Induced earthquake damage assessment methodology for potential hydraulic fracturing sites: Application to Manaus, Brazil

Andréia HA Silva¹,², Gonzalo L Pita³, José A Inaudi⁴,⁵, and Luiz CM Vieira Jr¹

Abstract
The number of seismic events induced by the exploitation of unconventional oil and gas reservoirs has escalated considerably in the last decade. This has raised concerns in several sectors of society, and in consequence, research efforts have been launched to ascertain the risk associated with induced seismicity. This article presents a procedure to quantify potential damages caused by induced seismicity to the built infrastructure of a region. The technique adapts the probabilistic seismic hazard analysis framework to the features of induced seismicity. The risk is then evaluated by the probability of exceeding economic loss. The estimation of potential disturbance of the population as injuries or loss of life caused by several factors, such as damage in the interior building components, is the fundamental risk assessment estimates that govern important policy decisions, but were not considered in this initial study which is focused on assessing direct damage. In a future study, however, these metrics will be addressed. The procedure is applied in a case study in Manaus, a city located on a large shale gas basin which is potentially exploitable. The results of the study indicate that the tectonic parameter ($b$) of the adjusted Gutenberg–Richter model is a governing parameter in the loss analysis. Two damage mitigation strategies are proposed: one that limits volume injected using loss thresholds and other that restricts injection location based on loss modeling. Insights from the case study emphasize that these type of activities should be avoided near urban areas where seismic standard prescribes low natural seismicity, and with a high proportion of the poorly built residential infrastructure. The study contributes to the literature a

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technique to inform the decision-making associated with the establishment and characteristics of unconventional oil and gas exploitation projects that is applicable to several places and situations.

Keywords
Loss assessment, risk assessment, induced seismicity, oil and gas exploitation, seismic risk

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Introduction
Earthquakes caused by anthropogenic activities are termed induced seismic events. Examples of operations which trigger earthquakes are subsurface fluid injection or withdrawal, reservoir impoundment, and mining, which affect the existing stress state of the underlying tectonics. The correlation between oil and gas exploitation and seismic events has been noticed since the 1920s. However, during the last decade, the economic prospects and the technological advances brought about significantly more oil, gas, and geothermal energy projects, and induced earthquakes (National Research Council, 2013).

Since 2008, there has been a marked increase in the number of earthquakes induced by the exploitation of oil and gas in Central and Eastern United States (US) (Keranen and Weingarten, 2018), that is, from an average of 21 M ≥ 3 earthquakes per year before 2000 to more than 300 between 2010 and 2012 (Ellsworth, 2013). It has recently been observed that wastewater disposal is responsible for the majority of the US induced earthquakes (Rubinstein and Mahani, 2015). Moreover, due to the increase in hazard, life-safety risk in buildings near induced seismicity zones in Oklahoma may have increased more than 100 times (Liu et al., 2019).

Induced earthquakes related to hydraulic fracturing (HF), however, are more common in Canada (Schultz et al., 2018) with magnitudes up to M4.1, and in China (Lei et al., 2017, 2019) where earthquakes of magnitude above 5 have caused damage and collapse of hundreds of dwellings.

Several studies are currently focused on understanding how induced earthquakes occur and on identifying the main parameters that govern the triggering mechanism (e.g. McGarr, 2014; Norbeck and Rubinstein, 2018; Segall and Lu, 2015). Induced seismicity forecast is an important factor for the subsequent risk analysis. There are also several efforts in the literature that present induced seismic risk assessment techniques, and a series of risk reduction mechanisms, such as hazard reduction through injection management, exposure reduction by relocation of injection points, vulnerability reduction by retrofitting or isolation, risk communication to affected population, and economic compensations (Bommer et al., 2015; Majer, 2013; van Elk et al., 2019; Walters et al., 2015).

This study presents a seismic risk assessment methodology applied to Manaus. The intended significance of this study is twofold: anticipatory and methodological. Anticipatory in that it assesses potential future damages to an urban region located near large reservoirs of unconventional oil and gas, which has not been exploited as of yet, but which could realistically become an appealing opportunity for exploitation ventures. It adds to the relevance of the situation that the state of the population and the construction in the region are highly vulnerable from many perspectives—not unlike many other similar
cases around the world—and so, the potential damages resulting from even relatively minor earthquakes are although uncertain, but could be significant. As such, this study is intended as an anticipation for a state of affairs that Brazilian decision-makers may face in a fairly possible future.

The significance of this study is also methodological; the techniques for estimating induced earthquakes are relatively new, subject to ongoing developments, and scaffolded by conjectures about the problem dynamics stemming from lack of data and knowledge about the underlying mechanisms of unconventional oil operations. As such, in our project, several assumptions were made about the hazard recurrence, ground motion models, and building vulnerability to cover for the inexistent data and knowledge in the region of Manaus. The exercise is thus a first step toward revealing research needs in Brazil and as a case for discussion and exchange in the international induced seismicity community.

