Back to the Future:
Gaining New Perspective on Hurricanes through Data Rescue and Environmental Seismology

by

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Contents

List of Figures

Past and Future Hurricanes

In early August 2014 Hurricane Iselle, a Category Four storm, was barreling west across the Pacific and making a beeline for the Big Island of Hawai‘i. In Hilo, news coverage had been warning of danger from the approaching storm for days. I remember creating crisscross patterns of duct tape on the windows of my childhood home in Hilo while my mother checked and double-checked our two weeks of emergency supplies. However, I also distinctly recall the sharp contrast between my family's reaction and that of many older folks in town. The typical unworried attitude amongst older members of the community stemmed from experiences of other hurricanes on the Big Island and the belief that they invariably turned away; this was just the way it was, the way it had always been.

Iselle kept on coming, but, luckily for all of us on the island, it weakened to a tropical storm by the time it made landfall. Nonetheless, it was an unprecedented event. It was the strongest storm to make landfall on the island in recorded history, and it brought over 12 inches of rain to Hilo and winds that gusted to 90 miles per hour atop Mauna Kea. Between de-roofed houses, widespread power failures, and devastation of crops, Iselle did over $125 million in damages. Experiencing the storm itself was significant, but what was especially striking to me was the difference in reactions along generational lines, highlighting rapid change brought by a changing climate and the increased uncertainty which accompanies it.

Of course, because climate change is a global phenomenon, it's not just Hawai‘i which is facing this uncertainty, but rather every coastal city on Earth. Just in the United States, 127 million people—more than 40% of the population—live in coastal counties and cities vulnerable to hurricanes and the havoc they can wreak (*Cutter et al.*, 2007). The frightening

Figure 1: (left) Satellite image of Hurricane Iselle as it moved west across the Pacific towards Hawai‘i. Image credit: *NASA Earth Observatory.* (right) Locals surveying damage and downed trees on the Big Island of Hawai‘i after Hurricane Iselle. Image credit: *Honolulu Star Advertiser.*

prospect of the next Katrina or Sandy drives many efforts to increase public awareness and build more resilient communities, and climate change is only increasing the sense of urgency (*Knutson et al.*, 2021). However, these preparations are made more difficult by uncertainties over how exactly hurricane behaviors are changing (*Walsh et al.*, 2016): Are they getting more frequent? Longer? Stronger? Affecting different areas? Or some deadly combination of these?

At the most fundamental level, understanding changes in hurricane behavior is approached through looking for trends, that is, reviewing historical hurricane activity and looking for differences from decade to decade. The most definitive historical record of hurricane activity is the National Oceanic and Atmospheric Administrations Hurricane Database, or HURDAT, which covers activity in the Atlantic Ocean from 1851 to present (*Landsea et al.*, 2015). Naturally, due to the long time span covered, HURDAT is compiled using data from a variety of sources and observation methods. Generally, the observations can be split into two broad eras: the era of satellite observation starting in the 1960s and 1970s and the pre-satellite era during which the dominant source of data is ship logs.

Satellite data was a revelation for meteorologists and storm watchers. Prompted by NASA's needs for high-accuracy weather forecasts to determine safe launch windows for the space program, the first weather satellite was launched in 1960. By the end of the decade, the Television Infrared Observation Satellite program had launched nearly a dozen satellites, and no hurricane anywhere on Earth was going to escape their combined fields of view. This sharply contrasted with the state of observation in the preceding decades. Without an eye in the sky, the only way to know of the existence of a storm was if it approached shipping lanes and caught some hapless vessel in the strong winds, driving rain, and rolling seas. Reports from this ship would allow for diversion of other shipping to avoid the storm, improving overall safety. However, because shipping lanes only cover a fraction of the vast ocean, it is likely that some storms were never encountered by a ship and are thus missing from the record (*Vecchi and Knutson*, 2008).

Concerns surrounding completeness of the record in the pre-satellite era have prompted several HURDAT reanalysis efforts. These studies conducted more thorough searches of historical weather data not previously incorporated into HURDAT and made adjustments that accounted for the calibration of historical meteorological equipment, revealing several previously unrecorded storms (e.g., *Landsea et al.*, 2015). Even so, the great majority of observations are from ships and thus highly dependent on historical trade routes. For example, more storms were observed in the Caribbean when more shipping started traveling through the area after the Panama Canal opened in 1914 (Figure 2). Studies analyzing the biases based on the density of these ship tracks indicate that a few storms per year are still likely

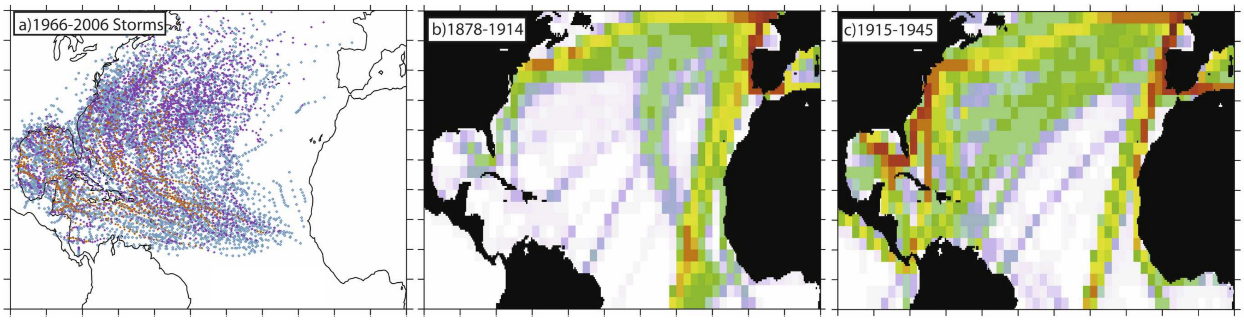

Figure 2: (left) The tracks of all storms in the Atlantic from the satellite era, 1966 to 2006. (middle) Locations where observations of storms were made in the period from 1878 to 1914, prior to the opening of the Panama Canal. Areas with warmer colors (red) have more observations and those with cooler colors (blue) have fewer observations. White areas have no observations. (right) Same as the previous panel for the period from 1915–1945 after the opening of the Panama Canal. Note the greater density of observations in the Caribbean. All modified from *Vecchi and Knutson* (2008)

missing during the first half of the 20th century (e.g., *Vecchi and Knutson*, 2008).

A few missing storms per year may not seem significant, especially if they were small or far out to sea. However, consider that, on average, about ten storms develop each year in the Atlantic and Gulf of Mexico, and a few missing storms a year adds up to quite a significant error of 10–20%. This level of uncertainty becomes particularly worrying in the context of defining a baseline behavior for oceanic storms during the early part of the 20th century, prior to the marked acceleration of warming in the 1970s. For example, missing data prior to the 1970s may result in falsely attributing an increase in the number of storms after this time to a changing climate rather than to issues with catalog completeness. Therefore, among climate modelers, there is motivation to seek out novel data which can complement historical catalogs and increase catalog completeness, thereby increasing the certainty in both historical trends of storm activity and predictions for future storm behavior. Perhaps surprisingly, a prime candidate for such a data source is the collection of historical archives of seismologic recordings, that is, ground motion data. If successful, use of these records to study hurricanes could represent a win-win for climate scientists and seismologists looking to secure resources for data rescue.

