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A FRAMEWORK AND CASE STUDY FOR URBAN SEISMIC RISK FORECASTING

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ABSTRACT

Current seismic risk assessment practice characterizes the components of risk—hazard, exposure and vulnerability—in a static state. This paper provides a conceptual framework for an urban risk assessment model that accounts for spatial and temporal dynamics of urban environments. Specifically, it incorporates spatial and temporal variations in exposure and vulnerability in order to predict future risk. The framework is then applied on a case study of Kathmandu, Nepal. Based on sparse data from the Nepalese national census, the results show a very significant increase in seismic risk over time. These results point to the importance of time-dependent risk models that can forecast future risk, and points to several possible avenues for future developments.

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Current seismic risk assessment practice characterizes the components of risk—hazard, exposure and vulnerability—in a static state. This paper provides a conceptual framework for an urban risk assessment model that accounts for spatial and temporal dynamics of urban environments. Specifically, it incorporates spatial and temporal variations in exposure and vulnerability in order to predict future risk. The framework is then applied on a case study of Kathmandu, Nepal. Based on sparse data from the Nepalese national census, the results show a very significant increase in seismic risk over time. These results point to the importance of time-dependent risk models that can forecast future risk, and points to several possible avenues for future developments.

Introduction

Key to making informed policy decisions to promote resilient and sustainable future communities is the ability to predict risk as it relates to dynamic changes in our urban environments, reflecting increases in population, specific urban growth patterns and evolving vulnerability linked to deterioration, incremental expansions and other time-dependent processes.

The urban transformation of the past century has been described as "one of the most powerful, irreversible, and visible anthropogenic forces on Earth" [1]. By 2030, the global population will reach 9 billion, of which 60% will reside in cities [2]. This shift in population has also led to a shift in the landscape of risk, with cities becoming the major source of global risk [3].

While much research has been done on probabilistic risk assessment and its different components (inventory creation, vulnerability curves, hazard modeling), all models use the current condition of infrastructure. These static models have the effect of underestimating risk in most cases, but they also constricts policy-makers to a hopeless catch-up mode, their scope of action limited to mitigating risk to existing assets, rather than proactive actions to reduce future risk arising from a larger than present-day asset base.

This paper provides a conceptual framework for a dynamic urban risk assessment model that accounts for time-dependent changes in exposure and vulnerability. The case-study of Kathmandu city in Nepal is used the demonstrate the application of this framework for data-poor

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contexts, and provide preliminary results showing growth of urban risk of a city very important for its historic, economic, cultural and human assets.

Dynamic Urban Risk Framework

Probabilistic disaster risk assessment consists of taking the convolution of the hazard, exposure and vulnerability. Hazard refers to the potential occurrence of an event that may have adverse impacts on vulnerable and exposed elements (people, infrastructure, the environment, etc). Exposure describes the elements that are impacted by the hazard due to their spatial and temporal overlap. Vulnerability describes the propensity of adverse effects from exposure to a particular hazard. It becomes clear from these definitions that the fundamental components of risk are not fixed in time, particularly in rapidly changing urban environments.

$$\text{Risk} = \text{Hazard} \otimes \text{Exposure} \otimes \text{Vulnerability}$$

Time-dependent hazards

- Large earthquakes do not occur following a Poisson process. The occurrence of an event depends on the time since the last event, consistent with elastic rebound theory of earthquakes.
- Similarly, hydrometeorological hazards (e.g., floods and hurricanes) have recently received a lot of attention as research is predicting increasing rate and intensity of extreme weather events.

Time-dependent exposure

- Population growth and migration are rapidly changing the global landscape of risk exposure.
- Cities in particular are sites of very rapid exposure change, often reflecting significant migration into and within cities.
- Urban land markets often create pressures to settle on increasingly hazardous land, including steep slope, flood-planes and reclaimed land.

Time-dependent vulnerability

- The vulnerability of buildings changes in time due to deterioration, retrofits, and alterations.
- Most buildings in the world's growing cities are not static, but are continually being expanded upward or outward. These practices have significant impact on building vulnerability.
- New construction practices further result in changes in vulnerability of the built environment.

Figure 1: The three components of risk and their time-dependence.

Dynamic Exposure Modeling

Natural disasters are the man-made consequences of natural hazard events. It is the spatial and temporal intersection between a hazard and vulnerable assets that results in creating risk. This overlap defines the exposure.

