

**Assessing the utility of high-spatial-resolution remote sensing
to monitor shoreline change
in three coastal National Park units**

Halle Cooper and Cédric G. Fichot (PI)
Boston University

Project report

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Abstract

In this pilot study for the National Park Service (NPS), we assessed the feasibility of using two commercial remote sensing satellite programs, Planetscope and Maxar, to reliably document and monitor shoreline change. This study is in response to NPS's growing interest in using remote sensing to better track shoreline change across their 88 coastal National Park units. While field efforts of shoreline monitoring are typically limited to a few key locations, remote sensing provides an unparalleled level of spatial and temporal information. Planetscope and Maxar have significantly more frequent (Planetscope) and fine-resolution (Maxar) imagery than other satellite programs, giving them potential to facilitate expansive and accurate shoreline monitoring and detect change on small spatial scales (a few meters). In this pilot study, we analyzed shoreline change in three contrasting coastal National Park units from 2016 to 2021 using two methodologies. By comparing the outputs obtained from the Planetscope and Maxar satellite imagery, we were able to identify how each dataset can provide information about shoreline change. Our results demonstrate the difficulty of mapping small-scale shoreline change amidst water level variation caused by tides, net precipitation, and seasons, and the importance of Planetscope's frequent acquisition in overcoming this difficulty. While the finer spatial resolution of Maxar is appealing (30-60 cm vs ~3-5 m for Planetscope), its value is limited for shorelines and areas that experience frequent water level variation (e.g. from tides) due to sporadic data collection. However, Maxar's fine spatial resolution may aid in the analysis of bluffs or lakeshores that do not experience significant water level variation. Overall, the two satellite programs have the potential to complement each other. Combining Planetscope imagery that allows for automated high-level analysis and the fine resolution of Maxar imagery for further exploration of bluff or other non-inundated areas creates a two-step workflow that can provide accurate and detailed shoreline analysis. While we found that varying levels of remote sensing difficulties arise depending on geographic location and tidal influence, the study was successful in detecting areas of rapid shoreline change that may need careful monitoring and management. Adoption of this remote sensing workflow could greatly influence shoreline monitoring and facilitate management decisions for the entire suite of coastal National Park units.

1. Introduction

Along the U.S. coastline, rapid environmental change is jeopardizing coastal resources and a population of 13 million with a socio-economic impact of \$990 billion through 2100 (Hauer et al., 2016; Neumann et al., 2015). Among these changes, sea level rise, increased occurrence of large storms, and human development are all influencing coastal erosion and are constantly reshaping the U.S. coastline in ways that are often difficult to predict (Masselink and Russell, 2013; Toimil et al., 2020, 2017). Such change is also impacting or threatening to impact coastal units of the National Park Service (NPS). These units provide key ecosystems services and resources managed by NPS, including natural resources and habitats, cultural and historical resources, and essential infrastructure and buildings.

The continuous monitoring of shoreline change can provide NPS managers with critical information for: assessing erosion hazards; understanding the vulnerability of national parks' natural, historical, and cultural resources and infrastructure; and ensuring safe staff and visitor access and recreational opportunities. However, monitoring change over hundreds of miles of shorelines is often impractical as it typically relies on ground surveys limited to a few key locations within selected parks, or on the costly acquisition and processing of aerial imagery or aerial LiDAR surveys. Monitoring shoreline change over the entire coastline of the 88 coastal national park units therefore requires a different and more practical approach.

Remote sensing has the potential to facilitate the monitoring of shoreline change by providing a much higher level of spatial and temporal information. Optical sensors from the Landsat program have continuously monitored land cover change for more than 40 years now (Sakai et al., 1983). However, unsuitable temporal coverage (revisit time of 16 days) and spatial resolution (30-m) of the sensors has limited the utility of the program for monitoring changes over relatively small spatial or temporal scales. The high-spatial-resolution (a few meters) imagery now provided globally by commercial satellite programs offer new opportunities to facilitate the accurate monitoring of shoreline change in the NPS coastal units.

In this pilot study, we assess the feasibility of monitoring shoreline change in three selected NPS coastal units with two commercial satellite services: PlanetScope and Maxar. We specifically seek to assess the utility of their datasets and to understand their potential to be implemented more broadly across the NPS. The two datasets have contrasting advantages and disadvantages: PlanetScope imagery is at a spatial resolution of ~4 meters with daily acquisition, whereas Maxar imagery has higher spatial resolution (30-60 cm) with sporadic temporal coverage (typically on demand image acquisition).

As the U.S. shoreline becomes increasingly impacted and vulnerable, it is critical to enact effective monitoring approaches that can aid in coastal management and protection. With expansive land covering their 88 coastal National Park units, NPS could greatly benefit from the regular use of these commercial remote sensing programs to monitor and manage coastlines efficiently and effectively. In the rest of this document, we compare the utility of PlanetScope and Maxar imagery and discuss the benefits of spatial resolution versus temporal coverage for monitoring shoreline change in the U.S. NPS coastal units.

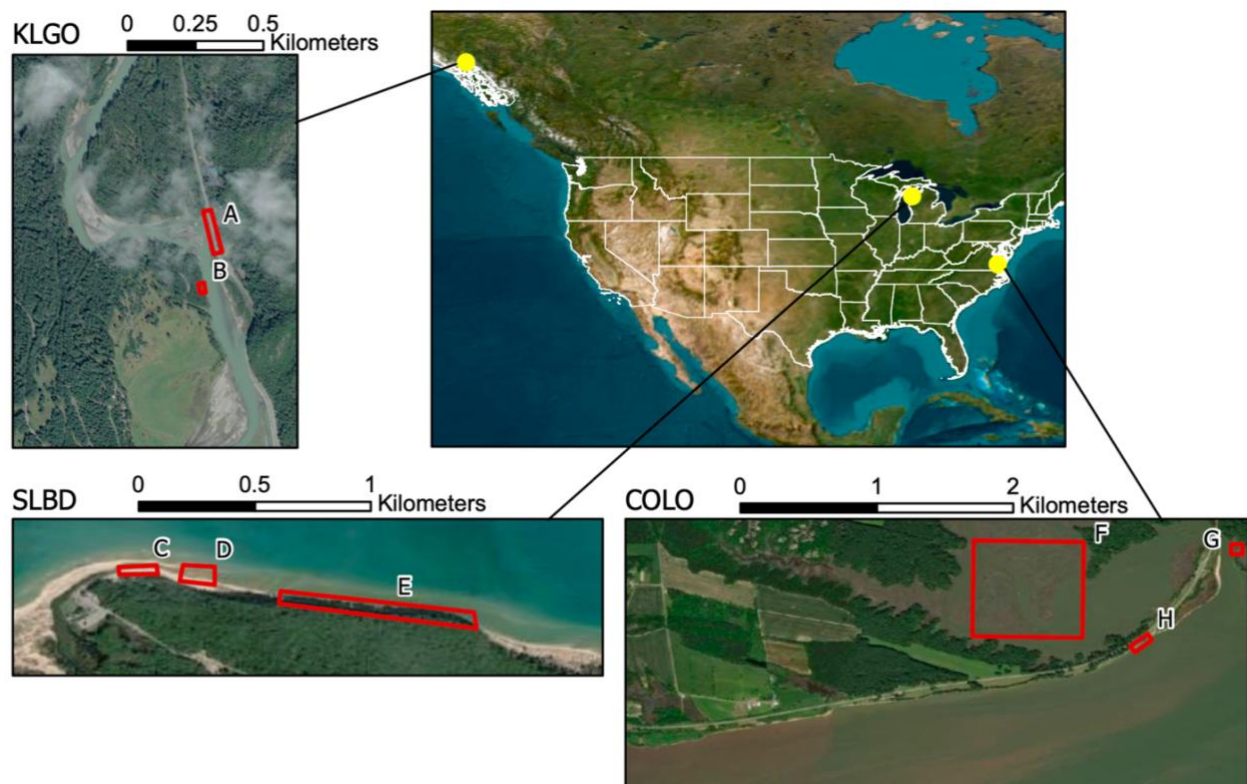
2. Study Sites

In this pilot study, three contrasting NPS coastal units were selected to assess the feasibility of using Planetscope and Maxar imagery (**Figure 1**):

1. Sleeping Bear Dunes National Lakeshore Park (SLBD) in Michigan
2. Colonial National Historic Park (COLO) in Virginia
3. Klondike Goldrush National Historic Park (KLGO) in Alaska

The parks were selected by NPS to cover a range of shoreline type, extent and frequency of water-level change, latitude, and seasonality that correspond to different technical challenges for monitoring shoreline change using remote sensing. In addition, while cloud cover was not a consideration when selecting parks, this also was a factor in assessing technical challenges.

