Development and validation of fragility functions for buried pipelines based on Canterbury earthquake sequence data

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This paper presents parametric fragility functions for buried pressurized water pipelines based on data collected following the 22 February and 13 June 2011 events in the Canterbury, New Zealand earthquake sequence. The fragility of buried pipelines is expressed as a repair rate and utilizes the peak ground velocity, pipe characteristics and soil liquefaction susceptibility expressed by the cyclic resistance ratio. The model explicitly takes into account both within-model uncertainty (the misfit to the data) as well as between-model uncertainty, based on unknown model parameters, such that for each unknown parameter the between-model uncertainty increases. The adopted framework enables a wide application of these fragility functions to analyse the seismic performance of pressurized water pipeline networks, irrespective of the available information on the analysed system. Utilized in a retrospective analysis via Monte-Carlo simulations, the proposed fragility functions yield good predictive results.

INTRODUCTION

Lifeline seismic performance is recognised as an important contributor to the resilience of modern societies. Following the 1994 Northridge earthquake, for example, the damaged water system in some areas of the city of Los Angeles could not be utilized by fire protection services to counter fires ignited by gas network failures (Borden, 1997). Davis (2014) estimates that the functionality of the water supply network of Los Angeles, CA was approximately 35% following the earthquake, reducing the total water delivery by a maximum of approximately 20%. To emphasise the economic importance of lifelines, Chang et al. (2002) estimated that a water supply outage in Memphis, Tennessee due to a $M_w$ 7.5 North Fault rupture would cost around

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USD 100M. Economic importance of lifelines is further emphasized by Tierney (1997); Rose et al. (1997); Brookshire et al. (1997); Dahlhammer et al. (1999); Stevenson et al. (2012, 2017).

The M$_w$ 7.1 Darfield and the M$_w$ 6.2 Christchurch earthquakes struck the Canterbury area in New Zealand on the 4$^{th}$ of September 2010 and 22$^{nd}$ of February 2011, respectively. They were notably followed by the M$_w$ 6.0 13$^{th}$ of June and the M$_w$ 5.8 23$^{th}$ of December 2011 earthquakes. This series of earthquakes is known as the Canterbury Earthquake Sequence (CES) and their seismological features and physical impacts have been extensively described by Gledhill et al. (2010); Cousins and McVerry (2010); Quigley et al. (2010); Bradley and Cubrinovski (2011); Wood et al. (2011). The February event, in particular, caused widespread liquefaction (Cubrinovski et al., 2011) in the Christchurch urban area and severely damaged the built environment (Palermo et al., 2011; Dizhur et al., 2011). Multiple civil infrastructure systems have also been studied. In particular, Giovinazzi et al. (2011); Eidinger and Tang (2012) investigated the performance and service restoration of the electric power distribution, the waste water and water supply networks. Cubrinovski et al. (2014) studied the effects of liquefaction on the waste water, water supply and road networks.

Following the CES, the liquefaction and lateral spreading that occurred in Christchurch was closely studied and several liquefaction-related damage maps were published. In a careful study of two sites during the 4 September 2010 and the 22 February 2011 earthquakes, Bowen et al. (2012) showed that ‘rapid and complete liquefaction of susceptible layers is required to trigger lateral spreading’. Based on the 56m LiDAR survey that took place after the 22 February 2011 earthquake, O’Rourke et al. (2014) developed the ground strains and angular distortion maps. To characterize liquefaction severity, van Ballegoooy et al. (2014) introduced the liquefaction severity number (LSN), an integral of the calculated post-liquefaction volumetric reconsolidation strain over the depth. It was compared with the liquefaction potential index (LPI) (Iwasaki et al., 1984), the former showing a better between-event correlation across the CES than the latter. From the liquefaction observations following the 22 February 2011 earthquake, Cubrinovski et al. (2014) developed the liquefaction resistance index (LRI), which is a representation of the aggregated cyclic resistance ratio (CRR) of the top layers (up to 3.5m deep) of Christchurch soils using the simplified procedure for liquefaction evaluation proposed by Youd et al. (2001). Utilizing the Christchurch liquefaction database, van Ballegoooy et al. (2015) compared different liquefaction triggering procedures coupled with several liquefaction severity metrics, showing that the use of different models could yield significantly different results. Toprak et al. (2018) assessed the influence of the ground strains and displacement estimates gathered from LiDAR
4m, LiDAR 56m, air photography and satellite imagery on pipe vulnerability assessment. Most
of these datasets as well as the raw conical penetration test (CPT) data can be found on the New

From the aforementioned data collections, several fragility (probability of failure given a
specific ground motion intensity) models have been developed based on the observed asset
seismic vulnerability. For spatially-distributed systems, the vulnerability of an asset is gen-
erally expressed as a repair rate (number of repairs per unit of length). Cubrinovski et al.
(2014) developed predictive repair rate functions for asbestos cement pipelines depending on
the magnitude-weighted ($M_w = 7.5$) peak ground acceleration and LRI (discussed in a subse-
quent section) zone in which pipelines were buried. O’Rourke et al. (2014) and Bouziou and
O’Rourke (2015, 2017) used angular distortion and horizontal ground strain to derive repair
rate functions for several existing pipe materials in liquefied soils. To compare the results using
horizontal ground strain and angular distortion with other intensity measures, O’Rourke et al.
(2014) also used the geometric mean peak ground velocity (PGV) to estimate reported repair
rate in non-liquefied soils. Toprak et al. (2017) proposed a relation between the repair rate and
LSN. In addition to the PGV, other models (e.g. Isoyama et al., 2000) also incorporate categori-
cal parameters dependent on the soil conditions and severity of observed liquefaction. Eidinger
et al. (2001) and HAZUS (Federal Emergency Management Agency, 2003) both use a combina-
tion of PGV-based and permanent ground deformation (PGD)-based models to describe damage
due to transient and permanent ground deformations. O’Rourke and Deyoe (2004) express the
pipeline vulnerability given the ground strain induced by either the seismic wave propagation
and the permanent ground deformation in a single regression.

In the context of seismic loss estimation of water supply networks, the aforementioned mod-
els have their own realm of applicability. Ground strain and PGD-based models are particularly
useful to assess damage following an earthquake in regions subject to large permanent ground
deformations. However, they miss capturing the damage caused by transient ground deforma-
tions in the absence of ground failure. Moreover, due to the difficulty to accurately predict
PGD and ground stains, these models also remain hard to apply within a predictive loss anal-
ysis. PGV-based fragility functions can more easily be used in such cases. However, they do
not cover the possibility that PGD may occur, and the inclusion of a qualitative and local ge-
ologic parameter such as the type of deposit and the observed liquefaction severity makes the
application to networks built in other regions difficult.
To address the aforementioned difficulty assessing predictive loss estimation in liquefaction-prone regions, the present study combines PGV with a quantitative soil parameter independent from the ground motion, CRR and utilizes some of the CES datasets, namely: the network dataset, the pipe repair report dataset, the simulated ground motion maps for each CES event and the estimated Christchurch soil liquefaction resistance index map. This parameter combination allows the assessment of networks subjected to transient ground motions and liquefaction-induced permanent ground deformations by proxy. The developed parametric repair rate functions are utilized in a Poisson distribution to express the fragility of the pipeline.

The next sections present the adopted datasets, the developed methodology and its numerical application details. Subsequently, the fitted functions and their uncertainties are presented and discussed. The proposed fragility functions are finally tested in a retrospective validation analysis via Monte-Carlo simulations (MCS).

