

Smart Cameras for Coastal Monitoring

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Abstract

Coastal engineering practitioners are regularly faced with the difficulty of managing areas subject to beach erosion and inundation while having limited monitoring data of the coastal zone. In most cases, coastal data is sporadic, outdated or no longer represents the constantly changing nature of the nearshore which often hinders the long-term success of coastal management decisions. While routine monitoring of the nearshore using camera-based systems is a well-established technique, these systems have traditionally been costly to establish and generally beyond the resources available for most projects. A low-cost smart camera system is presented here to overcome these challenges by combining state of the art machine learning algorithms with established image processing techniques to quantify beach usage and track shoreline change. The innovative system is completely self-contained and can be easily installed on existing beach infrastructure such as on lifeguard towers to provide long term continuous data that allows for analysis of coastal change in response to storm events and patterns of beach use to understand the value of beaches to our communities. This paper presents the capability of the system applied on a number of projects on the NSW Central Coast to investigate the morphological impact of a nourishment program as well as supporting operational coastal management of lagoon entrances. Shorelines extracted from the system are shown to demonstrate close agreement with data captured through an intensive drone photogrammetry campaign. Insights into ‘the business of the beach’ are also provided through analysis of patterns of beach usage including daily and seasonal trends in beach visitation. The smart camera system detailed in this paper is shown to provide a cost-effective solution to unlock unprecedented information about shoreline change and beach visitation data. This information is becoming increasingly critical as we attempt to understand the value of beaches to our communities and develop sustainable future management strategies to protect our beaches for future generations.

Keywords: coastal management, coastal monitoring, machine learning, smart cameras, beach erosion

1. Introduction

Coastal engineering practitioners are regularly faced with the difficulty of managing areas subject to beach erosion and inundation while having limited monitoring data of the coastal zone. In most cases, coastal data is sporadic, outdated or no longer represent the constantly changing nature of this area which often hinders the long-term success of coastal management decisions. Using camera-based systems to monitor the coastline is a well-established technique including its use for over 20 years to monitor shoreline change on Gold Coast, QLD [2]. Recent camera and software technology advances have opened up new opportunities in the availability and analysis of coastal images such as citizen science shoreline monitoring [5], wave breaking analysis of rip zones [7] and pedestrian detection using machine learning [4]. Coastal monitoring systems have traditionally been costly to establish, challenging to configure and difficult to install due to the requirement for a permanent power supply and dedicated internet connection [8]. These factors have limited widespread adoption of this monitoring method on coastal projects as the systems are beyond the resources available for most coastal monitoring studies. Breakthroughs in recent years in the fields of robotics and autonomous driving have led to significant progress in the use of machine learning to detect pedestrians in images however this is yet to be widely applied to quantify beach usage in coastal areas. A low-cost smart camera system is presented here to

overcome these challenges by combining state of the art machine learning algorithms with established image processing techniques to quantify beach usage and track shoreline change.

2. Materials and Methods

2.1 Camera system

To provide cost-effective coastal monitoring we developed the Beachstat smart camera system with features as described in Table 1. Each system comprises a self-contained Swift Enduro 4G camera which is capable of data transfer of images and videos via the cellular network. The system is powered indefinitely through a solar panel to collect an image and a 10 second video clip every 15 minutes during daylight hours. The system settings can be programmed remotely as needed; such as to increase image capture frequency in the lead up to a coastal storm event.

Table 1 Features of the smart camera system

Feature	Details
Camera model	Swift Enduro 4G
Price	AUD \$700
Power and data transfer	Solar powered with 4G transfer via cellular network
Data frequency	Image and 10 sec video every 15 minutes during daylight hours
Features	<ul style="list-style-type: none"> • Shoreline monitoring • Beach user counting



Figure 1 The WRL Beachstat smart camera system. Clockwise from top left: installation on a lifeguard tower; disguised inside a possum box to prevent vandalism; directly mounted to a tree; camera view of lagoon entrance at Avoca Beach, NSW; machine learning based user detection at Ettalong Beach, NSW.

