SURF ZONE INJURY STUDY ALONG THE DELAWARE
ATLANTIC-FRONTING COAST:
QUANTIFICATION, PREDICTION, AND
DIRECTED AWARENESS

by

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ABSTRACT

Surf zone injury (SZI) data were collected along the ~24 miles of Atlantic-fronting Delaware coast for eight summer seasons from 2010 to 2017 to quantify injuries, predict injuries, and direct an awareness campaign. Beebe Healthcare in Lewes, Delaware collected SZI data, including but not limited to time of injury, gender, age, and activity. SZI occurring at the five most populated beaches exceeded 2000 and included six fatalities. The relative demographics of the injured population are similar despite fluctuating injury totals (mean [standard deviation (SD)], 253.1 [104.4]). Non-locals (n = 1757) were 6.7 times more likely to be injured as their local (n =264) counterparts (relative risk (RR), 2.62; 95% CI, 2.08 - 3.31). Males (n = 1258) were 1.7 times more likely to be injured than their female (n = 763) counterparts (RR, 1.29; 95% CI, 1.21 - 1.37). Serious injuries, defined as patients requiring admission to a trauma service, represented 9.1% (n = 184) of injuries. Wading (50.1%) was found to be the dominant activity associated with injury followed by body surfing (18.4%), and body boarding (13.3%). Beachgoer questionnaires suggest knowledge for non-locals is lacking as only 16.6% of those surveyed had seen information about SZI or shore break warnings.

Of the eight summers of data collection, 32.9% of days there were no injuries and 3.6% of days there were more than 10 injuries (max = 24 injuries in one day). The episodic nature of SZI indicate the importance of linking the environmental conditions and human behavior in the surf to predict days with high injury rates. Higher order statistics are necessary to effectively consider all associated factors related to SZI. Two Bayesian networks (BN) using Netica software (Norsys, Netica v. 6.03, www.norsys.com) were constructed to model SZI and predict changes in injury rate.
and likelihood on an hourly basis. The models incorporate environmental data collected by weather stations, wave gauges, and researcher personnel on the beach. The models include prior (e.g., historic) information to infer relationships between provided parameters. Sensitivity analysis determined the most influential parameters related to injury rates were significant wave height, foreshore slope, and water temperature. Exposure parameters (e.g., air temperature) influenced the number of people in the water, resulting in strong correlation between injury likelihood and the related meteorological conditions (variance reduction > 0.4%). Log likelihood ratio (LLR) scores indicate the network predicts SZI likelihood with more skill than prior predictions with the best performing model improving prediction 69.1% of the time. When all parameters were included, the BN set up as a binary problem predicting injury likelihood during an hour performed better (positive LLR = 69.1%) than the BN predicting injury rate (positive LLR = 36.7%). Issues persist with predicting SZI that have an LLR $\ll -1$ (< 5% of 2017 injuries) and occur in conditions different than when most other SZI occur. Better understanding of SZI will improve awareness techniques to both educate beachgoers and assist beach patrol decision making during high risk conditions.
Chapter 1

INTRODUCTION

1.1 Beach Hazards

Beaches are widely associated with tourism and recreation. People visiting beaches as tourists are often unaware or unfamiliar of oceanic processes, resulting in neglect of beach dangers (Ballantyne et al., 2005). Lack of awareness of potential beach hazards is problematic and results in several hundred injuries to water users each summer in Delaware alone (Puleo et al., 2016). Water users (WU) were defined as those beachgoers who were clearly in the water and potentially at risk of injury. Surf zone injuries (SZI) range in severity from minor sprains and fractures to life altering spinal injuries and even fatalities (Puleo et al., 2016).

Hazards presented to beachgoers evolve in response to fluctuating hydrodynamic and morphodynamic conditions. Beach hazards include, for example, rip-currents, shore-break, coastal structures, and marine life (Short and Hogan, 1994). Rip currents and drowning occurrences are well documented in the United States (USA) and internationally. Rip currents are estimated to be the source of 80% of beach related rescues in the USA (USLA, 2016), resulting in research to enhance prediction and understanding (Brander et al., 2011; Fletemeyer and Leatherman, 2010; Gensini and Ashley, 2010; McCarroll et al., 2014). However, rip current rescues might not be as prevalent as other hazards in locations like DE, due to the local morphology and hydrodynamic conditions. For example, in 2016 there were double the number of surf
zone injuries (SZI) as there were rip-related rescues at Dewey Beach, Delaware (USLA, 2016).

The Atlantic-fronting coast of Delaware generally has moderate to steep beaches with no offshore sand bar (Roberts et al., 2013). Moderate to steep sloped beaches result in a narrow surf zone, and lead to potentially dangerous shore break conditions (Wright and Short, 1984). Rough conditions associated with shore break results in numerous Delaware SZI (>100) to beachgoers each summer (Puleo et al., 2016). SZI range in severity, from minor abrasions to spinal injuries and even fatalities in some years. Medical costs for severe cases can reach millions of dollars in lifetime care (Cao et al., 2011). The emotional damage can be devastating, especially in the case of permanent disability or fatality.

1.2 Surf Zone Injury Research

SZI including hydrodynamic-driven impact (HDI), shallow water diving, and wave-riding activities have received comparatively less research and attention than rip current hazards. Most documentation of activities in prior studies were focused primarily on demographics and statistics of a particular activity. Prior SZI research includes shallow water diving (Aito et al., 2004; Beratan and Osborne, 1987; Chang et al., 2006; Falcon, 2016; Robles, 2006), surfing or body boarding (Barucq et al., 2009; Chang et al., 2006; Falcon, 2016; Hay et al., 2009; Meir et al., 2012; Nathanson et al., 2002), wind surfing (Kalogeromitros et al., 2002), and skim boarding activities (Williams et al., 2006). The demographic-focused studies are important, but do not necessarily relate the prevailing forcing conditions to SZI to determine injury causation.
Several studies have related environmental factors to other beach hazards (Beratan and Osborne, 1987; Chang et al., 2006; Short and Hogan, 1994). Puleo et al. (2016) investigated SZI occurrence at Delaware beaches by collecting ocean, beach, and weather conditions at the time of SZI. There was weak direct correlation between SZI and any environmental factors. For example, an increase in significant wave height did not correlate well with injury rates. Higher injury rates were associated with moderate significant wave heights (0.6 m) suggesting an unknown human factor. Also, the variability in the temporal distribution of SZI indicates some degree of randomness. However, the expected Poisson’s (random) injury distribution did not describe the observed SZI distribution. Therefore, a possible relationship should exist between SZI and some measureable parameters to model occurrence (Puleo et al., 2016).

The episodic nature of SZI and difficulty in quantifying the human factor require an alternative approach to modelling. Statistical modelling can incorporate prior knowledge, in the form of collected data, to make predictions. Statistical methods are less computational and can provide a simplified approach to numerical schemes. Probabilistic inference is a statistical method that can define the joint probability density function, relating initial conditions and forcing conditions. A Bayesian network (BN) uses probabilistic inference to make predictions with historical data. BNs act as both quantitative tools and conceptual tools, as they can evaluate conditional probabilities between parameters, while forming a visual representation of the problem to help guide a decision making process (Pollino et al., 2007).
BNs are increasingly popular with coastal applications including coastal morphology (Gutierrez et al., 2015; Palmsten et al., 2014; Plant and Stockdon, 2012; Wilson et al., 2015), geology (Hapke and Plant, 2010; Milheiro-Oliveira, 2007), hydrodynamics (Camacho and Martin, 2013; Gutierrez et al., 2011; Passeri et al., 2016; Plant and Holland, 2011a, 2011b; Scotto and Guedes Soares, 2007), and hazards (Egozcue et al., 2005; Grezio et al., 2010; Gutierrez et al., 2011; Poelhekke et al., 2016; van Verseveld et al., 2015). The Bayesian approach is also a suitable method for the injury prediction problem as it handles missing or unknown data well. For example, BNs were applied previously to predict injury risk associated with all-terrain vehicles (Rubinfeld and Rodgers, 1992), and to predict road accident severity data for two-car traffic collision injuries (Simoncic, 2004). BNs were applied to the SZI problem to relate associated hydrodynamic, morphological, and meteorological data simultaneously to two injury response variables.

1.3 Outline

This thesis is composed of the results and analysis of eight summers of SZI data collection. The SZI study was aimed at quantifying, predicting, and directing an awareness campaign to ultimately reduce injury occurrence. The methods taken for this research are not site-specific so that a similar SZI study outside of Delaware is possible.

The analysis of the SZI data set includes a demographic study and a probabilistic study, each with unique objectives. Chapter 2 details the injury data that were recorded. The chapter also outlines demographic analysis methods for determining high risk populations and some directed awareness measures. Some
figures (Figures 2.1, 2.3, 2.4, 2.5, and 2.6) and text were re-produced from Doelp et al. (2018) in this thesis, with permission from © 2018 Elsevier.

Puleo et al. (2016) identified the need for a study to relate the environmental conditions to SZI occurrence and rates. Chapter 3 discusses collection of environmental condition data related to SZI. Environmental variables were categorized as meteorological, morphological, or hydrodynamic. Human data were also collected in the form of population counts to estimate daily fluctuations to SZI exposure. Chapter 4 proposes a higher order statistical method to predict SZI likelihood and rates. Chapter 5 summarizes the former three chapters, and discusses the direction of future SZI work. The goal of the thesis is to outline methodology and analysis beach managers can apply universally to ultimately reduce SZI.
Chapter 2
SURF ZONE INJURY DEMOGRAPHICS

2.1 Introduction

Prior SZI research that documented demographics were primarily activity-based. These SZI studies include ones investigating shallow water diving (Aito et al., 2004; Beratan and Osborne, 1987; Chang et al., 2006; Falcon, 2016; Robles, 2006), surfing or body boarding (Barucq et al., 2009; Chang et al., 2006; Falcon, 2016; Hay et al., 2009; Meir et al., 2012; Nathanson et al., 2002), wind surfing (Kalogeromitros et al., 2002), and skim boarding activities (Williams et al., 2006). However, these single activity studies are typically no more than a few years in duration and therefore limited by a small injured population size in most cases. Hoag Hospital, Orange County, CA has collected SZI data for over 30 years. However, Hoag’s medical data collection was reserved to spinal column and cord injuries only. Long term and extensive data documenting demographics of SZI population are needed to draw inferences about the injured population. The present study uses eight years of injury data recorded by a trauma registrar data to better understand Delaware SZI statistics.

