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The Role of Climate Change in the Assessment of the Seismic Resilience of Infrastructures

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Abstract: Climate change is modifying scientific attitudes toward pre- and post-event assessments of natural hazards. Unprecedented levels of destruction need renewed focus on addressing and protecting communities forcing the decision makers to change their attention to vulnerability and risk assessment. In particular, society and economy rely heavily on infrastructures, as fundamental links for movement of goods and people, and are extremely vulnerable to multiple hazards (such as droughts, floods, storms, and coastal hazards). In this regard, resilience quantifies the recovery time and procedures to facilitate and enhance pre-hazard and post-hazard event mitigation and emergency response strategies of systems and entire communities. Resilience calculation depends on two important contributions: loss and recovery models that need to consider the effects of climate change. This paper aims to propose a methodology that implements the most recent approaches to assess climate change inside the traditional framework of resilience. The proposed framework is then applied to a case study of a bridge.

Keywords: climate change; resilience; infrastructure; earthquake; case study

1. Introduction

System vulnerability to natural hazards is an interesting topic in scientific literature, with many recent contributions (e.g., [1–4]). In particular, many risk-based frameworks were developed to assess long-term effects (such as deterioration and life-cycle loads) considering the opportunity to include the effects of climate change which impacts multi-sectors, such as the environment, civil structures and infrastructures, biology and economy. In this regard, [5] summarized the state of the art on cost assessment methods for natural hazards (NHs), by proposing the EU project "Costs of Natural Hazards" (CONHAZ) (from February 2010 to January 2012) that considered several NHs and different sectors. Extensive literature (summarized in [6]) proposed adaptation plans (i.e., [7–9]), some focused on multiple social, environmental, organisational, and conceptual with integrated [10,11] and holistic approaches [12,13], including uncertainties [14].

The main contributions that studied the impacts of climate change concentrated on hurricanes. For example, [15] studied the impact of climate change with scenario-based analyses to explore the cost effectiveness of various adaptation strategies. Ref. [16] investigated repair cost evaluations for several future climate scenarios and examined a statistical model to study hurricanes in the Atlantic Ocean. Recently, the authors of [17] applied artificial neural networks to estimate the economic losses in the Southeastern US coastal regions (encompassing eight states from Texas to North Carolina). They proposed predictions to forecast future hurricanes to assess different climate change scenarios: current climate conditions, near-term projection, and long-term projection.

In the past, climate damage functions (CDF) have been adopted in global-scale climate impact analyses (e.g., [18,19]) to estimate the relationship between environmental variables (i.e., temperature change) and the magnitude of sectoral damages [20]. In particular, Ref. [21] showed significant relationships between the global mean temperature increase above the 1961–1990 levels and the predictions of global-scale impacts in 2050 by considering selected

indicators. CDF were also used for the estimations (e.g., [22–24]) of the social cost of carbon and damages due to climate change [25–28]. Moreover, estimations of climate damage generally focus on temperature-denominated CDF (by estimating damages per unit of temperature change) since temperature is closely correlated with other climate stressors (e.g., changes in precipitation and extreme events). For example, [29] proposed specific temperature thresholds to perform damage estimates within a climate policy framework. In additions, some recent studies focused on the assessment of seismic fragility and vulnerability of structures following mechanical (i.e., [30]) and empirical (i.e., [31]) approaches.

The present paper aims to move from these previous contributions by proposing a novel approach based on resilience that has been applied in civil engineering to assess the seismic vulnerability of structures and infrastructures. In particular, the paper aims to extend the well-credited definition proposed by [32] to include the long-term effects due to climate change. The ultimate objective is to predict how the change of specific environmental variables will impact on the resilience, as a parameter to define the vulnerability to natural hazards. In this regard, the paper shows a formulation that may be applied in long-term assessments that can be useful by several stakeholders, such as public administrators, infrastructure owners, or other decision makers. This paper proposes to include climate change effects inside the resilience framework in order to calculate the increase of losses as an evolutionary process that depends on one selected environmental variable. The multi-dimensional nature of resilience and the easy-to-read results will allow to perform the proposed methodology for applications in many disciplines, such as environmental sciences, civil engineering, and economy.

