Remote Coastal Monitoring of Beach Usage on Tairua Beach

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Abstract

Research that gathers data from public reporting is susceptible to population bias, which arises from lack of knowledge on the probability of a person's ability to witness an event. Data collection based on public reporting is often used in coastal research relating to litter, stranded marine animals or bird spotting. It is biased by the probability of a person being in the vicinity, noticing and informing the appropriate organizations about the event. There is potential to improve population biased data by correcting for the probability of a person being present in a particular coastal vicinity. This thesis aims to better understand spatial and temporal beach usage at Tairua Beach in New Zealand. Building on existing literature, this research incorporates modern techniques to detect people on beaches from images taken every hour, during daylight, over a six-year period (2008 to 2013) from Tairua Beach, New Zealand. These methods include histogram matching, signal detection, machine learning-based classification, image registration and rectification, and various data cleaning techniques.

Analysis of the data showed that patterns of beach usage varied on scales of hours, days, months, seasons, and years, and variations followed general expected trends, such as there were more beach users over weekends and summer, reported in the literature. However, annual variations in beach usage did not behave as expected, having a couple of extreme values, likely caused by a change in camera equipment that improved image quality. Annual variations in beach usage were distributed spatially in a way that reflected changes in beach morphology, particularly in 2008 to 2010. Interpretation of spatial patterns in beach usage was obscured by resolution bias that required correction. Images were taken from a fixed position east of Tairua Beach with a scope of approximately 1.2 km of beach area. Naturally, the east end, which was closest to the camera, had higher resolution thus more people were detected on that end of the beach. The relative probability that someone occupied a position on the beach was derived from spatial distribution of the number of people counted in each image.

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I would like to acknowledge the very few positives from the covid-19 pandemic. Whilst it has been a difficult period for everyone, lockdown removed many distractions and the ability of escaping my studies by leaving my house.

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Chapter One

Introduction

New Zealand beaches are highly valued, dynamic environments that draw locals and tourists alike. Often held in high regard by the public, these areas are popular for a wide range of recreational and commercial activities. Computation of beach usage intertwines coastal research with culture and tourism. In this research, I aim to gain quantitative insights into beach usage at Tairua Beach. A large span of current coastal research is anthropocentric, whether that be with respect to management, hazards, or impacts. There is a danger that coastal research focused on human aspects may be biased, in the case that it is based on public reporting, as in observations for litter, marine stranding and bird spotting. This thesis emanates from a coastal and marine science perspective, with the objective of aiding in the correction of bias in observer-based data, by providing methods for automated ground-truthing.

Tairua Beach (also known as Tairua Ocean Beach or Ocean Beach) is located on the eastern coast of the Coromandel Peninsula, in New Zealand. Currently little is known about Tairua Beach usage, although it is expected to be linked to the population boom that the adjacent town experiences over summer, particularly during new year celebrations. Peak population for Tairua and the Coromandel Peninsula is quantified by the Thames-Coromandel District Council on a non-regular basis, approximately every three years. During the period of this research, estimated surges reached a peak of six times the residential population (Thames-Coromandel District & Council, 2010) . A large majority of tourism comes from nearby Auckland and Waikato regions. These high levels of tourism are to be expected because Tairua boasts a high natural character rating for its coastal terrestrial and marine area (Ryder et al., 2016).

Surprisingly, there is limited overall research on users of beaches in New Zealand. The literature that does exist tends to be older and indirect. Focus tends to be on the impacts or risks of human use and from that, brief characteristics of beach usage are derived. For example, there is a small span of research on beach related injuries and drownings, since they are high for our population size. Within these studies, surveys often include a question regarding beach usage (McCool et al., 2008).

Other countries like Australia and USA have a larger scope of research on beach users. Literature from the USA tends to revolve around paying for beach usage, which is required on most popular beaches in certain states like New Jersey (McConnell, 1977). However, translating this data into actual beach usage can be messy since beach passes may be sold in categories of daily, weekly or seasonal use. Australia appears to be leading the field with research into beach usage using a variety of methods, such as surveys, interviews, flyovers and people detection from images and video using computer vision (Drummond, 2020; Maguire et al., 2011; Mercer, 1972; Rolfe & Gregg, 2012; Zhang & Wang, 2012)

The goal in this research is to gain an understanding of Tairua Beach usage with an emphasis on quantifying the timing, spatial distribution, and probability of occurrence, using sub-aerial video imagery that is routinely collected by the Waikato Regional Council and the National Institute of Water and Atmospheric Research as part of their Cam-Era network. Research of this nature is essential for the correction of the population bias in coastal research that relies on public reporting. Demonstrated within this thesis is a new succession of methods for identifying people across a range of resolutions from a single camera perspective. This sequence could be altered to adapt for different beaches or even different environments.

This thesis follows a traditional format. The literature review gathers and summarizes concepts and knowledge relevant to beach usage, methodologies, implications, and Tairua Beach. Next the methodology chapter lays out a sequence of processes used for extracting the information, ranging from data collection to analysis and evaluation. The results chapter then displays and explains quantitative temporal and spatial findings. This is followed by discussion, allowing an exploration of the results, their implications and relevance. This chapter includes whether the results met expectations, possible explanations for any anomalous findings, and suggestions for future research. Lastly, the conclusion summarizes the thesis and concisely answers the research question, while reflecting on its importance and implications.

Chapter Two

Literature Review

The Waikato Regional Council funded this MSc thesis, mainly to support their work in determining the state of endangered dolphins in New Zealand. This review will therefore start by overviewing knowledge on these dolphin populations before moving on to research on beach usage, Tairua Beach, and image analysis methods.

2.1 Māui and Hector's Dolphin

Hector's Dolphin, Cephalorhynchus hectori, is nationally endangered and has a population estimated at 14,849 dolphins (Mackenzie & Clement, 2014). Endemic to New Zealand, approximately 5,388 of these animals were estimated to roam on the West Coast of the South Island, from Farewell Spit to Milford Sound (Slooten et al., 2002) There are four genetically and geographically distinct subspecies. One of these is the Māui Dolphin, *Cephalorhynchus hectori maui*, which is found on the west coast of the North Island; the three others are located around the South Island (Pichler & Baker, 2000). The Maui sub-species is critically endangered with an estimated population of 55 individuals (Hamner et al., 2014). They have an estimated rate of population decline of 3 to 7.6% per year (Hamner et al., 2014). Their population is threatened by set-netting and trawling, with an estimated 95.5% of human-induced mortality related to fishing (Ministry for Primary Industries, 2013). Available scientifically robust data is an issue with observer coverage too low in many areas to provide quantitative estimates on dolphin catches (Slooten, 2013).

Another threat to these dolphins is toxoplasmosis, a disease from an infection of *Toxoplasma gondii*, a parasite commonly found in cats but also found in humans and many animals such as cattle, deer, birds, and dolphins. A study (Roe et al., 2013) investigated 28 hector dolphins' deaths (bycaught or beach-cast) and found seven were caused by disseminated toxoplasmosis. Three of the examined deaths were Māui dolphins of which two were due to toxoplasmosis.

Department of Conservation (Slooten et al., 2002) records data of alive, injured, or dead dolphins stranded, at sea or bycaught. Varying unknown beach usage supports a population bias in beach-cast animals. The probability of a person being in the vicinity of a stranded animal is dependent on the beach usage which is related to the nearby population. The West Coast of the South Island where many Hector's Dolphins are present is sparsely populated by people.

2.2 Beach Usage

Beach usage covers site specific characteristics and information regarding commercial and recreational usage. It also includes non-site-specific literature regarding spatial and temporal patterns of beach users.

2.22 Tairua Beach Commercial Usage

Beach usage is defined as the use of the beaches by humans for a wide range of purposes usually falling under either commercial or public recreational use. Commercial beach usage is limited on Tairua Beach by the Thames-Coromandel District Council. They require a Commercial Operators License, are restricted to certain areas, and are prevented from intruding and obstructing the general public's space and access (Thames-Coromandel District Council, 2021). As of 2019, the Tairua-Pauanui area had given commercial concessions to four businesses, none of which were located on Tairua Beach, its access points or nearby reserves. The NGO Tairua Surf Life Saving Club (TSLSC) holds the only license for Tairua Beach valid till 2027 (Thames-Coromandel District Council, 2021)

2.23 Tairua Beach Recreational Usage

Tairua Beach, known locally as Ocean Beach, is popular with recreational users, especially significant over summer holidays. There is a wide variety of possible recreational beach usages such as walking, dog-walking, swimming, sunbathing, shore-based fishing, bodyboarding, and kayaking. The negative impacts of beach usage are dependent on the frequency and type. Impacts vary from littering, dune erosion, species reduction and fires. Although there are six public access points to the beach, many properties have individual walkways over the dunes. Foot traffic has caused the depletion of dune binding plants leaving trails and large areas barren. Restricting the number of tracks would help protect these dunes. Additionally, endangered New Zealand Dotterels are present in the area and can be disturbed by dune degradation, human activities, and dogs (Dowding, 2017).

2.21 Tairua Beach Access Points and Facilities

There are six public access points (Access points 1 to 6) on Tairua Beach: northwest to southeast; Ocean Beach access road (North end), 106-108 Ocean Beach Road, 138 Ocean Beach Road,16-18 Paku Drive, 38 Paku Drive (Tairua Surf Life Saving Club) and Hemi Place. There is a toilet block at the north end of the beach, where there are also parking, overnight camping for self-contained vehicles and picnic facilities (Thames-Coromandel District Council, 2013). The next three access points are grass paths. Tairua Surf Life Saving Club access point has many parks opposite and a wide gravel path. The last access point at the end of Hemi Place has a gravel path, limited road parking and a rubbish bin.

2.3 Patterns of Beach Users

In general, spatial, and temporal patterns in beach usage are influenced by weather, seasonal climate, time of the week, holiday periods, temperature, beach area and population near the beach (Houghton, 1989; Provost et al., 2021; Zacarias et al., 2011) The temporal patterns are broken down into hourly, daily, monthly, seasonal, and annual patterns. While the spatial patterns are divided into site-specific locations and beach selection.

2.31 Hourly Patterns of Beach Users

Hourly patterns vary greatly on different days of the week, months, seasons, and weather conditions (Zhang & Wang, 2012). Studies at different sites have found peaks in beach usage between around 1 pm to 6 pm and change relative to weather and day of the week. In Paralia Katerinis, Greece, during the 2014 summer, a study conducted showed the peak beach usage on a sunny day was at 5 pm and on an overcast, rainy or windy day, the peak was less and at around 6 pm (Trygonis et al., 2015). Balouin et al. (2014), found that the number of people counted over weekend periods is usually lower during the morning and peaks between 1 pm to 4 pm. Over July and August 2012 (Northern Hemisphere summer), the average maximum number of people counted from Monday to Saturday peaked at 3 pm, while Sunday peaked at 1 pm. Houghton (1989) observed trends that were influenced by daily weather patterns. He concluded strong southwesterly winds prevalent on summer afternoons, made sunbathing uncomfortable, explaining the morning peaks and afternoon dips in beach visits.

2.32 Daily Patterns of Beach Users

Literature on weekday versus weekend beach usage shows variable results tending to favour an increase during the weekend. On 75 Southern California beaches, almost half (48%) of all visits recorded occurred during the weekend with the most popular day being Saturday (27%) (Dwight et al., 2007). They also found that holidays caused increases in usage. However, two other studies had mixed results. They had multiple observation periods and found that at least one period showed steady use throughout the week, while the other periods displayed an increase over the weekend (Balouin et al., 2014).

2.33 Monthly & Seasonal Patterns of Beach Users

Multiple studies have found increases in beach usage over summer with similar usage in autumn and spring and low use during winter. However, data on specific months (correcting for Northern Hemisphere seasons) seems to be more variable and may be influenced by localized climate patterns, tourist visits, school, and public holidays. Over half (53%) of beach usage recorded on Southern California beaches (Dwight et al., 2007) occurred in June, July and August (Northern Hemisphere summer). They also found the lowest usage in winter, followed by autumn and spring. A study in Germany (Kammler & Schernewski, 2004) determined that there were more people at any time between 11 am to 6 pm in the mid to late summer months (July and August), than peaks in the off-season. Also in the Northern Hemisphere, Balouin et al. (2014) in France compared beach usage from May to September, finding July and August had the highest use followed by May, September, and June. In Perth, a study (Blackweir & Beckley, 2004) over three months, December 2003 to January 2004, found a significant increase (tested using an ANOVA) in daily beach usage each month.

2.34 Annual Patterns of Beach Users

Annual patterns of beach usage are not well researched because of the short duration of most beach usage data. The higher end of the study period tends to be one to two years (Rolfe & Gregg, 2012). In some cases, particularly when quantifying tourism or economic benefits of beach recreation, the annual beach usage is assumed to be stagnant (Pendleton & Kildow, 2006). Dwight et al. (2007) found no significant variation from 2000 to 2004 irrespective of weather variability. They only found a trend of 5% increase between years which they attributed to population growth.

2.35 Spatial Patterns of Beach Users

Research on spatial patterns of beach users is difficult because of the insufficiently understood, seemingly random, human behaviour and dynamic physical nature of beaches. Balouin et al. (2014) investigated a relationship between weather conditions and spatial positions of beach users. They found during high temperatures and lower wind beach users gathered within 20 m of the shoreline, taking advantage of the lower sand and air temperatures. This trend is present in summer with exceptions. These are when the temperature is more tolerable or when there are cooler tramontane offshore winds. During these exceptions, people appear randomly dispersed across the beach site.

2.36 Beach Selection Patterns of Beach Users

Studies that analysed the visitation rates at multiple beaches have found that beach usage appears to be highly concentrated in a few popular beaches.
Dwight et al. (2007) found that of 75 beaches observed in Southern California, one-third of beach usage occurred at six beaches and over half (54%) occurred at 15 beaches. In Perth, Australia (Houghton, 1989), six beaches made up 5% of the coastline of the study area while they accounted for 42.6% of all beach users. These beaches were thought to be the most popular due to nearby public transport, hotels, food outlets and beach facilities. While beaches with lower popularity tended to have less desirable physical beach characteristics, less parking and restricted access.
Provost et al. (2021) used a generalized linear mixed model to analyze patterns of beach users and potential predictor variables. They observed significant relationships ($P < 0.01$) of total beach users and beach area, solar radiation and people per household adjoining the beach. Overall, total visitors were not significantly impacted by the nearby environment being rural or urban. However, sunbathers were more prevalent on urban than rural beaches when in combination with high solar radiation.

2.4 Method of Counting People

Methods of counting people may be direct or indirect, collecting quantitative or qualitative data. Direct methods can be further divided into interviews, questionnaires and surveys, or video and imagery. Indirect methods consist of, for example, evaluating human impact to derive qualitative data on beach usage.

2.41 Direct: Interviews, Questionnaires & Surveys:

A common direct method of measuring beach usage is through interviewing beach users. This method may include counting people at the beach. Interviewers are often set up at beach facilities or access points across multiple beach areas (McConnell, 1977; Mcbride et al., 1998; Mercer, 1972) and ask various questions focusing on their school of thought. In one such study, beach users were interviewed between 10 am and 5 pm in January and February of 1970 about their and their group members' ages and their suburb of origin. These interviews occurred at 27 beaches on one day, each week, for 5 consecutive weeks. This required a large labour force with an average of two trained interviewers at each site (Mercer, 1972).

A variation of this method is surveying residents of coastal areas. In one such study, self-administered questionnaires were delivered to coastal residents in Australia across multiple populations (Maguire et al., 2011). This can provide a more diverse response that is not limited by selected beach locations and personnel. Depending on the ultimate use of the data, this variation may be preferred to avoid oversampling of frequent users (Rolfe & Gregg, 2012)

This method was commonplace in Australia & the USA particularly in the 1970s to 1980s. The USA tended to focus on willingness to pay for beach usage (McConnell, 1977; Silberman & Klock, 1988), while Australian studies were interested in general patterns, like travel distance and type of recreational use (Mercer, 1972). Other themes of surveys concentrated on congestion on the beach, preferred beaches, effects of renourishment and health related to water quality (Corbett et al., 1993; Mcbride et al., 1998;).