2.2 Study Location

Data were collected from the five most populated Delaware beaches on the Atlantic-fronting coast of Delaware. SZI occurring at beaches other than the five most populated beaches included in the study represented only < 0.2% of the total injuries recorded. The beaches are guarded between the hours of 0900 and 1700, seven days a week from Memorial Day (last Monday of May) until Labor Day (first Monday in September). They are heavily used with estimated summer attendance at five of the most populated beaches exceeding 7.5 million persons (USLA, 2016). Puleo et al
(2016) estimated 1 - 2.5 WU per linear meter of beach on crowded days, consisting of both domestic and international visitors. However, most visitors arrive from upstate Delaware, or the surrounding Mid-Atlantic states of Virginia, Maryland, Pennsylvania, and New Jersey.

Delaware beaches (Cape Henlopen State Park, Rehoboth Beach, Dewey Beach, Delaware Seashore State Park, and Bethany Beach; Figure 2.1) typically have moderate to steep foreshores with no offshore sand bar (Roberts et al., 2013). Hazards are highly dependent on beach morphological and hydrodynamic conditions, thus making them spatially and temporally dependent (Wright and Short, 1984). For example, rip-circulations are characteristic of beaches that tend to reflect incoming wave energy (Short and Hogan, 1994). Reflective beaches, such as those associated with the Delaware coast typically have steep foreshore. The steep foreshore results in a narrow surf zone dominated by shore break.
2.3 Methods

2.3.1 Data Source

Injury data along the Atlantic-fronting Delaware coast from the five most populated beaches (Figure 2.1) were collected by the Department of Emergency Medicine at Beebe Health Care in Lewes, DE (ACS Level III trauma center). Survey data did not include physical characteristics of the patients, but did provide demographic details. Demographics of the injured populations were used to assess similarities between years and determine higher risk groups. However, it is important to determine if the higher risk of a group was due to disproportionate populations in the water, or due to a behavioral component of that group.
Population data of WU were collected by researchers on the beach between the summers of 2014 and 2016. One weekday population count and one weekend count were taken each summer to estimate the daily variation of WU throughout the day. Two WU counts were taken at hourly intervals between 0900 and 1700 (guarded hours) and averaged. For practical purposes, counts were taken along a fixed 100-m alongshore stretch of each beach near a beach access point and in direct vicinity of a beach patrol stand. The summer counts were then averaged to estimate the distribution of WUs during a weekday and weekend day. The number of males and females in the water along the same stretch of beach was also counted once daily between the hours of 1300 and 1500. The daily counts between 1300 and 1500 were then extrapolated to total daily counts using the daily counts variation (see Puleo et al., 2016 for complete description of methodology).

Questionnaires were distributed to beachgoers during the 2016 and 2017 summer seasons to quantify population demographics on the beach in relation to injured and WU populations. Questionnaires were filled out by individuals over the age of 18, who either were at the beach while responding to the questions, or had attended a Delaware beach at some point during the summer. Beachgoers are defined as individuals that completed a questionnaire, but did not necessarily enter the water.

2.3.2 Study Variables

Injury patient demographic and medical information were extracted by the trauma registrar from Beebe Healthcare. Patient data include, for example, time of injury, activity, age, gender, zip code, and location of injury (one of the five beaches). Injury activity was grouped into eight categories: wading, body surfing, body boarding, skim boarding, diving, surfing, swimming and other. Of the 47 “other”
injuries, six were rafting or tubing, four were kayaking, and two were paddle-boarding. The other 35 injuries were recorded as “unknown” by the trauma registrar. Wading injuries, defined as injuries occurring while the individual is standing in shallow water (< 1 m), were considered “low risk” SZI. These injuries resulted from the WU being in the water, and not by participating in a sporting activity in the surf. Injured individuals were considered locals if their documented zip code began with a 199XX (southern Delaware zip codes) and non-locals otherwise (Figure 2.2). Serious injuries were categorized as patients requiring admission to a trauma service.

WU population counts provided estimates as to the distribution of individuals in the water at different times during the day to compare with timing of injury. Beachgoers questionnaires determined the age, gender, home zip code, and number of family members of surveyed persons on the beach. An additional question also asked whether or not the person had observed rip current-related material, SZI, or shore break warnings.
2.3.3 Data Analysis

Data are reported with descriptive statistics as case counts, means, medians, standard deviations, standard error (SE), and percentages to describe the injury sample and patterns. Demographics are organized by injury activity, and reported as distributions by age, gender, and locals vs. non-locals. Statistical analyses were conducted using MATLAB (version R2016b; The MathWorks, Inc., Natick, MA). Estimates of beach population demographics were made with beachgoer
questionnaires for $\chi^2$ goodness of fit analysis and relative risk (RR) ratios. Statistical analysis also included significance of mean t-tests and z-tests between proportions.

2.4 Results

2.4.1 Population and Temporal Trends

Injury data were used to better understand the injured population demographics and long-term trends. Hourly injury distributions for weekends and weekdays were plotted against averaged hourly WU distributions at each of the five beaches (Figures 2.3 and 2.4). Peak hours of WU populations occurred between the hours of 1300 and 1500 for both weekends (50.8%) and weekdays (49.2%). None of the averaged hourly WU counts were normally distributed ($p < 0.001$).

WU counts were supplemented with population distribution estimates of beachgoers that were derived using the questionnaires handed out to beachgoers. The percent distribution of injuries to each population were separated by year of occurrence (2.1). Each year, there was minimal fluctuation in the demographics of the injured population including gender ($\sigma = 4.7\%$; $\sigma$ is standard deviation) and locals vs. non-locals ($\sigma = 3.4\%$). The differences of the injury percentage for different age groups relative to the total injured population ranged from 1.3% to 12.4%. For example, the injury percentage for the 41 - 50 age group was 8.7% in 2017 and 21.1% in 2010 (range = 12.4 %).
Figure 2.3: Weekday hourly variation of WU Population (2014 – 2016) against percentage of hourly injury occurrence.

Figure 2.4: Weekend hourly variation of WU Population (2014 – 2016) against percentage of hourly injury occurrence.
Table 2.1: Injury demographics and beachgoer population (as %) by year.

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*Row contains proportion of total injuries for the year.*
2.4.2 Gender

The total numbers of injuries to each population were separated by injury activity (Table 2.2), including the number and type of injuries occurring to males and females. Daily WU population counts at the five beaches between 2015 and 2016 indicated that 50.7% of the WU population was male and 49.3% of the WU population was female. Statistically similar gender distributions between the WU population (50.8% male) and beachgoer population (52.9% male) suggest the demographics of the two populations are comparable.

There was significant difference between the WU population proportions and injured population proportions (p < 0.001). Roughly 63% of the 2021 injuries between 2010 and 2017 were sustained by males (n = 1258) with 37.2% sustained by females (n = 763). The proportion of each injury activity for different populations of interest was separated (Figure 2.5). Injury data were also categorized by low risk (e.g., wading) and high risk (e.g., body boarding, body surfing, skim boarding) activity (Figure 2.6). Injuries sustained by the female population mostly occurred during low risk activities; wading injuries (70.6%, n = 523; Relative Risk (RR), 1.76; 95% CI, 1.62 - 1.92). The male population had a higher percentage of injuries occur from more risky activities (60.3%, n = 744; RR, 1.94; 95% CI, 1.73 - 2.18). The activities in which males had a higher percentage of injuries than females include: body surfing (84.4%), body boarding (73%), skim boarding (85%), diving (78%), and surfing (80%). Serious injuries (88%) were predominantly sustained by males (RR, 4.47; 95% CI, 2.89 - 6.91).
Figure 2.5: Distribution of injury activity for: a) Female b) Male c) Non-Local d) Local e) 11 – 20 Age Group f) 41-60 Age Group and g) Serious Injuries. Injury percentages less than 6% are not labeled.
Figure 2.6: High risk and low risk activities based on demographic.
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2.4.3 Age

The age of the 2021 injured individuals ranged from 1 to 88 years (mean [SE], 33.5 [0.44] years; median 32 years). The average age of females (mean [SE], 36 [0.74] years; median 37 years) was higher than males (mean [SE], 32 [0.44] years; median 28.5 years). A two-sample t-test indicated a significant difference of mean injury age between males and females (p < 0.001). There are trends in the distribution of mean injury age across age groups for each year. All eight study years portrayed a similar bimodal distribution with peaks in the 11-20 and 41-60 (includes both 41 – 50 and 51 – 60) age groups (Table 2.2). The 11-20 age group accounted for 20% – 30% of all injury activities except skim boarding (65.5%). There was significant relative risk for that age group (RR, 1.14; 95% CI, 1.07 - 1.21) compared to the beachgoer population. The only other age groups that had a relative risk greater than 1 was the 41-60 age group (RR, 1.08; 95% CI, 1.03 - 1.14).

There was significant difference between injured and beachgoer population percent distributions for the 0 – 10, 11 – 20, 21 – 30, and 41 – 50 age groups (p < 0.001). Alternatively there was no significant difference between the two populations for the 31 – 40, 51 – 60, 61 – 70, and older than 71 age groups (e.g., 51 – 60 injured population = 12.7% and beachgoer population = 12.6%).

2.4.4 Locals vs. Non-Locals

A majority of SZI occurred to non-locals (RR, 2.62; 95% CI 2.08 - 3.31) both for the entire injured population (86.9%), and for individual injury activities (Table 2.2). Of the injured wader population, 89.6% (n = 907) were defined as non-locals. Locals accounted for just 10.4% (n = 105) of the total wading injuries. The local injured population was more likely to sustain an injury in a higher risk activity such as
body surfing (35.7%) or skim boarding (24.8%). The proportion of non-locals to locals for low risk activities (8.6:1) is significantly greater than the overall injured population of non-locals to locals (p < 0.01). The proportion of non-locals to locals for high risk activities (4.0:1) is significantly less than the overall injured population of locals to non-locals (p < 0.001).

There were 1.6 times as many non-locals compared to locals as identified by beachgoer surveys (n = 1455). A two-sample z-test indicated significant difference between the local to non-local ratios for the injured population and beachgoer population (p < 0.001) indicating that non-locals are injured at a higher proportional rate.

Data on wading WU orientation (facing waves or back to waves) at the time of injury was also recorded from 2015 to 2017. Of the wading injuries, 72.4% (n = 113) of the WU had their back to the waves. Of the total back to wave injuries, 85.4% (n=97) were non-locals. It is unknown for prior years what percentage of wading injuries were related to WU having their backs to the waves.

