 m **Horiz. accuracy:** +/- 6 m true ground.	Four-band imagery (R, G, B, NIR) collected using a Leica ADS80 digital sensor. Imagery was orthorectified, radiometrically balanced, mosaicked, and inspected. (TNRIS - Only color balanced with 3 of 4 bands. Recommended for base map purposes.)
2007 TIGER/Line Shapefiles for Galveston Co. **Source:** U.S. Census Bureau **Format:** Shapefile	**Geographic:** GCS_North_American_1983 **Datum:** D_North_American_1983 **Spheroid:** GRS_1980	**Status:** All legal boundaries and names are as of January 1, 2007. **Released:** March 31, 2008.	Random testing of road line intersections are in compliance with Federal Spatial Data requirements.	All data for Galveston Co. , e.g. roads, inland hydrography. This was 1st release of TIGER spatial data from modernized Census Bureau's MAF/TIGER database in shapefile format.
2008 TIGER/Line Shapefiles for Galveston Co. **Source:** U.S. Census Bureau **Format:** Shapefile	**Geographic:** GCS_North_American_1983 **Datum:** D_North_American_1983 **Spheroid:** GRS_1980	**Status:** All legal boundaries and names are as of January 1, 2008 **Released:** Dec. 8, 2008.	Random testing of road line intersections are in compliance with Federal Spatial Data requirements.	All data for Galveston Co. including roads. Roads looked identical to the 2007 version.
2009 TIGER/Line Shapefiles for Galveston Co. **Source:** U.S. Census Bureau **Format:** Shapefile	**Geographic:** GCS_North_American_1983 **Datum:** D_North_American_1983 **Spheroid:** GRS_1980	**Status:** All legal boundaries and names are as of January 1, 2009. **Released:** Oct. 1, 2009.	Random testing of road line intersections are in compliance with Federal Spatial Data requirements.	All data for Galveston Co. including roads. Roads looked identical to the 2007 version.
USGS National Hydrography Dataset Best Resolution HU8-12040202 **Source:** USGS **Format:** Shapefile	**Geographic:** GCS_North_American_1983 **Datum:** D_North_American_1983 **Spheroid:** GRS_1980	**Start Date:** May 2, 2003 **End Date:** Jan. 29, 2016 **Released:** Feb. 22, 2016	High resolution at the 1:24,00/1:12,000 scale.	National Hydrography Dataset (NHD) is a database that includes stream segments or reaches nation's surface water drainage system, also waterbodies and approximate shorelines.

Appendix 2: 2008 OBIA classifications - Larger scale view



Arrows link the same area on the same page
Stars link the same area on adjacent pages


2008 - view 3
2008 - view 4


2008 - view 5
2008 - view 6

Appendix 3: 2008 Accuracy Assessment for Buildings

To determine the accuracy of building classifications, the accuracy AOI was subdivided into smaller regions (Figure 21). Then each building visible in the imagery was compared to the OBIA classified building objects, and discrepancies or comments were documented. Omitted buildings were compared to the nDSM to determine if they were new, too short to meet the 10-foot height cutoff, or basic omissions. Commission errors (false buildings) were labelled. The accuracy summary table for all regions is shown in Table 2 and the marked buildings assessment for each region follow.

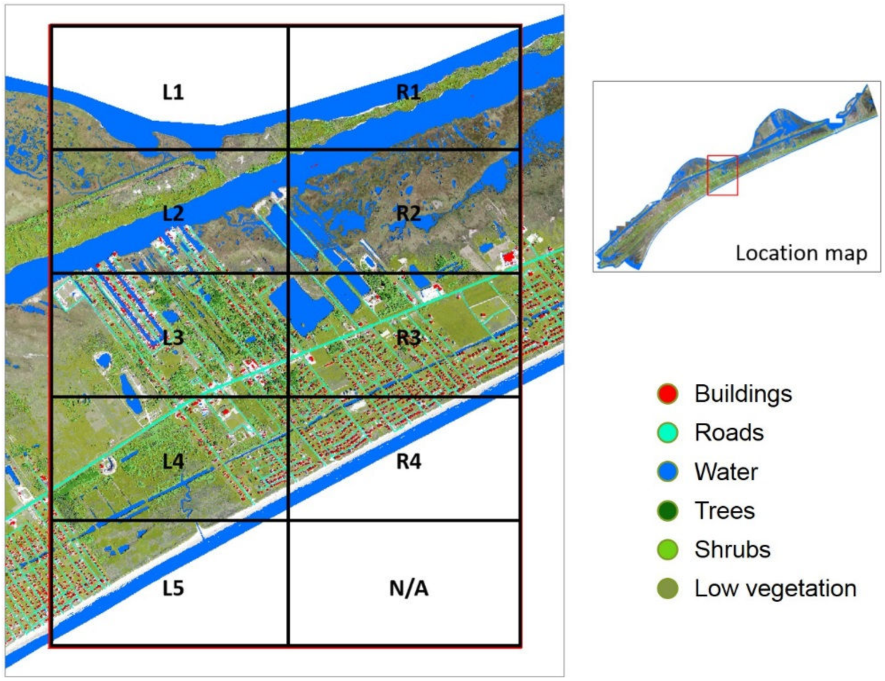
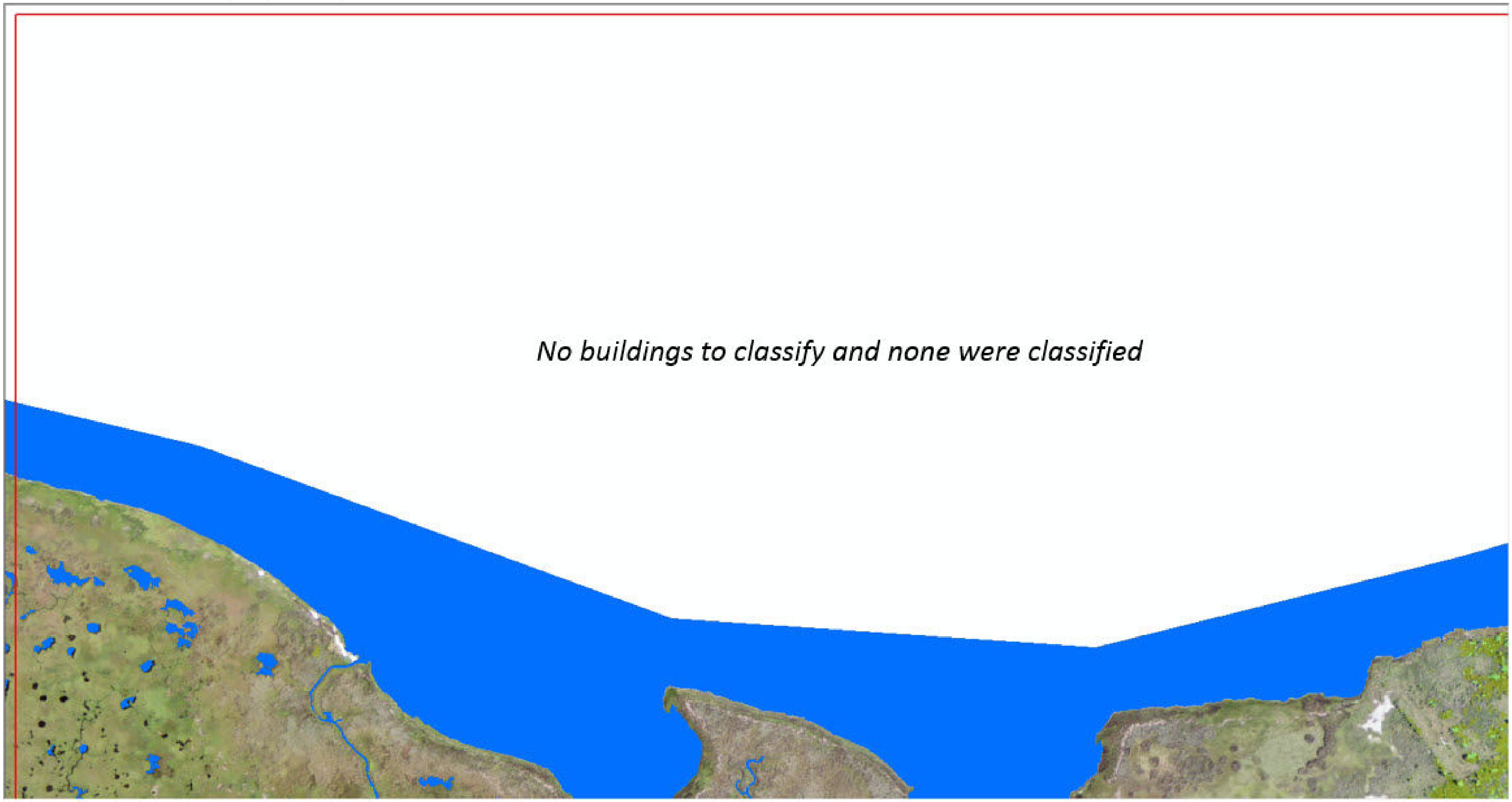


Figure 21 – Index map showing the nine regions examined at greater detail.