Current risk-assessment methodologies characterize exposure in its present state. This is a significant limitation for assessing risk in rapidly changing environments, in particular cities. The proposed approach builds on current practices by integrating urban growth models to forecast exposure, providing more accurate risk assessment and enabling policy makers to take preventative measure to reduce future risk.

The simplest method to model future exposure is simply to project exposure trends based on past data. Census data of population or building inventory at a minimum of two separate dates can be used to develop projections for future times. Auxiliary data such as general migration rate, natural population growth, economic growth and others can further be used to improve these projections. Alternatively, agent-based models can be used to simulate patterns of urban growth, creating numerous alternatives of future urban form [4].

Dynamic Vulnerability Modeling

One of the assumptions implicit in current risk assessment models is that vulnerability is constant over time. Increase in vulnerability of structures with deterioration has been the subject of increasing study [5-8]. Recent work by Rao [9] provides a time-dependent framework for modeling structural deterioration of individual bridges and their resulting increased seismic risk. The proposed framework builds on this research to incorporate time-dependent fragility into large-scale risk assessment models, and looks at other common drivers influencing fragility. In particular it investigates incremental construction as a significant cause of changes in vulnerability, as well as changing building practices (due to changes in building code, its enforcement, material quality or other), and structural deterioration.

In rapidly urbanizing cities, the pay-as-you-go process of informal building construction and expansion is the de facto pattern of growth. Indeed the informal sector builds an estimated 70% of all urban housing in developing countries [10]. This process starts with a simple shelter and, given enough resources and time, transforms incrementally to multi-story homes and rental units. However no robust studies have investigated the effect of these incremental expansions on vulnerability, particularly to seismic hazards.

The proposed framework defines typical stages within building evolution, and associated earthquake fragility curves reflecting the changes in vulnerability induced by each building expansion. Alternatively, these increments can be linked not to new fragility curves, but can be treated as additional vulnerability indicators in multivariate fragility models.

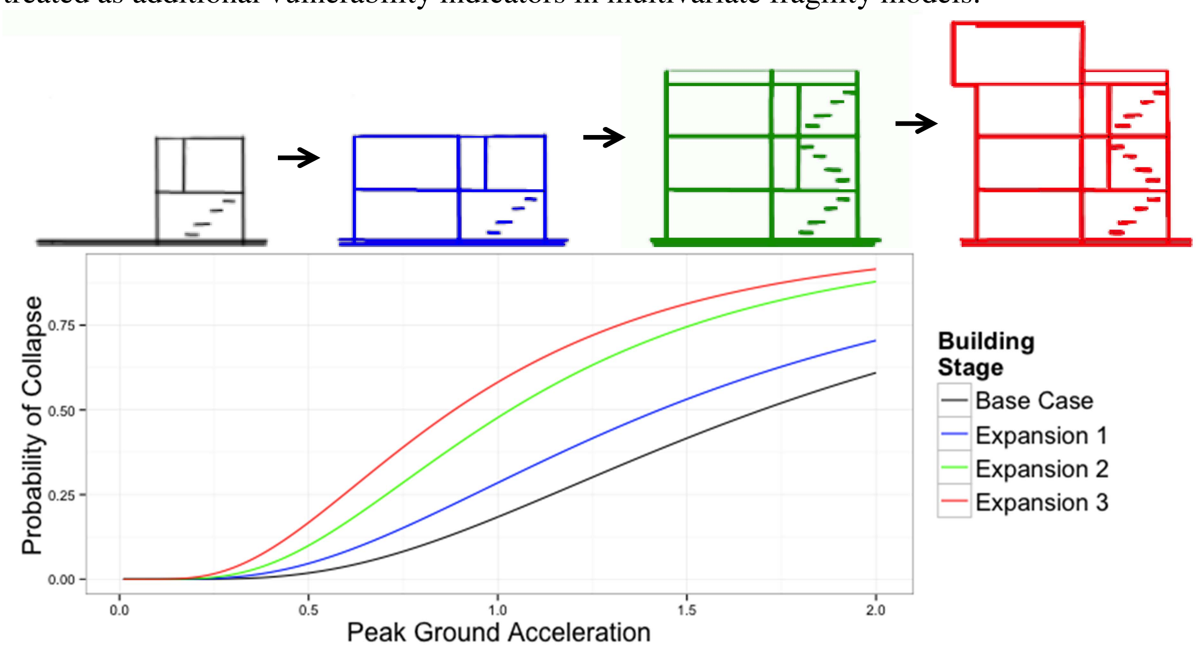


Figure 2:Diagram of the process of incremental building construction typical of cities throughout the world, and corresponding hypothetical fragility curves reflecting the fact that vulnerability tends to increase with additional floors and discontinuous expansions.

m – grid locations (spatial aggregate)

o – building types

p – building stages

Value of building type k, at stage s.