The method is useful to quantify beach usage and gauge beach users' habits, opinions and general patterns. It is beneficial for health and sociological applications. An alternative interview method was used while studying the health effects of swimming related to water quality (Corbett et al., 1993). It was beneficial to use this method at beach sites to establish which interviewees swam and who became sick following their beach visit. This procedure was favoured as multiple factors needed to be accounted for and it allowed a follow-up interview to ascertain who became unwell.

A downfall of this method is its reliance on people's availability and beach users' honesty and openness. Staff are required at every site that is selected to be monitored to conduct interviews and additional personnel are required at every beach access point to accurately quantify beach users at any given time. Thus, these kinds of methods are not feasible over the longer term.

2.42 Direct: Video and Imagery

A direct method of analyzing beach usage using video or imagery has become more popular with reductions of cost and increased capability of cameras and data storage. The images or video can be collected from a stationary camera, satellite, unmanned aerial vehicle, crewed aircraft, or drone (Provost et al., 2021) encompassing the beach sites. Beach usage data can then be extracted using hand counting, machine learning or traditional computer vision techniques like feature detection.

People count data may be categorized further for specific focuses. Location information can be added regarding the use of facilities, singular or clusters of people, or whether people are in the water or on the beach. Orthorectification is often required to take advantage of location information. High-resolution imagery offers the ability to distinctively categorize recreational activities like dog-walking, swimming, kayaking, surfing, or sunbathing. Digital advancement of this method, particularly in machine learning, has been helped due to the increased use of people detection for self-driving vehicles and security cameras (Luna Da Silva et al., 2017).

This method tends to concern safety, traffic, tourism, and extension of other beach monitoring. In Australia, Chris Drummond (2020), used machine learning to track shoreline changes and people on the beach. Another study focused on a system to track people and then emit an alert if they go into a certain area of a beach that has a higher risk of shark attacks (Luna Da Silva et al., 2017). This method is limited by proximity, if a camera is at an angle that it shows people of different sizes there is often a discrepancy in people counting based on what the AI or algorithm was trained on. Hand counting has a significant issue in that it is time consuming, thus it is not applicable to large sets of data.

2.43 Indirect: Human Impact

An indirect method of estimating the people count or more broadly beach usage is through the anthropological impact at a particular site. The focus of these types of studies is often on human impacts, preventative measures, and rehabilitation of coastal areas with the estimation of beach usage being a byproduct. One such study measured different flora and fauna at multiple sites to gauge the types and locations of beach usage. Leatherman & Steiner in 1979, used species as a biological indicator of disturbance on Assateague Island, USA. This is a good method for estimating and comparing beach usage across multiple sites or a long stretch of beach with similar naturally occurring biological indicators. However, this method cannot be used to provide quantitative estimates of beach usage.

2.5 Previous Applications of the Dataset

The data set used in this thesis was a part of the “Cam-Era Project”, a joint project between the Ministry for the Environment (MfE), National Institute of Water and Atmospheric Research (NIWA), Coastal Marine Group – The University of Waikato, Institute of Information Sciences and Technology - Massey University, Waikato Regional Council (WRC), Environment Bay of Plenty, Environment Canterbury, Eastland Port, Westgate Ltd (Port Taranaki), Taranaki District Council, Tourism Taranaki, Taranaki Polytechnic, WEBCAM New Zealand and the Port of Greymouth. This is an ongoing project started in 1997 (NIWA, n.d.-a) and the image datasets at different sites have been used in a wide range of research and management applications. These range from sand bar migration (Tairua)(van Maanen et al., 2008) beach rotation (Tairua) (Blossier et al., 2015; Bryan et al., 2013), monitoring rip-currents (Tairua), shoreline changes (Tairua, Pauanui, Raglan)(Bryan et al., 2009), ebb tidal delta variations (Raglan) (Harrison et al., 2017), lagoon water level changes (Ashburton) (Hart, 2007), and spit geometry variations (Mokau) (Bryan et al., 2008). This dataset has wide, interdisciplinary potential on various areas of research.

Chapter Three

Methodology

3.1 Methodological Approach

My aim was to gain a more in-depth understanding of how beach users' habits changed spatially and temporally over an extended period. The specific goal was to quantitatively determine the variation of beach usage over different hours, days of the week, months, seasons, and years, while additionally observing where people congregate on this specific beach. Do they tend to congregate at particular access points, or do they quickly move away from access points to disperse along the beach? This data will allow us to determine the probability that a beach visitor may encounter an object washed up on the beach from the ocean, and how that probability changes with season and along the beach. To meet my aim, primary quantitative data were extracted from a database of consistent digital images collected over the long-term provided by Waikato Regional Council and images were analyzed to ascertain the number of people in each pixel of the image ('the people count"). Several difficulties needed to be overcome, including the changing resolution of the image, and determining whether an object on the beach was a person or something else.

The image processing methodology was divided into several steps. A flow chart of the methodology is provided in Figure 3.1. Firstly, the images were histogram matched, which is a common method for automatic enhancement in order to, for example, remove noise (Gonzalez & Woods, 2008). This was particularly important as the next step searched every line of pixels in each image for possible signals that represented people. The data were then thoroughly cleaned by following a number of 'cleaning rules' to ensure a person was not marked more than once by applying a proximity limit on two or more signals or was marked as vegetation using a time limit on movement.

The next step was to associate the people counted in the image with real-world location on the ground. To do this, rectification of pixel coordinates into ground coordinates was required. Once pixels were rectified, then the positions could be compared between images. The raw pixel locations could not be compared because the cameras moved with time, and so the resolution and position of each pixel changed from time to time. Rectification of images was required prior to further cleaning of data. Rectification required the calculation of intrinsic (internal) and extrinsic (external) camera parameters using ground control points. Prior to rectification, the unrectified image was checked to see if it aligned with the position of the reference photo, in which case the same camera parameters could be used for rectification. If it did not align, fixed points in the image were used to transform the image until it was oriented in the same way as the reference image and then it was rectified. Various methods were trialed for automating this labour-intensive process. However, in the end, manual digitization was the most robust.

Rectified images were then classified into categories using a machine learning algorithm to recognize beach areas (sandy areas) and non-beach areas (vegetated or in the water). When data were identified as occurring in a partial or fully non-beach area, they were removed. The data of people-counts that remained after this intensive cleaning process, were eventually used for analysis.

Figure 3.1. Summary of methods used to extract people count data from Tairua beach images.

3.2 Data Collection

Observational raw data were recorded at Tairua Beach from 2008 to 2013 in the form of photos taken from a fixed position every 60 minutes during daylight hours. These are a subset of a 20-year database of images, which were chosen because a very detailed ground control point survey was undertaken 2009, and so inaccuracies in rectification could be minimized. The Tairua Beach camera was one of the seven cameras set up in a collaboration, “The Cam-Era Project”, between the Ministry for the Environment (MfE), National Institute of Water and Atmospheric Research (NIWA), Coastal Marine Group – The University of Waikato, Institute of Information Sciences and Technology - Massey University, Waikato Regional Council (WRC), Environment Bay of Plenty, Environment Canterbury, Eastland Port, Westgate Ltd (Port Taranaki), Taranaki District Council, Tourism Taranaki, Taranaki Polytechnic, WEBCAM New Zealand and the Port of Greymouth. At each site, the camera is controlled and recorded by a PC running Microsoft Windows (NIWA, n.d.-b) and images are transferred back to a base station at NIWA in Hamilton for processing.

3.3 Methods of Analysis

Beach images were histogram matched to a bright and clear image chosen for each year. Histogram matching adjusts the distribution of each of the three colour bands in the image (red, green, and blue) until the histograms in each band match the reference image. This adjusts both the colour and the intensity of the image to make each image more similar. The colour depends on the relative proportion of red, blue, and green (on a scale of 1 to 256) and the intensity is related to the magnitude of the average of all three bands. The reference images that were chosen for each year had muted colours on the beach area, limited areas of dark or wet sand and no cloud cover. Figure 3.2 shows the difference caused to an image by histogram matching for a cropped area of the image. The wet sand is brightened, allowing a heightened contrast between sand (yellow areas) and people (dark areas). Histogram matching helped make the thresholds used to detect people work more consistently.

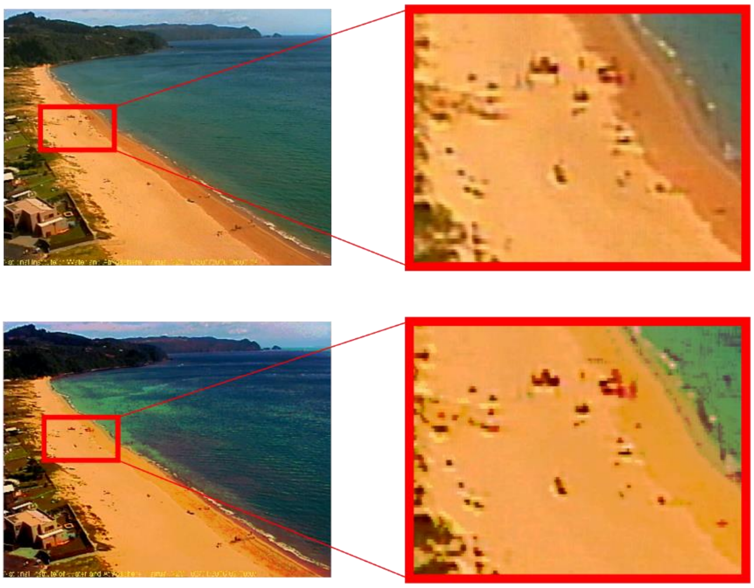

Figure 3.2. An example of before (top panels) and after (bottom panels) an image is histogram matched. The right panels show a detailed image of the region outlined in red on the left panel.

A general mask for the beach area was created to remove regions of the image used in the detection of people, which included the toe of vegetation and the ocean at low tide. An algorithm in Matlab was developed where the image (I) was searched vertically along rows of pixels *I(i,j)* in the unmasked region, where *i* is the row number and *j* is the column number. At each row *i*, the pixels were analyzed for changes to the RGB spectrum. These differences are detected by subtracting each intensity value from its neighbor in the intensity series at each row. For example, *I(20,j+1)-I(20,j)* for row 20*.* A sharp change in intensity in the image, was interpreted as a person, which was indicated by a spike in the difference series, with a threshold criterion of a -20 signal followed by a signal of +30 within 10 pixels of each other. Figure 3.3 displays a person successfully counted by detecting this signal.

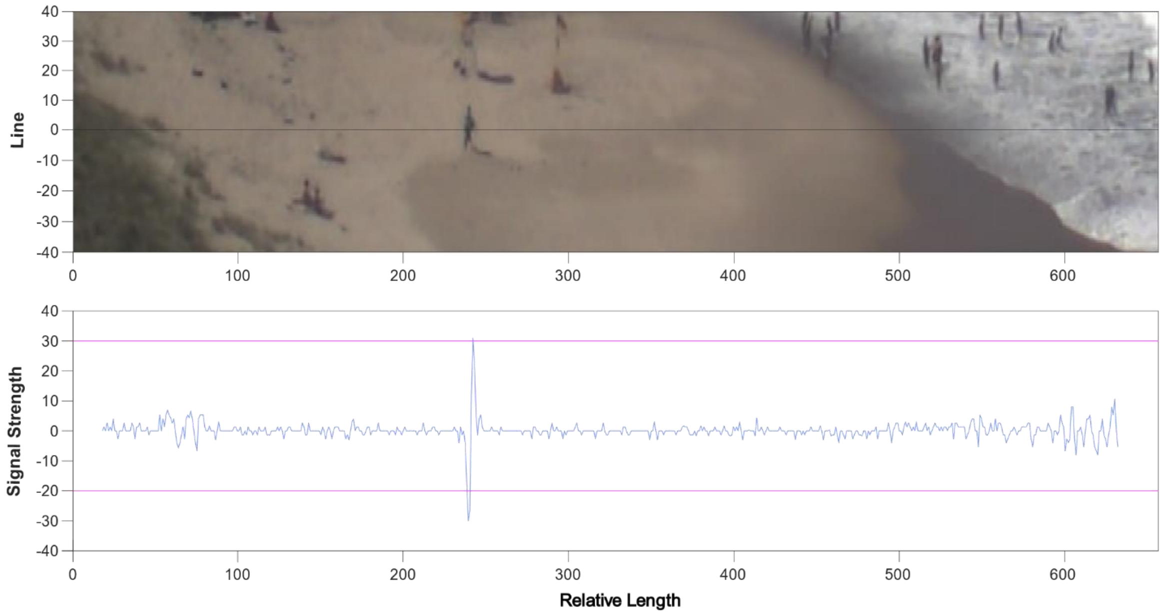

Figure 3.3. Example of a person recognized by signal analysis and difference in strength of the intensity signal across a row of pixels (the bottom panel). The pink lines represent the criterion that a signal is required to meet to be counted.

Digital signals were recorded then cleaned by proximity and occurrence. Proximity cleaning consisted of removing one of the detected points when the separation between two points was less than or equal to one pixel. An example of this is seen in Figure 3.4. Occurrence cleaning consisted of removing a point which occurred in multiple consecutive images, for more than six images in a row. Proximity cleaning was undertaken first, then occurrence cleaning.

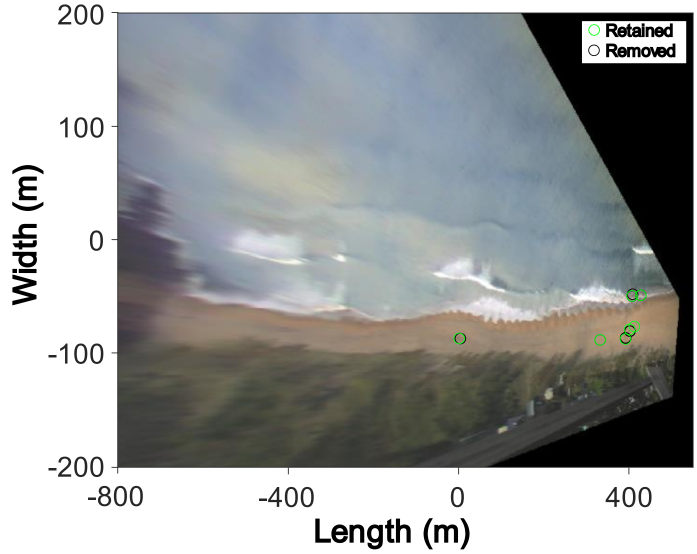

Figure 3.4. Rectified image displaying example of retained and removed data by proximity.

The camera position needed for rectifying the images was calculated from an image of Tairua beach on the 7th of October 2009 at 20:30 and corresponding GPS coordinates. This reference image was rectified and corrected by intrinsic and extrinsic camera parameters for distortion that was lens and site-specific.

The intrinsic parameters were provided by NIWA and were calculated using the MATLAB lens calibration toolbox written by Danail Stoyanov (2011). This toolbox uses a suite of images of a black-and-white checkerboard pattern to estimate the radial and tangential lens distortion coefficients, along with the focal length, image center point and the aspect ratio of the image.