Methodology

The methodology developed aims at quantifying the potential damages caused by induced seismicity to the structural and non-structural components of the built environment located in the proximity of an injection well. The general framework for this study is the seismic risk analysis, given by the probabilistic overlap of hazard, exposure, and vulnerability functions. Risk is evaluated through economic loss, by means of exceedance probability loss curves. This is a primary output of the model; however, other risk metrics, such as life-safety risk, should also be addressed in future studies. The hazard is assessed through the probabilistic seismic hazard analysis (PSHA) technique (Cornell, 1968; McGuire, 2004), generating a stochastic catalog of events of 100,000 synthetic years. Exposure is characterized with census data and satellite imagery. Fragility functions are adopted from the literature for similar typologies to those in Manaus. The loss analysis of the spatially distributed exposure is performed, accounting the variability of the hazard and fragility functions. The main results are hazard curves, hazard maps, loss curves, a sensitivity analysis of input parameters, and risk mitigation strategies. Moreover, the model presented herein can be used as an assessment tool within risk management frameworks to inform and evaluate risk control mechanisms.

Characterization of the hazard

The PSHA methodology consists of four steps: location and typification of seismic sources, modeling of the law of recurrence of earthquake’s magnitudes, estimation of ground motion at a site caused by the events generated at various distances, and calculation of the probability of different levels of ground motion at study site (Cornell, 1968). Uncertainties are also inputted in the modeling process: aleatory variability is modeled with Monte Carlo sampling and epistemic uncertainties are represented with logic trees (McGuire, 2004).

The typical PSHA must be modified to model the induced seismicity hazard, especially in the law of occurrence of events. Different modification schemes have been developed recently, but no generally acceptable approach has been, or probably can be, reached. In the absence of a consensus, the simplest method that is suitable to represent the induced seismicity activity at the place of study must be adopted. This has been the philosophy in this work for representing the hazard in Manaus as discussed below.
Natural seismicity

The maximum magnitude of an induced earthquake is controlled by local tectonics, and the number of earthquakes is related to the volume of injected fluid, as recent studies have suggested (Van der Elst et al., 2016). Overall, Brazil is in a stable continental region and has not experienced, particularly, severe events. Studies to quantify the natural seismicity of Brazil exist but are tentative because of the infrequency of severe events and the paucity of historical data (Figure 1a) due to the recent installation of a seismic network (RSBR, 2014). In Manaus, in particular, a recent seismicity study of the Amazonas Basin considered it as an area source of homogeneous seismicity, whose maximum magnitude is 7.0 (Abreu Diniz de Almeida, 2002). This study derived a hazard curve for Manaus where a peak ground acceleration (PGA) of 0.011 g has an annual probability of exceedance of 1/1000. Also, the study deemed adequate attenuation functions from Toro et al. (1997) for the local geology. Another study by Petersen et al. (2018) developed a hazard map for South America, which uses a smoothed gridded seismicity model, with maximum magnitude between 7.1 and 7.4 for the craton region and eight different attenuation functions (Figure 1b).

Modeling of induced seismic hazard—stochastic catalog

Four aspects of the PSHA must be modified for addressing induced seismicity: distance of potential earthquake hypocenters from injection point (area of influence), law of occurrence of induced events as a function of injected water volume and local tectonics, depth of earthquake epicenters triggered by water injection operations, and attenuation functions for determining the induced ground motion.

It has been observed in HF operations that seismic activity generally occurs within 1 km from the injection well (Verdon et al., 2019). At the same time, it was observed in western Canada that induced seismicity was concentrated within a 2 km distance from
injection wells (Bao and Eaton, 2016), and in China that most earthquakes’ epicenters were also located within a 2 km distance of the lateral extent of the well pads (Lei et al., 2019). In this study, the latter studies are followed and an area source of seismicity of 2 km radius around the injection point was simulated to represent a conservative scenario.

The occurrence of induced earthquakes is a non-stationary process that depends to a certain extent on the cumulative volume injected. However, it has been argued by a number of authors that the stationary Gutenberg–Richter (GR) law (Gutenberg and Richter, 1944) can be used to adequately represent the recurrence of induced events, provided that certain modifications are made (Shapiro et al., 2007). The original GR law is given by:

\[ N_{\geq M} = 10^{a - bM} \]

where \( N \) is the number of events per unit of time given by a truncated exponential distribution with magnitude greater than \( M \), \( a \) is a constant related to events’ frequency, and \( b \) is a constant that defines the relation between the number of small and large magnitude events.

The influence of the underlying tectonics is weighed in with a seismogenic index \( \Sigma \) to measure the potential of triggering induced earthquakes per quantity of volume injected at a specific location related to the characteristics of the seismotectonic state of a reservoir (Dinske and Shapiro, 2013):

\[ \Sigma = \log_{10} \left( \frac{10^a}{F_t S} \right) \]

where \( S \) is the poroelastic compliance and \( F_t \) is the tectonic potential of the reservoir-building rock. The modified GR law which accounts for the number of events triggered given a volume injected now becomes:

\[ N_{\geq M} = V \cdot 10^{\Sigma - bM} \]

This model has been applied successfully in a number of case studies (Bao and Eaton, 2016; Dinske and Shapiro, 2013; Lei et al., 2017; Schultz et al., 2018). Table 1 shows the values of the parameters in the modified GR law found in each reference.