ADOPTED DATASETS

WATER SUPPLY NETWORK ATTRIBUTES

The Christchurch water supply network is owned and managed by the Christchurch City Council (CCC). CCC classifies its assets into four categories based on their functionality: (1) Trunk main: diameter greater than 300 mm, used for water transmission from main pump stations to large mains; (2) Main: diameter between 80 to 300 mm, used to distribute water in residential and industrial areas; (3) Submain: diameter between 15 to 80 mm, used to distribute water to a small group of buildings; and (4) Crossover: diameter between 15 to 80 mm, connection between the mains and submains, relatively short. The network is 3246 kilometres long and contains 1612 kilometres of trunk main and main pipelines (49.9% of the network) and 1624 kilometres of submain and crossover pipelines (50.1% of the network). Note also that 192 kilometres (5.9% of the network) are located in the Port Hills area and situated in stiff soil. The network is mainly composed of high-density polyethylene (HDPE, 28.7%) and asbestos cement (AC, 26.2%) pipelines. Large portions of the network are also made of polyvinyl chloride (PVC, 14.4%) and medium-density polyethylene 80 (MDPE80, 14.0%) pipelines. The use of galvanized iron (GALV, 5.8%), cast iron (CI, 5.7%), concrete-lined steel (CLS, 1.6%), ductile iron (DI, 1.5%) and steel (STEEL, 1.0%) remains marginal. A negligible quantity of segments are built with other types of materials (1.0%). Note that the utilized dataset also contains other types of polyethylene pipes, namely PE100, MDPE100 and LDPE (low density polyethylene), which
Figure 1. Composition of the Christchurch city network by: (a) construction material; (b) LRI zone; and (c) construction material and LRI zones

have been grouped under the category MDPE80 as their respective density does not qualify them as high density and their age of installation correspond to this type of pipes (Cubrinovski et al., 2014, Figure 3). Figure 1 graphically summarises the pipe network composition and also subdivides each material based on the different LRI zones (introduced in a subsequent section). Figures A.1 and A.2 show the topology of the water supply network and Table A.1 summarizes the pipeline attributes and their possible values.

REPORTED PIPE REPAIRS FOLLOWING THE CANTERBURY EARTHQUAKE SEQUENCE EVENTS

The pipe repair dataset was created and managed by the Stronger Christchurch Infrastructure Rebuild Team (SCIRT). A consistent data collection of executed repairs started after the 22 February 2011 Christchurch earthquake as mentioned by Cubrinovski et al. (2014, pp. 17-22).
As a result, the majority of the repairs from the 4 September 2010 earthquake was not documented adequately and therefore, not considered in the analysis to follow.

The SCIRT repair dataset inventories all pipe repairs, regardless of their cause. Therefore, a screening is necessary to remove pipe repairs which were unlikely to have been earthquake-induced (i.e. repairs that have no or little effect on the global seismic system performance). Excluding the central business district areas cordoned off following the 22nd February 2011 (for safety reasons, access restriction was enforced for 15 months in the Christchurch Business District, see Chang et al. (2014) for more details), Giovinazzi et al. (2011) report that 95% of the buildings had recovered water access approximately one month following the February earthquake. Eidinger and Tang (2012) estimate that the repair period lasted approximately six weeks (i.e. that the repairs ended circa the 5th of April 2011). O’Rourke et al. (2014) defines the so-called transitional frequency of repairs period as a period during which the weekly repair rate of main pipelines is lower than the one observed during the emergency phase but still higher than the post-earthquake steady state frequency of repairs. O’Rourke et al. (2014) define the start of the former circa the 15th of April 2011 and circa the 21st July 2011 for the February and June earthquakes, respectively. In this analysis, repair periods proposed by O’Rourke et al. (2014) are selected to screen the earthquake-related pipe repairs. In total, 3039 pipe repairs are attributed to the February event and 732 to the June one. Changes in the pipe network materials and extent due to growth and repairs between the February and June earthquakes have been considered. Nonetheless, very few changes can be observed as the repairs were carried out following a like-for-like strategy as noted by Eidinger and Tang (2012, p. 170). The daily observed repair rate and cumulative number of repairs as well as the aforementioned key dates are given in Figure 2. The grey areas show the considered repair periods for each earthquake. Figure A.5 shows the map of the spatial distribution of pipe repairs and Table A.2 provides their attributes.

Despite the accuracy and completeness of the pipe repair dataset, several limitations are worthy of note. First, when reported, the repaired pipe part (fitting, coupler or pipe hull) was not consistently described across the dataset due the non-uniform nomenclatures used by contractors. And second, pipe repairs were binarily recorded (i.e. failed or undamaged), making it impossible to classify repairs as either breaks or leaks. For these reasons, the developed functions express the fragility of pipelines as a whole (i.e. no discrimination between pipes, fittings and couplers are made) and do not provide a quantitative measure of the damaged pipe performance.
Figure 2. (a) Number of detected pipe repairs per day on the water supply network; and (b) Cumulative number of detected pipe repairs. In both figures, red lines indicate the exact date of each major earthquake. Grey areas indicate the periods when pipe repairs are considered as a direct consequence of an earthquake, with the end of the effective repair period considered by prior studies, also explicitly noted.
GROUND MOTION INTENSITY

For the purpose of correlating pipe damage with ground motion intensity, the geometric mean peak ground velocity (PGV) maps computed by Bradley (2014) for each considered event of the CES are adopted. These maps are uniformly-spaced grids, where points represent the ground motion estimation in the form of a log-normal distribution of PGV (defined by a median value and logarithmic standard deviation). The predicted distribution of PGV is based on a combination of an empirical ground motion model (Bradley, 2013) and recorded ground motions at strong motion stations, such that lower standard deviations in the prediction occur in the vicinity of strong motion stations. Figures A.6 to A.9 show the ground motion intensity and its lognormal standard deviation of the 22 February and 13 June 2011 events.

SOIL LIQUEFACTION SUSCEPTIBILITY

Previous observations and analyses (e.g. Eidinger et al., 2001; Cubrinovski et al., 2014; Bouziou and O’Rourke, 2015, 2017) have identified higher repair rates in liquefaction-susceptible areas as a result of greater ground deformation for a given level of ground motion intensity. In the context of the CES, the LRI developed by Cubrinovski et al. (2014, pp. 13-14) summarizes the observed liquefaction-related land damage and the susceptibility of the ground to liquefy given the measured CRR of the different ground layers present in a particular area. In Christchurch, five LRI zones have been estimated for a shallow depth of the deposits. Each zone is defined by a range of CRR based on observed ground failures during the 22 February 2011 earthquake. Cubrinovski et al. (2014, Table 2) also provide an estimate of the CRR at the groundwater table depth for each zone (i.e. 0.065, 0.13, 0.195 and 0.26 for $LRI = 1$, $LRI = 2$, $LRI = 3$ and $LRI = 4$, respectively). Table A.3 provides the CRR range for each zone as well as their associated ground settlement and lateral displacement amplitudes. Figure A.10 presents the spatial extent of each zone.

To develop the subsequently-proposed model, a single value of CRR per LRI zone is used. The selection of this value is based on the assumed installation depth of the pipelines (between 0.75 and 1.5 meters, see Christchurch City Council (2014, pp. 25-29) for more details) and the estimated groundwater table depth at the time of the earthquakes. van Ballegooy et al. (2014, pp. 40-42) estimated the groundwater table to lie mostly between 0 and 2 metres deep. Hence, the CRR at the groundwater table depth is selected to represent the liquefaction susceptibility of the soil at pipeline installation depth. Further reference to the CRR in the development of
fragility functions refers to the estimated CRR at the groundwater table depth. Note that as the
value of CRR at the groundwater table depth for \( LRI = 0 \) is undefined by Cubrinovski et al.
(2014), it is assumed to be 0.032. This value is chosen as the mid-point between an infinitely
liquefaction-susceptible soil and the estimated CRR for \( LRI = 1 \) at the groundwater table
depth.

FRAGILITY FUNCTION METHODOLOGY

GENERAL FRAMEWORK

To create a widely applicable set of fragility functions for buried pipelines, the functions are
built in a way such that they can be applied to pipelines for which some characteristics re-
main unknown. To achieve this goal, a parametric model is developed by combining the pipe
segment, soil profile liquefaction susceptibility and ground motion intensity characteristics. Pa-
rameters considering the various dependencies have specific values if known and otherwise are
random variables. Hence, the more parameters that are known, the smaller the between-model
uncertainty is (as discussed in a subsequent section). The next section details the development
of the model and the subsequent section provides its numerical implementation.