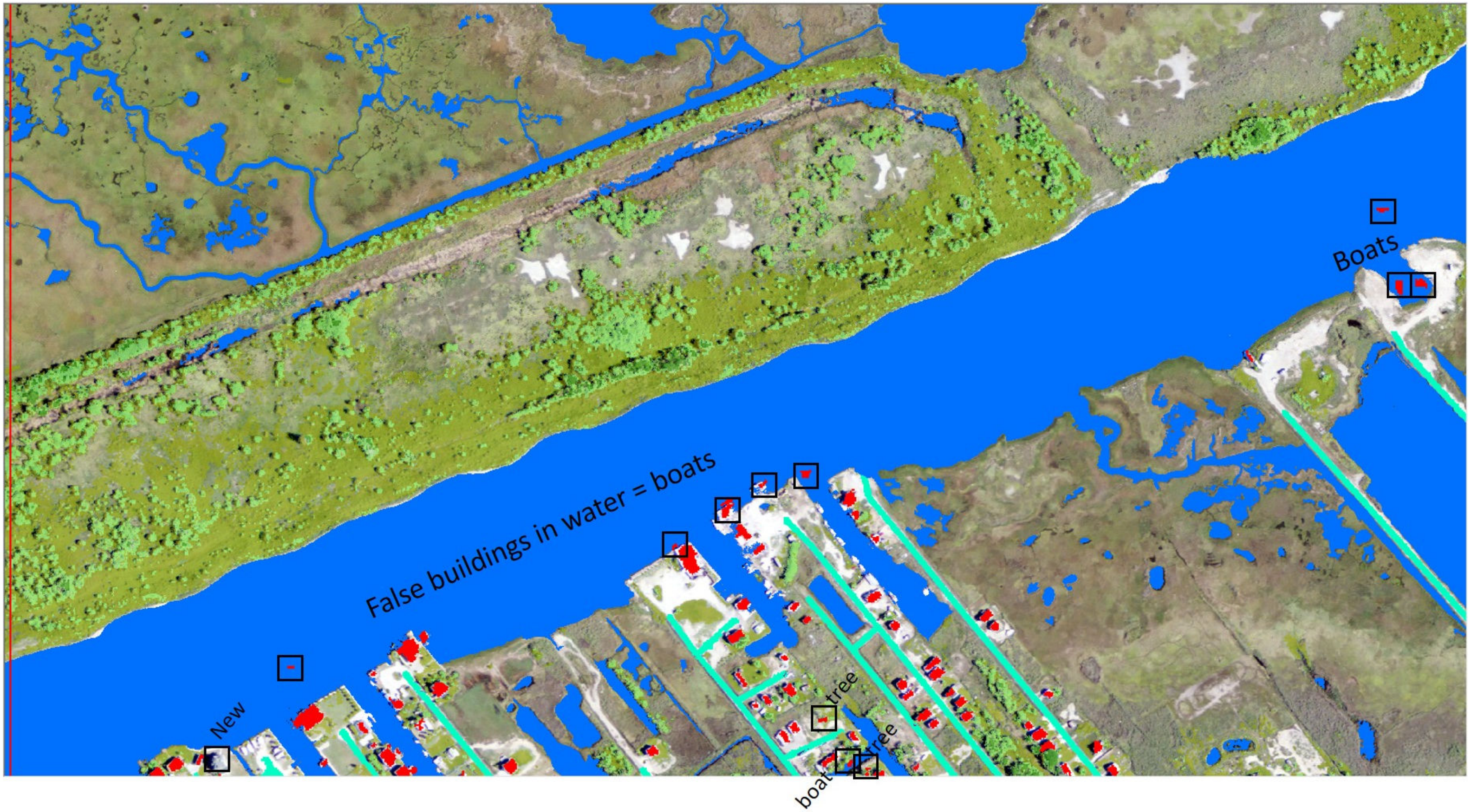
Table 2: Buildings accuracy table listed by region and totaled by accuracy category.

		Buildings Classification Accuracy					
				Omission Errors		Commision Errors	
	Reference buildings	Total OBIA classified buildings	Correctly classified	Data inconsistency	Basic omission	False buildings	False building types
2008: L1	0	0	0	0	0	0	
2008: L2	61	71	60	1	0	11	9 boats; 2 tree canopy
2008: L3	351	370	331	15	5	39	32 tree canopy; 1 microwave tower; 1 windmill; 1 water tower; 4 unknown
2008: L4	165	169	161	3	1	8	6 tree canopy; 2 water slides
2008: L5	155	150	146	8	1	4	2 tree canopy; 2 unknown
2008: R1	0	2	0	0	0	2	2 boats
2008: R2	5	9	5	0	0	4	3 tree canopy; 1 boat
2008: R3	437	423	419	16	2	4	4 tree canopy
2008: R4	272	269	266	6	0	3	2 unknowns; 1 tree canopy
Totals	**1446**	**1463**	**1388**	**49**	**9**	**75**	

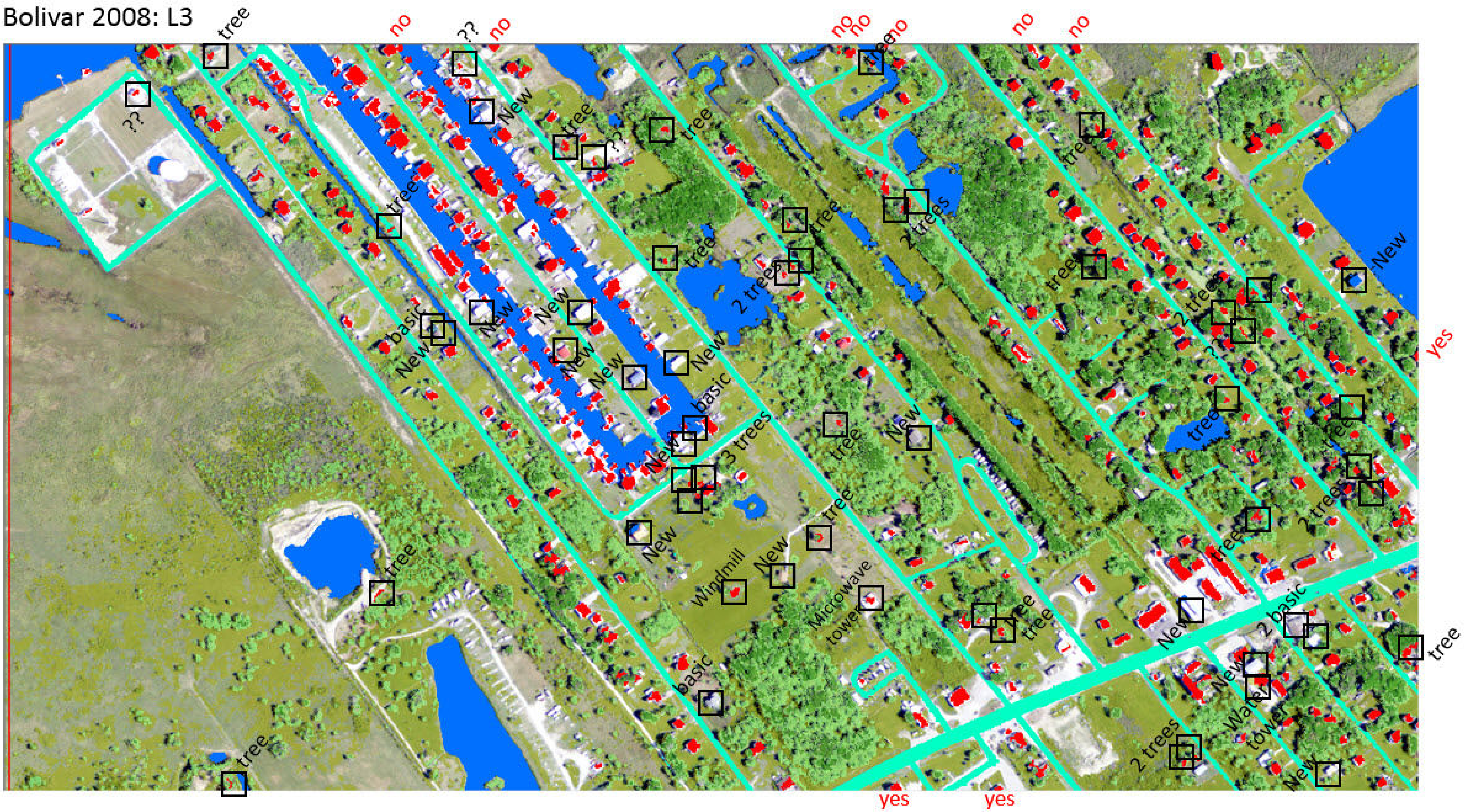
Bolivar 2008: L1 (Top Left)



Bolivar 2008: L2



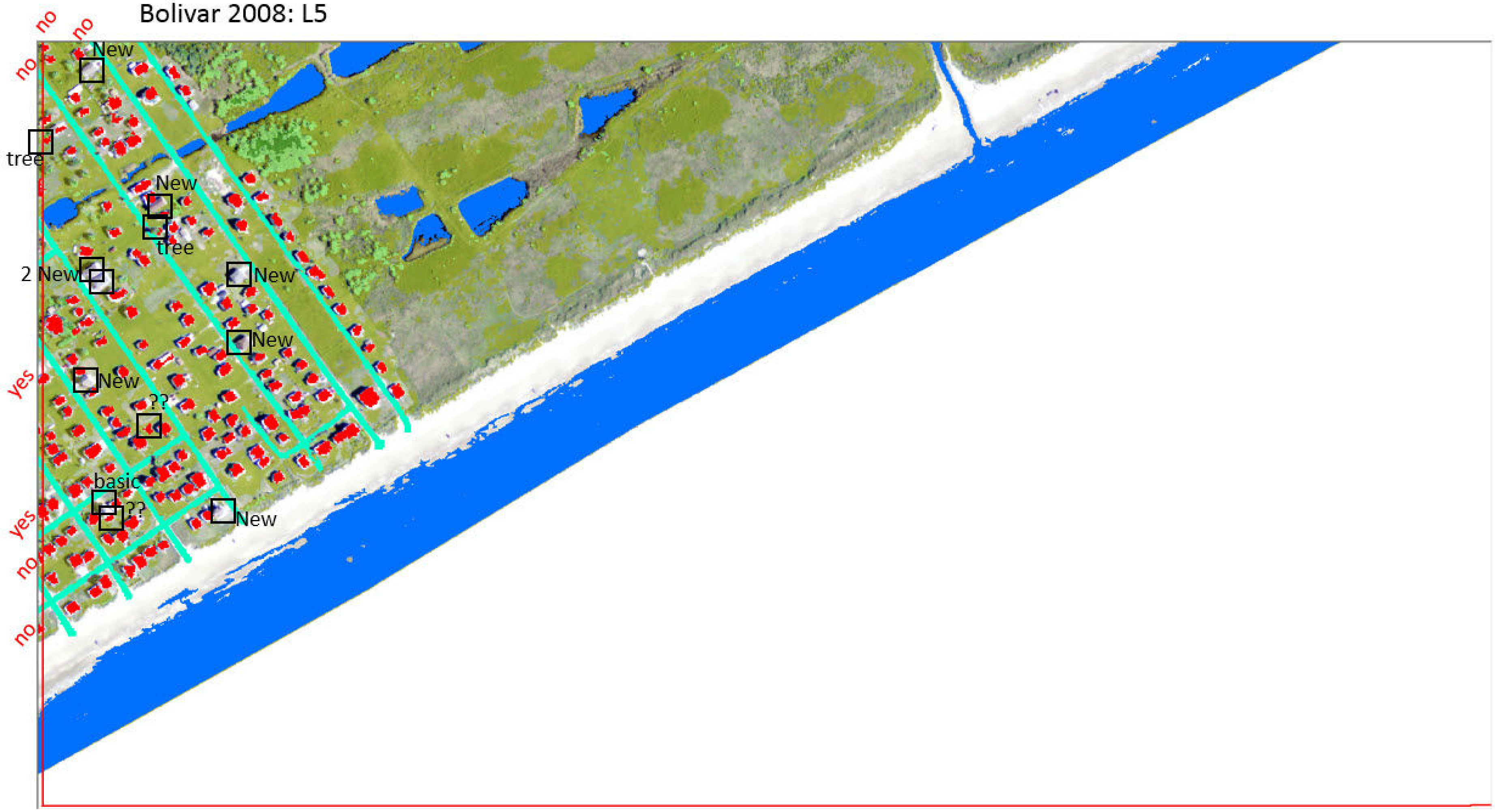
Bolivar 2008: L3



Note: No and yes refers to whether a building was counted on this view (yes) or on an adjacent view. These images overlapped slightly.