More Than Just Earthquakes

When people hear that someone is a seismologist, their minds tend to jump to earthquakes. This is not unwarranted; the detection and characterization of earthquakes is indeed the bread and butter of seismologists. However, because one can never know when an earthquake may strike, ground-motion data is continuously recorded all over the world and has been since the late 1800s (*Richards and Hellweg*, 2020).

As a result of constantly monitoring the way the ground moves, seismologists record not only earthquakes, but many other signals related to both natural and anthropogenic phenomena. Any process that takes place on Earth wherein force is applied to the ground can be recorded on a seismometer. This broader view of seismic data as a “pulse of the Earth” means that all sorts of processes may be studied by looking at seismic records. On the anthropogenic side, football fans celebrating a touchdown can be distinguished from dancing concertgoers (*Malone et al.*, 2015), reductions in road and foot traffic can be used to assess COVID lockdown compliance (*Lecocq et al.*, 2020), or the size of nuclear explosions can be calculated (*Gutenberg*, 1946). On the natural side, vibrations from volcanic eruptions can be used for monitoring (*Shelly et al.*, 2007), wind causing trees to sway and water flowing through rivers can be quantified (*Smith and Tape*, 2019), and glacier calving can be detected (*Amundson et al.*, 2008). Among all of these, one of the earliest and most prevalent nonearthquake signals to catch the eye of seismologists was a nearly constant background motion with fairly coherent and consistent shape, dubbed “microseism” (*Gutenberg*, 1931).

It was not long before seismologists linked microseism to low-pressure weather systems over the ocean, i.e., oceanic storms (*Lee*, 1935). However, there was debate over how exactly a storm over the ocean was generating signals recorded on land, sometimes thousands of miles away. Perhaps the most commonsense explanation was the initial one: ocean waves stirred up by storms were crashing against steep coasts and causing the Earth to shake (*Gutenberg*, 1931)—after all, anyone standing near a steep cliff with the roaring sea below can certainly attest to the slightly disconcerting but regular shaking caused by the breaking waves. While this explanation had its proponents, observations of microseism in places where there were no cliffs and waves tended to gently lap up on beaches with gradual slopes necessitated a revision or expansion of this theory. These changes came about when it was recognized that ocean waves transferred their energy to the solid Earth in any sufficiently shallow water, rather than only at steep cliff faces (*Longuet-Higgins*, 1950). In this new theory, transfer of energy from ocean to Earth is achieved through pressure variations at the seafloor. While seemingly less intuitive than waves crashing on the shore, this mechanism is also quite elegant. Imagine the increase in pressure you feel when diving into a swimming pool, even under just a few feet of water. Similar to this phenomena, the change in the amount of water from wave trough to crest above a point on the seafloor is enough to cause the Earth to “feel” the pressure pulse, a signal that travels through the ground and is subsequently recorded on land as microseism.

With this understanding of how ocean waves transfer energy into the Earth, all sorts of parameters could be investigated. Changes in microseism reflect changes in the shape of ocean waves, that is, their height and their frequency—how many oscillations occur in one second. Additionally, networks of seismometers spread around the world allow for assessment of the global distribution of these changes. Thus, seismic data can be used to paint a picture not only of the global ocean wave climate, but how it has changed over decades (*Aster et al.*, 2008). Other processes which change ocean wave behavior such as ice coverage (*Grob et al.*, 2011), and hurricanes (*Ebeling and Stein*, 2011) have also been effectively investigated using microseism.

Studies on the sensitivity of microseism to oceanic storms have had a history of boom, bust, and boom. Spurred on by military interest in more accurate wave and weather forecasts to facilitate amphibious landing operations during the Second World War, identifying distant storms using microseism was a topic of great interest during the 1940s and 1950s (*Leet*, 1949). At this time, microseism were seen as having great potential as a more cost-efficient and longer-ranged alternative to expensive and line-of-sight-limited aerial weather reconnaissance conducted by long-range patrol planes leftover from the war. However, these microseism analyses were somewhat limited by the methods of the day for extracting frequency[1] information. Because the frequency of the microseism—i.e., how much of a wave passes (or how many waves pass) by a fixed point in the time span of one second—is related to the shape of the related ocean waves, it is a crucial parameter for characterizing microseism and hence storm behavior. Efficient ways of extracting frequency information were not developed until the late 1960s (*Cooley and Tukey*, 1965), and even then, widespread and systematic use would have to wait for computational developments to catch up. By this time, satellite observation was widespread and the identification of storms via microseism

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[1] Here, and throughout the rest of this essay, we shall understand frequency to be the characteristic of a wave (whether seismic or oceanic) measured in Hertz, number of oscillations per second, rather than the more general meaning of how often an event occurs.

was seen as both archaic and unnecessary.

Today, microseism studies are seeing something of a renaissance. Modern signal processing techniques and computer analysis have allowed new levels of details to be extracted from the pulse of the ocean represented by microseism. Not only can microseism observe storms and sea ice when cloud cover or darkness stymies satellite observation, but the fact that the microseism is physically coupled to the ocean allows greater detail resolution to be achieved on both global and local scales (*Gerstoft and Tanimoto*, 2007). For example, while satellites can determine the visible extent of a storm, microseism allows for assessment of the strength of the winds and waves within. Additionally, with climate change and the nature of its effects an ever-present and often-inscrutable question in science, many have recently seen a golden opportunity to examine physical processes related to climate change using long-running analysis of microseism (Figure 3). In particular, changes in ocean waves over time have been investigated at global scale with digital seismic data which dates back to the 1980s (*Aster et al.*, 2008), as well as on local scale using select rescued paper data from a station in California dating back to the 1930s (*Bromirski*, 2023).

This resurgence in microseism research has increased both the level of detail with which processes are viewed and the temporal scope over which they are investigated. However, the particular gap of applying modern processing to oceanic storm microseism from historical recordings has yet to be bridged. This is likely the result of two salient challenges, both of which arise out of the nature of the data. First, the level of detail that older instruments were capable of recording must be determined in order to determine what type of modern computational analyses can be supported. Second, while analyses will take advantage of decades of advances in computers and signal processing, they should be possible to perform