2. Methodology

Resilience is a well-credited concept currently applied to perform multi-dimensional risk assessment. Multiple definitions of resilience have been proposed since [33] defined resilience as "the capacity to cope with unanticipated dangers after they have become manifest, learning to bounce back." During the following decade the concept became more specific and [34] considered that resilience is "the buffer capacity or the ability to a system to absorb perturbation, or magnitude of disturbance that can be absorbed before a system changes its structure by changing the variables." A similar definition that extended the application of resilience to "individuals, group and organisations, and systems" was also proposed by [35]. The definition of resilience started to include the issue of recovery and [36] defined resilience as "the ability of an individual or organisation to expeditiously design and implement positive adaptive behaviours matched to the immediate situation, while enduring minimal stress." Another definition was given by [37] who considered the possibility of an "amount of assistance from outside the community." The authors of [38] extended the concept of resilience to "the capacity to adapt existing resources and skills to new systems and operating conditions." The authors of [39] described resilience as "an active process of self-righting, learned resourcefulness and growth the ability to function psychologically at a level far greater than expected given the individual's capabilities and previous experiences" and thus extending considerably the original definition of resilience by referring to individuals. In the early 2000s, other definitions were proposed (i.e., [40–42]) and a more inclusive definition was developed in [43] that considered resilience as "the capacity of a system, community or society potentially exposed to hazards to adapt, by resisting or changing in order to reach and maintain an acceptable level of functioning and structure. This is determined by the degree to which the social system is capable of organising itself to increase this capacity for learning from past disasters for better future protection and to improve risk reduction measures." It is worth noting the importance given to the social dimension and the role of learning from the past and future protection actions. Ref. [44] proposed an inter-related concept of resilience that considers technical, organizational, social and economic dimensions and it may assess the performance of critical systems (i.e., electric power, water, road infrastructures, and critical structures) and the social and economic dimensions of communities. Later, [32,45] developed a mathe-

matical formulation that assesses the level of functionality or performance by including recovery time [32,45–47], as the period necessary to restore the functionality of the system to a desired level. This paper follows the theoretical formulation of resilience proposed by [32] that allows to calculate quantitatively resilience of a system subjected to an event at a specific time (*t0e*):

$$R = \int_{t0E}^{t0E+\text{RT}} \frac{Q(t)}{RT} dt \qquad (1)$$

where

- *t0E* is the time of occurrence of the event *E*,
- *RT* is the repair time (or recovery time) necessary to restore the functionality,
- *Q(t)* is the recovery function that quantifies the recovery process to return to the pre-event level of functionality.

Resilience is graphically designed as the normalized shaded area underneath the recovery function *Q(t)* and thus its quantification is based on the definition of *Q(t)* functions and depends on two important contributions [48,49]: (1) A loss model is necessary to assess the reduction of functionality due to the impact of natural hazards in correspondence with the time of occurrence. Risk assessments require probabilistic-based approaches to consider all the possible damage and failure scenarios. (2) A recovery model describes a series of events, actions, or changes to enhance the capacity of an affected system or a community, when faced with singular, multiple, or unique shocks and stresses. Recovery functions are essential for evaluating resilience but influenced by many variables, time and spatial dimension with disparities among different geographic areas, in the same community or state and showing different rates and quality of recovery.

When climate change is considered, it affects both previous models. (1) Loss model needs to consider the role of climate change in modifying the damage of the systems. In particular, models of damage may be described by the existing CDF [25,26] and defined in terms of a specific environmental variable (i.e., temperature) and consequently losses need to be assessed from these models. (2) Recovery model describes at every step of the considered environmental variable, the repair time TR and the final functionality (QE) that the system will recover at the repair time. These quantities depend on the way the community preparedness and available resources are affected by climate change.

Therefore, the proposed methodology aims to introduce a dependency on the environmental variable inside the definition of recovery functions. In this regard, resilience may be extended to climate change as:

$$R(t, \Theta) = \int_{\Theta_0}^{\Theta_1} \frac{1}{\Delta\Theta} \int_{t0E}^{t0E+RT(\Theta)} \frac{Q(t, \Theta)}{RT(\Theta)} dt d\Theta \qquad (2)$$

where

Θ is the environmental variable (EV) for describing the climate change,

Θ_0 and Θ_1 are the EVs at the beginning and at the end of the considered period of time (intended as an evolutionary process).

The paper considers the temperature as the reference environmental variable for assessing the role of climate change on resilience.

3. Recovery Model (RM)

Recovery model presents disparities among different geographic areas in the same community or state, showing different rates and quality of recovery. Different types of recovery functions (shown in Figure 1) can be selected depending on the system and society preparedness response and this paper investigates the three possible recovery functions proposed in the literature: linear, exponential [50], and trigonometric [51]. Therefore:
Linear:

$$Q(t, \Theta) = \frac{t \cdot (Q_E - Q_I + L)}{T_R} + Q_I - L \qquad (3a)$$

Exponential:

$$Q(t,\Theta) = (Q_I - L)\cdot e^{\frac{t}{TR}\ln\frac{QE}{QI-L}} \tag{3b}$$

Trigonometric:

$$Q(t,\Theta) = (Q_E - Q_I + L)\cdot sen\left(\frac{t\cdot\pi}{2TR}\right) + Q_I - L \tag{3c}$$

that satisfy two conditions: (1) $Q = Q_I - L$ (for $t = 0$) and (2) $Q = Q_E$ (for $t = TR$) and where