The external camera parameters need to be estimated once the camera is installed onsite. The tools needed to do this are also provided by Danail Stoyanov in a MATLAB-based toolbox, and consist of determining the optimal camera rotation, translation and magnification using a suite of points in the image that have known ground locations (Ground Control Points, GCPs). These were measured by a PhD student Chris Daly using points collected on the beach and in the water (by boat) on the 7th October 2009 and correspond to ground control points shown in Figure 3.5. In addition, the focal length was also optimized because the camera was focused differently on the field than it was when taking images of a checkerboard pattern in the laboratory. Figure 3.5 shows that a very good rectification was obtained, with a very small error between the rectified and actual position of the ground control points. Beach images where the camera was in the same position as the reference image (collected on 07/10/2009) were geo-rectified and rotated by 57 degrees counterclockwise so that the beach appeared horizontally in the image.

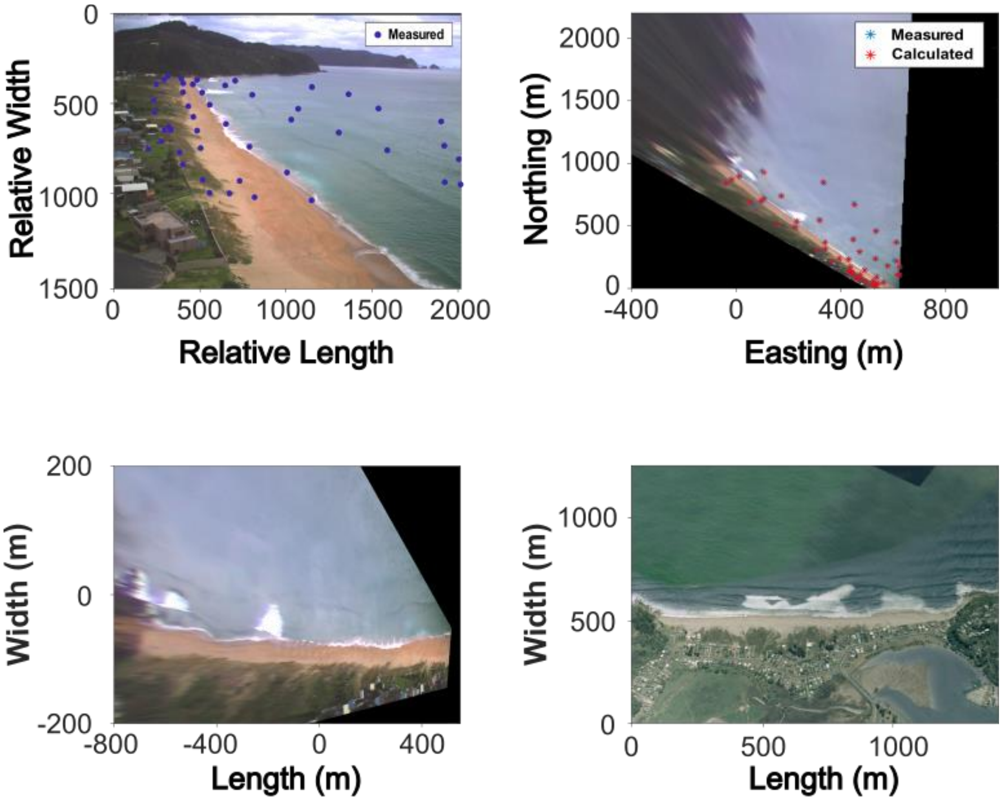

Figure 3.5. Top left panel: original reference image with measured points highlighted. Top right panel: transformed reference image with measured and calculated points highlighted. Bottom left panel: rectified reference image. Bottom right panel: satellite image of Tairua site. Maps Data: Google, © 2021 CNES/Airbus.

Images with a different camera external parameter (tilt, swing, or azimuth) to the reference image were identified by the classification of the headlands present at the north end of the beach being in different locations. An area of 20 by 20 pixels was selected, and the area of headlands was classified as one and sky as zero. This was repeated on the same area in a different image. The binary representation of the areas was summed giving a result of zeros and twos if the camera position had not moved as the headlands were aligned. When zeros, ones and twos were present it signified a move in the camera azimuth. Different ratios of zeros, ones and twos in the selected area signified different camera movements. These ratios allowed images to be grouped together. One image from each group was adjusted until the 20 by 20 pixels aligned with the reference image. Images were then all geo-rectified from the same position.

The next task was to remove areas that were in the water or on the vegetated dune, where the general mask had not already moved them. The general mask was set at some distance from the beach on the landward/seaward side so that a new mask was not needed as the tide changed, or as the vegetated line moved. To remove the points along these variable fringing regions, a neural net-based classification scheme was used. A consecutive selection of 20 unrectified training images following the reference image were used to classify the colours into 16 categories (or clusters of points) (NC tool, MATLAB). Three categories were combined to identify the beach area (the sand tended to be divided into 3 consistent classes). This is shown in an example image in Figure 3.6. The image was segmented into 16 categories, the first three picked up areas of beach (sandy areas) in different weather conditions and lighting. Panels 4, 8, 12 & 15 categorize the land, while 5, 6, 7, 9, 10, 11, 13 & 14 categorize the ocean. Whitewater (swash and breaking waves) appear in panels 5 & 9 along with occasional sun glint, particularly nearing sunrise, or sunset. Panels 8 & 15 show light green vegetation, usually dune binding plants below the beach area. The headland to the west, denser vegetation and trees tend to be displayed in panels 12 & 15. While panel 16 consistently picked up the black area outside the camera's view that was generated from rectification. Figure 3.7 displays 16 panels, each a different classification of a rectified image.

In order to remove non-beach points, a 5 by 5 pixel area surrounding each data point was analyzed. Each pixel was assigned either as beach (1) or non-beach (0). If the 25-pixel area had less than 80% beach area the data point was removed and if the area had 80% or above beach area the data point was retained. Data were removed or retained based on its relative pixel area irrespective of whether the point itself was classed as beach or non-beach. An example of retained and removed data is shown in Figure 3.8 and 3.9 with a rectified image and classification area respectively.

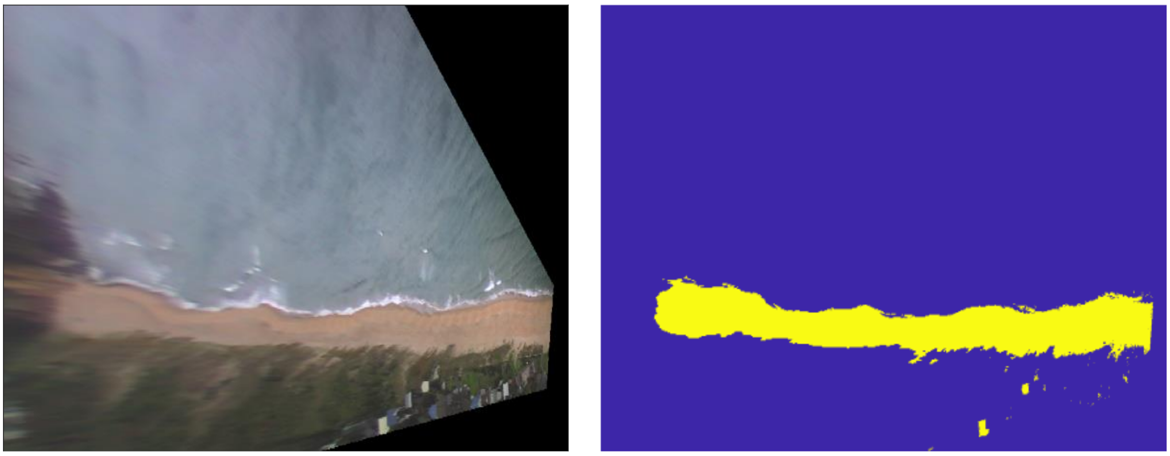

Figure 3.6. Left panel: example rectified image (12 pm 14th of October 2009). Right panel: example classification of rectified image (12 pm 14th of October 2009). Beach area, seen in yellow, is a combination of the first three categories. Non-beach area classification is seen in purple.

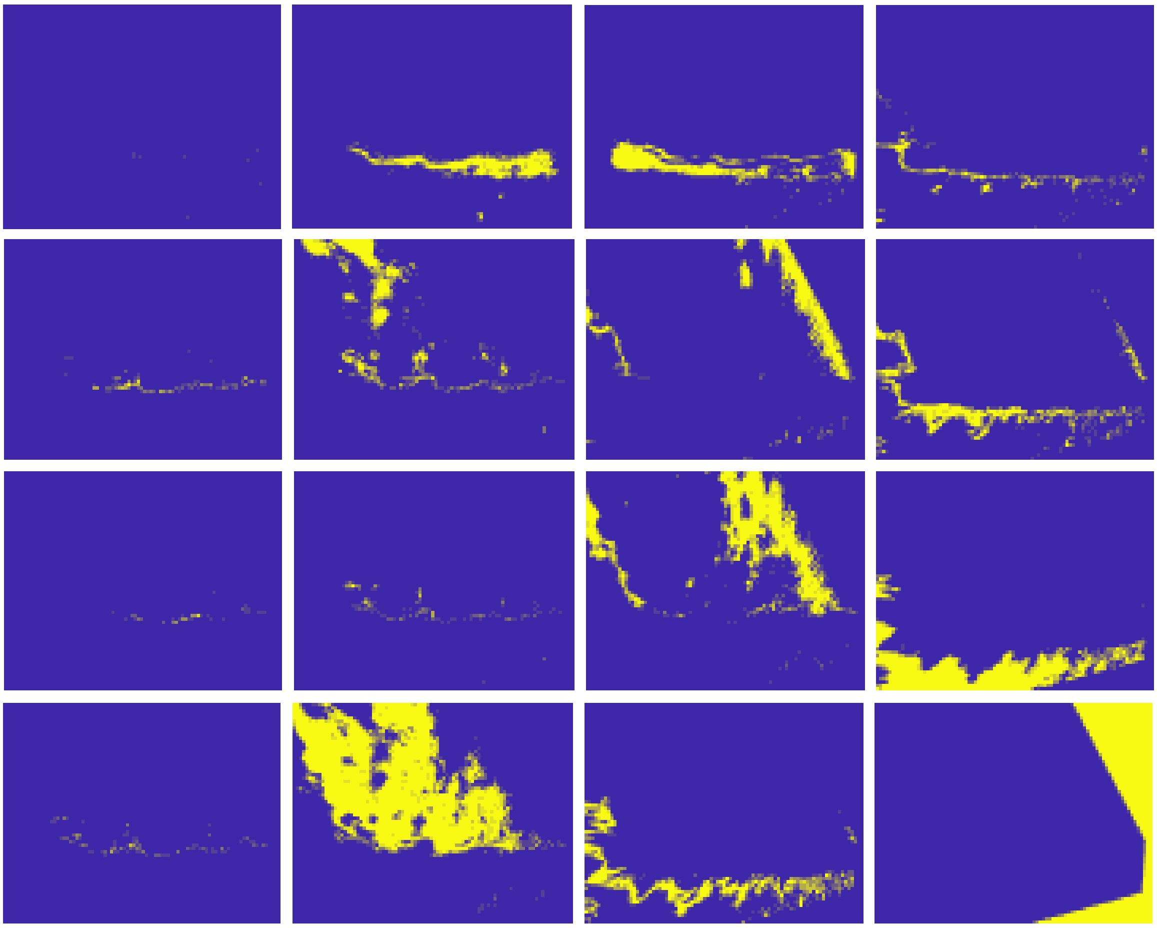

Figure 3.7. Example of rectified image (12 pm 14th of October 2009) classified into 16 categories (neural network classification, MATLAB).

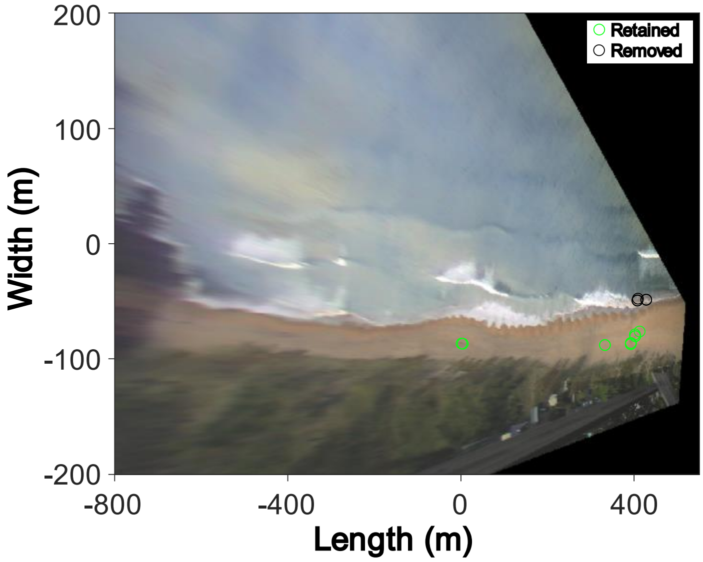

Figure 3.8. Rectified image displaying example of retained and removed data by classification of nearby area.

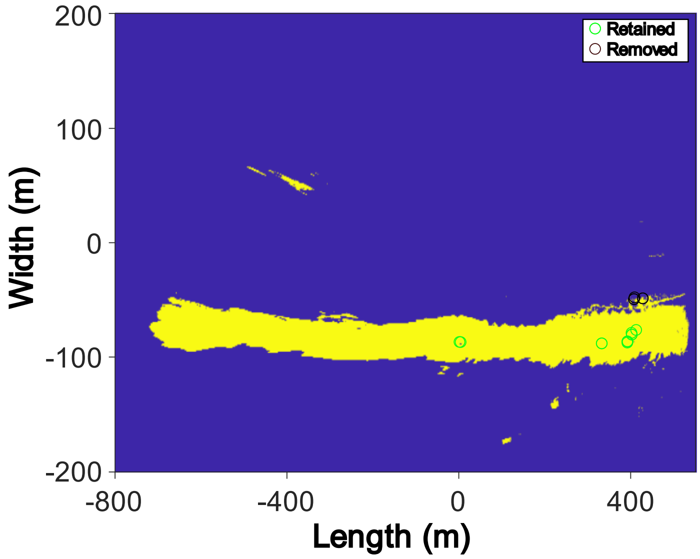

Figure 3.9. Classified rectified image displaying example of retained (green circles) and removed data (black circles) by classification of nearby area.

The resolution of the images changed across the length of the beach with east having the highest and west the lowest pixel density. This is due to the extremely poor resolution because the camera is approximately 1.2 km away. This heavily biased spatial length-based results to a degree that patterns were largely indiscernible, displaying exponential beach usage from west to east (Figure 4.20). To correct for this a model of the resolution was created using the change in resolution of a rectified image from west to east of the beach area. To calculate a line was added to an unrectified image representing the maximum actual length of Tairua Beach (Figure 3.10). This line is shoreward due to the tapering of the beach area towards the western headland and camera angle, which allows more of the eastern end towards the shoreline to be included. Pixels within this line were then rectified as is displayed by the blue circles in Figure 3.11. Relative resolution is the differentiation in pixel abundance seen once rectified. A model of relative resolution is shown in Figure 3.12 spanning the length of the beach area captured. As the resolution model was a primary factor in length distribution of beach usage, it was able to be divided from the linear length distribution. This removes a generally positive trend caused by the resolution bias. Seen in the results chapter, is the unaltered length distribution histogram and corrected line graph (Figure 4.20 & 4.22). With the removal of this length-based trend, resolution bias is compensated for allowing distinct length beach usage patterns to be observed. However, correcting for resolution bias has its limitations. The amplification of beach usage in the west causes large variability which still makes patterns in this area difficult to recognize. Overall, correcting for resolution bias was extremely helpful in analysing length distribution patterns as they were no longer overwhelmed by the impact of relative resolution.