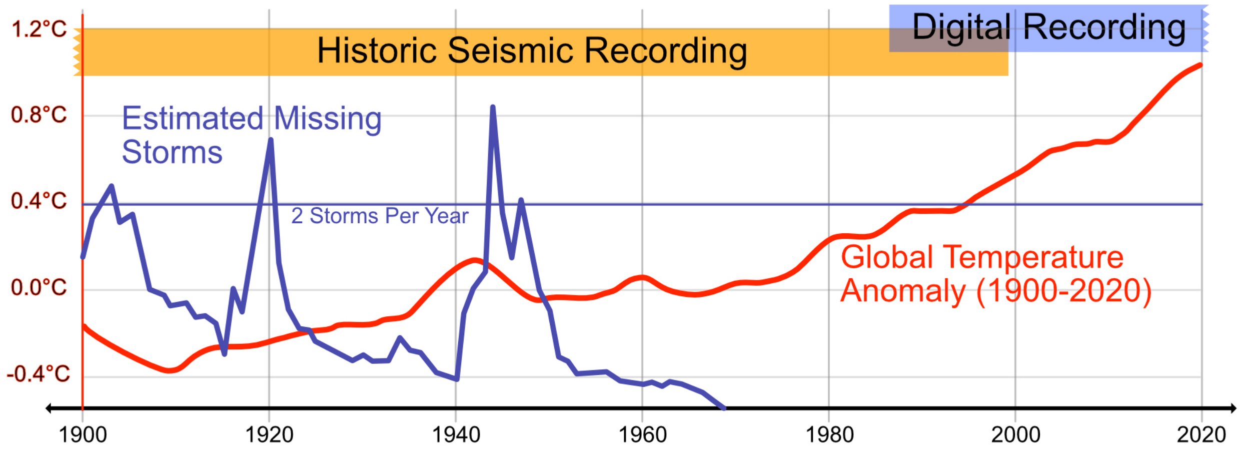

Figure 3: Timeline showing the eras of historical and digital seismic recording as well as the global average surface temperature anomaly (red) and the estimated number of storms missing from historical catalogs (blue) estimated by *Vecchi and Knutson* (2008). Note the acceleration of warming seen after 1970, and the coverage of times where storms may be missing by historical seismic data.

with just a single station and be based on first principles because old data may be sparse and its fidelity unclear.

Can Old Data Do New Tricks?

To understand how the detail recorded in seismograms has changed over the years, one must first understand how the data was recorded and how methods for doing so have evolved. In most basic form, a seismometer is a large mass suspended in a frame. When the ground moves, momentum causes the mass to stay in place while the frame moves with the Earth. Measuring how the position of the mass changes with respect to the frame is analogous to a measurement of how the Earth is moving (Figure 4). Isolating a mass from the Earth itself is a theoretically beautiful and elegant concept. In a perfect instrument, the mass would magically float in the exact same position, completely independent of its surroundings, remaining unaffected as the Earth and frame moved around it. However, in the real world, the mass must be suspended via a physical connection, most typically a spring or system of springs. Imagine holding a spring with a bowling ball hanging from the end of it; if you rapidly move your hand up and down, the ball will remain stationary, but if you move slowly enough or far enough the ball will move with you. A seismogram is imperfect in exactly the same way. Much work has been undertaken in the century since the beginning of instrumental seismic recording to reduce this imperfection as much as possible. In particular, leaps and bounds of progress have been made in developing more effective ways of both isolating the mass from the frame and measuring its motion (*Dewey and Byerly*, 1969). The main result of the decades of progress in seismic instrumentation is what is referred to as a broadband response (*Steim*, 1986). This means that a seismometer will faithfully record motion at a very wide range of frequencies, i.e., rapid (high frequency) oscillations will not be any more or less amplified in the recording than slower (low frequency) oscillations.

To characterize storms using microseism, it is crucial to accurately measure the frequency of the microseism oscillations; the microseism frequency is related to the frequency of the ocean waves and to the speed of wind generated by a storm. Therefore, before undertaking such characterizations with historical data, it is of paramount importance to understand how the non-broadband response exhibited by historical instruments may affect the data. In short, one must understand how ground motion at different frequencies is recorded on historical instruments in comparison to modern instruments. To determine this, one ideally would have both a modern and historical instrument recording in the exact same place at the exact same time. In this situation, determining the frequencies for which historical

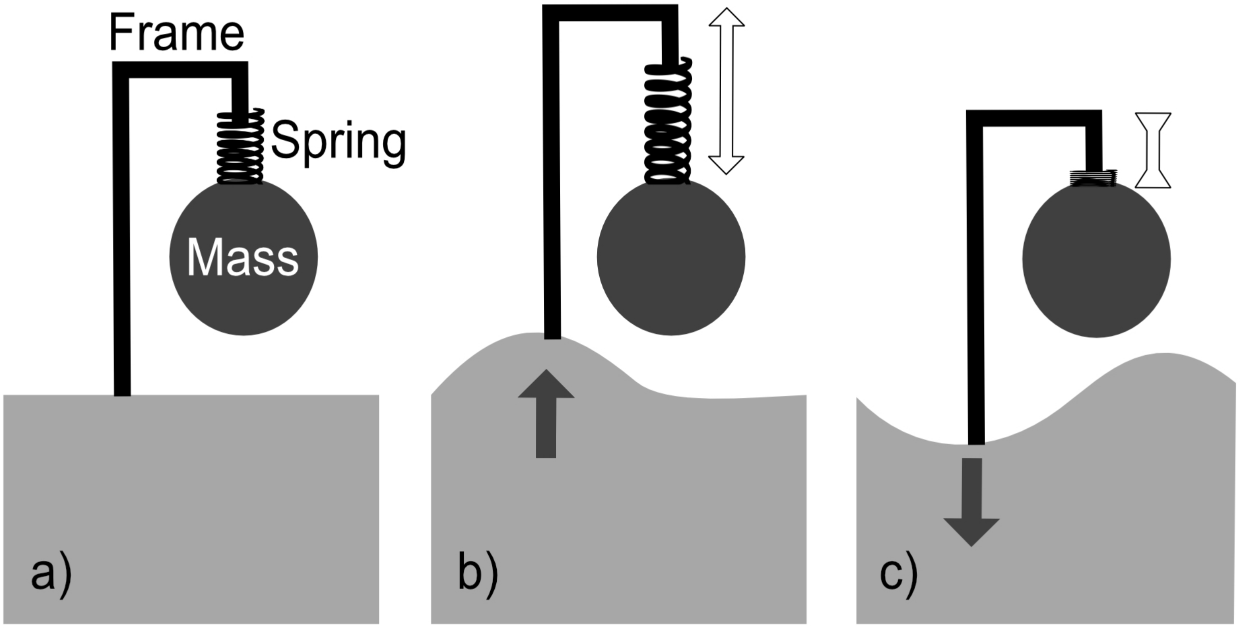

Figure 4: (a) Diagram of a simple seismogram with a mass suspended from a frame by a spring. (b) Upwards ground motion moves the frame up (gray arrow), and the spring extends as the mass stays in place (white arrow). (c) Same as (b) for downwards ground motion. Note the increase in the distance from frame to mass from (a) to (b), and the decrease from (b) to (c).

instruments are robust would simply be a matter of comparing the recordings from the two instruments side by side.

While having operational historical instruments, let alone operating them alongside modern instruments, sounds far-fetched, such a setup is not nonexistent. One of the rare places in the world where this occurs is in the small one-room museum of the Albuquerque Seismological Laboratory (ASL) where a full set of operational half-century-old instruments sit. After finding a few staff scientists at the ASL open to the challenge of figuring out how to get a computer to read output from an instrument made in the 1950s[2], I made a trip to

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[2] I extend my thanks Dr. Adam Ringler and Dr. Robert Anthony for their enthusiasm and help.

Albuquerque to put a modern instrument alongside the historical seismometers and record several weeks of data.

