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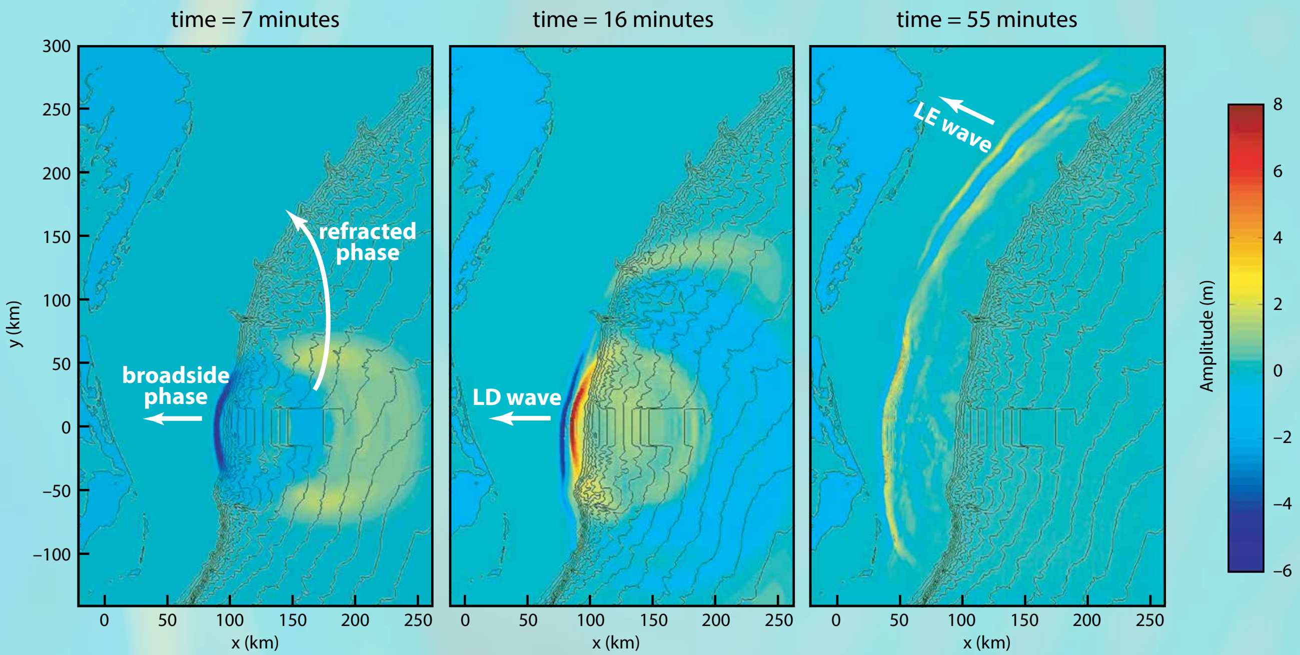
Source Processes for the Probabilistic Assessment of Tsunami Hazards

BY ERIC L. GEIST AND PATRICK J. LYNETT

ABSTRACT. The importance of tsunami hazard assessment has increased in recent years as a result of catastrophic consequences from events such as the 2004 Indian Ocean and 2011 Japan tsunamis. In particular, probabilistic tsunami hazard assessment (PTHA) methods have been emphasized to include all possible ways a tsunami could be generated. Owing to the scarcity of tsunami observations, a computational approach is used to define the hazard. This approach includes all relevant sources that may cause a tsunami to impact a site and all quantifiable uncertainty. Although only earthquakes were initially considered for PTHA, recent efforts have also attempted to include landslide tsunami sources. Including these sources into PTHA is considerably more difficult because of a general lack of information on relating landslide area and volume to mean return period. The large variety of failure types and rheologies associated with submarine landslides translates to considerable uncertainty in determining the efficiency of tsunami generation. Resolution of these and several other outstanding problems are described that will further advance PTHA methodologies leading to a more accurate understanding of tsunami hazard.