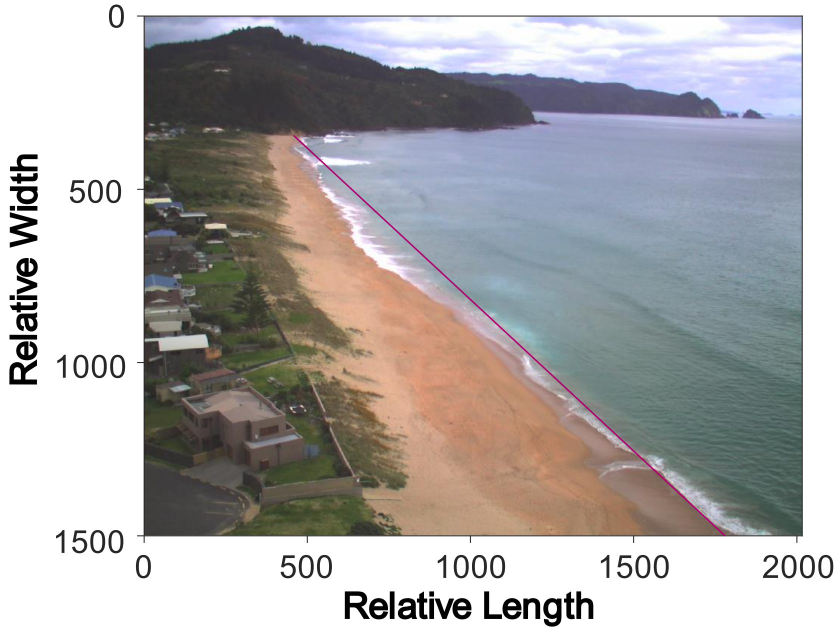

Figure 3.10. Maximum length of beach area in an unrectified image.

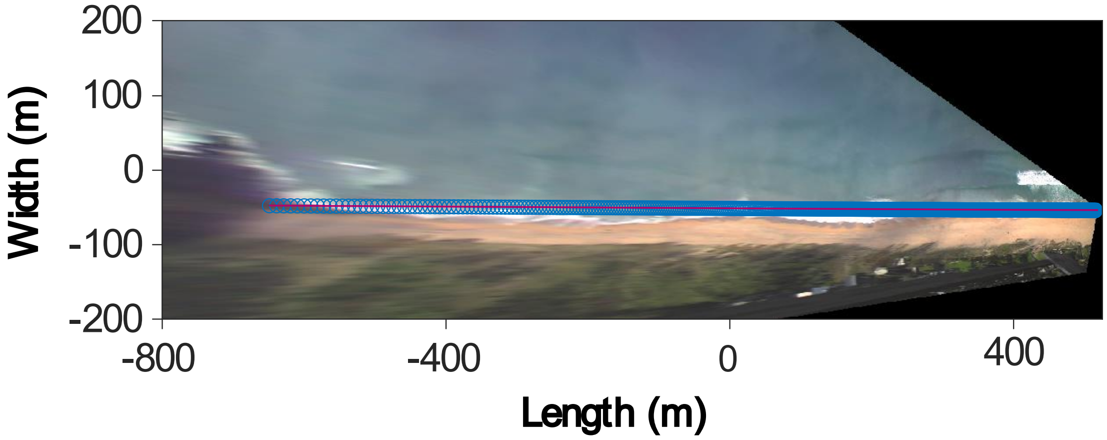

Figure 3.11. Beach length (red line) and pixel abundance (blue circles) in a rectified image.

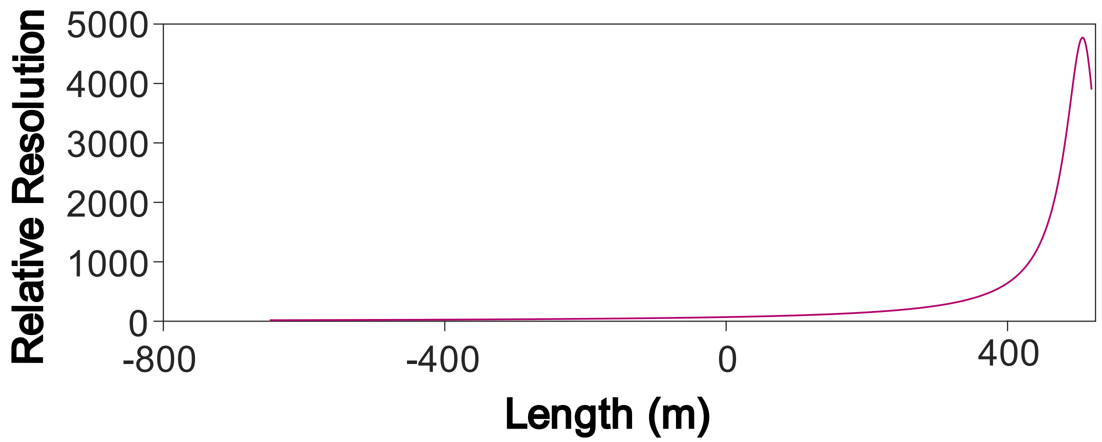

Figure 3.12. Relative resolution across the length of the beach.

3.4 Evaluation of Methodology

There were several stages in the processing pipeline that were aimed at reducing random returns. Beach images were histogram matched to images with consistent beach colours to decrease false positives when identifying people. The reference image had a uniform cloud cover to reduce the impact of shadows cast by clouds and small areas of wet sand that decrease the contrast between people and background colour (Kautsky et al., 1984). Aligning groups of unrectified imagery using a window of 20 by 20 pixels to determine a line is a robust method to perform image transformations like rotation and scaling (Guru et al., 2004).

To test the validity of the methodology, a subset of images was subjected to manual counting. This was undertaken for the 25 images in 2008, when the beach was crowded so there were a lot of data collected. The results of which are shown in Figure 3.13. The automated methodology tends to slightly underestimate people count, appearing to diverge at higher values. The computer counted 40% of those under 20 (by hand count) as no people present. This is likely due to the level of cleaning of the automated dataset that occurred.

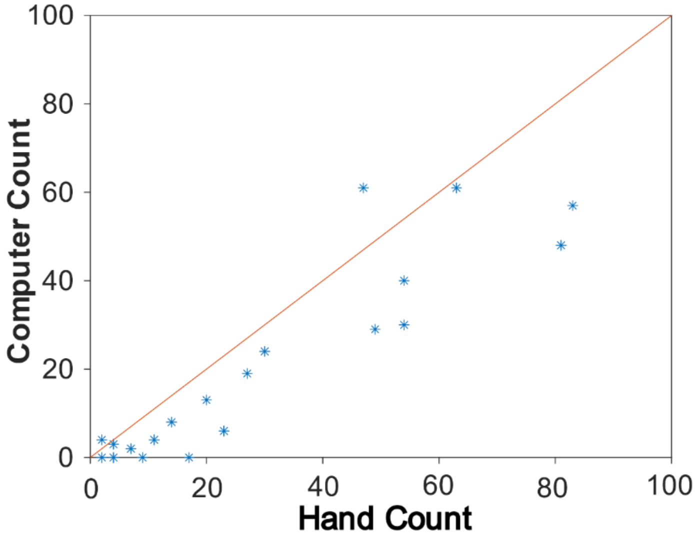

Figure 3.13. Testing validation by hand count and computer count. The red line represents 100% accuracy.

3.5 Methodology Summary

This methodology chapter explains in detail the sequence of methods used to collect and process data from images. A variety of techniques, such as histogram matching, signal detection, data cleaning, rectification, registration, and machine learning based classification, and their applications are explained to allow repeatability. Relevant examples in histogram matching, signal detection, data cleaning, and classification were given to provide an understanding of their functionality in this thesis. Reasoning and methodology for correcting for resolution bias seen in length distribution results was described. The combination of these methods was evaluated by testing the validity of these results. This was done by countering the computer count with a hand count of 25 images.

Chapter Four

Results

The methods outlined in chapter three, were applied to beach imagery data collected over the years to examine temporal, spatial variability in beach usage, and the probability of that a person might visit a particular location on the beach. This chapter shows the results of these investigations, and how beach usage varied on Tairua Beach.

Due to their nature, beach usage results are sectioned into temporally summarised and spatially summarised data. Temporal results are then sub-divided into scales of hours, days, months, seasons, and years. These periods are displayed in bar graphs showing the number of images processed, the number of people counted and the relative frequency of those counts, including the ratio of people. Showing three bar graphs for each time span allows for the analysis of input images, whether they influence the relative people counted and what that effect may be. Spatial results are either segmented into an annual distribution or the location where people are found on the beach is summed over all available data. This allows yearly and general patterns to be distinguished. Overall patterns are further segmented into how they are distributed along the length and width of the beach.

4.1 Temporal Results

The temporal results constituted the variation of the number of people counted on each day, which was divided into categories of hours, days, months, seasons, and years. The number of people counted over time depends on the number of images collected over the same period. Therefore, the people count data may be strongly influenced by the image count and so the relative frequency is also graphed.

Figure 4.1 shows a reasonably uniform input of images from 8 am to 4 pm, with input symmetrically and steadily declining over three hours on both sides (caused by limited sunlight in winter) to span 15 hours. The camera software is set to change the collection schedule so that no dark images are collected in winter, and so a smaller number of daily images is collected in winter compared to summer. One can assume that the uniform sample of images between 8 am and 4 pm does not significantly bias the people count during the same time span. However, the same cannot be assumed for the reduction in image input on either end. The people count, seen in Figure 4.2, shows a bimodal distribution with peaks a dominant peak at 10 am and a smaller peak at 2 pm. This figure exaggerates the tapered ends seen in the image count figure (Figure 4.1). When plotted relative to image availability (Figure 4.3), the trend from 8 am to 4 pm does not change. Therefore, we can assume that the higher numbers of people at 10 and 2 is real. The difference between patterns in Figure 4.2 and Figure 4.3 is only noticeable in non-uniform periods of image input from 5 am to 7 am and 5 pm to 7 pm.

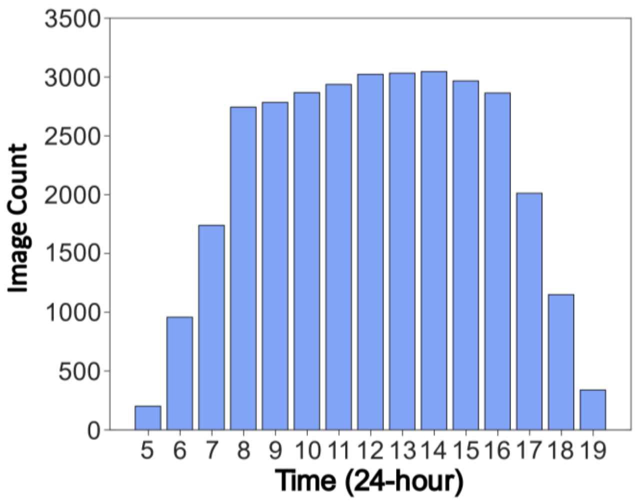

Figure 4.1. Total image count (sum of all years) by time (24-hours).

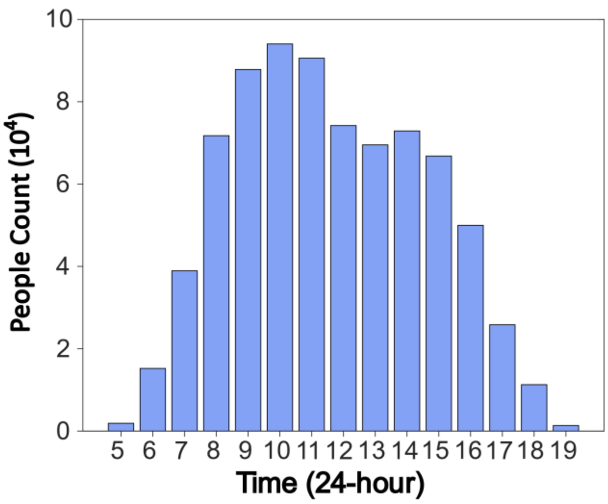

Figure 4.2. Total people count (10^4, sum of all years) by time (24-hours).

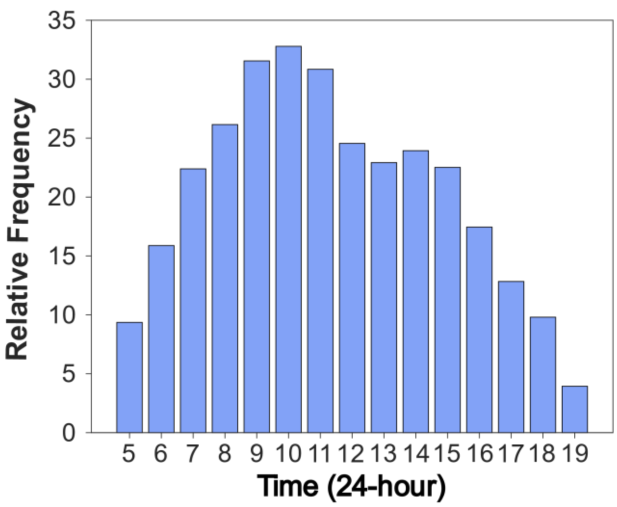

Figure 4.3. Total relative frequency (ratio of the sum of people count and the sum of image count) by time (24-hours).

Figure 4.4 shows that the image count throughout days of the week is relatively uniform, and there is no weekly bias in the way that images are collected. Sunday shows slightly lower amounts of input images. Figure 4.5 shows that the weekly distribution of people count is consistent overall days with a slight dip on Tuesday, a slight peak on Friday and a larger peak on Saturday. This pattern is reproduced in Figure 4.6 (the data normalized by image availability) with slight changes. Saturday, Sunday, and Friday respectively have the highest relative frequency. Monday, Wednesday, and Thursday have moderate relative frequency, while Tuesday has the lowest. The relative frequency (average people count per image) varies from 20.54 on Tuesday to the highest 27.44 on Saturday.

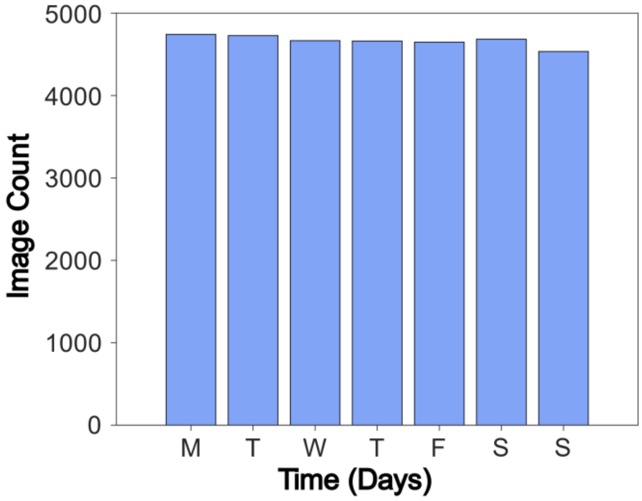

Figure 4.4. Total image count (sum of all years) by time (day of the week).

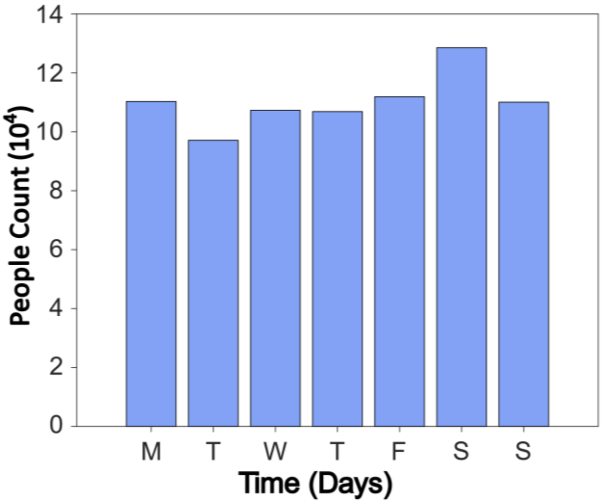

Figure 4.5. Total people count (10^4, sum of all years) by time (day of the week).