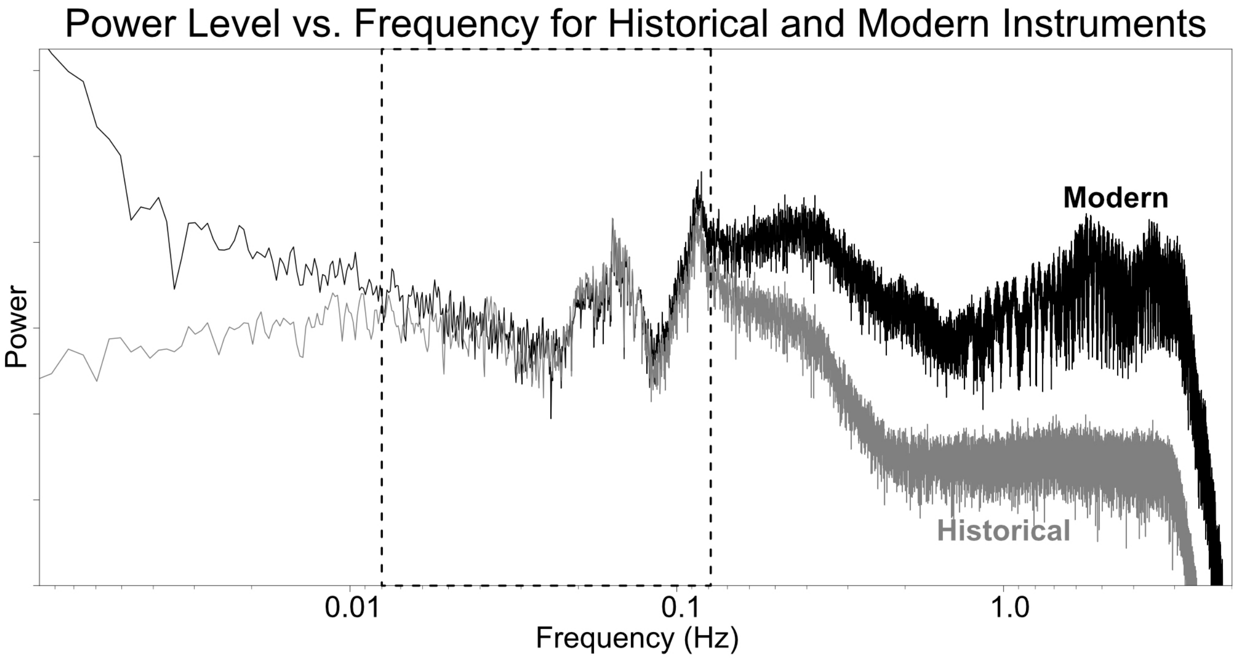

Figure 5: Seismic power at different frequencies for both a modern instrument (black) and a historical instrument (gray) recording at the same time. The area in which the two instruments agree, i.e., record ground motion in the same way, is bounded by the dashed lines.

Analyzing the data that came from this experiment allowed me to directly address the robustness of the historical instruments. Both instruments were subjected to exactly the same ground motion. Therefore, for frequencies where the historical instrument is robust, the two recordings should look identical. Examining the power levels at different frequencies of motion in the two recordings revealed that these instruments agree well between frequencies of 0.03 Hz and 0.3 Hz (Figure 5). Crucially, ocean swell and the microseism that arises from it have frequencies of between 0.05 Hz and 0.2 Hz, within the range where data from historical instruments can be trusted.

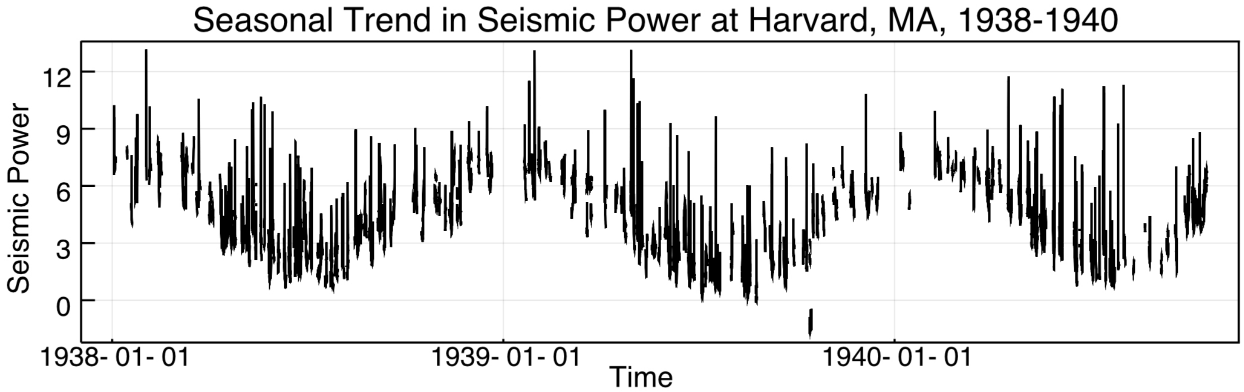

Figure 6: Seismic power extracted from digitized historical records from Harvard, MA, from 1938 to 1940. Note the increase in power observed during the winter months caused by higher microseism levels that result from the stormy North Atlantic.

In addition to challenges related to instrument behavior, working from legacy seismic data involves complications arising from the transfer of data from a physical media, i.e., large-format photographic paper, to a digital format readable by computers (*Richards and Hellweg*, 2020; *Ishii and Ishii*, 2022). While the field of legacy seismic data rescue faces several challenges including funding, standardization, and distribution (*Hwang et al.*, 2020), several collections of scanned—and in rare cases digitized[3]—seismograms do exist.

The collection of seismograms that covers the 1933 to 1954 operations of the Harvard Seismographic station in Harvard[4], MA, is among those scanned archives with significant portions digitized[5](*Ishii et al.*, 2015). Because this data is already in a format readily readable by computers, an initial analysis to verify sensitivity to the microseism can be made. Being located in the Northeast, the station at Harvard should be sensitive to the seasonal

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[3] In legacy seismic data rescue, scanning refers to obtaining a digital image of a paper seismogram, whereas digitizing refers to tracing lines from the images to get digital data representing ground motion as a function of time.

[4] Perhaps confusingly, a small town located about an hour west of Cambridge, MA.

[5] I would like to thank Hiromi Ishii whose tireless efforts were indispensable in scanning and digitizing data from Harvard.

patterns of waves in the North Atlantic Ocean. Namely, the stormier winters should result in higher microseism levels than in the summers. I assessed the seasonal microseism level by calculating the seismic power for each day of digitized data for 1938 through 1940. This analysis revealed a strong seasonal trend (Figure 6), verifying the sensitivity of the legacy data to microseism and the ocean. In other words, the signals are there, and the remaining piece is the development of analytical tools to parse them.

