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Overlap Function Based Fuzzified Aquatic Behaviour Information Extracted Tsunami Prediction Model

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ABSTRACT

Past natural hazards have produced numerous biological and physical indicators that can be used to predict similar instances in the future. These indicators can be sensed dynamically underwater or on land to generate real time alerts. This article proposes the first validated fuzzified system to predict tsunamis (FABETP) using an overlap-based algorithm. This proposed algorithm can predict seismicity based on underwater marine animal's anomalous behavior, characterized and implemented as biological indicators (i.e., aquatic animal behavioral attributes). Relevant information is extracted from these attributes and used to design fuzzy rules that generate opinion-based alerts. More precisely, the proposed algorithm, Overlap-based Fuzzified rated Marine Behavior, (OBF_MB), derives alert rules when executed on a sea turtle behavior dataset obtained from an online repository. The deployed underwater sensor-collected dataset includes the following measurements: induced electromagnetic field, undersea turtle count, and angle of deviation (in terms of the turtles' navigation direction formulated per month and per day). These values are used as the inputs to the proposed system. To generate an opinion, an information gain-based opinion score is used to calculate the opinion deviations from the generated opinions of the default rule. For future data values, 2004 is used here as the default opinion year and the scenarios is the default rule. This paper formulates three classes of opinions using the proposed algorithm: Alert, Pre-Alert and No-Alert. These opinions can be used in the future to generate real-time alerts based on aquatic animal behavior.

KEYWORDS

Information Gain, Marine Behavior, Opinion, Rules, Sea Turtle Fuzzification, Tsunami Alert

INTRODUCTION

The South Asian Tsunami is the common name given by the scientific community to a massive underwater earthquake that occurred in 2004 along the western coasts of Sumatra and Indonesia (Munich RE, 2013), and was one of the deadliest events in history. Several countries: Indonesia, Srilanka, India and Thailand were victimized by this terrible event (Lay et al., 2005; Lovholt et al.,

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2006). This tsunami lead to the deployment of the Indian Ocean Tsunami Warning System (TWS) (Joseph, 2011) which was designed to predict tsunamis in real time and well in advance and generate warning messages for alerts or for mandatory evacuations. Despite the existence of this developed and operational tsunami warning system, there have been past instances when the expected alert warning messages were not generated (Lovholt et al., 2014). One such example stems from a recent report by the BBC, where the well-established Tsunami Early Warning System (TEWS) failed to generate any warning in response to a 7.8-scale earthquake that struck off the coast of West Sumatra on March 2, 2016 (BBC News, 2016). While many rationales (NewsNow, 2016) were cited for this catastrophic failure, distinctive gaps based on on-site experiences were addressed in a recent report (Lassa, 2016) by a research activist that addressed the following topics:

1. Failure of tsunami sirens in remote areas;
2. Forcing local authorities to revisit the monitoring of sea coasts and the effectiveness and authenticity of the generated warning messages;
3. The dependency of local communities on buoys that analyze ocean wave behavior as the critical and sole indicators of tsunamis.

Similarly (as mentioned above) inspections have also been cited as culprits in various other scenarios (VoaNews, 2011) where experts have highlighted the inefficacy of prevailing warning systems. It is important to note that these warning systems were developed only after devastating events that had occurred years before (Lay et al., 2005; Lovholt, 2006) Figure 1a (Tsunami Bulletin, 2010) shows a still image taken after the fatal tsunami that hit Japan in 2011.

Figure 1. (a) A still image from the 2011 tsunami in Japan; (b) Whale beaching in New Zealand before the 2011 tsunami

(a)

(b)

Clearly, such recent phenomena, which caused worldwide surprise and fear, highlight the dire need for efficient, alternative and complementary warning systems that would be effective in preparing for similar future tsunami events (UNISDR 2005). It is interesting to note that post-occurrence analysis of various historic tsunami events from various parts of world report on signs and signals produced by nature prior to such events. Anomalous and ambiguous behavioral responses towards seismicity have been cited in both animals and plants. These reports have been surveyed and debated by various researchers, scientists and risk reduction organizations (Waltham, 2005; Mott, 2005; Corea, 2008; Yamauchi et al., 2011).

However, the existing tsunami warning prediction systems focus solely on geophysical indicators such as underwater earthquake magnitude sensors, bottom pressure recorders, tide gauge analysis, and waveform inspection (Grasso et al., 2011; Beltrami, 2008). In these systems, the mentioned parameters are sensed using wireless sensor nodes placed under water, and these sensed values are then used for real time prediction. A significant improvement in Tsunami prediction modeling is required. This article proposes and validates the need for employing a new dimension (i.e., animal behavioral responses) to improve the model of tsunami prediction. Initiatives have been launched by various disaster management and risk reduction-based organizations to encourage and educate populations to perceive and report on the changes in animal behavior that occur before a hazardous crisis, which can help in creating global alerts (Red Cross 2015; Red Cross 2015).

Marine life, which comprises the aquatic animals and micro-organisms present underwater, forms a significant part of nature. The responses of marine life, if studied and analyzed, can improve the chances of predicting tsunamis with greater accuracy. Scientists and researchers believe that nature does produce messengers: animals and plants whose behavior can be used to propagate alarm signals to mankind. Among these, animals provide visible signals through their abnormal behavioral responses (Mott, 2005). Apart from simply raising awareness, these signals should be integrated and become part of the design and implementation of automated and diverse warning systems.

No current global warning system monitors and analyzes anomalous animal behavior worldwide to generate tsunami alerts and warnings. Therefore, the focus of this paper is to redefine and validate existing tsunami warning systems by adding a concomitant aquatic animal behavioral sensor component using an opinion-based fuzzified approach. This newly added system (on its own) will analyze and create alerts based on anomalous animal behavioral responses to changing environmental conditions that occur before a critical event.

The novel highlights of this paper are as follows:

- We present a comprehensive survey of the tsunami warning algorithms and systems proposed thus far to highlight the lack of global tsunami behavior predicated on irregular aquatic physiological practices;
- We identify and quantify aquatic anomalous behavioral attributes for pre-seismic activity detection;
- We have used the quantified attributes in response to changing environmental conditions to formulate conjunction-based decision rules. These fuzzy if-then constraints are derived from a proposed overlap-based fuzzification rating of marine behavior algorithm using a retrieved sea turtle activity dataset prepared for seismic prediction;
- We perform case-by-case rule validation by opinion mining and gained-information extraction to identify tsunami-alert and tsunami-no-alert years. The proposed system's identifications coincide with the historical data; thus, they flag the Indian Ocean tsunami of 2004 as an alert year.

In this paper, we propose and implement an overlap-based fuzzification algorithm to infer prediction rules for tsunamis rated on marine animal behavior. Using these rules, mined opinions are characterized as No Alert or Alert opinions based on the information gain (ΔIfGain) obtained in comparison to a default rule. The default rule is formulated and comes out be for the scenario of year

2004 data values. Historically 2004 was a tsunami year, hence we mark the rules pertaining to it as a default rule. Information gain (ΔIfGain) produces binary polarities as positive and negative values to identify (or not identify) 2004 as an alert year. To evaluate these rules and obtain the data polarities, a dataset that collected the behavior patterns of sea turtles near Reunion Island from 2004–2012 was obtained from a free public source and prepared. These behaviorally attributed parameters have been tapped for sea turtles in response to changing geophysical conditions (here, induced electromagnetic fields: EMF of ocean flows) Evidence and tagging of the behavioral parameters with regard to changing EMF values along with the reasons why sea turtles were chosen as a specific case are cited in further sections.

PREMISES AND TYPES OF TSUNAMI WARNING SYSTEMS

A tsunami, as a hazard, is defined in terms of a wave system generated from short duration underwater disturbances (Monserrat et al., 2006). Tsunamis can be caused by earthquakes, volcanic eruptions or landslides (Grilli et al., 2002). Environmental hazards are categorized as "Ongoing" and "Creeping (Slow-Onset)." Tsunamis is classified as "ongoing" hydro-meteorological hazards that require hours of generation time (greater than an earthquake itself). Table 1 shows a categorization of hazards in terms of their generation time (UNEP Global Environmental Alert Service (GEAS) 2012). It can be easily inferred that pre-tsunami activities, if monitored effectively, can aid in constructing a warning system (UNISDR-UN 2006). In the subsequent sections, using highlights of a variety of surveyed tsunami warning products and base algorithms, we have categorized the existing systems into three broad categories.

Geophysical Warning Systems

Use of underwater and in-environment changing conditions (i.e., bottom pressure, tide gauge recorded changes, bathymetry, sea-level measurements or waveform height and run up records) to predict tsunamis has always been a highly researched area (Titov et al., 2005; Wei, 2003; Beltrami. 2008; Grasso et al., 2011; Beltrami, 2011; Cecioni, 2014; Mulia, 2016; Inazu, 2014; Horspool, 2014).

A tsunami has been characterized as a tidal wave produced from the displacement of large volumes of water. Tsunamis can be generated from earthquakes, landslides, volcanic eruptions, and so on. The subsequent section explores and presents the highlights of proposed and existing warning products and algorithms.

Society

Finding ways to identify and exemplify alert conditions or situations to communities and individuals based on observations or other knowledge has been the goal of a variety of people-oriented warning systems (UNISDR 2006). Society itself has reported various distinguishing pre-alert observations that typically herald the arrival of tsunami such as anomalous aquatic or terrestrial animal behavior and changes in coastline water conditions (Arce Ricardo San Carlos et al., 2017). These reports have

Table 1. Sample table

Name of Hazard	Type	Warning Time
Earthquake	Quickest Onset threat	Seconds
Volcanic Eruptions	Medium sudden	Days to Hours
Tsunami	Quick to medium onset threat	Hours
Drought	Slowest ongoing threat	Months

led to various methods and systems that rely on community awareness or respond to these reported conditions to identify major alert situations.

Nature

Nature comprises living and non-living elements, both of which have responded to abrupt changes in physical state of environment. Non-living element feedback was discussed in the first category of warning systems. Living organisms such as fishes and whales have been identified as natural messengers who send visible signals through abrupt behavioral responses (Tiwari et al., 2011; Haryo et al., 2005). Case studies have been presented, and natural signal-based systems have been discussed as listed in Table 2.