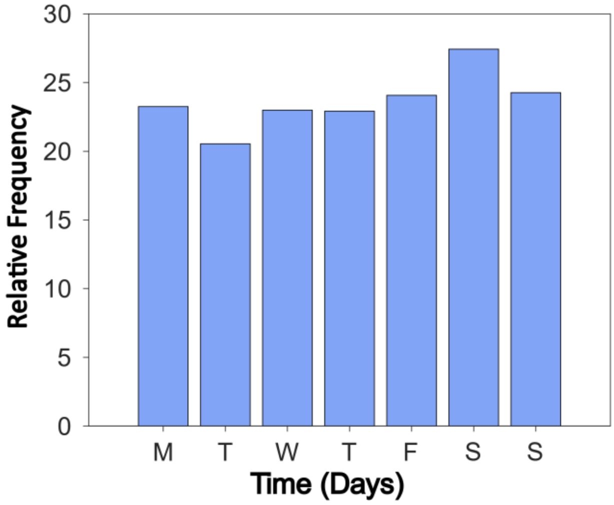

Figure 4.6. Total relative frequency (ratio of the sum of people count and the sum of image count) by time (day of the week).

The image count distributed into monthly occurrence is shown in Figure 4.7. A rolling peak is seen in February, while the end of the year shows two peaks in October and December. There is a dip from June to August (which is probably due to winter conditions lowering visibility on the beach and fewer daylight hours). There is also a dip in November likely explained by multiple factors. Firstly, the camera in November 2010 malfunctioned with changes of hue from green to pink over four days. This reduced the effectiveness of people counting so images from these days were removed. Then in November 2011 and 2012, the camera did not take or effectively store images for 14 days (4^{th} to 17^{th} and 5^{th} to 18^{th}, respectively). Additionally, the data available for 2013 ended in October, reducing images input in November and December. The sizable variance seen in this figure may influence the people count. In Figure 4.8, the people count in shows a significant peak in January which steadily declines until May, leading to a dip in June and July, followed by a steady increase till the end of the year. The end of year peak does not exceed the people count observed in January, February, or March. Figure 4.9 (where the data are normalized by image availability), a similar pattern to that seen in the people count is apparent. November breaks the trend as it is distinctly higher in the relative frequency. It is around the same frequency of March, higher than that of December which was the end of year peak in the unnormalized people count figure. The range varies greatly with an average of 10.75 people counted from any image in June to a peak of 44.51 in January.

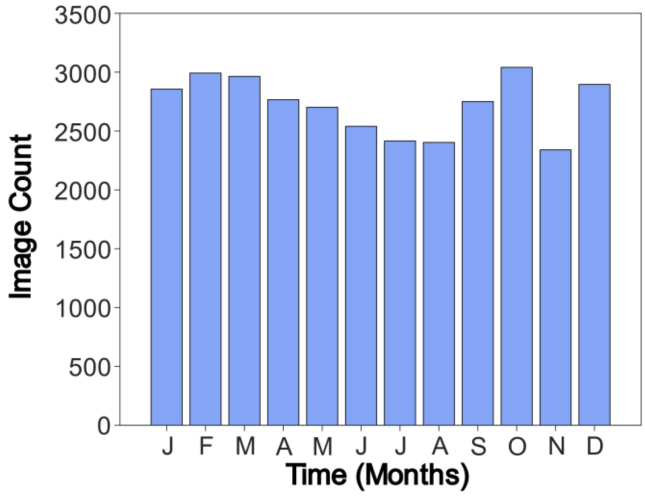

Figure 4.7. Total image count (sum of all years) by time (months).

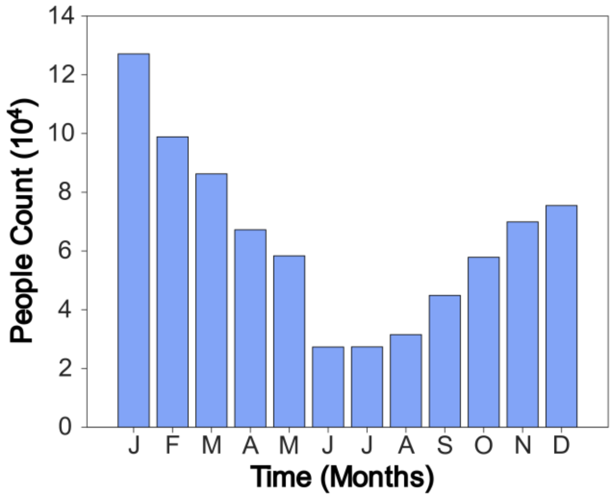

Figure 4.8. Total people count (10^4, sum of all years) by time (months).

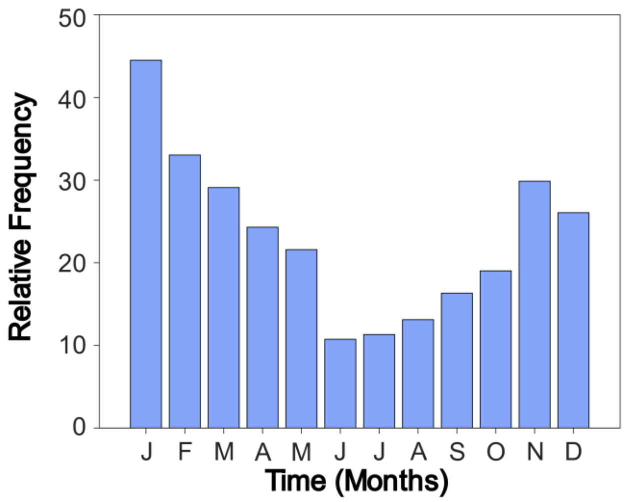

Figure 4.9. Total relative frequency (ratio of the sum of people count and the sum of image count) by time (months).

Seasonal patterns are like monthly patterns since they are the sum of three months but provide broader patterns that are less influenced by variations on specific months. The image count for seasons is variable by a couple of thousand images shown in Figure 4.10 Images inputs are reasonably uniform with the highest from summer, followed by autumn, spring and winter. This follows patterns seen in the image count for months (Figure 4.7). The changes in image count likely align with changes in daylight hours over which the images can be obtained. This translates into an exaggerated pattern in the people count data plotted in Figure 4.11. The people count could be influenced by poor visibility during rainy or cloudy periods, which are more frequent over the New Zealand winter. The normalized people count data is plotted in Figure 4.12 repeats this pattern since it is fixed by the image and people count.

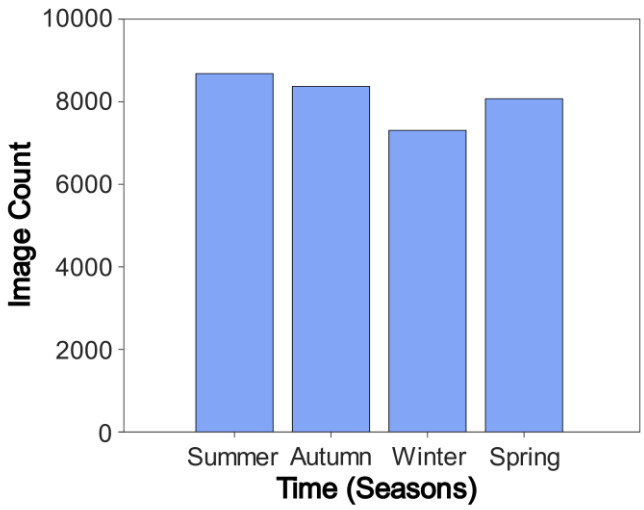

Figure 4.10. Total image count (sum of all years) by time (seasons).

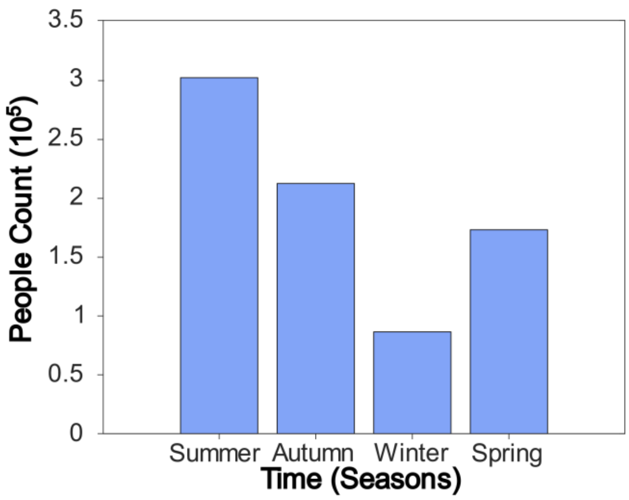

Figure 4.11. Total people count (10^5, sum of all years) by time (seasons).

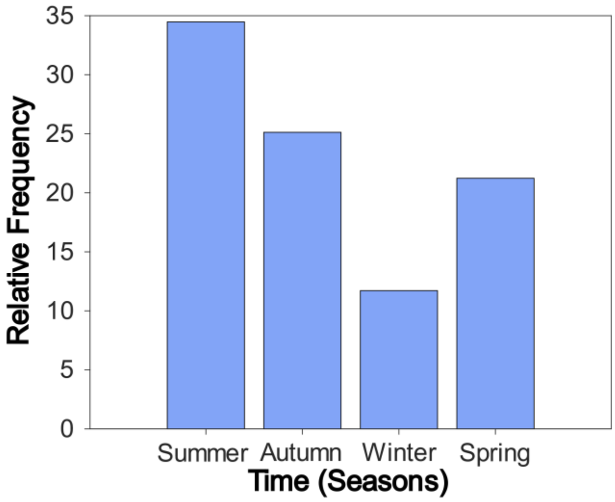

Figure 4.12. Total relative frequency (ratio of the sum of people count and the sum of image count) by time (seasons).

Figure 4.13 shows interannual patterns in image count over the time spanning 2008 to 2013. There is an overall increase of images from 2008 to 2012 (except in 2013). In Figure 4.14 a very different pattern emerges, seemingly not influenced by the image count. Compared to other years, the people count in 2010 is very high, followed closely by 2011. Overlooking these two years, the general pattern is a steady increase in people count from 200 to 2013. Relative frequency, in Figure 4.15, imitates this arrangement with noticeable decreases in 2011 and 2012 caused by an increased image input during this time span.

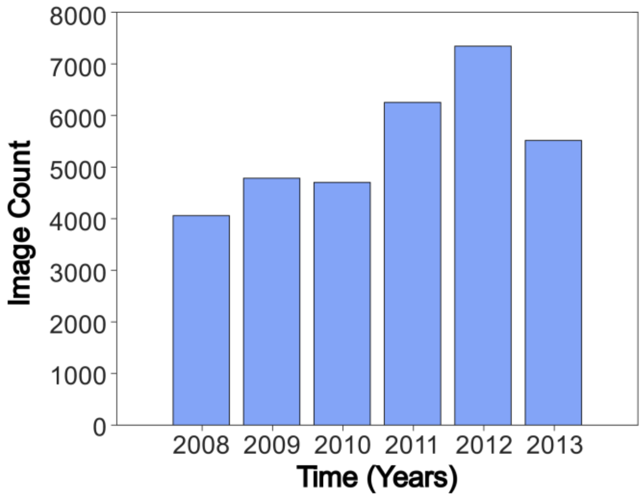

Figure 4.13. Total image count (sum of all years) by time (years).

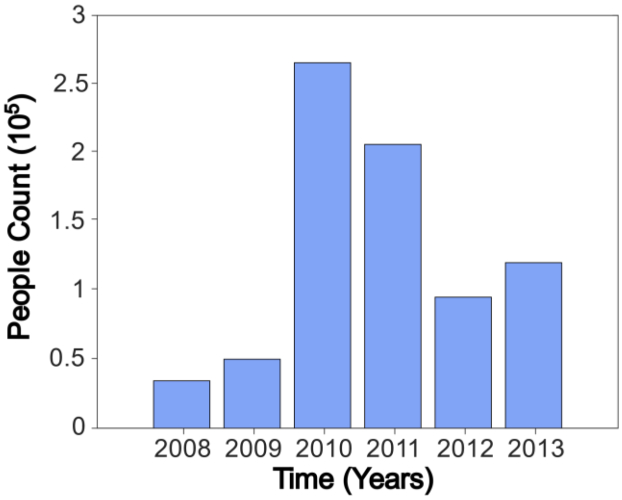

Figure 4.14. Total people count (sum of all years) by time (years).

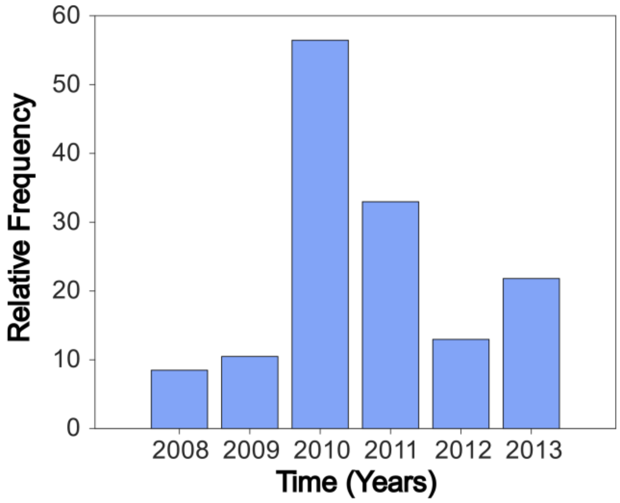

Figure 4.15. Total relative frequency (ratio of the sum of people count and the sum of image count) by time (years).

4.2 Spatial Results

The spatial results have a pronounced resolution bias in which more people are more easily recognized where the resolution of the images is higher. The remote sensing camera was located on the south eastern end of the beach, causing a higher detection rate of people closer to the camera. The far end of the beach is over one kilometer from the camera.

These results show how the number of people counted (‘the people count’) varies spatially along the image. The people counted plot has been orientated horizontally (by rotating the data), so that the north west end is on the left and the south east end would be on the right. The data were rotated using this formula:

$$Y_{new} = Y_{old}\cos(\theta) + X_{old}\sin(\theta)$$

$$X_{new} = -Y_{old}\sin(\theta) + X_{old}\cos(\theta)$$

Where θ is set at 53 degrees, and X and Y are the spatial coordinates of each person detected. The people count stops at the shoreline (lower area of the beach) at the top of the cross-shore axis (data returns seaward of the shoreline were removed in the cleaning algorithms discussed in Section 3.3).

The distribution of people counted in Figure 4.16 shows an extreme concentration gradient with a high density of people counted in the south east which declines and becomes sparse in the northwest. The number of people counted appears particularly high from 515 to 230 meters and then lower with clearer clusters from 230 to 0 meters. From then on to -600 meters, the number of people counted becomes very sparse in all years except for 2010. Additionally, one can observe the mismatched distribution of people counted throughout the years. This is the clearest closest to the camera position in the east end. The spread of 2008 and some of 2009 bulges around 25 meters towards the shoreline. Presumably, the shoreline has moved seaward during this time, either from beach rotation, or the appearance of patterns such as rip-current embayments. Following this, the cross-shore distance in this eastern area from 2010 to 2013 is very uniform averaging around 55 m. The general pattern is a smaller spread in the south east moving towards a higher spread in the northwest. A curve can also be seen in the shoreline area with people's usage peaking in cross-shore distance at both ends of the beach and reducing in cross-shore distance towards the centre of the beach.