A First-Principles Microseism Model

As opposed to the multinational global standardized seismic networks of today, historical data were generally recorded at independent seismological observatories. As a result, these data typically remain archived with these independent operators, meaning it is relatively easy to obtain large chunks of data for a single station, e.g., data from Harvard. However, significant complexity is added to data rescue efforts when other stations and archives are considered. Thus, a first-principles analysis, which can be considered at a single station, is crucial in efforts to analyze historical microseism. In this way, early efforts can be undertaken with data from a single station. Later, when momentum for data rescue has been built up and resources to involve more archives have been obtained, greater resolution will be gained from multiple-station analysis. Additionally, by illustrating the minimum of complexity needed to characterize microseism storm responses, this first-principles analysis will highlight the most important factors at play in a complex system of atmosphere-ocean and ocean-Earth interactions.

In simplest form, modeling microseism involves representing the transfer of energy from

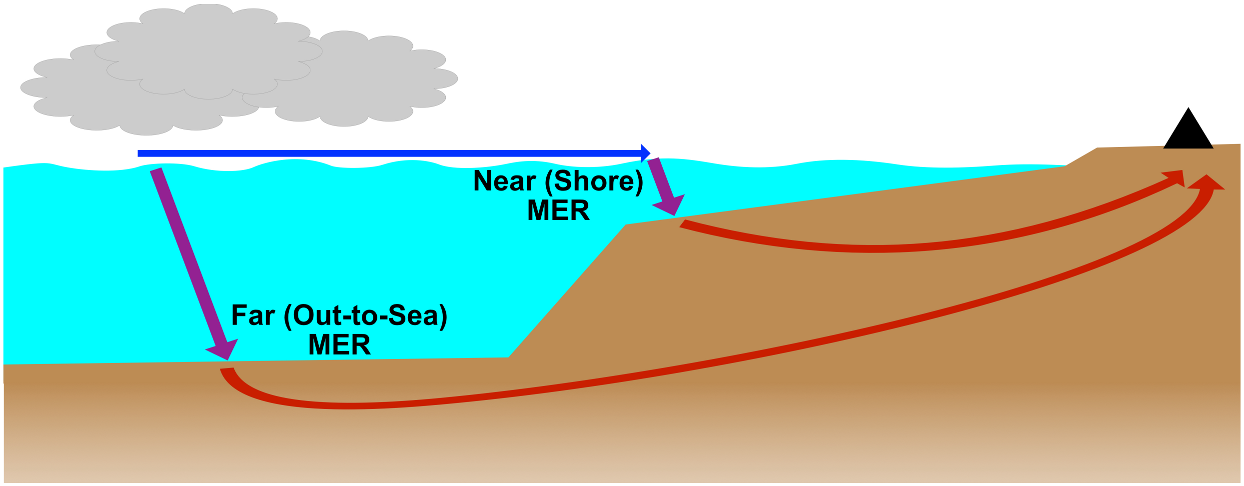

Figure 7: Cartoon showing the possible paths of energy from an oceanic storm (gray cloud) to a seismic station on land (black triangle). Energy can travel as oceanic swell (blue arrow), as vertical pressure pulses connecting the sea surface to the solid Earth (purple arrow), and as seismic waves (red arrow). Points where energy from the ocean is transferred to the solid Earth are marked as a Microseism Excitation Region (MER).

wind in a storm to swell in the ocean, and then again to seismic waves in the Earth. There are two general pathways which this energy can take (Figure 7), and both are considered here. In both these pathways, winds from the storm whip up ocean waves, and energy from these ocean waves causes pressure variations at the seafloor which transfer the energy into the Earth. The two pathways differ in where the transfer of energy into the Earth occurs. In the first pathway, referred to here as the far Microseism Excitation Region (MER), energy travels straight down to the seafloor below the location of the storm and then travels as seismic waves. In the second pathway, referred to here as the near MER, the energy travels as oceanic swell along the sea surface for some time before transferring to the solid Earth at some location between the storm and the coast, e.g., the continental shelf or in shallow water near the shore. Characterizing how energy propagating via these two paths manifests itself at a seismic station is crucial to understanding the effects of these different paths.

My first-principles microseism model uses fundamental relationships that govern the propagation of ocean waves and seismic waves to predict what the microseism signal observed at a seismic station will be, based on the maximum windspeed and storm track for a storm. In particular, based on the maximal windspeed of a storm at a given time, the model calculates the speed of the ocean waves. To do this, the speed ratio between wind and rain is required. For example, a speed ratio of 0.3 would mean that the waves travel at 30% the speed of the wind. Combining this information with the known location of the storm and the seismic station along with seismic wave speed allows for the calculation of the total time it takes for the energy to go from storm to station for both pathways. For the far MER, this simply involves calculating the distance from the storm to the station and dividing that by the speed of seismic waves. For the near MER, it involves computing the total length of time it takes to travel two legs: first, the ocean waves to travel towards the seismic station until they reach the point where the depth of the ocean is 50 meters; second, they travel the remaining distance to the station as seismic energy.

Because the speed and frequency of oceanic waves are fundamentally related (*Ardhuin and Orfila*, 2018), the frequency can also be calculated from the speed of the ocean waves. Combining this information with the time of arrival at the station (calculated earlier) means that a prediction can be made for when microseism of a given frequency will be observed. Additionally, by working under the assumption that waves with greater height are generated by stronger wind (*Fry*, 1967), a prediction of what the microseismic power is can be made by scaling the magnitude of the predicted observations with the strength of the wind from which they originated.

Telling the Story of a Storm

As with any model, it is prudent to make sure the results are reasonable before using it to make any conclusions about the real world. Therefore, before the first-principles microseism model is applied to historical data, I tested it to make sure that its predictions capture the main features of microseism observed in the real world. For this study, doing so means using modern microseismic and hurricane data where there are relatively few uncertainties in either the behavior of the instruments or the storms themselves. In particular, I obtained storm data for the Atlantic from HURDAT (*Landsea et al.*, 2015) and seismic data from the modern seismic station in Harvard, MA, for the time span from 2010 to 2022. There are almost 250 storms in this record, and using the first-principles model, I calculated the microseismic prediction for each of these and compared them to the observations at Harvard. Crucially, this work also allows us to map what the wind and ocean wave speed ratios are at different locations.

To understand the overall results of applying the model to modern data, it is helpful to consider a single storm. Hurricane Arthur of 2014 is an ideal candidate for this demonstration because of its proximity to the U.S. East Coast, relatively high strength, and temporal separation from other storms (Figure 8a); if the model cannot predict the microseism response from Arthur successfully, there is little point in going further. The observations of microseism from Hurricane Arthur should be examined before comparisons are made to predictions from the model. I extracted both the frequency and the power of the microseism as a function of time from the seismic data recorded at Harvard (Figure 10b,c). The frequency slowly decreases and the power slowly increases starting about July 2nd, which continues for several days. This is followed by a sharp increase in power and decrease in frequency