Geo-Physiological Hybrid Systems

This paper proposes adding a new warning system termed FABETP to the list of existing systems. The proposed system is a hybrid of both the natural and geophysical parameters identified individually in the previous sections. Figure 3 provides a template pictorial representation for the proposed multiple and diverse parameter-based system. Note that a new global system based on a conjunction of the given classes does not yet exist. Conjunction-based associations between aquatic species behavior and changes in earth's geophysical conditions such as electric and magnetic fields date back to observations presented by Indian professor Dr Arunachalam Kumar, who reported whale beaching along the New Zealand and Australian coastlines in 2004 before the Indian Ocean tsunami (Stephen 2011) Similarly, 50 melon-headed whales beached themselves 6 days before the 2011 tsunami in Japan, Figure 1b (Seaburn, 2015) depicts the New Zealand whale beaching. Researchers reported that these whales had no signs of disease and speculated that one reason for the "mass suicide" of whales all across the world was due to disturbances in the electromagnetic field co-ordinates and to possible realignments of the geotectonic plates (Rediff News, 2016). The overall structure of the existing systems is shown in Figure 2, and the formulas and parameter of FABETP are explained in the next sections.

Figure 2 captures the essential three dimensions of the existing warning systems. Concatenating them synchronously, where one change causes reactions in the other dimensions can form the basis of a new system. AOD=Angle of deviation; EMF = Electromagnetic Field; Count=Marine animal population count; Awareness=creating awareness among society.

As argued by various researchers and cited above, tsunamis are an "ongoing" type of crisis event whose generation time is counted in hours. Thus, it affects the animal community well before its physical generation. This community is composed of both aquatic and terrestrial species. The behavioral effects shown by such species can occur days or even months before the creation of any hazardous waves. In this paper, we explore, propose, and validate the system called FABETP, which, if it were presently tracking the geophysical influences of aquatic behavior, can produce advance warnings of tsunamis.

Figure 2 highlights the need for a new system in which all three dimensions of the existing warning systems are associated and interact with each other to produce another domain of warning system development. The focus of this paper is to present a novel fuzzified rule extraction algorithm to infer prediction rules for tsunamis based on marine animal behavior. An opinion score is formulated from the extracted rules and then classified into a No Alert or Alert decision based on the information gain (opinion score) obtained in reference to the default rule.

Synchronizing the existing facets of prevailing warning systems can create further insights to predict tsunamis well before their arrival. The current state of the art highlights the dependence of coastline inhabitants such as fisherman (the society itself) on the ability of the existing precursors to predict or identify threats from underwater disturbances. An automated system that extracts time-synchronized information from all three facets (society, nature and geophysical aspects of the environment) can produce warnings at a higher trust level. Past analysis (Rikitake, 1978) shows that moderately short-range precursors based on observations of a few geophysical features (i.e., waves,

Table 2. Existing and proposed tsunami warning techniques

Authors	Title	Publisher	Year Published	Considered Parameters	Type
Titov et al.	Real time Tsunami forecasting: Challenges and Solutions	Natural hazards and Earth systems	2003	Water level data with a database of pre-computed scenarios	Geophysical
Wei et al.	Inverse Algorithm for Tsunami Forecasts	Journal of waterway, Port, Coast and ocean Engineering	2005	Use of inversion algorithm technique based on the Green function	Geophysical
Beltrami,	An ANN algorithm for automatic, real-time tsunami detection in deep-sea level measurements	Ocean Engineering	2008	An artificial neural network (ANN) implemented on Bottom Pressure Recorders (BPRs) and compared to the one developed under the Deep-ocean Assessment and Reporting of Tsunamis (DART) program	Geophysical
Grasso et al.	Early Warning Systems: A state of Art	A report by UNEP and GEAS	2011	Warning system developed on factors like seafloor bathymetry, topography, sea level data and tide gauge patterns	Geophysical
Beltrami,	Algorithm for automatic Real-time Tsunami detection in Wind-wave Measurements: Using Strategies and Practical Aspects	Coastal Engineering	2011	Use of an amplitude-discriminating algorithm based on an infinite impulse response-time domain filter that characterizes the actual tsunami waveform in 'quasi-real-time'	Geophysical
Cecioni, et al	Tsunami Early Warning System based on Real-time Measurements of Hydro-acoustic Waves	Proceedia Engineering	2014	A numerical model to reproduce tsunami generation and propagation based on surface elevation measurements using the inversion technique	Geophysical
Mulia et al	Real-time forecasting of near-field tsunami wave-forms at coastal areas using a regularized extreme learning machine	Coastal Engineering	2015	Application of extreme learning machine as a universal function approximator, thus improving the standard inversion algorithm to capture non-linearities exhibited by the tsunami	Geophysical
Inazu, et al	Near-field tsunami forecast system based on near real-time seismic moment tensor estimation in the regions of Indonesia, the Philippines, and Chile	Earth, Planets and Space: Springer Open	2016	A forecast system based on an automatic centroid moment tensor estimation using regional broadband seismic observation networks	Geophysical
Horspool, et al	A probabilistic tsunami hazard assessment for Indonesia	Natural Hazards and Earth System Sciences	2014	Forecasts of tsunami hazards sourcing for epistemic and aleatory uncertainty in the analysis through the use of logic trees and sampling probability density functions.	Geophysical
Chatfield et al	Twitter Early Tsunami Warning System: A Case Study in Indonesia's Natural Disaster Management	46th Hawaii International Conference on System Sciences	2013	A Twitter-content analysis-based warning system based on data collected from e-government websites of agencies involved in disaster preparedness	Society
Ulutas et al	Web-based Tsunami Early Warning System: a case study of the 2010 Kepulaunan Mentawai Earthquake and Tsunami	Natural Hazards and Earth System Sciences	2012	Response analysis of the information received from Global Disasters Alerts and Coordination System (GDACS) using models based on the long wave theory with a pre-calculated simulation for tsunami scenario database for that region	Geophysical
Dominey D et al	Letter to the Editor: The Australian Tsunami Warning System and lessons from the 2 April 2007 Solomon Islands tsunami alert in Australia	Natural Hazards and Earth System Sciences	2007	A proposed system called Geo-science Australia (GA) which must detect, locate and evaluate potential tsunamis based on probable wave height along Australia's coasts, deep water tsunami detection buoys, and tide gauges at various points in the SW Pacific and Indian Oceans	Geophysical

continued on following page

Table 2. Continued

Authors	Title	Publisher	Year Published	Considered Parameters	Type
Allen et al	Model-based tsunami warnings derived from observed impacts	Natural Hazards and Earth System Sciences	2010	Consideration of observed coastal impacts for nine past events leading to retrospective or "ideal" warning schemes in which the 95th percentile values of maximum amplitude within designated coastal zones are examined and thresholds that produce the best match for the ideal schemes are selected.	Geophysical
Salamon, A.	Potential tsunamigenic sources in the eastern Mediterranean and a decision matrix for a tsunami early warning system in Israel	Ministry of national infrastructures, geological survey of Israel	2010	Proposed a decision matrix subject to landslide distance with the magnitude of the assumed epicenter and the magnitude of historical sea waves coming from seismogenic slumps.	Geophysical
Kamogawa, et al	A possible space-based tsunami early warning system using observations of the tsunami ionospheric hole	Scientific Reports	2016	A quantitative relationship between initial tsunami height and the Total electron content depression rate caused by a Tsunami ionospheric hole from seven tsunamigenic earthquakes in Japan and Chile used to design a tsunami early warning system.	Geophysical
Chaturvedi et al,	A brief review on tsunami early warning detection using the BPR approach and post analysis by SAR satellite dataset	Journal of Ocean Engineering and Science	2017	A decision-based matrix has been prepared to provide the early warning issues based upon the bottom pressure rate measurements. The model was then followed up by the enhancing SAR image processing techniques with the removal of speckle noise using wiener filters	Geophysical
Suppasri, A. et al	The 2016 Fukushima earthquake and tsunami: Local tsunami behavior and recommendations for tsunami disaster risk reduction	International Journal of Disaster Risk Reduction	2017	People response towards tsunami wave height observations to be prioritized over fault mechanisms for actual categorization of warnings. Such prioritization can improve the current warning system	Society
Charnkol, T et al,	Tsunami evacuation behavior analysis: One step of transportation disaster response	IATSS research 30.2	2006	Analyzing people response towards tsunami warning using logistic regression and identifying thrust areas of improving the response-effectiveness of a warning system	Society
Haryo Dwito Armono et al	Natural Early Warning System for Tsunami	International Seminar Disaster Early Warning System	2005	People response towards anomalous animal behavior carries more weightage for efficient warning distribution. Such prioritization can improve the current warning system	Nature
Grant et al	Predicting the unpredictable; evidence of pre-seismic anticipatory behavior in the common toad	Journal of Zoology	2010	Pre-response of toads in Ruffino lake to the April 6, 2009 earthquake in Italy where they declined in number considerably	Nature

electric fields, magnetic fields, water currents, etc.) can be more effectively used if supported by bio-system parameters in an integrated approach to predicting abnormal seismic disturbances [here Tsunami]. Here, the bio-system parameters include behavioral changes, breeding activities, and migration patterns of aquatic animals, all of which are majorly affected by impending tsunamis.