- Q_I is the initial functionality at $t0$;
- Q_E is the final functionality at the end of the recovery process and that the system will recover at the repair time;
- L is total loss that determinates the level of functionality due to the NH and the first point of the recovery function (at the occurrence time $t0E$).
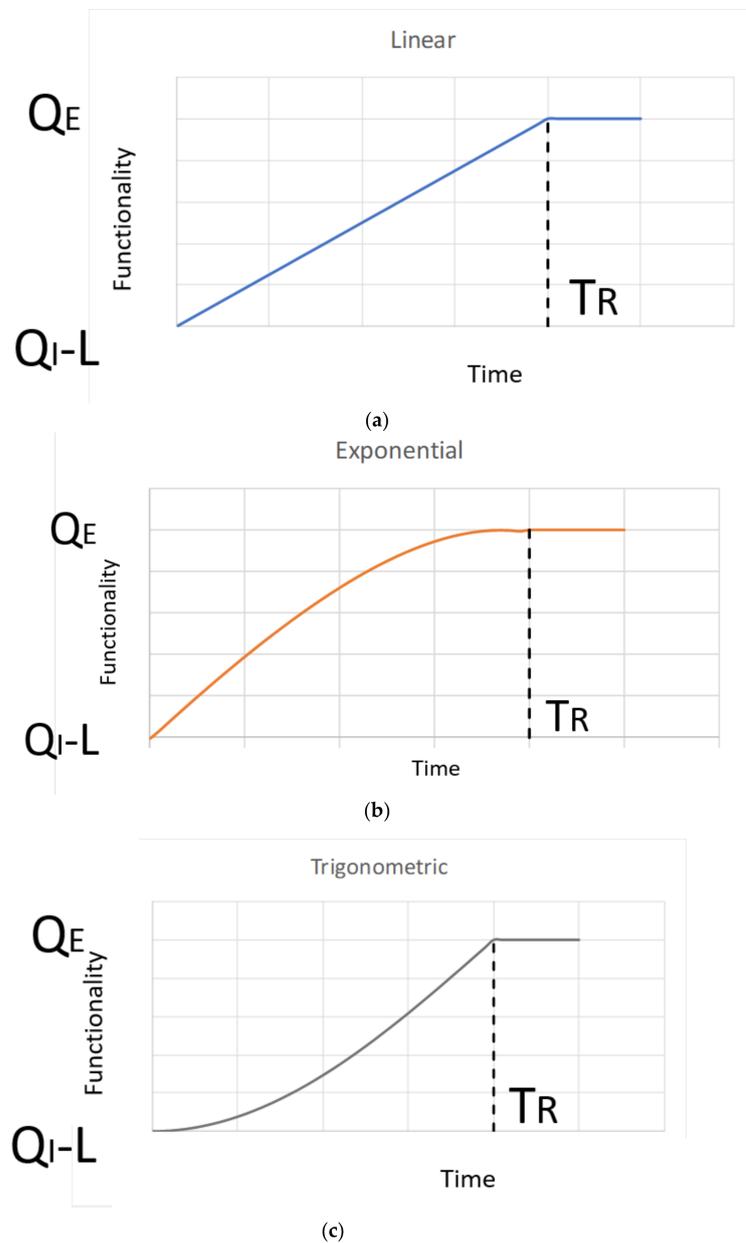

(a)

(b)

(c)

Figure 1. (**a**) Recovery model (linear); (**b**) recovery model (exponential); (**c**) recovery model (trigonometric).

It is worth noting that Q_I, Q_E, and L are described as functions of the EV but constant during the recovery process, following the original assumptions made by [32].

Introducing (3) into (2) and developing the calculations, it is possible to define resilience in the (t, Θ) domain (Figure 2) and referring to three recovery models:

Linear:

$$R(t, \Theta) = \int_{\Theta_1}^{\Theta_2} \frac{1}{\Delta\Theta} \left(\frac{Q_E + Q_I}{2} - L \right) d\Theta \tag{4a}$$

Exponential:

$$R(t, \Theta) = \int_{\Theta_1}^{\Theta_2} \frac{1}{\Delta\Theta} \left(\frac{Q_E - Q_I + L}{ln\frac{Q_E}{Q_I - L}} \right) d\Theta \tag{4b}$$

Trigonometric:

$$R(t, \Theta) = \int_{\Theta_1}^{\Theta_2} \frac{1}{\Delta\Theta} \left(\left(\frac{2}{\pi} - 1 \right) \cdot (Q_I - L) + \frac{2}{\pi} \cdot Q_E \right) d\Theta \tag{4c}$$