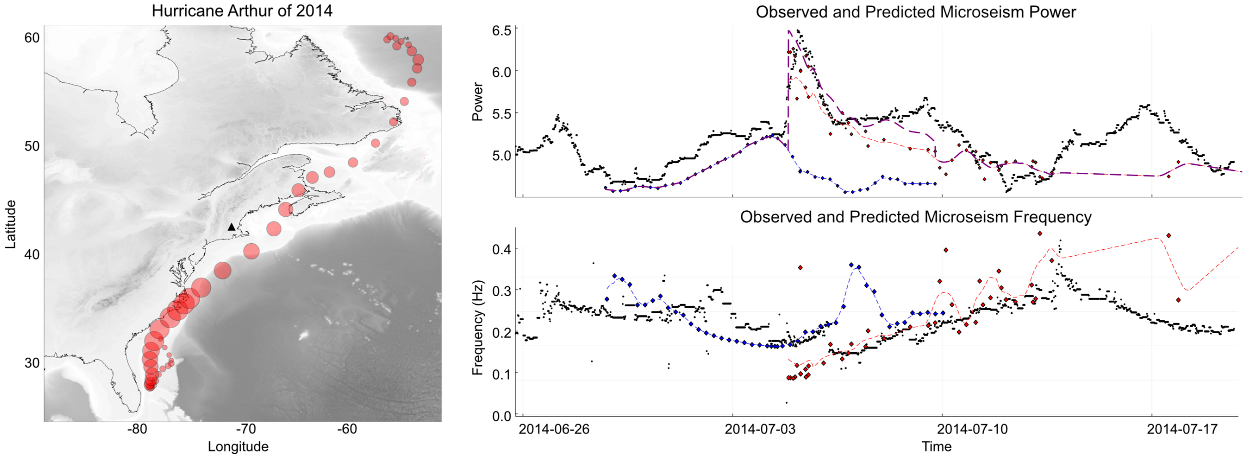

Figure 8: (left) Map showing the track of Hurricane Arthur (red circles) and the location of Harvard, MA (black triangle), over topography and bathymetry, i.e., ocean depth, of the U.S. East Coast. The strength of the hurricanes is indicated by the size of each red circle. (top right) Observed power of microseism at Harvard from Hurricane Arthur (black), the prediction of microseism generated with the far MER (blue markers and line) and near MER (red diamonds and line), and the combination of the two predictions (purple line). (bottom right) Same as the previous panel for the frequency of the microseism. Note that the predictions are not combined for the frequency, because while power is summative, frequency is not.

taking place on July 5th. Consequently, the power decreases and the frequency increases back towards baseline with a rate of change similar to the initial changes.

Running the microseism model yields a wind-to-wave-speed ratio of about 0.3. Overlaying the resultant microseism frequency and power predictions onto the observations reveal a close match (Figure 8b,c) with the near and far MER explaining different parts of the observations. The far MER explains the gradual decrease in frequency and increase in power initially seen; the near MER prediction has a lot of energy arriving at once and causing the sudden decrease in frequency and increase in power seen on July 5th. The difference between the two MERs is largely due to differences in speed of ocean waves and seismic waves. Ocean waves are much slower, and therefore the energy reaching the station via the near MER is delayed and overlaps itself as a result of movement of the storm and differences in speed arising from the increasing windspeed. Additionally, the relative contributions from the two MERs that yield the closest match to the observed power when added together are calculated. For Arthur, the contribution from the near MER to the observations is 70% and that from the far MER is 30%. Altogether, this result illustrates not only that microseism response can be reasonably modeled for a single station, but also that the model can be used to gain real insight into physical processes, for example the efficiency of generating waves from wind, and the importance of different microseism pathways.

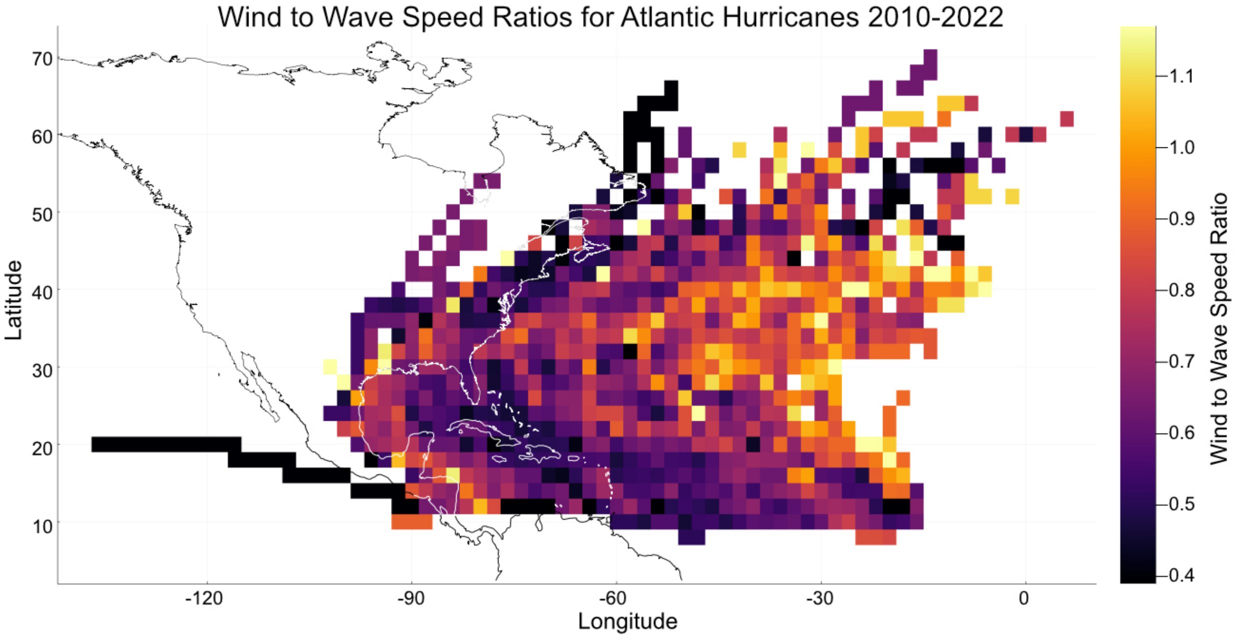

Figure 9: Map showing the variations in the wind-to-wave-speed ratio as a function of geographic location found from analysis of all storms from 2010 to 2022. Note the higher ratio indicating more efficient transfer of energy from atmosphere to ocean in the middle of the Atlantic.

When considering the model fits for all of the storms from 2010 to 2022, two broader patterns in storm behavior that agree well with first-order interpretation of the physical world emerge. First, mapping the wind-to-wave-speed ratio across the Atlantic reveals higher values in the middle of the ocean and lower values close to shore and in the Caribbean (Figure 9). Physically, this can be interpreted as more efficient transfer of energy from atmosphere to ocean in large unobstructed tracts of open sea where there are no landmasses to slow the wind or interrupt the propagation of the newly formed waves. Second, if the relative contributions for the near and far MER are considered, it is found that the most common partitioning is a 75% contribution from the near MER and a 25% contribution from the far MER. This indicates that the near MER is generally more important, and therefore generation of microseism is more common and more efficient at shallower depths, i.e., 50 meters, than in the deep ocean. This again makes physical sense when considering the amount of water that pressure changes have to travel through. If the seafloor is closer to the ocean waves, then the excitation will be more efficient. Overall, the application of the model to modern data not only successfully demonstrates the viability of this simple processing, but also reveals information about the physics of the natural world that can be used to improve future iterations of the analysis.

