Ease of Use, Applicability, and Automation of Crowd-sourced Imagery for Shoreline Change Maps

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Introduction

For most stretches of coast, observational data is limited and the sparse observational record introduces uncertainty into coastal management practices that require a data-driven understanding of shoreline stability and dynamics (Harley 2019). Frequent and long-term beach monitoring records are necessary to quantify a variety of physical processes, ranging from event-based shoreline response due to extreme storms to seasonal and inter-decadal shoreline trends at individual beaches and regional coastlines (Barnard et al. 2015; Kuriyama et al. 2012; Splinter et al. 2013; Stockdon et al. 2002; Turner et al. 2016; Walker et al. 2017). In spite of the need for regular observational data, the costs and logistics of regular and long-term coastal monitoring efforts using conventional in situ survey and established remote sensing techniques can be prohibitive.

Technological advances in survey and analysis methods have resulted in the evolution of coastal monitoring from in situ measurements to remote sensing techniques (Splinter et al. 2018; White and Wang 2003). In particular, the development of Argus and related coastal imaging systems that utilize fixed camera stations and sophisticated image processing methods have led to this shift (Holman and Stanley, 2007). Advancements in coastal imaging have ultimately resulted in the establishment of observation stations that measure nearshore processes and collect routine shoreline data that would be otherwise difficult to sample (Allen, Oertel and Gares 2012). However, coastal imaging stations require access to electricity and communications, protection from the elements in harsh coastal environments, and require significant setup and maintenance costs. Collectively, these factors can make the use of fixed coastal imaging stations impractical in some locations (Harley et al. 2018).

Recent advances in shoreline change mapping initiatives that utilize crowd-sourced imagery have demonstrated comparable accuracies to that of established coastal imaging systems and offer a low cost alternative. CoastSnap is a global citizen science project, developed by researchers at the University of New South Wales (UNSW), which aims to measure and quantify shoreline change using crowd-sourced cellphone imagery (Harley et al. 2019). CoastSnap relies on repeat imagery taken at the same location to track shoreline change resulting from processes such as storms, rising sea levels, and human activities. The crowd-sourced imagery provides a frequent and low cost data source that has the potential to aid coastal managers, planners, and engineers in better understanding shoreline dynamics and drivers of change on both a local and regional scale.

CoastSnap utilizes a simple and low-cost stainless steel camera mount that is installed at overlooking a coastal region of interest and used to constrain camera extrinsic parameters (Harley et al. 2019). The cellphone camera cradle is accompanied by signage detailing instructions for sharing participant's images to a central database. At a CoastSnap station, citizen scientists are prompted to scan a QR code, which opens an ArcGIS Online webpage. They are then instructed to place their cell phone in the metal bracket and take a snapshot image that is automatically submitted via Survey123 for image processing. When the CoastSnap station is installed, permanent ground control points (GCPs) within the field of view are measured and used to solve for the focal length of the smart phone lens and determine camera extrinsic parameters (Harley 2019). Since the images submitted by citizen scientists are roughly the same frame, the ground control points enable the rectification of the oblique cell phone image into map space. The shoreline position is then mapped on georectified images using an edge detection technique that uses the red (sand) and blue (water) color channels (Harley 2019).

At this time, there are CoastSnap stations operating in the United States of America, Australia, New Zealand, Belgium, Spain, France, Portugal, the UK, Brazil, and Fiji. In particular, a growing regional network of CoastSnap Stations is managed by the United States Army Corps of Engineers (USACE) across the Southeastern portion of the United States. With the most recent install, there are now five CoastSnap stations across North Carolina and Virginia, with plans to continue regional expansion. CoastSnap incorporates community involvement, serves as an outreach platform and provides a frequent and free data source that has the potential to aid Army Corps Districts, planners and engineers.

Currently, the Jennette's Pier CoastSnap station, located in Nags Head, North Carolina, is being used as a pilot for the USACE. The Jennette's CoastSnap station has averaged over 7 submissions per day, since May 17th and consistent monitoring of image submissions has already led to improvements in the CoastSnap submission process for other stations in the southeastern United States (Figure 1). Prior to May 17th, CoastSnap images were submitted via social media hashtags or email. It was determined that participants were not immediately submitting their shoreline images, or would fail to submit their images at all. Recreating the sign and submission process and creating a QR code, that would allow for images to be submitted automatically via Survey123 and ArcGIS Online resolved this issue and led to a significant increase in image submissions. The utilization of Survey123 and ArcGIS infrastructure have also made it possible to begin streamlining the current, user intensive CoastSnap workflow, and provide a platform to post public CoastSnap related data products and maps.