As the unit is self-contained and self-powered, it significantly lowers the cost barrier required for installation and allows for flexible installation in remote locations or easily on coastal infrastructure such as lifeguard towers (Figure 1). Captured images are backed up locally on an SD card as well as being transmitted which mitigates the risk of lost data in the event of theft or vandalism of the system. The systems are robust and weather proof with deployments ideally suited for 12 month periods however some cameras continue to be operational after over two years in the field. The system transmits between 5GB to 15GB of data per month which can be covered under relatively low-cost mobile data packages (AUD\$50/month). The system transmits imagery in real time to a cloud-based server paired with a bespoke online dashboard to streamline access to live and archived imagery, timelapse videos showing the past week of beach change, shoreline analysis alongside environmental monitoring data of water levels, waves and weather forecasts (Figure 2).

2.2 Central Coast NSW smart camera network

A network of ten smart camera systems were installed on the NSW Central Coast located 100 km north of Sydney to assist the local Council in management of their coastline. The first camera was initially installed in April 2019 onto the Ocean Beach lifeguard tower to monitor the shoreline

response to a nourishment exercise that included placement of 10,000 m³ of sediment on the beach area. This camera deployment was combined with collection of monthly drone photogrammetry surveys which have been used to validate the accuracy of camera derived shorelines. Since the success of this initial camera deployment, the network has expanded to currently (at July 2021) monitor nine other coastal locations. This network is used by Central Coast Council to support operational management of five coastal lagoon entrances (Figure 4) and to monitor coastal change at erosion hotspots located at Wamberal Beach and The Entrance North. The dashboard associated with this network presented in Figure 2 and is available for viewing at <https://arcg.is/15y54T>.

2.3 Shoreline analysis

Shoreline change mapping using imagery from the smart camera system is routinely undertaken using the Coastsnap shoreline detection algorithm [5]. This methodology is based on a four-step process comprising of:

1. A precise survey of the camera and multiple ground control points within the field of view;
2. Georeferencing of oblique images into real world coordinates using the survey to calculate the roll, tilt, azimuth and lens distortion of the camera (Figure 3);

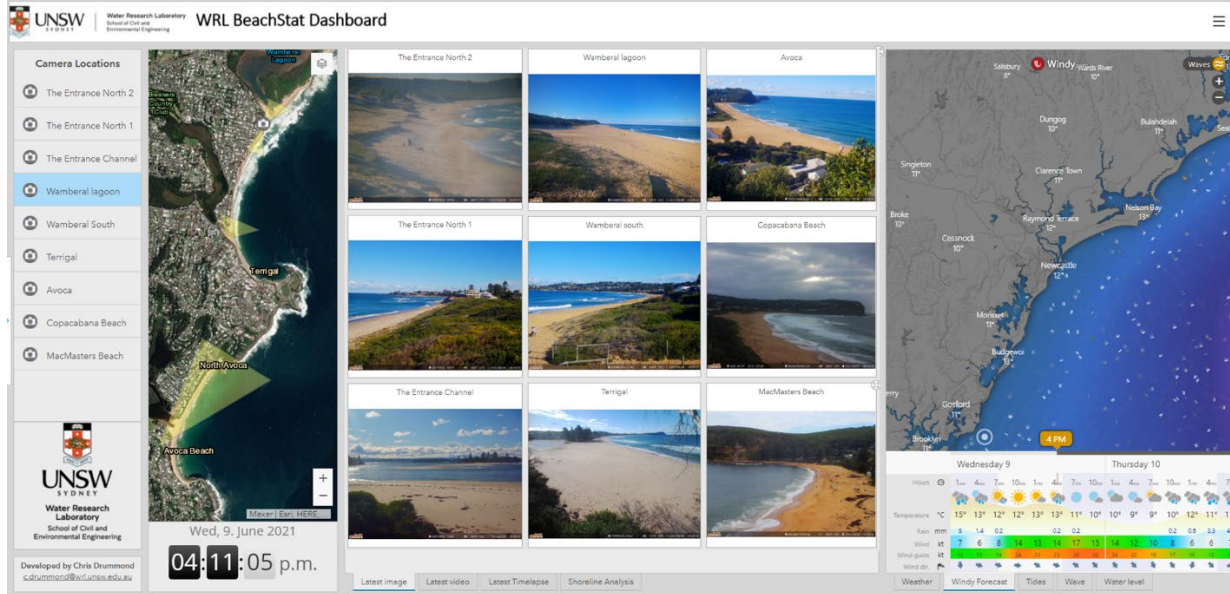


Figure 2 Beachstat Dashboard providing access to real-time images from a network of nine smart cameras deployed on the NSW Central Coast to support operational management of beach activities by Central Coast Council.