Opening New Doors to the Past

Having developed a model which is compatible with a single station, and verified that historical data from that station is sensitive to microseism, the exciting work of bringing together these two components can be undertaken. As a first step, two hurricanes which are currently in the storm catalog from 1938 have been analyzed using records from HRV as the first proof of concept. In particular, I compared Hurricane Three and Hurricane Four[6], both of which

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[6] Naming of tropical cyclones and hurricanes did not officially begin until 1953.

occurred in August of 1938, against all of the available seismic data from Harvard for that month (Figure 10), and observed a close match.

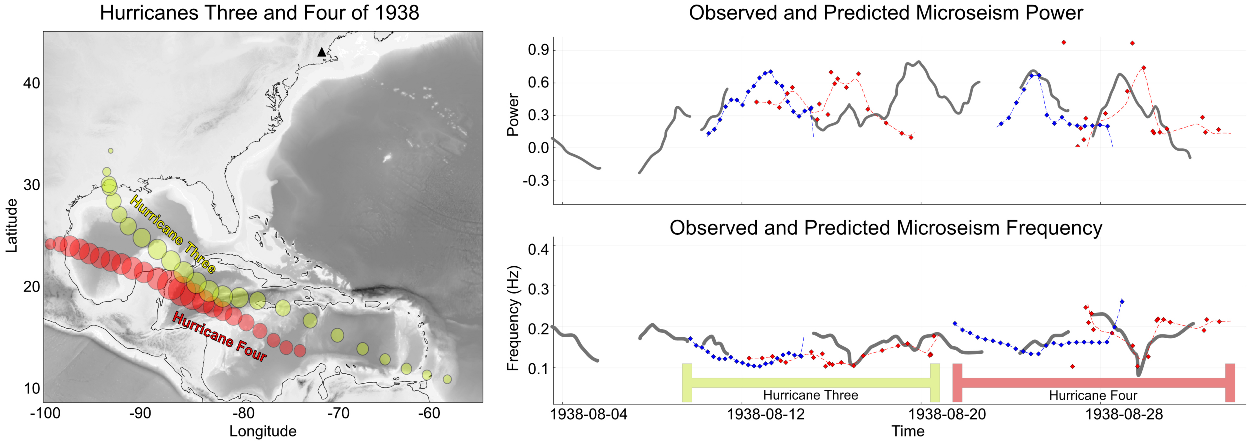

Figure 10: (left) Map showing the tracks of Hurricanes Three (yellow circles) and Four (red circles) of 1938, and the location of Harvard, MA (black triangle), over topography and bathymetry, i.e., ocean depth, of the U.S. East Coast and Caribbean. The strength of the hurricanes is indicated by the size of each red circle. (top right) Observed power of microseism at Harvard from Hurricane Arthur (gray), and the prediction of microseism generated with the far MER (blue markers and line) and near MER (red diamonds and line). Note the gaps in the observations where data was missing. (bottom right) Same as the previous panel for the frequency of the microseism.

There are two notable things about this analysis. First, it is clear that there are gaps in the seismic data. This is because data was either not kept in the first place, or deteriorated to the point of being unrecoverable over the near century over which it was stored (*Ishii et al.*, 2015). Nonetheless, the storm microseism signals are still visible with a few days worth of gaps. If signals are visible even with gaps, the prospects of searching for storms using archives that were better kept are very promising. This is especially true in light of the overall goal of supplementing existing storm catalogs; so long as large gaps on the order of weeks are not present during every window where there is a missing storm, microseism analysis will make a significant contribution. Moreover, statistical analysis of the gaps can be performed to determine the new lower uncertainty for the resultant storm catalogs.

The second notable conclusion involves the model performance. It is important to note that the model was run using the average wind-to-wave-speed ratio for the Caribbean from the 2010 to 2022 analysis. That is, no tuning or fitting of the model parameters to the historical observations was performed. Thus, the good match of the model predictions to the observations is a testament to the applicability of a model tuned on modern data to historical seismic data. Importantly, this also indicates that improvements made to the model using high-fidelity modern data will also improve performance when applied to historical data.

While this analysis only consists of a few storms, it is a good indication that the current model makes up a solid groundwork for future systematic searches for storm signals. By creating lists of storms from historical seismic data and contributing these to the current storm inventories, the overall historical record can be moved towards completion. This promise is not only good news for this particular science question, but also for the preservation of legacy data overall.

Many collections of legacy data are not secure. These data are on large, heavy sheets of paper that make for bulky storage headaches, especially for extensive collections where seismograms can number in the millions. Naturally, storage costs are not insignificant. Thus, many archives lead a tenuous existence, where the uncertainty of scientific funding means the risk of having to throw out data is always lurking around the corner (*Hwang et al.*, 2020). Studies of uniquely large earthquakes (e.g., *Kanamori and Cipar*, 1974) and nuclear tests (e.g., *Gutenberg*, 1946) recorded only on historical data have long been the main use cases for these records. However, because these are relatively short-lived discrete events, discussions of triage in the form of throwing out any records without nuclear or earthquake signals have been common (*Richards and Hellweg*, 2020). This work provides evidence that all of the data—given that microseism is an ever-present signal—can be used to answer scientific questions relevant to the existential threat of climate change (*Walsh et al.*, 2016). Not only does this make a case for wholesale preservation of this valuable quantitative record, but also shows its utility in making contributions to solving problems that guide funding decisions (National Academies of Sciences Engineering et al., 2020).

While demonstrating the value of legacy seismic data for improving storm catalog completeness is crucial for giving data-rescue efforts momentum, the impacts of preserving such data are much larger. Seismology is the pulse of the Earth and records many physical processes beyond the earthquakes which it is usually known for. In a similar vein to this study, legacy seismic data can be used to paint a more detailed picture of Nor'easters and wave climate over the past century. It can also be used to constrain groundwater levels (e.g., *Lecocq et al.*, 2017), reanalyze volcanic risk (e.g., *Fehler*, 1983), and reconstruct ocean temperature (e.g., *Wu et al.*, 2020) over similarly long timescales. Having quantitative information that covers such long timescales is crucial to understanding most Earth processes, since they operate over similar periods of time. Certainly, data can slowly be amassed day-by-day by continuing our current observational campaigns into the future, but the rate at which we gain utile data could be massively increased through leveraging the value of historical archives. Decades of critical information is already there, but it has sat stagnant because heretofore we have not had the techniques to extract it.

In short, my work shows the viability of historical seismic data reanalysis for studying problems outside of the traditional scope of seismology. It not only lays a solid groundwork for similar and more systematic future studies, but also opens up a new field at the crossroads of historical and environmental seismology. This new field would acknowledge and take advantage of two facts: first, seismology is a quantitative record of almost all physical processes on Earth; second, it has a remarkably long recording history. If all of the available data were rescued and leveraged against the host of problems which they have relevance to, then seismology, natural science, and society would all benefit. In some ways, this is perhaps a call to a more efficient scientific future—one in which using modern tools to reuse and recycle old data is more commonplace, allowing for extraction of all the knowledge we possibly can from the significant body of work tirelessly acquired over previous generations. And, at the end of the day, all of this means that Marty McFly and Doc Brown were right: the best course forward is to go back to the future.