Ground motion simulation i at site l.

$$loss_i = \sum_{l=1}^{m}\sum_{k=1}^{o}\sum_{s=1}^{p} n_{l,k,s}(t)\, q_{k,s} \sum_{r=1}^{u} (DV \mid DM_r) \times P\left(DM_r \mid IM_{l,i}, k, s\right)$$

Single simulation of loss

n = number of buildings of type k, stage s, at location l.

Decision variable given damage state DM_r (e.g. normalized replacement cost)

Vulnerability curve

$$loss_i = \sum_{l=1}^{m}\sum_{k=1}^{o}\sum_{s=1}^{p} n_{l,k,s}(t)\, q_{k,s} \sum_{r=1}^{u} (DV \mid DM_r) \times P\left(DM_r \mid IM_{l,i}, k, s\right)$$

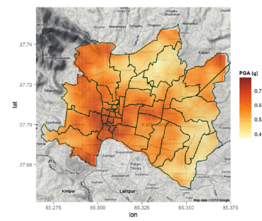
Hazard assessment:

Simulate spatially correlated ground-motion elds.

Can also simulate liquefaction and land slides.

Can also conduct full PSHA by developing stochastic event sets.

$$\log\left(IM_{i,l}\right) \sim f\left(Mag, Dist, Soil, \ldots\right)_l + \varepsilon_{i,l}$$
$$\varepsilon_{i,l} \sim N\left(0, \sigma, \phi_{\varepsilon\varepsilon}(\Delta d)\right)$$



Vulnerability curves:

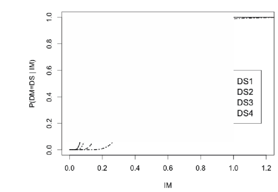
Vulnerability curves can be developed for each building type k and stage s.

Alternatively, each stage can be associated with a modi er to standard vulnerability curves for each building type, or additional variable in multi-variate fragility curve.

Could be parametric (e.g. lognormal, glm) :

$$P(DM_r \mid IM) = \Phi\left(\frac{\ln\left(IM_{i,l}\right) - \mu_{k,s,r}}{\beta_{k,s,r}}\right)$$
$$P(DM_r \mid IM) = g^{-1}\left(\beta_{0(k,s,r)} + \beta_{1(k,s,r)} \log\left(IM_{(i,l)}\right)\right)$$

Could be non-parametric (e.g. t by kernel smoothing, generalized additive models, etc)



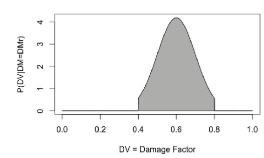
Simulate decision variables:

Precent Loss (damage factor):
Typically modeled by trunctated lognormal or normal distirbution

Fatality rate:
Commonly based on deterministic semi-empirical model based on collapse rate.

Can be deterministic or stochastic.

$$P(DV \mid DM_r) = \frac{\frac{1}{\sigma}\phi\left(\frac{DV - \mu_r}{\sigma}\right)}{\Phi\left(\frac{b-\mu_r}{\sigma}\right) - \Phi\left(\frac{a-\mu_r}{\sigma}\right)}$$



Number of buildings in location l, of type k and stage s:

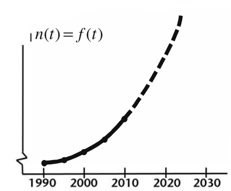
This framework reduces the time- dependent element solely to the variable n(t).

Can be a simple projection based on census past:

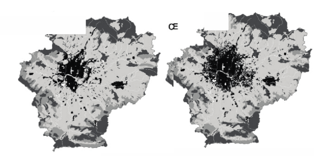
$$n(t) = f(t)$$

Can be a prediction based on population, economic growth and other dynamics:

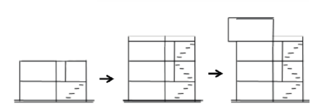
$$n(t) = f(population, economic\ growth, etc)$$



Can include urban growth model (e.g. agent-based modeling of urban growth).