3. Mapping of the horizontal position of a shoreline using a shoreline edge detection technique that exploits the variation in the RGB colour spectrum between the land and the ocean;
4. Correction of the shoreline position based on the predicted tide level and elevation associated with any given image.

A number of equally spaced transects are used to extract the beach width between a fixed landward benchmark in the backshore to the shoreline edge. These beach widths are then averaged alongshore to provide an estimate of the beach width at each timestep. Using this method allows for quantification of changes to the intertidal shoreline on sub-daily intervals (i.e. every 15 minutes). While shorelines extracted during storm conditions are useful for understanding processes such as wave runup, they are generally excluded from analysis of beach width. This is because storm conditions are usually dominated by factors such as wave setup, runup and wind/barometric forcing which are not accounted for in the analysis technique which only

considers water level corrections for astronomical tides.

2.4 Machine learning beach user detection

Recent advances in machine learning algorithms have led to significant improvements in the accuracy of pedestrian detection in imagery. A state-of-the-art pedestrian detection model [6] was used as the basis for beach user counting images captured by the smart camera system. This pre-trained machine learning detection model was retrained using over 10,000 manual annotations to improve its reliability to count beach users located on the dry beach and in the water. Detection of swimmers in the water was achieved by the model despite the challenge that this class is often obscured and has a smaller pixel footprint. The machine learning model outputs a bounding box around each detection of a beach user as well as a confidence score of the detection (Figure 5). Spatial trends in beach usage were also explored by translating detections into real world coordinates using the image rectification process (Figure 5).

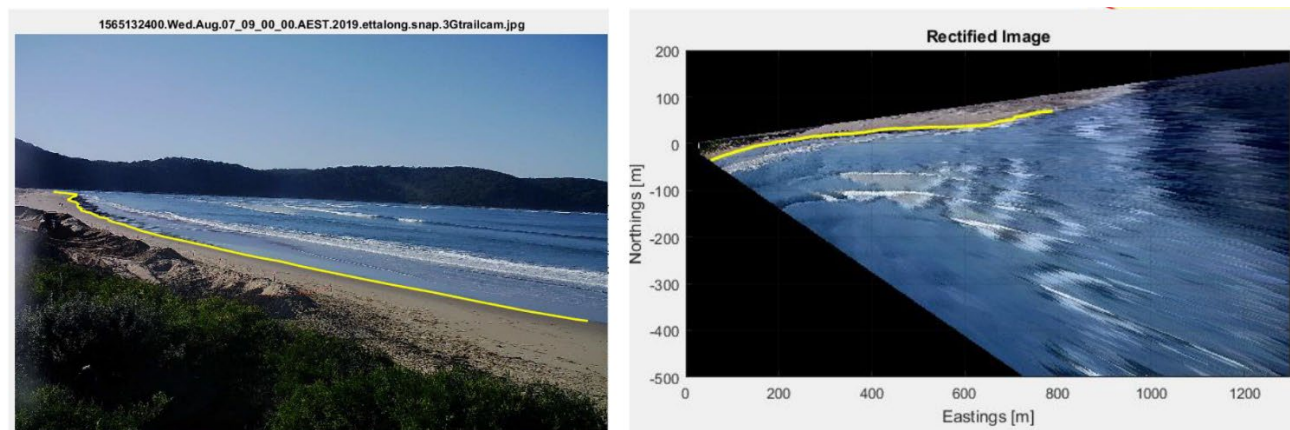


Figure 3 Example of the image rectification process from oblique camera imagery at the Ocean Beach camera during a beach nourishment exercise as well as the shoreline detection on the same image georeferenced to world coordinates.