**Table 1. Modified GR law parameters reported in the literature.**

<table>
<thead>
<tr>
<th>Reference</th>
<th>Region</th>
<th>Period of catalog</th>
<th>Volume injected (m³)</th>
<th>( b )</th>
<th>( \Sigma ) (log₁₀ m⁻³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lei et al. (2017)</td>
<td>Well pads in Sichuan Basin (China)</td>
<td>~4 months</td>
<td>1.2 to 2.5 × 10⁵</td>
<td>0.9–1.43</td>
<td>−1.11 to 1.66</td>
</tr>
<tr>
<td>Bao and Eaton (2016)</td>
<td>Well pads in Fox Creek (Canada)</td>
<td>Months</td>
<td>10⁵</td>
<td>“near unit”</td>
<td>−2.7 to −1.5</td>
</tr>
<tr>
<td>Schultz et al. (2018)</td>
<td>Duvernay Play Canada</td>
<td>&gt;1 year</td>
<td>10³ to 10⁶</td>
<td>0.7–1.7</td>
<td>−2.5 to −0.5</td>
</tr>
<tr>
<td>Dinske and Shapiro (2013)</td>
<td>Diverse (geothermal energy)</td>
<td>2–16 days</td>
<td>10⁴ to 3 × 10⁴</td>
<td>0.74–2.18</td>
<td>−3.8 to 0.4</td>
</tr>
<tr>
<td>Dinske and Shapiro (2013)</td>
<td>USA (hydrocarbon)</td>
<td>2.5–6 h</td>
<td>3 × 10² to 10³</td>
<td>2.16–4.12</td>
<td>−4.42 to −9.25</td>
</tr>
</tbody>
</table>
The depth of the hypocenters of induced earthquake events is shallow in comparison with natural events (Atkinson, 2015). For that reason, to establish a distribution of earthquake depths, a probability density function was fitted to empirical data from HF induced earthquakes from the database HiQuake (Wilson et al., 2017). Fracking-induced earthquakes amount to 19 cases in the database. The depth data are well represented by a lognormal distribution ($\mu = 3.72$ km, $\sigma = 1.8$ km). The distribution has been truncated in the simulation between 1 and 10 km, based on previous observation that a $M \geq 3$ earthquake is unlikely to be induced at depths smaller than 1 km and larger than 10 km. In fact, the shale basin in Manaus lies at a depth between 1 and 5 km (US Energy Information Administration, 2015), and the proposed distribution encompasses 81% of depths within 1 and 5 km; therefore, the remaining hypocenters occur outside of the shale layer, which is consistent with the literature (e.g. Lei et al., 2019; Schultz et al., 2015).

Attenuation relationships—also called ground motion prediction equations (GMPEs)—are used to relate the event magnitude and distance to the resulting ground motion, such as peak acceleration, probabilistically. Attenuation functions of natural seismicity are not suitable to represent induced seismicity due to discrepancies between both in the ranges of depth and magnitude. Moreover, induced earthquakes have shallow focal depths and lower stress drops when compared to natural seismicity, resulting in similar shaking intensities near ($<10$ km) the epicenter and lower shaking intensities at large distances when compared to natural seismicity for magnitude lower than 6 (Atkinson et al., 2018). Therefore, GMPEs have been developed for induced seismicity cases, some for specific regions (e.g. The Geyers in California, Groningen in the Netherlands, Montney in Canada) and others for generic application (e.g. Atkinson, 2015; Douglas et al., 2013). In Manaus, no induced seismicity events have yet been recorded, thus no attenuation functions exist. Consequently, the GMPEs from Douglas et al. (2013) and Atkinson (2015) are adopted because these are suitable to be used for any site, according to the authors. To span the possible scenarios and to simplify the calculation of ground motion, three GMPEs are selected—lower, medium, and higher intensity (Figure 2), from Douglas et al. (2013) with the empirical GMPE from Atkinson (2015) falling within their range. Note that the GMPEs adopted do not explicitly consider the effects of depth on the stress drop. Also, the blind choice of kappa ($\kappa$) and quality factor ($Q$) result is a logic tree with very different GMPEs, which reflects the high level of uncertainty in the current scenario.

The minimum magnitude of the simulation should be that which does not affect the risk metric considered (Bommer and Crowley, 2017). Consequently, a minimum magnitude of 3.0 is chosen in this study to generate the stochastic catalog, as tests showed that smaller magnitudes exhibit negligible losses. There is also support in the literature that earthquake damage caused by magnitudes lower than 3.0 is unlikely (Nievas et al., 2020).

Site effects
Seismic waves are affected by local soil conditions at the surface. The adopted GMPEs were developed assuming a reference rock site with shear wave velocity of 30 m depth ($V_{S30}$) of 1100 m/s (Douglas et al., 2013). Therefore, their use is restricted to the application of a soil amplification factor related to site conditions.