Each stage S within the incremental building evolution is modeled stochastically. For instance building expansions can be modeled as a oisson process with non-constant rate.



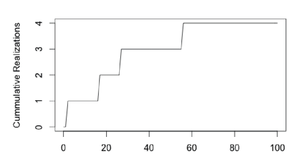


Figure 3: Diagram of framework for simulating spatially and temporally varying risk

Case Study of Kathmandu, Nepal

The framework described above was applied in order to forecast the earthquake risk of Kathmandu city in Nepal. Since the main interest is to capture changing risk driven by time-dependent exposure and vulnerability, the study describes the risk at several times based on a single scenario: a reproduction of the 8.1 magnitude Bihar earthquake of 1934.

This example demonstrates a simplified application of the framework described, based on very limited data and simple models. The results themselves are therefore not aimed at accuracy of risk forecasting but simply to demonstrate the importance of including urban dynamics in risk assessment of cities. A discussion is included explaining the additional complexity which could be added to better reflect the uncertainties and real urban dynamics.

Spatially correlated ground motion fields for peak ground acceleration were generated based on Jayaram & Baker's correlation model [11] applied with the Chiou & Young 2008 ground motion prediction equation [12]. Figure 4 demonstrates several ground motion fields simulation generated within the Kathmandu municipal boundary:

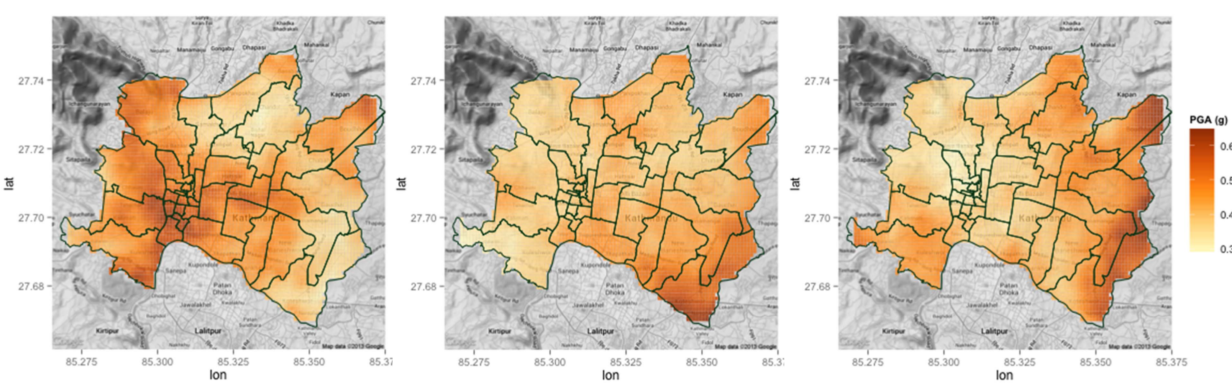


Figure 4: Three simulations of spatially correlated peak ground acceleration fields overlaid with the 35 wards comprising the Kathmandu municipality.

Four exposure models were used in this study. Census data for population was obtained for years 1991 and 2001. No census data was available for more recent years. The population for years 2010 and 2020 were therefore projected based on a simple compounded annual growth rate:

$$pop(t) = \left(pop(t_1) / pop(t_0)\right)^{\frac{t-t_0}{t_1-t_0}} \times pop(t_1) \tag{1}$$

The census data is available at the "ward" level, the administrative boundaries of which are shown in Figure 4. Since the spatial resolution of the ward-level census data is larger than the ground motion correlation distance, such aggregated data would result in overestimating extreme losses. This is because the probability of any single site having large ground motion is higher than for numerous dispersed sites. Hence aggregating entire ward exposure at its centroid could amplify the probability of extreme loss. For this reason the population data was spatially interpolated on a 500m x 500m grid.