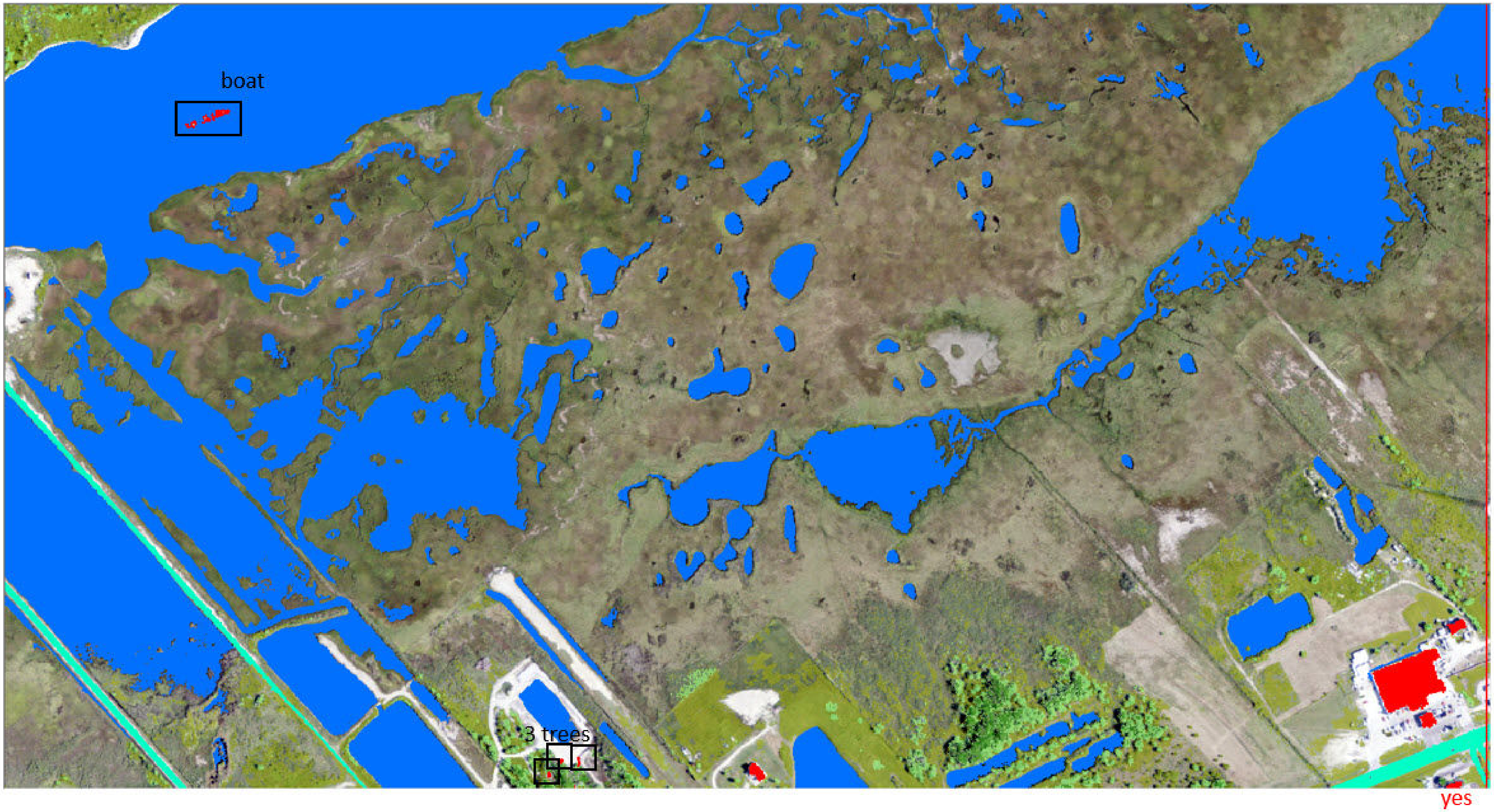
Bolivar 2008: L4

Bolivar 2008: L5



Bolivar 2008: R1 (Top Right)