The soil horizons of Manaus consist of clays, sand, and clayey sands (Souza, 2006). The standard penetration tests (SPTs) performed at several locations of Manaus (Figure 3) indicate that soil belongs to the class E in the NEHRP taxonomy (Federal Emergency Management Agency (FEMA), 1997). The soil does not have the characteristics of class F
soils, and most of the SPT values \((N_{SPT})\) are below 15 bpf. Even though soil type in the fringes of the city may depart from class E, for example, boring 2 (Figure 3), this does not affect the results. Thus, following HAZUS (FEMA, 2003) guidelines, the suggested soil amplification factor from NEHRP (FEMA, 1997) for soil type E is applied.

![Figure 2](image)

**Figure 2.** Comparison between GMPEs for peak ground acceleration (PGA). Gray lines are the 36 stochastic GMPEs from Douglas et al. (2013), from which the lower, medium, and higher ones are depicted by a solid black curve. The empirical GMPE from Atkinson (2015) is depicted by a black dashed curve. The soil amplification factor from Seyhan and Stewart (2014) was applied to match Atkinson’s (2015) GMPEs (site B/C) to the site of reference B \((V_{S30} = 1.100 \text{ m/s})\).

![Figure 3](image)

**Figure 3.** (a) Manaus satellite image (Instituto Nacional de Pesquisas Espaciais, 2016), with neighborhood boundaries and identified geotechnical tests boreholes. (b) SPT’s depth and mean result \((N_{SPT})\); the blue shaded area represents the results that fall within soil E classification and green shaded area represent soil D classification.
Inclusion of uncertainty in hazard parameters

The aleatory uncertainties in the magnitude, location, and ground motion intensity can be accounted for in the PSHA. The variability of ground motion in different events and different locations is accounted through the use of GMPEs’ between-event ($\tau$) and within-event($\phi$) variabilities, respectively (Douglas et al., 2013). It is important to account them separately when analyzing a spatially distributed exposure since previous studies (Crowley and Bommer, 2006) have shown a difference in the loss exceedance curves caused by simply accounting the total variability.

Epistemic uncertainties are assessed with a logic tree where each node represents an uncertain parameter. A summary of the currently unknown parameters and respective assumptions adopted herein is presented in the logic tree of 37 branches with four values of $b$, three of $\Sigma$, and three GMPEs (Figure 4). In the logic tree, the central branch has a larger weight (0.6 for the central GMPE and $\Sigma$, and 0.3 for each central $b$-value), and smaller weights for external branches (0.2), following previous studies (i.e. Atkinson et al., 2015; van Elk et al., 2019).

There is currently no data from induced earthquakes in Manaus and so the values of the parameters used to modify the GR law—$b$-value and seismogenic index $\Sigma$—were adopted from the range of values found in Table 1. For the case study, ranges of values for seismogenic index ($\Sigma$) and for the $b$ parameter for HF activity lasting for months to years were adopted (i.e. Bao and Eaton, 2016; Lei et al., 2017; Schultz et al., 2018; in Table 1). It must be noted that the parameters were selected from cases where HF activity induced appreciable seismicity ($M \geq 3$ earthquakes), which is not the case for every HF well operation. In fact, Atkinson et al. (2016) found that HF wells in western Canada are associated to $M \geq 3$ induced earthquakes in only 0.3% of the cases. Consequently, the logic tree has a branch which represents the no earthquake-induced possibility with a weight of 99.7%. If new information becomes available, this weight should be updated.
Setting the maximum magnitude ($M_{\text{max}}$) is a complex modeling decision as it involves adopting the maximum credible earthquake of a fault or a region. In the literature, this parameter is related either to tectonic parameters (Anbazhagan et al., 2015) or to existing earthquake data and related statistics (Kijko and Singh, 2011). Moreover, in the PSHA, $M_{\text{max}}$ is assigned an epistemic uncertainty. Specification of the $M_{\text{max}}$ parameter in the induced seismicity community has been even more challenging and has been treated on an ad hoc basis. Reasons for this are that past induced earthquakes have exhibited lower magnitudes than that of natural earthquakes, and at the same time, they are triggered by stress changes in pre-existing tectonic faults.

A number of approaches have been implemented in the literature to set the value of $M_{\text{max}}$ for induced earthquakes, for example, $M_{\text{max}}$ considered smaller than that of observed natural earthquakes, with a disclaimer that this is an expert judgment (Atkinson et al., 2015); for the Groningen gas field, the selection of $M_{\text{max}}$ was controversial and a panel of experts developed a 14-branch logic tree (Bommer and van Elk, 2017); finally, the USGS adopted an $M_{\text{max}}$ for induced earthquakes in the United States equal to the value for natural earthquakes, the reason being to entertain the possibility of triggering large regional earthquakes (Petersen et al., 2015).

In this study, a value of $M_{\text{max}} = 5$ is assumed for two main reasons: first, the 1690 event reported in Veloso (2014) may not provide sufficient evidence to select a higher value of $M_{\text{max}}$ given the historical uncertainty. Second, HF activities commonly have a relatively short duration, and so it seems justified to consider a lower operational $M_{\text{max}} = 5$ which may differ from the long-term tectonic maximum possible magnitude. Admittedly, as more knowledge becomes available, this assumption should be revisited. It is also recognized that $M_{\text{max}}$ represents an epistemic uncertainty, which for risk metrics related to low-probability events (i.e. fatalities) may have a high impact on the results (van Elk et al., 2019).