Despite overcoming problems with image submission, image processing for Coastsnap requires significant user input (Figure 2). As the regional CoastSnap network grows and photo submissions increase, the need for an automated file management system and automated image processing procedures will become a necessity. Currently, a user is required to manually download and name individual CoastSnap images, one at a time. Each of the files must then be moved to a specific folder that the CoastSnap code, which is written in Matlab, accesses. The code makes use of an Excel database, which also requires significant user input to populate. Once the information in the database has been entered, the images are rectified manually using preselected ground control points in the camera field of view using the Matlab-based CoastSnap graphical user interface (GUI) (Figure 3). Once the image has been rectified, the shoreline is mapped and saved.

Objectives

The CoastSnap Jennette's location will be used to evaluate and improve the ease of use, accuracy and applicability for different Army Corps Districts. The major objectives of this assessment are listed as follows:

- Determine the sensitivity of CoastSnap derived shorelines to changes in water elevation due to varying tide and wave runup parameters

• Compare CoastSnap shoreline accuracy to Lidar derived shorelines and shorelines derived from Global Positioning System (GPS) surveys

• Improve the data management and image processing system that is currently in place for CoastSnap.

Methods

I will first determine the sensitivity of CoastSnap derived shorelines to changes in water elevation under two different scenarios. I will compare the default CoastSnap shoreline mapping process, which uses a combination of tide data and a user specified average wave condition, to shorelines created using only a tidal correction, and a water level corrected using solely wave runup. I will first plot each of the three shorelines for a given CoastSnap image, and then plot them against each other to compare cross shore variability between each of the three water elevation scenarios.

I will also assess the accuracy of CoastSnap images taken at Jennette's Pier by comparing CoastSnap shoreline positions to the position of shorelines derived from Lidar surveys, and shorelines walked with a GPS backpack. I will first extract shorelines from LAS datasets using Quick Terrain Modeler. Then I will compare the Lidar derived shorelines to shorelines created using CoastSnap images that were submitted on corresponding dates. I will also visit the CoastSnap Jennette's station under four different wave and tide scenarios, take a CoastSnap, and then walk the shoreline with GPS backpack. I will visit the Jennette's station during a high tide, high wave event, a low tide, low wave event, a high tide, low wave event, and a mid-tide, wave event. After walking the shoreline under a given scenario, I will return to the station and take a second photo. I will then compare the shoreline position of the CoastSnap shorelines to the shoreline measured using the RTK backpack.

The final objective of this project is to streamline the current workflow for data management and image processing, thus reducing user input, with Python scripts created using the ArcGIS API for Python (Figure 4). I will write a program that runs multiple times a day, and downloads new CoastSnap imagery from the hosted ArcGIS Online web layer to a centralized database with the appropriate naming convention that the current CoastSnap Matlab program requires. I will also write a script that uploads processed CoastSnap data, including rectified imagery and shorelines to ArcGIS Online, and a CoastSnap Storymap, allowing the crowd-sourced data to be viewed by participating citizen scientists, students, planners and engineers online.

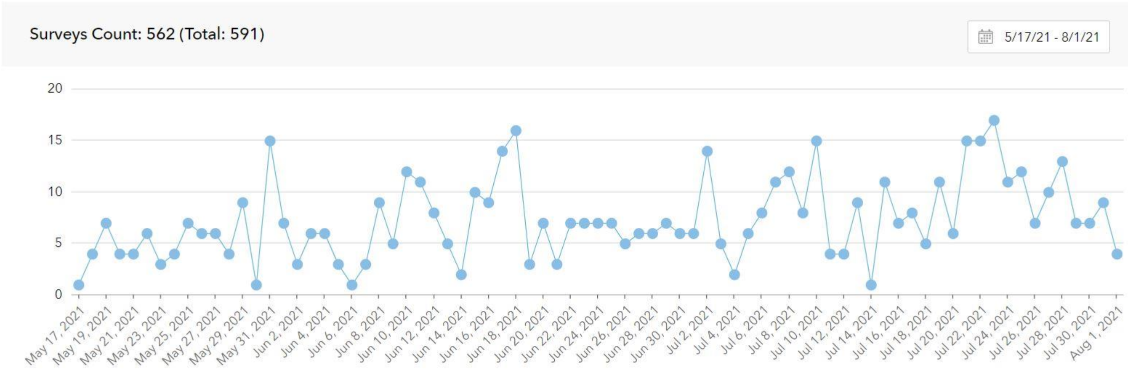

Figure 1: Graph depicting CoastSnap submissions by citizen scientists between 5/17/21 and 8/1/21. Daily submissions counts are logged in Survey123 and graphed by date through time.