Figure 1. Geographic locations of the three study sites considered in this pilot study, with accompanying detailed maps showing specific areas of interest (AOIs) closely examined later in this study (red squares). Study areas include Klondike Goldrush National Historic Park (KLGO) in Alaska, Sleeping Bear Dunes National Lakeshore (SLBD) in Michigan, and Colonial National Historic Park (COLO) in Virginia.



◆ Sleeping Bear Dunes National Lakeshore (SLBD)

SLBD is located in Honor, MI on the shore of Lake Michigan (**Figure 1**). This freshwater system is located at mid latitudes on a lake shore and is therefore subject to slower variations in water level compared to tidally influenced systems. However, anthropogenic dredging efforts have

occurred throughout the past decade at the mouth of the Platte River (D), with potential impacts on the tree line bluff located downstream (E). The dredge spoils were deposited west of the dredge site (C). Monitoring the long-term effects of anthropogenic shoreline manipulation will aid in the protection of these ecosystems and an understanding of best practice in future stewardship.

♦ Colonial National Historic Park (COLO)

COLO is located in Yorktown, VA. Part of the Chesapeake Bay, this wetland-rich area is heavily influenced by tidal fluctuation. In recent years, spatially small-scale areas of interest have been recognized in the field due to bluffs rapidly eroding on the southern, ocean-facing shoreline (H) and College Creek Inlet eroding (G). Monitoring shoreline dynamics near H is imperative to the management of this National Park because of infrastructure built along this thin land bridge, namely the Colonial National Historic Parkway. It is also important to monitor the marsh system (F) to protect the ecosystem services it provides.

♦ Klondike Goldrush National Historic Park (KLGO)

KLGO is located in Skagway, AK and is part of a dynamic riverine system, subject to extreme water level variability both tidally (timescale of hours) and seasonally (due to precipitation and snow/ice melt). These intense river flow changes sculpt the shape of the channel, affecting the ecosystems and infrastructure along it. The road along the eastern side of the river (A) and archaeological sites on the western side of the river (B) have been subject to erosion in recent years. Monitoring the movement of this channel is important for protecting the adjacent ecosystems and infrastructure. However, due to the geographic location of this site, high cloud cover percentages and a lack of daylight throughout winter months makes satellite data collection more difficult than in many other sites.

3. Data and Methods

Because of major differences in temporal coverage between the PlanetScope and Maxar data sets, assessing shoreline change in this comparative study involved using two distinct methodologies. The different temporal coverages led to a large difference in the number of images available for analysis (**Table 1**). The method applied to the PlanetScope data set (section 3.1) involved the automated processing of large sets of imagery and the production of synthetic maps using a land-water index (e.g., Normalized Difference Water Index (NDWI)). The method applied to the Maxar data set (section 3.2) involved the manual delineation between land and water of two or three images with similar water level. Both methods resulted in maps that facilitated the analysis of land loss and land gain over time in the study areas.

Table 1. Number of images downloaded per site from Planet (from January 2017 – December 2021 with <10% cloud cover) and Maxar (all clear images from archive, from 2010 - 2022).

	COLO	SLBD	KLGO
Planet	811	629	381
Maxar	14	12	10

3.1 Method 1: PlanetScope

PlanetScope Data: As described in Moon et al. (2021), the PSScene4Band product from PlanetScope provides quasi-daily atmospherically corrected blue (455-517 nm), green (500-585 nm), red (590-682 nm), and near-infrared (780-885 nm) surface reflectance data. In this study, the “Analytical Ortho Scene” product was used, which has a uniform resolution of 3 m. Complete details of PlanetScope imagery can be found in PlanetScope’s technical product documentation (<https://developers.planet.com/docs/apis/data/items-assets/>).

PlanetScope Image Database Acquisition: All available PlanetScope imagery from January 1st, 2017 (the earliest available data) to December 31st, 2021 was compiled. Images with >10% cloud cover (as indicated in their metadata) were excluded.

Mosaicking of images for study area: Details about the mosaicking methodology are provided in Moon et al. (2021). Briefly, an unusable data mask (UDM) file was used for pixel-based quality assurance, thereby allowing the evaluation of images pixel by pixel and the subsequent removal of data contaminated by clouds or snow. When the swath of some downloaded PlanetScope images did not cover the entire study site, adjacent images collected on the same day were mosaiced together in order to cover the study area of interest.

NDWI Calculation: To automate the geoprocessing and analysis of the PlanetScope imagery, the Normalized Difference Water Index (NDWI) was calculated from the compiled and mosaicked surface reflectance data. The NDWI is a ratio often used in remote sensing to effectively measure moisture content or to discriminate land from water. Previous studies have calculated NDWI using various reflectance band combinations (Li et al., 2016). In this pilot study, given the available bands in the 4-band PlanetScope imagery (R, G, B, NIR), we used the following formulation of the NDWI:

$$\text{NDWI} = (\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR}) \quad (1)$$

where Green and NIR refer to surface reflectance for the green and NIR bands. Water is typically characterized with high green reflectance relative to low NIR reflectance. In contrast, land is characterized with high NIR reflectance relative to green reflectance. Because of these characteristics, NDWI values above a given threshold (typically a value close to 0) is indicative of water, and values below this threshold are indicative of land.

Image Analysis: Image analysis was performed using MatLAB® with the objective of producing a categorized land/water change map. In order to facilitate the analysis of NDWI time series for each site, the raster images were converted to matrices (one for each band) and stacked into data cubes in MatLAB® with dimensions x, y, and z corresponding to latitude, longitude, and day of year, respectively. These cubes had a z dimension of 1826, corresponding to the number of total days from January 1st, 2017, to December 31st, 2021. The data cubes for each site facilitated the pixel-based calculation of trendlines (linear fit) of the corresponding NDWI time series. Mapping the slopes of each pixel’s trendline produced site-specific maps of NDWI trends across each study area. They also facilitated the determination of the first and last point of each trendline to produce synthetic maps at the initial time point (T_{initial} or January 1st, 2017) and final time point (T_{final} or December 31st, 2021) of the time series. After conducting a threshold sensitivity analysis, we chose NDWI thresholds between -0.2 and 0 (depending on site) to differentiate land (NDWI < threshold) from water (NDWI > threshold). Using this threshold,

binary (land/water) versions of the synthetic NDWI maps were generated. Lastly, binary land/water maps of the derived synthetic maps at T_{initial} and T_{final} were used to create a corresponding land/water change map that revealed the shoreline change that occurred throughout the study period.

3.2 Method 2: Maxar

Maxar Data: The “Color Infrared” product of Maxar imagery was used, which provides reflectance data in the green, red, and near-infrared wavelengths. This imagery has a spatial resolution of 30-60 cm. Detailed information about Maxar imagery can be found here:

<https://resources.maxar.com/optical-imagery>

Maxar Manual Image Compilation: Because of the sporadic coverage of Maxar imagery, the images used in this study could be selected for manual download on the Maxar EGD page. All swaths of imagery without cloud cover over the study areas were added to the Maxar library and downloaded. It should be noted that the available Maxar imagery spanned a different time frame than Planetscope; Maxar images were downloaded from as early as September 2010 and as late as September 2022.

Maxar Image Selection: The corresponding water level data from the date of acquisition of each image was downloaded from the geographically closest NOAA water level station for each study site. Water levels for SLBD, KLGO and COLO were obtained from the following NOAA stations, respectively: 1) Ludington, MI [9087023], 2) Skagway, Taiya Inlet, AK [9452400], and 3) Yorktown USCG Training Center, VA [8637689]. To accurately compare temporal trends of the imagery, 2-3 images were selected from the available pool (**Table 1**) that were from similar seasons and had a similar water level according to the NOAA dataset (**Table 2**).

Table 2. Maxar imagery available for each study site, downloaded with corresponding NOAA water level data. Rows highlighted in blue are the images selected for manual delineation based on season and water level.

SLBD		KLGO		COLO	
Date	Water level (ft)	Date	Water level (ft)	Date	Water level (ft)
10/16/2011	577.29	9/21/2010	8.28	11/28/2010	2.01
10/22/2012	576.78	8/1/2014	-4.99	11/8/2014	1.27
3/18/2015	579.06	5/13/2015	1.09	1/31/2015	-1.01
5/13/2015	579.48	6/6/2017	5.26	12/10/2015	1.31
11/5/2016	579.59	3/25/2018	-3.96	3/18/2016	-0.3
4/12/2017	579.74	11/29/2019	2.6	11/10/2016	0.25
5/10/2017	580.27	4/1/2020	-6.11	5/2/2017	-0.44
4/2/2018	579.91	8/31/2021	-0.72	7/11/2017	1.32
9/6/2021	580.56	1/18/2022	6.42	12/12/2018	1.5
9/24/2021	580.61	3/20/2022	-2.37	7/4/2019	1.8
8/24/2022	580.17			1/9/2021	0.85
9/9/2022	579.98			2/24/2021	-0.36
				2/9/2022	-0.45
				2/20/2022	0.59

Image Analysis: Incorporating NOAA water level data based on the date of acquisition of each downloaded image facilitated the selection of scenes with comparable water levels for manual delineation (**Table 2**). The NOAA Tides and Current database (<https://tidesandcurrents.noaa.gov/stations.html?type=Water+Levels>) provided water level data from specific stations across the United States. We gathered verified hourly water level data from the geographically closest station for each site and pulled the corresponding data for each MAXAR image collected. Due to the low frequency of imagery, we shifted the methodology from automated synthetic maps based on NDWI trends to manual delineation of the shoreline in 2-3 images from each site using QGIS. In order to find the most comparable images, we selected those from similar times of year and with a similar water level. This represented a challenge because of limited data availability. This challenge highlights the limitation of working with temporally limited data sets.