Figure 4 Sequences of mechanical openings of ICOL entrances at Terrigal Lagoon by Council prior to a flood event in May 2020 (top) and unauthorised opening of Cockrone Lagoon, Macmasters Beach by the community in Nov 2020 (bottom)

It should be noted that while this analysis technique provides counts of instantaneous users visible in an image captured by the system every 15 minutes, it does not identify or track them between each image. The ability to track unique beach users is not possible without implementing a costly continuous video feed analytics solution. An assumption of a typical duration of a beach visit was therefore required to convert from instantaneous people counts to total daily users. There is very limited data available on the typical duration of a beach visit with the only data known to the authors contained in [1] and [4] which included on-site and online surveys for users of Manly Ocean Beach (Sydney), Collaroy-Narrabeen Beach (Sydney) and Waikiki, (Hawaii) and estimated the following beach visit durations:

- Manly Ocean Beach:
 - Average visit duration: 2.5 hours
 - \pm Standard deviation: 1 hour to 4 hours
- Collaroy-Narrabeen Beach:
 - Average visit duration: 2 hours
 - \pm Standard deviation: 0.5 hour to 3.5 hours
- Sans Souci Beach, Waikiki:
 - Average visit duration: 3.9 hours

The best available data indicates that a typical beach visit at this/our/name of place location would last for an hour and could typically range from 0.5 to 4 hours. Based on this range, instantaneous people counts have been converted to total daily users by assuming a typical visit of 1 hour.

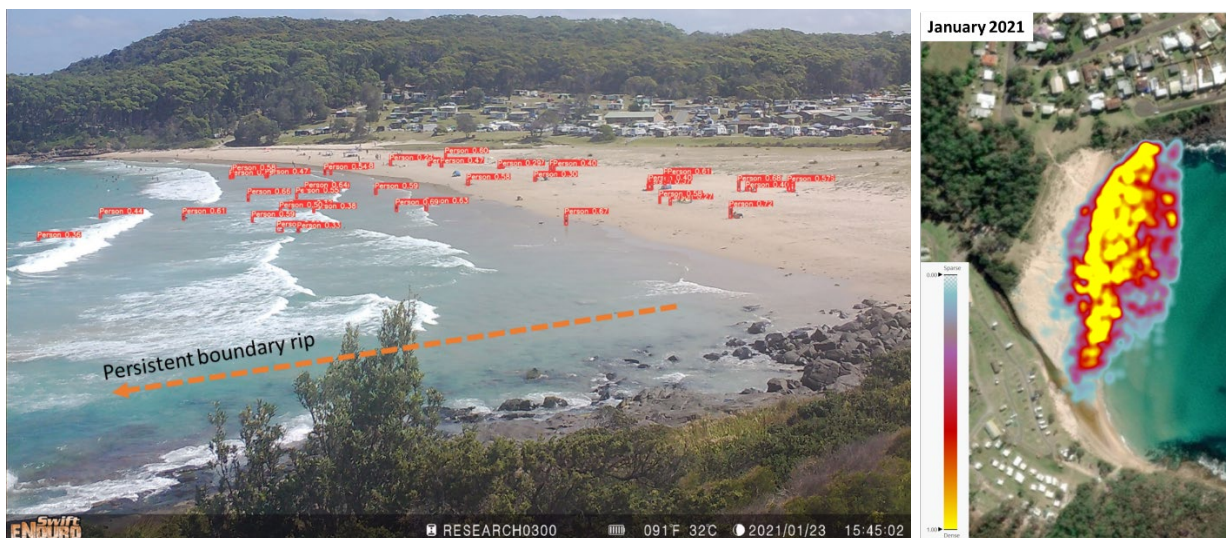


Figure 5 Results of the model to detect beach users on the dry beach and in the water (left) and heat map of detections showing spatial patterns of beach usage (right)