2.5 Discussion

2.5.1 Study Limitations

Study limitations include the possibility of missing data and that data are limited by the detail provided by patients to the trauma registrar and assistants. Characteristics of the injury such as activity might be incorrectly documented as the record is dependent on the recount of the event. Beebe Healthcare does not follow up with injured individuals to determine a final disposition. Thus, any change in
disposition related to SZI after initial disposition (e.g., admitted, transferred to a higher level of care) are unknown.

Also, injured individuals may have decided to not go to Beebe and go home or to an alternate medical facility. Consequently, some populations might be underrepresented in the study, altering the injury distribution. Some injury data from locals may be unaccounted for because locals may be more likely to seek care at their primary care office or other healthcare facility. The potential lack of locals in the data set can inflate the proportion of non-locals recorded. However, the year to year consistency of the data suggests missing SZI reports would be a small component of the study. Future work might try to compare records of injuries by beach patrol and at Beebe Healthcare to quantify the percentage of injured persons missing in the Beebe Healthcare data set. Another possibility is to initiate partnerships with smaller local healthcare facilities to document SZI.

2.5.2 Higher Risk Demographics

The Delaware SZI study is one of only a few investigating the population demographics of SZI data across surf zone activities. Other SZI research focused on the demographics of spinal SZI in Ocean City, MD (Falcon, 2016) or on a single activity basis such as surfing (e.g., Klick et al., 2016). Previous research based on a subset of these data (Puleo et al., 2016) were consistent with the demographics of the aggregate data analyzed. The number of injuries fluctuated from year to year (standard deviation [SE], 104.4 [36.9]), but the individual year demographics were consistent with the aggregate data.

Injuries sustained by males accounted for nearly two-thirds of the total injuries (62.2%), similar to prior studies involving beach hazards (Pollard et al., 2013). The
22.7% increase in percentage between injured males and male WU suggests a
difference in the behavior of males and females that is apparent in similar surf hazard
studies (Aito et al., 2004; Barucq et al., 2009; Chang et al., 2006; Gensini and Ashley,
2010; Hay et al., 2009; Klick et al., 2016; Morgan and Ozanne-Smith, 2013;
Nathanson et al., 2002; Puleo et al., 2016; Williamson et al., 2012). Only 39.2% of the
total male injuries were associated with wading compared to 69.0% of female injuries.
Males were more likely to be injured as a result of more risky activities like skim
boarding (85.0%), body surfing (84.4%), and surfing (80.0%). Increased risk taking by
males partially explains differences in observed injury activity between genders
(Morgan and Ozanne-Smith, 2013).

Three main age groups accounted for over half of the injured population, the
11-20 (26.1%) and the 41-60 age groups (30.9%). SZI in the 11-20 age group are more
commonly associated with high risk activities (e.g., skim boarding, body surfing, body
boarding), and reflect the behavior of persons in that age group. Similar high numbers
of Australian surf rescues (Morgan and Ozanne-Smith, 2013) have been documented
for males in the 11-30 age group. However, the Australian study found a maximum
number of injuries between 20-29 years, an age group that accounts for only 10.7% of
Delaware SZI and does not have a significant risk (RR, 0.87; 95% CI, 0.79 – 0.95).
Male non-locals in the age group of 11-20 are much more likely (22.0% of total
injuries) to sustain injury relative to other populations (RR, 1.17; 95% CI, 1.13 –
1.21). The lower age group peak for Delaware SZI indicates a potential lack of beach
safety education, assuming risk perception is held constant.

The numerous SZI in the 41-60 age groups were responsible for the greater
mean age (mean = 33.5 years) relative to other SZI studies with mean ages in the
range of 22 - 29 (Aito et al., 2004; Beratan and Osborne, 1987; Falcon, 2016; Hay et al., 2009; Klick et al., 2016; Nathanson et al., 2002). The proportion of SZI for individuals in the 41-60 age groups are 1.4 times greater than rip-related fatalities (Gensini and Ashley, 2010), and 1.6 times greater than surfing injuries (Klick et al., 2016) and warranted further research (as described in Puleo et al. 2016). Beachgoer questionnaires conducted in 2016 indicated that most individuals in the 41-60 year old range came to the beach with children (88.4%). Wading injuries represented the most common activity prior to injury for injured persons in the 41-60 year old range. One possible explanation of the high injury rate in this age range is associated with parents paying more attention to their children than the waves while standing in < 1 m of water. The rates of other types of SZI for this age group could be low because older WU tend to participate in less risky activities. Recommendations of methods to reduce injuries to this age range are similar to those catered to non-locals in the subsequent section.

2.5.3 Injuries to Non-Locals

The number of injuries sustained by non-locals was over six times greater than the number of injuries sustained by locals (n = 1757 vs. n = 246). Results from other beach studies suggest that non-locals are more likely to engage in risky behavior at the beach (e.g., Ballantyne et al., 2005), and that there is a correlation between the level of knowledge about the ocean, and beach accidents (da F. Klein et al., 2003). Those studies did not report beach or WU demographics to compare to the injury data set.

Bertatan and Osborne (1987) found the proportion of tourist and local SZI were similar to the overall beach usage in southern California. The results of the Delaware SZI study contradict the southern California study as the locals to non-locals
ratio for the injured population (6.7) had a 57.7% increase over the ratio of locals to non-locals of beachgoers (2.6). The number of wading injuries sustained by non-locals was 8.7 times the number of wading injuries (n = 907 vs. n = 105) sustained by locals.

### 2.5.4 Directed Awareness

A directed awareness campaign is crucial to inform beachgoers of shore break hazards. The distribution of questionnaires to beachgoers is an action beach managers can take to gauge beachgoer understanding of ocean processes, and directly engage people on the beach. Researchers involved in the Delaware SZI study dispensed over 500 questionnaires (Appendix A) in 2016 and 2017 to quantify beachgoer knowledge of beach related hazards including shore break. Of the surveyed beachgoers, about half of the non-locals surveyed (52.2%) had seen rip-current-related information, but a smaller percentage had seen any information about SZI or shore break warnings (16.6%).

The difference in the proportion of injured wading population and the beachgoer population points to a possible lack of knowledge of ocean processes (or ability in the ocean) of the non-local population, quantified by the distributed survey. Educational awareness materials directed at non-locals may help reduce SZI (Puleo et al., 2016), especially low-risk injuries.

Possible methods of quickly relaying information about SZI to non-locals is with a pamphlet or double sided educational card. A pamphlet with shore break information on one side, and rip current information on the other was developed (0) for Delaware beach managers to distribute on the board walk, at local reality offices, and events (e.g., Delaware Coast Day). The pamphlet provides recommended precautions and steps to avoid injury.
Another possible pathway for the pamphlets to reach more people is through the distribution to school children. During a beach safety presentation at a local Delaware elementary school, several hundred pamphlets were distributed to students to pass along to their parents. However, presentations to students in coastal community schools alone is not sufficient. With a high proportion of injuries to 11 – 20 year old non-local children, a mandatory beach safety class or curricula in PE classes nationally would be beneficial to reaching a larger population. However, the majority of SZI in the 11 – 20 age group are the result of high risk activity (60%). Awareness to reduce high risk activity injury rates must be treated differently as they are tied to risk perception (McCool et al., 2008). In high risk activity injuries, the individual likely knows the inherent risks associated with the activity and alternative statistic-based awareness methods are recommended (Chowdry and Kelly, 2013).

2.6 Conclusion

The numerous injuries to non-locals, and predictability of injury demographics each year indicate a need for increased prevention efforts and awareness. Many of these injuries to non-locals occur during low risk activities that are preventable with basic knowledge. Beachgoer questionnaires suggest knowledge for non-locals is lacking as only 16.6% of those surveyed had seen information about SZI or shore break warnings. Future SZI demographic work should consider measuring the effectiveness of awareness methods for different populations and long-term reduction in injuries.
Chapter 3
ENVIRONMENTAL VARIABLE DATA SET

3.1 Background

Eight years of human and environmental variable data (e.g., meteorological, morphological, and hydrodynamic) related to SZI were collected. Human data in the form of daily water user counts estimated daily exposure of beachgoers to SZI occurrence. Prior research involving beach counts quantified the number of people on dry beach using imagery analysis (Jiménez et al., 2007). However, the method used did not include counts of people in the water. Daily WU counts were necessary to cast SZI occurrence as a normalized value based on the exposure. Exposure is the number of WUs integrated across all five beach that are exposed to risk. As mentioned in Chapter 2, WU counts just estimated male and female proportions, but did not measure any other demographic distributions (e.g., non-locals vs. locals, age).

Environmental variable data were collected by weather station, wave gauge, or by researcher personnel on the beach. The number of injuries varied throughout each summer (2017 distribution shown as example to demonstrate daily variability; Figure 3.1). Over the entire study period 2010 to 2017, 32.1% of the days had no injuries and 3.6% had more than 10 injuries (Figure 3.2). Some of these data were ultimately processed and included as environmental parameters in a Bayesian network probabilistic model proposed in Chapter 4.
Figure 3.1: Daily distribution of 2017 injuries

Figure 3.2: Number of days that a particular number of injuries occurred
3.2 Water User Data

Instantaneous population counts of WU were collected daily at each beach during the summer study period for four summers (2014 to 2017). Ideally, total WU along the entire stretch of each beach throughout the day would be known to obtain an injury rate \( (IR) \). However, the length of each beach in the alongshore was greater than 1 km so that determining the total daily WU counts along the entire stretch of each beach was unfeasible. A practical approach proposed by Puleo et al. (2016) by taking daily counts along a 100 m stretch of beach between 1300 and 1500 (most populated hours) was taken. The selected stretch of beach was in direct vicinity of a beach patrol stand and near a dune crossover. The same two researchers made counts each day to minimize variability of considered WU.

On one weekday and one weekend, a full day count was taken every half hour to estimate the daily distribution of WU between 0900 and 1700 and capture the temporal variability. These intraday counts along the 100-m stretch of beach were scaled with a count along the entire stretch of beach. The resulting daily WU weekend and weekday curves for each beach were stretched or compressed based on the ratio between the curve at the time of the daily count and the actual daily count. The results of the hourly distribution of the mean annual population are summarized with corresponding SZI counts and \( IR \) (Table 3.1).

The WU along the entire stretch of all five beaches were summed for each hour of each day. The estimated WU of each hour were used as a normalization of SZI occurrence in the form of an hourly \( IR \):

\[
IR_i = \frac{(Number \ of \ injuries)_i}{(WU \ population)_i} \quad (i = hour).
\]  

(3.1)
Table 3.1: Hourly distribution of mean annual total population, SZI, and IR.