PIPELINE FRAGILITY MODEL DESIGN

The pipeline fragility functions proposed in this study are developed as pipeline repair rate
functions (i.e. number of reported pipe repairs per kilometre) assuming a Poisson distribution of
repairs along pipelines as adopted in similar studies (e.g. O’Rourke and Ayala, 1993; Eidinger,
1998; Isoyama et al., 2000; O’Rourke and Deyoe, 2004; O’Rourke et al., 2014; Bouziou and
O’Rourke, 2015, 2017). The specific functional form for the repair rate, \( \lambda \), is given by Equation
1.

\[
\ln(\lambda) = f_0(PGV) + \sum_{i=1}^{n} C_i(h_i) + \epsilon
\]

where \( \ln(\lambda) \) is the natural logarithm of the repair rate, \( f_0(PGV) \) is the so-called backbone
function depending on \( PGV \), \( C_i(h_i) \) is the correction term corresponding to the \( i^{th} \) known
model parameter which depends on the parameter vector \( h_i \). The number of known parameters
is expressed by \( n \) and the uncertainty of the model by \( \epsilon \), a zero-centred normally distributed
random variable.

The backbone function \( f_0 \) estimates the repair rate of a pipeline knowing only the PGV it
experiences. This first estimate is then corrected by the terms $C_i$ given the known parameters $h_i$. The pipeline characteristics-related correction terms depend on the pipe material and pipe diameter. To group brittle and ductile materials together, the material ductility parameter is added as a binary variable (i.e. the material is classified as brittle or ductile). To correct the repair rate based on the soil liquefaction susceptibility, another correction term depending on CRR is created. This allows the soil liquefaction susceptibility to be described by a continuous variable, facilitating the use of the proposed functions on other networks. Hence, the backbone curve $f_0$ can be corrected by a maximum of four correction terms $C_i$ depending on ductility, material, diameter and CRR. To account for the function misfit and unknown parameters, the uncertainty term $\epsilon$ is added to the corrected repair rate. The backbone function $f_0$ and the correction terms $C_i$ are fitted on the observed repair rate or their difference with less develop model sharing the $n - 1$ identical characteristics, respectively.

To ensure that the data points used to estimate the backbone function $f_0$ and the correction terms $C_i$ are statistically valid, the screening criteria proposed by O’Rourke et al. (2014) is applied with the recommended values. Assuming a Poisson distribution, this criterion verifies that the pipe length used to compute the repair rate is long enough.

In order to minimize the model error, multiple functional forms for the backbone function $f_0$ are tested via a K-Fold cross-validation process as described in (Friedman et al., 2008, pp. 241-247). This method consists of splitting the dataset into K smaller subsets, which are subsequently used to estimate the error of each functional form fitted on the data belonging to the K-1 other folders. The functional form with the smallest error is the model that is then chosen. In the present case, subsets are created with an approximately equal length of pipelines. Note that errors are estimated on the entire repair rate function set as detailed in Appendix B.

As the created model is built by adding correction terms $C_i$ to the backbone function $f_0$, it inherently contains two types of uncertainties: the within-model uncertainty due to the misfit of the parametric model to the empirical data, and the between-model uncertainty due to the additive feature of the model (i.e. the difference between levels of corrections of the backbone function $f_0$). The within-model uncertainty is computed as the standard deviation from the fitting residuals of $C_i$ or $f_0$. It is considered as a normally distributed random variable with zero mean as the curve fitting process aims to converge on this particular value.

The between-model uncertainty is estimated by computing the standard deviation of the residuals between the most detailed repair rate functions (i.e. depending on ductility, mate-
rial, diameter and CRR) and the analyzed, less detailed function. Note that, by doing so, the
between-model uncertainty of the most detailed repair rate functions is non-existent. To be
considered valid, repair rate functions have to show a between-model residual mean close to
zero (i.e. the most detailed functions must show both positive and negative residuals with the
analysed one). The between-model uncertainty is also assumed to follow a normal distribu-
tion. It is subsequently demonstrated that the normal distribution for $\ln(\lambda)$ is an appropriate
approximation. As both uncertainties are considered as independent normally distributed ran-
dom variables with zero mean, the total uncertainty of a specific repair rate function can be
sampled as a combination of two zero-centred normal distributions.

In addition, physics-based constraints are set to estimate the correction term functions $C_i$.
First, according to the observations, a pipeline buried in soil with lower CRR (i.e. more sus-
ceptible to liquefaction) should experience, on average, more damage than a pipeline buried
in soil having a higher CRR. Therefore, to remain physically consistent, the repair rate must
increase with the reduction of CRR (i.e. the partial derivative of the correction term function $C_i$
corresponding to the soil characteristic CRR must be negative with respect to CRR).

Furthermore, observations also show an increase in the mean repair rate with increasing
ground motion intensity. To ensure that repair rate functions remain monotonically increasing
for expected ground motion intensities, the partial derivative of the newly computed correction
term $C_n$ with respect to PGV must remain greater than the partial derivative of the repair rate
function sharing the $n-1$ identical parameters. Details of the fragility function fitting process
can be found in Appendix B.

**IMPLEMENTATION OF THE PROPOSED FRAMEWORK**

This section details the modelling choices and numerical implementation of the proposed frame-
work. First, groupings of certain parameter values are justified. Then, functional forms of the
backbone function $f_0$ and correction terms $C_i$ are proposed. Finally, numerical values for the
physics-based constraints and K-fold cross-validation are given.

As the sample length tends to be relatively small for some parameter combinations, certain
values are grouped together to increase it. Based on the distribution of diameters and function-
ality of pipes (see Figure A.3), diameters between 0-80 mm, 80-300 mm and 300-600 mm are
grouped. Table 1 presents the brittle and ductile materials as well as the materials referenced
under the same label. This distribution produces a distinct differentiation between the brittle
Table 1. List of considered brittle and ductile materials

<table>
<thead>
<tr>
<th>Material behavior</th>
<th>Material names</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brittle</td>
<td>AC, CI, CLS and GALV</td>
</tr>
<tr>
<td>Ductile</td>
<td>DI, HDPE, MDPE80 (incl. MDPE100, LDPE and PE100), PVC (incl. UPVC and MPVC)</td>
</tr>
</tbody>
</table>

Figure 3. CDFs of the difference between the screened repair rate data from the backbone curve and from the classifications based on (a) material ductility; and (b) LRI zones and ductile materials as shown in Figure 3 (a).

In addition, pipes situated in the LRI = 4 and No observed liquefaction zones are grouped together. Figure 3 (b) shows the empirical cumulative distribution of the residuals between the observed repair rates of the backbone function and the CRR-corrected function. It can be observed that the LRI = 4 curve is significantly below the No observed liquefaction curve. As the LRI = 4 zones are located exclusively on the western part of the city (see Figure A.10), they experienced significantly smaller PGV (see Figures A.6 to A.9) and therefore smaller repair rates. As a result, they can reasonably be associated with the No observed liquefaction zones. Pipes in the Port Hills areas are considered for the development of CRR-independent functions, but excluded otherwise. Specific repair rates functions for the pipelines located in the Port Hills area are developed in Appendix C.

To perform the K-fold cross-validation on the backbone function \( f_0 \), three functional forms are tested: the linear function (Equation 2), the power function (Equation 3) and the ‘corrected’ power function (Equation 4).

\[
\begin{align*}
  f(PGV) &= a \cdot PGV + b \quad \text{(2)} \\
  f(PGV) &= a \cdot PGV^b \\ % (3)
\end{align*}
\]
The functional forms utilized to fit the correction term functions \( C_i \) depending on the pipe (ductility, material and diameter) and the soil characteristics are the linear function (Equation 6) and the power function (Equation 5), respectively.

\[
f(PGV) = a \cdot PGV^b + c
\]  

\[
C_{\text{Soil}}(CRR) = a \cdot CRR^b + c
\]  

\[
CX(PGV) = ax \cdot PGV + bx
\]

where \( X \) is either the ductility, the material or the diameter dependence.

The monotonically increasing behaviour of the repair rate functions is guaranteed for PGV inferior or smaller than 150 cm/s. Five folders are created to realize the K-fold cross-validation. It is also worth mentioning that, to reduce the effect of soil condition and ground motion spatial variability, the pipelines are discretized such that their maximum length does not exceed 50 m (the longest asset is longer than 2 km).

**REPAIR RATE FITTING RESULTS**

This section provides the results of the K-fold cross-validation and of the fitting process using the selected functional form for the backbone function \( f_0 \). The developed repair rate functions are plotted against the PGV and their uncertainties are discussed. The final form of the repair rate function is then explicitly given. Finally, some of the proposed functions are compared to existing ones, which also use PGV as ground motion intensity measure.