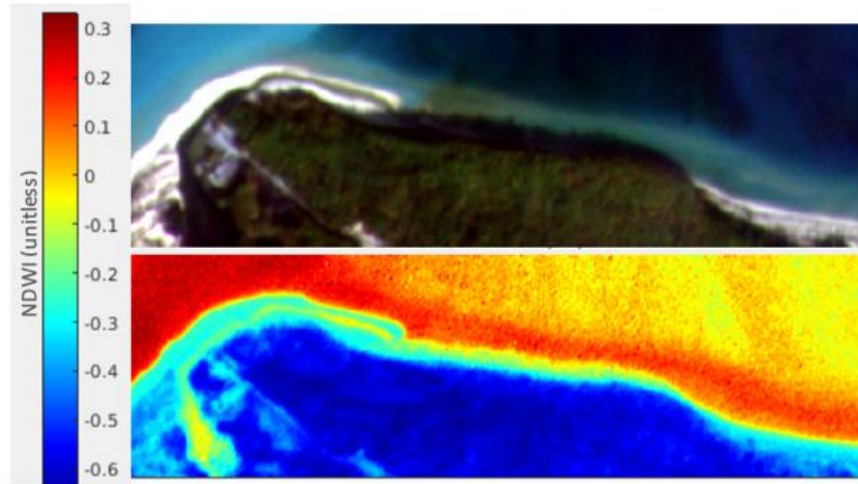
Using QGIS, the shoreline (represented by the land-water interface) in the selected images for each site was manually delineated. After outlining the shoreline, two classes were created, land and water, as a single shapefile layer. This shapefile was then converted to a raster with a binary attribute for each pixel; “0” was assigned for land and “1” for water. After repeating the process with each image for a given site, the raster calculator was used to produce a land/water change map similar to the final result of Planetscope.

4. Results

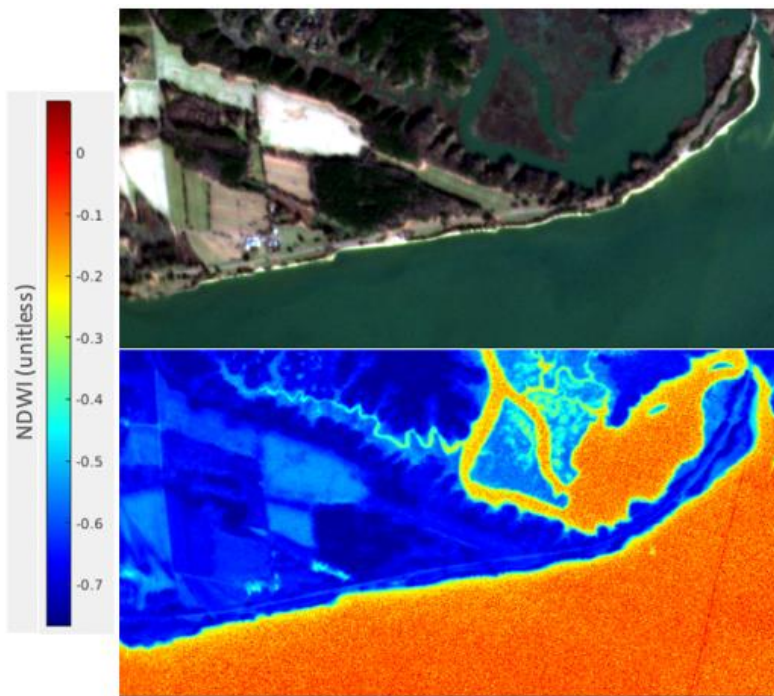
4.1 Analysis of Shoreline Change Using Planetscope Imagery

The NDWI calculated from the Planetscope reflectance data clearly identified and discriminated water from land/ice/snow on each individual scene (**Figure 2**). As can be seen in the images, land always exhibited low NDWI values, whereas water showed high NDWI values. Using a threshold value between -0.2 and 0 (site-dependent), NDWI values higher than the threshold consistently identified water pixels, as expected from this index. **Figure 2** demonstrates the visual accuracy of mapping an individual scene using NDWI compared to the quasi-true color images.

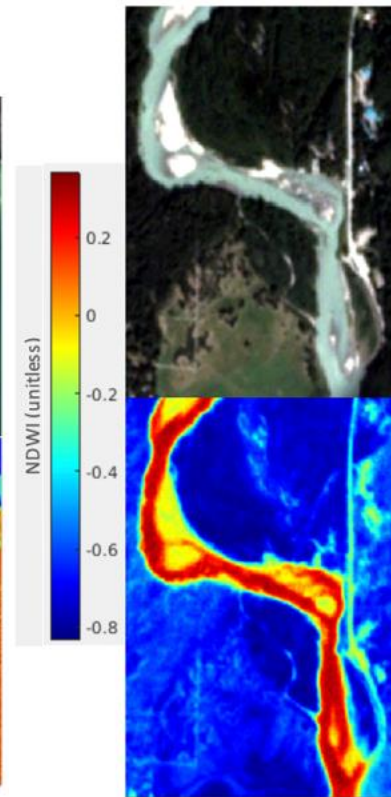
Calculation of the NDWI on all the available Planetscope images helped generate time series of NDWI values for every pixel location within the study areas (**Figure 3**). The high data density provided by Planetscope data (**Table 1**) greatly facilitated the determination of trendlines in NDWI over time at each pixel location. Here, simple linear fits of the time series produced a slope and intercept value at each pixel location. The slope provided a measure of the average rate of increase or decrease in the NDWI for the 2017-2021 time period at each pixel location. Maps of the slope thus provided an overview of the NDWI change observed at each site. Regions with positive slope values (increasing NDWI over time) indicated an increase in water-like characteristics over time, thereby revealing they were experiencing long-term flooding or erosion. In contrast, regions with negative slope value (decreasing NDWI over time) indicated an increase in land-like characteristics over time, thereby revealing they were experiencing accretion (land build up) or drainage.



A. SLBD



B. COLO



C. KLGO

Figure 2. Quasi-true color maps (top) vs. NDWI maps (bottom) for one selected scene at each site (A. SLBD; B. COLO; C. KLGO). Low NDWI (lower than threshold value of -0.2 to 0) are indicative of land, where high NDWI (higher than threshold value of -0.2 to 0) are indicative of water.