Characterization of the building exposure

The reasons for studying Manaus are that the city is located on a large shale gas reservoir which could be exploited in the future (Ministério de Minas Energia, 2012), and yet, a considerable fraction of the building stock in Manaus is in a vulnerable state because it consists of precarious dwellings, non-engineered low-rise buildings, and buildings designed for low seismic magnitudes (0.025 g) as per the provisions of the national seismic code NBR:15421-2006 (Associação Brasileira de Normas Técnicas (ABNT), 2006).

Manaus has a population of approximately 1.8 million and has 510,000 dwellings (IBGE, 2010). The city is divided in 63 neighborhoods. IBGE (2010) calculates the quantity of dwellings and average per-capita income per neighborhood (Figure 5). However, this resolution is too coarse for the analysis, and so, the granularity of the exposure layer was enhanced discretizing the city in grid cells of 1 km x 1 km. The steps detailed next were implemented to enhance the exposure layer granularity:

1. Identification of most frequent typologies: Using the PAGER taxonomy (Jaiswal and Wald, 2008), the predominant typologies identified were low-rise buildings with reinforced concrete frames and masonry infill walls (C3L) and unreinforced fired brick masonry bearing walls with cement mortar (UFB5-1 and UFB5-2, for 1 and 2 stories, respectively (Singh et al., 2013)). Mid- and high-rise buildings are
assumed to be reinforced concrete frames with unreinforced masonry infill walls (C3M and C3H) because it is the most frequent construction type in Brazil for multi-family dwellings. All typologies are classified as Pre-Code, as per HAZUS (FEMA, 2003) because the Brazilian seismic standard NBR15421 (ABNT, 2006) was enacted in 2006 and its provisions are generally not applied (Santos and Lima, 2005), and also because the prescribed characteristic acceleration value for Manaus is low \( (a_g = 0.025 \text{ g}) \).

2. Buildings were further classified by height (Figure 6) as low (1 to 3 stories), mid-rise (4 to 7 stories), and high-rise buildings (8 or more stories). Mid- and high-rise buildings were counted; the number of low-rises was estimated subtracting the number of mid/high rises from the total number of buildings.

3. The low-rise buildings at each neighborhood were classified as C3L, UFB5-1, and UFB5-2. The relative proportions were estimated inspecting satellite imagery (Google Inc., 2019).

Figure 5. (a) Number of residences in Manaus divided by neighborhood. (b) Average per-capita income divided by neighborhood.

Figure 6. Percentage of low-, mid-, and high-rise buildings in Manaus. The size of each circle is related to the number of buildings per region.
4. The spatial distribution of buildings in each neighborhood is homogeneously discretized in cells of 1 km × 1 km (Figure 7).

The suburbs of the city are composed by poorly resistant dwellings (UFB5), while downtown concentrates mid- and high-rise buildings, and medium- to average-income quality dwellings.

A simplification was made for estimating the replacement costs by typology of the building inventory. First, the area by typology was calculated using Google Earth (Google Inc., 2019) satellite imagery of approximately 60 buildings of each typology to determine the average area of each typology (Figure 8).

Next, the average cost of construction in Manaus was retrieved from the SINAPI monthly index, produced by the Brazilian Institute of Geography and Statistics for each state (IBGE, 2019). The index averages the cost of 37 standardized projects with four quality types: minimum, low, normal, and high, combining the regional cost of the building
material and labor, which are defined per step of construction (structure, walls, hydraulic, electric, finishes, etc.)

The remote survey detailed above showed that the quality of construction in Manaus is uneven for different neighborhoods. Thus, different costs were chosen from the index to represent the varying structural type and quality (Table 2). Regional typology costs were classified by per-capita income: low (0–1 minimum wage), medium (1–2 minimum wage), and high (2 or plus minimum wage).

The total residential built-up area of Manaus was estimated as approximately 81.8 million square meters, representing a total exposed value (TVE) of US$21.8 billion.

### Characterization of building vulnerability

To define vulnerability, it is necessary to superimpose fragility and cost functions. In this study, fragility functions for structural damage states and non-structural damage states were used. In the first case, reinforced concrete structures fragility functions are adopted from HAZUS (FEMA, 2003) for typologies that resemble the existing buildings in Manaus. Fragility curves for non-structural damage states are defined for both: acceleration sensitive components and inter-story drift-sensitive components. Fragilities for the UFB5 typology are adopted from Singh et al. (2013) because HAZUS does not have these. However, in Singh et al. (2013), there are no separated fragility functions for structural and non-structural components. Instead, damage states and cost functions are adopted from Kappos et al. (2006), whereupon each damage state is related to loss as a percentage of the total replacement cost, that includes the non-structural parcel (Table 3).