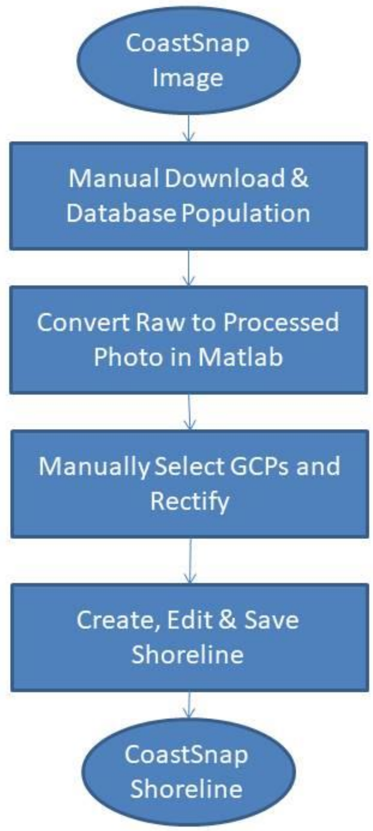

Figure 2: Flowchart diagram depicting the current CoastSnap workflow. The workflow that is currently in use requires significant user input, including manually downloading and naming individual CoastSnap images, populating an Excel Database and processing the CoastSnap imagery in Matlab.

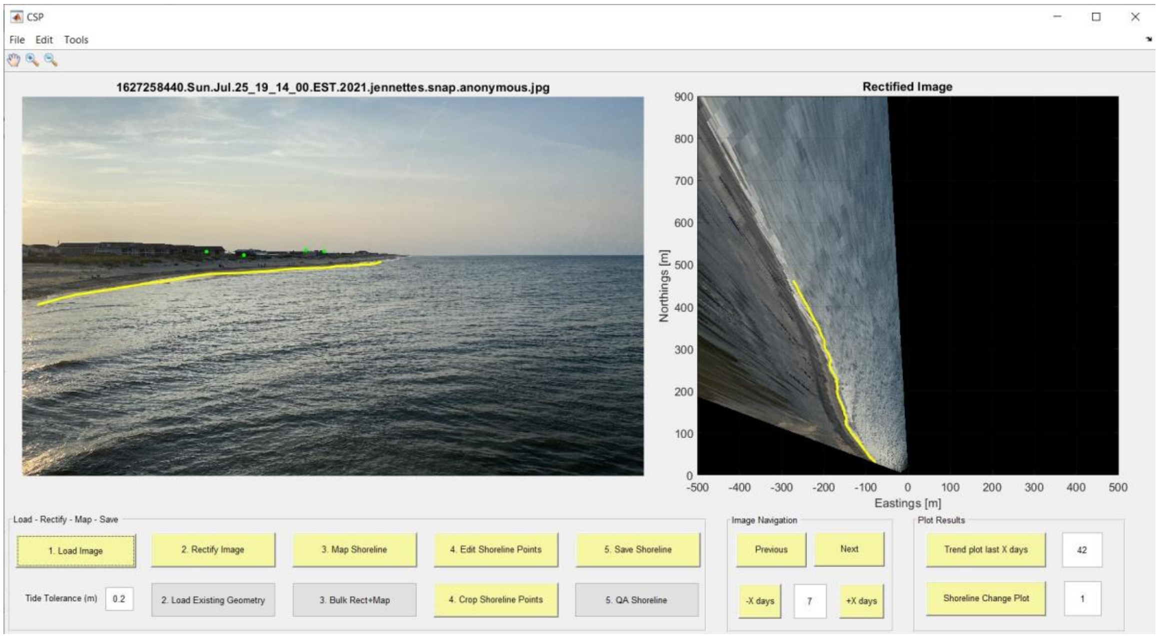

Figure 3: Example image of the Matlab-based CoastSnap graphical user interface (GUI). The window to the left depicts an example of a rectified CoastSnap image, manually selected ground control points shown in lime green, and a final shoreline, shown in yellow. The window to the left shows a planar map view of the CoastSnap image and shoreline. The toolbar below represents the basic CoastSnap workflow that is utilized within the GUI.