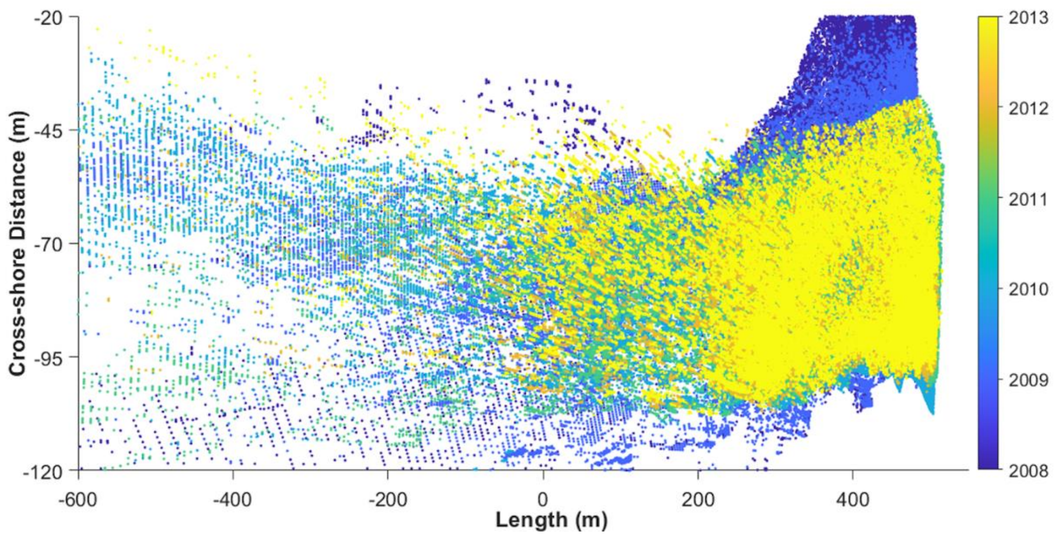

Figure 4.16. People count scattered by length (meters) and cross-shore distance of the beach (meters), coloured by year.

The splitting of the spatial distribution by year in Figure 4.17 is useful to examine interannual patterns. In 2008, 2009 and 2010 there are distinct patterns, while 2011 to 2013 have similar trends. There is a distinct curve in 2008 between 50 and 350 meters in the lower region of the beach. There are two areas representing a local morphological feature in the spatial distribution of the people count data in this region. One is between 0 and 400 meters with a cross-shore distance of approximately 30 meters located on the upper area of the beach, the other stretches from -600 to 60 meters and is approximately 40 meters in width, located on the center to lower part of the beach. It appears there are three horizontal linear areas where people are counted on the north western end of the beach. Two are parallel and emerge around 0 meters and thin towards the west, while the other thicker one diverges around 100 m. The latter may be associated with an imperfect estimate of the camera orientation. The distribution of data in 2008 and 2009 displays a bulge towards the lower end of the beach on the south eastern side as discussed earlier. The curve in 2009 is less pronounced and overall, there are fewer people counted, creating sporadic areas particularly on the north western side. In 2010, there is an even spread across the width of the beach with a curve along the shoreline area. There is a slight decrease in people count towards the north western side of the beach, although it is less profound than any other year. On the shoreward side of the beach, there is a distinct cut off people counted where the dunes are located. The next three years show a reasonably uniform distribution on the south eastern side, with the people count data dwindling and becoming more scattered towards the west. In 2011, the spread on the south eastern end of the beach has the narrowest cross-shore distance out of all the years, while the west end has one of the largest widths, spanning almost 80 meters. 2012 and 2013 have the lowest people counted on the west side of the beach while having a similar count to other years on the south eastern side.

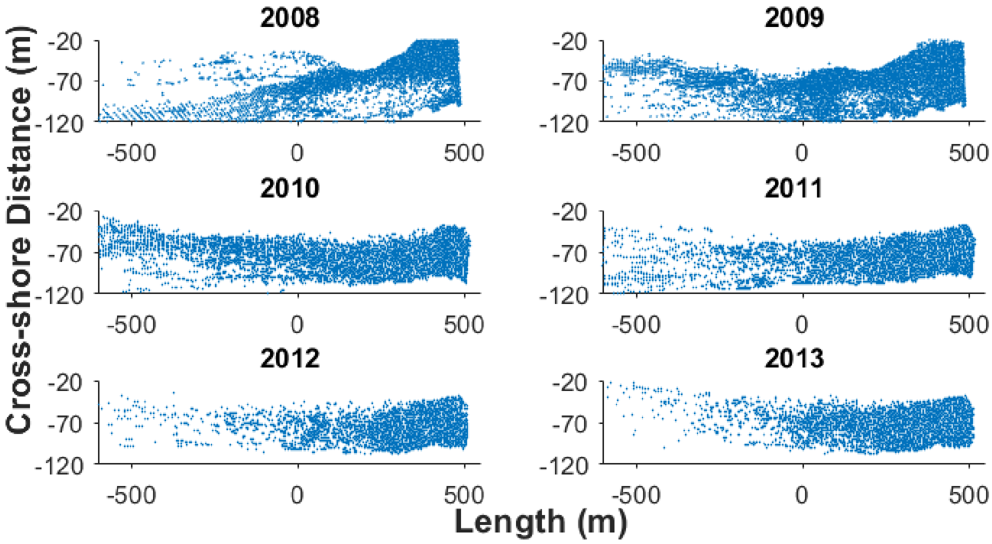

Figure 4.17. People counted scattered by length (meters) and cross-shore distance of the beach, separated by year.

Figure 4.18 shows the overall people count data plotted spatially to better understand the probability that a person might be found at a particular location on the beach. Resolution bias is clearly displayed, with more people counted towards the south east. The influence of this biased data on the spatial distribution makes it difficult to identify genuine patterns of beach usage. A large cluster of high people count data is located on the south eastern upper center of the beach around 200 to 400 meters and –90 to –110 m. The western two-thirds of the bivariate histogram does not show any particular pattern as the high range of people counted on the south eastern end dominates the graph.

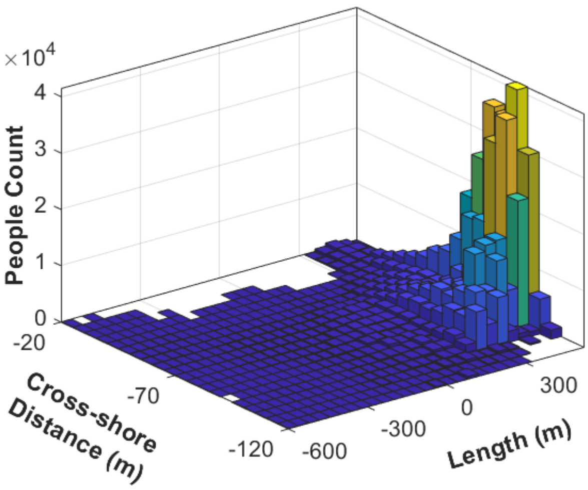

Figure 4.18. Overall bivariate histogram distributed by people count (10^4), length (meters) and cross-shore distance of the beach (bin: cross-shore distance 5 meters, length 40 meters).

Figure 4.19 shows the annual breakdown of the people count data to see if smaller-scale patterns might be evident when they are not overwhelmed by the contribution of extreme values seen in Figure 4.18. Colours are for visibility purposes and do not indicate a scale. In 2008 and 2009, there are the largest spread of people counted. A large clustering of people counted is visible at the south eastern low end of the beach in 2008. There is also a vertical linear spike at 500 meters and two clusters around an alongshore distance of 100 m. The larger radiates from the main cluster until a cross-shore location of -90 meters, while the smaller, standalone peak is between the cross-shore distance of -105 to -110 meters and alongshore distance of 80 to 120 meters and is present in 2008, 2009, 2012 and 2013 in roughly the same position. In 2009, there are many spread out clusters with high people counts on the central to south eastern side towards the shoreline. There is one extreme value on the eastern edge at the width -90. Like in 2008, there are also areas in the north western side that lack people. Years 2010 to 2013 have similar patterns of a flatter spread of people counted in the west and higher bin values located on the far east towards the upper end of the beach.

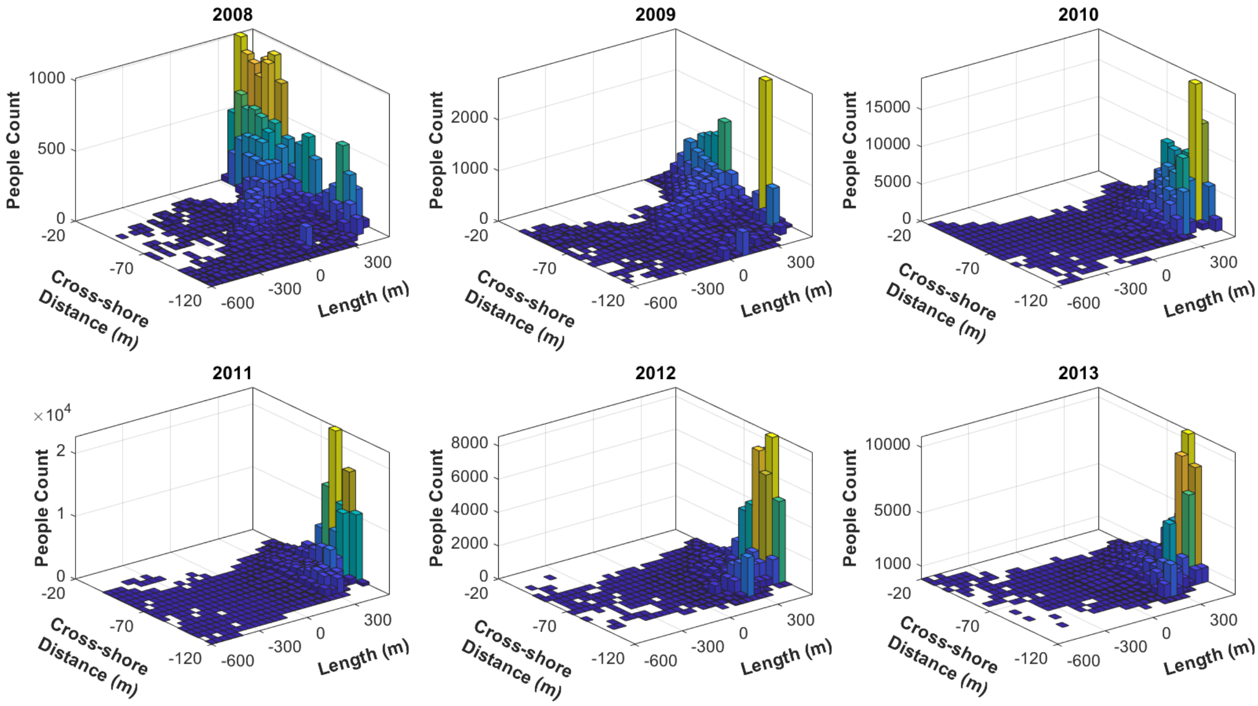

Figure 4.19. Bivariate histogram divided into years showing the distribution of people count by length (meters) and cross-shore distance of the beach (bin: cross-shore distance 5 meters, length 40).

Figure 4.20 and 4.21 shows a 2D profile of the distribution of people counted on a log scale to show general trends. The length profile has a peak on the second to the most south eastern bin which dramatically declines towards the western side. There appear to be four regions that are flatter around -450, -70, 115 and 370 m. These do not agree with the resolution bias and may form peaks in beach usage once corrected. In the cross-shore distance profile, there's a peak around -92 meters with a steep, sharp decline on the left followed by a plateau, while the right-side steadily declines.

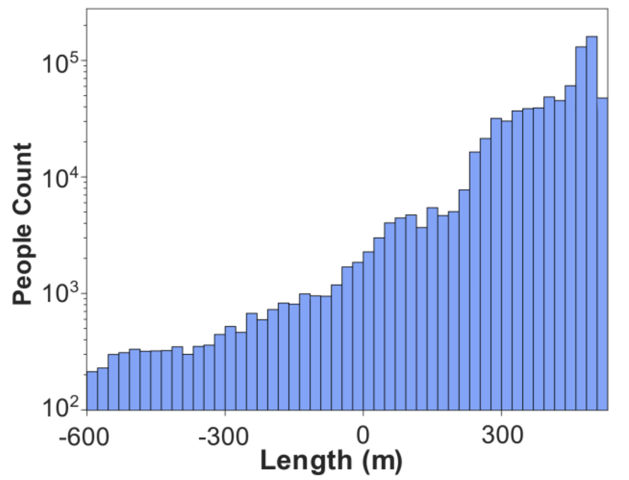

Figure 4.20. Histogram of the whole data set of log-transformed people count data plotted against the length (meters) of the beach (bin: length 23.08 meters).

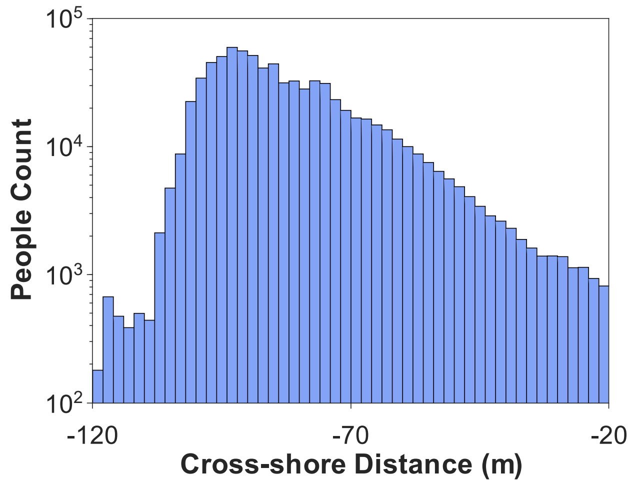

Figure 4.21. Histogram of the whole data set of log-transformed people count data plotted against the cross-shore distance of the beach (bin: cross-shore distance 2 meters).

The people count was corrected for the resolution bias using the model provided in Figure 3.9 (methods chapter). Figure 4.22 shows the corrected people count (original and smoothed by a running mean of ten meters) distribution along the length of the beach, this the access points marked. The access points from west to east are: (one to six) Ocean Beach access road (North end); 106-108 Ocean Beach Road; 138 Ocean Beach Road;16-18 Paku Drive; 38 Paku Drive (Tairua Surf Life Saving Club); and Hemi Place. Even when corrected for the resolution bias, the south eastern end of the beach appears more popular with a shift in use towards the center. The original correction had large variability, particularly in the north west, which made identifying patterns difficult. The smoothed line shows a relatively flat people count across the beach on the north western half, -600 to -60 meters. Then the usage climbed towards the south east, peaking multiple times, most noticeably around 80, 290, and 480 meters. The beach access points from one to three do not line up with peaks in the smoothed line. One and three align with regions of high variation in the original line. Access points four to six distinctively align with noticeable peaks. Four aligns in a shallow dip between two close peaks. This peak appears to build 155 meters to the west of the access point and declines till 115 meters in the east, after which it is seemingly influenced by a larger peak. Access point five is aligned with the largest peak with a slight right-skewed distribution that spreads across approximately 230 meters. Lastly, access point six lines up with a small peak that is cut off to the east because of the camera range.