EXISTING WARNING SYSTEMS AND TECHNIQUES: THE STATE OF THE ART

Tsunami prediction has been a long-standing challenge to the research and scientific community; however, tsunamis are unpredictable events, and even efficient and precise techniques and systems have failed to provide predictions in time. The goal of this paper is to supplement the existing features of current Tsunami warning systems (TWS) because there more dimensions must be added to improve their performance. Table 2 presents a comprehensive survey of both the current and past warning

Figure 2. Current view of existing warning systems

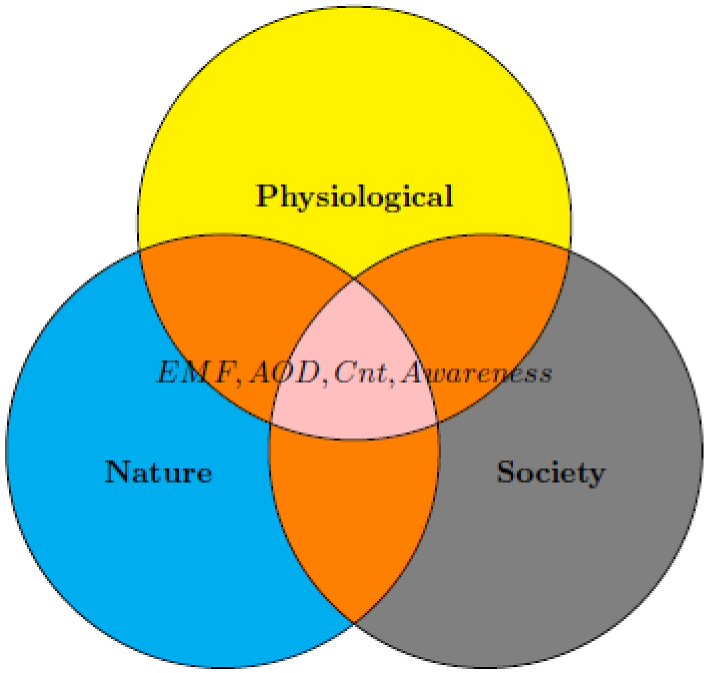
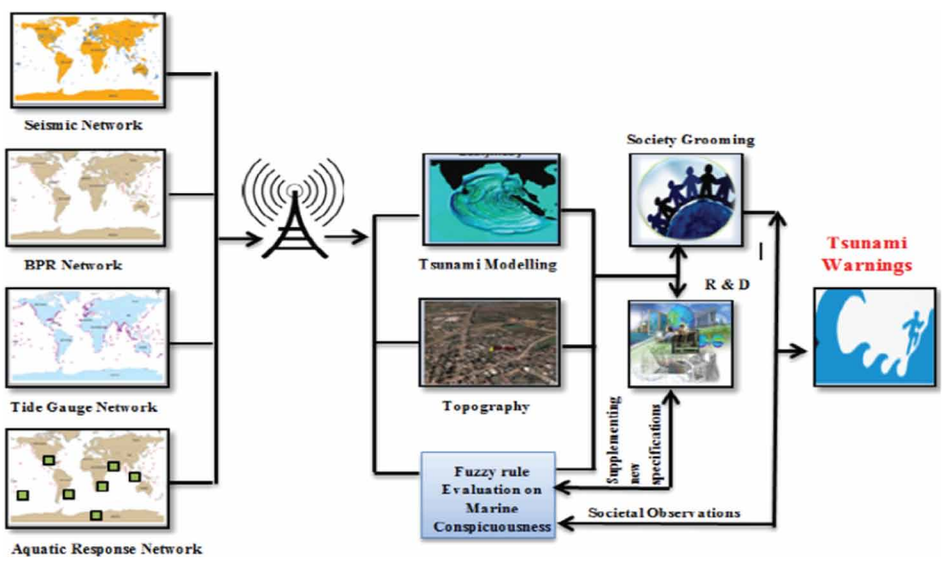


Figure 3. Proposed system for tsunami warnings: FABETP



techniques/methods/systems along with their key features and parameters. Every mentioned and surveyed technique or system from the previous section has been mapped to the category of warning system to which it belongs.

To explore the existing methodologies and systems proposed by various active researchers, we have followed a "true blue" approach that exemplifies certain assumption. This assumption is that certain scientific journals from specific publishers serve as the "real McCoy" of computer science scrutiny related to hazard mitigation. Some other publications are reviewed in this survey. However, a surfeit of publications and articles exist in tsunami hazard mitigation; the articles selected and reviewed for this survey consist of the most highly cited papers or were published in the past 5–7 years. These papers highlight the difference in the approach to societal and natural warning systems in specific in a gap of more than 10 years.

It can be inferred from the surveyed articles that there is a high bias toward analyzing geophysical features to predict tsunamis. Another example of analyzing bathymetry was reported by (Chidambaram et al., 2010). While we acknowledge that a tsunami is a hazard resulting from abnormal changes in geological and physical conditions of waves or bathymetry, tsunamis also elicit "natural warnings" (Gregg et al., 2007).

Considering the listed studies, numerous case studies exist that have noted abnormal reactions in both terrestrial and aquatic animals—before the occurrences of underwater and underground seismicity. The prevailing case studies focus primarily on animal responses to earthquakes (Chen et al., 2000; Snarr, 2005; Fujimoto, 2008; Hanamura, 2008); few articles have focused on abnormal pre-tsunami aquatic animal behavior. This again reflects the necessity for a global system. One validated case study by (Grant et al 2010) cited in our survey reports a mass suicide by underwater toads prior to seismic reactions along the coastline of Italy (Matt Walker 2012).

In (Charnkol & Tanaboriboon, 2006), (Chatfield & Brajawidagda, 2013) and (Suppasri et al., 2017) the community responses of society in response to either warnings or to visible changes in wave heights have been analyzed either on the web or through questionnaires. Little investigation has focused on how people specifically react to or perceive aquatic animal behavior as adaptive or abnormal. In the FABETP system proposed here, societal responses to anomalous animal behavior are not considered because no such global system exists; thus, there is a lack of data.

THE NEED FOR A NEW HOMOGENIZED SYSTEM: WHY SEA TURTLES?

The previous sections have described why there is a need for a new and more diverse system. The well-known fact that tsunamis are still unpredictable has motivated the research and scientific community to find and demonstrate more trustworthy factors to predict tsunamis in real time. Such systems should be able to raise warnings days and months before tsunamis rather than a few hours or minutes. Aquatic animals sense various signals to maintain their orientation and navigation patterns in variable underwater conditions. These underwater conditions are characterized by varying parameters such as induced electric fields or changing electromagnetic forces across a given column of water. These parameters vary with respect to oceanic water movements across earth's geomagnetic field (Kirschvink, 2000). Any abnormalities in these cues can affect aquatic species' normal behavior, for example, by affecting their direction-finding capabilities or ability to find food, and in some cases can lead to mass suicides or beach stranding.

Past researchers have demonstrated that marine animals with magnetic and electric receptors show significant reactions to induced underwater magnetic and electric fields (Schaal, 1988) Such reactions can result in behavioral and physiological changes, loss of orientation, or changes in migration patterns over time. In our new system, our proposed OBF_MB technique exploits this facet of animal response by capturing such reactions in the form of fuzzified attributes and manifesting them as if-then-else decision propositions. Messages received by sensors are processed using these rules to produce tsunami warning messages. The messages tap animal responses to abnormal geophysical conditions that humans have also observed (Meenakshi, 2013).

Here, we use existing state-of-the-art (Schultz et al., 2010; Tricas, 2012; Dodds, 2012) reports that identify the effects of abnormal electro-magnetic fields on marine animals. These effects can act as deterministic precursors for designing a tsunami warning system. On a qualitative basis, the weight of the available evidence suggests that sea turtles are most likely to be affected by exposure to changes in induced magnetic fields (Lohmann, 2008). Thus, the proposed system works by analyzing sea turtle behavioral patterns. In an experiment conducted by (Lohmann, 2008), turtles exposed to strong magnetic fields from the north area swam south, whereas turtles exposed to strong magnetic fields from the south swam north. These turtles lost navigational and prey-tracking capabilities; thus, they were delayed in reaching their nesting areas. Similar experiments concluded that both juvenile and adult sea turtles evacuated their breeding nest area and swam toward deeper offshore areas when exposed to strong magnetic fields, thereby decreasing the population count in the upper water column.

ANATOMY OF THE FABETP SYSTEM

In 2016, the United Nations Office for Disaster Risk Reduction proposed the Sendai framework, which is the first major agreement of the post-2015 development agenda for sharing and recognizing roles and responsibilities in implementing disaster risk reduction.

As per the report, a hazard early-warning system should include the following components:

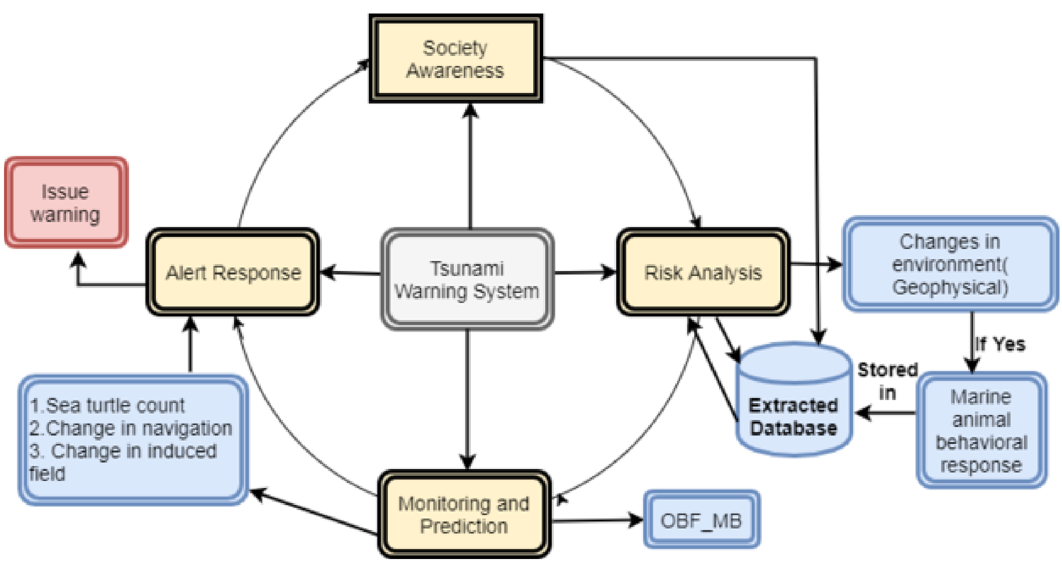
- Risk information;
- Hazard data and forecasts;
- Communication and dissemination;
- Preparedness and early response.