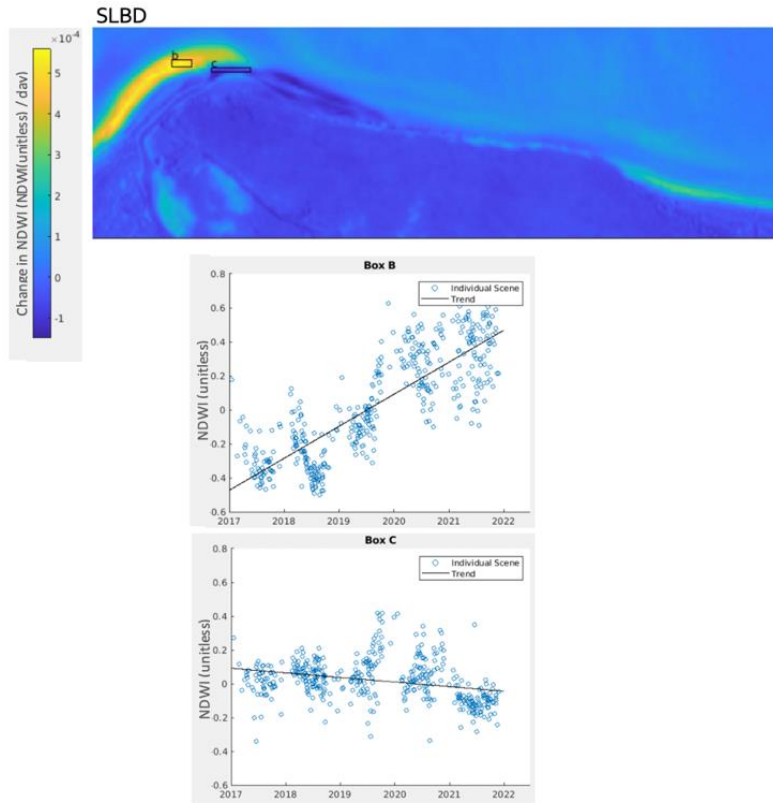
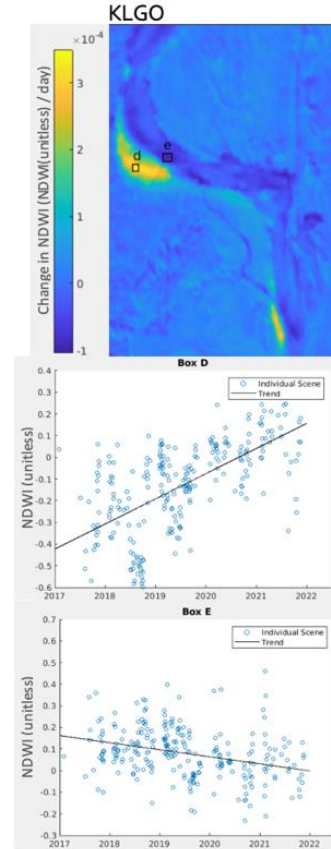
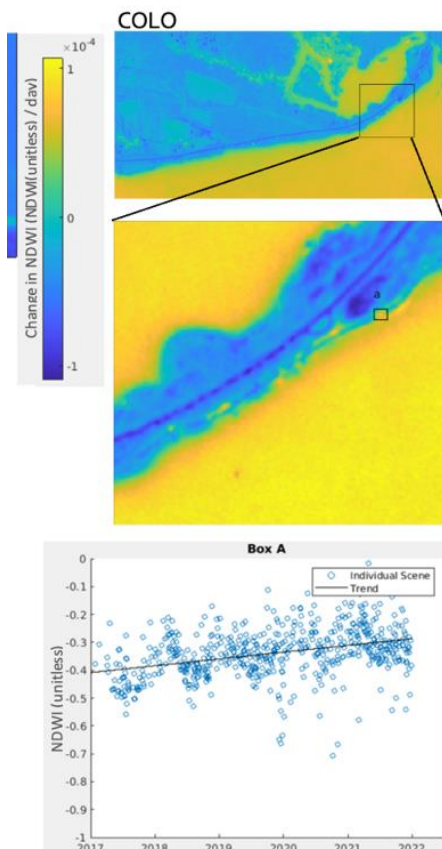


Figure 3. NDWI trend maps and example plots across all scenes at each site. Each point in the plot represents the average of a group of pixels throughout the time series. Positive slopes (increasing trends) of linear fit (yellow) indicate a trend toward water-like characteristics. Negative slopes (decreasing trends) of linear fit (dark blue) indicate a trend toward land-like characteristics.



The quasi-continuous time series at each pixel location and the trendline analysis (e.g., linear fits of NDWI on day of year) facilitated the production of synthetic images corresponding to the NDWI conditions at the initial time point (day = 0) and at the final time point (day = 1826) of the time series (**Figure 4**). Using an NDWI threshold of -0.2 to 0 (site dependent), we could distinguish pixels as either land or water and create a categorized land/water map from the synthetic images (**Figures 4 and 5**). The NDWI threshold was chosen after conducting a simple threshold sensitivity analysis with the three study areas. Using this threshold, any pixels with NDWI values below -0.2 or 0 (site dependent) are categorized as land; any above -0.2 or 0 (site dependent) as water. These simplified synthetic maps at the initial and final time point are useful in geospatially analyzing the temporal trend in NDWI (**Figure 5**).

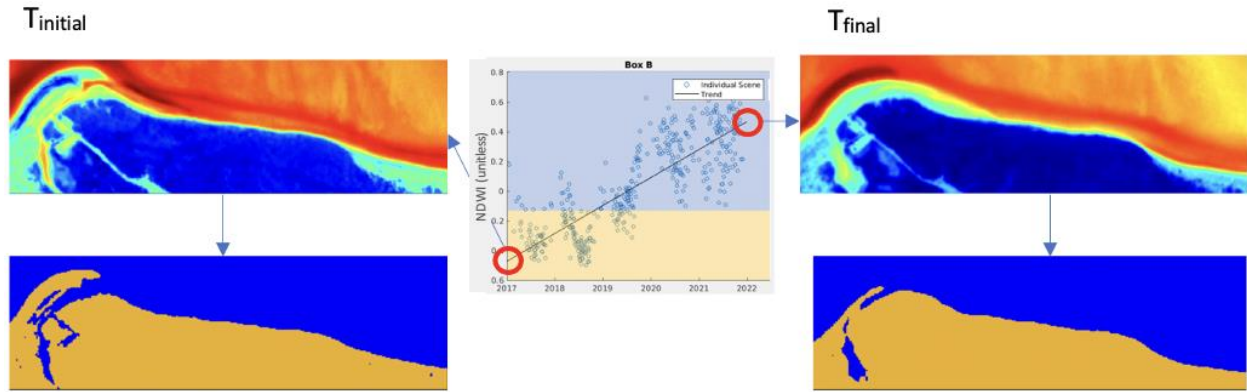


Figure 4. Example of synthetic land-water map creation for SLBD at $T_{initial}$ and T_{final} . The trend line for the complete time series of each pixel was calculated (middle), and the NDWI value of the fitted line at $T_{initial}$ (day=0 ; 01/01/2017) (top left) is what is mapped for the $T_{initial}$ synthetic map (bottom left). The NDWI value of this line at T_{final} (day=1826 ; 12/31/2021) (top right) is what is mapped for the T_{final} synthetic map (bottom right). A threshold of -0.2 – 0 (site dependent) was used to differentiate between land (brown) and water (blue) for the synthetic maps.

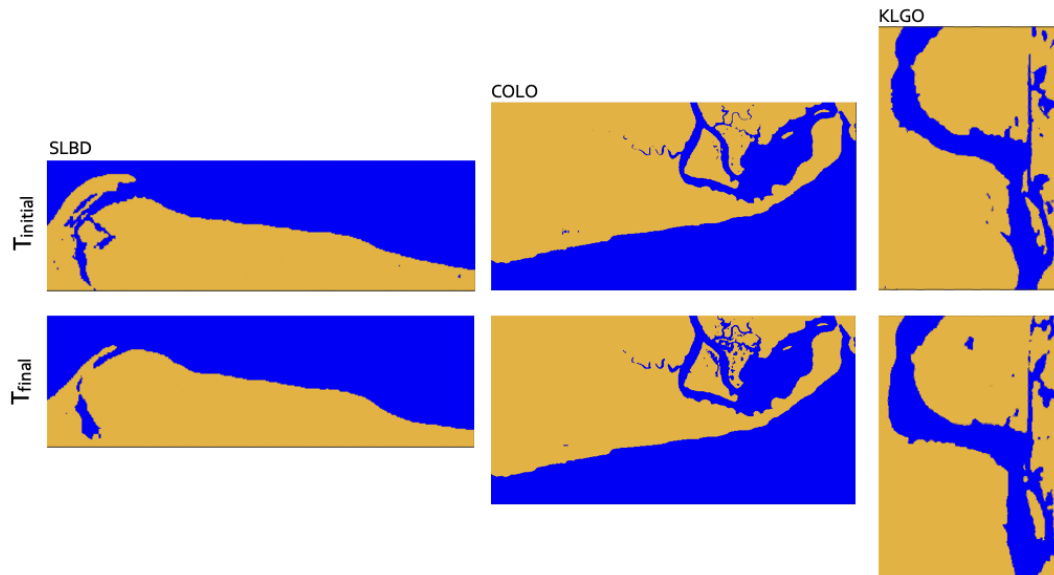


Figure 5. Synthetic land-water maps at $T_{initial}$ (top row) and T_{final} (bottom row) for each site. Land is shown in brown; water is shown in blue.

Comparison of the synthetic maps at the initial and final time point allowed areas of change to be identified in each study area (**Figure 6**). Overlaying the images at $T_{initial}$ and T_{final} allowed us to generate a corresponding image of change with four classes: 1. Water, 2. Land, 3. Areas of Land Loss, 4. Areas of Land Gain. Areas of change that went from water to land characteristics are shown in green, indicating land gain. Areas of change that went from land-like to water-like characteristics are shown in red, indicating land loss.

As can be seen in **Figure 6**, SLBD appears to experience significant land loss on the western portion of the Platte River as well as on the tree line bluff downstream, and land gain at its mouth and on the eastern portion. COLO demonstrates small areas of land loss along the ocean-facing shoreline as well as an overall trend of land loss in the marsh region. KLGO seems to experience a shift in the trajectory of the river, with land loss on the eastern outer bank of the meander and some land gain along the western bank.