**K-FOLD CROSS-VALIDATION AND REPAIR RATE FITTING RESULTS**

K-Fold cross-validation errors for the linear, power and ‘corrected’ power models are 1.86, 1.85 and 1.76 respectively. The difference between the linear and power functions are insignificant. However, the score of the ‘corrected’ power model shows a clear 5.5 % model accuracy improvement. Hence, the ‘corrected’ power function is chosen over the linear and power ones to model the backbone function \( f_0 \). Due to the absence of individuals for some parameter combinations, numerous possible repair rate functions are not modelled (e.g. large diameter GALV). In addition, some functions are rejected as the sample length they are derived from is too small. Namely, all CLS, DI and Steel as well as the small diameter AC and PVC related functions are discarded. However, data from these discarded functions are integrated into their less developed form (e.g. small diameter PVC data is integrated into the PVC data and CLS data is included.
Figure 4. CRR-independent repair rate functions for (a) generic pipes (backbone function) and generic brittle and ductile pipes; (b) pipes made of brittle materials; (c) pipes made of ductile materials into brittle data). It is recommended to replace the discarded functions by their associated less developed form (e.g. PVC D 0-80mm should be replaced by PVC and CLS-CRR should be replaced by Brittle-CRR). Further discussion is directed only toward the remaining valid 30 functions.

Figure 4 presents the fitted, CRR-independent repair rate functions. As expected and pictured in Figure 4 (a), pipelines made of brittle construction materials experience significantly higher repair rates than pipelines made of ductile construction materials. Among the brittle construction materials present in Figure 4 (b), GALV is most vulnerable, whereas other materials have similar vulnerability curves. For construction materials classified as ductile in Figure 4 (c), PVC performs best, followed by MDPE80. HDPE pipelines have a higher repair rate. Due to the lack of data, diameter-dependent functions tend to show repair rates similar to their less developed forms and are therefore not graphically presented.

Figure 5 presents CRR-dependent repair rate functions. For conciseness, the plotted functions represent only the three most basic CRR-dependent functions (namely, PGV - CRR, PGV - Brittle material - CRR and PGV - Ductile material - CRR functions). Figure 5 (a) shows that
Figure 5. CRR-dependent repair rates functions for (a) generic pipes; (b) generic brittle pipes; and (c) generic ductile pipes. Colour intensity indicates the liquefaction susceptibility characterized by the CRR. CRR values presented correspond to the five LRI zones.

for a given pipeline, regardless of its characteristics, the liquefaction susceptibility of the soil significantly contributes to its vulnerability. This trend is particularly pronounced when looking only at pipelines made of brittle construction material. However, the influence of the liquefaction susceptibility of the soil is less marked for pipelines made of ductile material. General trends related to material and diameter observed in Figure 4 remain valid for CRR-dependent functions.

Quantile-quantile plot (QQ plot) is a graphical, statistical tool, that helps compare the empirical distribution (the data) with an assumed distribution (the hypothesis). A good alignment of the data along the identity line validates the original assumption that the lognormal distribution is appropriate for the repair rate. Figure 6 presents the QQ plots for both the within-model and between-model uncertainties of the PGV-CRR repair rate function shown in Figure 5 (a). This function is selected as it is fitted on a statistically-relevant number of points and has the maximum number of most developed forms (ductility, material, diameter and CRR-dependent functions). With the exception of the between-model uncertainty left tail in Figure 6 (b), both plots show that the normal distribution of $\ln(\lambda)$ is a reasonable assumption.
Fig. 6. QQ plots of (a) the within-model; and (b) the between-model uncertainties of the PGV-CRR repair rate function

REPAIR RATE UNCERTAINTY MODELLING

Figures 7 (a) and (b) present the within-model and between-model uncertainties, respectively, in terms of mean residual and its standard deviation for all valid repair rate functions. The within-model uncertainty is expected to increase as the dataset size decreases. Hence, as the number of parameters increases, the data becomes scarcer and the within-model uncertainty increases. As their formulation is more complex (i.e., based on two continuous variables, namely, the PGV and the CRR), the CRR-dependent functions tend to show a higher within-model uncertainty. Due to the almost exclusivity of material use for a certain functionality (which is directly linked to the diameter), diameter-dependent functions for these materials show almost no change in their within-model uncertainty.

The between-model uncertainty tends to decrease with the number of parameters (i.e., the analysed function becomes more similar to its most detailed form). For the PVC-dependent functions, the between-model uncertainty mean is significantly above zero (which means that the model tends to underestimate these repair rates). As the data from the removed small diameter PVC functions tend to show higher repair rates, their integration into the diameter-independent functions leads to this overestimate. Furthermore, data points from the PVC and CI fitted functions for the $LRI = 4$ zones have been manually excluded as they were showing equivalent repair rates as data points for the $LRI = 2$ zones, explaining both the positive value in within-model and between-model uncertainty for these two materials. As it can be observed in Figure 1, the amount of CI pipes in LRI = 4 zones is extremely low. Hence, a few observed pipe repairs in these areas yield a large repair rate. Albeit less marked, the same tendency can
Figure 7. (a) Within-model uncertainty; and (b) between-model uncertainty given in terms of mean and standard deviation of residuals for all developed repair rate functions. Note that some parameters are not explicitly listed in the labels (e.g. PGV for all functions except the backbone curve and ductility for material and diameter-dependent functions).

be observed for PVC. In addition to this factor, LRI = 4 zones are concentrated toward the West of the city (see Figure A.10), and experienced only low PGV (see Figures A.6 and A.8). Hence, data points for LRI=4 are concentrated around low PGV values. Acknowledging that PVC pipes were among the most resistant during the CES (Eidinger and Tang, 2012, p. 166 and O’Rourke et al., 2014), the observed vulnerability in zones with $LRI < 4$ was relatively low for this range of PGV, leading to this inconsistency that have been manually removed. All numerical results from the fitting process and uncertainty estimation are gathered in Appendix D.
Equations 7 and 8 give the fully-developed repair rate model for pipelines buried in soft soils. Table D.1 provides the coefficient values for all repair rate functions included in this model. A value of zero is assigned to every unknown pipeline or soil characteristic.

\[
\ln(\lambda) = \left[ a_0 \cdot PGV + b_0 \right] + \left[ a_1 \cdot PGV + b_1 \right] + \left[ a_2 \cdot PGV + b_2 \right] + \left[ a_3 \cdot PGV + b_3 \right] + \left[ a_4 \cdot CRR + b_4 \right] + \epsilon
\]

\[
\epsilon \sim N \left( 0, \sqrt{\sigma_W^2 + \sigma_B^2} \right)
\]

where index 0 represent the backbone function of the model \( f_0 \), index 1 the material ductility correction term, index 2 the material correction term, index 3 the diameter correction term, index 4 the CRR correction term and \( \epsilon \) the normally distributed uncertainty term constituted of a within-model and a between-model standard deviations. For practical applications, Equation 7 can be rewritten as proposed in Equation 9.

\[
\ln(\lambda) = (c_0 + b_1 + b_2 + b_3 + c_4) + (a_1 + a_2 + a_3) \cdot PGV + a_4 \cdot CRR + a_0 \cdot PGV + \epsilon
\]

**COMPARISON WITH EXISTING PIPE VULNERABILITY FUNCTIONS**

To compare the herein-presented functions the following models are selected: the brittle and ductile repair rate functions given by HAZUS (Federal Emergency Management Agency, 2003), the backbone function from Eidinger et al. (2001) as well as the backbone function and its liquefaction-dependent forms from Isoyama et al. (2000). It should be noted that both HAZUS (Federal Emergency Management Agency, 2003) and Eidinger et al. (2001) models propose PGD-dependent repair rate functions, which generally yields greater repair rates than their PGV-dependent counterparts for large PGD-prone areas. However, as the aim of the proposed model is to remove the liquefaction severity estimation from the seismic network analysis, only the PGV-dependent models are compared. Both models from HAZUS (Federal Emergency Management Agency, 2003) are the ones presented by O’Rourke and Ayala (1993) based on four US and two Mexican earthquakes. The brittle material model is assumed valid for AC, CI and RCC (reinforced cement concrete) pipelines, with the ductile material valid for DI, Steel and PVC. The Eidinger et al. (2001) repair rate function is based on a dataset where the CI construction material is most prevalent (38%). The Isoyama et al. (2000) backbone model expresses the repair rate of CI pipelines of diameters between 100 and 150 mm in alluvial soils, in which
no liquefaction was observed. Coefficients for the liquefaction-dependent functions given by
Isoyama et al. (2000) are provided for “No liquefaction”, “Partial liquefaction” and “Total liq-uefaction”. Existing functions are compared with the herein-presented backbone and ductility functions with low liquefaction susceptibility (i.e. equivalent to the CRR of $LRI = 4$ zones)
Given the construction material used to develop the Isoyama et al. (2000) backbone function, the CRR-dependent brittle construction material repair rate is used for the liquefaction-dependent functions.