<table>
<thead>
<tr>
<th>Beach</th>
<th>900</th>
<th>1000</th>
<th>1100</th>
<th>1200</th>
<th>1300</th>
<th>1400</th>
<th>1500</th>
<th>1600</th>
<th>1700</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population*</td>
<td>204</td>
<td>264</td>
<td>289</td>
<td>642</td>
<td>796</td>
<td>771</td>
<td>1045</td>
<td>668</td>
<td>305</td>
<td>5043</td>
</tr>
<tr>
<td>SZI</td>
<td>4.9</td>
<td>10.3</td>
<td>24.4</td>
<td>36.4</td>
<td>36.6</td>
<td>41.4</td>
<td>39.7</td>
<td>33.2</td>
<td>22.1</td>
<td>250.2</td>
</tr>
<tr>
<td>IR**</td>
<td>0.0024</td>
<td>0.0039</td>
<td>0.0084</td>
<td>0.0057</td>
<td>0.0046</td>
<td>0.0052</td>
<td>0.0038</td>
<td>0.0049</td>
<td>0.0072</td>
<td>0.0049</td>
</tr>
</tbody>
</table>

*Thousands of people
**Percentage
3.3 Environmental Variable Data Collection

3.3.1 Meteorological Data

Meteorological data were collected by the Delaware Environmental Observatory System (DEOS; www.deos.udel.edu/data/), operated by the University of Delaware. DEOS operates stations throughout the state with three in particular that are in close proximity to the beach study sites: Bethany Beach station (DBBB), Rehoboth Beach station (DRHB), and Indian River Inlet station (DIRL). Data collected include air temperature (°C), solar radiation (W/m²) as a proxy for the amount of cloud cover, wind speed (m/s), wind direction relative to N (°), and precipitation (mm). Water temperature was recorded daily by Dewey Beach Patrol.

Air temperature ranged between 12 and 38 °C (Table 3.2), with a mean of 24.9 °C and standard deviation of 3.6 °C (Figure 3.3). Solar radiation had low values (< 300 W/m²) for cloudy days and greater values otherwise. Both air temperature and solar radiation portrayed diel trends in daily distribution. Water temperature ranged from 13.0 °C in the early summer to over 26 °C in late summer. Wind speeds were typically small (< 2 m/s) in the morning hours and increased throughout the day, with a mean of 2.6 m/s. The majority of weaker winds were land breezes directed west in the morning, or from southeast to northeast sea breeze winds in the afternoon (Figure 3.4). Stormy days experienced strong winds out of the south, and even stronger storms brought winds from the east-northeast. Precipitation totals were low with less than 15% of days receiving any rainfall. Rainfall persisted the entire day on only a few of the study days.
<table>
<thead>
<tr>
<th>Environmental Variables</th>
<th>Statistic</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Meteorological</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Air Temperature (°C)</td>
<td></td>
<td>39.0</td>
<td>12.0</td>
<td>24.9</td>
<td>3.6</td>
</tr>
<tr>
<td>Water Temperature (°C)</td>
<td></td>
<td>28.2</td>
<td>13.6</td>
<td>22.8</td>
<td>2.6</td>
</tr>
<tr>
<td>Solar Radiation (W/m²)</td>
<td></td>
<td>1040.0</td>
<td>0.0</td>
<td>551.1</td>
<td>275.1</td>
</tr>
<tr>
<td>Precipitation (mm)</td>
<td></td>
<td>4.1</td>
<td>0.0</td>
<td>0.02</td>
<td>0.1</td>
</tr>
<tr>
<td>Wind Direction (°)</td>
<td></td>
<td>330.0</td>
<td>0.0</td>
<td>161.7</td>
<td>81.5</td>
</tr>
<tr>
<td>Wind Speed (m/s)</td>
<td></td>
<td>14.1</td>
<td>0.0</td>
<td>2.6</td>
<td>1.4</td>
</tr>
<tr>
<td><strong>Morphological</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inverse of Foreshore Slope</td>
<td></td>
<td>23.5</td>
<td>3.6</td>
<td>9.7</td>
<td>2.1</td>
</tr>
<tr>
<td><strong>Hydrodynamic</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$H_s$ (m)</td>
<td></td>
<td>3.8</td>
<td>0.2</td>
<td>0.62</td>
<td>0.27</td>
</tr>
<tr>
<td>Peak Wave Direction (°)</td>
<td></td>
<td>360.0</td>
<td>0.0</td>
<td>114.1</td>
<td>54.6</td>
</tr>
<tr>
<td>$T_p$ (s)</td>
<td></td>
<td>18.3</td>
<td>2.6</td>
<td>8.2</td>
<td>2.4</td>
</tr>
</tbody>
</table>
Figure 3.3 Normalized probability distributions of (a) air temperature, (b) solar radiation, (c) water temperature, and (d) wind speed from 2010 to 2017. Precipitation was not included as a majority of hours received no rainfall (> 94%).
Figure 3.4: Wind rose of wind speed and direction from 2010 to 2017. Strong winds were primarily out of the south or east-northeast
3.3.2 Morphology

3.3.2.1 Beach Profiles

The variability of foreshore slope alters wave breaking type and wave breaking distance from the shoreline (e.g., Iribarren and Nogales, 1949). Daily topographic beach profile measurements along the same transect were collected at all five study beaches with a real time kinematic (RTK) global positioning system (GPS). Surveyed data were collected in the Universal Transverse Mercator (UTM) coordinate system (NAVD88 vertical datum). The GPS antenna was pushed on a three-wheeled dolly during summer months between 2014 and 2017. A cross-shore profile was taken from the dune base to the seaward limit of backwash and back to the dune base (Figure 3.5). The extent of the cross-shore profile depended on the conditions at the time of the survey (e.g., tide, wave conditions).

The foreshore slope ($\tan \beta$) was defined as a linear fit through the data from the berm crest to the most seaward surveyed point. The inverse of the beach slope ($1/\tan \beta$), termed inverse foreshore slope ($IFS$), represented the daily variation of the foreshore slope. For example, an $IFS$ value of 8.5 is read as “1 on 8.5”. The mean of $IFS$ values during hours of SZI occurrence (mean = 9.1) was less than the mean of across all $IFS$ values (mean = 9.5).
Figure 3.5: RTK-GPS profiles of the five beaches included in the study. The color bar identifies temporal variation.
Figure 3.6: Distribution of *IFS* values averaged across all beaches (2010 to 2017) in black (mean = 9.5). The distribution in blue are the *IFS* values of hours during an SZI occurrence (mean = 9.1).

### 3.3.2.2 Sediment Samples

Two sediment samples (50 - 100 cm³) were collected in approximately the same location daily during the 2014 to 2017 summers of all five beaches. Sample locations were along the beach survey transects, as close to low tide as possible. The first sample location along the transect was taken at the foreshore and the second sample at the approximate location of the berm. Sediment samples were removed at a depth < 3 cm from the beach surface. Roughly 325 samples were collected at each location, or 650 at each of the five beaches during the four year collection period.
Sieving samples from all five beaches (3200 - 3300) was impractical. Instead, a transferable wavelet method (Buscombe, 2013) was used to estimate grain size distribution from images of the sediment. The camera was mounted at a predetermined distance (~10 cm away) from the sediment sample, to maintain a 0.05 mm per pixel ratio for each image (Figure 3.7).
Figure 3.7: Example an image of sediment sample that was processed to estimate a grain size distribution. This sample was collected at the berm location of the Delaware Seashore State Park profile transect on June 21st, 2016.
Samples analysis returned distribution statistics, for example, median grain size (d50), mean grain size, skewness and kurtosis. Sediment samples were also classified by their sorting (σφ) based on statistics using the phi (φ) scale (Krumbein, 1936) as:

$$\sigma_\phi = \frac{\phi_{84} - \phi_{16}}{2}$$  \hspace{1cm} (3.2)

where

$$\phi = -\log_2 d_{50}. \hspace{1cm} (3.3)$$

The distribution of d50 (φ) grain sizes for both berm and foreshore locations (e.g., 2016 IFS vs. d50; Figure 3.8) were narrowly distributed with 93% of all samples between 0.2 mm (2.3) and 0.3 mm (1.75). The sediment sizes correspond to medium sands on the Wentworth scale, and are slightly finer than the medium to coarse sand classification by Ramsey (1999). The σφ values of 2016 samples ranged from 0.52 to 0.66, indicating moderately well sorted sediment distribution (Folk and Ward, 1957).
The mean $d_{50}$ of the berm samples (mean $d_{50} = 0.266$ mm) was 8.6% greater than the mean $d_{50}$ of foreshore samples (mean $d_{50} = 0.245$ mm). The findings confirm previous classification of sediment distribution in the cross-shore (Silva et al., 2009). The lower median sediment size on the foreshore was likely attributed to swash processes. Following wave breaking at the beach step, coarser grains settle out faster than the finer grains that are carried farther up the foreshore due to density differences. Samples also were collected at the surface. For most foreshore sample collections, coarser sand was found residing underneath the top layer. However, this statement is only qualitative, as most samples analyzed consisted of sediment close to the surface.
3.3.3 Hydrodynamic Data

Hydrodynamic data were collected from the United States Army Corps of Engineers wave gauge (USACE DE003), located ~650 m off Bethany Beach in roughly 11 m depth (geographic: 38°32'22'' N 75°02'76'' W; UTM: 4265400.0 N; 495990.9 E). Reported hourly buoy data include significant wave height ($H_s$), peak wave period ($T_p$), peak wave direction (corresponding to $T_p$) relative to true north, and water temperature. Wave data (DE003) were compared to data from sensors deployed in ~3 m depth from June 2, until September 12, 2014 (Puleo et al. 2016). Data at the 3 m locations mimicked trends observed from USACE DE003 data and similarity was
quantified using $r^2$ (0.74 to 0.89) and regression slopes (0.98 to 1.08). The agreement with sensors at all five beaches justified the use of the USACE DE003 wave gauge as a proxy for nearshore $H_s$ to train the hydrodynamic parameters of the model presented in Chapter 4.

$H_s$ values were typically < 1.5 m (~99 %) with a mean of 0.62 m. The distribution of $H_s$ during injury hours was similar, with a slightly greater mean of 0.67 m (Figure 3.10). However, the distribution of $H_s$ during injury hours had a smaller proportion that were > 1 m. Possible explanation for the difference in distribution is a human factor, so that the decision to enter the ocean or perform particular activities in the ocean changes under larger $H_s$. $T_p$ exhibited similar distribution characteristics between all hours and SZI occurrence hours to $H_s$. $T_p$ typically fell between 6 and 12 s with a mean of 8.2 s. During injury hours, $T_p$ were slightly greater (mean = 8.8 s). Puleo et al. (2016) found no significant correlation between either variable and SZI occurrence.
Figure 3.10: a) Probability distribution of $H_s$ values averaged across all beaches (2010 to 2017) in black (mean = 0.62 m). The distribution in blue are the IFS values of hours during an SZI occurrence (mean = 0.67 m). b) Probability distribution of $T_p$ values averaged across all beaches (2010 to 2017) in black (mean = 8.2 s). The distribution in blue are the IFS values of hours during an SZI occurrence (mean = 8.8 s).