Regional wavefield of tsunami from Currituck landslide at three time steps. Evident in this simulation is a secondary wave that refracts up the continental slope and toward shore north of the Currituck landslide. LD wave: Leading depression wave. LE wave: Leading elevation wave. *From Geist et al. (2009)*

INTRODUCTION

Recent events such as the 2004 Indian Ocean and 2011 Tōhoku tsunamis, among many others, have demonstrated the tremendous destructive nature of tsunamis as they impact coastlines. Traditionally, tsunami hazards have been assessed deterministically using the concept of a maximum credible event or worst-case scenario. There is, however, no single accepted way of determining this scenario. In some cases, the physically largest earthquake or landslide is used to assess the tsunami hazard at a coastal site, whereas in other approaches, the largest historical event is defined as the worst-case scenario. Furthermore, the deterministic scenario is created under an implicit assumption of a minimum likelihood, though the likelihood limit is often not explicitly stated. For example, tsunami hazards from asteroid impacts are rarely considered, owing to the long mean return period associated with this source. Finally, uncertainty associated with these scenarios is often not rigorously defined or used in deterministic hazard assessments. To address these problems, tsunami hazards have recently been assessed probabilistically. While these assessments are resource intensive compared to deterministic assessments, they provide a systematic method for defining the hazard for a probability of interest specific to applications such as tsunami preparedness, determining flood insurance rates, and impact on infrastructure.

In contrast to deterministic analysis that estimates the severity of natural hazard as a single value, the primary result from probabilistic analysis is a hazard curve that plots the probability that a given severity will be met or exceeded. The hazard curve can be used in two different ways (Figure 1). The most common application is using a pre-specified design probability to determine the exceedance value at that probability (Figure 1a). For tsunami hazards, the hazard value of interest is typically runup (runup is a measurement of the maximum height of the water that the tsunami pushed onshore observed above a reference sea level; see http://walrus.wr.usgs.gov/tsunami/basics.html), although other impact metrics such as current speed or momentum flux can also be considered. A less common application of the hazard curve is using a pre-specified tolerance level to determine the probability of exceedance from the hazard curve (Figure 1b). For example, engineers may be interested in the probability that a sea wall of a certain height will be overtopped by a tsunami. Finally, probabilistic inundation maps can also be constructed by calculating the hazard at a specific design probability over a given region (González et al., 2009), useful for setting flood insurance rates (e.g., at 1% annual probability of exceedance). With information regarding vulnerability and exposure of a community, hazard curves permit a risk calculation.

Ideally, historical data from a nearby water level station could be used to construct a hazard curve. However, there are few locations in the world where there is a sufficiently long record of tsunami observations. A computational method, termed probabilistic tsunami hazard analysis (PTHA; Geist and Parsons, 2006), is therefore required to construct the tsunami hazard curve. These methods require specifying all relevant tsunami sources that may affect the site, performing numerical hydrodynamic modeling for each source, and aggregating the results to form the hazard curve. In contrast to deterministic analysis, probabilistic analysis directly incorporates different sources of uncertainties into the construction of the hazard curve. In this article, we review the framework of PTHA that was established using just earthquake sources and discuss recent advances in the methodology for including landslide sources.

PTHA FRAMEWORK

PTHA was developed by adapting a long-standing probabilistic method for determining ground motion exceedance caused by earthquakes: probabilistic seismic hazard analysis (PSHA) (Cornell, 1968). The main differences between PSHA and PTHA relate to which sources are considered and how the hazard is calculated for earthquakes and tsunamis. For PTHA, it is important to consider large tsunamigenic earthquakes, including those at far distances, as well as other tsunami sources such as submarine landslides and volcanic processes that can rapidly displace the water column. For PSHA, it is more important to consider a wider range of earthquake magnitudes, including small events, close to the site of interest. For the hazard calculation, empirical attenuation relations are used in PSHA that relate earthquake parameters to ground motion, whereas physics-based numerical hydrodynamic models are used in PTHA so that less uncertainty can be expected, given sufficiently accurate input data. In this regard, PTHA shares some similarities with probabilistic storm surge forecasts that also rely on numerical modeling (e.g., Resio et al., 2009).

There are four basic steps in conducting PTHA (Figure 2, middle): (1) specification of source parameters, including rate of occurrence, (2) choice of probability model that describes source occurrence in time (most often Poisson, as described below), (3) hydrodynamic modeling for each source location and set of source parameters to compute tsunami hazard characteristics at a site, and (4) aggregation of the modeling results and incorporation of uncertainty. It is easy to see, with the number of sources involved and the many possible combinations of source parameters, that the computational load associated with PTHA can become a major obstacle in performing the analysis. There are several methods for decreasing the computational load. First, usually there is a primary parameter, such as earthquake magnitude, that has a dominant effect on the tsunami hazard at a site. Other parameters scale with the primary parameter, reducing the range of parameters that need be considered. In addition, random sampling of possible parameter combinations (Monte Carlo simulation) can decrease the computational workload.