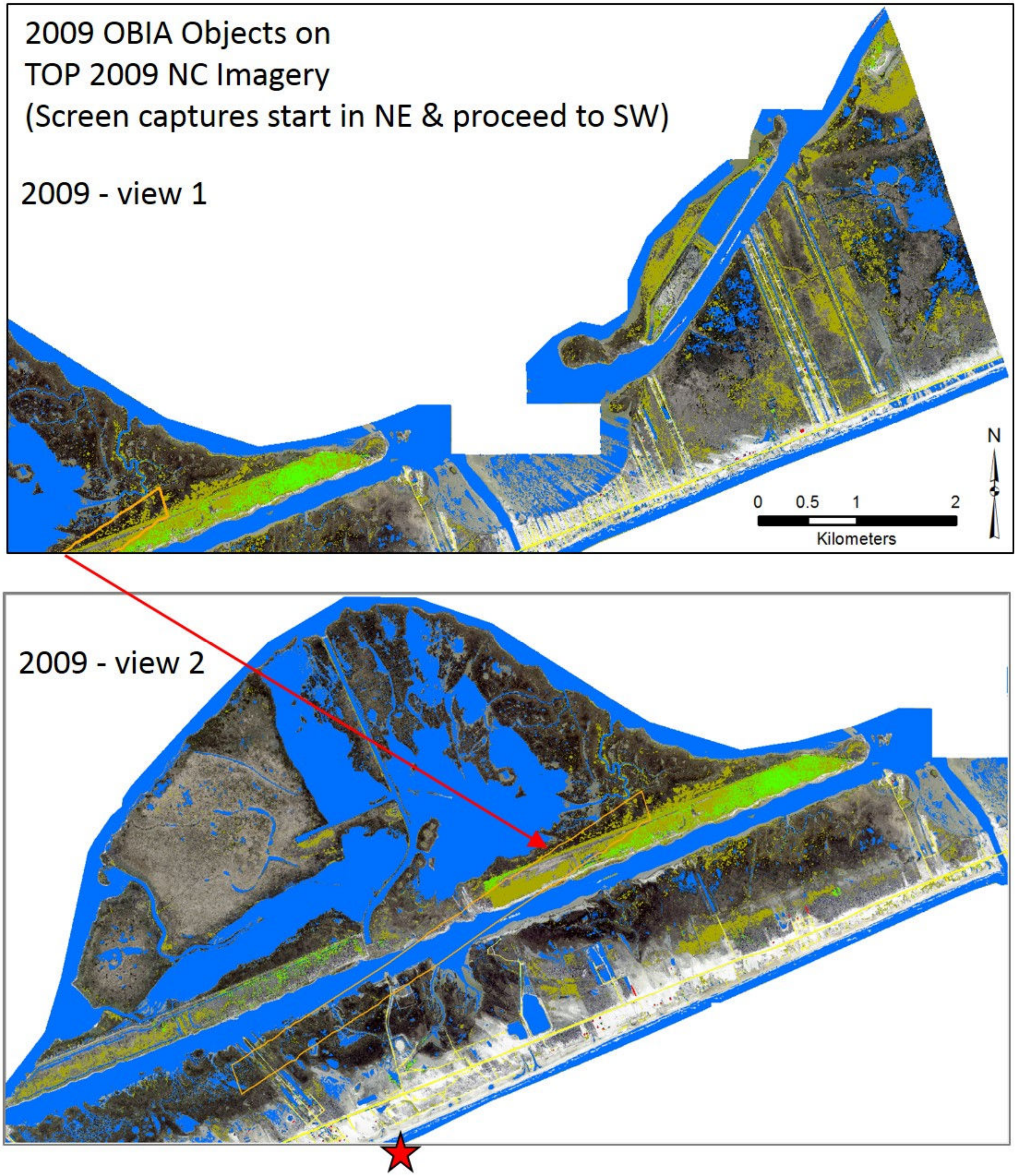
Bolivar 2008: R2



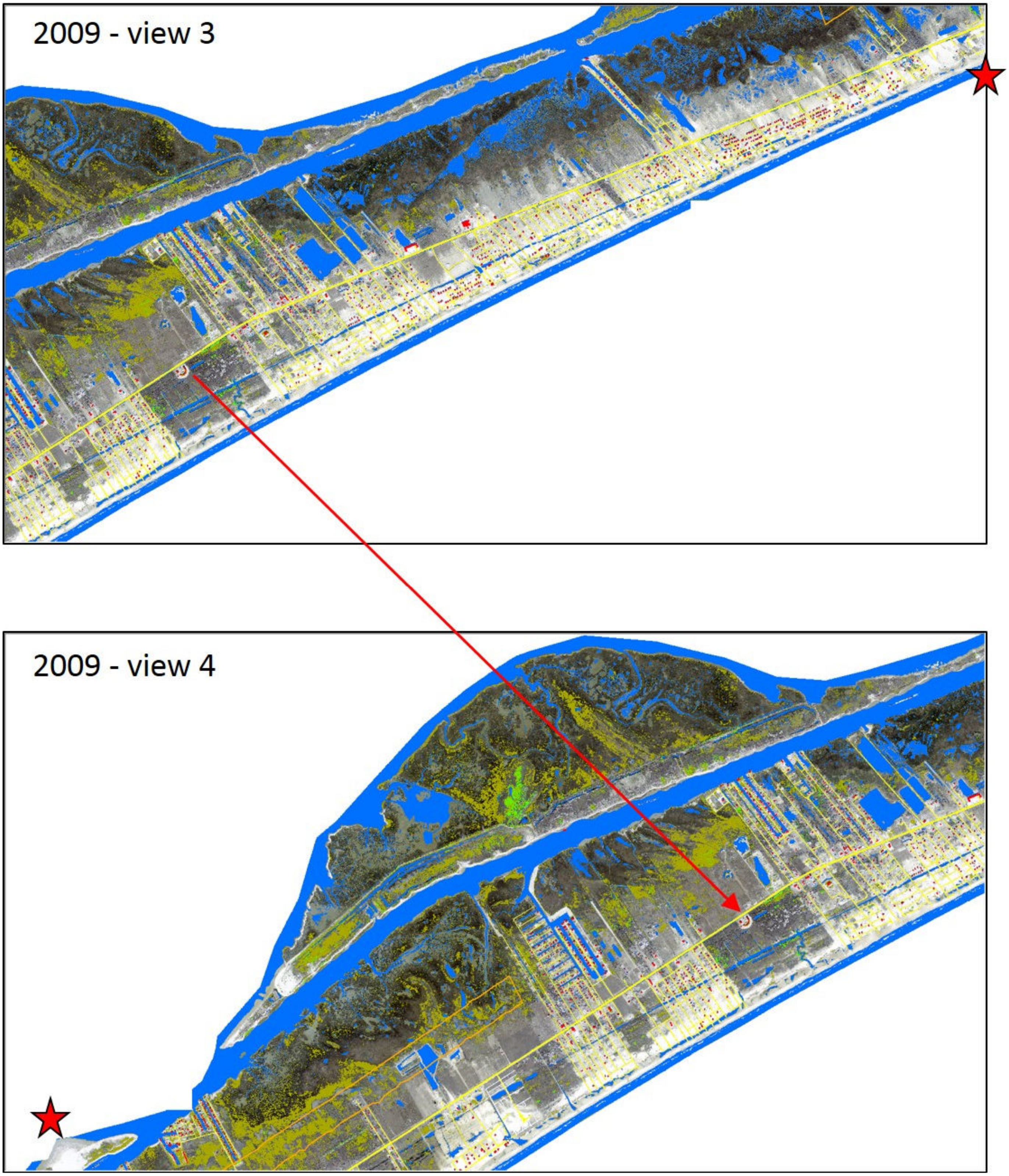
Bolivar 2008: R3

Bolivar 2008: Central 1: (R4)

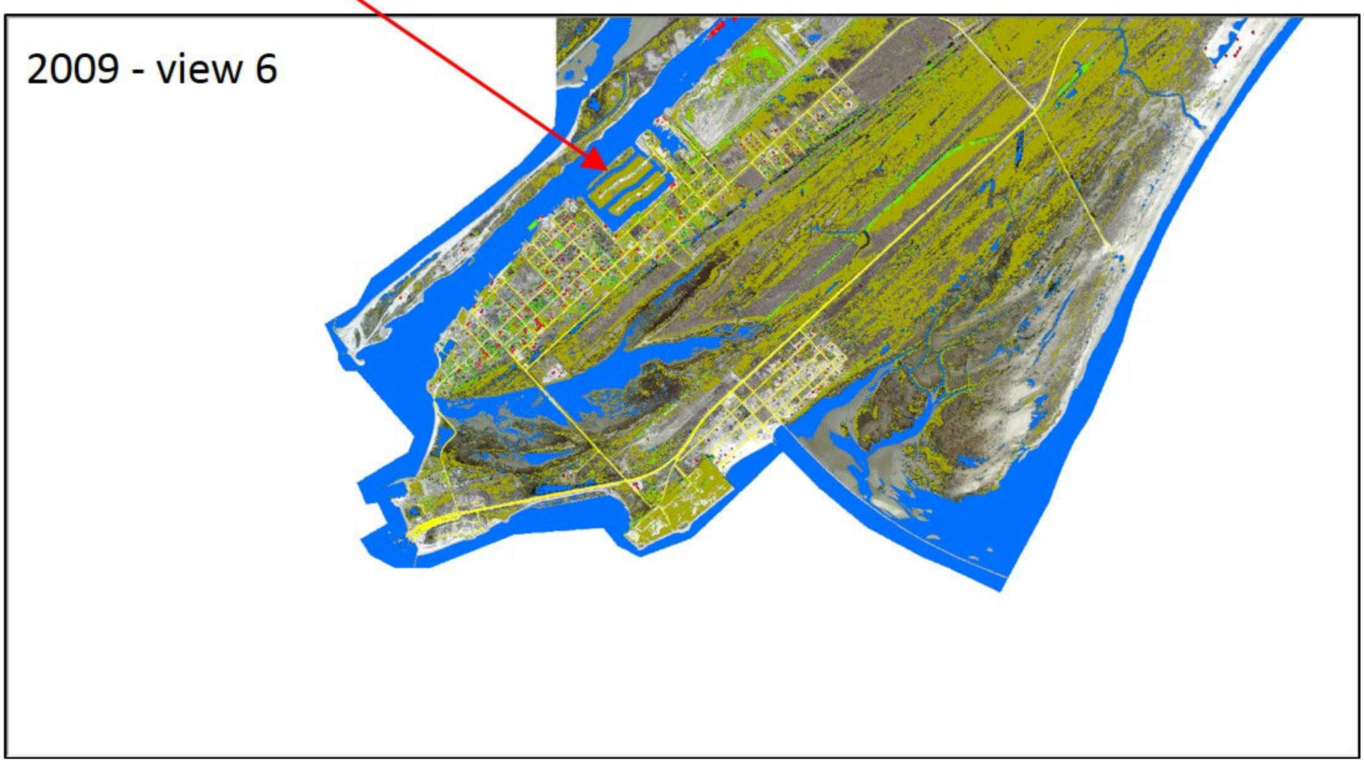
Appendix 4: 2009 OBIA Classifications – Closer views



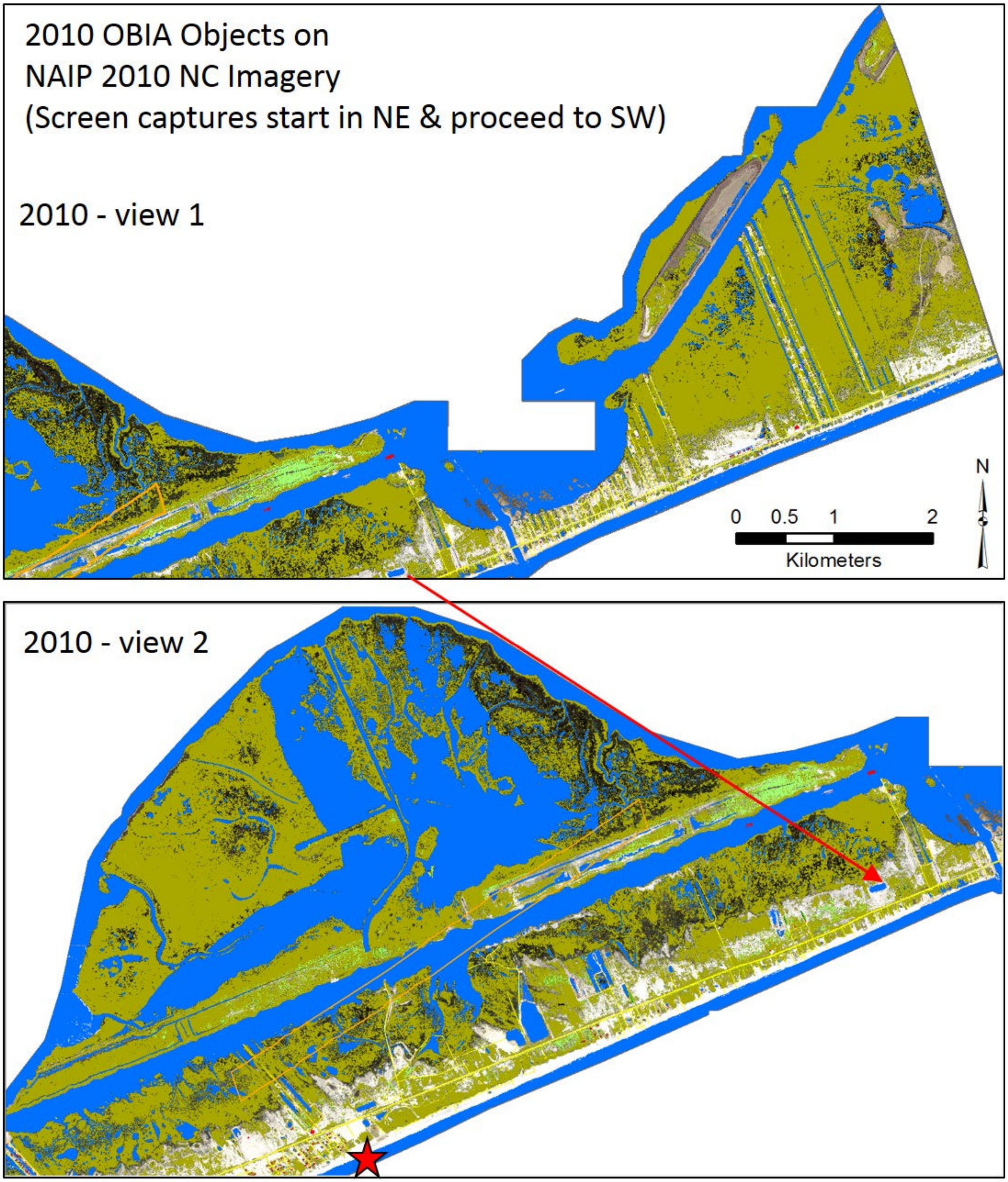
Arrows link the same area on the same page
Stars link the same area on adjacent pages