The majority of smaller waves ($H_s < 0.5$ m) arrived from the east-southeast direction ($90^\circ$ to $120^\circ$; Figure 3.11). Larger swell ($H_s > 1$ m) generated from offshore
storms were recorded from the east-northeast (60° to 90°). These waves arriving from the northeast are typical of northeaster storms that generate $H_s$ atypical of Delaware wave climate. The $T_p$ fluctuated between 2.6 s and 18.3 s (Figure 3.12). $T_p$ tended to decrease before a storm, and gradually increase as the larger wave event arrived (Puleo et al., 2016).

An additional hydrodynamic parameter considered to be related to SZI is the non-dimensional Iribarren number (Iribarren and Nogales, 1949) expressed as:

$$\xi = \frac{\text{slope}}{\sqrt{\text{wave steepness}}} = \frac{\tan \beta}{\sqrt{\frac{H}{L}}},$$

(3.4)

where $H$ is a wave height and $L$ is the wave length. The $H$ and $L$ values are either deep water (offshore) or breaking wave heights (nearshore). Puleo et al. (2016) found values for $\xi_b$ (b denoting breaking) to range from 0.4 and 2.0, indicating plunging waves breaking in shallow water near the plunge step. The lack of variability in breaker type based on the Iribarren number indicates weak SZI correlation.
Figure 3.11: Wave rose of $H_s$ and corresponding peak wave direction from 2010 to 2017. Proportionally, larger $H_s$ magnitude waves arrived from the east-northeast (45º to 90º) and smaller waves arrived from the east-southeast (90º to 140º).
Figure 3.12: Wave rose of $T_p$ and corresponding peak wave direction from 2010 to 2017. $T_p$ magnitude were proportionately distributed across waves recorded from the dominant peak wave direction (80° and 140°).
3.4 Conclusion

Environmental condition data were collected from 2010 to 2017. Data were categorized as human data (WU counts), meteorological, morphological, and hydrodynamic. The variables associated were considered to be related to SZI occurrence due to the temporal variability (Figure 3.1 and 3.2). Puleo et al. (2016) analyzed a subset of these data (2014) and found that single environmental conditions did not correlate well with IR (greatest $r^2$ of 0.08 for $H_s$). However, the expected Poisson’s (random) injury distribution did not describe the observed SZI distribution. Therefore, a possible relationship should exist between SZI and some measureable parameters (Puleo et al., 2016). Chapter 4 discusses the ability of a probabilistic model to relate environmental factors to SZI occurrence.
Chapter 4

BAYESIAN NETWORK

4.1 Background

Two BNs were derived to relate environmental conditions to SZI. The first BN (referred to as IR model) modelled injury rate \( (IR) \) as a response variable to primary forcing parameters. The second BN (referred to as the IL model) modelled SZI likelihood as a binary problem with an injury occurring during the hour (1) or no injury (0). The developed BNs consist of 13 nodes separated into two groups: forcing parameters (e.g., \( H_s, IFS, T_p \)) and exposure parameters (e.g., air temperature, water temperature, solar radiation).

4.1.1 Bayes’ Theory

Bayes’ theorem is a probabilistic inference formula that can derive probability distributions with an associated uncertainty (Wikle and Berliner, 2007). Bayes’ theorem relates the probability of an event, \( I \), given the observation of another event, \( O \), that is related to event \( I \) (Bayes, 1763):

\[
p(I_l | O_j) = \frac{p(O_j | I_l) p(I_l)}{p(O_j)} \tag{4.1}
\]

\[
p(I_l | \{O_j\}) = f(O_j) \tag{4.2}
\]

where

\[
O_j = [H_s, T_p, IFS, °C ...]_j \tag{4.3}
\]
4.1.2 Bayesian Network Structure

A BN is a probabilistic (graphical) model that represents the relationships (e.g., conditional dependencies) of a set of random variables using Bayes’ theorem. Netica software package (Norsys, Netica v. 6.03, www.norsys.com) was chosen to construct a BN for the SZI data. In the graphical model, each node represents a single parameter (e.g., $H_s$) that has an associated prior probability distribution based on historical data. The prior probability distributions were determined by the environmental data collected from 2010 to 2017.

Each arc (arrow) represents the conditional probabilities between parent and child nodes. The model accounts for joint correlations between some of the nodes that are connected with an arrow. Each node can be a considered a child node if it has incoming links to other nodes. The source nodes are considered parent nodes and the relationship between parent and child is defined by Bayes’ theorem in the form of a joint probability. Each node in the network has a specified joint probability distribution between each child node. The node is associated with a probability function that takes, as an input, the conditional dependencies of each parent node, and gives, as an output, the probability of observing the different bin states of that node. Nodes that are not connected, represent parameters that are conditionally independent.

4.1.2.1 Parameterization of Environmental Variables

Parameters were chosen based on existing knowledge of the problem and consultation of other studies (Falcon, 2016; Puleo et al., 2016) that may correlate SZI with environmental conditions. Parameters were chosen from the environmental variables data that were collected from 2010 to 2017. The parameters were categorized as forcing, exposure or both. Forcing parameters were categorized as either primary if
they physically influence SZI or secondary if their influence is indirect (e.g., peak wave direction). Exposure parameters did not physically cause SZI, but instead influenced the number of WU exposed to risk (e.g., air temperature; Falcon, 2016). $IR$ and $IL$ were the chosen response variables connected to the forcing and exposure parameters. Some parameters that were omitted due to lack of SZI prediction reliability in previous studies include tide and Iribarren number (Falcon, 2016; Puleo et al., 2016). Some were also omitted at our own discretion (e.g., grain size), to increase model experience. Hourly data were chosen to provide sufficient temporal resolution, without being too computationally expensive for the model.

4.1.2.1.1 Forcing Parameters

Primary forcing parameters included in the model were $H_s$, $T_p$, and $IFS$. The $H_s$ and $T_p$ parameters included hourly data collected from the DE003 gauge. The $IFS$ parameter included extracted $IFS$ data from the daily profiles collected from 2014 to 2017. All five beaches maintained a fairly constant $IFS$ over the eight year period with standard deviations between 1.9 and 2.7, so that a single beach $IFS$, obtained from Bethany Beach, was included. The mean $IFS$ of Bethany Beach (mean = 9.3) was closest to the mean across all beaches (mean = 9.5). Bethany Beach is also the closest beach to DE003. Secondary forcing conditions that did not physically cause SZI, but influenced primary forcing parameters included peak wave direction, wind speed (also considered exposure parameter), and wind direction.

4.1.2.1.2 Exposure Parameters

Exposure parameters that influenced the number of WU exposed to risk included air temperature, water temperature, wind speed, precipitation, solar radiation
as a proxy for cloud cover, and day of the week. The DBBB station was chosen to relate conditions to SZI as it is in close proximity to the wave gauge used to collect to the hydrodynamic variables.

4.1.2.2 Discretization of Nodes

Each parameter node must first be discretized into bins (Table 4.1), with edges that encompass the full range of the input variable (continuous) data. The predictive capability of the BN depends on the discretization of the variables. The width of each bin must balance the need to have enough bins to resolve significant situations, but not exceed the limits constrained by data resolution requirements. Edges were chosen to distribute prior probability equally amongst bins. The inclusion of too many bins and links for the data set results in lower predictive skill due to overfitting (Fienen and Plant, 2015).

Table 4.1: Bin edges for BN environmental parameters.

<table>
<thead>
<tr>
<th>Environmental Parameter</th>
<th>Bin Edges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meteorological</td>
<td></td>
</tr>
<tr>
<td>Air Temperature (°C)</td>
<td>12, 23, 26, 39</td>
</tr>
<tr>
<td>Solar Radiation (W/m²)</td>
<td>0, 500, 730, 1040</td>
</tr>
<tr>
<td>Precipitation (mm)</td>
<td>0, 0.13, 4.13</td>
</tr>
<tr>
<td>Wind Direction (°)</td>
<td>0, 90, 160, 240, 330</td>
</tr>
<tr>
<td>Wind Speed (m/s)</td>
<td>0, 1.9, 2.9, 14.1</td>
</tr>
<tr>
<td>Morphological</td>
<td></td>
</tr>
<tr>
<td>IFS</td>
<td>3.6, 7.8, 9.5, 10.5, 23.5</td>
</tr>
<tr>
<td>Hydrodynamic</td>
<td></td>
</tr>
<tr>
<td>Hₜ (m)</td>
<td>0.21, 0.43, 0.55, 0.65, 0.85, 2.0</td>
</tr>
<tr>
<td>Peak Wave Direction (°)</td>
<td>0, 80, 110, 130, 360</td>
</tr>
<tr>
<td>Tₚ (s)</td>
<td>2.6, 6.0, 9.0, 11.0, 18.3</td>
</tr>
<tr>
<td>Water Temperature (°C)</td>
<td>13.6, 22.4, 24.3, 28.2</td>
</tr>
</tbody>
</table>
4.1.2.3 Conditional Probability Distributions

The learning of the BN is based on a simple counting-learning algorithm (Norsys, Netica v. 6.03 www.norsys.com). This algorithm requires each of its entries to be satisfied by multiple cases such that it can gain “experience”. The BN uses a conditional probability table (CPT), consisting of the joint probability distributions to describe the relationship between child nodes and parent nodes. The IL model had 6026 joint probabilities contained in the network and the IR model had 35251. Each joint probability describes the probability of possible combination of parent-child bin selections.

Increasing the number of parents and bins of nodes expands the CPT. For Bayes’ theorem to function effectively, each combination of bins between nodes needs to be satisfied by multiple data cases such that the network can gain “experience.” In the case that the number of CPT entries is too large for the data set, experience values will be low and probabilities close to uniform resulting in an uninformative network. A well-trained BN has high experience values and provides predictions with small standard deviations and large occurrence probabilities. Posterior probabilities of the nodes in question can be readily computed under observed conditions following network training with a CPT.