Overriding this formulated framework, we instead propose a new system called Fuzzified Aquatic Behavior Extracted Tsunami Prediction model, or FABETP with anatomy shown in Figure 4. The four components of our new system are explained in the following sections.

Risk Analysis

This component analyzes tsunami-related risk prior to its onset. Changes in environmental geophysical conditions prior to tsunamis have been observed in the past by various scientists. These conditions are strongly related to oceanic flows and waves with short wavelengths generated before the onset of devastating tsunami hazards. Such parameter-based warning system/methodologies were cited above

Figure 4. Anatomy of FABETP



in our survey. In (Bleier et al., 2005) claimed that a network of passive sensors (magnetometers) could be used for earthquake prediction by monitoring the transient changes in earth's magnetic field that occur prior to imminent earthquakes. Similar observations have been cited for tsunamis; thus, integration of these magnetometers can improve the current warning systems. The abnormal changes observed before tsunamis (Tatehata et al., 2015, Manoj, 2011) typically include induced electric and magnetic fields, one of the geophysical conditions we address in our system. Animals (here, turtles) easily sense any changes in adaptive electro-magnetic fields—well before humans. Their consequent reactions include changes in their nesting, breeding and migration patterns. Using the cited evidence (Sugioka, 2005; Tyler, 2005; Nair et al., 2010) for electromagnetic field values, a linguistic mapping of "low", and "high" labels was performed to map the existing. The corresponding value mappings are shown in Table 4.

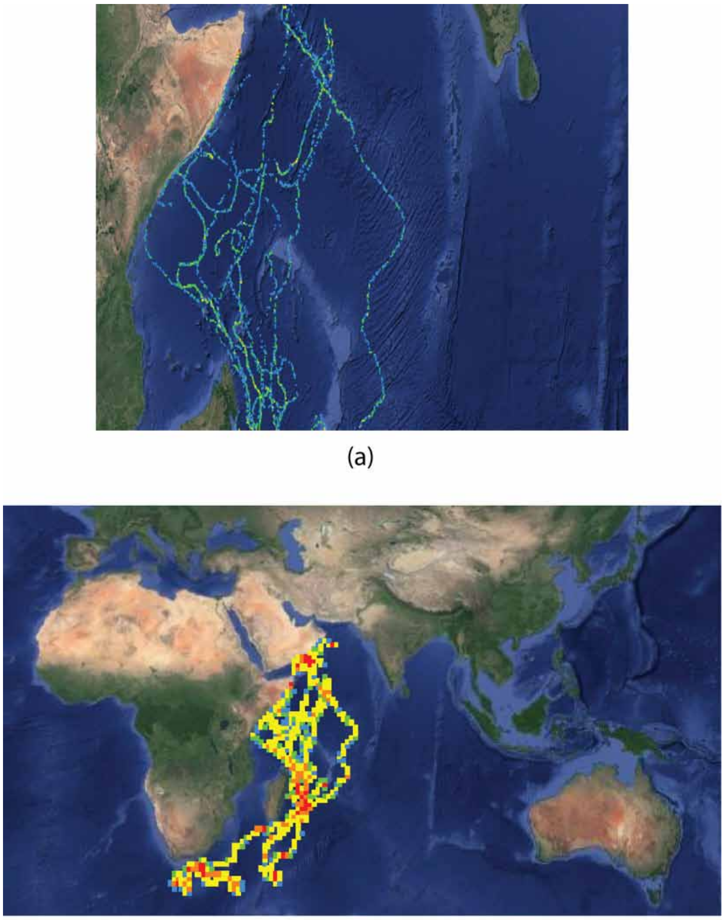
Sea turtle activity data was obtained from (OBIS-seamap) which has tracked loggerhead turtle navigation and counts for the mentioned years (Scientific Name: Caretta Caretta) as shown in Figure 6 for Reunion Island near the Indian Ocean. The Boxing Day tsunami in 2004 (also known as the Andaman-Sumatra earthquake) affected 11 countries including Reunion Island (Ramalanjaona, 2011) (also shown in Figure 5. This information is sensed by same-species communities of turtles as shown by the different colors. The raw data includes the locations of different turtles in communities in the form of latitude and longitude. The deviation is obtained by grouping the common species IDs and then applying haversine equations (Rosettacode.org, 2012). As presented in (Virmani & Jain, 2016), sea turtles exhibit a complete reversal in direction corresponding to a deviation in opposite direction. An overview of the turtle activity is obtained from available plots

Monitoring and Prediction

This component monitors the inferred rules from our proposed algorithm OBF_MB using the overlap between activation hyper-boxes of merged yearly datasets obtained from the above component. Each year's dataset is attributed with further prepared parametric values explained

Figure 5. Islands affected by the 2004 tsunami

Figure 6. (a) Dataset plots: Turtle trajectory plotted for the complete dataset; (b) Dataset plots: Overview of the complete dataset



(a)

(b)

in the next section. The algorithm weights the attribute based on the overlap obtained between the minimum and maximum values from the activation hyperbox of the tagged year. This min-max to "LOW", "MED" and "HIGH" classifier is constructed (Quteishat, 2008) to extract Fuzzy if-then-else rules to rate pre-seismic marine behavior. Mining the opinion score from every rule produces a polarized information-gain. Therefore, this component of the proposed system FABETP monitors and predicts future tsunami based on observable marine animal patterns and responses to changing geophysical conditions prior to any risk.

Alert Responses

This component of our system produces response messages based on the value deviations of the monitored attributes, producing warning alerts when sufficient deviation occurs.

Society Awareness

This is a self-explanatory component where initiatives from DRR (Disaster Risk Reduction) based agencies and organizations must be implemented to monitor the behavior of aquatic species in real time.

DATA DESCRIPTION AND PREPARATION

The proposed OBF_MB technique works on data prepared from marine turtle behavioral statistics acquired from Reunion Island near the coastline of the Indian Ocean. Table 3 shows the metadata of the mentioned attributed dataset.

The parameters were obtained and prepared from the attributed dataset for the years 2004–2012 described below:

1. Angle of Deviation (between consecutive months) calculated between consecutive months obtained for each year of the complete dataset and linguistically mapped as shown in Table 4;
2. Angle of Deviation (between available days) calculated between consecutive or next day available obtained for every year of the complete dataset;
3. Marine turtle count (underwater sea turtle count);
4. Electromagnetic Field: the induced EMF's (linguistically mapped as discussed in the previous section) during underwater seismic perturbations. Using a common timestamp (wherever applicable), a behavioral turtle activity dataset with respect to changing Electromagnetic field is prepared. From the above process, we found that some values were unknown in different years and at various timestamps. These included days close to the December tsunami of 2004.This we assume to be a cause of unavailability or inability of sensors to track the information prior to hazardous event or otherwise and thus is one of the limitations here.

Table 3. Metadata of turtle activity dataset

Attribute	Description
Tag_ID	Unique ID provided by Owner of Dataset
Lat	Latitude (In Decimal Degrees)
Lon	Longitude (In Decimal Degrees)
Sp_code	Specie code of the observed Species
Obs_Count	Number of Animals Sighted
Obs_ Date_Time	Date and time of Observation in UTC

Table 4. Parameter to range variable mapping from OBF_MB

Parameter (P_k)	Name	Rule Extracted Parameter Variable	Range of Values Observed
k=1,2	Angle of Deviation(Month)	low	<= 100 degrees
	Angle of Deviation(day)	medium	>=100 & <=140 degrees
		high	>=140 & <160 degrees
		very high	>=160 Degrees
k =3 k=4	Sea Turtle count Electromagnetic Field	low medium high low high	<=3 >=5 &<=7 >=8 <=1 nTesla >= 1 nTesla till 4 nTesla

FABETP WORKFLOW

Figure 7 shows a flowchart of FABETP, which is designed to generate real-time Alert or No Alert decisions. The sensed and prepared parameters identified above form the input to the system. The following steps describe the stages of the proposed system.

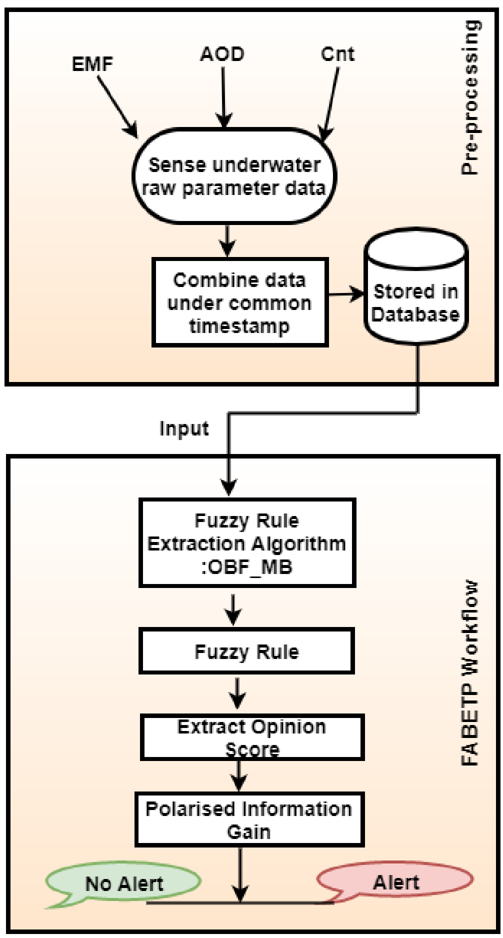
OBF_MB Approach: Stage 1

As discussed in the previous section, the dataset is segregated in a year-wise fashion as per the algorithm OBF_MB (described in the previous section). The preliminaries associated with the proposed algorithm are as follows.