It is worth noticing that the terms Q_I, QE, and L define the variability of R along the EV associated to the climate change.
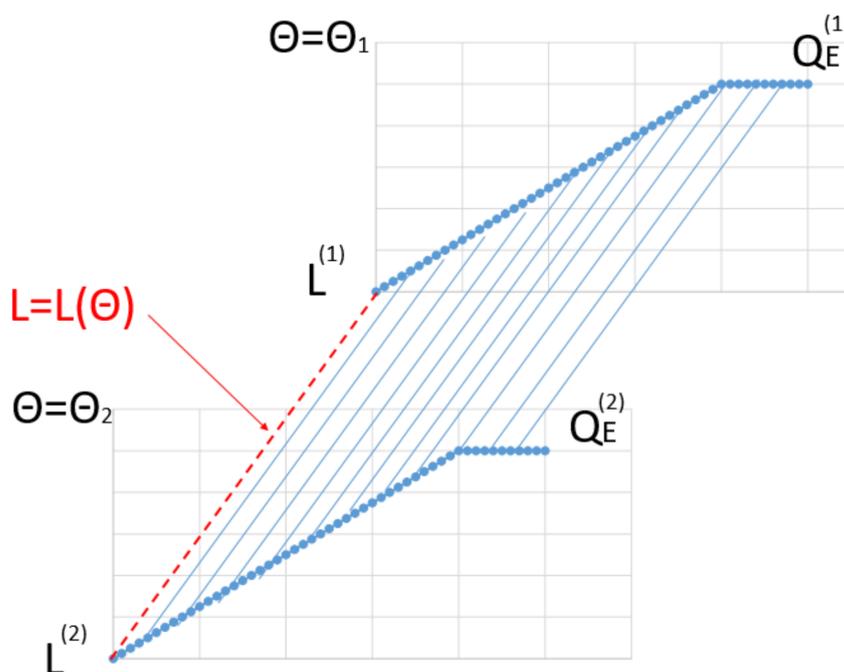

Figure 2. Resilience in the domain (t, Θ), linear recovery model.

4. Loss Model (LM)

This paper proposes to model the evolutionary process due to climate change by including the environmental variable inside the loss model. The evolutionary process is based on CDF that uses regression analyses to derive relationships among damage parameters derived from the various sectoral models [20]. However, CDF presents some important limitations that need to be considered. First of all, they generally consider only one region of the world and they cannot comprehensively address all sectors that are impacted by climate change. In addition, they cannot integrate completely cross-sectorial results into the system of economic impacts and thus CDF may underestimate the economic and social context in which the biophysical and economic damages from climate changes are expected to occur. Finally, natural events associated with climate change are characterized by very high uncertainty, which greatly complicates the modelling of their economic impact. For example, for the infrastructure arena, it is fundamental to considering

indirect losses [50–52] and their interactions (i.e., impacts of transportation and energy failing at once). In addition, CDF may only allow incomplete coverage and valuation of ecosystem effects and incomplete treatments of the impacts of extreme events in general (i.e., the modification of the Atlantic Meridional Overturning Circulation). Therefore, the loss model is calculated as a function of the environmental variable (particularly the temperature) to define the increase of the losses due to climate change (and graphically shown in Figure 2 with a red line). In the way the framework is built, CDF curves may be included inside the framework (4) to have semi-empirical assessments to describe the increase of losses derived by climate change. In order to show a case study and discuss the results, two analytical formulations were herein considered to model the evolutionary process: (a) a linear and (b) an exponential function that describe the increase of losses over the EV. Therefore, the role of climate change on resilience quantification was considered.
Linear:

$$L(\Theta) = \frac{Q_I}{\Theta_2 - \Theta_1} (\Theta - \Theta_1) \tag{5a}$$

Exponential:

$$L(\Theta) = Q_I \left(e^{\frac{\Theta - \Theta_2}{\Theta_2 - \Theta_1}} + \frac{1}{e} \frac{\Theta - \Theta_2}{\Theta_2 - \Theta_1} \right) \tag{5b}$$

that satisfy two conditions: (1) $L = 0$ (for $\Theta = \Theta_1$) and (2) $L = Q_I$ (for $\Theta = \Theta_2$).
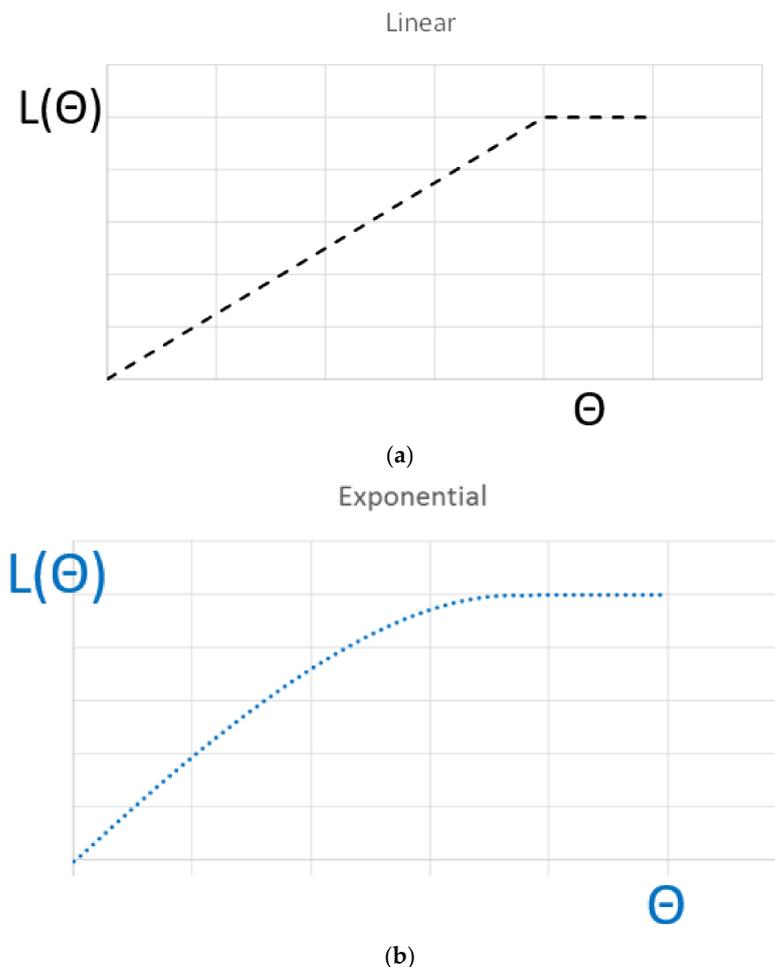Figure 3 shows Equation (5).