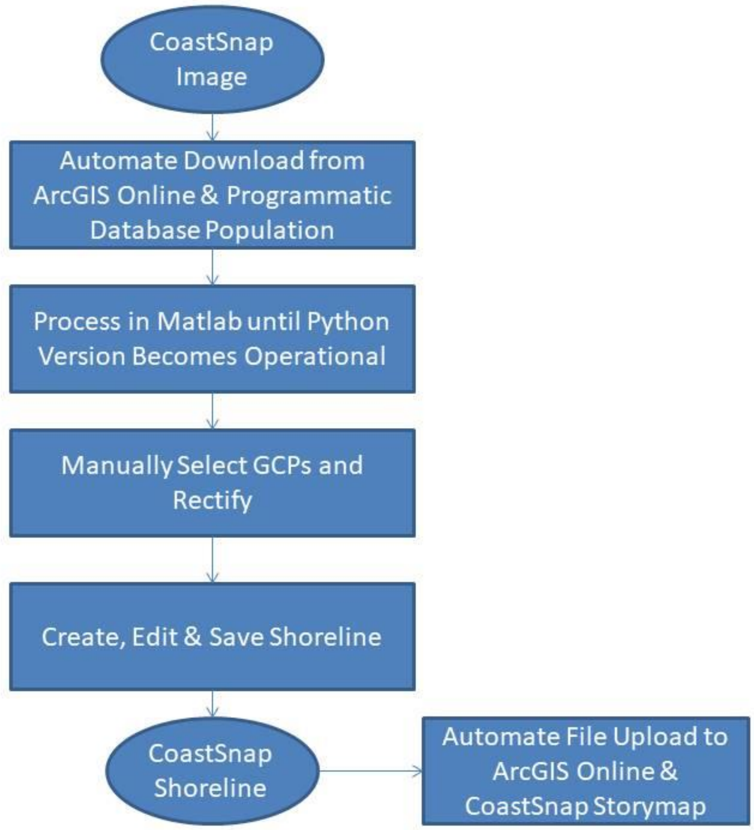

Figure 4: Flowchart diagram depicting the streamlined CoastSnap workflow. The proposed workflow will feature a programmatic element, and the automated download and upload of CoastSnap data to ArcGIS Online. This proposed workflow will increase operating efficiency and expedite the amount of CoastSnap imagery that can be processed by a single user or group of users managing regional network of CoastSnap Stations.

Literature Cited

Allen, Thomas R., George F. Oertel, and Paul A. Gares. 2012. "Mapping coastal morphodynamics with geospatial techniques, Cape Henry, Virginia, USA." *Geomorphology* 137 (1): 138−149.

Barnard, P.L., Short, A.D., Harley, M.D. Splinter, K.D., Vitousek, S. Turner, I.L., Allan, J. Banno, M. Bryan, K.R., Doria, A., Hansen, J.E., Kato, S., Kuriyama, Y., Randall-Goodwin, E., Ruggiero, R., Walker, I.J., Heathfield, D.K. 2015. "Coastal Vulnerability across the Pacific Dominated by El Nino/Southern Oscillation" *Natural Geoscience* 8: 801−807.

Harley, Mitchell D. 2019. "Shoreline Change Mapping Using Crowd-sourced Smartphoone Images". *Coastal Engineering* 150: 175-1891.

Holman, R.A., and Stanley, J. 2007. "The History and Technical Capabilities of Argus". *Coastal Engineering* 54 (6−7): 477-491.

Kelly, Joshua and Gontz Allen. 2019. "Rapid Assessment of Shoreline Changes Induced by Tropical Cyclone Oma Using CubeSat Imagery in Southeast Queensland, Australia." *Journal of Coastal Research*. doi:10.2112/JCOASTRES-D-19-00055.1.

Kuriyama, Y., Banno, M., Suzuki, T. 2012. "Linkages Among Interannual variations of shoreline, wave and climate at Hasaki." *Geophysical Research Letters* 39 (6): 2−5.

Splinter, K.D., Turner, I.L., Davidson, M.A. 2013. "How Much Data is Enough? The Importance of Morphological Sampling Interval and Duration for Calibration of Empirical Shoreline Models". *Coastal Engineering* 77: 14-27.

Splinter, K.D., Harley, M.D., Turner, I.L. 2018. "Remote Sensing is Changing our View of the Coast: Insights from 40 Years of Monitoring at Narrabeen-Collaroy, Australia". *Remote Sensing* 10 (11): 1744.

Stockdon, Hilary F., H. Sallenger Asbury, Jr., H. List Jeffrey, and A. Holman Rob. 2002. "Estimation of Shoreline Position and Change Using Airborne Topographic Lidar Data." *Journal of Coastal Research* 18 (3): 502−513.

Turner, I.L., Harley, M.D., Short, A.D., Simmons, J.A., Bracs, M.A., Phillips, M.S., Splinter, K.D. (2016). "A Multi-Decade Dataset of Monthly Beach Profile Surveys and Inshore Wave Forcing at Narrabeen, Australia". *Scientific Data* 3: 14-27.

Walker, Ian J., Bernard O. Bauer, Robin G.D. Davidson-Artnott, Irene Delgado-Fernandez, Patrick A. Hesp, Jeff Ollerhead, Thomas A.G. Smyth. 2017. "Scale-dependent Perspectives on the Geomorphology and Evolution of beach-dune systems". *Earth Science Reviews.* 171: 220-253.

White, Stephen A., and Yong Wang. 2003. "Utilizing DEMs derived from LIDAR data to analyze morphologic change in the North Carolina coastline." *Remote Sensing of Environment* 85 (1): 39–47.