Let T_i be the tuple input data from the prepared marine turtle dataset in a given year i = 2004 denoted as:

$$T_i = \begin{cases} P_k \ \ for\ 1 \le k \le 4 \\ \phi \qquad otherwise \end{cases} \tag{1}$$

Figure 7. FABETP workflow



In accordance with historical statistics, December 2004 is marked as a Tsunami event. The proposed technique analyzes the differences in behavioral attributes between the year 2004 and other prepared years from the dataset. These differences reveal the abnormal marine behavior that occurred in 2004. As shown in lines 18–20 of Algorithm 1, the input tuple data from the source dataset include every parameter P_k in a given year i as defined above. The region is defined as follows:

$$R_{ik} \ or \ R_{jk} = \begin{cases} T_{ik} \ for \ \min_{ik} 1 \le k \le Max_{ik} \\ \phi \qquad otherwise \end{cases} \tag{2}$$

where $R_{ik\ i}$s the activation hyperbox that includes the minimum and maximum of parameter k in the year i tuple data. Using the proposed algorithm (OBF_MB), the parameter P_k (k =1, 2, 3 and 4) values are mapped to range commonly referred as linguistic terms: 'low', 'medium, 'high' and 'very high'. The number of terms obtained for every parameter depends on the diversity of values present. Table 3 shows the parameter to range mapping derived using OBF_MB. As mentioned in the previous section, angle of deviation (month and day) i. e k =1 and k = 2 respectively is obtained by application of haversine formula to turtle marked latitude and longitude values. Figure 8 and Figure 9 shows box plot representing median latitude and longitude for all years. The mentioned figures depict the deviation in position across the considered years.

The Overlap Function: Stage 2

This function is used to build a min-max rule-based classifier to identify the parametric data points further used for fuzzification. The function specifically overrides the classic fuzzy classifier region overlap function; here, it extracts a feature representing the intersecting values in every year data values as an input to the proposed algorithm.

Considering the year windows as generated under lines 1–4 of the algorithm, activation hyperbox regions are created based on [min, max] flags for every parameter k in the given years i and j. To obtain the overlap states, the following cases were identified for fuzzy rule extraction used in seismic prediction. The reason for categorizing these windowed values for the i to j years is to study their overlap or differences with the known historical values for the days or months prior or 2004 tsunami:

Case 1: For given years i and j such that |i-j| > 3.
Case 2: For given years i and j such that |i-j| < 3 and > 1.
Case 3: For given years i and j such that |i-j| = 0 (i.e., within the year 2004 data range).

Equation 3 shows the overlap function used by OBF_MB:

$$Ovl_{ij} = \frac{(min_i, Max_i \cap min_j, Max_j)}{minimum \ of \ (min_i, Max_i), (min_j, Max_j)} \tag{3}$$

Predictive Fuzzy Rule Extraction: Stage 3

From the divided cases presented in the previous sections, the dataset for every case-based scenario is explored. From Equation 3, the following rule set is obtained.

Case 1

Because the gap between years is high, the input values do not overlap for all the considered parameters. Figure 10 shows the overlap scores obtained for all four parameters. As the majority values coincide

Algorithm 1. OBF_MB: Overlap based fuzzification for rated marine behaviours

Algorithm 1: OBF_MB : Overlap based fuzzification for rated marine behaviour

```
Function DivideintoYear (Dataset D)
    for each Year i;
    Actf_i ← [min_i,Max_i];
    return Actf_i
Function FindActivationHyperbox (min,Max)
    for each Year i and Parameter P_k;
    Actf_ik ← [min_ik,Max_ik];
    return Actf_ik
Function FindOverlap(Actf_ik,Actf_jk)
    for year i and j;
    Ovl_ijk ← = CallOverlap[Actf_ik,Actf_jk];
    return Ovl_ijk;
Function RuleExtractor(Ovl_ijk // Add "THEN Output
  = Y" with every rule formulated)
    if (!Ovl_ijk) then
        Obtain Fuzzy Rule with existing attribute
          values for different permutations ;
    else
        For each Parameter P_k;
        R_ik←Actf_i for P_k;
        R_jk←Actf_i for P_k;
        Overlap _score_Maxk= Max of R_i-Max of R_j;
        Overlap _score_mink= min of R_i-min of R_j;
        if ( Overlap _score_Maxk OR Overlap _score_mink
          ≈ 0) then
            Max[R_ik]= Max[R_ik];
            or min[R_jk]= min[R_jk];
        else
            continue;
        end
        if ( Overlap _score_Maxmink) then
            if (Max[R_ik)] OR [Max(R_jk)] < Mean of
              (Value ([P_k in year i]) then
                Obtain Fuzzy Rule with(R_ik or R_jk as
                  HIGH) ;
            else
                Obtain Fuzzy Rule with(R_ik or R_jk as
                  VERY HIGH) ;
            end
        else
        end
        if (min[R_ik)] OR [min(R_jk)] < Mean of (Value
          ([P_k in year i]) then
            Obtain Fuzzy Rule with(R_ik or R_jk as
              LOW) ;
        else
            Obtain Fuzzy Rule with(R_ik or R_jk as
              MEDIUM) ;
        end
        continue;
    end
Function Overlap (Actf_i,Actf_j)
    return (|x∩y|)/ (minimum (|x|, |y|))
```

Figure 8. Box plot representing median Latitude for all years

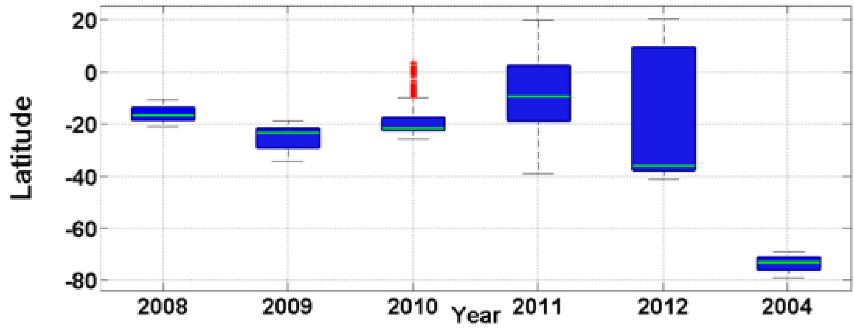


Figure 9. Box plot representing median longitude for all years

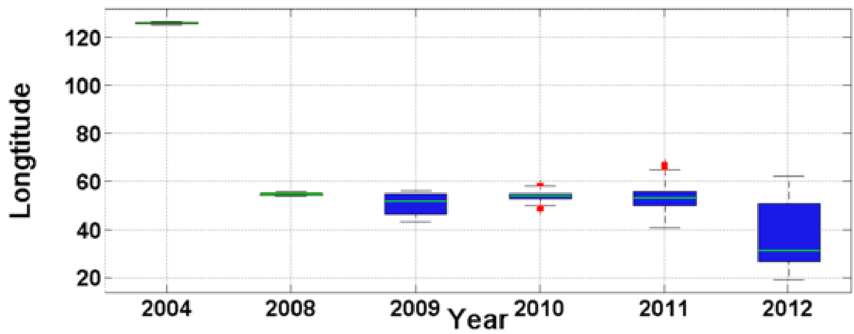
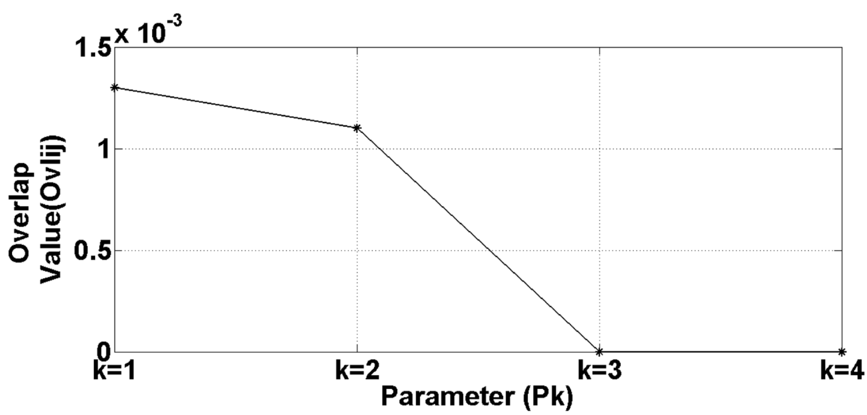


Figure 10. Overlap score values (Ovl_{ij}) for case 1 identified above



with 0 hence Equation 4 gives overlap value for this case. The calculated observations coincide with the assumption that no overlap occurs in any attribute value between no-alert and tsunami-alert years. The dataset includes the values of the different attributes (discussed later) as EMF = low, AOD(M) = low, AOD(D) = low and Cnt = High..To validate and propose this rule, here, out of every possible rule permutation certain permutations are listed in form of rule 1A, 1B, 1C. The progress from 1A TO 1B TO 1C is marked by closer observations of the dataset in which the multiple values are reduced to fixed values:

$$Overlap_{ij} = 0 \tag{4}$$

The rules for the considered case are described below.

Rule 1A: Statement: IF Electromagnetic field € [low; high] ∩ Count € [high] ∩ angle of deviation(day) € [low; med; high; very high] ∩ angle of deviation(month) € [low; med; high; very high] THEN Output = Y.

Explanation: The formulated rule starts with all possible permuted values of every attribute considered here except the count. The data values for the count attribute were observed to be close to constant over the majority of the segmented data, demonstrating that the sea turtle population faced no abnormalities over a considerable period of years before the tsunami year of 2004. The small count variations are assumed to be due to the turtles' reproduction cycle; thus, the count increases at a slow pace, which is reflected here in weeks to months.

Rule 1B: Statement: IF Electromagnetic field € [low] ∩ Count € [low; med; high] ∩ angle of deviation(day) € [low; med; high; very high] ∩ angle of deviation(month) € [low; med; high; very high] THEN Output = Y.

Explanation: The progression to this rule is based on observation of the next attribute value: Electromagnetic field, after fixing the Count attribute value to high in the previous rule. In this rule, every attribute except EMF (Electromagnetic field) is permuted under every possible value.

Rule 1C: Statement: IF Electromagnetic field € [low] ∩ Count € [high] ∩ angle of deviation(day) € [low] ∩ angle of deviation(Month) € [low; med; high; very high] THEN Output = Y.

Explanation: As per the observation of previous two rules, the values of two attributes, EMF and Count, are held to low and high respectively under the previously cited observed reasons. The next attribute, angle of deviation(day) is kept low due to similar observations over the complete dataset. The last attribute here, angle of deviation(month) is permuted for every value.