Throughout the analysis, different causes of uncertainty in the calculation are tracked (Figure 2, top). A distinction is made between uncertainty in our knowledge of parameters or processes (epistemic uncertainty) and uncertainty owing to the natural variability of tsunami evolution (aleatory uncertainty). The latter is directly integrated into the hazard curve through a defined probability distribution that models the uncertainty. The former is incorporated through the use of logic trees (Figure 2, bottom). Each branch of the logic tree is a separate calculated hazard curve that is weighted according to a specific subjective (i.e., expert consensus) or objective (i.e., normal distribution) scheme. The final hazard curve is defined as the median or some other fractile of the ensemble hazard curves from the logic tree.

Data available from nearby water level stations and other observations can be used to check the PTHA calculations. Tsunami observations may be censored at low runups and undersampled at high runups (Geist and Parsons, 2006). With this in mind, if the empirical hazard curve results in higher hazard values for a given probability than the PTHA hazard curve, then there is a problem with which sources are included and the validity of assumptions used in PTHA. The available data can also be used to fill in the PTHA calculations for rare or unknown sources using Bayesian analysis (Parsons and Geist, 2009; Grezio et al., 2010).

A perhaps subtle assumption in many probabilistic analyses of tsunamis and other natural hazards is that events are random in time and unrelated to one another, termed a Poisson process. The time between tsunami events in such a process follows an exponential distribution. Accordingly, the hazard curve represents the probability that one or more tsunamis will meet or exceed the corresponding runup on the horizontal axis over a given exposure time (T) given by $P(R \geq R_0) = 1 - exp(-\lambda T)$, where λ is the rate of occurrence of these tsunamis and is constant with time. For tsunamis and other floods, annualized probabilities are often considered (exposure time T of one year). For small values of λT, P approximately equals λ and hazard curves are often calculated in terms of λ rather than P. The exceedance rate λ is critically dependent on the probability model chosen for the tsunami sources in step 2 of PTHA (Figure 2, middle), with the Poisson model being a common starting model.

The choice of design probability depends on the particular application of PTHA. For determining flood zones for insurance purposes, an annual probability of 1% and, less often, 0.2% is considered (Burby, 2001). The mean return period is given by $1/\lambda$ and these designs are often termed the 100- and 500-year floods, although these terms often generate confusion in the public that is caused by not understanding the

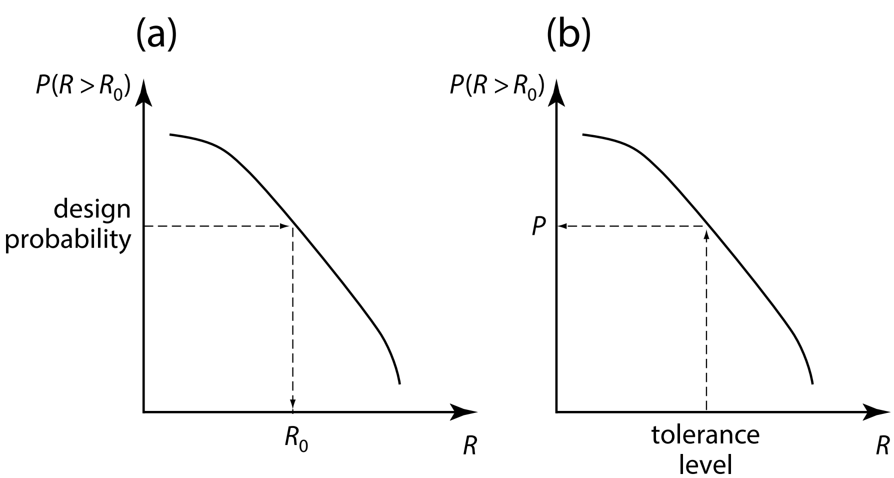


Figure 1. Schematic tsunami hazard curve showing different applications: (a) exceedance runup (R_0) determined from design probability, and (b) probability (P) determined from specified tolerance level.

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random nature of the hazard (Bell and Tobin, 2007). For example, there is a 63% chance of the 100-year flood occurring in any given 100-year time period. In other cases, such as for ground motion from earthquakes (Frankel et al., 2000), the design is a specific probability over a period of time, such as the 5% in 50 years event that is equivalent to an annualized rate of 1/974.8 years. For nuclear applications, the annual design probability can be as low as 10^{-4} to 10^{-6} (Nicholson and Reed, 2013).