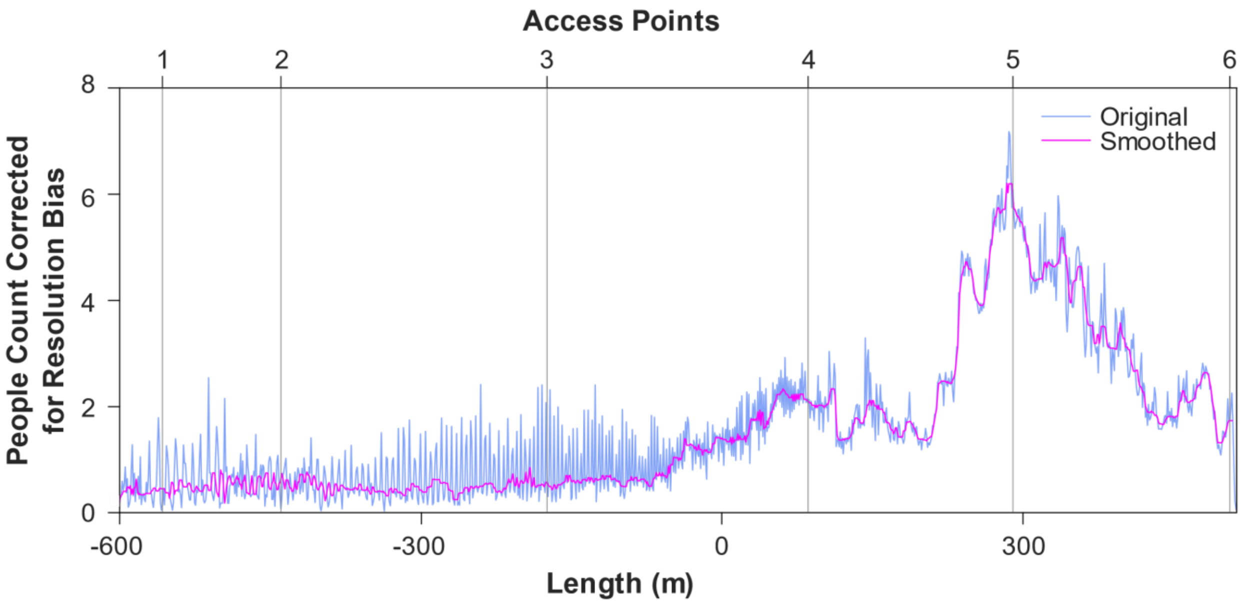

Figure 4.22. Line graph of people counted, corrected for the resolution bias (original and smoothed by ten meters) plotted as a function of length. Access points across the length of the beach are marked with vertical dashed lines.

The relative probability of a person being in one of 280 regions of 20 by 20-meter area was analyzed. The sum of each area is less than or equal to one, v_i is the bin value, c_i Is the number of elements in the bin, N is the number of elements in the input data (MathWorks Australia, n.d.).

$$v_i = \frac{c_i}{N}$$

Figure 4.23 shows a scaled grid of these areas relative to the beach. On the right side, the grid is unoccupied by the image due to its distortion from rectification, so these areas are less than 400 meters squared and may have a lower probability. As a result, an area in the top right is void of representing any beach area. Figure 4.24 displays the probability of a person being in any square at any given hour during daylight hours. Blank areas have a probability of 0 as no person has ever been recorded in that location. The blank areas towards the shoreline likely have never recorded people as the minimum low tide is a limiting factor and removed by the cleaning processes (only people on land were counted). All high probabilities are in the upper south east area of the beach, with the highest in yellow representing P = 0.1162. The rest of the grid displays a deep blue colour depicting a probability closer to 0. Figure 4.25 displays the probability with a fixed upper end of >0.010. This shows the pattern of those with probabilities closer to 0. A large yellow area in the south eastern end between -60 and -100 meters portrays an area with its probability equal to or above 0.010. Few orange areas surround the yellow block, representing a probability of around 0.008. There is a larger area of probability ranging from 0.006 to 0.002 that extends from the yellow block towards the west. From -600 to 0 meters, the probability does not exceed 0.001 for any given area. However, the colour map is shifted towards 0 to display patterns close to P=0. One can see darker areas of very low probability are in the north west around the shoreline and dune areas.

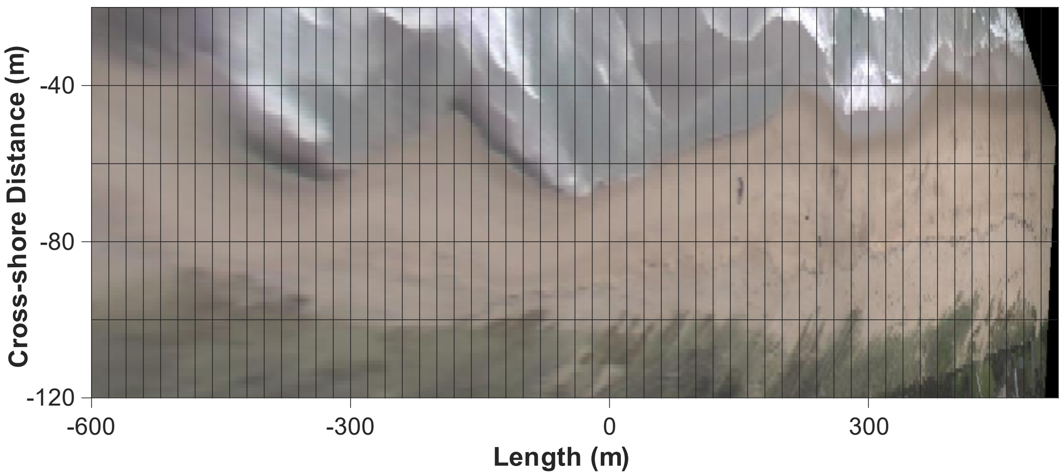

Figure 4.23. Overlay grid (20 x 20 meters) for probability assessment on low tide, rectified image of Tairua Beach (4 pm 21st February 2011).

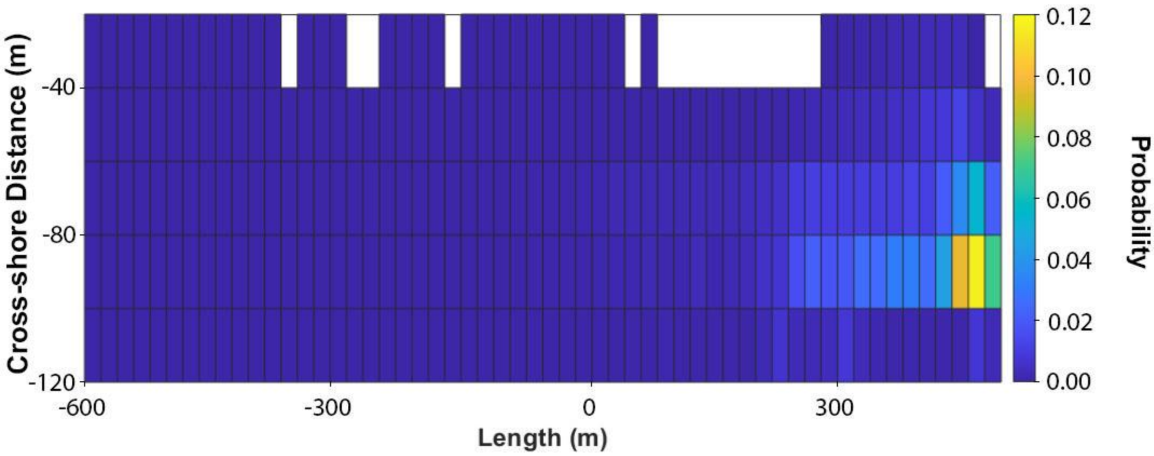

Figure 4.24. Overall probability assessment of the location of people counted on a colour map grid (20 x 20 meters).

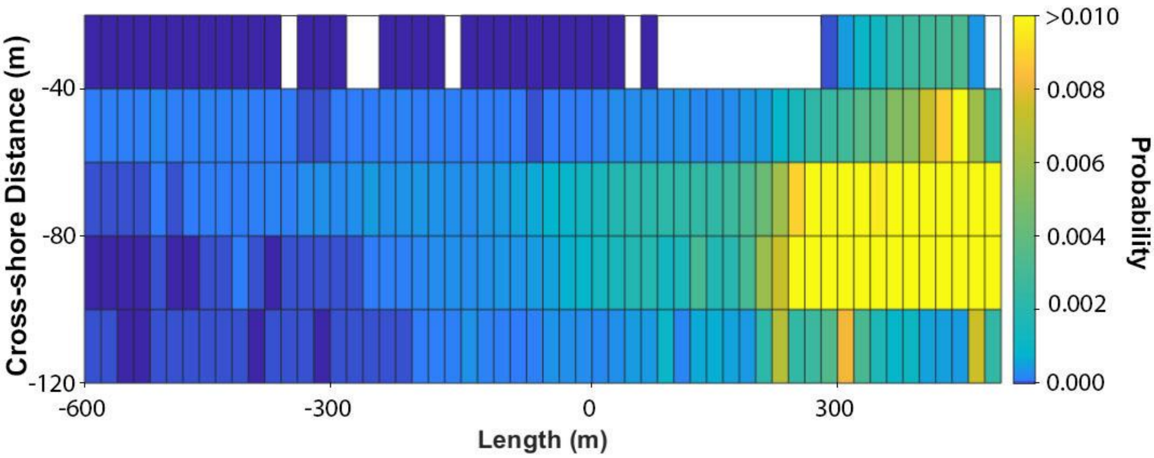

Figure 4.25. Probability assessment of the location of people counted on a colour map grid (20 x 20 meters) with a specified range (0.000 to >0.010).

4.5 Results Summary

These results cover a wide perspective of beach usage on Tairua Beach, displayed in various graphs. The analysed data are concise and objectively provide insight into temporal and spatial beach usage. Three bar graphs describe each period of beach usage, allowing the influence of image count to be balanced. Spatial results are displayed annually and overall to recognize unique and overall patterns and trends. Overall results are additionally dissected into length and cross-shore distance to view relationships with resolution bias and access points respectively. Resolution bias was modelled and corrected and distribution of beach usage by length reexamined. Lastly the probability of beach usage was assessed and displayed on two different scales for each 20-by-20-meter area of the beach. The evaluations of specific findings are found in the discussion chapter below.

Chapter Five

Discussion

5.1 Key Findings

My research aim was to use remote video monitoring data to gain a better understanding of beach usage and how it varies temporally and spatially. In the thesis, automatic algorithms to detect people were developed, and applied to hourly video images for 6 years. From this dataset, the probability of observing wildlife and marine debris at a certain time or place could be calculated. An understanding of the probability would allow managers to assess or even correct for bias in observational data collected by the public, such as on issues like stranded marine animals, bird spotting or litter. The dataset could also be used in the calculation of hazards influenced by or affecting beach users. The methods were good at indicating changes to the number of people that visit the beach each day, and how that varies between years and seasons. The spatial distribution of the detected people was much more difficult to provide robust numbers on, mainly due to the changing resolution of the camera caused by the oblique viewing angle.

5.2 Interpretations

The relative frequency (average number of people counted in each image) shows a bimodal pattern of beach usage that peaks at 10 am and then again at 2 pm with a shallow dip in the number of people at the beach between the peaks at 1 pm. This pattern is not surprising given the beach's reported high use over the summer holiday. Although it was assumed there would be some resemblance to a typical workday (increases before and after work hours, 9 am to 5 pm), this pattern may be overwhelmed by general patterns of high use on weekends and summer holidays when Tairua's population greatly increases. The reduction at around 1pm may be associated with people returning home for lunch combined with efforts to avoid being outside during the middle of the day when the UV predictions are at their highest. Previous studies at different sites (see Section 2.3), have shown great variability of beach usage over hourly timescales, with peaks ranging from 1 pm and 6 pm, so it is not surprising these results do not closely align. Hourly trends may be inherently inconsistent; some studies break down the hourly time scale datasets even further, separating them by days of the week and relating them to observed weather conditions to clarify trends. Different sites may have their own distinctive patterns, possibly influenced by climate, types of recreational beach usage, available facilities, local and non-local tourism, nearby businesses, beach quality, accessibility, and cultural importance.

Examining how the people usage data was distributed over days of the week showed that the usage decreased on Tuesday and increased from Friday till Monday, peaking on Saturday. Additionally, the average number of people counted on each image has a relatively small range over the week, ranging from 20.54 to

27.44. In this limited range, expected patterns still emerge showing higher beach usage on weekends. Literature on a weekday vs weekend beach usage shows differing results. Overall, on Southern California beaches almost half of all visits occurred during the weekend (Dwight et al., 2007). However, two other studies that were broken down into multiple observation periods found that at least one period showed steady use throughout all days, while the other periods displayed an increase over the weekend (Balouin et al., 2014; Blackweir & Beckley, 2004). The observation periods in Blackweir & Beckley's study were in between November and January 2003/04, and so may be less influenced by the work week as the study occurred over popular holiday periods in the summer. Meanwhile, in Blouin et al.'s study, many weeks show the beach usage is highest over the weekend with one week showing a stable pattern. This week, in July 2012, may have been influenced by high tourism in the region over the peak of summer (Northern Hemisphere) and holiday periods. The two weekdays with the highest relative frequency of beach users are Monday and Friday. This correlates with the occurrence of national public holidays from 2008 to 2013, of which 46% fall on a Monday (due to Mondayisation) and 20% on a Friday, while all other days of the week are below 10%. Public holidays on Monday or Friday allow for a three- or four-day weekend which may encourage local and regional tourism, and beach usage.

In terms of months, the relative frequency dataset shows significantly more people counted in each image from November till March, while fewer people were counted in the period from April to October. These months have large variability (range: 10.75 to 44.51), probably because of the six-year time span over which that data was collected. The trend is relatively smooth from the peak in January to the low in June with a steeper drop off from May to June and a steep increase from October to November. There is also an uncharacteristic drop in the number of people observed in the period from November to December. The monthly variations in the dataset behaved as expected; positively correlated to the average temperature in Tairua and negatively correlated to the average rainfall in Tairua (Climate-Data: Tairua, n.d.). Increased average rainfall in December, unique for that time of year, may explain the uncharacteristic drop that occurred in the dataset, assuming fewer people use the beach on rainy days.

The seasonal variation of the relative frequency dataset has a consistent scale of beach usage from the highest in summer, followed by autumn, spring, and winter. There are large variations in the average number of people observed in each image from 34.47 people per image in summer to 11.71 people per image in winter. Seasonal results are calculated from the monthly results and so they show the same correlations with temperature and rainfall. The summer increase was also foreseen as Tairua is known as a summer holiday town with a population that multiples by six over summer (Thames-Coromandel District & Council, 2010).

There is a large range in the dataset between years (8.49 to 56.45 people per image) with a general increasing trend from 2008 to 2013 with two high values in 2010 and 2011. These results did not fit the expected trend of a gradual increase aligned with the regional population trends. This may be due to several factors like changes in image resolution, camera angle, input images, false positives, and methodology of signal detection. Figure 5.1 shows unprocessed images prior to 2010 have a resolution of 760 x 570 pixels; this resolution was increased to 2016 x 1528 pixels in the period from 2010 to 2013. Resolution of images is key for distant signal detection; better resolution allows more signals from the far end of the beach to be detected. This may explain why 2008 and 2009 have the lowest people counted per image. The spike in 2010 and 2011 may be caused by the camera angle that shows a similar beach range spread across more area. Meanwhile the camera scope in 2011 and 2012 was cut off on the popular eastern end by a tree growing into the view of the camera. Camera angle from 2010 to 2013 gradually increases the amount of sky shown, essentially showing the same beach range within a smaller area of pixels, which reduces the relative resolution.

While large storms and cyclones occur every year, two in 2010 affected the Tairua area and were classed as moderate. The first storm occurred on June 1st bringing heavy rain (110mm to 138 mm) and winds to the Coromandel causing flooding on the roads around Tairua(NIWA, 2018a). Next, a one in 10-to-50-year event occurred with multiple storms affecting the country over seven days, from the 17th to 23rd of September. Whangamata’s weather station, approximately 22 km south of Tairua recorded 130 km per hour gusts along with an extended period of heavy rain (NIWA, 2018b). Large storms may bias the relative people count by reducing image input as the camera may not record during these periods. High winds can cause an increase in seaweed washed up on the beach which may also lead to false positive detection. While these may cause an increase in the number of people counted in each image, there is also an issue with visibility during a storm, causing people to not be detected.

Figure 5.1. Unprocessed images from 2008 to 2013 at low tide (0.65 m below mean sea level) display annual changes in camera angles, resolution, and beach morphology (4:00 pm 12/01/2008, 4:00 pm 13/01/2009, 2:30 pm 10/02/2010, 2:30 pm 05/01/2011, 3:00 pm 12/01/2012, 7:30 am 05/01/2013).