Figure 3. (**a**) Loss model L (Θ), linear; (**b**) loss model L (Θ), exponential.

5. Resilience Assessment

The assessment of resilience consists of implementing (5) inside (4) and assuming that QF and QI are not functions of Θ. Table 1 shows the results of the calculation of resilience for all the proposed cases: linear, exponential, and trigonometric RM and linear and exponential LM. It is possible to define a coefficient γ called recovery efficiency that allows to estimate the effect on resilience of the recovery model. In particular, the trigonometric loss model is generally used when the recovery process is driven by less resources than those available for the linear process and here it is demonstrated that the recovery efficiency ($\gamma = 1 - \frac{2}{\pi}$) is around 36.33%. On the contrary, the exponential model represents a system with a big amount of resources in the beginning of the recovery process and they rapidly decrease at the end. If compared with the linear case, recovery efficiency ($\gamma = e - 1$) increases by +71.82%.

Table 1. Resilience calculation for linear, exponential, and trigonometric Recovery Model and linear and exponential Loss Model.

Resilience	Linear LM	Exponential LM
Linear RM	$\frac{Q_E}{2} + Q_I$	$\frac{Q_E}{2} + Q_I \frac{3-e}{2e}$
Exponential RM	$\left(\frac{Q_E}{2} + Q_I\right)(e-1)$	$\left(\frac{Q_E}{2} + Q_I \frac{3-e}{2e}\right)(e-1)$
Trigonometric (RM)	$\left(\frac{Q_E}{2} + Q_I\right)\left(1 - \frac{2}{\pi}\right)$	$\left(\frac{Q_E}{2} + Q_I \frac{3-e}{2e}\right)\left(1 - \frac{2}{\pi}\right)$

Comparing the results for linear and exponential loss models, it is worth noting that when losses increase rapidly, the system may not be fast enough to react and thus its resilience decreases. In particular, resilience depends on QE and QI. The contribution of QE is insensitive to the loss model and contributes for 50%. QI significantly depends on the rate of increase of the loss model and for the exponential model it contributes only with a rate of $\frac{3-e}{2e}$ (0.52%).

Overall, resilience is a commonly used parameter for a wide range of stakeholders and multi-sectorial actors, such as infrastructure owners, transportation authorities, and public administrators that may be interested in considering the long-term effects due to climate change. Therefore, considering the effects of climate change in terms of resilience allows to improve the readability of the outputs. When climate change is included, the results show an increase of losses due to the evolutionary process of the temperature, selected as the environmental variable. The dependency of such evolutionary process allows to estimate the effects of climate change on the resilience of the system.