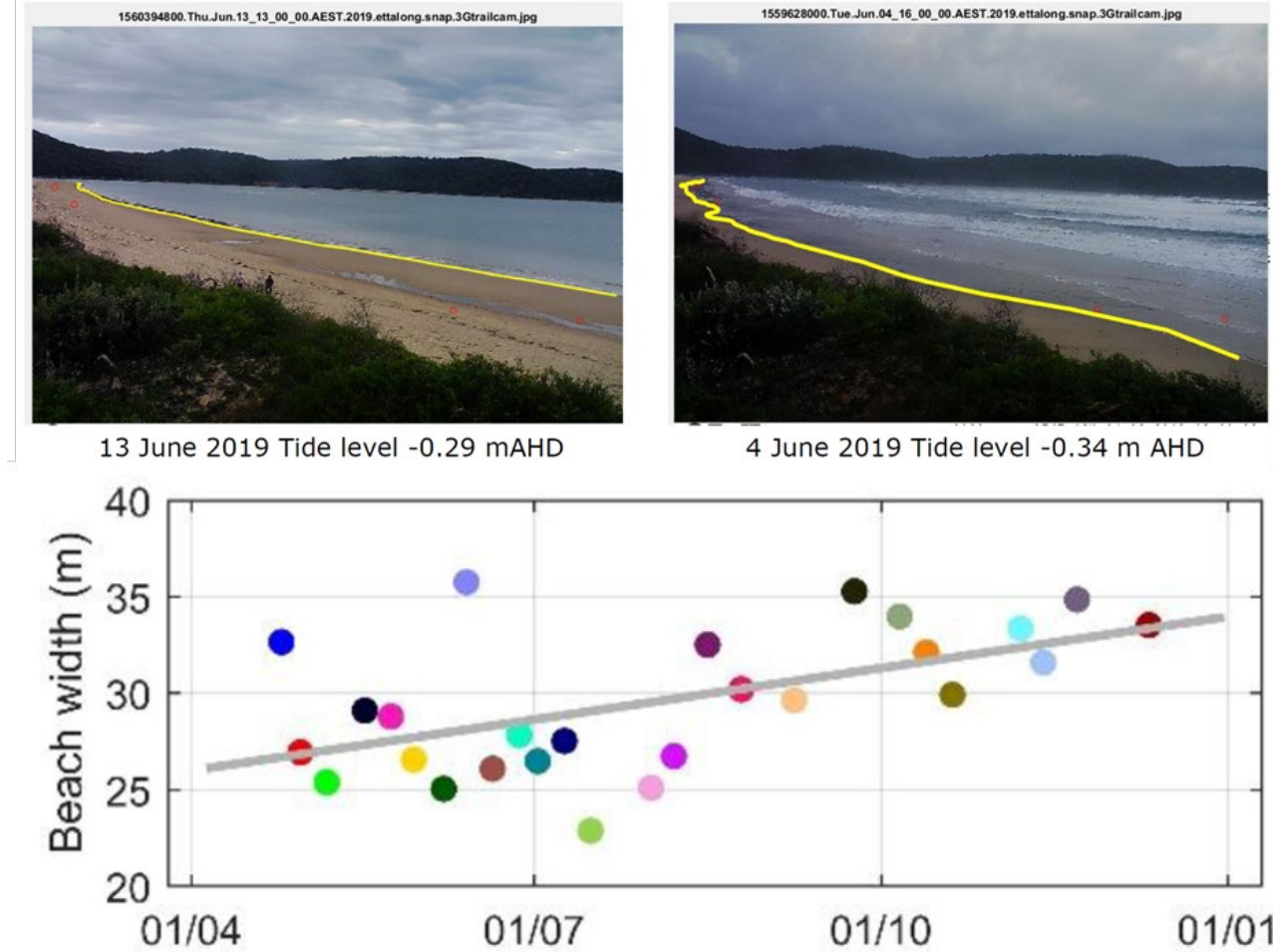


Figure 6 Results of shoreline analysis of Ocean Beach, NSW throughout 2019 during a beach nourishment exercise involving placement of 10,000m³ of beach material dredged from the adjacent navigation channel.

3. Results

3.1 Shoreline monitoring

Results of shoreline monitoring of the nourishment exercise at Ocean Beach identified an overall accretionary trend at a rate of +1 m per month for the period between April and December 2019 (Figure 6). The widest beach width identified during the monitoring period occurred on 13th June 2019 when a low tide terrace bar welded to the shoreline, whereas the most landward waterline captured during monitoring occurred on 4th June 2019 midway through a major storm. The accuracy of camera derived shorelines were investigated through comparison with in situ field measurements collected via drone photogrammetry (Figure 7). This comparison identified shoreline positions were located within +/- 1 m horizontally from both techniques. These results demonstrate confidence in the accuracy of the camera derived shorelines which were able to provide monitoring data at a much higher temporal frequency than the drone survey deployments at a much lower cost.