The adopted fragility curves are defined in terms of spectral displacement and acceleration and so it was necessary to convert them to vulnerability functions for PGA, so that they match the hazard calculated (see section “Characterization of the Hazard”). Techniques for transforming the fragilities exist, the most common being the capacity spectrum method (Freeman, 1998) adapted in HAZUS (FEMA, 2003). In this study, the version developed in Porter (2009a, 2009b) was adopted to develop vulnerability functions because it applies the capacity spectrum method, HAZUS fragility database (for both structural and non-structural components), and repair cost ratios. The procedure relates

<table>
<thead>
<tr>
<th>Typology</th>
<th>Average area (m²)</th>
<th>Finishing type</th>
<th>Cost per m² (US$)</th>
<th>Replacement cost (US$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UFB5-1</td>
<td>92</td>
<td>Low</td>
<td>212.15</td>
<td>19,518</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium</td>
<td>243.87</td>
<td>22,436</td>
</tr>
<tr>
<td>UFB5-2</td>
<td>202</td>
<td>Low</td>
<td>212.15</td>
<td>42,854</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium</td>
<td>243.87</td>
<td>49,262</td>
</tr>
<tr>
<td>C3L</td>
<td>463</td>
<td>Low</td>
<td>277.54</td>
<td>128,501</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium</td>
<td>328.48</td>
<td>152,086</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High</td>
<td>356.08</td>
<td>164,865</td>
</tr>
<tr>
<td>C3M</td>
<td>1971</td>
<td>Low</td>
<td>277.54</td>
<td>547,031</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium</td>
<td>328.08</td>
<td>647,434</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High</td>
<td>356.08</td>
<td>701,834</td>
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<tr>
<td>C3H</td>
<td>7730</td>
<td>Low</td>
<td>277.54</td>
<td>2,145,384</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium</td>
<td>328.48</td>
<td>2,539,150</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High</td>
<td>356.08</td>
<td>2,752,498</td>
</tr>
</tbody>
</table>
the capacity curve with the damped demand spectrum at each discretization point. For this point, the probability of exceeding each damage state is defined by the fragility curves. Finally, the vulnerability function is estimated using the repair cost ratio assigned to each damage state (Figure 9).

The capacity curve parameters are taken from FEMA (2003) and Singh et al. (2013), the response spectra (24 functions) are defined using HAZUS (FEMA, 2003) recommendations, and GMPEs for different magnitude and distance ranges (Table 4), and finally, the repair cost ratios shown in Table 5 are adopted. It must be noted that in HAZUS, repair cost ratios are defined for both, occupancy classes and according to structural and non-structural damage. For this, HAZUS typologies were assumed as multi-family dwelling (RES3).

### Simulation of damages caused by induced earthquakes

The losses are expressed probabilistically with loss exceedance curves built with a Monte Carlo simulation, which enables the evaluation of the distribution of loss in a stochastic catalog. The technique consists of the following steps:

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**Table 3.** List of fragility functions used and respective references

<table>
<thead>
<tr>
<th>Typology</th>
<th>Type</th>
<th>IM</th>
<th>DS</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>C3L, C3M, C3H</td>
<td>Structural</td>
<td>Sd</td>
<td>Slight</td>
<td>HAZUS (FEMA, 2003)</td>
</tr>
<tr>
<td></td>
<td>Pre-code</td>
<td></td>
<td>Moderate</td>
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<td></td>
<td>Non-structural</td>
<td>Sa</td>
<td>Extensive</td>
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<tr>
<td>AS pre-code</td>
<td>Non-structural</td>
<td>Sd</td>
<td>Complete</td>
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<tr>
<td>DS pre-code</td>
<td>Non-structural</td>
<td></td>
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<tr>
<td>UFB5-1</td>
<td>Total</td>
<td>Sd</td>
<td>DS1</td>
<td>Singh et al. (2013)</td>
</tr>
<tr>
<td>UFB5-2</td>
<td>Total</td>
<td></td>
<td>DS2</td>
<td></td>
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<td></td>
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<td>DS3</td>
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<td>DS4-5</td>
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</table>

AS: acceleration sensitive; DS: drift sensitive.
1. A stream of events with magnitude, time of occurrence, epicenter location, and depth is generated into a stochastic catalog for 100,000 synthetic years (see section “Characterization of the Hazard” and Atkinson and Goda (2013)).

2. For each event, multiply the inter-event aleatory variability ($\tau$) by a random number $e_{\text{inter}}$, sampled from a standard normal distribution.

3. For each event and each grid cell, a normally distributed value is generated ($e_{\text{intra}}$). A spatial correlation between these random numbers is applied following Goda and Atkinson (2010). The resulting $e_{\text{intra}}$ values are used to multiply the intra-event variability ($\varphi$) defined in Douglas et al. (2013) for the GMPE chosen herein.

4. For each event and grid cell, calculate the hazard magnitude ($h$ in PGA) with the corresponding GMPE and its variabilities and modify with soil amplification factor.

5. For each event and each grid cell, evaluate the expected loss (equation 4)

$$E(L|h) = \sum_{i=1}^{N_{\text{building}}} N_{b,i} \cdot RC_i \cdot f_v(H = h)$$  \hspace{1cm} (4)

where $E(L|h)$ is the expected loss for a given hazard magnitude $h$ (calculated in step 4), $N_{b,i}$ is the number of buildings of typology $i$ in the grid cell, $RC_i$ is the replacement cost of typology $i$ (Table 2), and $f_v(H = h)$ is the damage ratio estimated from a vulnerability function for hazard magnitude $h$ (defined in section “Characterization of building vulnerability”).