4.1.2.4 Prior Probabilities

The BN probability distributions, after training the model with environmental parameter data, reflect the prior probability distributions between parameters. The IL model (Figure 4.1 and 4.2) was trained with 2010 – 2016 data and the IR model (Figure 4.3 and 4.4) was trained with 2014 – 2016 data. The 2010 – 2013 data were withheld from the IR model as there were no population data to derive $IR$. The trained
model converts the prior probability distribution to a posterior probability distribution with data observations each hour. The posterior probabilities of the IL and IR models were $IL$ and $IR$ respectively.
Figure 4.1: Prior probability BN for the IL model. Each box (node) displays the bin divisions and the prior probability distributions for a single parameter. The first column in each node contains the bin boundary ranges. The second column (adjacent to the histogram) is the percentage of the prior distribution found in each bin. The value at the bottom of each node is the mean of the prior distribution values one standard deviation. The probability distribution of IL from 2010 to 2016 is what the model is predicting. Inclusion of 2017 data as observations tests the model.

Figure 4.2: Example BN of the IL model given an injury occurrence. The remaining nodes reflect the probability distributions based on 2010 to 2016 hours that an injury occurred.
Figure 4.3: Prior probability BN for the IR model. The bin divisions and the prior probability distributions are shown for each parameter. The first column in each box contains the bin boundary ranges and the second column (adjacent to the histogram) is the percentage of the prior distribution found in each bin. The value at the bottom of each node is the mean of the prior distribution values one standard deviation.

Figure 4.4: Example BN of the IL model given medium IR (0.005% to 0.01%). The remaining nodes reflect the probability distributions based on 2014 to 2016 hours that had a similar IR.
4.2 Evaluation Methods

4.2.1 Variance Reduction Percent

The relative importance of each parameter to the response variable was found with the sensitivity to findings feature of Netica. The sensitivity analysis measures the changes in probabilities of nodes in question when parameter inputs are changed. The analysis returns a variance reduction (VR) value as a percent based on a change in model results due to input variations. The VR percent was calculated as:

$$VR = \frac{V(I) - V(I|O)}{V(I)} * 100, \quad (4.4)$$

where $V(I)$ is the variance of the real value of $I$, the query variable, prior to observation update. $V(I|O)$ is the variance of the forecast after updating with observations. The VR for the response variable node is 100%, and all other nodes are less than or equal to 100% (Fienen et al., 2013; Norsys, Netica v. 6.03, www.norsys.com).

4.2.2 Log Likelihood Ratio

A common method to test the user-established relationships between nodes is the log likelihood ratio (LLR). The LLR value is dependent on the chosen nodes and discretization of the model structure. The LLR compares the performance of the network to an alternative network, usually the prior probability network. LLR is determined by:

$$LLR_i = \log\{p_i(O_i)\} - \log\{p^{prior}_i(O_i)\} \quad (4.5)$$
where $LLR_i = 0$ indicates that the updated probability, $\log\{p_i(O_i)\}$ with observation $i$ is not an improvement over $\log\{p_i^{prior}(O_i)\}$, the prior probability at hour $i$. Hours ($i$) that receive positive LLR, indicate improved prediction compared to the prior model. A negative LLR results if the likelihood of the updated prediction is more uncertain than the prior, or it is more confident but wrong. Therefore, the score determines the skill of the BN to make estimates of the uncertainty and mean value of the variable in question. Optimization of the log likelihood ratio is important to ensuring the network makes the best possible predictions. The percentage of the total tested data hours that scored positive LLR values was used as a performance metric.

### 4.2.3 Quantile – Quantile Plot

A linear regression model was used in the form of a quantile – quantile (Q – Q) plot to evaluate the models. Q – Q plotting is a graphical technique to determine if two data sets, in this case the predicted and observed probabilities, are similar. Quantile bins of 0.005 width were chosen for the IL model and 0.0001 were chosen for the IR model. Bin widths were chosen as roughly 1/20th of the mean value of each response variable. Quantile bins in which no observed data were present were removed from the plot. The data are fit to the equation of a line:

$$y = a_1 + a_2x$$  \hspace{1cm} (4.6)

where $a_1$ is the intercept, $a_2$ is the regression slope, $x$ is the bin center of the predicted quantile, and $y$ is the bin center of the observed quantile. The proximity of the computed regression slope to one is a measure of accuracy or how well predictions match the observed data. A regression slope less than one indicates a model that over-predicts SZI and a regression slope greater than one indicates a model that under-
predicts SZI. The square of the residuals is a measure of the precision of the predictions.

4.3 Results

Both the IR and IL models were assessed by a hindcast of 2017 data to evaluate performance. Each model was updated with four unique cases. The first update included 2017 data for all parameters. The other three updates removed 2017 data for one of the parameters to test sensitivity of the response variable to that missing parameter. Three evaluation methods were used to evaluate the performance of all eight model updates: variance reduction percent (sensitivity analysis), linear regression model (Q – Q plot), and LLR (Table 4.2).

Table 4.2: Model metrics for cases with all parameters included and one variable (labeled) removed.

<table>
<thead>
<tr>
<th>Model Update</th>
<th>Metric</th>
<th>Q – Q Plot ($r^2$, regression slope)</th>
<th>LLR (% &gt; 0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Injury Likelihood Model (IL)</td>
<td>All Parameters</td>
<td>0.79, 1.41</td>
<td>69.1%</td>
</tr>
<tr>
<td></td>
<td>No $H_s$</td>
<td>0.78, 1.55</td>
<td>67.7%</td>
</tr>
<tr>
<td></td>
<td>No IFS</td>
<td>0.57, 1.46</td>
<td>67.5%</td>
</tr>
<tr>
<td></td>
<td>No Water Temperature</td>
<td>0.75, 1.45</td>
<td>59.1%</td>
</tr>
<tr>
<td>Injury Rate Model (IR)</td>
<td>All Parameters</td>
<td>0.74, 0.68</td>
<td>36.7%</td>
</tr>
<tr>
<td></td>
<td>No $H_s$</td>
<td>0.21, 0.57</td>
<td>34.3%</td>
</tr>
<tr>
<td></td>
<td>No IFS</td>
<td>0.64, 0.53</td>
<td>32.7%</td>
</tr>
<tr>
<td></td>
<td>No Water Temperature</td>
<td>0.73, 0.68</td>
<td>36.7%</td>
</tr>
</tbody>
</table>

4.3.1 IL Model Skill Assessment

The IL model updates were tested with 122 days (1098 hours) of data from 2017. Parameters that provided significant $VR$ percent to IL include water temperature
(Figure 4.5; 0.86%), $H_s$ (0.56%), solar radiation (0.48%), $IFS$ (0.44%), air temperature (0.38%), weekday (0.15%), $T_p$ (0.13%), and wind speed (0.10%). Parameters not listed had low $VR$ percent ($VR < 0.05$%)

The $r^2$ value was largest for the all parameter IL model update (Table 4.2), indicating that the model was most efficient when all parameters were included. However, the updates with $H_s$ and water temperature withheld had $r^2$ values of similar magnitude (0.78 and 0.75 respectively). All four IL model updates under-predicted SZI (regression slope < 1; Figure 4.6), with the no $IFS$ update closest to a regression slope of one. Each model update improved predictions over the prior model with a majority of positive LLR values.

![Figure 4.5: Sensitivity analysis for the (a) IL model and (b) IR model. Higher $VR$ percent indicate greater influence in the prediction of the variable of interest (e.g., IR or IL).](image-url)
Figure 4.6: Predicted vs. observed Q-Q plots for the four model updates of each IL and IR models. The top plots (a-d) are IL and bottom (e-h) are IR model updates in the following order: all parameter, no $H_s$, no IFS, and no water temperature updates. The circles are the observed probability quantiles for each predicted quantile, with the dashed line as a best fit and solid line as 1:1 (predicted = observed).
4.3.2 IR Model Skill Assessment

Each IR model update was evaluated on 82 test days (732 hours) from the 2017 data set. These data were withheld from the calibration data set. The model was only trained and tested on days on which a population was counted, and therefore an IR was known. Population counts were not collected from 2010 to 2013 (no population counts) and for several days during the 2014 to 2017 summers due to inclement weather. Parameters that provided significant VR percent to the IR model include $H_s$ (Figure 4.5; 1.61%), $IFS$ (0.97%), peak wave direction (0.21%), and $T_p$ (0.098%). Limited VR percent were provided by the exposure parameters ($VR < 0.005\%$).

The $r^2$ value was largest for the IR model in the all parameter case (Table 4.2), indicating that the model was most precise when all parameters were included (Figure 4.6 e – h). The regression slope was closest to 1:1 with the all parameter and no water temperature updates. All four IR model updates over-predicted the IR for the majority of the represented quantile bins. Poor predictions were made when $H_s$ was removed ($r^2 = 0.21$), confirming the high VR percent. All IR model updates had less than 37% of all hours with positive LLR values.

4.4 Discussion

4.4.1 Prediction Skill and Sensitivity to Parameters

All four IL model updates outperformed the prior probability model for the majority of the 2017 data hours. There was a select number of hours (< 3%) in which the model update was less robust than the prior model (LLR << -1). These hours were considered anomalies due to the low frequency of occurrence. During the hours, an injury occurred when there were either few people in the water, or the forcing
conditions were atypical of other SZI (e.g., $H_s < 0.4$ m) so that the model predicted low $IL$. Model performance was particularly vulnerable to the aforementioned anomalous injuries. In response, the model was penalized with a negative LLR score because the BN prediction indicated a low probability of a large error (low uncertainty), and it was wrong. The BN is not robust at predicting these anomalous SZI because the injuries occur in conditions the model was not trained to identify, potentially due to behavioral tendencies. Since SZI occur in a range of conditions, the BN must be trained to predict the most likely conditions to maximize SZI prediction efficiency.

The low percentage of positive LLR values for the IR model when tested on 2017 data indicate the prior model makes improved predictions. The majority of hours (90.4%) there are no injuries at any of the five beaches. Therefore, the $IR$ is often 0% and the prior probability of $IR$ is almost zero. The IR model takes the mean value across the probability distribution between bins, so that it tends to predict a rate higher than the prior model when the $IR$ is 0%. The worse prediction than the prior model results in a negative LLR. The poor skill performance sustained by the IR model indicates that a BN does not predict the small changes in $IR$ well. The IR model instead was best used to analyze parameters, with the removal of hours of no SZI occurrence (i.e., $IR > 0$).