Case 2

From Equation 3, the following function is obtained:

$$Overlap\_score(Ops) = \begin{cases} < 0.551 \text{ for } 1 \leq Ovl \leq 4 \\ 0 \qquad \text{otherwise} \end{cases} \tag{5}$$

Figure 11 shows the overlap scores obtained for all four parameters. As the majority values fall below 0.55 hence equation 5 gives overlap value for this case.

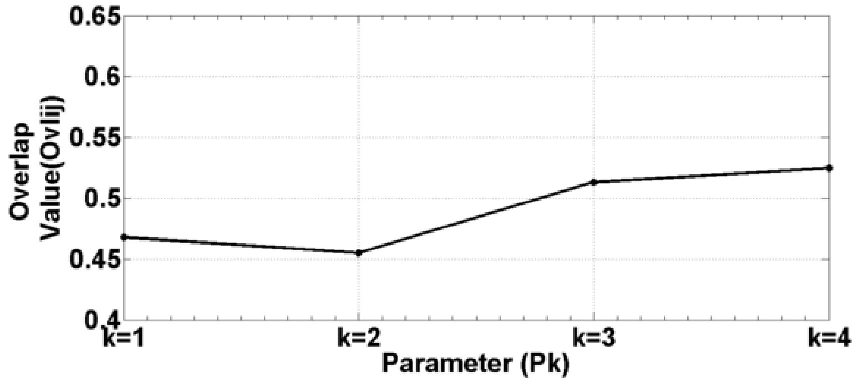
Using the OBF_MB approach, the rules extracted from the above case are described below:

Rule 2A: Statement: IF Electromagnetic field € [high] ∩ Count € [medium] ∩ angle of deviation(day) € [very high] ∩ angle of deviation(month) € [medium] THEN Output = Y.

Explanation: As the dataset window becomes closer to the alert year of 2004, the values of the parameter attributes considered here are reduced to fixed values highlighted in the rule itself. There is a considerable change in the EMF and Count values as well as the turtles' navigation directions in terms of angle of deviation. OBF_MB shows the conditions (lines 29 and 36 of OBF_MB) from which this rule is obtained.

Rule 2B: Statement: IF Electromagnetic field € [high] ∩ Count € [low] ∩ angle of deviation(day) € [high] ∩ angle of deviation(month) € [high] THEN Output = Y.

Figure 11. Overlap score values (Ovl_{ij}) for case 2 identified above



Explanation: In the latter part of the dataset, the attribute values depict a change that is captured by OBF_MB.

Case 3

Using Equation 3 and the proposed Algorithm 1, the following function is obtained:

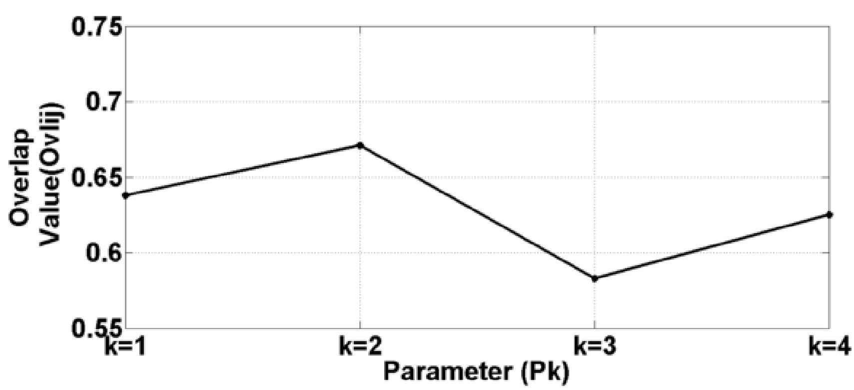
$$Overlap\_score(Ops) = \begin{cases} > 0.551 \text{ for } 1 \leq Ovl \leq 4 \\ 0 \qquad \text{otherwise} \end{cases} \tag{6}$$

Figure 12 shows the overlap scores obtained for all four parameters. As the majority values fall above 0.55 hence equation 6 gives overlap value for this case 3.

A high overlap indicates a change in the marine behavior that existed just before the onset of the tsunami at the end of 2004. This observation can also be justified by the fact of that the extracted rules stem from data with less information collected on the days closer to the tsunami of 2004. This therefore indicates that sea turtle behavior became abnormal days before the onset of the tsunami.

Rule 3: Statement: IF Electromagnetic field € [high] ∩ Count € [low] ∩ angle of deviation(day) € [very high] ∩ angle of deviation(month) € [very high] THEN Output = Y.

Figure 12. Overlap score values (Ovl_{ij}) for case 3



Explanation: Considering the dataset window, which has narrowed down in this case, OBF_MB captures a strict value-oriented fuzzy rule with yet-to-be-validated output. This rule expresses the conditions of the marine as well the geophysical behavior closest to the tsunami day of 2004 near the Indian Ocean.

RESULTS AND DISCUSSION

Opinion Score

To evaluate the inferences obtained from the fuzzified rules obtained using the calculated overlap score (see Equation 3), the information gain (ΔIfGain)is evaluated using Equation 7 for every case corresponding to a rule. The opinion score mines the information in terms of the polarized output Y. Equation 7 coins an overridden score formulation following (Afzaal M. et al 2016) to mine a score-based opinion regarding the alert situation from each fuzzy rule. The score thus produces a deviation from the default rule obtained in Case 3. Case 3 is a typical representation of year 2004 tuple data. The information gain, denoted as Delta ΔIfGain, formalizes the opinion scoring to extract the polarized output Y in the form of a deviation from year 2004 using Equation 8.

The polarized data forms the basis for obtaining the alert, pre-alert or no-alert ternary classification. This classification based on marine behavior can then be used with other sensed data, comparing the collected patterns with existing scores to extract ternary classified information. Equation 7, used to acquire the information gain-based opinion score is shown below, in which N_L' and N_H' represent the number of LOW and HIGH valued instances participating in the rule, respectively. Similarly, N_L and N_H respectively represent the number of LOW and HIGH valued instances participating in the default rule. The default rule here corresponds to the case 3:

$$OpNScore_{ij} = N_L{}' * \left(\log_2 \frac{N_L{}'}{N_L{}' + N_H{}'} \right) - \log_2 \frac{N_L}{N_L + N_H} \tag{7}$$

Using Equations 7 and 8, Table 5 shows an analysis for every case-based rule. A default opinion for the year 2004 (the known tsunami year) is shown in Table 5 as +2. Figure 13 and Figure 14 present the opinion score vs. the mean overlap score for all cases and the corresponding information gain, respectively. The ternary classification is well-reflected in both figures. Calculating opinion score over default rule is identified as change in score from the already known year of 2004 data values. The change in polarity characterizes the shifts in opinion and information over the previous year data marine behavior values.

Information Gain

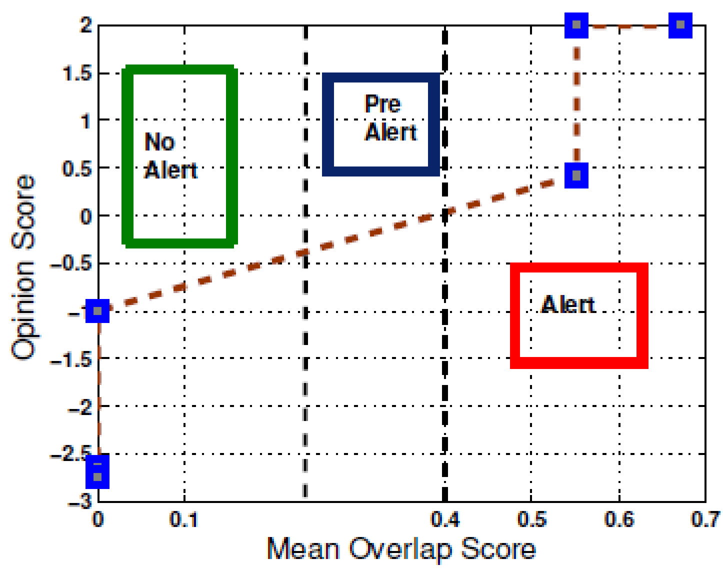
The within-year 2004 analysis discussed in Case 3 generates a high positive opinion (also known as the default opinion (DefaultOp)), while the other, subsequent years (any year i) produce very low opinions, which results in a high deviation in terms of information gain.

$$\begin{aligned} \Delta IfGain = {} & O_p NScore_{ij}[Opinion_i] \\ & - O_p NScore_{ij}[DefaultO_p] \end{aligned} \tag{8}$$

Table 5. Extracted Fuzzy rules with opinion and ΔIfGain values along with predicted output Y

Case Number	Fuzzy Rule	OpNScore	ΔIfGain	Output = Y
Rule 1A	IF Electromagnetic field € [low; high] ∩ Count € [high] ∩ angle of deviation(day) € [low; med; high; very high] ∩ angle of deviation(month) € [low; med; high; very high] THEN Output = Y	-2.64	-4.64	Y = No Alert
Rule 1B	IF Electromagnetic field € [low] ∩ Count € [low; med; high] ∩ angle of deviation(day) € [low; med; high; very high] ∩ angle of deviation(month) € [low; med; high; very high] THEN Output = Y	-2.74	-4.74	Y = No Alert
Rule 1C	IF Electromagnetic field € [low] ∩ Count € [high] ∩ angle of deviation(day) € [low] ∩ angle of deviation(Month) € [low; med; high; very high] THEN Output = Y	-1	-3	Y = No Alert
Rule 2A	IF Electromagnetic field € [high] ∩ Count € [medium] ∩ angle of deviation(day) € [very high] ∩ angle of deviation(month) € [medium] THEN Output = Y	+0.42	1.58	Y = Pre Alert
Rule 2B	IF Electromagnetic field € [high] ∩ Count € [low] ∩ angle of deviation(day) € [high] ∩ angle of deviation(month) € [high] THEN Output = Y	+2	0	Y = Alert
Rule 3	IF Electromagnetic field € [high] ∩ Count € [low] ∩ angle of deviation(day) € [very high] ∩ angle of deviation(month) € [very high] THEN Output = Y	+2	0	Y = Alert