EARTHQUAKE SOURCES

Earthquake sources considered for PTHA are located primarily along subduction zones. Here, the world's largest earthquakes occur on the interface fault that separates the downgoing plate from the overriding plate, often termed the "megathrust." The geometry of these massive faults can be defined from geophysical methods and the precise location of instrumentally recorded earthquakes (Hayes et al., 2012). Although relative plate convergence rates and slip rates on specific faults can be determined using modern geodetic methods, a significant source of uncertainty is how much of the slip on megathrusts is released seismically. A combination of both earthquake statistics and plate tectonic models is currently the best method for constraining the rate of occurrence for megathrust tsunamis (Bird and Kagan, 2004). Devastating tsunamis have been historically generated on faults other than subduction megathrusts, such as faults along the outer trench slope and outer rise of subduction zones and in the back arc, although it is even more difficult to assign slip rates to these faults.

A long-running controversy in seismology that affects PTHA is how earthquake magnitudes are distributed along a fault zone (Parsons et al., 2012). The characteristic earthquake hypothesis is that the largest earthquakes that occur along an individual fault or fault segment are of similar magnitude throughout time. The competing hypothesis is that earthquake magnitudes are distributed according to a power-law relationship (termed the Gutenberg-Richter relationship) that is tapered at the highest magnitudes. For the characteristic model, at design probabilities less than but near the mean recurrence rate of the characteristic earthquake, the contribution to the overall hazard will be higher than for the Gutenberg-Richter relationship. For lower design probabilities, the contribution to the overall hazard under the characteristic hypothesis is significantly lower, although not zero if various uncertainties are considered because earthquakes larger than the characteristic magnitude do not exist, by definition. For example, the mean return period for magnitude 9 earthquakes along the northern Cascadia subduction zone is approximately 500–540 years. (Atwater and Hemphill-Haley, 1997). PTHA analysis at an annual design probability of 0.2% for coastal sites in the Pacific Northwest would be higher under the characteristic hypothesis compared to the Gutenberg-Richter hypothesis, but lower for a design probability of 0.1%. One of the significant advantages of PTHA analysis, however, is that both hypotheses can be considered sources of epistemic uncertainty and included in a logic-tree framework. The occurrence of the 2011 Tōhoku earthquake is seen by many as a refutation of the characteristic hypothesis (see Opinion by Kagan et al., 2012), and at the very least demonstrates the difficulty in assigning a maximum magnitude using the characteristic model (Geist and Parsons, 2014).

LANDSLIDE SOURCES

For landslide-generated tsunamis, specification of the seafloor time history, which is used to force generation of the ocean surface wave, is a difficult

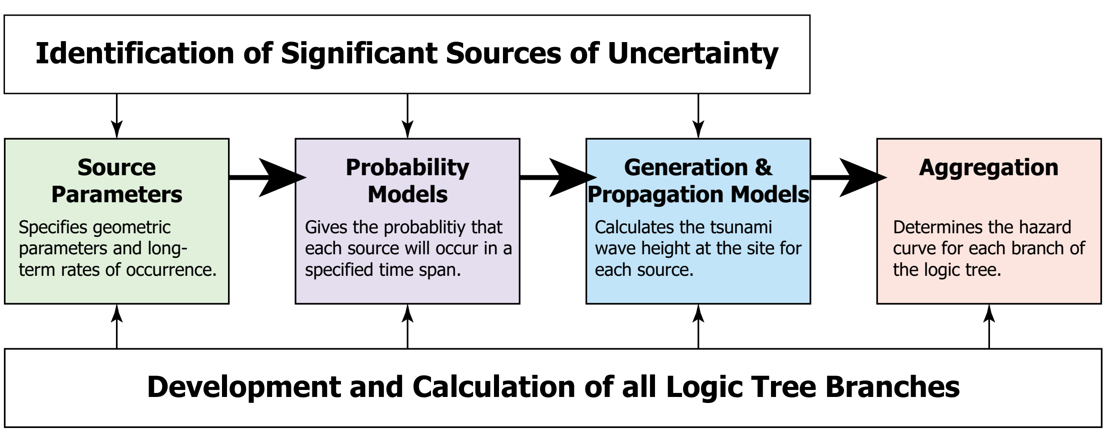

Figure 2. (middle) General steps in probabilistic tsunami hazard analysis (PTHA). (top) Throughout the specification of tsunami sources, probability models, and tsunami simulations, various epistemic and aleatory uncertainties are identified. (bottom) Epistemic uncertainty is included in a logic tree and a hazard curve is computed for each logic tree branch during the aggregation phase.