6. Find total aggregated loss for each event adding losses at every grid cell.

7. Build the loss probability curve, recording the maximum loss per synthetic year.
Results and discussion

The case study to illustrate the procedure was defined as follows: an injection well was arbitrarily located in the northwest region of the city of Manaus because it meets the requirements that could potentially make it attractive for a real extraction project, for example, a large nature reserve with good roads’ access (Figure 10).

Loss analysis

Loss curves are estimated by Monte Carlo simulation for each branch of the logic tree for two injection volumes: 50,000 m$^3$ and 100,000 m$^3$ (Figures 11 and 12).

The resulting loss distribution functions show that the average loss in terms of the Manaus’ TVE is 0.0017% (US$ 0.38M) and 0.0026% (US$ 0.57M) for 50,000 m$^3$ and 100,000 m$^3$, if it is not known if the well will trigger seismicity. If it is known that the well causes appreciable seismicity, the AAL increases to 0.58% (US$126M) and 0.87% (US$189M). This difference is shown in Figure 11 by the continuous line and dashed line.

These values are estimated using the following assumptions: the injection point is located 13 km away from the city center (Figure 10); some branches of the logic tree combine low $b$-values, high seismogenic index, and high GMPE (high stress drop and low $\kappa$). Therefore, the difference found between the loss curves calculated for each branch of the logic tree is high (Figure 12). Thus, a sensitivity analysis of the parameters is necessary.

Identification of the governing variables of the problem

The variables that govern the losses were identified with a sensitivity analysis performed for the logic-tree parameters. Each loss exceedance curve (Figure 12) was averaged to
analyze how different volumes, GMPE, $b$-value, and $\Sigma$ affects the results. Then, a scatter plot of the average values was produced (Figure 13).

It is possible to see in Figure 13 that larger $b$-value leads to smaller losses (Figure 16), smaller seismogenic index $\Sigma$ leads to smaller losses; based on the GMPE, however, larger stress drop $\Delta \sigma$ and smaller $\kappa$ leads to larger losses. Also, this pattern of changes is constant for all branches.
In addition, the variables that govern the losses were identified with a tornado diagram. The baseline case consists of the median value of all parameters (i.e. \( b = 1.0 \), \( S = 2.5 \), GMPE of \( \Delta \sigma = 10 \) bar, \( \kappa = 0.02 \) s, and \( Q = 600 \); whose average is 0.30\% of TVE for \( V = 100,000 \) m\(^3\)).

The tornado diagram in Figure 14 shows that the \( b \)-value is the variable that most affects losses, for \( b = 0.7 \), losses increases 8.1 times, while for \( b = 1.3 \), losses decrease by a factor of 11.8. The seismogenic index \( S \) is the second most influential variable on the losses, for \( S = 2.5 \), loss reduce by a factor of 9.2, while for \( S = -0.5 \), loss increase by a factor of 6.1.

The GMPEs have the smallest impact of all variables of the logic tree on loss increase: an increase in 2.3 times and a decrease in 3.3 times on loss. The accumulated injected volume, not a parameter in the logic tree, has a lower participation than the previous parameters. In the baseline case, a twofold decrease in volume causes a 1.9 decrease in loss.

The baseline case for 50,000 m\(^3\) is used to plot disaggregation of damage per structural typology and zone in the city. The contribution of each typology to damage is depicted in

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**Figure 13.** Scatter plot of average values of each loss distribution function of each branch of the logic tree and four different volumes.

**Figure 14.** Tornado diagram of variables analyzed in the logic tree for different volumes.
Figure 15. Probability of exceedance curves: (left) for loss as a fraction of TVE by typology (horizontal bars); (right) for damage as a fraction of built area (m²) by typology. Both are presented for the baseline case (b = 1.0, S = 2.1.5, GMPE of ∆σ = 10 bar) and 50,000 m³ of volume injected.

Figure 16. Probability of exceedance of damage per region for the baseline case (b = 1.0, S = −1.5, GMPE of ∆σ = 10 bar) and 50,000 m³ of volume injected; (left) damage as a fraction of total m² of the region (right) total damage per region. The regions are presented in the map, which are West (gray), North (orange), Center-West (red), Center-South (green), South (blue), and East (purple).

Figure 15 for different probabilities of exceedance. Note the large dependency of damage and loss on the vulnerability of the building typologies UFB5-1 and UFB5-2, which highlights the importance on reassessing these variables once more studies are carried out on the vulnerability of UFB5-1 and UFB5-2 typologies in Brazil.