2009 - view 3
2009 - view 4


2009 - view 5

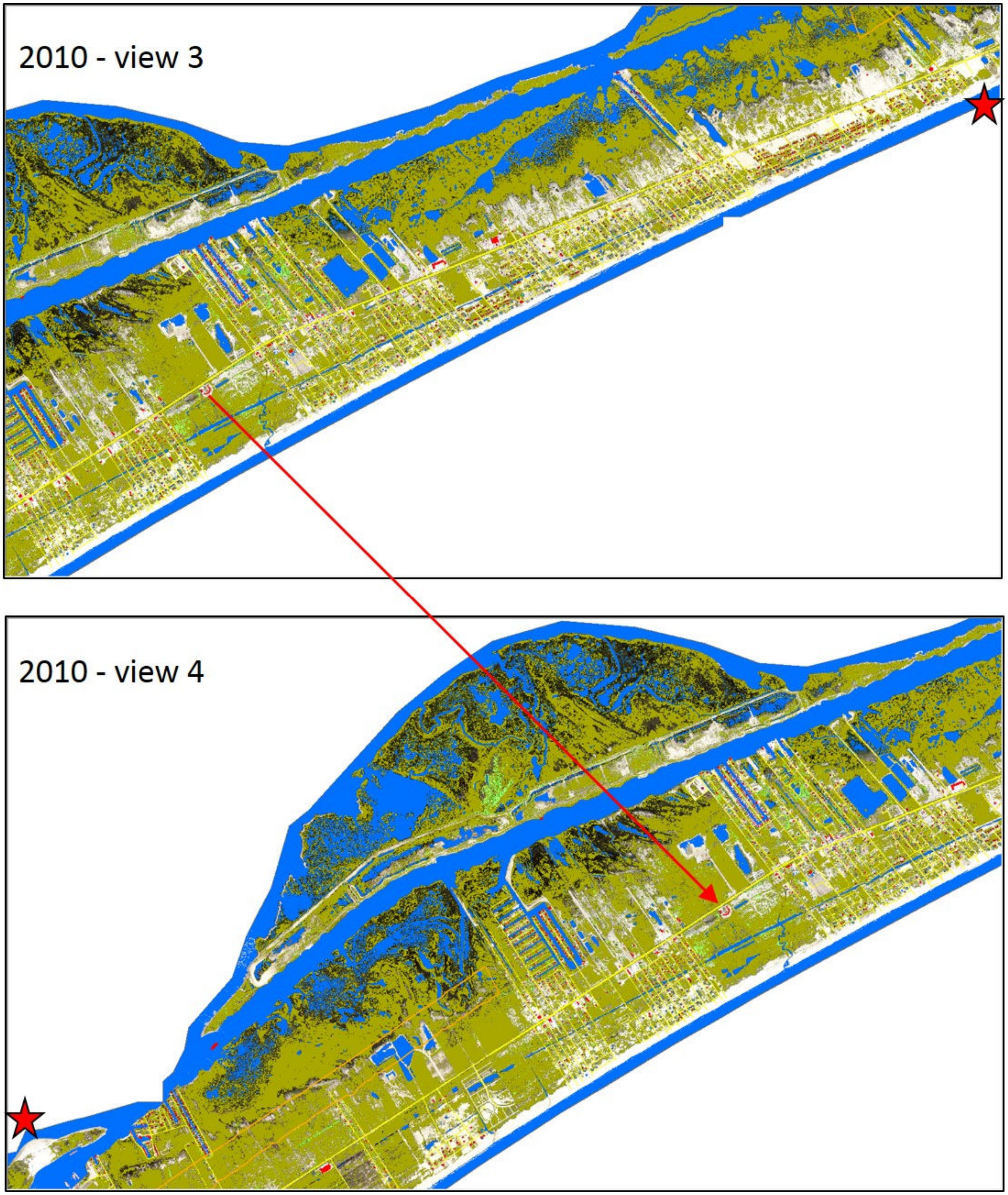

2009 - view 6

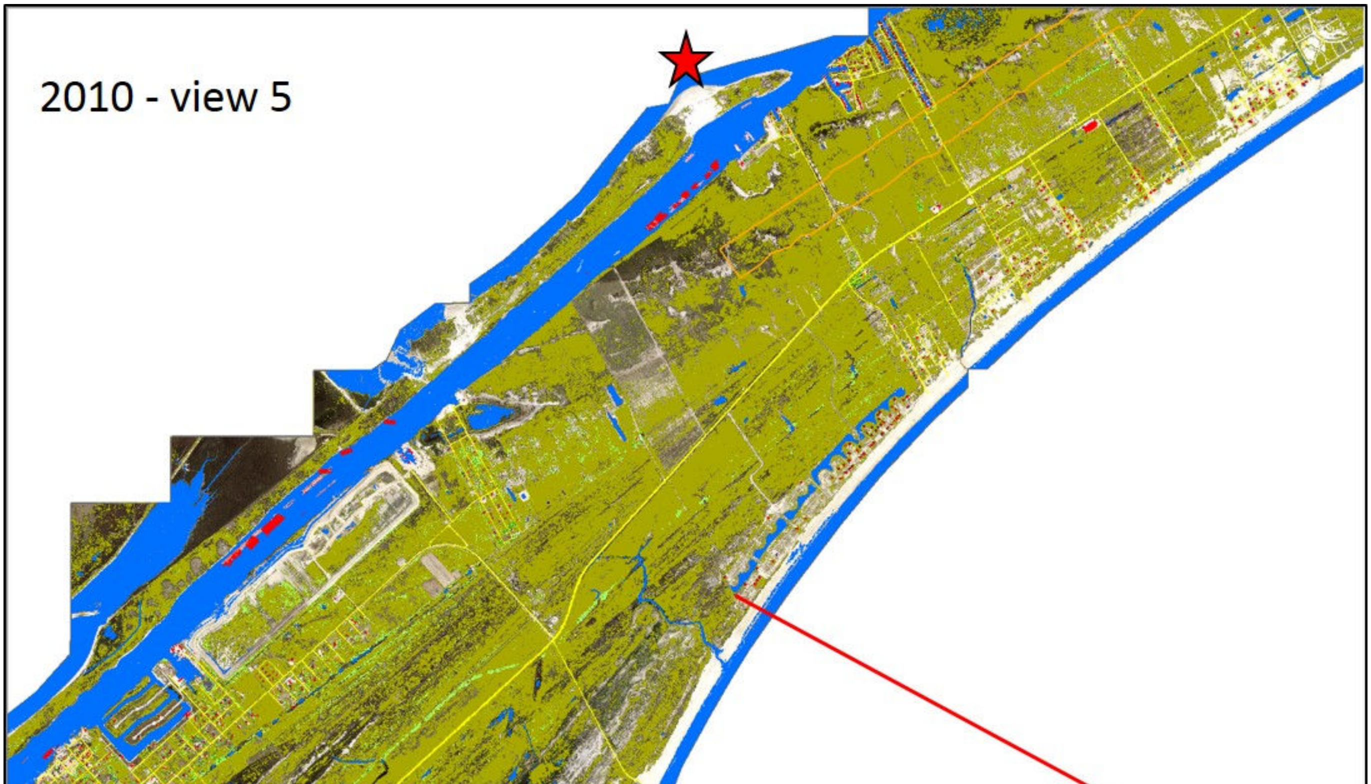
Appendix 5: 2010 OBIA Classifications – Closer views