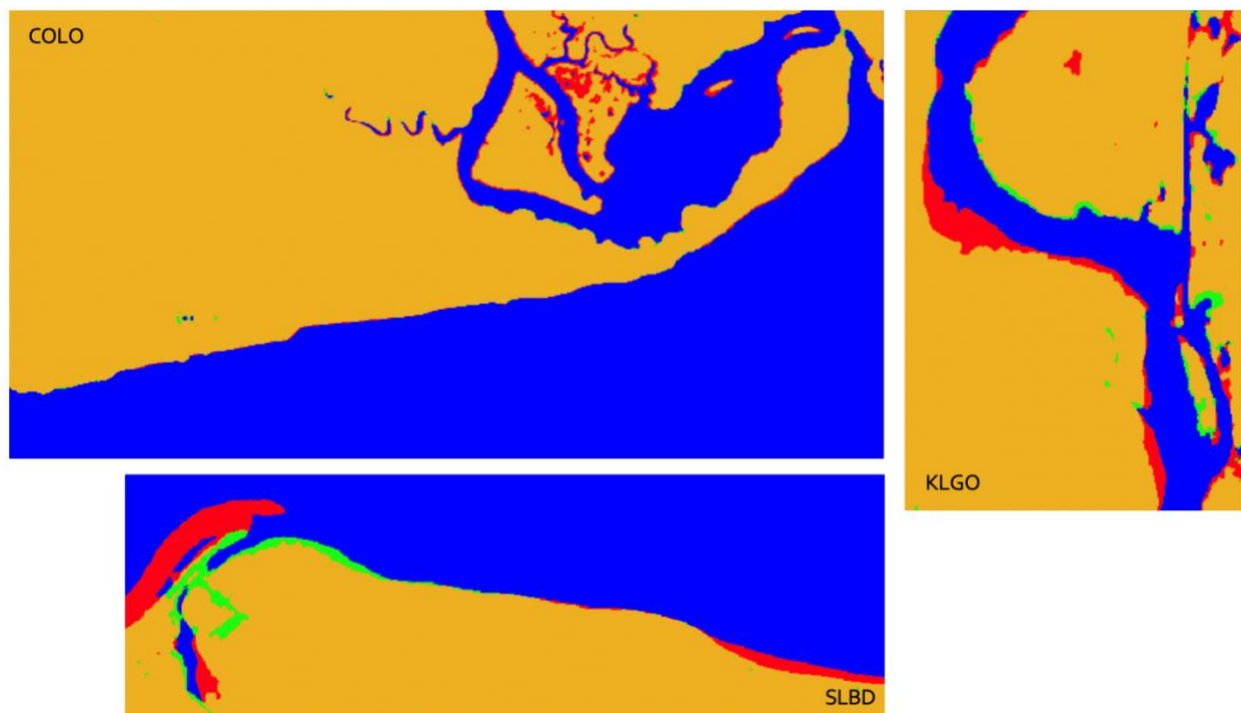


Figure 6. Synthetic NDWI change map at each site showing the difference from $T_{initial}$ and T_{final} . Brown = land; blue = water; red = land loss; green = land gain.

4.2 Maxar Analysis of Shoreline Change

Manual delineation of the shoreline for each of the three sites using Maxar imagery collected on the selected dates enabled us to identify areas of shoreline change (**Figures 7-10**). The manual delineations of SLBD visually demonstrate a significant shift in the mouth of the river as well as land loss in the Northwest portion of shoreline, while maintaining relatively consistent water level data (**Figure 7**). The selected COLO images provided the most consistent water level data, and the manual delineation captured the marsh region well. However, there are no clear areas of change in the delineations (**Figure 8**). The manual delineations for KLGO were the least comparable, as the water level data was very inconsistent (**Figure 9**). The manual delineations

could then be overlaid to create land/water change maps, mimicking the final result created for the Planetscope dataset (**Figure 10**).

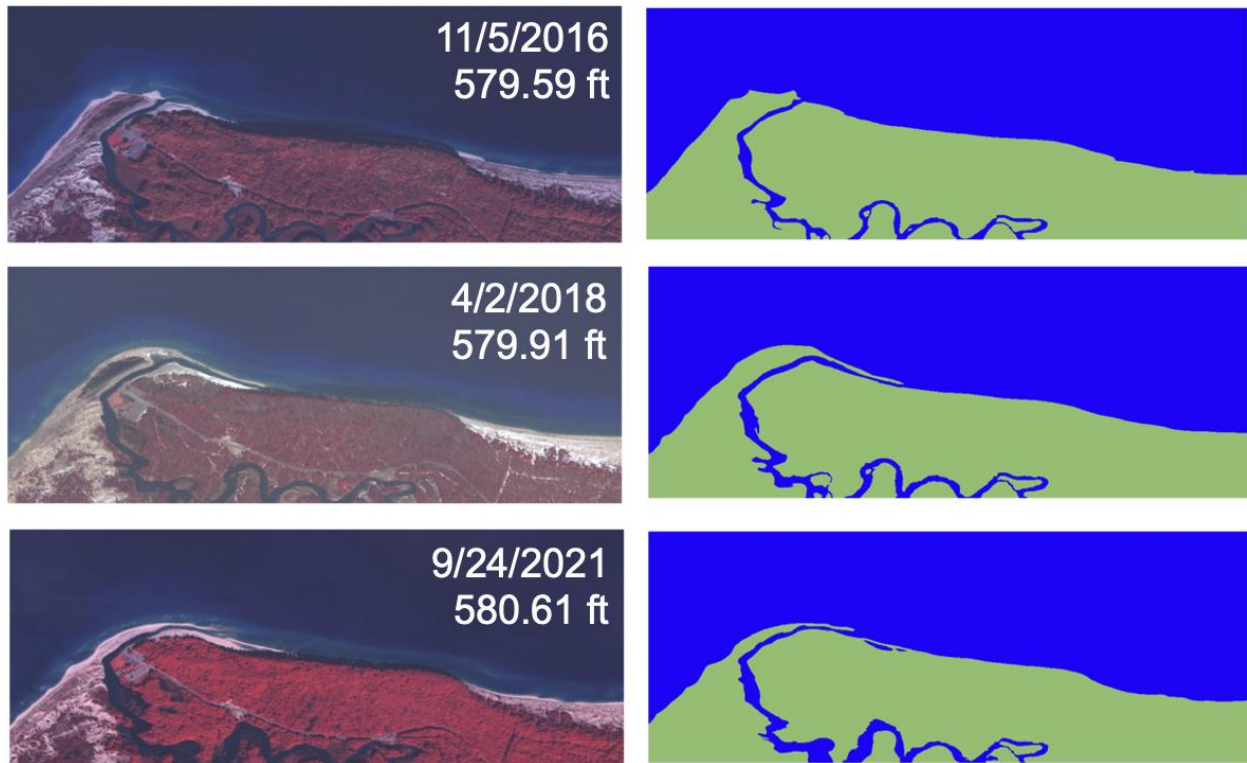


Figure 7. Manual delineation results for each SLBD image selected (date and water level noted on quasi-true color image). Land is shown in green; water is shown in blue.