Figure 8 shows both the comparisons between the CRR-independent (a) and CRR-dependent functions (b). Figure 8 (a) shows that the proposed model yields similar results than the HAZUS (Federal Emergency Management Agency, 2003) model. However, both the Eidinger et al. (2001) and Isoyama et al. (2000) models return substantially lower repair rates. The same general trends can be observed for liquefaction susceptibility-dependent functions in Figure 8 (b): here also, the Isoyama et al. (2000) functions tend to underestimate the damage.

RETROSPECTIVE ANALYSIS

To ensure that the presented fragility functions are reliable, they are tested in a retrospective analysis. This analysis is conducted via a Monte-Carlo simulation (MCS) process first at network level (i.e. using the entire network), and then at repair catchment level (i.e. for smaller portions of the network). The repair catchments are network portions, that were delineated by SCIRT during the Christchurch rebuild. Figure A.4 presents the 94 repair catchments spatial distribution and their respective cumulative pipe length. The network level analysis allows to assess the predicting model performance of total number of pipe repairs, whereas the catchment level are used to assess the statistical validity of the model via a Pearson’s residual analysis, as well as a geospatial comparison between the observed and simulated repair rates for both the February and June events.

MONTE CARLO SIMULATION METHOD AND RESULTS AT NETWORK LEVEL

For the simulations, the maximum pipe length is set to 100 m. Longer pipelines are split into smaller segments of approximately equal size. PGV intensities are estimated on a rectangular grid of stations located at 500 meters and 100 meters from each other for the network level and catchment level analyses, respectively. A pipe segment is assumed to experience the same PGV as the nearest station to its centroid. For the network level analyses, two different MCS are
Figure 8. (a) Comparison between selected and proposed CRR-independent and ductility-dependent repair rate functions; and (b) comparison between Isoyama et al. (2000) and the proposed CRR-dependent and brittle material repair rate function.
performed. First, a conventional MCS is executed and second, to mimic reality, a threshold is applied on the maximum number of repairs a pipe can experience. The threshold is determined by the maximum repair rate observed on a 20+ meters long asset for each event, the minimum value of the threshold being 1. Based on observations, this threshold is set to 18 and 3 repairs on the same 100 meters long pipeline for the February and June event, respectively. This type of simulation is further referenced as a “capped” simulation. For the network level analyses, results are given in terms of mean, median, uncertainty and difference of number of repairs. For the catchment level analyses, results are given in terms of Pearson’s residuals of number of pipe repairs and graphically exposed in terms of median simulated repair rates to geospatially assess the model performance. For each analysed area (network and catchments), 2000 simulations are realized. Each MCS run consists of the following five steps:

1. Generate a spatially-correlated, multivariate random field to sample the ground motion residuals using the semi-variogram-based correlation model proposed by Jayaram and Baker (2009).

2. Compute PGV intensity at each station utilizing the simulated median and generated residuals

3. Evaluate the repair rate mean and standard deviation for each pipeline given the experienced ground motion intensity and the known characteristics of the repair rate model

4. Sample the repair rate for each pipeline

5. Simulate the number of repairs for each pipe segment.

In order to determine some of the result metrics, it is necessary to estimate the distribution of the number of pipe repairs. Figure 9 (a) presents the results at a network level for the 22 February 2011 event using the standard MCS scheme. The pipe repair number on the network is log-normally distributed, which is confirmed by the aspect of the logarithmic number of repairs QQ plot presented in Figure 9 (b). Therefore, further metrics are estimated assuming log-normally distributed number of pipe repairs.

Table 2 presents the results for the four different network level analyses. The February simulations (standard and capped) show little difference and are relatively well-predicted. The June simulations (standard and capped) are relatively close from each other but tend to largely overpredict the number of pipe repairs. In this case, it is believed that the most vulnerable assets
Figure 9. (a) Distribution of the simulated number of pipe repairs for the February earthquake; and (b) QQ plot of the logarithmic simulated number of repairs for the February event.

Table 2. Number of pipe repair results at network level. Percentiles and deviations are expressed for the associated normal distribution of number of repairs.

<table>
<thead>
<tr>
<th>Analysis</th>
<th>Mean</th>
<th>Median</th>
<th>Log. std dev.</th>
<th>Observation</th>
<th>Percentile</th>
<th>Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>February</td>
<td>2988</td>
<td>2895</td>
<td>0.337</td>
<td>3039</td>
<td>58%</td>
<td>+0.14σ</td>
</tr>
<tr>
<td>February (capped)</td>
<td>2971</td>
<td>2894</td>
<td>0.320</td>
<td>3039</td>
<td>59%</td>
<td>+0.23σ</td>
</tr>
<tr>
<td>June</td>
<td>1520</td>
<td>1403</td>
<td>0.446</td>
<td>732</td>
<td>8%</td>
<td>−1.40σ</td>
</tr>
<tr>
<td>June (capped)</td>
<td>1362</td>
<td>1279</td>
<td>0.400</td>
<td>732</td>
<td>9%</td>
<td>−1.34σ</td>
</tr>
</tbody>
</table>

would have already failed during the February event, leading to a more resistant network. The maximum number of simulated repairs per pipe reduces the variance of the model for both the February and June event.

PEARSON’S RESIDUAL ANALYSIS OF OBSERVED VS. PREDICTED REPAIR RATES

For all catchments and events, Pearson’s residuals are computed following Equation 10 using the results’ associated normal distribution.

\[ r_{i,j}^P = \frac{y_{i,j} - \mu_{i,j}}{\sigma_{i,j}} \]  

where \( r_{i,j}^P \) is the Pearson’s residual of catchment \( i \) for the event \( j \), \( y_{i,j} \) is the logarithmic observed number of repairs and \( \mu_{i,j} \) and \( \sigma_{i,j} \) are the associated mean and standard deviation of predicted number of repairs. Pearson’s residual analysis is a common technique to assess the statistical
validity of a model by studying their dispersion and histogram shape. Figures 10 (a)-(d) show residuals plotted against median predicted number of repairs, catchment cumulative pipe length, estimated median PGV at the catchment centroid and logarithmic standard deviation of the PGV at the catchment centroid, respectively. Figure 10 (e)-(f) shows the distribution of the residuals for both events separately, whereas Figure 10 (g) exposes them together. Figure 10 (h) presents the observed number of repairs against the median predicted number of repairs. As it can be observed in the aforementioned figures, the model has a small negative bias and appears to be homoskedastic (i.e. residual value does not vary with the predicted median number of repairs). Apparently, none of the presented variables (cumulative pipe length, median PGV and its logarithmic standard deviation) tends to influence the model. In other words, no clear trend is observable while plotting Pearson’s residuals against these variables. The three histograms show that the model is overdispersed (i.e. the predicted variability is smaller than the one observed in the dataset). It can be observed that the February and June residual histograms tend to balance themselves: The February one tends to be positive, whereas the June one is clearly negative. As the model is built on data from two distinct earthquakes at the same location, this can be interpreted as the between-event residuals being distributed around zero (note that more data would be required to strongly verify this assumption). Interestingly, the dispersion tends to be lower for the June event than for the February event. Figure 10 (h) shows that the difference between the observed and simulated median number of repairs tends to increase toward zero in the logarithmic space, but remains well distributed around the identity function for higher values.