$IR$ data were subdivided into five bins of equal probability (roughly 20% of observations per bin; Table 4.3) to evaluate changes in forcing parameter values when $IR = 0$ data were removed. The mean $H_s$ for four of five positive $IR$ bins was greater than the mean value for the entire data set (0.62 m). The greatest mean $H_s$ (0.74 m) of the five bins occurred when $IR$ was between 0.046 % and 0.098 %. The mean $H_s$ was
0.13 m greater during hours of $IR > 0.046 \%$ than $IR$ between 0.0 \% and 0.00015 \%. $T_p$ did not have any noticeable trend with increasing $IR$, confirming the lower $VR$ percent (0.098\%). Foreshore slope tended to be steeper ($IFS < 9.5$) during times of increasing $IR$, with steepest slopes occurring when $IR > 0.098 \%$.

Table 4.3: Mean forcing parameter values during positive $IR$ hours

<table>
<thead>
<tr>
<th>$IR$</th>
<th>$H_s$ (m)</th>
<th>$T_p$ (s)</th>
<th>$IFS$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0 – 0.00015</td>
<td>0.63</td>
<td>8.6</td>
<td>9.9</td>
</tr>
<tr>
<td>0.00015 – 0.00046</td>
<td>0.54</td>
<td>9.4</td>
<td>10.2</td>
</tr>
<tr>
<td>0.00046 – 0.00098</td>
<td>0.74</td>
<td>8.8</td>
<td>9.8</td>
</tr>
<tr>
<td>0.00098 – 0.0019</td>
<td>0.69</td>
<td>8.9</td>
<td>9.3</td>
</tr>
<tr>
<td>0.0019 – 0.01</td>
<td>0.72</td>
<td>8.5</td>
<td>9.2</td>
</tr>
</tbody>
</table>

Exposure parameters like water temperature, solar radiation, and wind speed provided little $VR$ to the $IR$ node. Future BN models of $IR$ do not need to include exposure parameters. Alternatively, these exposure parameters provided significant $VR$ to the $IL$ node. The number of WU exposed to danger were a function of the meteorological and temporal conditions, consistent with a prior SZI study in Ocean City, MD (Falcon, 2016). Greatest exposure occurred when the model observed high water temperature (> 24.3 °C), high solar radiation (> 740 W/m²), and low wind speed (< 2 m/s). Air temperature, while important, provided less $VR$ than expected for the IL model, likely due to the fact that temperatures were primarily above 21 °C during the day (mean [SD], 24.9 [3.6] °C). Also, the population was not as sensitive to precipitation because the few days (< 14\%) that accumulated any precipitation between the hours of 0900 and 1700 during the summer, precipitation did not necessarily coincide with the daily counts.
4.4.2 Improved Prediction

The BNs described are suitable starting points for future work in SZI prediction. Further data collection to include in model training will improve predictions. Additional data collection also increases model experience (i.e., enhance CPT quality), and allows for increased bin resolution. SZI data from other beach communities could strengthen predictions by training the model with additional scenarios. Future work with SZI should evaluate the performance of the model when applied to additional regions beyond the Delaware coast.

Most of the aforementioned missed predictions stem from the limitations attributed to human factors (e.g., decision making, risk taking) that are not directly incorporated into a node. The human factor should be quantified to train/enhance the BN. One quantification method would be a tourist density index (Vitabile et al., 2013). The BN could account for the proportion of tourists in the water with the tourist density index (TDI) when making predictions. Tourists are roughly seven times more likely to be injured than locals (e.g., Doelp et al., 2018; Puleo et al., 2016), so that quantifying the proportion of tourists is a reasonable first step towards quantifying the human factor. The use of waste water production as a population proxy (Falcon, 2016) is a potential method to quantify TDI. The waste water population proxy assumes that people use an average amount of water each day, and that a surplus of tourists will proportionally affect waste water flows. Other human factors that influence risk tendencies in the water include age and gender. Quantifying the proportion of age and gender demographics in the water would improve predictions. A BN trained on TDI or different quantifiable human factor would identify times in which risk-taking tendencies are high and that prediction certainty must be reduced.
4.4.3 Beach Patrol Application

The BN applied to the SZI problem has potential applications for beach patrol use. Beach patrol, tasked with pre-emptive warning and post-incident rescues, might find the probabilistic-assisted decision making helpful. The BN returns a range of both quantitative and qualitative responses that leaves interpretation up to the user. The beach patrol, tasked with relaying any warnings to the public, could use a BN report to supplement their own knowledge. A direct application with an existing warning system would be to incorporate the BN with the colored flag system, indicating a variety of surf hazards.

The ability of BNs to make quick, probabilistic estimations with incomplete data also makes for a useful decision-making tool. The BN can compile and update probabilities based on beach patrol observations. For example, beach patrol can input hourly observed environmental conditions to the pre-trained model to make an SZI likelihood prediction. In the example below (Figure 4.7), some possible observed bin states are selected to determine IL. These observation selections do not require precise values, an ideal characteristic of the BNs for beach patrol use.
Figure 4.7: Example IL model with partial observations made. The observations selected do not require much judgement by the observer.

A more extensive approach could develop an application that uses real time weather station and wave gauge data to output SZI likelihood. A forecast based on data one or two days ahead would give beach patrol and the public advanced notice of potentially dangerous conditions.

### 4.5 Conclusion

A Bayesian approach to modelling SZI along the Delaware coast was developed to predict changes in injury likelihood based on the changing conditions. Environmental and human (WU) data related to forcing and exposure parameters were collected from 2010 to 2017 to train and test the BN. Two BNs were derived to predict SZI. The first BN predicted IR and the second predicted IL as a probability between zero and one. The removal of any parameters resulted in declining model performance so that performance was strongest when all parameters were included. Sensitivity analysis determined water temperature, $H_S$, IFS, and solar radiation to provide significant VR percent (> 0.5%). The IR model struggled to accurately predict when
SZI would occur (positive LLR = 36.7%), instead performing well as a tool to identify dangerous conditions because the additional bins provided greater resolution than the IL model. High $IR (> 0.1\%)$ occurred during $H_s$ of 0.65 to 0.85 m. The IL model performed well at identifying hours of increased injury likelihood (positive LLR = 69.1%). However, predictions were hampered by anomalous SZI (< 5% of total injuries) that had an LLR $\ll -1$. Future work with BNs and SZI prediction should define how to categorize these anomalous injuries and consider removal to not skew prediction of SZI in characteristic conditions. Inclusion of a human factor node to the BN, quantified by, for example, a TDI might capture some of these anomalous injuries in the prediction. Future SZI work should also determine implementation methods of model outputs to assist beach patrol decision making.
Chapter 5

CONCLUSIONS AND FUTURE WORK

5.1 Summary of Findings

5.1.1 SZI Demographics

SZI data were collected along the Atlantic-fronting Delaware coast for eight summers. Patient data include, for example, time of injury, activity, age, gender, zip code, and location of injury. Injury activity was grouped into eight categories: wading, body surfing, body boarding, skim boarding, diving, surfing, swimming and other. SZI occurring at the five most populated beaches along the ~24 miles of Atlantic-fronting coastline exceeded 2000 and included 196 spinal injuries and six fatalities.

The relative demographics of the injured population are similar despite fluctuating injury totals (mean [SD], 253.1 [104.4]). Non-local males (RR, 2.86; 95% CI, 2.014 - 3.36) were the most likely demographic to be injured. Of the non-local males, individuals in the 11 – 20, 41 – 50, and 51 – 60 were injured more frequently than other age groups. Wading (50.1%) was found to be the dominant activity associated with injury followed by body surfing (18.4%), and body boarding (13.3%).

5.1.2 Predicting SZI

Environmental variable data were collected to quantify any relationship between injury occurrence and the conditions. Of the eight summers of data collection, 32.9% of days there were no injuries and 3.6% of days there were more than 10 injuries (max = 24 injuries in one day). The episodic nature of SZI indicate the importance of linking the environmental conditions and human behavior in the surf to predict SZI. Puleo et al. (2016) found weak correlation between any single variable
and SZI occurrence. Therefore, higher order statistics in the form of two Bayesian networks (BN) using Netica software (Norsys, Netica v. 6.03, www.norsys.com) were constructed to model SZI and predict changes in IR and IL on an hourly basis. The models include prior probabilities derived from the training data set to infer relationships between provided parameters.

Sensitivity analysis determined the most influential parameters related to IR were water temperature, $H_s$, IFS, and solar radiation. Exposure parameters (e.g., air temperature) influenced the number of WU exposed to risk, resulting in strong correlation between injury likelihood and the related meteorological conditions ($VR > 0.4\%$). LLR scores indicate the IL model improved prediction 69.1\% of the time over the prior probability distribution.

5.2 Future of SZI Work

The long-term documentation of SZI is important in recognizing temporal injury trends and for developing awareness strategies for beach safety. The consistency of long-term demographics at Atlantic-fronting Delaware beaches suggest safety awareness campaigns be directed at particular populations (e.g., non-locals, youth, males). SZI are essentially instantaneous and do not necessarily occur in the most extreme conditions, with large $H_s$, for example (e.g., Falcon, 2016; Puleo et al., 2016), so that predicting high injury days is a challenge. Beach patrol are only able to pre-emptively warn beachgoers of hazards through awareness, and administer initial medical care (Falcon, 2016). The administration of aid may reduce the injury severity, but awareness and educational efforts influence SZI rate (Falcon, 2016).

Routine evaluations of SZI demographics allow beach patrol to monitor groups that are injured in higher proportions, to ensure proper awareness and education efforts
are allocated effectively. Possible awareness methods include, for example, beach signage, information pamphlet distribution, PE class devoted to beach safety provided nationally, and the provision of SZI statistics to demographics that are more likely to make risky decisions in the surf. Beach patrol and managers can directly engage people on the beach with the distribution of questionnaires to regularly monitor knowledge of ocean processes. Engagement with beachgoers also reflects well on the beach itself, indicating a beach management that cares about the safety of its visitors.

Future SZI studies should evaluate the ability of probabilistic SZI prediction models to reproduce results regionally. The ability of a model to predict injury occurrence at other beaches suggests that injury data sets can be merged to better train models. The more experience a BN has with unique conditions, the more likely it is to make successful predictions. Also, having someone with beach patrol experience co-develop the BN would be beneficial to the accommodation of BN predictions to beach patrol decision making. Finally, future SZI studies should measure the success of awareness initiatives, to determine best practices and further reduce SZI.
REFERENCES


HUMAN SUBJECTS PROTOCOL
University of Delaware

Protocol Title: Surf Zone Injuries and Beach Safety along the Delaware Coast

Principal Investigator:
Name: Jack Puleo
Department/Center: Center for Applied Coastal Research, Civil and Environmental Engineering
Contact Phone Number: 302-831-2440
Email Address: jpeleo@udel.edu

Advisor (If student PI):
Name:
Contact Phone Number:
Email Address:

Other Investigators:

Investigator Assurance:
By submitting this protocol, I acknowledge that this project will be conducted in strict accordance with the procedures described. I will not make any modifications to this protocol without prior approval by the IRB. Should any unanticipated problems involving risk to subjects occur during this project, including breaches of guaranteed confidentiality or departures from any procedures specified in approved study documents, I will report such events to the Chair, Institutional Review Board immediately.