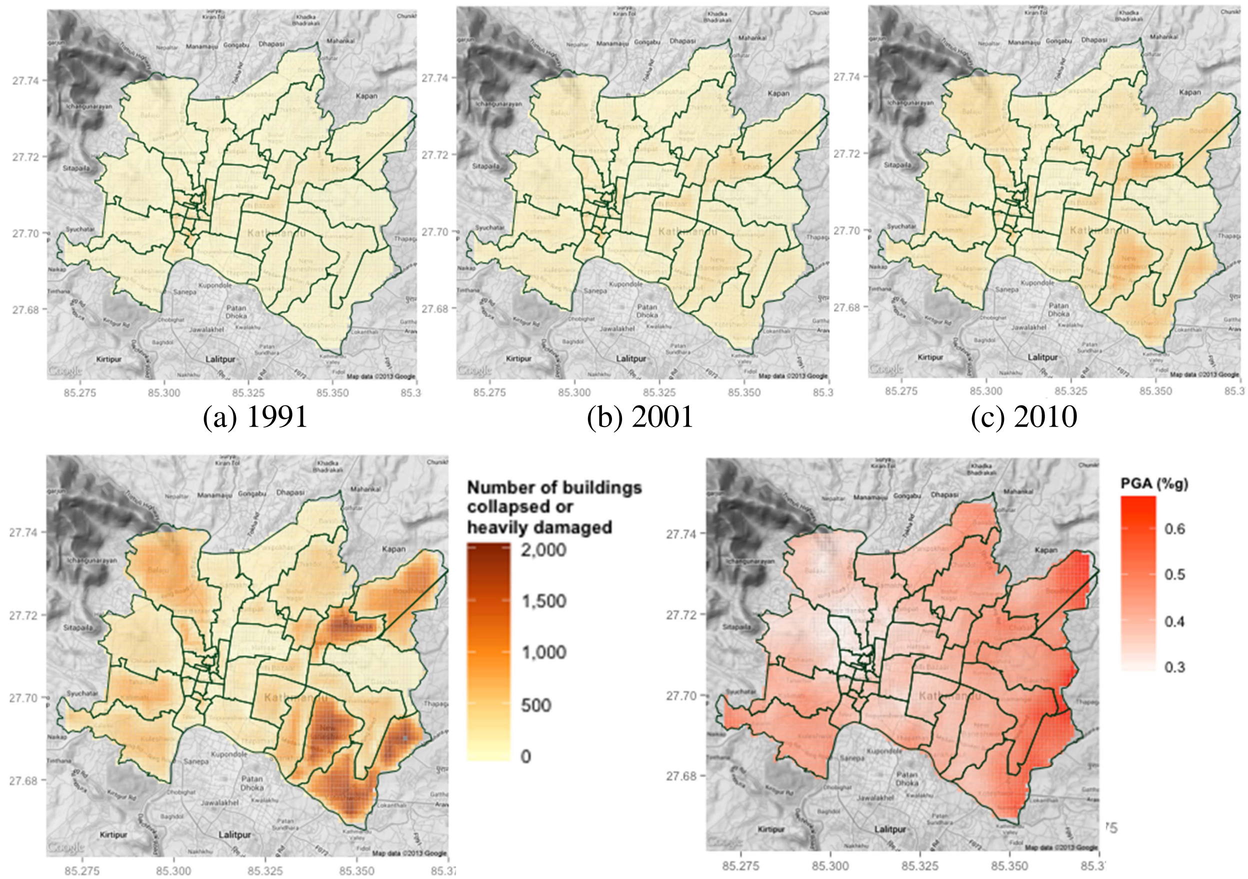
The population data was converted to a building inventory based on the 2001 census, which provides the number of buildings for each ward as well as a distribution of buildings within five categories: (1) stone with mud mortar, (2) adobe with mud mortar, (3) brick with mud mortar, (4) brick with cement mortar, and (5) reinforced concrete frame with masonry infill. These construction types are shown in Figure 5. Since the majority of new construction is reinforced concrete frames with masonry infill, the ratio of this building type increases with time.

Stone + mud mortar (ST) (5%)	*Adobe (AD) (19%)*	*Brick + mud mortar (BM) (27%)*
		
Popular in rural areas, round riverbed rocks and squared dressed stones	*Old type of building composed of sun-dried bricks with mud mortar mainly in rural areas, can be found in old urban or sub-urban areas, mainly on elevated ground*	*Traditional style with burned bricks using timber on the floor or / and roofs, usually.*
Brick + cement mortar (BC) (26%)	*RC + masonry (RC) (23%)*	
		
Cement and Sand have become popularly used in last 30 years. BC becomes popular structure.	RC has been adopted in the last 20 –30 years. Vulnerable higher stories become popular.	