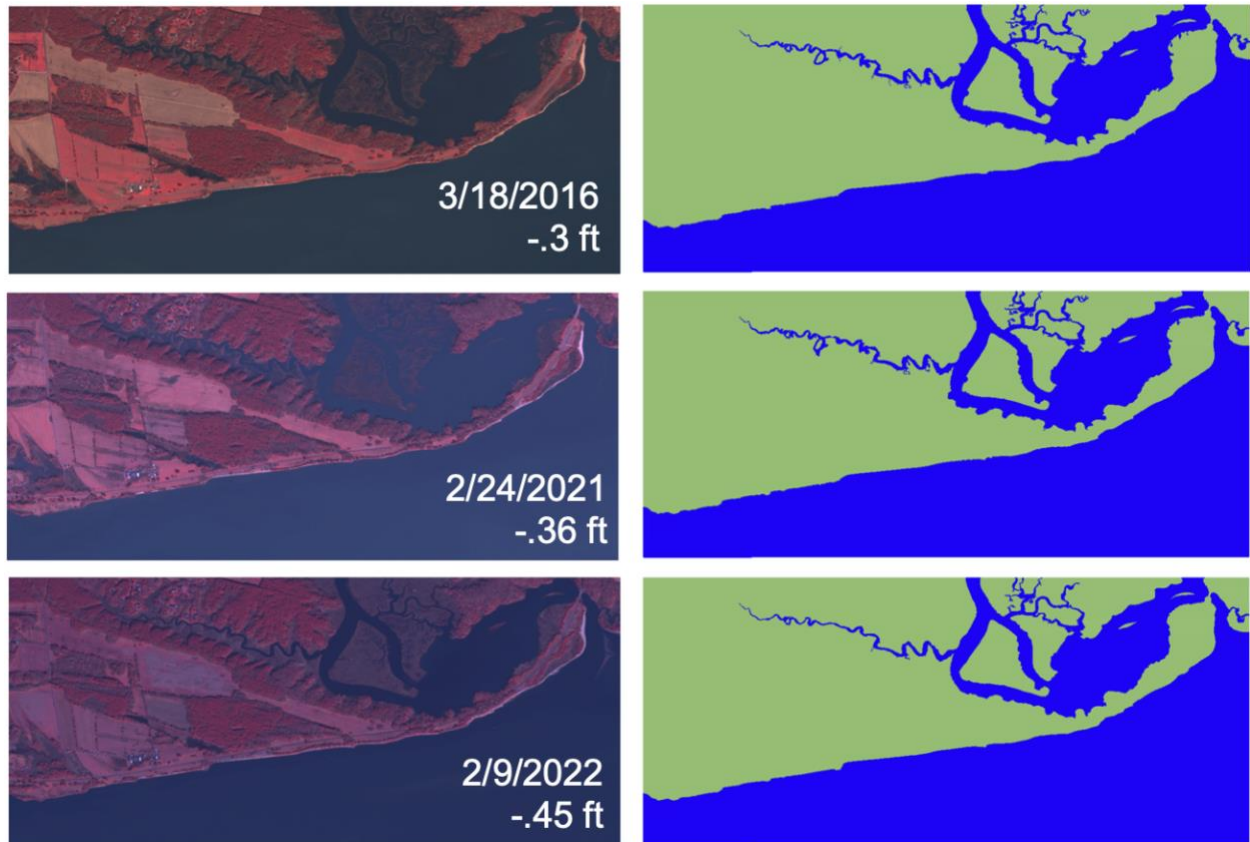


Figure 8. Manual delineation results for each COLO image selected (date and water level noted on quasi-true color image). Land is shown in green; water is shown in blue.

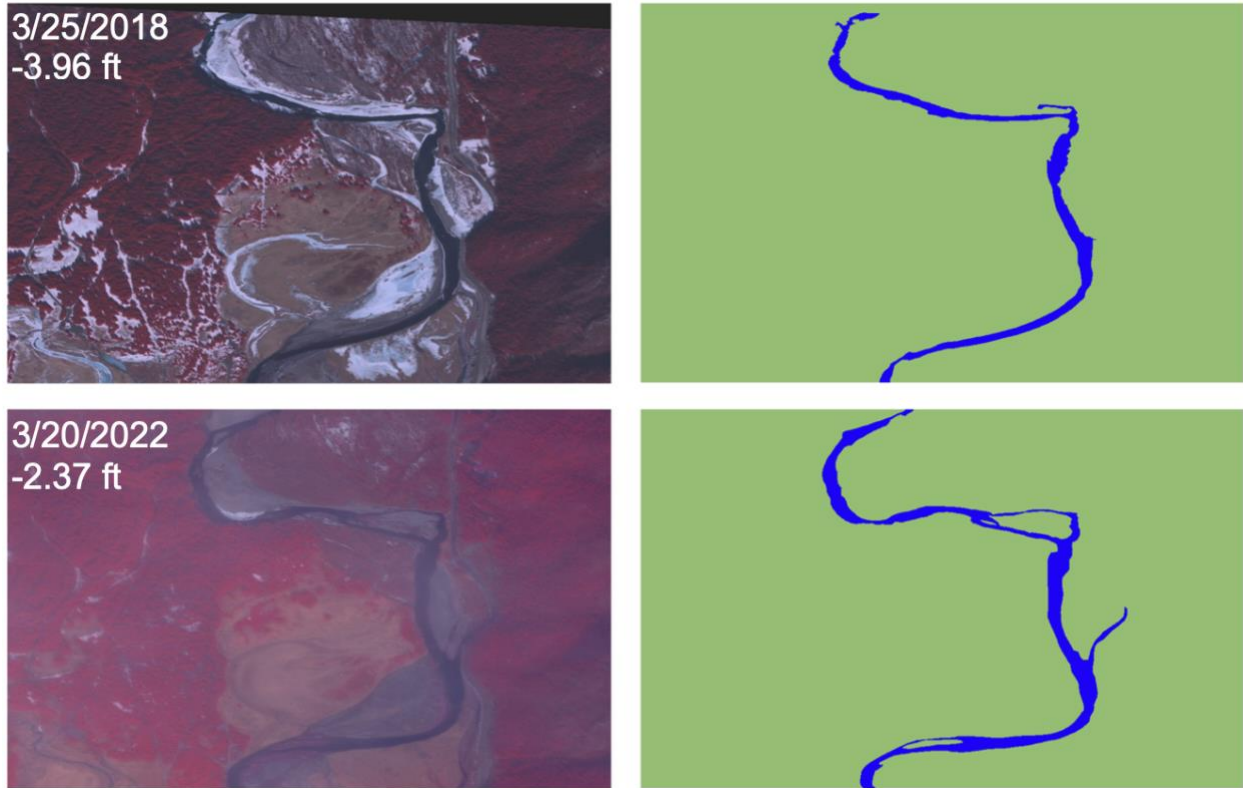


Figure 9. Manual delineation results for each KLGO image selected (date and water level noted on quasi-true color image). Land is shown in green; water is shown in blue.

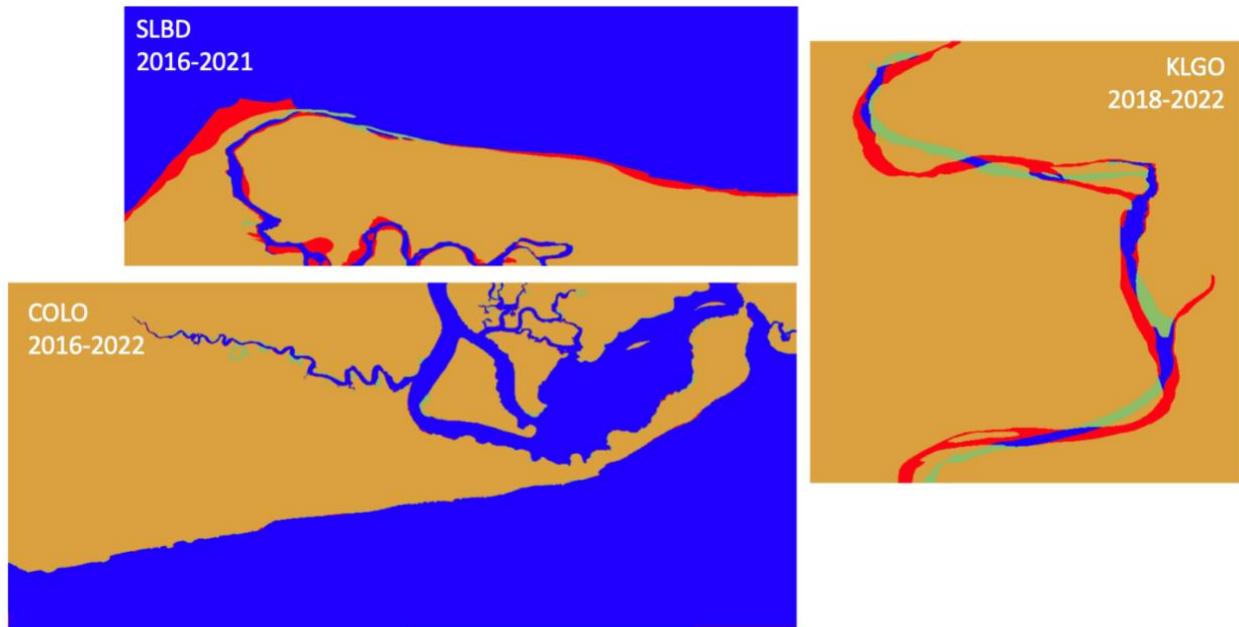


Figure 10. Land-water change maps. Brown = land; blue = water; red = land loss; green = land gain.

4.3 Comparisons between Planetscope and Maxar

Comparing the image frequencies of the Planetscope and Maxar databases emphasized a major difference between the two data sets (see **Table 1**). Maxar does not have sufficient image frequency to produce accurate trendlines, as can be seen in **Figure 11**. For example, while Planetscope had 811 images (i.e., data points) from 2017-2021 with which to produce a trendline, Maxar offered a much smaller datasets with 14 images from 2010-2022. The sporadic data availability coupled with the large variability in water levels can dramatically skew the change trendline. This is especially true in dynamic systems with strong tidal and seasonal variability. To demonstrate this limitation, we plotted the complete Maxar dataset from 2017-2021 (points and trendline shown in red) overlaid on the complete Planetscope dataset (points shown in blue and trendline shown in black). As can be seen in the figure, the trendlines are substantially different between the two datasets. For SLBD and COLO, the datasets show a trend in the same direction (positive). For KLGO, the Planetscope trend indicates positive change (land loss), whereas the Maxar trend based on few data points erroneously suggests a lack of change.