GEOSPATIAL ASSESSMENT OF THE REPAIR RATE MODEL PERFORMANCE

Figure 11 presents the spatial distribution of the observed, simulated median and residual repair rates per considered event. The repair rate of a vast majority of catchments is well predicted for both events (|residual| < 0.25). It is noteworthy that, despite its smoother behaviour, the model captures the general trends relatively well. However, significant absolute errors can be noted between the observed and simulated repair rates. Great underprediction (residual > 1) occurs in areas that experienced extreme events such as the Red Zone (abandoned residential area due to infeasibility to rebuild) along the Avon River (north-eastern quadrant) due to severe lateral spreading and liquefaction (Cubrinovski et al., 2011), the Cashmere Hills (South of the city) due to landslides and rock falls and along the road to Sumner (South-East of the city) due to rockfalls and cliff collapse (Dellow et al., 2011). Great overprediction (residual < −1) occurs only in
Figure 10. Pearson’s residuals of both the 2011 February and June events against (a) median predicted repair rate; (b) SCIRT catchment cumulative pipe length; (c) simulated median PGV; (d) logarithmic standard deviation of PGV; Pearson’s residual distribution for (e) the 2011 February event; (f) the 2011 June event; (e) both the 2011 February and June events; and (g) observed number of repairs by median predicted number of repairs for each SCIRT catchment.
the Bromley area during the February earthquake. As no damage was reported following the 
earthquake and given that the size of these networks is slightly less than five kilometres, small 
absolute errors leads to large overestimates. Moderate under- and overpredictions ($0.25 < 
|\text{residual}| < 1$) can be explained by potential inaccuracy of the soil condition characterization, 
variability of the ground motion intensity, asset degradation status or different construction 
quality and standards that are not captured by the model.

CONCLUSION

This study presented a parametric, additive fragility function model for water-pressurized pipelines 
utilizing the data collected in Christchurch City after the 22 February and 13 June 2011 earth-
quakes. Among the available data, the selected parameters considered in the model are the PGV, 
the pipe ductility behaviour, the pipe material and the pipe diameter, as well as the CRR to re-
present its liquefaction susceptibility. In order to take into account the misfit and the potentially 
unknown characteristics, the proposed model incorporates both the within-model and between-
model uncertainties. It has been observed that soil liquefaction susceptibility significantly 
influences the experienced repair rate. Therefore, it is recommended that CRR-independent 
functions are applied only where soil characterization justifies it (i.e. where uncertainties are 
extremely high). For pipes in non-liquefiable soils, it is recommended that CRR-dependent 
functions are used with high CRR values (e.g. comparable to the value estimated for the No 
observed liquefaction zones in Christchurch).

The retrospective analysis shows that the proposed model yields good estimates of the dam-
age extent and location, when tested via MCS on the Christchurch repair catchment. However, 
some limitations of the model and its applicability are worth mentioning. First, the impact 
of extreme liquefaction and lateral spreading observed during the 22 February 2011 earthquake 
remains underestimated. Second, where PGV or liquefaction-induced strains are not the govern-
ing mode of pipe repairs (e.g. landslide or rockfall), the functions also underestimate damage. 
Furthermore, according to the June results, direct aftershock damage seems to be overestimated. 
Moreover, applications to other water supply networks should consider the potential changes in 
technology and construction quality, which often varies with the local standards and suppliers. 
One way to account for potential changes can be to use more primitive forms of the model, 
which will ultimately increase its uncertainty (e.g. ductility and soil-dependent functions in-
stead of material and soil-dependent functions). Finally, high level functions (e.g. the backbone 
function alone or the PGV-CRR repair rate function) remain governed by the most prevalent
Figure 11. Maps of the (a)-(b) observed; (c)-(d) simulated median; and (e)-(f) residual repair rates for each SCIRT repair catchment. The left-hand side column gives the results for the 2011 February earthquake, whereas the right-hand side column provides them for the 2011 June earthquake.
pipe type in their analysed data, leading to potential biases. These biases are nevertheless bal-
anced by the explicit integration of the between-model uncertainty in the repair rate functions.

In order to reduce the influence of these limitations, additional data could be used to re-
fine the model and reduce the data scarcity for some of the discarded functions. Moreover,
if more observations from other events are gathered, these can be used to further validate the
proposed model. Finally, the developed methodology could be applied to other distributed in-
frastructure components such as fibre-optic cables, sewerage pipelines or underground power
distribution lines, enabling a consistent assessment of the spatially-distributed infrastructure
across liquefaction-prone regions.

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Figure A.1. Map of the Christchurch water supply network showing the Trunk main and main pipelines. Colours indicate construction materials with the following acronyms: AC: asbestos cement, CI: cast iron, CLS: concrete-lined steel, DI: ductile iron, GALV: galvanized iron, HDPE: high-density polyethylene, MDPE80: medium-density polyethylene 80, PVC: polyvinyl chloride, STEEL: steel
**Figure A.2.** Map of the Christchurch water supply network showing the submain and crossover pipelines. Colours indicate construction materials with the following acronyms: AC: asbestos cement, CI: cast iron, CLS: concrete-lined steel, DI: ductile iron, GALV: galvanized iron, HDPE: high-density polyethylene, MPDE80: medium-density polyethylene 80, PVC: polyvinyl chloride, STEEL: steel

**Figure A.3.** Distribution of pipe diameters in the Christchurch city network as a function of their typology
Figure A.4. SCIRT repair catchment. Colours indicate the cumulative pipe length per SCIRT repair catchment.
Table A.1. Pipe attributes in the Christchurch city water supply network dataset

<table>
<thead>
<tr>
<th>Pipe attributes</th>
<th>Possible values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location of the repair</td>
<td>Collection of point segments [Lat./Long.]</td>
</tr>
<tr>
<td>Pipe material</td>
<td>[AC; CI; CLS; DI; GALV; HDPE; MDPE80; PVC; STEEL; Other]</td>
</tr>
<tr>
<td>Pipe diameter</td>
<td>Millimeters</td>
</tr>
<tr>
<td>Pipe functionality</td>
<td>[Trunk main; Main; Submain; Crossover]</td>
</tr>
<tr>
<td>Pipe functional status</td>
<td>[In service; Decommissioned; Abandoned; Planed; Removed]</td>
</tr>
<tr>
<td>Year of construction</td>
<td>[YYYY]</td>
</tr>
<tr>
<td>Trench type</td>
<td>[Pre-1984, locally excavated backfill; Pre-1984, hill soils; Pre-1984, imported backfill; Pre-1984, estuary/reclaimed land; 1984 to 2000, AP40 backfill; Post-2005, AP20 backfill]</td>
</tr>
<tr>
<td>Date of decommission (if applicable)</td>
<td>[DDMMYYYY]</td>
</tr>
<tr>
<td>Unique key identifier given by the CCC</td>
<td>[Ws000000]</td>
</tr>
</tbody>
</table>
Figure A.5. Map of the Christchurch water supply network and the pipe repairs induced by the 22 February and 13 June 2011 earthquakes. The histograms provide the number of reported pipe repairs per event as a function of the latitude and longitude.

Table A.2. repair attributes contained in the dataset

<table>
<thead>
<tr>
<th>repair attributes</th>
<th>Possible values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unique key identifier of the pipe given by the CCC</td>
<td>[Ws000000]</td>
</tr>
<tr>
<td>Location of the repair</td>
<td>[Lat./Long.]</td>
</tr>
<tr>
<td>Date of repair detection</td>
<td>[DDMMYYYY]</td>
</tr>
<tr>
<td>Priority of repair</td>
<td>[Urgent 1 Day; 1 Day; 3 Days; 10 Days]</td>
</tr>
<tr>
<td>Type of repair</td>
<td>[Unknown; Fitting; Pipe]</td>
</tr>
<tr>
<td>Unique key identifier given by the SCIRT</td>
<td>[0000000]</td>
</tr>
</tbody>
</table>
Maps of the estimated PGV intensity in Christchurch during the considered CES events.