Figure 5: Pictures of five building types described in 2001 census. Credit to Segawa et al. [13].

Fragility curves for each of these building types were obtained from a previous study which calibrated fragility curves based on the 1988 Udayapur earthquake damage assessment [14]. This study provided for each building a vulnerability curve describing the damage ratio given peak ground acceleration, and a fragility curve of "heavy damage or collapse" given peak ground acceleration.

For simplicity, we look at rates and distribution of "heavy damage or collapse" as a metric to measure time-varying risk. Figure 6 shows the distribution of the number of heavily damaged or collapsed buildings for each of the four exposure models, based on the same ground motion field simulation.



(a) 1991 (b) 2001 (c) 2010

(d) 2020 (e) Ground Motion Field

Figure 6: Number of buildings sustaining heavy damage or collapse for (a) 1991, (b) 2001, (c) 2010 (projected), (d) 2020 (projected) from a single ground motion field (e).

The results clearly show significant changes in risk driven by urban growth patterns and changes in primary construction type. The changing risk reflects both the high growth rates of specific wards, as well as the distribution/re-distribution of vulnerable building types. However, the absolute values of damage are not only emblematic of changing risk, since the maps are generated from a single ground motion field. Therefore the east side of the city sustains heavier damage in part as a result of higher ground motions from this specific simulation shown in Figure 6(e).

The process above is therefore repeated for every ground motion field simulation (n = 2500) in order to characterize the full distribution of heavy building damage for the entire Kathmandu municipality. The total number of heavily damaged or collapsed buildings is computed for every ground motion field simulation. We can then compute the expected (mean) risk due to changing exposure and vulnerability, but also the full empirical probability distribution of damage.

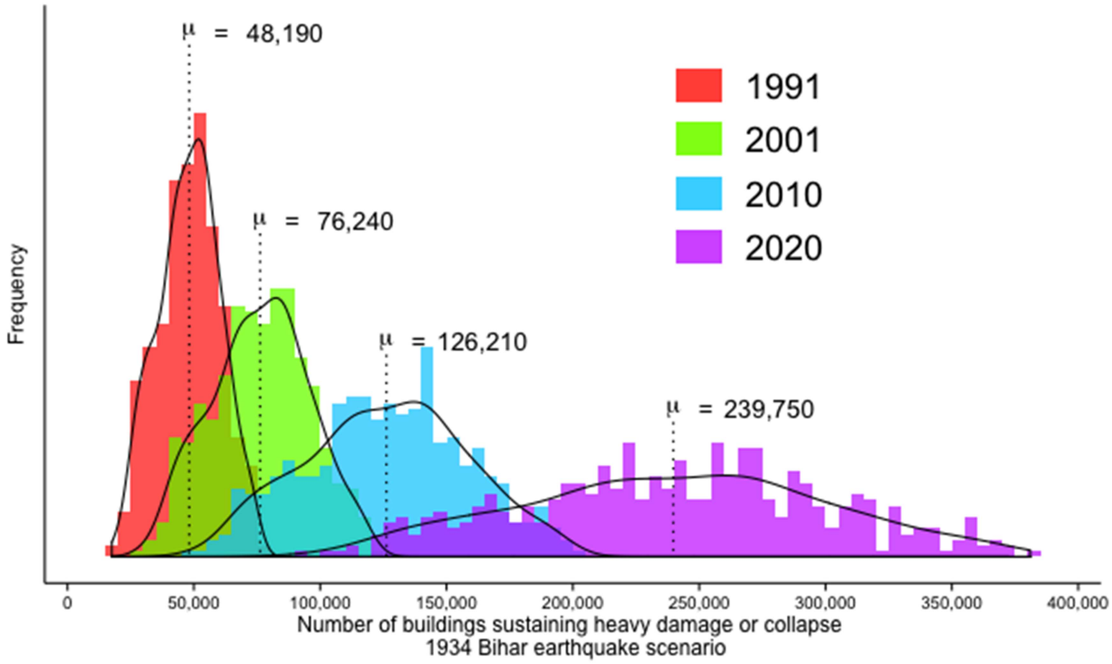


Figure 7: Full distribution of the number of buildings sustaining heavy damage or collapse, for four different time frames.