References

Amundson, J. M., M. Truffer, M. P. Lüthi, M. Fahnestock, M. West, and R. J. Motyka (2008), Glacier, fjord, and seismic response to recent large calving events, Jakobshavn Isbræ, Greenland, *Geophysical Research Letters*, *35*(22).

Ardhuin, F., and A. Orfila (2018), Wind waves, *New Frontiers in Operational Oceanography*, pp. 393–422.

Aster, R. C., D. E. McNamara, and P. D. Bromirski (2008), Multidecadal climate-induced variability in microseisms, *Seismological Research Letters*, *79*(2), 194–202.

Bromirski, P. D. (2023), Climate-induced decadal ocean wave height variability from microseisms: 1931–2021, *Journal of Geophysical Research: Oceans*, *128*(8), e2023JC019,722.

Cooley, J. W., and J. W. Tukey (1965), An algorithm for the machine calculation of complex Fourier series, *Mathematics of Computation*, *19*(90), 297–301.

Cutter, S. L., L. A. Johnson, C. Finch, and M. Berry (2007), The US hurricane coasts: increasingly vulnerable?, *Environment: Science and Policy for Sustainable Development*, *49*(7), 8–21.

Dewey, J., and P. Byerly (1969), The early history of seismometry (to 1900), *Bulletin of the Seismological Society of America*, *59*(1), 183–227.

Ebeling, C. W., and S. Stein (2011), Seismological identification and characterization of a large hurricane, *Bulletin of the Seismological Society of America*, *101*(1), 399–403.

Fehler, M. (1983), Observations of volcanic tremor at Mount St. Helens Volcano, *Journal of Geophysical Research: Solid Earth*, *88*(B4), 3476–3484.

Fry, H. T. (1967), The emergence of the Beaufort scale, *The Mariner's Mirror*, *53*(4), 311–313.

Gerstoft, P., and T. Tanimoto (2007), A year of microseisms in Southern California, *Geophysical Research Letters*, *34*(20).

Grob, M., A. Maggi, and E. Stutzmann (2011), Observations of the seasonality of the Antarctic microseismic signal, and its association to sea ice variability, *Geophysical Research Letters*, *38*(11).

Gutenberg, B. (1931), Microseisms in North America, *Bulletin of the Seismological Society of America*, *21*(1), 1–24.

Gutenberg, B. (1946), Interpretation of records obtained from the New Mexico atomic bomb test, July 16, 1945, *Bulletin of the Seismological Society of America*, *36*(4), 327–330.

Hwang, L. J., T. Ahern, C. J. Ebinger, W. L. Ellsworth, G. G. Euler, E. A. Okal, P. G. Okubo, and W. R. Walter (2020), Rescuing Legacy seismic data FAIR'ly. *Seismological Research Letters*, *91*(3), 1339–1340.

Ishii, M., and H. Ishii (2022), Digitseis: software to extract time series from analogue seismograms, *Progress in Earth and Planetary Science*, *9*(1), 1–16.

Ishii, M., H. Ishii, B. Bernier, and E. Bulat (2015), Efforts to recover and digitize analog seismograms from Harvard-Adam Dziewoński observatory, *Seismological Research Letters*, *86*(1), 255–261.

Kanamori, H., and J. J. Cipar (1974), Focal process of the Great Chilean Earthquake May 22, 1960, *Physics of the Earth and Planetary Interiors*, *9*(2), 128–136.

Kimberlain, T. B., and M. J. Brennan (2015), *HURRICANE ISELLE (EP092014)*, Department of the Commerce, National Oceanic and Atmospheric Administration, National Hurricane Center.

Knutson, T. R., M. V. Chung, G. Vecchi, J. Sun, T.-L. Hsieh, and A. J. Smith (2021), Climate change is probably increasing the intensity of tropical cyclones, *Critical Issues in Climate Change Science, Science Brief Review. https://doi. org/10.5281/zenodo*, *4570334*(4).

Landsea, C., J. Franklin, and J. Beven (2015), The revised Atlantic hurricane database (HURDAT2). United States National Oceanic and Atmospheric Administration National Weather Service.

Lecocq, T., L. Longuevergne, H. A. Pedersen, F. Brenguier, and K. Stammler (2017), Monitoring ground water storage at mesoscale using seismic noise: 30 years of continuous observation and thermo-elastic and hydrological modeling, *Scientific reports*, *7*(1), 14,241.

Lecocq, T., S. P. Hicks, K. Van Noten, K. Van Wijk, P. Koelemeijer, R. S. De Plaen, F. Massin, G. Hillers, R. E. Anthony, M.-T. Apoloner, et al. (2020), Global quieting of high-frequency seismic noise due to Covid-19 pandemic lockdown measures, *Science*, *369*(6509), 1338–1343.

Lee, A. (1935), On the direction of approach of microseismic waves, *Proceedings of the Royal Society of London. Series A-Mathematical and Physical Sciences*, *149*(866), 183–199.

Leet, L. D. (1949), Microseisms, *Scientific American*, *180*(2), 42–45.

Longuet-Higgins, M. S. (1950), A theory of the origin of microseisms, *Philosophical Transactions of the Royal Society of London. Series A, Mathematical and Physical Sciences*, *243*(857), 1–35.

Malone, S., K. Hall, L. Simmons, and J. Vidale (2015), How to recognize a “beast quake” and a “dance quake”, *Seismological Research Letters*, *86*(3), 1006–1008.

National Academies of Sciences Engineering, and Medicine; Division on Earth and Life Studies; Board on Earth Sciences and Resources; and Committee on Catalyzing Opportunities for Research in the Earth Sciences (CORES): A Decadal Survey for NSF’s Division of

Earth Sciences (2020). *A vision for NSF Earth sciences 2020-2030: Earth in time*. National Academies Press.

Richards, P. G., and M. Hellweg (2020), Challenges and opportunities in turning large US archives of analog seismograms into a modern usable resource, *Seismological Research Letters*.

Shelly, D. R., G. C. Beroza, and S. Ide (2007), Non-volcanic tremor and low-frequency earthquake swarms, *Nature*, *446*(7133), 305.

Smith, K., and C. Tape (2019), Seismic noise in Central Alaska and influences from rivers, wind, and sedimentary basins, *Journal of Geophysical Research: Solid Earth*, *124*(11), 11,678–11,704.

Steim, J. M. (1986), *The very-broad-band seismograph*, Harvard University.

Vecchi, G. A., and T. R. Knutson (2008), On estimates of historical North Atlantic tropical cyclone activity, *Journal of Climate*, *21*(14), 3580–3600.

Walsh, K. J., J. L. McBride, P. J. Klotzbach, S. Balachandran, S. J. Camargo, G. Holland, T. R. Knutson, J. P. Kossin, T.-c. Lee, A. Sobel, et al. (2016), Tropical cyclones and climate change, *Wiley Interdisciplinary Reviews: Climate Change*, *7*(1), 65–89.

Wu, W., Z. Zhan, S. Peng, S. Ni, and J. Callies (2020), Seismic ocean thermometry, *Science*, *369*(6510), 1510–1515.