6. Case Study

This section applies the previous formulations to a case study that was proposed in [52–54], where the assessment of Soil Structure Interaction (SSI) effects was carried out. The present paper does not consider SSI since the effects of soil deformability were neglected. The structure (Figure 4) consists of a typical Californian Ordinary Standard Bridge (OSB) designed according to the Caltrans Seismic Design Criteria, [55]. The bridge was modeled with a 3D finite element model (Figures 5 and 6) with Opensees [56,57] and some assumptions to reduce the computational cost (see [54]). The soil was considered stiff, by as assuming a 200 m × 200 m × 20 m 3D soil mesh (6360 modes and 5330 non-linear "Bbar brick" elements). The element dimensions and absorbent boundary conditions were assumed the same as those performed in [54]. The bridge was founded of a stiff layer (named STIFF in [54]) in order to reduce the effects of the soil, modelled with the PressureIndependMultiYield (PIMY, [57]), whose representative parameters are shown in Table 2.
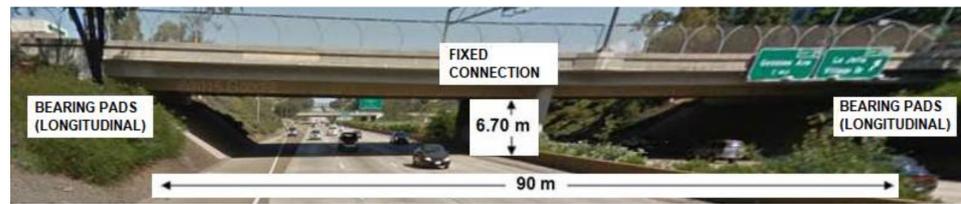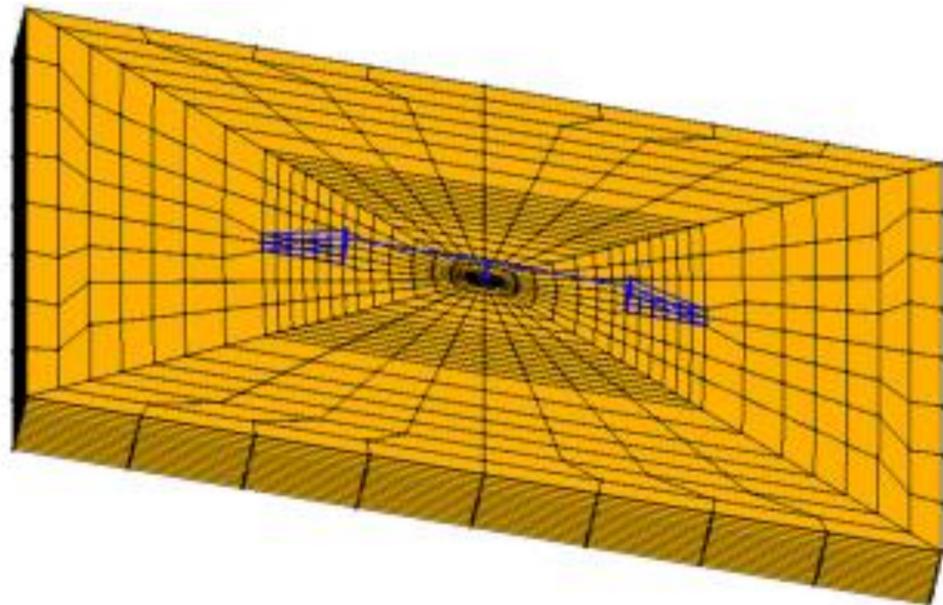
Figure 4. Case study.
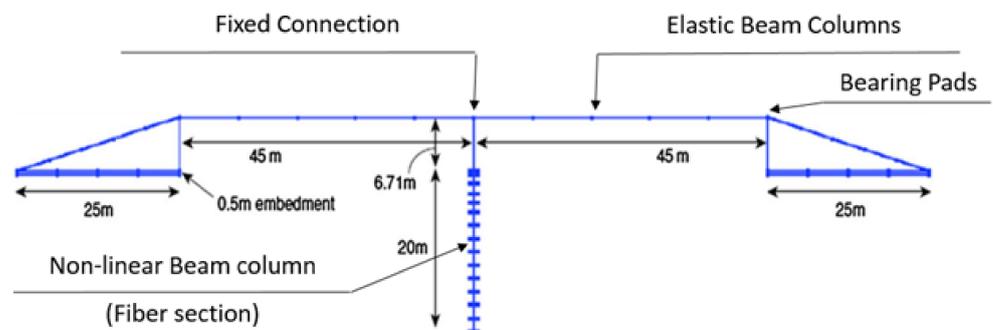

Figure 5. Finite element model.

Figure 6. Benchmark bridge.

Table 2. PressureIndependMultiYield model: soil parameters.

Soil Properties	
Mass density (kN/m^3)	18
Shear Modulus (MPa)	150
Bulk Modulus (MPa)	750
Cohesion (kPa)	75
Shear wave velocity (cm/s)	430

The abutment foundations consisted of 0.5 m concrete slabs, modelled with rigid-link elements for both abutments. The foundation of the column was modelled as a single Type I Caltrans 20 m-pile shaft. The 25 m-embankments were founded on 0.5 m foundations with a total weight of 30,000 kN. The 90 m-deck was modelled with elastic beam elements

(cross section: 5.72 m^2, moment of inertia about transversal axis: 2.81 m^4 and vertical axis: 53.9 m^4, distributed loads: 130.3 kN/m), with elastic material (Young modulus: 2.8×10^7 kPa, shear modulus: 1.15×10^7 kPa, density: 24 kN/m^3). The column was connected with the deck with a fixed connection by restraining all the components of deformations in the 6 directions. Non-linear forced-based beam elements and fiber-section (cross section: 0.95 m^2, moment of inertia about longitudinal and transversal axis: 0.108 m^4) were applied to model the 6.71 m-column that was connected with the deck with Equaldof (fixed connection). Deck and abutments were connected with zero-length elements (with high stiffness) in the transversal and vertical directions and with bearing pads along the longitudinal connections, realized with Soft Damping Rubber Bearings (modulus of elasticity: G = 0.4 MPa and equivalent viscous damping: n = 10%), more details in [54].