Figure A.6. Geometric mean PGV of the 2011 February earthquake estimated by Bradley (2014).
Figure A.7. Logarithmic standard deviation PGV of the 2011 February earthquake estimated by Bradley (2014)

Figure A.8. Geometric mean PGV of the 2011 June earthquake estimated by Bradley (2014)
Figure A.9. Logarithmic standard deviation PGV of the 2011 June earthquake estimated by Bradley (2014)
Figure A.10. Christchurch LRI map estimated by Cubrinovski et al. (2014)

Table A.3. LRI characteristics, defined by Cubrinovski et al. (2014, Table 2)

<table>
<thead>
<tr>
<th>LRI [-]</th>
<th>Equivalent CRR [-]</th>
<th>Ground settlement [mm]</th>
<th>Lateral displacement [mm]</th>
<th>CRR at watertable depth [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>&lt;0.065</td>
<td>&gt;500</td>
<td>&gt;400</td>
<td>-</td>
</tr>
<tr>
<td>1</td>
<td>0.065 - 0.11</td>
<td>250 - 500</td>
<td>200 - 400</td>
<td>0.065</td>
</tr>
<tr>
<td>2</td>
<td>0.11 - 0.16</td>
<td>50 - 250</td>
<td>40 - 200</td>
<td>0.13</td>
</tr>
<tr>
<td>3</td>
<td>0.16 - 0.23</td>
<td>20 - 50</td>
<td>20 - 40</td>
<td>0.195</td>
</tr>
<tr>
<td>4</td>
<td>&gt;0.23</td>
<td>&lt;20</td>
<td>&lt;20</td>
<td>0.26</td>
</tr>
</tbody>
</table>

APPENDIX B: REPAIR RATE FUNCTION DEVELOPMENT DETAILS

This appendix provides the details of the repair rate development. First, the K-fold cross-validation used to determine the best functional form of the backbone function $f_0$ is explained. Then, the fitting process of repair rate is detailed, and finally, the formal derivation of physics-based constraints are given.
K-FOLD CROSS-VALIDATION METHOD USED IN THE DEVELOPMENT OF THE PIPELINE REPAIR RATE FUNCTIONS

In order to minimize the model error, multiple functional forms are tested using the K-fold cross-validation method. This appendix briefly reviews the concept of the K-fold cross-validation and provides the details of the implementation of this method in the context of repair rate function development for spatially-spread objects. As detailed by Friedman, Hastie, and Tibshirani (2008, pp. 240-249), the K-fold cross-validation is a common method used to evaluate the performance of predictive models. The standard procedure for a K-fold cross-validation can be decomposed into four steps.

1. First, the potential functional forms \( f(x) \) are carefully selected based on the observable trend in the data and indexed with the tuning parameter \( \alpha \).

2. In a second step, the dataset is subdivided into \( K \) subsets of approximately equal size. Classically, \( K \) is equal to five or ten.

3. Then, each selected functional form is evaluated using the subsequent procedure:

   (a) For each created subset \( i \in [1, \ldots, K] \), the model is first trained with the data from all subsets except the \( i^{th} \) one.

   (b) The subset \( i \) is then utilized to estimate the error between the data \( y \) and the trained function \( \hat{f}(x) \) using an appropriate loss function \( L(y, \hat{f}(x)) \). Commonly adopted loss functions are the squared error or the absolute error functions presented in Equation B.1.

   \[
   L(y, \hat{f}(x)) = \begin{cases} 
   (y - \hat{f}(x))^2, & \\
   |y - \hat{f}(x)| & 
   \end{cases} \tag{B.1}
   \]

   (c) Finally, once all subsets have been used for validation, the average error of the model is estimated. Equation B.2 given by Friedman, Hastie, and Tibshirani (2008, p. 242) formalizes the evaluation of a functional form \( f(x) \) using K-Fold cross-validation.

   \[
   CV(\hat{f}, \alpha) = \frac{1}{N} \sum_{i=1}^{N} L(y_i, \hat{f}^{\kappa(i)}(x_i, \alpha)) \tag{B.2}
   \]

   where \( \hat{f} \) is the evaluated functional form, \( \alpha \) the tuning parameter indexing the evaluated functional forms \( \hat{f} \), \( N \) the number of folders, \( L(y, \hat{f}(x)) \) the loss function.
measuring errors between the data \( y \) and \( \hat{f}(x) \), \( y_i \) the target data from subset \( i \), 
\( \hat{f}^{-\kappa(i)}(x_i, \alpha) \) the evaluated functional form \( f \) with the \( i \)th subset removed.

4. The functional form \( f(x, \alpha) \), of which \( \alpha \) minimizes \( CV(\hat{f}, \alpha) \), is picked to be trained with the entire dataset.

In the development of repair rates for spatially-spread objects, like pipelines, this procedure remains identical. However, because the sampling unit is the length of the analysed objects and not the objects themselves, the construction of the subsets is realized so that each of them has approximately the same pipe length rather than number of objects.

**DETAILS OF THE REPAIR RATE FITTING PROCESS**

The repair rate functions are derived following the subsequent five steps. First, the subset of interest is isolated from the pipe segment K-fold subset of interest corresponding to the analysed characteristics \( h_i \) (e.g. GALV pipelines with diameter between 1 and 150 mm experiencing a PGV between 40 cm/s and 50 cm/s). Second, the observed repair rates are computed for the subset of interest using Equation B.3.

\[
\lambda_h = \frac{N_h}{L_h} \tag{B.3}
\]

where \( h \) is the vector of analysed pipe and soil characteristics at a given PGV, \( N_h \) is the number of pipe repairs in the dataset corresponding to the parameters \( h \), and \( L_h \) is the total pipe length in the dataset corresponding the parameters \( h \). To ensure that the computed values are statistically significant (i.e. that the pipe length on which repairs are observed is sufficiently long), the screening criteria developed by O’Rourke et al. (2014) is applied to each computed repair rate point \( \lambda \). This criteria assumes a Poisson distribution repair occurrence as given in Equation B.4.

\[
L_h \geq \frac{[\phi^{-1}(\beta_c)]^2}{\alpha^2 \cdot \lambda_h} \tag{B.4}
\]

where \( \phi^{-1}() \) denotes the inverse probability density function of the standard normal distribution, \( \beta_c \) the confidence interval and \( \alpha \) the percentage of observed number of repairs. The recommended values of \( \beta_c = 90\% \) and \( \alpha = 50\% \) (O’Rourke et al., 2014) are adopted in this study. Then, the pipe repair residuals between the fitted functions utilising \( n - 1 \) parameters \( \lambda_{fit,n-1} \) and observation depending on \( n \) parameters \( \lambda_{obs,n} \) are computed. If the analysed function is not the backbone function \( f_0 \) (i.e. the number of model parameter \( n \) is zero), the residuals \( \Delta_\lambda \) between the computed logarithmic repair rates and the ones from the function sharing the same
\[ \Delta_\lambda = \ln(\lambda_{obs,n}) - \ln(\lambda_{fit,n-1}) \] (B.5)

The backbone function \( f_0 \) and the correction terms \( C_i \) are evaluated by fitting the computed residuals \( \Delta_\lambda \).

**PHYSICS-BASED CONSTRAINTS APPLIED TO THE REPAIR RATE FITTING PROCESS**

The CRR-dependent physics-based constraint discussed in Section 3 can be written as proposed in Equation B.6.

\[ \frac{\partial C_{Soil}(CRR)}{\partial CRR} \leq 0 \] (B.6)

where \( C_{Soil}(CRR) \) is the correction term for the soil depending on the CRR. The condition ensuring that the repair rates remain monotonously increasing with PGV can be written as proposed by Equation B.7.

\[ \frac{\partial \ln(\lambda)}{\partial PGV} = \frac{\partial \left[ f_0(PGV) + \sum_{i=1}^{n-1} C_i(h_i) + C_n(h_n) \right]}{\partial PGV} \geq 0 \] (B.7)

where \( C_i(h_i) \) is a known correction term \( i \) depending on \( h_i \) and \( C_n(h_n) \) is the fitted correction term \( n \). Hence, the newly fitted correction term \( C_n \) can be constrained as formulated in Equation B.8.

\[ \frac{\partial C_n(h_n)}{\partial PGV} \geq - \frac{\partial \left[ f_0(PGV) + \sum_{i=1}^{n-1} C_i(h_i) \right]}{\partial PGV} \] (B.8)

**APPENDIX C: REPAIR RATE FUNCTIONS FOR BURIED PIPELINES IN THE CHRISTCHURCH PORT HILLS AREA**

**INTRODUCTION**

The southern part of Christchurch is built on hills, which are referred as the Christchurch Port Hills (CPH). These hills are part of the Lyttleton Volcanic Group and are mainly composed of (1) ‘basaltic to trachytic lava flows interbedded with breccia and tuff (Mvl)’, and (2) ‘yellow-brown windblown silt on Banks Peninsula greater than 3m thick and commonly in multiple layers (mQe)’ (Forsyth et al., 2008). During the 22 February and 13 June 2011 earthquakes, the network assets located in the CPH areas were subjected to ground repairs governed by landslides and rockfalls (Dellow et al., 2011). Hence CRR-dependent repair rate functions are not appropriate to assess the vulnerability of these assets. Therefore, in order to exploit
the full potential of the data gathered during the restoration of the Christchurch water supply network following the CES and coherently assess its future losses, repair rate functions for pipelines located in the CPH areas are proposed. They are then used in the retrospective analysis presented in Section 5.