task. Submarine mass movements can take a wide variety of forms, such as translational slides, rotational slumps, and debris flows, and each will have different tsunamigenic efficiency. Here, efficiency is a measure of the transfer of the energy of the mass movement into free ocean surface waves. In general, the most efficient mass movements are those that are "shallow" (meaning the horizontal length scale of the slide is much greater than the local depth), "coherent" (meaning that the mass fails as a single piece, not as a group of smaller, spatially and temporally separated segments), and "fast" (meaning that the time scale of motion of the movement is on the order of the generated wave period) (e.g., Lynett and Liu, 2002). Note that the discussion above details efficiency and does not address tsunami potential, which is a function of the efficiency and is also closely related to metrics such as landslide volume and mass discharge rates (Harbitz et al., 2006).

A great challenge to including landslide-generated tsunamis into PTHA is the understanding of local sources with significant heterogeneity in their spatial geometry and time evolution. This would be classified for the most part as epistemic uncertainty, driven by our lack of understanding of how small-scale spatial and temporal details generate and evolve. If this heterogeneity can be quantified, as it can to a reasonable extent for earthquake sources, and coupled with statistical information about local slope stability mechanisms and landslide probability of occurrence, then proceeding with a PTHA is justified. For landslides, this is a great challenge. Furthermore, the mean return periods of submarine landslides in a given area, which are integral to PTHA, are often accompanied by leading order imprecision and uncertainty. Figure 3 provides an example methodology for integration of landslides in PTHA, focusing only on modeling the landslide time history. Note that Figure 3 represents an expansion of detail for the "generation and propagation" box shown in Figure 2 associated with landslide tsunamis. The first pieces of information are functional relations between the mean return period and both slide volume and horizontal slide area. Note that slide area is equally important, as without this piece of information it is not possible to estimate slide thickness, which largely controls the generated wave height (e.g., Lynett and Liu, 2005). Alternatively, relating slide volume to slide area (and/or maximum slide thickness), when used in conjunction with a slide volume to return period relationship, would close this problem. These relations come from statistical data from previous landslides, geophysical information, and geotechnical samples. Currently, these types of data are sparse, so only limited information is available for building these