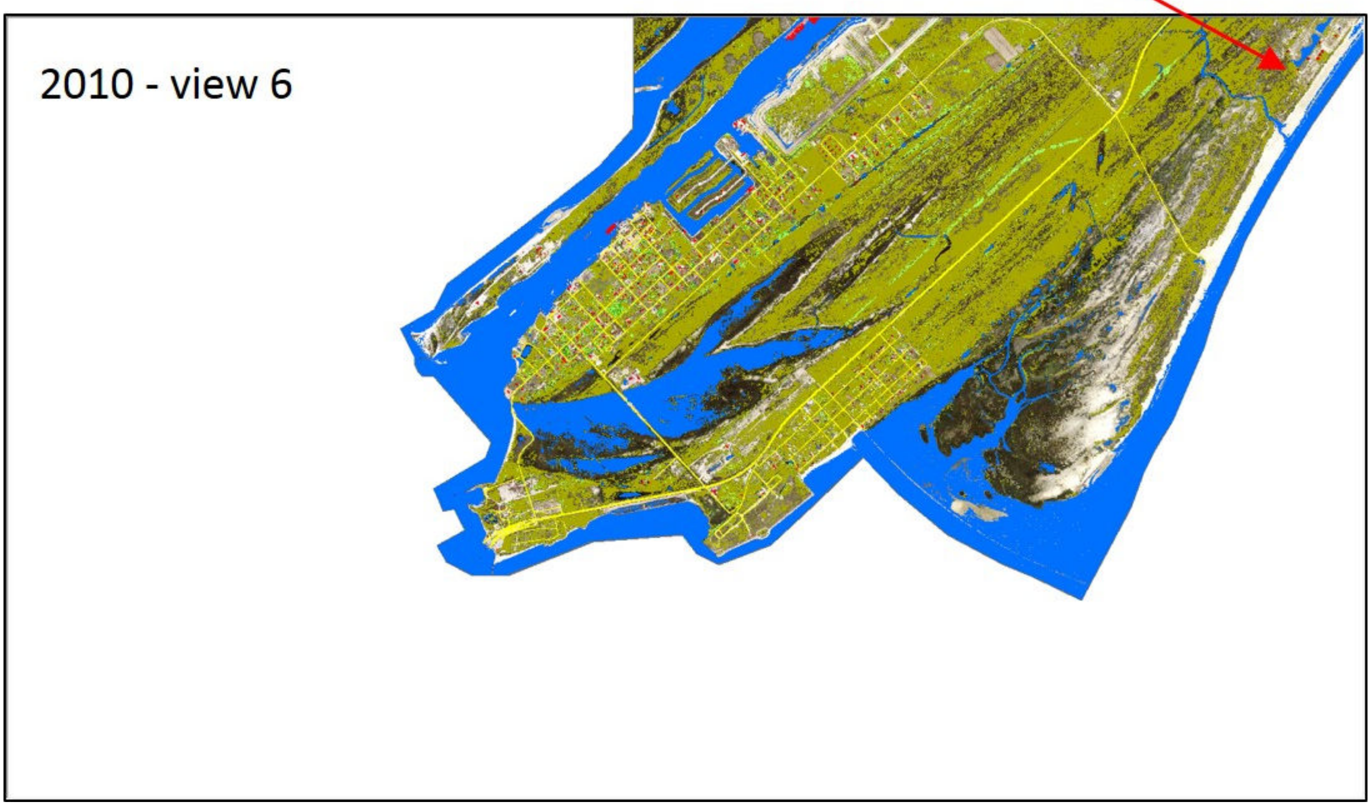


Arrows link the same area on the same page

Stars link the same area on adjacent pages


2010 - view 3
2010 - view 4


2010 - view 5


2010 - view 6

Appendix 6: Final eCognition rule sets for 2008, 2009, and 2010

Final rule set for 2008

- Bolivar 2008 Final Rule Set
  - delete 'Level 1'
  - delete 'Level 2'
  - Segmentation
    - quadtree: 10 creating 'Level 1'
    - [at Level 1: spectral difference 12]
    - layer arithmetics (val "(NIR-Red)/(NIR+Red)", layer NDVI[32Bit float])
    - layer arithmetics (val "(Red + Green + Blue)/3", layer Vis Bright[32Bit float])
  - Classify Bright Buildings
    - with Mean Vis Bright >= 150 at Level 1: HiVisBright
    - HiVisBright with Mean nDSM >= 10 at Level 1: TallHiVisBrite
    - TallHiVisBrite with Mean NDVI <= 0.05 at Level 1: BuildingsA
    - BuildingsA at Level 1: merge region
    - BuildingsA with Area >= 60 Pxl at Level 1: BuildingsB
    - BuildingsA at Level 1: quadtree: 10
    - BuildingsA, HiVisBright, TallHiVisBrite at Level 1: unclassified
  - Classify Rough Trees Shrubs
    - unclassified with Mean NDVI >= 0 at Level 1: ModHiNDVI
    - ModHiNDVI with Mean nDSM >= 16 and Mean Vis Bright < 150 at Level 1: Trees1
    - ModHiNDVI with Mean nDSM >= 2 and Mean nDSM < 16 and Mean Vis Bright < 150 at Level 1: Shrubs
    - ModHiNDVI at Level 1: LowVeg
  - Classify Water
    - unclassified with Mean NDVI < 0 at Level 1: LowNDVI
    - LowNDVI with Mean nDSM >= 10 and Mean NDVI <= -0.3 at Level 1: Buildings1
    - LowNDVI with Mean NIR <= 30 and Mean NDVI >= -0.5 at Level 1: Shadows1
    - LowNDVI with Mean NIR <= 14 at Level 1: Water1
    - Water1 at Level 1: merge region
    - Water1 with Area >= 650 Pxl at Level 1: Water2
  - Classify Buildings
    - Buildings1 at Level 1: merge region
    - Buildings1 with Border to BuildingsB >= 3 m and Border to Shadows1 >= 3 m at Level 1: BuildingsC
    - BuildingsC with Area >= 950 Pxl and Compactness >= 2.1 at Level 1: Shadows3
    - Shadows3 at Level 1: quadtree: 6
    - Shadows3 with Mean Vis Bright >= 70 at Level 1: TallVegGT10
    - Buildings1 with Border to BuildingsB >= 3 m at Level 1: BuildingsD
    - BuildingsD with Area >= 950 Pxl and Compactness >= 2.1 at Level 1: Shadows4
    - Shadows4 at Level 1: quadtree: 6
    - Shadows4 with Mean Vis Bright >= 70 at Level 1: TallVegGT10
    - BuildingsC, BuildingsD at Level 1: BuildingsE
    - Buildings1 at Level 1: quadtree: 6
    - Buildings1 with Mean Vis Bright >= 70 at Level 1: TallVegGT10
    - Buildings1 with Mean Vis Bright < 70 at Level 1: Shadows5
    - BuildingsE with Mean Vis Bright < 100 at Level 1: LowNDVI2
    - LowNDVI2 with Mean Vis Bright >= 70 at Level 1: TallVegGT10
    - LowNDVI2 with Mean Vis Bright < 70 at Level 1: Shadows6
    - Shadows2, Shadows3, Shadows4, Shadows5, Shadows6 at Level 1: Shadows
    - BuildingsE, unclassified at Level 1: quadtree: 10
    - BuildingsE at Level 1: spectral difference 10
    - BuildingsE with Mean nDSM >= 10 and Mean NDVI <= 0 at Level 1: Buildings
    - BuildingsE with Mean nDSM >= 10 and Mean NDVI >= 0 at Level 1: TallVegGT10

- BuildingsE with Mean nDSM < 10 and Mean NDVI < 0 at Level 1: LowNDVI
- TallVegGT10 with Mean nDSM >= 16 and Mean NDVI > -0.5 at Level 1: Trees
- Trees1 at Level 1: Trees
- TallVegGT10 with Mean nDSM < 16 and Mean nDSM >= 2 and Mean NDVI >= -0.5 at Level 1: Shrubs
- TallVegGT10 with Mean NDVI <= -0.5 at Level 1: BuildingsF
- BuildingsF at Level 1: Buildings
- BuildingsB at Level 1: Buildings
- Buildings at Level 1: merge region
- Buildings with Area <= 100 Pxl at Level 1: LowNDVI
- Shadows1 with Distance to Buildings <= 12 m at Level 1: Shadows8
- Water1 with Area <= 300 Pxl and Distance to Buildings <= 14 m at Level 1: Shadows9
- Shadows1 at Level 1: merge region
- Shadows1 with Area <= 2750 Pxl and Border to Buildings >= 2 ft at Level 1: Shadows6
- Shadows6 at Level 1: Shadows
- Shadows with Border to Water >= 5 ft at Level 1: Water3
- Water3 at Level 1: quadtree: 8
- Water3 at Level 1: spectral difference 6
- Water3 with Border to Buildings >= 3 m or Distance to Buildings <= 14 m at Level 1: Shadows
- Water3 at Level 1: Water
- Water at Level 1: merge region
- Water with Area <= 25 Pxl at Level 1: Shadows6
- Water at Level 1: merge region
- LowVeg with Mean nDSM >= 10 and Compactness <= 1.9 at Level 1: BuildingsG
- BuildingsG with Border to Buildings >= 1 m at Level 1: Buildings
- BuildingsG with Area <= 150 Pxl at Level 1: unclassified
- BuildingsG at Level 1: Buildings
- Buildings at Level 1: merge region
- Buildings with Shape index >= 2.7 at Level 1: LowNDVI
- Water1 at Level 1: merge region
- Shadows1, Water1 with Distance to Buildings <= 15 m at Level 1: Shadows7
- Shadows1, Shadows7 with Border to Water2 >= 1 m at Level 1: Water
- Water2 at Level 1: Water
- Shadows1, Shadows2, Shadows3, Shadows4, Shadows5, Shadows6, Shadows7, Shadows8, Shadows9 at Level 1: Shadows
- Water1 at Level 1: Water
- LowNDVI with Mean NDVI <= -0.6 at Level 1: Water5
- Water5 at Level 1: merge region
- Water5 with Mean NIR >= 30 at Level 1: LowNDVI
- Water5 with Border to Water >= 2 ft at Level 1: Water
- Water5 with Mean NIR <= 24 at Level 1: Water10
- Water10 with Border to Buildings >= 3 ft at Level 1: LowNDVI
- Water10 at Level 1: Water
- Water at Level 1: merge region
- Water5 at Level 1: LowNDVI
- Shadows with Rel. border to Water = 1 at Level 1: Water
- Water with Area <= 200 Pxl at Level 1: Shadows
- Water with Area <= 1500 Pxl and Border to Buildings >= 10 m at Level 1: Shadows

- Refinements
  - LowNDVI with Area >= 1000 Pxl and Mean NDVI <= -0.5 and Mean NIR < 50 and Mean nDSM > 10 at Level 1: Buildings
  - Water with Area <= 95000 Pxl at Level 1: Water6
  - Water6 with image object distance to Roads (outline) <= 11 ft at Level 1: Water7
  - Water6 with image object distance to StHwy87 (outline) <= 28 ft at Level 1: Water7
  - Water7 at Level 1: quadtree: 10
  - Water7 with Mean NIR <= 14 at Level 1: Water8

- Water at Level 1: merge region
- Water with Area <= 25 Pxl at Level 1: Shadows6
- Water at Level 1: merge region
- LowVeg with Mean nDSM >= 10 and Compactness <= 1.9 at Level 1: BuildingsG
- BuildingsG with Border to Buildings >= 1 m at Level 1: Buildings
- BuildingsG with Area <= 150 Pxl at Level 1: unclassified
- BuildingsG at Level 1: Buildings
- Buildings at Level 1: merge region
- Buildings with Shape index >= 2.7 at Level 1: LowNDVI
- Water1 at Level 1: merge region
- Shadows1, Water1 with Distance to Buildings <= 15 m at Level 1: Shadows7
- Shadows1, Shadows7 with Border to Water2 >= 1 m at Level 1: Water
- Water2 at Level 1: Water
- Water7 with Mean NIR <= 14 at Level 1: Water8
- Water8 with image object distance to Roads (outline) <= 3 m at Level 1: Water7
- Water7 at Level 1: LowNDVI
- Water6 with Area >= 3000 Pxl at Level 1: Water
- Water6 with Border to Buildings >= 1 m at Level 1: Water9
- Water9 at Level 1: LowNDVI
- Water6, Water8 at Level 1: Water
- Water at Level 1: merge region
- Water with Area <= 200 Pxl at Level 1: Shadows
- Buildings with Asymmetry <= 0.04 and Area >= 2000 Pxl at Level 1: Tank

- Classify RoadsBridges
  - LowNDVI at Level 1: quadtree: 20
  - LowNDVI with image object distance to Roads (outline) <= 11 ft and Mean Vis Bright >= 130 at Level 1: Roads1
  - LowNDVI with image object distance to StHwy87 (outline) <= 28 ft and Mean Vis Bright >= 130 at Level 1: RoadStHwy87
  - RoadStHwy87, Roads1 at Level 1: RoadsFull
  - RoadsFull at Level 1: merge region
  - RoadsFull with Area <= 6400 Pxl at Level 1: NotRoads1
  - NotRoads1 with Mean NDVI <= -0.2 at Level 1: Roads2
  - RoadsFull, Roads2 at Level 1: Roads
- Export
  - Trees at Level 1: merge region
  - Roads at Level 1: merge region
  - Shrubs at Level 1: merge region
  - LowVeg at Level 1: merge region
  - Buildings at Level 1: export object shapes to NewCentral3Build2008
  - LowVeg at Level 1: export object shapes to NewCentral3LowVeg2008
  - Roads at Level 1: export object shapes to NewCentral3Roads2008
  - Shrubs at Level 1: export object shapes to NewCentral3Shrubs2008
  - Trees at Level 1: export object shapes to NewCentral3Trees2008
  - Water at Level 1: export object shapes to NewCentral3Water2008
  - BuildingsA, BuildingsB, BuildingsC, BuildingsD, BuildingsE, BuildingsF, BuildingsG, Buildings1, HiVisBright, Low NIR, LowND...