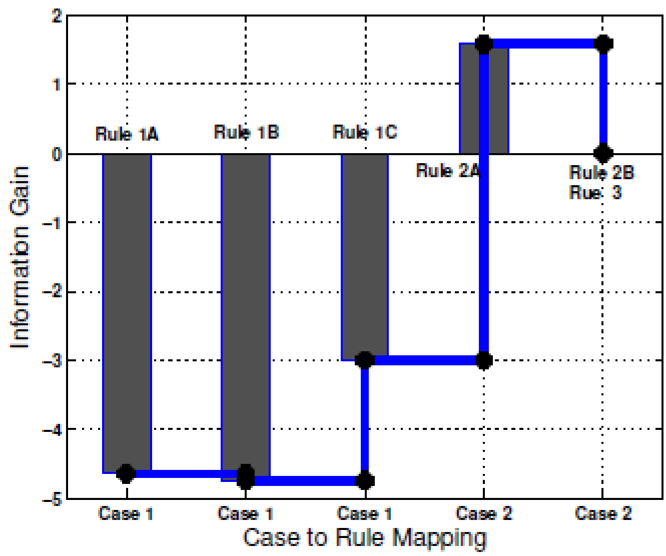
Figure 13. Overlap score values (Ovl_{ij}) for case 3 identified above



CONCLUSION

This article focused on the need for an automated system to create tsunami alerts based on marine behavior. The system is proposed here, FABETP, provides a polarized information-based classification in terms of opinion and information gain. This system extracts information from the attributes of a sea turtle activity dataset that includes the data values for 2004. Various marine and terrestrial species

Figure 14. Overlap score values (Ovl_{ij}) for case 3 identified above



have been reported to respond to seismic perturbations in the past. This paper adds and validates sea turtles as another passive messenger whose behavioral activities can be sensed to predict tsunamis. The produced classification is based on fuzzified constraints commonly called rules produced by the proposed OBF_MB technique, which utilizes the overlap function evaluation to extract fuzzy if-then rules. A clear change in opinion and corresponding information gain can be observed when an induced physical attribute and the consequent marine behavioral attributes for the year 2004 are compared with themselves and with other no alert-tsunami tears. The OpNScore ranges from +2 to -2.64 and the Delta IfGain ranges from 0 to -4.64. A striking coinciding opinion of +2 is observed in the days close to 2004, depicting the pre-tsunami effects of waves that initially affect marine behavior. This score can be accounted as a default or baseline for any future prediction. To the best of our knowledge, this is the first system that mines opinion from extracted fuzzy rules based on sea turtle behavior to predict tsunamis. The proposed opinion-based fuzzification rules and information gain can be used to design a marine-based tsunami-meter to generate real time alerts.

REFERENCES

Afzaal, M., Usman, M., Fong, A. C. M., Fong, S., & Zhuang, Y. (2016). Fuzzy Aspect Based Opinion Classification System for Mining Tourist Reviews. *Advances in Fuzzy Systems*, *2016*, 2. doi:10.1155/2016/6965725

Allen, S. C. R., & Greenslade, D. J. M. (2010). Model-based tsunami warnings derived from observed impacts. *Natural Hazards and Earth System Sciences*, *10*(12), 2631–2642. doi:10.5194/nhess-10-2631-2010

Arce, R. S. C., Onuki, M., Esteban, M., & Shibayama, T. (2017). Risk awareness and intended tsunami evacuation behaviour of international tourists in Kamakura City, Japan. *International Journal of Disaster Risk Reduction*, *23*, 178–192. doi:10.1016/j.ijdrr.2017.04.005

Armono, H.D. & Suntoyo. (2005). Natural Early Warning System for Tsunami. In *Proceedings of the International Seminar Disaster Early Warning System* (pp. 136-171).

Beltrami, G. M. (2008). An ANN algorithm for automatic, real-time tsunami detection in deep-sea level measurements. *Ocean Engineering*, *35*(5), 572–587. doi:10.1016/j.oceaneng.2007.11.009

Beltrami, G. M., & Di Risio, M. (2011). Algorithms for automatic, real-time tsunami detection in wind–wave measurements Part I: Implementation strategies and basic tests. *Coastal Engineering*, *58*(11), 1062–1071. doi:10.1016/j.coastaleng.2011.06.004

Bleier, T. (2005). Earthquake alarm. *IEEE Spectrum*, *42*(12), 16–21.

Cecioni, C., Bellotti, G., Romano, A., Abdolali, A., Sammarco, P., & Franco, L. (2014). Tsunami early warning system based on real-time measurements of hydro-acoustic waves. *Procedia Engineering*, *70*, 311–320. doi:10.1016/j.proeng.2014.02.035

Charnkol, T., & Tanaboriboon, Y. (2006). Tsunami evacuation behavior analysis: One step of transportation disaster response. *IATSS Research*, *30*(2), 83–96. doi:10.1016/S0386-1112(14)60173-4

Chatfield, A. T., & Brajawidagda, U. (2013, January). Twitter early tsunami warning system: A case study in Indonesia's natural disaster management. In *2013 46th Hawaii international conference on System sciences (HICSS)* (pp. 2050-2060). IEEE.

Chaturvedi, S. K., Srivastava, P. K., & Guven, U. (2017). A Brief Review on Tsunami Early Warning Detection using BPR Approach and Post Analysis by SAR Satellite Dataset. *Journal of Ocean Engineering and Science*.

Chen, A. T., Ouchi, T., Lin, A., Chen, J., & Maruyama, T. (2000). Phenomena associated with the 1999 Chi-Chi earthquake in Taiwan, possible precursors and after effects. *Diqiu Kexue Jikan*, *11*(3), 689–700.

Chidambaram, S., Ramanathan, A. L., Prasanna, M. V., Karmegam, U., Dheivanayagi, V., Ramesh, R., & Manikandan, S. et al. (2010). Study on the hydrogeochemical characteristics in groundwater, post-and pre-tsunami scenario, from Portnova to Pumpuhar, southeast coast of India. *Environmental Monitoring and Assessment*, *169*(1), 553–568. doi:10.1007/s10661-009-1196-y PMID:19859821

Corea, R. (2008) Nature: Eyewitness accounts. Retrieved from http://www.pbs.org/wnet/nature/can-animals-predict-disaster-ravi-corea/137/

Dodds, W. K., Robinson, C. T., Gaiser, E. E., Hansen, G. J., Powell, H., Smith, J. M., & Kratz, T. K. et al. (2012). Surprises and insights from long-term aquatic data sets and experiments. *Bioscience*, *62*(8), 709–721. doi:10.1525/bio.2012.62.8.4

Dominey-Howes, D., Papathoma-Köhle, M., Bird, D., Mamo, B., & Anning, D. (2007). Letter to the Editor: the Australian Tsunami Warning System and lessons from the 2 April 2007 Solomon Islands tsunami alert in Australia. Natural Hazards and Earth System Science, 7(5), 571-572.

Fujimoto, M., & Hanamura, S. (2008). Responses of wild chimpanzees (Pan troglodytes schweinfurthii) toward seismic aftershocks in the Mahale Mountains National Park, Tanzania. *Primates*, *49*(1), 73–76. doi:10.1007/s10329-007-0052-3 PMID:17885734

Grant, R. A., & Halliday, T. (2010). Predicting the unpredictable; evidence of pre-seismic anticipatory behaviour in the common toad. *Journal of Zoology*, *281*(4), 263–271.

Grasso, V. F., & Singh, A. (2011). Early warning systems: State-of-art analysis and future directions. UNEP.

Gregg, C. E., Houghton, B. F., Paton, D., Johnston, D. M., Swanson, D. A., & Yanagi, B. S. (2007). Tsunami warnings: Understanding in Hawaii. *Natural Hazards*, *40*(1), 71–87. doi:10.1007/s11069-006-0005-y

Grilli, S. T., Vogelmann, S., & Watts, P. (2002). Development of a 3D numerical wave tank for modeling tsunami generation by underwater landslides. *Engineering Analysis with Boundary Elements*, *26*(4), 301–313. doi:10.1016/S0955-7997(01)00113-8

Horspool, N., Pranantyo, I., Griffin, J., Latief, H., Natawidjaja, D. H., Kongko, W., & Thio, H. K. et al. (2014). A probabilistic tsunami hazard assessment for Indonesia. *Natural Hazards and Earth System Sciences*, *14*(11), 3105–3122. doi:10.5194/nhess-14-3105-2014

Inazu, D., Pulido, N., Fukuyama, E., Saito, T., Senda, J., & Kumagai, H. (2014). Near-field tsunami forecast system based on near real-time seismic moment tensor estimation in the regions of Indonesia, the Philippines, and Chile. *Earth, Planets, and Space*, *68*(1), 73. doi:10.1186/s40623-016-0445-x

Joseph, A. (2011). *Tsunamis: Detection, monitoring, and early-warning technologies*. Academic Press.

Kamogawa, M., Orihara, Y., Tsurudome, C., Tomida, Y., Kanaya, T., Ikeda, D., & Toyoda, A. et al. (2016). A possible space-based tsunami early warning system using observations of the tsunami ionospheric hole. *Scientific Reports*, *6*(1), 37989. doi:10.1038/srep37989 PMID:27905487

Kirschvink, J. L. (2000). Earthquake prediction by animals: Evolution and sensory perception. *Bulletin of the Seismological Society of America*, *90*(2), 312–323. doi:10.1785/0119980114

Lassa, J. A. (2016). The west Sumatra earthquakes: not learning our lessons?..

Lay, T., Kanamori, H., Ammon, C. J., Nettles, M., Ward, S. N., Aster, R. C., & DeShon, H. R. (2005). The great Sumatra-Andaman earthquake of 26 December 2004. *Science*, *308*(5725), 1127–1133. doi:10.1126/science.1112250 PMID:15905392

Lohmann, K. J., Lohmann, C. M., & Endres, C. S. (2008). The sensory ecology of ocean navigation. *The Journal of Experimental Biology*, *211*(11), 1719–1728. doi:10.1242/jeb.015792 PMID:18490387

Løvholt, F., Bungum, H., Harbitz, C. B., Glimsdal, S., Lindholm, C. D., & Pedersen, G. K. (2006). Earthquake related tsunami hazard along the western coast of Thailand.