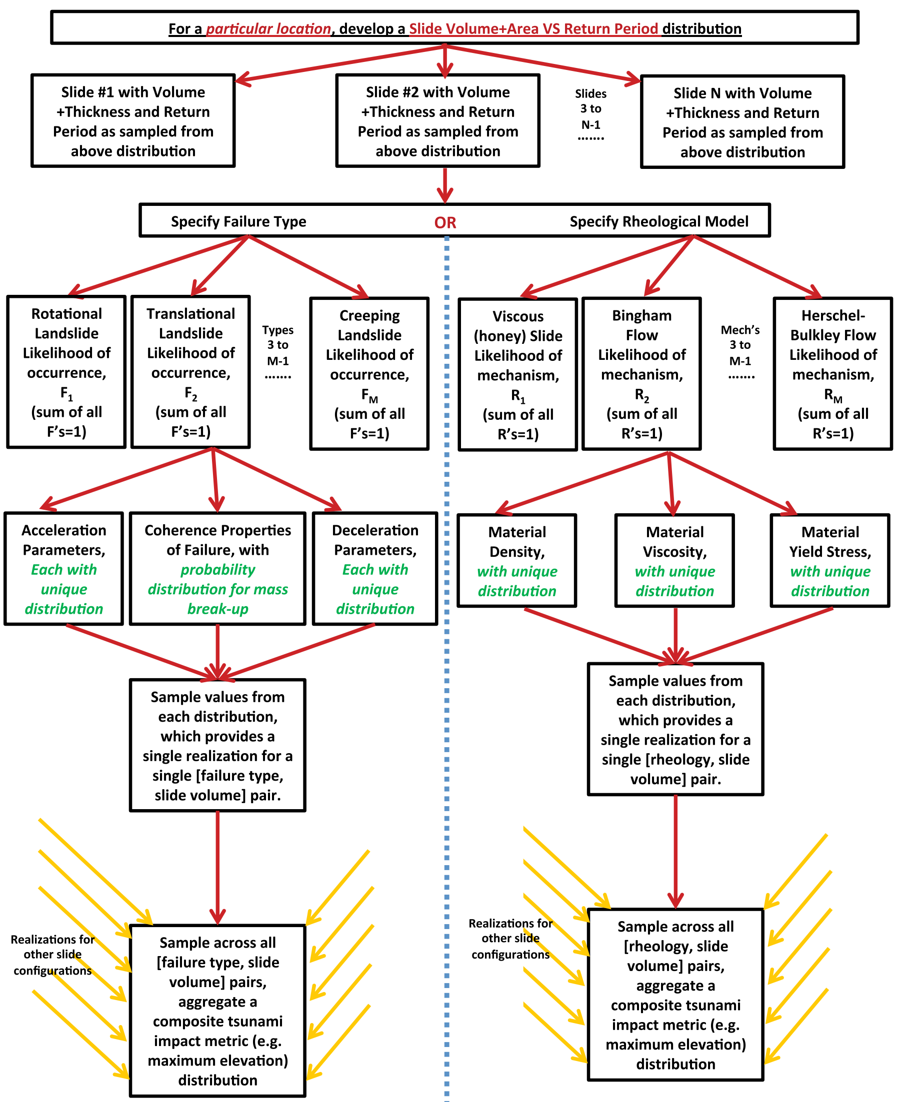

Figure 3. Example procedure tree for the inclusion of slide variability and uncertainty into a PTHA. Note that this flowchart represents an expansion of detail for the "generation and propagation" box shown in Figure 2.

starting-point relationships.

With these relationships in hand, however, they can be sampled to arrive at a set of landslide volume + thickness combinations. For each member of the set, a distribution of possible slide time histories should be determined. The first step in this procedure is for the user to decide how to describe the motion (Figure 3). There are two main categories of choice (which could also be combined into a single category, if desired): (1) specify the failure type, or (2) specify the rheological model. In the "Specify Failure Type" route, a set of different types of failure mechanisms are included, such as rotational slides, translational slides, block slides, debris flows, and avalanches. These slide motions are defined as "prescriptive," meaning that their temporal and spatial evolution profiles are known a priori. Each of these different types will yield different tsunamigenic efficiencies as well as different generated wave properties. This step represents a branching logic tree, and thus a weighting factor must be assigned for each different type. The variety and number of types can likely be reduced based on site-specific conditions, and indeed the weighting factors must be location specific as well. Once a type is chosen, the parameters that govern its evolution must be selected. With a translational landslide, for example, its initial motion would likely follow solid body (block) motion, and therefore parameters such as drag coefficient, added mass, and material density must be given (Enet and Grilli, 2007). These parameters, which are location specific, should be selected from distributions created for each parameter; though such information could likely be generated, it is not currently known to formally exist for submarine landslides. It is also worth noting that while the evolution model for a translational slide (solid body motion) is established in the literature, the same cannot be said for any of the other "types" of motion, such as rotational slumps, creeping slides, and debris flows. With the parameters necessary for the failure model provided, the slide time history can be imported into the hydrodynamic model, and a single realization can be generated. In a Monte Carlo analysis, this procedure is repeated until enough realizations are generated so that distributions can be constructed for whichever tsunami impact metric is under analysis.

Instead of choosing the "failure type" route, it is possible to specify a set of different rheological models. Here, slide motion is not specified a priori; rather, the landslide motion is a function of an initial condition, boundary conditions, and a set of differential equations to evolve the material in time. Rheological models are meant to cover the full spectrum of materials relevant to landslides, from fluids to solids and elastic to viscous materials. Similar to the "failure type" approach, the range and weightings of the employed rheological models are location specific. Rheological models tend to be more complex and computationally costly than the "prescriptive" models and require calibration of numerous submodels, such as closure equations for yield stress or basal friction. Furthermore, each submodel contains a handful of material and empirical parameters, and a distribution for each needs to be constructed.