Regarding the spatial distribution of the results, they are heavily influenced by resolution bias in which the east end of the beach that is closer to the camera detects people more effectively. However, in 2010, the number of people counted is spread relatively evenly from west to east at what appears to be a similar density to the density detected toward the east in the images from other years. It is not clear why the resolution bias seems less visible during 2010, but it could be explained by the camera angle that includes the same view of the beach, across a larger area of the image. It may also be less obvious because of the larger number of people counted during this year.

In 2008 and 2009, there is a “bulge” in the position of the people counted on the images, protruding on the eastern lower region of the beach. This may be influenced by a change in rectification of this image position, camera angle and beach morphology. When checked against other images with the same viewing geometry, the camera alignment compared favorably. The overall spread of data is similar to other years, although 2008 appears a little skewed in Figure 4.17. The camera perspective shown in Figure 5.1 includes more of the ocean in 2008; this may allow more beach area to be detected in the eastern side towards the shoreline. Beach morphology does not appear to change dramatically between images. However, when comparing images with the same tidal height (0.5 m) there appears to be a change in the eastern end, with a wider beach occurring in 2008 and 2009.

The cross-shore distribution of people counted on the beach peaks at approximately a quarter of the cross-shore distance from the dunes, shown in Figure 4.21. The spread is skewed and steady towards the shoreline, while there is a steep decline and small plateau towards the dunes. The steady decline towards the shoreline is expected as the shoreline shifts between low tide and high tide changing the area available to beach users. The steep drop off towards the sand dunes may display a preference for dry, level sand towards the center of the beach, while the plateau likely shows variation in the cross-shore distance across the beach. Additionally, the plateau may portray limited areas that expand the "beach area" by having little vegetation on the dune toe, allowing beach users to be counted on vegetation-free parts of dunes. People might also avoid the dune area to reduce impact on dune planting, or to reduce the chance of disturbing birds nesting in the dunes.

The graphs showing the log-transformed distribution of the number of people counted along the length of the beach, Figure 4.20, showed that there was a steady increase of people counted from west to east, with some areas flattening or decreasing. Once corrected for resolution bias, Figure 4.22, the data gave a clearer picture of where beach usage is higher. Access point five (surf club access) aligns with the highest beach usage along the length of the beach. There appears to be high beach usage spanning a considerable distance from the surf club, possibly due to its popularity and the shifting of beach flags indicating a safe swimming area monitored by lifeguards. Swimming area flags governed by Surf Life Saving New Zealand are likely to strongly influence beach users' location. They are placed in less hazardous areas of coastline nearby the club. The fluctuation of location in swimming area flags and their influence may explain the wide peak of beach usage seen along this stretch of beach. Access point four (16-18 Paku Drive) lines up with a smaller, wide peak of beach usage, appearing to be less popular than access point five. The spread of this peak is asymmetrical indicating people that enter from this access point often cluster close to the access point or move west. East of this access point there is a peak, possibly indicating the use of a nearby unofficial access point. Between access point four and five, satellite imagery shows dune vegetation degradation indicating at least four unofficial access points from private properties through the dunes to the beach. Access point six (Hemi Place) aligns with a small peak cut off by the field of view of the image nearing the east end of the beach, indicating it is a less popular access point. To the west of this access point, there is a higher peak suggesting beach users are using access point six and migrating approximately 30 meters to the west or this may be the influence of five nearby unofficial access points, observed by satellite imagery, from private property. Access points one through to three do not have distinguished peaks of beach usage. It is likely this is caused by methodological issues associated with distant points, like visibility and resolution rather than this area being rarely used. Dunes in this area also show multiple unofficial pathways from satellite images.

The spatial distribution of relative probabilities are calculated using the observed people count dataset. Since they are not corrected for resolution bias, we see the probability of a person being detected in the east is much higher than the west. The probability peaks above 0.10 almost exclusively in the most eastern quartile between -60 and -100 meters. This is likely a combination of the cross-shore distance axis being limited by the consistent beach area and the resolution bias influencing the length axis. Towards the dunes the “beach area” becomes limited and this is shown through changes in relative probability. Sections of higher probability (in the east ~0.008) are indicative of vegetationless parts of dunes, while sections of very low probability (in the west <0.001) represent a smaller cross shore distance, and sufficient vegetation density to be predominantly classed as a “non-beach area.” Towards the shoreline there is a lower relative probability (0.000 to 0.002) of beach usage as the area available is dictated by the tides. In the east, this is higher due to beach morphology; the cross-shore distance tends to be larger regardless of the tide and resolution bias.

5.3 Implications

These temporal trends in the dataset collected here build on existing evidence of beach usage regarding the variability over scales of hours, days, months, seasons, and years. The analysis over hourly timescales supports the wide variation of peak usage with a general trend of decreasing usage in the mornings and evenings. Findings with respect to the variability of beach usage with day of the week adds to evidence of higher beach usage during weekends. It also shows higher use on Mondays and Fridays, suggesting a strong effect of long weekends may have previously been overlooked. Monthly and seasonal differences correlate well with existing literature in the southern hemisphere and weather patterns for the area. However, yearly beach usage results do not fit with the theory that annual beach usage correlates with population growth. The experiment provides a new insight into the temporal variation of beach usage at a specific beach, Tairua Beach. It also expands on the limited research relating to spatial variability of beach usage. In particular, the spatial distribution of relative probability may be considered when attempting to reduce population bias in beach related data. Observational information needed for management, be it stranded marine animals, bird spotting or litter, is biased by the probability of people finding and reporting it. By using the spatial distribution of relative probability outlined in the results chapter, the data may be altered to be more robust. Thus, datasets become more valuable and comprehensive when the population bias may be estimated, corrected, and normalized.

Additionally, the spatial distribution of beach usage has far reaching implications on assessing and managing beach risks, safety, and hazards. The amount and location of beach users is crucial to almost all coastal hazards, like storm surges, dune erosion, rips, rogue or large waves, water quality, animal attacks and tsunamis. These issues may be caused by beach usage itself or affect beach users’ safety. Dune erosion can be caused by destabilization by vegetation disturbance by beach users occupying dune toe or embryo dunes and accessing the beach through unofficial access points. This can lead to coastal erosion, putting at risk nearby people and property and may increase the impact of other hazards. Beach users and their dogs in these areas may also be causing damage to nesting sites of endangered New Zealand dotterels. Quantitative spatially resolved data of beach usage in these zones could help to quantify the impact of people and mitigation methods. Other issues such as rogue waves in shallow water, endangers those within the wave run-up zone, close to the shoreline. When calculating hazards and the risk to the public it would be useful to know either the relative probability of a person in a particular location (site specific) or an average cross-shore distribution of people (possibly non-site specific).

5.4 Limitations of Research

The generalizability of the results is constrained as only one site was studied due to time restraints. The resolution bias reduced the spatial data’s reliability. Even when corrected, the west end of the beach did not display expected patterns in the same way as the southeastern side; the most likely reason for this is that the resolution bias was not completely removed. The reduced signal detection lowering the intensity associated with clusters of people in areas far from the camera. Due to the likelihood of fewer data points on the west end, the results cannot confirm the precision of the distribution of relative probability along the beach. However, the cross-shore distribution is much less affected by resolution bias as each profile is approximately the same distance from the camera. The east end of the beach, corrected for resolution bias is also less affected and variation is still noticeable.

The methodological choices were mostly limited by time. Data were available for Tairua and Ngarunui Beach, but variables like signal detection, beach area, rectification, elevation, classification of zones, intrinsic and extrinsic camera properties were site-specific. Ultimately signal detection criteria would need to be altered as Tairua Beach sand appears white to orange on camera, while Ngarunui Beach appears golden to black. Signal detection functioned by observing the difference in the RGB spectrum which may be unusable on black sand beaches. Other methods like flyovers/drone footage negate the need to correct for resolution bias but are out of financial reach.

It is beyond the scope of this study to generalize these results and assume that they are representative of beach usage at different locations. These results are only a sample of six years of beach usage at one location. Despite the limitations the results are still valid and interesting. Temporal results agree for the most part with existing literature, while the spatial results add to an area of limited research.

5.5 Future Research

Further research is needed to further establish an understanding on general spatial distribution of beach usage, preferably at a different site or multiple so differences and similarities may be analyzed. Similarities in beach usage may be more representative of general patterns of use and more applicable to a multitude of beaches. I would recommend a different data collection method to negate resolution bias. Future studies may use beach usage data to normalize and correct for population bias or for calculation of hazards caused by or affecting beach users.

This probability assessment from this dataset could be used with respect to whether people detected any washed-up animals on Tairua beach. One could potentially calculate the probability of missing events with the combination of other factors such as time and period of the animal being present.

Chapter Six

Conclusion

6.1 Introduction

This research aimed to understand the temporal and spatial variability of beach usage at Tairua Beach. Temporal usage was analyzed on a range of different time spans. While spatial usage was evaluated from different perspectives to determine distribution across the beach area and probability of visitation for different locations. Hourly camera images of the beach over six years (2008 to 2013) were taken from a stationary position above the south east end. In this thesis, the camera images were transformed and analyzed to identify people. The data were collated and sorted by periods of time and location. Patterns and trends of beach usage at Tairua Beach emerged and often reflected previous research at different sites. This raised the question of whether these results are indicative of beach usage at different locations. Temporal results tend to agree with existing literature, while there is limited prior research to compare to the spatial results.

6.2 Review

To achieve my aim, primary quantitative data were extracted from a database of digital images collected and provided by Waikato Regional Council. Images were pre-processed using histogram matching to enhance and normalize contrast within the dataset. A line-by-line signal detection method was used within an all-encompassing, consistent mask of the beach area. The criteria of the signal detection required a dip followed by a spike of certain amplitude within 10 pixels on one line to detect a potential beach user on Tairua beach. These were recorded by location and cleaned to remove double counting by proximity and false positives by occurrence. Extrinsic and intrinsic parameters of the camera were calculated using ground control points from a reference image. An image registration system checked and corrected images so that they aligned with the reference image. This allowed the data and their subsequent unprocessed images to be geo-rectified and rotated so the length of the beach may lay horizontally. This enabled the position of the data to be identified relative to the physical world. A small group of rectified images were then used to create a neural network classification system using MATLAB machine learning. This was simplified into beach (sandy area) and non-beach areas and used to classify every image rectified. Rectified data and neighbouring pixels were then scrutinized. If the nearby pixels had less than 80% classified as beach area the point was removed. This helped remove data that were not beach users and instead represented seaweed, beach debris, vegetation, and shoreline. Final data for each image were retained in a location format and collated into a “people count” dataset to be used to explore the aims of the thesis.

The temporal variability of the people count, image count and ratio of people to image count, was then condensed into periods of time. These were categories of hours, day of the week, months, seasons, and years. The most relevant is the ratio of people to image count (average people in each image) and will be summarized below. Hourly patterns agree with general trends seen in literature, decreasing use in morning and evenings. Yet it displays maximum use at 10 am outside of what is previously seen in studies, between 1 pm and 6 pm. The data within the hour category had a moderate variability. Days of the week beach usage showed low variability and correlated with previous research. It set forth higher beach usage on Saturday, followed by Sunday, Friday, Monday, Wednesday, Thursday, and Tuesday having the lowest use. Monthly beach usage data displayed similar use to other studies in the southern hemisphere with high variability across different months. The general pattern is maximum use in January decreasing until June, then increasing till November with a small dip in December. Analysing seasonal beach usage allows comparison to northern and southern hemisphere research. Seasonal beach usage is as expected with moderate variability, higher use in summer, autumn, spring, then winter. Autumn and spring have similar usage. Annual beach usage is highly variable and does not meet expectation of correlation with population growth. Extremely high beach usage is seen in 2010 and 2011, likely caused by a change in methodology. The camera used for image capture was upgraded, increasing the resolution from 760 x 570 to 2016 x 1528 and its angle was adjusted non regularly along the years, altering the scope and resolution of the beach area. Disregarding these two years, 2008 to 2013 shows slow steady growth.

The spatial variability of beach usage used the geo-rectified location of pixels within the image frame to determine position on the beach. Annual variability in the spatially resolved beach usage data was examined separately, allowing overall patterns to be viewed. All years showed strong resolution bias, people on the far end of the beach (~1.2 km away) were counted less often than those closer to the camera. Morphology of the beach area showed its dynamic nature, altering its well-defined shape in the eastern end. From 2008 to 2010 the area that beach users occupy reduces from the shoreline by approximately 20 meters and then becomes relatively stable for the remainder of the study period. From an annual perspective, distribution of beach usage is relatively even across all years with small variance. In 2008 and 2009, there is dominant beach usage towards the shoreline with 2008 displaying unexpected sparser areas. This is likely caused by limited people count due to the change in camera resolution in 2010 mentioned earlier. The average cross-shore distribution is skewed with a peak towards the upper center of the beach profile. Towards the dunes there is a steep drop off in use followed by a plateau, compared to the slower steady decrease towards the shoreline. The steep drop off and plateau is possibly caused by fewer people in this area combining with limitations of beach area leading into the sand dunes. Regarding the decrease towards the shoreline, the lower part of the beach is less used and beach area available is dynamic.

Exploring the dataset of average distribution of people along the beach, it is difficult to discern trends due to the strong resolution bias. The resolution bias was calculated using the change in resolution across a beach area in an untransformed reference image. Length distribution was then able to be corrected. Clear patterns of distribution of beach usage along the length of the beach emerged. However, these are still limited by the lack of substantial data on the western end. There is high variability in beach usage across the length of the beach. While patterns are not discernible on the west, the east has clusters of high usage areas. Peaks align with access point four, five and six (16-18 Paku Drive; 38 Paku Drive (Tairua Surf Life Saving Club); and Hemi Place). Access point four is significant and widespread indicating people move from their original access point. Access point five lines up with the highest beach usage by length and has multiple peaks nearby. This may be due to the influence of swimming flags signalling a safer swimming area with lifeguards on patrol. Access point six has a smaller, less distinct peak which is cut off by the camera scope of the research area and further to the east, the end of the beach. To the west of this point there is a larger peak of beach usage indicating people moving towards the centre of the beach or unofficial access points.

The spatial relative probability of beach usage was calculated directly from the location data, giving probabilities of a person being counted in a particular area. A grid spanning the beach area was divided 20 by 20 meter cells, for which the relative probability was assessed. Resolution bias is evident, due to the length of the beach and position of the camera. This bias predominantly affects length axis and has little effect on cross-shore element. Two extreme probability values of above 0.1 are seen in the eastern region close to the dunes. Most of the central eastern third range between 0.008 and 0.02. The probability drops of slowly to the west impacted by resolution bias and drops sharply towards the dunes and shoreline impacted by available beach area. Lowest probabilities, below 0.001, are seen closest to the shoreline and the western upper end of the beach.

6.2 Relevance

Understanding beach usage in New Zealand is key for a wide range of applications. The temporally resolved results build on existing beach usage over scales of hours, days, months, and years. While preliminary spatially resolved results build on limited research and open a gateway for future research to correct population bias. Coastal research that relies on public reporting is predisposed to bias stemming from the probabilities of a person being in a certain area at any given time to be able to observe and report the event. In this setting, focusing on people in the beach area allows relative probability for any given area on Tairua Beach to be calculated. This research can aid in correcting population biased data, notably in Tairua Beach. Generalizations of beach usage may be derived from this thesis along with other literature to aid in amending population bias at other locations. Data of this nature may be useful in assessing for casted marine animals, litter, or bird spotting.

There are far reaching implications on assessing and managing beach risks, safety, and hazards. The location and number of people is crucial to evaluate the risk of hazards on people. Additionally, this sequence of methods is repeatable and adaptable to different sites. The process is moderately automated and could be developed to function independently and automatically. This research has interdisciplinary implications. Quantitative beach usage data may be helpful to understand local tourism, economic value, and management Tairua Beach.

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