Shoreline monitoring was also used to quantify the impact on Wamberal Beach caused by a severe weather event that impacted the NSW coastline between the 14 and 19 July 2020. The event, termed an East Coast Low, created large wave

conditions that resulted in significant damage to beachfront properties at Wamberal Beach [3]. The storm produced a peak significant wave height of 6.9 m from a south-east direction and was the sixth most severe storm to occur over the past 62 years based on cumulative storm energy [3]. The response of Wamberal Beach to this storm event has been quantified through shoreline analysis from our smart camera system (Figure 8). This analysis identified a generally stable beach in the months leading up to the storm before rapidly narrowing by 30 metres over the course of a few days.

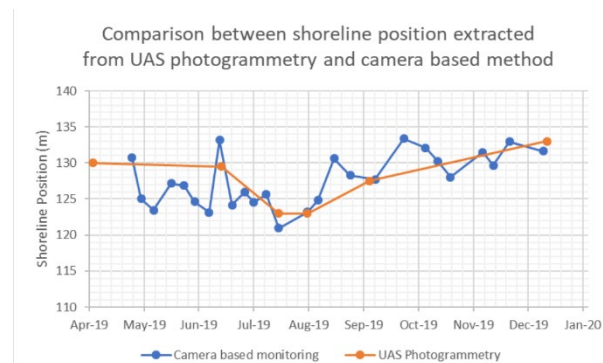


Figure 7 Comparison between camera derived shorelines and shorelines measured in situ using drone photogrammetry

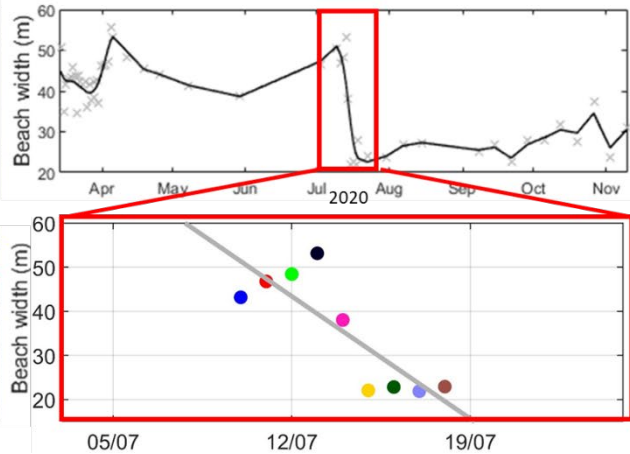


Figure 8 Results of shoreline analysis of Wamberal Beach throughout 2021 including beach response to a large east coast low storm event in July 2020 which resulted in a loss of 30 m in beach width and caused significant property damage.

3.2 Beach user detection accuracy

The accuracy of the automated detections of beach users were validated against a test set of 2000 manual annotations of people. This comparison demonstrated a detection accuracy of 80% or more which is more than adequate to gain insights into trends in beach usage (Figure 9).

3.3 Beach usage statistics

The machine learning algorithm identified over 20,000 people visited Ocean Beach throughout 2020 (Figure 10). Results indicate beach visitation was strongly impacted by season with the top three months of visitation occurring in January, April and October 2020 coinciding with the school holidays. Outside of these periods, beach visitation was considerably lower with the months of June, July and November having up to ten times less visitation compared to the busiest month in April 2021. Investigation into weekly trends visits to Turimetta Beach indicates that the weekend is by far the busiest period at this site with 50% of all visits occurring on these days. There was a clear preference for beach visitation to occur between midday and late afternoon. The most popular time of day to visit was between 1 pm to 3 pm which represented 40% of all beach visits. There was also a clear relationship between visitation and temperature. The hottest maximum temperature observed during the monitoring period (44.5 ° C) occurred on the 4 January 2020 which also coincided with the busiest day of visitation (265 visits). Conversely, lower temperatures associated with the winter months were also linked with much lower rates of beach visitation. The coldest day of the year occurred on the 7 August 2020, a peak temperature of 12 ° C and only 2 beach visits.