Note that the methodology outlined in Figure 3 is simply one suggestion for a probabilistic analysis incorporating landslides—an analysis procedure that is currently not well defined. Alternative methods are certainly viable, and significant simplifications may be made, with justification, to the generality given here. These simplifications will often exist in the description of the failure types/rheological models and distributions of the parameters that govern them. Our current state of knowledge of wave and landslide coupling may not justify a confident simplification to these models/parameters, and, hence, the current preference is for a highly conservative landslide source estimate with a deterministic modeling approach. Likewise, the computational cost for a PTHA-with-landslides, driven by the high computational cost of three-dimensional/dispersive models often needed for accurate physical representation of the slide and waves (e.g., Abadie et al., 2012), is significant and may only be justified for sites where a tsunami from a local landslide controls the design hazard level. Lastly, the reader is directed to Geist and ten Brink (2012) for a more complete and comprehensive review of the challenges in landslide tsunami modeling related to PTHA.

OUTSTANDING PROBLEMS

In addition to the challenge of including landslide sources, as well as volcanic sources (Paris et al., 2014), into PTHA, there are general issues that need to be addressed to improve the accuracy of PTHA in the future. These issues include incorporating (1) extreme sources not represented in the historical or recent geological record, (2) time-varying rates of recurrence for tsunami sources, and (3) dependencies among different models of source occurrence. In each case, resolving these issues will rely on a variety of statistical and other methodologies used the in the assessment of other natural hazards, such as storm-surge forecasting.

For the case of incorporating extreme

sources for low design probabilities, the issue comes down to how well we can extrapolate the historical record of source occurrence. The paleoseismic record can augment earthquake catalogs, especially for subduction zones where the occurrences of megathrust earthquakes are marked by coastal subsidence and sedimentary deposits left by the ensuing tsunami. Similarly, drill hole records and multichannel seismic data can yield information to assess that distribution of landslide sizes in a given region. The difficulty with these geologic and geophysical records is in assessing both the age and the size of prehistoric tsunami sources and quantifying the uncertainty in both of these parameters (Geist et al., 2013).

One of the basic assumptions for the probabilistic assessment of natural hazards is that the hazard rate is constant with time. This is contradictory to well-known observations that earthquakes cluster in time and space in the form of foreshock, mainshock, and aftershock sequences (Kagan and Jackson, 1991). Landslides also appear to cluster, as indicated from detailed geologic studies such as in Port Valdez, Alaska, where landslides were triggered by the 1964 Great Alaska Earthquake (Lee et al., 2007). Tsunami sources may also exhibit quasiperiodic behavior, being less random than a Poisson model. One of the steps in an advanced PTHA is determining the appropriate probability model for source occurrence (second step, Figure 2). Clustering and quasiperiodic behavior can be approximately included in a Poissonian PTHA framework using an equivalent annual rate parameter (Petersen et al., 2007), although other techniques are being developed to incorporate these time-dependent behaviors based on statistically defined patterns of earthquake occurrence (Beauval et al., 2006). In addition, there may be a long-term change in the rate of tsunami source occurrence, as Lombardi and Marzocchi (2007) describe for large earthquakes. For submarine landslide sources, the effect of climate change and glacial cycles may also systematically change the occurrence rate for these sources (Masson et al., 2006; Lee, 2009), although the significance of this connection is currently under debate (Urlaub et al., 2013).

Finally, different conceptual models for the occurrence of earthquakes and landslides are often included in PTHA in a logic tree. Occurrence models include how the sizes of the sources are distributed and the probability model for how they occur in time. In averaging the hazard curves that result from these models in a logic tree format, these models are treated independently; each model likely represents some "true" aspect of occurrence, but is not a complete model in and of itself (Page and Carlson, 2006). A similar issue arises also in climate change models (Dosio and Paruolo, 2011). Various ways of incorporating this uncertainty include Bayesian techniques and the use of copulas, which are techniques to estimate the dependence among different models.

SUMMARY

Probabilistic analysis of tsunami hazards provides a systematic way to define the severity of the hazard at an explicit likelihood. Because tsunami observations at most coastal locations are scarce, a computational method, PTHA, has been developed to calculate a tsunami hazard curve that includes known and quantifiable sources of uncertainty. These methods were originally based on well-defined earthquake statistics, but submarine landslides that are a dominant tsunami source for passive margins have recently been considered for probabilistic analysis. However, there are significant challenges in including these sources, ranging from the variety of landslide types and rheologies to the need for high-dimensional hydrodynamic modeling to compute wave heights and other impact metrics. Conducting the analyses requires substantial resources, although methods are being developed to reduce the computational load associated with probabilistic analysis, particularly when inundation calculations are needed. Resolution of several outstanding theoretical issues will improve probabilistic tsunami hazard analysis in the future based on focused acquisition of specific geological data sets and application of probability methods used for other natural hazards.

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