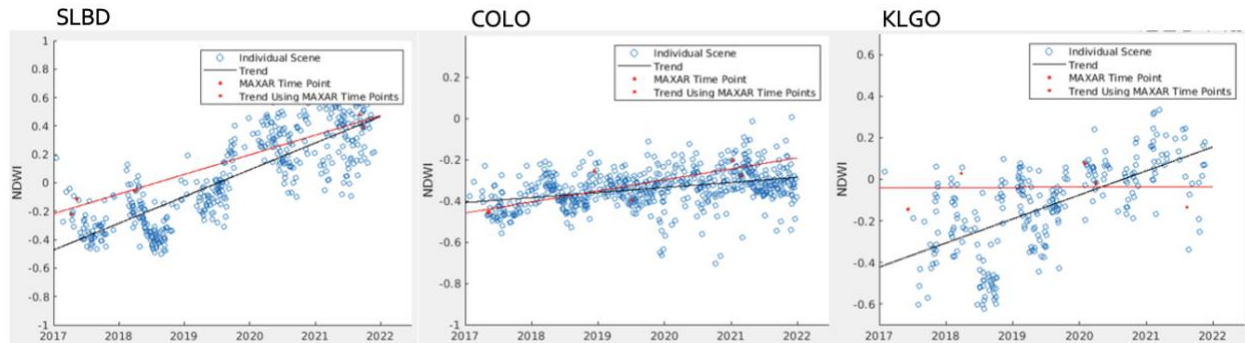


Figure 11. NDWI data (blue points) and trendline (black) derived from Planetscope dataset, compared to MAXAR dataset (red points) and corresponding trendline (red). The figure illustrates the sensitivity of the trendline when using data with a lower frequency of acquisition.

We can also visually demonstrate how Maxar images being collected infrequently poses limitations to assessing shoreline change over time. Mimicking **Figure 5**, we can first create synthetic maps demonstrating NDWI conditions at the initial time point (day = 0) and at the final time point (day = 1826) of the time series, and use the NDWI threshold of -0.2 to 0 (site dependent) to categorize the pixels into a land-water map (**Figure 12**). As can be seen in the figure, the low frequency of Maxar imagery acquisition demonstrates SLBD as significantly inundated at the initial timepoint. At COLO, the final time point demonstrates severely inundated marshland. At KLGO, the data at this frequency is not able to successfully detect the site.

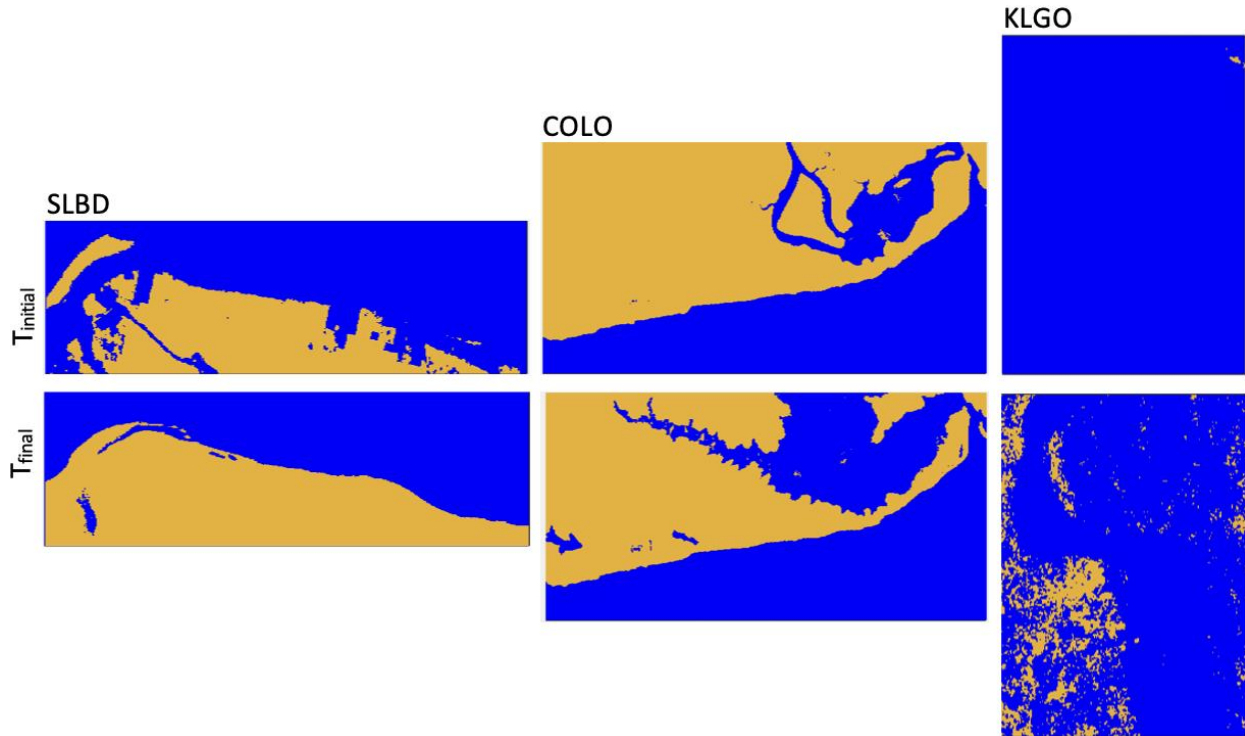


Figure 12. Synthetic land-water maps using the trendline derived from the Maxar image frequency at $T_{initial}$ (top row) and T_{final} (bottom row) for each site. Land is shown in brown; water is shown in blue.

To better highlight areas of change between the two time points, we can then overlay the images at $T_{initial}$ and T_{final} and generate a corresponding image of change with the same four classes: 1. Water, 2. Land, 3. Areas of Land Loss, 4. Areas of Land Gain (**Figure 13**) to mimic the analysis using the complete Planetscope data set (see **Figure 6**). Again, areas of change that went from water to land characteristics are shown in green, indicating land gain. Areas of change that went from land-like to water-like characteristics are shown in red, indicating land loss. As can be seen in **Figure 13**, the data suggest that there was significant land gain across the region at SLBD. At COLO, the marsh appears to undergo significant land loss. No change can be detected at KLGO.

Comparing the resulting synthetic land-water change maps derived from the Planetscope and Maxar datasets visually emphasizes the effect of low image frequency on our results (**Figure 14**). As can be seen in **Figure 13**, the loss coastline of SLBD was not properly delineated at $T_{initial}$ using the Maxar dataset. Because of this, the change map highlighted large areas of land gain that are actually not observed in the quasi-true color imagery. For COLO, the Maxar output depicts much more drastic land loss in the marsh than the Planetscope output. KLGO is not successfully detected using the Maxar dataset (**Figure 14**).

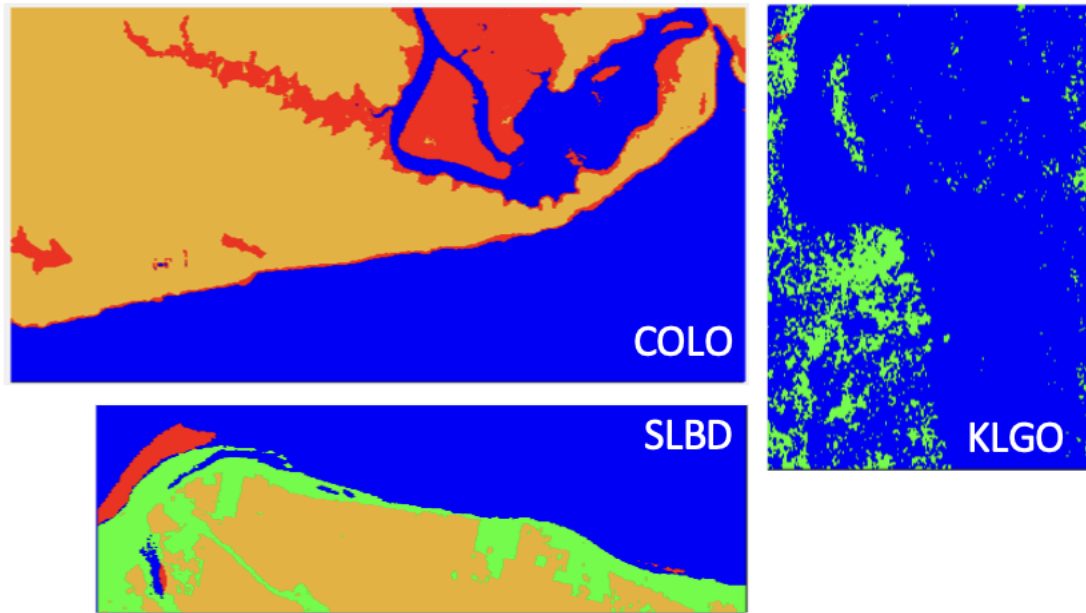


Figure 13. Synthetic NDWI change map using the trendline derived from the Maxar image frequency at each site. Brown = land; blue = water; red = land loss; green = land gain.