Løvholt, F., Setiadi, N. J., Birkmann, J., Harbitz, C. B., Bach, C., Fernando, N., & Nadim, F. et al. (2014). Tsunami risk reduction–are we better prepared today than in 2004? *International Journal of Disaster Risk Reduction*, *10*, 127–142. doi:10.1016/j.ijdrr.2014.07.008

Manoj, C., Maus, S., & Chulliat, A. (2011). Observation of magnetic fields generated by tsunamis. *Eos (Washington, D.C.)*, *92*(2), 13–14. doi:10.1029/2011EO020002

Meenakshi, A. N., & Juvanna, B. I. (2013). Tsunami detection system using unusual animal behavior-a specified approach. *Earth Science*, *2*(1), 9–13.

Monserrat, S., & Rabinovich, A. B. (2006). Meteotsunamis: Atmospherically induced destructive ocean waves in the tsunami frequency band. *Natural Hazards and Earth System Sciences*, *6*(6), 1035–1051. doi:10.5194/nhess-6-1035-2006

Mott, M. (2005). Did animals sense tsunami was coming. National Geographic News, 4.

Mott, M., & Systems, T. W. (2005): Lessons from Japan. National Geographic. Retrieved from http://news.nationalgeographic.com/news/2005/01/0104050104tsunamianimals:html

Mulia, I. E., Asano, T., & Nagayama, A. (2016). Real-time forecasting of near-field tsunami waveforms at coastal areas using a regularized extreme learning machine. *Coastal Engineering*, *109*, 1–8. doi:10.1016/j.coastaleng.2015.11.010

Nair, M. C., Maus, S., Neetu, S., Kuvshinov, A. V., & Chulliat, A. (2010, December). The magnetic fields generated by the tsunami of February 27, 2010. In *AGU Fall Meeting Abstracts*.

Rediff News. (2016.). An impending quake caused whale beaching in TN. Retrieved from http://www.rediff.com/news/report/an-impending-quake-caused-whale-beaching-in-tn/20160122.htm

News, B. B. C. (2016). Tsunami Early Detection Systems Across all of Indonesia is Broken. *Indosurflife*. Retrieved from http://indosurflife.com/2016/03/tsunami-early-detection-systems-across-indonesia-broken/

News Now. (2016.). An overhaul of the current Civil Defence structure is on the cards after the Government acknowledged the current network is failing. Retrieved from https://www.tvnz.co.nz/one-news/new-zealand/failure-tsunami-warning-system-after-mondays-quake-sparks-civil-defence-overhaul

OBIS-seamap. Ocean Biogeographic Information System Spatial Ecological Analysis of Megavertebrate Populations. (n.d.). Retrieved from http://seamap.env.duke.edu/

Pacific Tsunami Warning. (2010). Tsunami Bulletin.

Quteishat, A., & Lim, C. P. (2008). A modified fuzzy min–max neural network with rule extraction and its application to fault detection and classification. *Applied Soft Computing*, *8*(2), 985–995. doi:10.1016/j.asoc.2007.07.013

Ramalanjaona, G. (2011). Impact of 2004 tsunami in the islands of Indian ocean: Lessons learned. *Emergency Medicine International*. PMID:22046551

Rckversicherungs-Gesellschaft. MunichRE. (2013) Mnchener. Significant natural catastrophes 1980-2012, 10 deadliest worldwide events Geo Risks Research, NatCatSERVICE. Retrieved from http://mrphillipsibgeog.wikispaces.com/file/view/NatCatSERVICE_significant_dth_en.pdf/437739124/NatCatSERVICE_significant_dth_en.pdf

Red Cross, International Federation of and (IRFC). (2015). Red Crescent Societies. World disasters report. Retrieved from http://ifrc-media.org/ interactive/world-disasters-report-2015/

Red Cross, International Federation of and (IRFC), Red Crescent Societies. (2015). World disasters report: Focus on local actors, the key to humanitarian effectiveness. Retrieved from http://ifrc-media.org/interactive/wp-content/uploads/2015/09/1293600-World-Disasters-Report-2015en:pdf

Reduction, D. UNISDR(United Nations International Strategy for disaster reduction (2005). 10 preliminary lessons learned from the Indian Ocean tsunami of26December2004, http://www.unisdr.org/files/5605ISDR10lessonslearned:pdf

Rikitake, T. (1978). Biosystem behaviour as an earthquake precursor. *Tectonophysics*, *51*(1-2), 1–20. doi:10.1016/0040-1951(78)90048-3

Rosettacode.org. (2012) Haversine formula. https://rosettacode.org/wiki/Haversine_formula

Salamon, A. (2010). Potential tsunamigenic sources in the eastern Mediterranean and a decision matrix for a tsunami early warning system in Israel.

Schaal, R. B. (1988). An evaluation of the animal-behavior theory for earthquake prediction. *California Geology*, *2*(41), 312–323.

Schultz, I. R., Woodruff, D. L., Marshall, K. E., Pratt, W. J., & Roesijadi, G. (2010). *Effects of Electromagnetic Fields on Fish and Invertebrates (No. PNNL-19883). Pacific Northwest National Laboratory*. Richland, WA: PNNL. doi:10.2172/1012305

Seaburn, P. (2015) 160 Beached Whales May Be a Japanese Earthquake Warning. *Mysterious Universe*. Retrieved from http://mysteriousuniverse.org/2015/04/160-beached-whales-may-be-a-japanese-earthquake-warning/

Snarr, K. A. (2005). Seismic activity response as observed in mantled howlers (Alouatta palliata), Cuero y Salado Wildlife Refuge, Honduras. *Primates*, *46*(4), 281–285. doi:10.1007/s10329-005-0151-y PMID:16091980

Sugioka, H., Hamano, Y., Baba, K., Kasaya, T., Tada, N., & Suetsugu, D. (2014). Tsunami: Ocean dynamo generator. *Scientific Reports*, *4*(1), 3596. doi:10.1038/srep03596 PMID:24399356

Suppasri, A., Leelawat, N., Latcharote, P., Roeber, V., Yamashita, K., Hayashi, A., & Imamura, F. et al. (2017). The 2016 Fukushima earthquake and tsunami: Local tsunami behavior and recommendations for tsunami disaster risk reduction. *International Journal of Disaster Risk Reduction*, *21*, 323–330. doi:10.1016/j.ijdrr.2016.12.016

Tatehata, H., Ichihara, H., & Hamano, Y. (2015). Tsunami-induced magnetic fields detected at Chichijima Island before the arrival of the 2011 Tohoku earthquake tsunami. *Earth, Planets, and Space*, *67*(1), 185. doi:10.1186/s40623-015-0347-3

Titov, V. V., Gonzalez, F. I., Bernard, E. N., Eble, M. C., Mofjeld, H. O., Newman, J. C., & Venturato, A. J. (2005). Real-time tsunami forecasting: Challenges and solutions. In *Developing tsunami-resilient communities* (pp. 41–58). Springer Netherlands. doi:10.1007/1-4020-3607-8_3

Tiwari, R., & Tiwari, S. (2011). Animals: A natural messenger for disasters. *Journal of Natural Products*, *4*, 3–4.

Treehugger. (2011). Can Whale Strandings Help Predict Earthquakes? Retrieved from https://www.treehugger.com/natural-sciences/can-whale-strandings-help-predict-earthquakes.html

Tricas, T. (2012). *Effects of EMFs from undersea power cables on elasmobranchs and other marine species*. DIANE Publishing.

Tyler, R. H. (2005). A simple formula for estimating the magnetic fields generated by tsunami flow. *Geophysical Research Letters*, *32*(9), L09608. doi:10.1029/2005GL022429

Ulutas, E., Inan, A., & Annunziato, A. (2012). Web-based tsunami early warning system: A case study of the 2010 Kepulaunan Mentawai earthquake and tsunami. *Natural Hazards and Earth System Sciences*, *12*(6), 1855–1871. doi:10.5194/nhess-12-1855-2012

United Nations Environment Programme (UNEP) Global Environmental Alert Service (GEAS). (2012). Early warning systems: A state of the art analysis and future directions. In Environmental Development (pp. 136-171).

United Nations International Strategy for disaster reduction (UNISDR). (2006). Global Survey of Early Warning Systems. Retrieved from http://www.unisdr.org/2006/ppew/info-resources/ewc3/Global-Survey-of-Early-Warning-Systems.pdf

Virmani, D., & Jain, N. (2016, September). Intelligent information retrieval for Tsunami detection using wireless sensor nodes. In *2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI)* (pp. 1103-1109). IEEE.

VoaNews. (2011): Tsunami Warning Systems: Lessons from Japan. Retrieved from https://www.voanews.com/a/tsunami-warning-systems-lessons-from-japan-118017249/167190.html

Walker, M. (2012). Toads can 'predict earthquakes' and seismic activity. *BBC News*. Retrieved fromhttp://news.bbc.co.uk/earth/hi/earth_news/newsid_8593000/8593396.stm

Waltham, T. (2005). The Asian Tsunami disaster, December 2004. *Geology Today*, *21*(1), 22–26. doi:10.1111/j.1365-2451.2005.00495.x

Wei, Y., Cheung, K. F., Curtis, G. D., & McCreery, C. S. (2003). Inverse algorithm for tsunami forecasts. *Journal of Waterway, Port, Coastal, and Ocean Engineering*, *129*(2), 60–69. doi:10.1061/(ASCE)0733-950X(2003)129:2(60)

Yamauchi, H., Uchiyama, H., Ohtani, N., & Ohta, M. (2014). Unusual animal behavior preceding the 2011 earthquake off the Pacific Coast of Tohoku, Japan: A way to predict the approach of large earthquakes. *Animals (Basel)*, *4*(2), 131–145. doi:10.3390/ani4020131 PMID:26480033