One-hundred input motions were selected from the PEER NGA database (http://peer.berkeley.edu/nga/ (accessed on 10 February 2021)) and are composed of three perpendicular acceleration time history components (two lateral and one vertical), as in [52]. The ground motion hazard was selected in order to reproduce infrequent events of large magnitude by following [58,59] that considered 2%, 10%, and 50% probabilities of exceedance in 50 years for bridge configurations. Figure 7 shows the cumulative density function (CDF) for the 100 motions and PGA, chosen as the reference intensity measure.
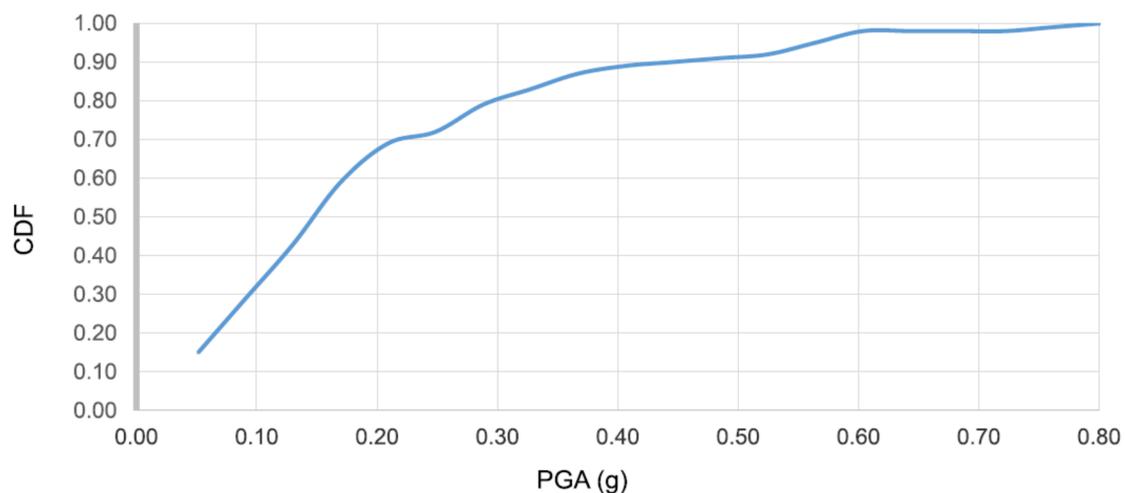

Figure 7. Benchmark bridge.

Figures 8 and 9 show the response in correspondence of CNP, chosen as the most severe seismic scenarios for shear forces at the top and at the base of the column, respectively. It is worth noting the importance of non-linearity in the performance of the bridge for both considered positions. In addition, the displacements at the base are not zero because soil deformability (even if small) was considered in the model. However, the displacements at the top of the column are mainly due to the effects of the structural flexibility because the effects of soil-structure interaction are not significant.
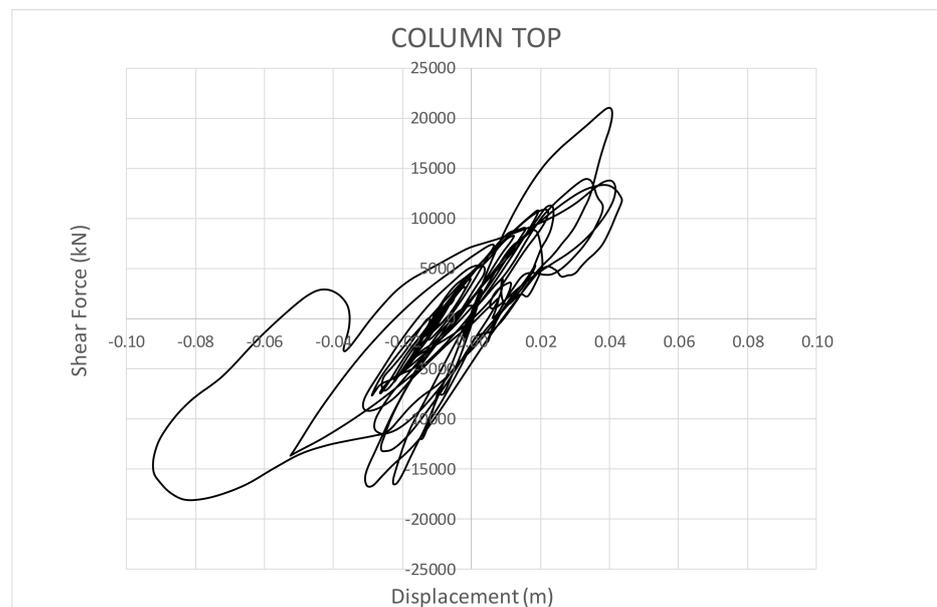
Figure 8. Displacement vs. shear force at the top of the column for the most severe earthquake.
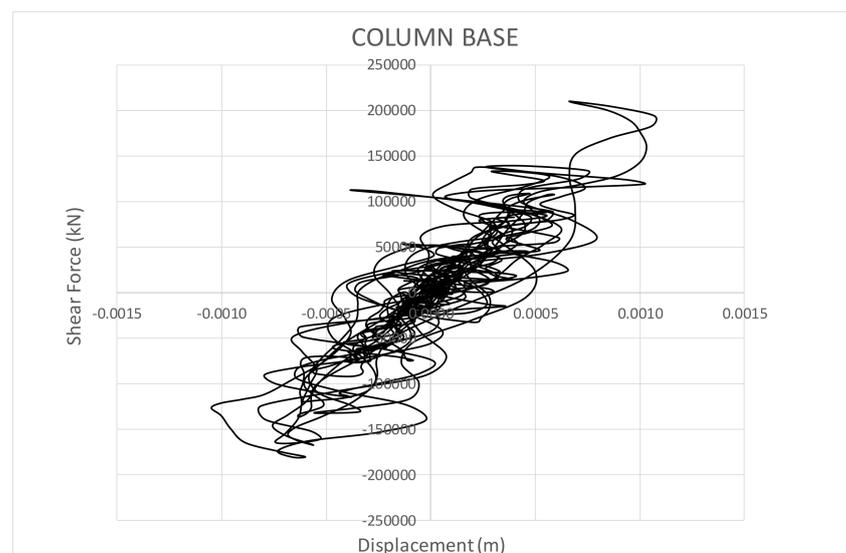