(all classes other than the six primary objects were re-classified as "unclassified")

Final rule set for 2009

- Bolivar_2009
  - delete 'Level 1'
  - Segmentation and Layer Arithmetics
    - quadtree: 10 creating 'Level 1'
    - layer arithmetics (val "(NIR-Red)/(NIR+Red)", layer NDVI[32Bit float])
    - layer arithmetics (val "(Red + Green + Blue)/3", layer Vis Bright[32Bit float])
  - Classify Bright and Tarped Buildings
    - with Mean Vis Bright >= 110 at Level 1: HiVisBright
    - HiVisBright with Mean nDSM >= 10 at Level 1: TallHiVisBrite
    - TallHiVisBrite with Mean NDVI <= -0.2 or Mean Blue >= 170 at Level 1: BuildingsA
    - TallHiVisBrite at Level 1: merge region
    - TallHiVisBrite with Area >= 100 Pxl at Level 1: Buildings3
    - BuildingsA at Level 1: merge region
    - BuildingsA with Area >= 60 Pxl at Level 1: BuildingsB
    - Buildings3 with Border to BuildingsB >= 7 m at Level 1: Buildings4
    - BuildingsA, Buildings3, TallHiVisBrite at Level 1: quadtree: 10
    - BuildingsA, Buildings3, HiVisBright, TallHiVisBrite at Level 1: unclassified
  - Classify Rough Vegetation
    - unclassified with Mean NDVI >= 0 at Level 1: ModHiNDVI
    - ModHiNDVI with Mean nDSM >= 16 and Mean Vis Bright < 150 at Level 1: Trees
    - ModHiNDVI with Mean nDSM >= 2 and Mean nDSM < 16 and Mean Vis Bright < 150 at Level 1: Shrubs
    - ModHiNDVI with Mean NDVI >= 0.05 at Level 1: LowVeg
  - Refine Buildings
    - unclassified with Mean NDVI < 0 at Level 1: LowNDVI
    - Trees with Mean Blue >= 170 at Level 1: BuildingsH
    - LowNDVI with Mean nDSM >= 10 and Mean NDVI <= -0.2 at Level 1: Buildings1
    - Buildings1 at Level 1: merge region
    - Buildings1 with Border to Buildings4 >= 3 m or Border to BuildingsB >= 3 m at Level 1: Buildings2
    - Buildings1 at Level 1: TallVegGT10
    - TallVegGT10 with Area >= 180 Pxl and Rectangular fit >= 0.85 at Level 1: Buildings5
    - BuildingsB, BuildingsH, Buildings2, Buildings4, Buildings5 at Level 1: Buildings
    - Buildings at Level 1: merge region
    - Buildings with Area >= 1780 Pxl and Shape index <= 1.2 at Level 1: TallLoNDVI
    - Buildings with Area <= 100 Pxl at Level 1: TallLoNDVI
  - Classify Water
    - LowNDVI with Mean NIR <= 40 at Level 1: Water1
    - Water1 at Level 1: merge region
    - Water1 with Area >= 1170 Pxl at Level 1: Water2
    - Water1 with Border to Buildings >= 3 m at Level 1: Shadows1
    - Water1 with Distance to Buildings <= 15 m at Level 1: Shadows2
    - Water1 with Area <= 60 Pxl at Level 1: Shadows3
    - Shadows3, Water1 with Length/Width >= 3.5 and Area >= 70 Pxl at Level 1: Water3
    - Water1 at Level 1: quadtree: 5
    - Water1 with Mean NIR <= 50 and Mean NDVI <= -0.4 at Level 1: Water4
    - Water2, Water3, Water4 at Level 1: Water
    - Water at Level 1: merge region
    - TallLoNDVI at Level 1: merge region
    - Water with Area <= 60 Pxl at Level 1: Shadows3
    - Water with Area >= 1362 Pxl and Area <= 1364 Pxl and Shape index >= 1.8 and Shape index <= 1.9 at Level 1: Shadows3
    - Water1 at Level 1: Shadows4
    - Shadows1, Shadows2, Shadows3, Shadows4 at Level 1: Shadows
  - Refine Buildings Further
    - LowNDVI with Mean NDVI <= -0.5 and Mean nDSM >= 10 at Level 1: Buildings6
    - Buildings6 at Level 1: merge region
    - Buildings6 with GLCM Homogeneity (all dir.) >= 0.1 at Level 1: Buildings7
    - Buildings7 with Border to Buildings >= 3 m at Level 1: Buildings
    - Buildings7 with Rectangular fit >= 0.85 and Area >= 200 Pxl at Level 1: Buildings
    - Buildings at Level 1: merge region
    - Buildings6, Buildings7 at Level 1: TallLoNDVI

- Classify Roads
  - LowNDVI at Level 1: quadtree: 20
  - LowNDVI with image object distance to Roads (outline) <= 11 ft and Mean Vis Bright >= 130 at Level 1: Roads1
  - LowNDVI with image object distance to StHwy87 (outline) <= 28 ft and Mean Vis Bright >= 130 at Level 1: RoadStHwy87
  - RoadStHwy87, Roads1 at Level 1: RoadsFull
  - RoadsFull at Level 1: merge region
  - RoadsFull with Area <= 550 Pxl at Level 1: NotRoads1
  - NotRoads1 with Mean NDVI <= -0.2 at Level 1: Roads2
  - RoadsFull, Roads2 at Level 1: Roads
  - Roads with Area >= 6500 Pxl and Area <= 8900 Pxl and Shape index >= 1.7 and Shape index <= 3.9 at Level 1: NotRoads2
- Refine Water
  - LowNDVI with Mean NDVI <= -0.25 and Mean NIR <= 70 at Level 1: Water6
  - Water6 with Border to Buildings >= 1 m at Level 1: WaterNot1
  - Water6 at Level 1: Water
  - Buildings with Rel. border to Water >= 0.8 at Level 1: Water7
  - Water7 at Level 1: Water
  - Water at Level 1: merge region
  - Water with Rel. border to Roads >= 0.59 and Area <= 450 Pxl at Level 1: Roads
  - Water with Area <= 200 Pxl at Level 1: WaterNot3
  - Water with Area <= 3000 Pxl and Border index >= 4.4 at Level 1: WaterNot4
  - BuildingsA, BuildingsB, BuildingsC, BuildingsD, BuildingsE, BuildingsF, BuildingsG, BuildingsH, Buildings1, Buildings2, Buildings3, Buildings…

(all classes other than the six primary objects were re-classified as "unclassified")

- Export
  - Trees at Level 1: merge region
  - Roads at Level 1: merge region
  - Shrubs at Level 1: merge region
  - LowVeg at Level 1: merge region
  - Buildings at Level 1: export object shapes to Center1Build09Final
  - LowVeg at Level 1: export object shapes to Center1LowVeg09Final
  - Roads at Level 1: export object shapes to Center1Roads09Final
  - Shrubs at Level 1: export object shapes to Center1Shrub09Final
  - Trees at Level 1: export object shapes to Center1Tree09Final
  - Water at Level 1: export object shapes to Center1Water09Final

Final rule set for 2010

- Bolivar_2010
  - delete 'Level 1'
  - Segmentation and Layer Arithmetics
    - quadtree: 10 creating 'Level 1'
    - layer arithmetics (val "(NIR-Red)/(NIR+Red)", layer NDVI[32Bit float])
    - layer arithmetics (val "(Red + Green + Blue)/3", layer Vis Bright[32Bit float])
    - layer arithmetics (val "(Red - Green - Blue)/3", layer Vis Dark[32Bit float])
    - layer arithmetics (val "(NIR + Red + Green)/3", layer NIR Bright[32Bit float])
    - layer arithmetics (val "(NIR Bright-NIR)/(NIR Bright+NIR)", layer Water Bright[32Bit float])
  - Classify Bright and Tarped Buildings
    - with Mean Vis Bright >= 110 at Level 1: HiVisBright
    - HiVisBright with Mean nDSM >= 10 at Level 1: TallHiVisBrite
    - TallHiVisBrite with Mean NDVI <= -0.25 or Mean Blue >= 200 at Level 1: BuildingsA
    - BuildingsA at Level 1: merge region
    - BuildingsA with Area >= 15 Pxl at Level 1: BuildingsB
    - HiVisBright, TallHiVisBrite at Level 1: unclassified
  - Classify LowNDVI Buildings
    - unclassified with Mean NDVI < 0 at Level 1: LowNDVI
    - LowNDVI with Mean nDSM >= 10 and Mean NDVI <= -0.2 at Level 1: Buildings1
    - Buildings1 at Level 1: merge region
    - Buildings1 with Border to BuildingsB >= 2 m at Level 1: BuildingsC
    - BuildingsA, Buildings1 at Level 1: quadtree: 10
    - BuildingsA, Buildings1 at Level 1: unclassified
    - unclassified with Mean NDVI < 0 at Level 1: LowNDVI
    - BuildingsB, BuildingsC at Level 1: Buildings
  - Classify Rough Vegetation
    - unclassified with Mean NDVI >= 0 at Level 1: ModHiNDVI
    - ModHiNDVI with Mean nDSM >= 16 at Level 1: Trees
    - ModHiNDVI with Mean nDSM >= 2 and Mean nDSM < 16 at Level 1: Shrubs
    - ModHiNDVI with Mean nDSM < 2 at Level 1: LowVeg
  - Classify State Highway
    - LowNDVI at Level 1: chess board: 1
    - LowNDVI with image object distance to StHwy87 (outline) <= 8.5 m at Level 1: RoadStHwy87
    - RoadStHwy87 at Level 1: spectral difference 10
    - RoadStHwy87 with Mean Vis Bright >= 168 and Mean Blue <= 200 at Level 1: LowNDVI3
    - LowNDVI3 at Level 1: merge region
    - LowNDVI3 with Rel. border to RoadStHwy87 >= 0.8 at Level 1: RoadStHwy87
    - LowNDVI3 at Level 1: chess board: 1
    - LowNDVI3 at Level 1: LowNDVI
  - Classify Water
    - LowNDVI with Mean NIR <= 60 at Level 1: Water1
    - Water1 at Level 1: merge region
    - Water1 with Area >= 200 Pxl at Level 1: Water2
    - Water1 with Border to Buildings >= 3 m at Level 1: Shadows1
    - Water1 with Distance to Buildings <= 15 m at Level 1: Shadows2
    - Water1 with Mean Vis Dark <= -35 at Level 1: Shadows3
  - Classify Bright Water
    - LowNDVI with Mean NDVI <= -0.33 at Level 1: WaterB
    - WaterB at Level 1: merge region
    - WaterB with Border to Water2 >= 10 m at Level 1: WaterC
    - LowNDVI with Mean NIR Bright >= 170 and Mean NIR Bright <= 225 and Mean NDVI <= -0.2 at Level 1: WaterD
    - WaterD at Level 1: merge region
    - WaterD with Border to WaterC >= 3 m or Border to WaterB >= 3 m at Level 1: WaterE
    - WaterE with image object distance to Roads (outline) <= 2 m at Level 1: LowNDVI
    - WaterD at Level 1: LowNDVI
    - WaterB with Border to WaterC >= 3 m or Border to WaterE >= 3 m at Level 1: Water2
    - WaterC at Level 1: Water2
    - WaterB with Area <= 4 Pxl at Level 1: LowNDVI
  - Classify New Buildings
    - WaterB with image object distance to Roads (outline) <= 300 m at Level 1: WaterF
    - WaterF with Area >= 20 Pxl and Border to Shadows3 >= 3 m and Area <= 200 Pxl at Level 1: BuildingsNewA
    - WaterF with Area >= 20 Pxl and Border to Shadows2 >= 3 m and Area <= 200 Pxl at Level 1: BuildingsNewB
    - WaterB at Level 1: LowNDVI
    - WaterF at Level 1: LowNDVI
  - Classify New Buildings Misclassified as Water
    - Water2 at Level 1: merge region
    - Water2 with image object distance to Roads (outline) <= 200 m at Level 1: WaterG
    - WaterG with Rectangular fit >= 0.8 and Area < 475 Pxl and Area >= 200 Pxl and Shape index <= 1.5 and Mean NDVI >= -0.26 and Mean NIR >= 44 at Level 1
    - WaterG with Area >= 20 Pxl and Border to Shadows3 >= 3 m and Area <= 200 Pxl at Level 1: BuildingsNewD