The regional spatial distribution of damage is shown in Figure 16, which provides a few insights to understand the role of exposure and vulnerability, for example: (1) north region is the most affected in absolute and relative (per m²) terms and not the west region that is closest to the injection point; (2) center-west region is the second most affected region in relative values because it is densely built if compared to the west region; (3) although the east region is relatively far from the injection point, it depicts large loss due to the large number of UFB5 building typologies and small number of C3 typology and its buildings are concentrated in the center part.
Model application and potential risk mitigation strategies

In the previous section, the significance of the $b$-value to the problem was highlighted; however, the frequency of earthquakes is influenced by the volume of fluid injected; therefore, it is possible to stop injections before a large event is triggered based on how many smaller events are triggered. Bommer et al. (2006) called this conditional decision analysis as traffic light system (TLS) by defining thresholds to limit injection. It must be mentioned, however, that the success of implementation of the TLS system should be carefully considered as its success, as applied to different injection-based activities, has been mixed; moreover, often with the largest induced event happening after the injection has ceased (see Baisch et al., 2019).

Using the proposed model, suppose an injection project starts being an expected total volume injected of 100,000 m$^3$, being 10,000 m$^3$ injected per month. The seismicity triggered in the first 3 months is registered, from which is possible to calculate the parameters of the GR law, in this case $b = 1.10$ and $S = 2.18$.

These values are used to select loss exceedance curves calculated previously (Figure 12) to estimate losses and related probabilities. For instance, loss curves were selected for 100,000 m$^3$ (Figure 17). For the average distribution function (black curve), the average loss expected is US$23.8M (0.11\% of TVE) and, for instance, for a 1\% probability of exceedance in 1 year, loss reaches US$347M (1.6\% of TVE). Loss exceedance curves may be used to identify safe thresholds of injection. The approach presented here enables a loss-driven decision-making for the TLS.

Another strategy for risk mitigation is to establish risky areas, in which TLS thresholds should be stricter, that is, Oklahoma and Ohio (Wong et al., 2015). Indeed, to avoid high losses, injection point shall not be located close to a densely populated area. In our case study, however, there are already many constraints on the location of an injection point; the city is surrounded by two major rivers and one natural reserve (Figure 18a). One may consider the option to move the injection point north (following the federal highway, BR-174).

Using the baseline model ($b$-value $= 1.0$, $S = -1.5$, GMPE of $\Delta\sigma = 10$ bar), five prospective injection points and two accumulated injection volume were applied to calculate

![Figure 17. Loss curves for 100,000 m$^3$ of the accumulated volume injected and selected $b$-values and $\Sigma$; their average is represented by the solid black line.](image-url)
the expected monetary loss for a given annual frequency of exceedance. As expected, the further the injection point the lower the expected loss for any accumulated injection volume; for example, when moving the injection point from point 2 to 3 (4 km away) average loss decreases ~22% for both volumes, from 2 to 5 (12 km away), average loss reduces by ~43% for both volumes. Therefore, TLS thresholds at point 2 should be stricter than at point 5.

For other strategies which were suggested, such as strengthening of structures and economic compensation, as proposed by Bommer et al. (2015), this study model output could also be used to provide insights.

**Conclusion**

This article presents the results of a risk assessment of induced seismicity due to unconventional oil and gas extraction near Manaus. The study was motivated in part by a recent raise in public awareness and opposition to these projects.

The methodology is based on the PSHA. The hazard parameters in the logic tree were characterized from information in the literature since there is no previous seismicity in Manaus. The sensitivity analysis shows that the variation in these parameters produces distant loss results. The $b$-value is the main parameter which affects losses, followed by the seismogenic index ($\Sigma$) and the attenuation functions. This emphasizes the importance of a seismograph network near injection wells to assess more accurately the hazard and allow to take adequate risk mitigation measures.

The proposed methodology can be enhanced in a number of ways. First, the model is fully statistical and so no specific study of the underlying tectonics and the triggering capability was made to describe the hazard. Also, no records of induced seismicity were
recorded in Manaus, consequently the choice of GMPEs was by similarity to other projects in the literature. The selection of maximum magnitude is arbitrary, and future work should add more branches to the logic tree to account other values. The capacity and fragility data for the exposed structures were adopted from available literature, which may not reflect the characteristics of Manaus’ building inventory; a specific vulnerability study of Brazilian structures is needed to improve the accuracy of estimates. Finally, the framework proposed could be expanded to include other risk metrics, such as population disturbance and life safety.

In spite of the limitations, the model presented allows to define potential risk mitigation strategies for cities like Manaus. Alternatives include applying a traffic light system, which limits the accumulated volume injected based on thresholds of loss values given a probability of interest. Another strategy is to base injection restrictions on its location. For the baseline case presented, the displacement of the injection 12 km away from the city implied in almost a half decrease in the estimated losses.

The framework applied to a vulnerable building inventory—where the building standard prescribes low seismic provisions and the population is mostly comprised by low-income families—emphasizes the need to inform industry and government of the risk of fluid injection procedures close to urban areas. It was possible to attain high values of loss even if low magnitude ($M < 5$) events are expected.

The proposed model is adjustable and computationally not intensive. In the occasion of occurrence of induced seismicity, the logic-tree parameters can be updated to attain more reliable estimates. The models may also be used to run deterministic scenarios for multiple magnitudes and hypocenter locations useful for financial analysis and decision-making. Finally, it is possible to update the exposure models to represent variations in repair cost ratios and building capacity.

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