4. Discussion

This study has demonstrated the value of using low-cost smart cameras for the purposes of shoreline change mapping and quantifying beach usage patterns. Through the simple yet innovative system, a significant amount of information is able to be unlocked to assist with coastal management

activities. The system provides powerful tools to monitor coastal lagoon entrances and has been used in the study area to promptly identify and document unauthorized opening of lagoon entrances by the community (Figure 4). The timelapse animations provided by the portal are capable of communicating complex issues around lagoon entrance management activities at community engagement events. By hosting live data from the smart camera system alongside environmental data is one centralised location, the dashboard provides unprecedented levels of actionable intelligence to support effective coastal management decisions. Insights into ‘the business of the beach’ are able to be provided through analysis of patterns of beach usage including daily and seasonal trends in beach visitation.

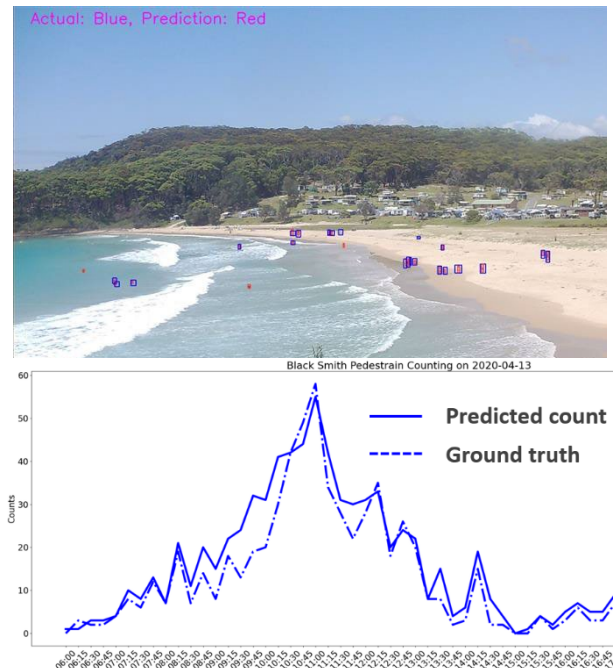


Figure 9 Validation of automated machine learning detection of beach users comparison between manual counts vs model detections for a single image (top) and timeseries comparison for a 24 hour period (bottom)