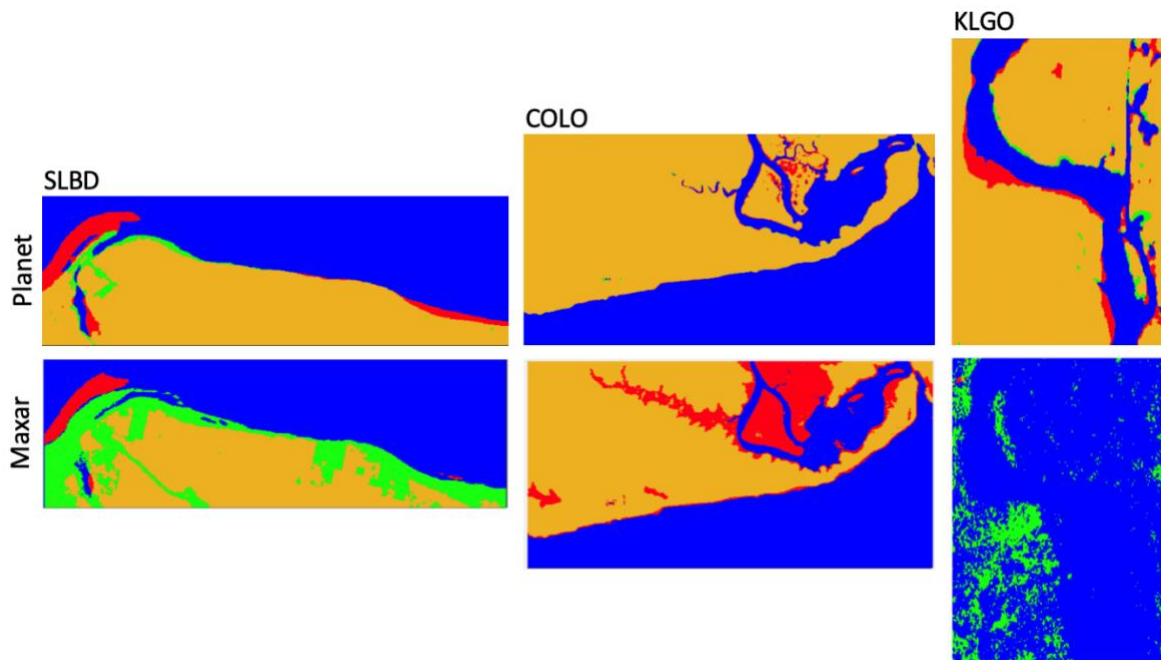


Figure 14. Comparison of synthetic Planetscope NDWI change maps using Planetscope frequency vs. synthetic Planetscope NDWI change maps using Maxar frequency. Brown = land; blue = water; red = land loss; green = land gain.

5. Discussion

5.1 Planetscope Data Analysis

The frequent acquisition of Planetscope imagery proved very useful for shoreline monitoring. Tidal and seasonal variations in water level can interfere with the accurate detection of the shoreline. Frequent temporally continuous image acquisition can help control for these seasonal and short-term changes in conditions by helping smooth out the influence of water level change, thereby facilitating analyses of long-term shoreline change. Planetscope, on average, had imagery every 2.25 days for COLO, 2.9 days for SLBD, and 4.8 days for KLGO. These temporally dense data set facilitated the production of reliable pixel-based trendlines by helping control for variation in water level.

The automated Planetscope methodology, ultimately creating a final synthetic land/water change map, was found to be efficient and can provide valuable information for coastal NPS unit managers. It provides an expansive analysis of the total site, rather than across specific sample points in small areas of interest, as on the ground fieldwork would provide. As a result, it has the potential to couple well with fieldwork methodology, providing a higher-level analysis that can highlight potential areas of interest worth further exploration. These results can be contextualized using local information from the NPS and could aid in management decisions regarding infrastructure and ecosystems in areas of land loss. One important limitation of Planetscope is the effective spatial resolution of a few meters (3-5 m), which can limit the ability to detect small shoreline changes. Another limitation is that analysis of shoreline change with Planetscope is mostly limited to the period after 2017 because of data availability.

5.2 Maxar Data Analysis

In contrast to Planetscope, Maxar had much lower image frequency, approximately 40-60 times less than Planetscope (**Table 1**). Our analysis clearly revealed that this low data density largely prevented the production of reliable trendlines, because the linear fits became much more susceptible to variations in water level or uncertainty in the reflectance measurements. Because of the sporadic nature of the data, the automated methodology was not sensible for the Maxar dataset. Instead, the 2-3 selected comparable images per site were manually delineated, which is a tedious and time-consuming process. An additional issue with the discontinuous frequency of Maxar imagery is that its availability for a given study is unreliable, depending on the time range and site.

A major advantage of Maxar over Planetscope is the much finer spatial resolution (< 1 m), which allows for the potential detection of smaller shoreline changes. However, there are tradeoffs to the value of this due to the lack of image frequency. Although such a fine spatial resolution is valuable when analyzing land cover change in most scenarios, water level variation due to tidal and seasonal influence can negate its value when analyzing shoreline change. Exceptions to this are areas like bluffs, where water level variation has little effect. Overall, the Maxar database may be best suited for small scale manual analyses of park unit areas less influenced by short-term variations in water levels (e.g., bluffs). An advantage of Maxar imagery is that data acquisition can date as far back as 2010.

5.3 Combined use of Planetscope and Maxar

The Planetscope workflow presented here can be used to quickly and automatically identify areas of shoreline accretion/erosion across all National Park Units. The approach can be largely automated, and provide rapid results for minimal manual labor. The quick identification of vulnerable/changing area can inform decisions for further investigations using high-spatial-resolution Maxar imagery, which can potentially provide more detailed and accurate assessment of shoreline change as long as images were acquired for very comparable water levels. One can envision using the Planetscope workflow to rapidly identify shoreline change in all NPS units, and identify the vulnerable areas to be studied using manual delineation using Maxar imagery. The need to acquire images for similar water levels can represent a limiting challenge, though one can potentially request new Maxar data acquisition that match previously collected images at a similar water level.

5.4 Future Work

At this stage, a careful validation of the shoreline change determined using the Planetscope workflow is needed. The next task is to implement this new workflow at a number of sites for which field measurements of shoreline extent have been acquired from 2017 and until 2021. A preliminary search has identified the Assateague Island (ASIS) and Fire Island (FIIS) NPS units as excellent targets for validation of this approach.

Additionally, more work is necessary to assess the utility of the Planetscope workflow to assess change in saltmarsh extent. Results from the COLO park unit presented here suggest the approach might be helpful in assessing change in saltmarsh extent, but it remains unclear if the observed change is real or a simple artifact.

5 Conclusions

6.1 Closing Remarks

This pilot study comparing the two methodologies revealed the importance of image frequency (more so than image resolution) when performing a desktop shoreline change analysis, leading to an overall recommendation of the Planetscope methodology for reliable and expansive shoreline monitoring. Dynamic water level conditions due to tidal and seasonal influence presented a major difficulty when using Maxar data that the automated Planetscope methodology was better suited to solve. While Maxar may be useful in areas with low tidal variation, such as bluffs, its discontinuous frequency makes it less reliable for NPS' large set of potential sites and temporal ranges of interest. Maxar's high spatial resolution may be useful for further analysis of areas of interest, and in this way may be well-suited for small-scale imagery analysis after the higher-level Planetscope analysis.

6.2 Logistical Management Considerations

A final consideration between Planetscope and Maxar is that of cost and total processing and data storage space needed. The present study of Planetscope used ~30,000 km² for the partial coverage of only three different NPS units. Evidently, the level of data needed to fully cover all 88 NPS units would be much greater, and this can represent a significant cost. This will also increase as the time period of analysis lengthens. Licensing costs of Planetscope vary and would

have to be up for negotiation, whereas NPS is already partnered with Maxar. Maxar allows for analysis of change through their software by creating gifs of multiple images ranging the same area, so shorelines could be briefly analyzed this way without downloading any imagery. However, this approach is very limited, and will not automatically highlight areas of change like the methodology using Planetscope imagery does.

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