1. Is this project externally funded? X YES □ NO
If so, please list the funding source: Delaware SeaGrant

2. Research Site(s)
- □ University of Delaware
- X Other (please list external study sites)
  Cape Henlopen State Park, Rehoboth Beach, Dewey Beach, Delaware Seashore State Park, Bethany Beach

Is UD the study lead? X YES □ NO (If no, list the institution that is serving as the study lead)
3. Project Staff
Please list all personnel, including students, who will be working with human subjects on this protocol (insert additional rows as needed):

<table>
<thead>
<tr>
<th>NAME</th>
<th>ROLE</th>
<th>HS TRAINING COMPLETE?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jack Pulse</td>
<td>PI</td>
<td>No</td>
</tr>
<tr>
<td>Matt Doelp</td>
<td>M.C.E student</td>
<td>No</td>
</tr>
</tbody>
</table>

4. Special Populations
Does this project involve any of the following:

Research on Children? No
Research with Prisoners? No
If yes, complete the Prisonees in Research Form and upload to IRBNet as supporting documentation
Research with Pregnant Women? No
Research with any other vulnerable population (e.g. cognitively impaired, economically disadvantaged, etc.)? please describe. No

5. RESEARCH ABSTRACT Please provide a brief description in LAY language (understandable to an 8th grade student) of the aims of this project.

Data collected by colleagues at Beebe Healthcare consist of information solely associated with those water users that are injured. There is no knowledge of the distribution of the general population using the Delaware beaches (locals vs tourists, male vs female) and how these distributions relate to those that sustain surf zone injuries. We will use a questionnaire for beachgoers, conducted during the duration of the field efforts, enabling us to determine anonymously information related to the general population on the beach. We are particularly interested in whether the beachgoer is a local or tourist (home zip code), their familiarity with beaches, their assumed knowledge of oceanic wave and current processes, their physical fitness level, the level of risk they may be willing to take when at the beach and whether or not they are familiar with any beach safety campaigns.
6. PROCEDURES Describe all procedures involving human subjects for this protocol. Include copies of all surveys and research measures.

Several days during the summer research periods: The student and the PI will visit the beaches in question and ask beachgoers if they are willing to answer several questions regarding beach hazards/safety. An example questionnaire is included below. The questionnaire indicates clearly that the subject can stop at any time and that it is anonymous.
Survey Date: Time: Beach: Researcher:

2016 Delaware Surf Zone Beach Safety Study - Adult

This survey is anonymous. You may stop answering questions at any time.

1) Please circle your age range:
16-20 21-25 26-30 31-35 36-40 41-45 46-50 51-55 56-60 61-65 66-70 71-75 76+

2) Please circle your gender: M F

3) Would you consider yourself a local or a tourist (circle answer below and indicate home zip code):
Local Tourist Home zip code

4) Do you have children or other family members with you today? Please provide their age and gender:
___ years M/F ___ years M/F ___ years M/F ___ years M/F ___ years M/F ___ years M/F

5) How long have you been injured while in the water at the beach? Was the injury serious?
Yes No

6) Please indicate how the following influence your likelihood of entering the water at a beach:

<table>
<thead>
<tr>
<th>Influence</th>
<th>Much Less Likely</th>
<th>Much More Likely</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waves</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
<tr>
<td>People</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
<tr>
<td>People</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
<tr>
<td>It is dark</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
<tr>
<td>Low tide</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
<tr>
<td>Alcohol</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
<tr>
<td>Water temp</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
<tr>
<td>Air temp</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
</tbody>
</table>

7) Please rate:

<table>
<thead>
<tr>
<th>Factor</th>
<th>Very Less</th>
<th>Moderate</th>
<th>Very More</th>
</tr>
</thead>
<tbody>
<tr>
<td>Swim</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
<tr>
<td>Familiar with ocean waves and currents</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
<tr>
<td>Knowledge of ocean waves and currents on the beach</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
<tr>
<td>Your ability to identify dangerous conditions at the beach</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
<td>1 2 3 4 5</td>
</tr>
</tbody>
</table>

8) Have you observed any beach safety awareness campaign material (flyers, brochures, signs)?
Yes No

If yes, please provide a brief description of your familiarity with beach safety information.
7. STUDY POPULATION AND RECRUITMENT
Describe who and how many subjects will be invited to participate. Include age, gender and other pertinent information.

This cannot be known in advance as it depends on the population distribution at the beach. The researchers do hope to obtain a range of ages and both genders so that we are not skewing the population in our research.

Attach all recruitment fliers, letters, or other recruitment materials to be used. If verbal recruitment will be used, please attach a script.

Hi, My name is XXX and I am from the University of Delaware studying beachgoers perception of beach safety. Do you have a few minutes to answer several questions regarding this topic?

Describe what exclusionary criteria, if any will be applied. Children under the age of 18 will not be used.

Describe what (if any) conditions will result in PI termination of subject participation. N/A.

8. RISKS AND BENEFITS
List all potential physical, psychological, social, financial or legal risks to subjects (risks listed here should be included on the consent form). There are none.

In your opinion, are risks listed above minimal* or more than minimal? If more than minimal, please justify why risks are reasonable in relation to anticipated direct or future benefits.

No. Risks are minimal and the PI believes this research should be exempt based on the descriptions provided at the University of Delaware IRB page (http://www.udel.edu/research/preparing/humansub-protcolreview.html#exemptions)

(*Minimal risk means the probability and magnitude of harm or discomfort anticipated in the research are not greater than those ordinarily encountered in daily life or during the performance of routine physical or psychological examinations or tests)

What steps will be taken to minimize risks? There are no risks.

Describe any potential direct benefits to participants. None.

Describe any potential future benefits to this class of participants, others, or society.

This research will enable us to determine how the perception of risk and beach safety relate to actual safety through other data analysis. These data are needed to assist in any future awareness
If there is a Data Monitoring Committee (DMC) in place for this project, please describe when and how often it meets. N/A

9. COMPENSATION
Will participants be compensated for participation? No

If so, please include details.

10. DATA
Will subjects be anonymous to the researcher? Yes.

If subjects are identifiable, will their identities be kept confidential? (If yes, please specify how) N/A

How will data be stored and kept secure (specify data storage plans for both paper and electronic files. For guidance see http://www.udel.edu/research/preparing/datasafety.html)

Security of data is not a concern since it is fully anonymous. However, data will be digitized and stored locally on external back up drives.

How long will data be stored? Indefinite.

Will data be destroyed? □ YES X NO (if yes, please specify how the data will be destroyed)

Will the data be shared with anyone outside of the research team? X YES □ NO (if yes, please list the person(s), organization(s) and/or institution(s) and specify plans for secure data transfer)

Dr. Paul Cowan, Chief of Medicine, Beebe HealthCare
Wendy Carey, Delaware SeaGrant
Kari McKenna, Delaware Department of Natural Resources and Environmental Control

Data will be shared in regular meetings via slide show and or excel sheet exchanges. Data will be shared via email and/or external hard drive.

How will data be analyzed and reported?

Data will be written in a Master’s thesis, presented at national conferences and in peer-reviewed publications.
11. CONFIDENTIALITY
Will participants be audiotaped, photographed or videotaped during this study? No.

How will subject identity be protected? We will not request subject names when providing questionnaire.

Is there a Certificate of Confidentiality in place for this project? (If so, please provide a copy).

No.

12. CONFLICT OF INTEREST
(For information on disclosure reporting see: http://www.udel.edu/research/preparing/conflict.html)

Do you have a current conflict of interest disclosure form on file through UD Web forms? Yes.

Does this project involve a potential conflict of interest?* No.

* As defined in the University of Delaware’s Policies and Procedures, a potential conflict of interest (COI) occurs when there is a divergence between an individual’s private interests and his or her professional obligations, such that an independent observer might reasonably question whether the individual’s professional judgment, commitment, actions, or decisions could be influenced by considerations of personal gain, financial or otherwise.

If yes, please describe the nature of the interest:

13. CONSENT and ASSENT

___ Consent forms will be used and are attached for review (see Consent Template under Forms and Templates in IRBNet)

___ Additionally, child assent forms will be used and are attached.

___ Waiver of Documentation of Consent (attach a consent script/information sheet with the signature block removed).

___X___ Waiver of Consent (Justify request for waiver)

This research provides the absolute minimum risk to the human subjects and is anonymous. Having the subject sign a consent form would actually do more damage in terms of linking the subject to the questionnaire.

14. Other IRB Approval
Has this protocol been submitted to any other IRBs? No.

If so, please list along with protocol title, number, and expiration date.

15. Supporting Documentation
Please list all additional documents uploaded to IRBNet in support of this application.

Re: 10/2012
Appendix B

SZI AND RIP CURRENT PAMPHLET

WAVE SAFETY

Most wave injuries occur when swimmers are knocked to the sand by a wave.

Understand the Surf Conditions

- Ask beach patrol if present waves are dangerous
- The ocean is variable and conditions can change throughout the day
- Local weather is not a sufficient indicator of wave conditions
- Talk to your children about wave and ocean safety
- When in doubt, do not go out

Safety Precautions

- Always swim near a lifeguard stand
- Keep arms in front of you while body surfing
- Do not dive into water of unknown depth
- Exit water between waves
- Do not turn your back on the ocean without awareness of approaching waves
RIP CURRENTS
Rip currents are channelized currents of water moving away from shore at surf beaches.

Rip currents can sweep even the strongest swimmer out to sea.

Safety Tips

- When you arrive at the beach, ask lifeguards about rip currents and other hazards.
- Learn to swim.
- Swim near a lifeguard.
- Never swim alone.
- If you can't swim, do not go in.
- If in doubt, do not go out.
- Assume there are rip currents at any surf beach.

How to Escape a Rip Current

- Stay calm—rip currents do not pull you under.
- Do not swim against the current.
- Swim out of the current, then to shore.
- If you can't escape, float or tread water.
- If you need help, call or wave for assistance.

For more information about rip currents:
www.nws.noaa.gov | www.usgs.gov/ripcurrents
Appendix C

SURF ZONE INJURY DUMMY (SZID)