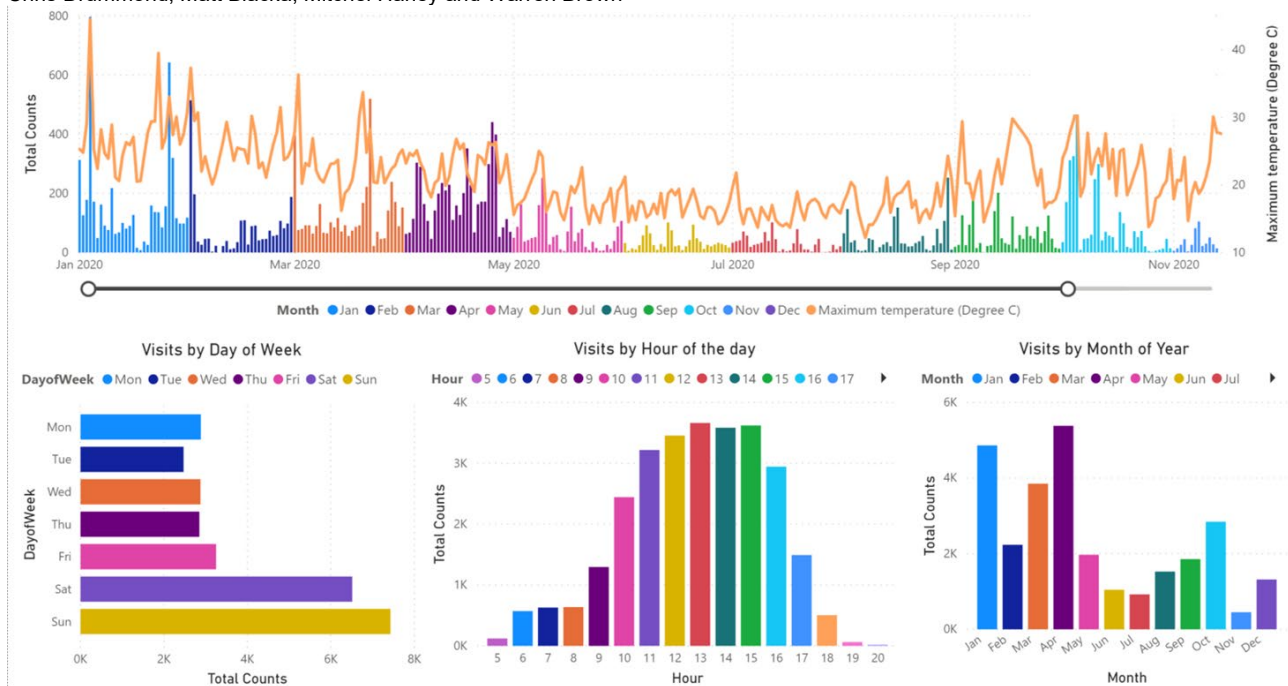


Figure 10 Results of machine learning based beach visitation data over a 12 month period at Ocean Beach showing seasonal trends (top), trends in time of day (bottom left), day of the week (bottom centre), and month of year (bottom right).

While there is room for further improvements in the accuracy of the beach user detection model used in the study, the method is likely to yield more reliable data compared to manual headcounts from lifeguards which can be subjective and inconsistent. Further improvements in this model should focus on efforts to identify how users are using a beach through detection of multiple classes such as sunbaking, dog walking, swimming or surfing. Combining this analysis with the remote camera systems outlined in this paper has huge potential to improve beach safety in unpatrolled locations by pairing this analysis with rip detection techniques. This study has demonstrated the value of using low-cost smart cameras to quantify patterns in beach usage at unpatrolled beach locations. Through the simple yet innovative system, a significant amount of information is able to be unlocked to greatly assist with beach safety planning.

5. Conclusions

A smart camera system has been detailed in this paper and has been shown to provide a cost-effective solution to unlock unprecedented information about shoreline change and beach visitation data. This information is becoming increasingly critical as we attempt to understand the value of beaches to our communities and develop sustainable future management strategies to protect our beaches for future generations.

6. References

[1] Anning., D (2012). "Estimation of the economic importance of beaches in Sydney, Australia, and

implications for management", PhD thesis, David Anning, School of Biological, Earth and Environmental Sciences, University of New South Wales.

[2] Blacka, M., (2017). Coastal Imaging: using coastline monitoring to observe and analyse coastal processes. Snapshot for CoastAdapt, National Climate Change Adaptation Research Facility, Gold Coast.

[3] Blacka, M., Harley, M. and Coghlan R. (2020), Wamberal July 2020 Storm Event, Expert Coastal Engineering Industry Report, WRL Technical Report 2020/28, August 2020

[4] City & County of Honolulu (2018), Draft environmental impact statement for the Waikiki war memorial complex.

[5] Harley, M., Kinsela, M., Sanchez-Garcia, E., Vos, K. (2019), Shoreline change mapping using crowd-sourced smartphone images, Coastal Engineering Volume 150, August 2019, Pages 175-189

[6] Irtiza Hasan, Shengcai Liao, Jinpeng Li, Saad Ullah Akram, Ling Shao. (2020), Generalizable Pedestrian Detection: The Elephant In The Room, <https://github.com/hasanirtiza/Pedestron>

[7] Holman, R.A. (2009), Nearshore remote sensing. In Proceedings of the Coastal Dynamics, Tokyo, Japan, 7–11 September 2009; American Society of Civil Engineers: New York, NY, USA, 2009; pp. 37–48.

[8] Power, H, Kinsela, M, Stringari, C, Kendall, M Morris, B, Hanslow, D. (2017) Automated Sensing of Wave Inundation across a Rocky Shore Platform Using a Low-Cost Camera System, Remote Sens. 2018, 10, 11