Figure 9. Displacement vs. shear force at the base of the column for the most severe earthquake.

The aim of the case study is to investigate the role of climate change in the assessment of resilience. In this regard, the two selected evolutionary processes were used to model the dependency of losses on the temperature, selected as the environmental variable. In particular, the assumptions at the base of the two loss models have important consequences in the increase of losses and therefore on the final calculation of resilience.

Assuming the formulation of losses proposed in [54]:

$$L = RCR + i \cdot RT \qquad (6)$$

where

- *RCR* is the total repair cost ratio defined as the ratio between the cost of repair and the cost of replacement (without including demotion and expressed in percentage).
- *RT* is the total repair time expressed in crew working days (CWD) and

- *i* is the coefficient that defines indirect costs.

Some assumptions were considered: (1) the final functionality equal to 100% (QE = 1) and (2) the indirect losses equal to 10% RT (*i* = 0.1). Then, it was possible to calculate the resilience from Table 3, by considering three specific probabilities of exceedance in 50 years (2%, 5%, and 10%), more details in [54].

Table 3. Repair Time and total Repair Cost Ratio values for several probability of exceedance.

Probability of Exceedance	RT (CWD)	RCR (%)
50%	4.0	2.5
10%	20.0	8.8
2%	52.2	33.3

Tables 4 and 5 represent the values of resilience when linear and exponential evolutionary processes are accounted for in the loss model, respectively. It is worth noting the reduction of resilience due to the exponential evolutionary process in comparison with the linear process: for a linear LS, the values are all more than 1, while for the exponential case, the system is much less resilient (with values smaller than 1 and for trigonometric RM, the value reaches 0.2). Such a reduction depends on the rate of losses that is too rapid for the system to react when the evolutionary process is modeled with an exponential formulation.

Table 4. Resilience linear LM (for the selected probability of exceedance).

Probability of Exceedance	Linear RM	Exponential RM	Trigonometric RM
50%	1.471	2.528	0.535
10%	1.392	2.392	0.506
2%	1.115	1.916	0.405

Table 5. Resilience exponential LM (for the selected probability of exceedance).

Probability of Exceedance	Linear RM	Exponential RM	Trigonometric RM
50%	0.550	0.946	0.200
10%	0.546	0.939	0.198
2%	0.532	0.914	0.193

7. Conclusions

Quantification of resilience should consider the effects of climate change to be used as an indicator for future plans in infrastructure engineering. This paper contributes to this issue by proposing a resilience-based framework that models the uncertainties connected with climate change. Three recovery models and two loss models were proposed based on different analytical formulations in order to realistically assess resilience under different conditions. The effects of climate change were introduced inside the loss model by accounting two evolutionary processes (linear and exponential) and thus to consider the increase of damage due to the selected environmental variable (the temperature). The proposed framework was applied to a two-span Californian highway bridge in order to estimate recovered functionality. The paper demonstrates the importance of considering climate change by presenting readable findings for a wide range of different stakeholders, particularly for infrastructural decision-makers.

Overall, the paper may be the base for many interdisciplinary applications in order to include future perspectives in the assessment of designs and recovery solutions.

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