CHRISTCHURCH PORT HILLS DATASET

Water supply network attributes

The considered network is a subset of the larger database presented in Section 2. Pipelines in this subset are selected given their altitude (above 15 meters) and location (in or near the CPH areas). The retained subset elements possess the same attributes as the other elements of the complete dataset (see Table A.1). The CPH network is 192.3 km long, out of which 93.1 km (48.43%) are trunk main or main pipelines and 99.2 km (51.57%) are submain or crossover pipelines. It is mainly composed of AC, PVC and HDPE pipelines, corresponding to 38.27 km (19.9%), 35.93 km (18.7%) and 34.69 km (18.0%), respectively. Large portions of the network are also made of GALV and MDPE80 pipelines, which correspond to 24.84 km (12.9%) and 23.72 km (12.3%), respectively. The use of other materials such as CI (17.05 km, 8.9%), DI (6.07 km, 3.1%), Steel (4.47 km, 2.3%) and CLS (1.82 km, <1.0%) remains marginal. Note that 5.68 km (2.9%) of the network is made of non-classified material. Figure C.1 presents both the trunk - main pipeline and the submain - crossover pipeline networks, on which the different colors indicate the construction material of the pipelines.
Figure C.1. Maps of the Christchurch Port Hills water supply network. (a) trunk main and main pipe network; and (b) submain and crossover pipe network. Colours indicate construction materials with the following acronyms: AC: asbestos cement, CI: cast iron, CLS: concrete-lined steel, DI: ductile iron, GALV: galvanized iron, HDPE: high-density polyethylene, MPDE80: medium-density polyethylene 80, PVC: polyvinyl chloride, STEEL: steel.

Reported pipe repairs following the Canterbury earthquake sequence events

Similarly to the CPH network dataset considered, the repair dataset is also a subset of the complete dataset used for the development of the fragility functions for pipelines in liquefiable soils. The reported number of repairs for the 22 February and 13 June 2011 earthquakes is 191 and 78, respectively. Figure C.2 shows the reported pipe repairs for each considered event.
METHODOLOGY

The methodology used to derive the vulnerability functions for pipelines buried in the CPH soils is composed of the first and last steps of the methodology presented in Section 3. First, based on the backbone function $f_0$ evaluated in Section 4, the correction terms $C_i$ are computed. Then, the uncertainty is computed following the procedure given in Subsection 3.2. As with the liquefaction-dependent functions presented in Subsection 3.2, the repair rate data is screened with the O’Rourke et al. (2014) criterion to ensure statistical significance of the results. However, no K-Fold cross-validation is performed. Although the procedures remain identical, some adjustments are necessary to achieve the development of repair rate functions for pipeline laying in the CPH soils. Namely, the considered characteristics and their number are modified. As the analysed subset represents only a fraction of the entire database, only three parameters are considered for the development of the new functions, in addition to the geometric mean PGV intensity: the CPH soil conditions, the material ductility and the construction material.

All CPH-specific correction terms $C_i$ are expressed as a PGV-dependent linear function given in Equation 6. The CPH-soil correction term $C_{CPH}$ is fitted on the residuals between the observed repair rates considering the PGV as the only parameter and on the observed repair rates considering the PGV and the CPH soil condition as parameters. The ductility and material characteristics are treated as subsequent subsets of the CPH soil one only. The physics-based constraint, which enforces the function to be monotonously increasing is applied to this model with a threshold of 150 cm/s. Finally, the uncertainties are computed using the material-dependent functions as the most detailed repair rate functions as described in Section 3.2 (i.e. the between-model uncertainty of the CPH and material-dependent functions is zero).
Results from the development of the CPH-related repair rate functions are presented in two steps, similarly to Section 4. First, the repair rate functions are shown and then, their uncertainties are discussed. Figure C.3 presents all CPH-related pipe repair rate functions. On Figure C.3 (a), it can be observed that pipelines laying in the CPH soils are less vulnerable than the one laying in the Canterbury Plains Flatland. Ductile and brittle materials follow the trend noticed in Section 4: brittle construction material pipelines are more vulnerable than ductile ones. Note also that construction material-dependent functions presented in Figures C.3 (b) and (c) are following the trends observed in Figures 4 (b) and (c) for CRR-dependent repair rate functions.

Coefficient values for the CPH-related functions are presented in Appendix D. Note that the CLS, DI and Steel related functions have not been developed as their counterpart for pipelines buried in soft soils are excluded.

Figure C.3. CPH-related repair rates functions for (a) generic pipes (backbone curve), generic brittle and ductile pipes ; (b) pipes made of brittle materials ; and (c) pipes made of ductile materials
set developed for pipelines laying in soft soils, no function needs to be excluded as their residual means remain close to zero. These functions are utilized in the retrospective analysis presented in Section 5.

![Graph](image)

**Figure C.4.** (a) Within-model uncertainty; (b) Between-model uncertainty for CPH repair rate functions

The fully-developed Christchurch Port-Hill-specific repair rate model is given by Equations C.1 and C.2. Table D.2 gives the coefficient values for the different repair rate functions included in this model.

\[
\ln(\lambda) = \left[ a_0 PGV^{b_0} + c_0 \right] + \left[ a_1 PGV + b_1 \right] + \left[ a_2 \cdot PGV + b_2 \right] + \left[ a_3 \cdot PGV + b_3 \right] + \epsilon \tag{C.1}
\]

\[
\epsilon \sim \mathcal{N} \left( 0, \sqrt{\sigma^2_W + \sigma^2_B} \right) \tag{C.2}
\]

where index 0 represents the backbone function of the model \( f_0 \), index 1 the Christchurch Port Hill soil correction term, index 2 the ductility correction term, index 3 the construction material correction term and \( \epsilon \) the normally distributed uncertainty term constituted of a within-model and a between-model standard deviations.

As a large number of repairs occurred in areas where landslides and rockfalls were the dominating ground repair mode, it is recommended to apply these functions to networks located in environments showing significant similarities (e.g. similar geologic formation, comparable slope and resembling hydrography).
APPENDIX D: COEFFICIENT TABLES OF BURIED PIPELINE REPAIR RATE FUNCTIONS

This appendix presents the model coefficients for the proposed repair rate functions computed using the methodology proposed in Section 3 and Appendix C for pipelines buried in soft soils and Christchurch Port Hills soils, respectively.

REPAIR RATE FUNCTION COEFFICIENTS FOR PIPELINE BURIED IN SOFT SOILS

Table D.1 provides the coefficient values for all repair rate functions included in this model. A value of zero is assigned to every unknown pipeline or soil characteristic.
<table>
<thead>
<tr>
<th>Function</th>
<th>PGV</th>
<th>Ductility</th>
<th>Material</th>
<th>Diameter</th>
<th>CRR</th>
<th>Uncertainty</th>
</tr>
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<td></td>
<td>$a_0$</td>
<td>$b_0$</td>
<td>$c_0$</td>
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<td>$a_2$</td>
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<td>0.0</td>
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<td>-0.8225</td>
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<td>MDPE D80-300mm CRR</td>
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<tr>
<td>HDPE D80-300mm CRR</td>
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<td>-0.0043</td>
<td>-0.6031</td>
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<td>0.8225</td>
</tr>
</tbody>
</table>

Table D.1: Repair rate function coefficient values and uncertainties for pipelines buried in soft soils.
Table D.2 gives the coefficient values for the different repair rate functions included in this model. A value of zero is assigned to every unknown pipeline or soil characteristic.

**Table D.2.** Repair rate function coefficient values and uncertainties for pipelines buried in Christchurch Port Hills soils

<table>
<thead>
<tr>
<th>Function</th>
<th>PGV</th>
<th>CPH soil</th>
<th>Material</th>
<th>Uncertainty</th>
</tr>
</thead>
<tbody>
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<td>-0.9061</td>
<td>1.9981</td>
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<td>Brittle CPH</td>
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For each function, the table lists the repair rate function coefficient values and uncertainties.