- WaterG with Area >= 200 Pxl and Area <= 410 Pxl and Mean NDVI <= -0.2 and Mean NDVI >= -0.32 at Level 1: BuildingsNewE
- BuildingsNewE with Length/Width >= 2 at Level 1: WaterG
- WaterE with Border to BuildingsNewD >= 3 m at Level 1: BuildingsNewD
- WaterG at Level 1: Water2

- Classify More New Buildings
  - Shadows2, Shadows3 with image object distance to Roads (outline) <= 200 m at Level 1: BuildingsNewShadows
  - BuildingsNewShadows at Level 1: merge region
  - BuildingsNewShadows with Area <= 15 Pxl or Length/Width >= 5 at Level 1: LowNDVI
  - BuildingsNewShadows with Mean NIR >= 45 and Mean NIR <= 47 at Level 1: Water3
  - LowNDVI at Level 1: 10 [shape:0.3 compct.:0.7]
  - LowNDVI at Level 1: spectral difference 10
  - LowNDVI with Area <= 500 Pxl and Area >= 30 Pxl at Level 1: Buildings4
  - Buildings4 with Border to BuildingsNewShadows >= 3 m at Level 1: BuildingsNew1
  - Buildings4 at Level 1: LowNDVI
  - BuildingsNew1 with Length/Width >= 3.8 at Level 1: LowNDVI
  - BuildingsNewShadows with Border to BuildingsNew1 >= 3 m at Level 1: BuildingsNew1
  - BuildingsNew1 at Level 1: merge region
  - BuildingsNew1 with Length/Width >= 3.5 at Level 1: LowNDVI
  - BuildingsNew1 with Border index >= 2.5 at Level 1: LowNDVI
- Classify Still More New Buildings
  - LowNDVI at Level 1: 10 [shape:0.3 compct.:0.7]
  - LowNDVI with Area <= 170 Pxl and Area >= 30 Pxl at Level 1: Buildings5
  - Buildings5 with Mean NDVI <= -0.25 and image object distance to Roads (outline) <= 200 m at Level 1: BuildingsNew2
  - [Buildings5 with Border to BuildingsNew2 >= 5 m at Level 1: BuildingsNew3]
- Consolidate Water and Buildings Classes
  - BuildingsNewE at Level 1: BuildingsNew
  - BuildingsNew1 at Level 1: merge region
  - BuildingsNew1 with Border to BuildingsNewA >= 3 m at Level 1: BuildingsNew
  - BuildingsNewA with Border to BuildingsNew >= 3 m at Level 1: BuildingsNew
  - Buildings5 at Level 1: LowNDVI
  - BuildingsNewD with Border to BuildingsNew1 >= 3 m at Level 1: BuildingsNew
  - BuildingsNewD at Level 1: merge region
  - BuildingsNewD with Border to Water2 >= 3 m at Level 1: Water2
  - BuildingsNew1 with Border to Buildings >= 3 m at Level 1: LowNDVI
  - BuildingsNew2 with Border to BuildingsNew >= 3 m at Level 1: BuildingsNew
  - BuildingsNew2 with Border to BuildingsNew1 >= 3 m at Level 1: BuildingsNew
  - BuildingsNew2 at Level 1: LowNDVI
  - BuildingsNew1 with Border to BuildingsNew >= 3 m at Level 1: BuildingsNew
  - Shadows1 at Level 1: LowNDVI
  - BuildingsNew1 with Border to Water2 >= 3 m at Level 1: LowNDVI
  - WaterE with Area <= 1000 Pxl and Rel. border to Water2 <= 0.1 at Level 1: LowNDVI
  - WaterE at Level 1: Water2
  - BuildingsNew1 with Area <= 102 Pxl at Level 1: LowNDVI
  - BuildingsNew1 at Level 1: BuildingsNew
  - BuildingsNewD at Level 1: BuildingsNew
  - BuildingsNewShadows at Level 1: BuildingsNew
  - BuildingsNew with Rel. border to Water2 >= 0.2 at Level 1: Water2
  - BuildingsNew at Level 1: merge region
  - BuildingsNew with Length/Width >= 2.5 at Level 1: Water2
  - Buildings with Rel. border to Water2 >= 0.9 at Level 1: Water2
  - BuildingsNewC at Level 1: BuildingsNew
  - BuildingsNewA at Level 1: BuildingsNew
  - BuildingsNewB with Border to BuildingsNew >= 3 m at Level 1: BuildingsNew
  - Shadows3 at Level 1: Water2
  - Water1, Water2, Water3 at Level 1: Water
  - BuildingsNew with Rel. border to Water >= 0.45 at Level 1: Water
  - Water at Level 1: merge region
  - Water with Rectangular fit >= 0.8 and Area < 562 Pxl and Area >= 218 Pxl and Shape index <= 1.76 and Mean NDVI >= -0.36 and Mean NIR >= 44 and image
  - LowNDVI with Area <= 20 Pxl and Rel. border to Water >= 0.95 at Level 1: Water
  - unclassified at Level 1: merge region
  - unclassified with Area <= 10 Pxl and Rel. border to Water >= 0.95 at Level 1: Water
  - Water with Mean nDSM >= 8 at Level 1: Buildings
  - Water with Distance to Buildings <= 30 m and Area >= 1269 Pxl and Area <= 1273 Pxl at Level 1: unclassified
  - Water with Area < 200 Pxl at Level 1: unclassified
  - Buildings with Area <= 20 Pxl at Level 1: LowNDVI
- Classify Local Roads
  - LowNDVI at Level 1: chess board: 1
  - LowNDVI with image object distance to Roads (outline) <= 11 ft at Level 1: Roads1
  - RoadStHwy87, Roads1 at Level 1: RoadsFull
  - RoadsFull at Level 1: merge region

RoadsFull with Area <= 137 Pxl at Level 1: NotRoads1
NotRoads1 with Mean NDVI <= -0.2 at Level 1: Roads2
RoadsFull, Roads2 at Level 1: Roads
Roads at Level 1: merge region
Roads with Area >= 6198 Pxl and Area <= 6202 Pxl and Shape index >= 2.09 and Shape index < 2.2 at Level 1: LowNDVI

- Finalize Water
  - LowNDVI with Mean NDVI <= -0.3 at Level 1: LowNDVI4
  - loop: Water at Level 1: <- LowNDVI4 <not found> = 0
  - loop: Buildings at Level 1: <- LowNDVI4 <not found> = 0
  - loop: BuildingsNew at Level 1: <- LowNDVI4 <not found> = 0
  - LowNDVI4 at Level 1: LowNDVI
  - LowNDVI, unclassified with Rel. border to Water >= 0.9 and Mean Vis Dark <= -55 at Level 1: Water
  - BuildingsNew with image object distance to Roads (outline) >= 30 m at Level 1: Water
  - BuildingsNew at Level 1: merge region
  - BuildingsNew with Area >= 1300 Pxl at Level 1: LowNDVI
  - BuildingsNew with Length/Width >= 2.8 and Width < 9 Pxl at Level 1: Water
  - Roads with Border to Buildings > 39 ft and Length < 120 Pxl at Level 1: NotRoads3
  - BuildingsNew with image object distance to Roads (outline) <= 1 m at Level 1: Water
  - Roads with Rel. border to Water >= 0.4 at Level 1: Water
  - BuildingsA, BuildingsB, BuildingsC, BuildingsD, BuildingsE, BuildingsF, BuildingsG, BuildingsH, BuildingsNewA, BuildingsNewB, BuildingsNewC, BuildingsNewE, B ...

(all classes other than the seven primary objects were re-classified as "unclassified")

- Export
  - Trees at Level 1: merge region
  - Roads at Level 1: merge region
  - Buildings at Level 1: merge region
  - Shrubs at Level 1: merge region
  - LowVeg at Level 1: merge region
  - Buildings at Level 1: export object shapes to Central1Build2010
  - LowVeg at Level 1: export object shapes to Central1LowVeg2010
  - Roads at Level 1: export object shapes to Central1Roads2010
  - Shrubs at Level 1: export object shapes to Central1Shrubs2010
  - Trees at Level 1: export object shapes to Central1Trees2010
  - Water at Level 1: export object shapes to Central1Water2010
  - BuildingsNew at Level 1: export object shapes to Central1NewBuildings2010