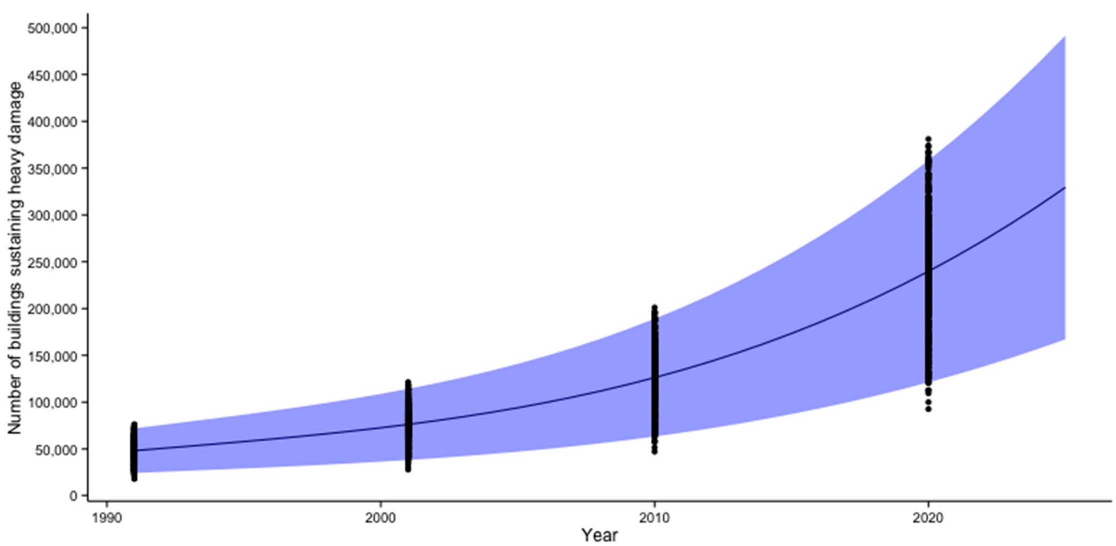


Figure 8: Expected and confidence interval of number of buildings sustaining heavy damage or collapse as function of time.

The results demonstrate that changes in exposure and vulnerability in Kathmandu drive a significant increase in risk. The expected number of buildings sustaining heavy damage or collapsing (mean values shown in Figure 7) nearly double every 10 years. Furthermore, the spread of the probability distribution of damage also increases. This increase is most likely the result of increased concentration of exposure. Indeed there is a higher probability of “tail events” (extreme damage or little damage) if sites of spatially concentrated exposure are within the spatial correlation length of ground motion intensity, as occurs with significant population growth.

This preliminary study of Kathmandu can be extended to more accurately capture the urban dynamics given additional data. Specifically, different population growth patterns could be explored other than the constant compound growth model over entire wards. The current model further does not directly incorporate changing vulnerability due to incremental construction. This will tend to underestimate damage, since incremental construction typically leads to increased vulnerability. In particular, the addition of floors to existing buildings is a ubiquitous practice in Kathmandu, a practice that is not accompanied with proper seismic strengthening. The effects of urban dynamics on exposure to secondary seismic hazards, in particular liquefaction and landslides can also be modeled.

Conclusion

This study proposes a framework of assessing time-dependent seismic risk. In particular, it enables the inclusion of dynamic exposure and vulnerability models in order to forecast future losses from earthquakes. The basic framework described can be applied for various levels of data availability and resolution. The spatial and temporal dynamics of urban exposure change can be modeled separately (e.g. simple compound growth model, agent-based simulation or other), and included in the model through a single time-dependent parameter of exposure. The study further demonstrates an application of the time-dependent seismic risk framework to a data-sparse context of Kathmandu in Nepal. Results show a very significant increase in seismic risk as a result of increases in exposure and the redistribution of building among various types. Further studies will look at adding further complexity to this model, including more realistic urban growth models, time-varying vulnerability linked with incremental construction, and capturing risk related to secondary seismic hazards such as liquefaction and landslides. Of particular importance is that by focusing on modeling future risk, the framework enables the investigation of risk consequences from various policy and planning decisions. It therefore can readily serve to inform risk-sensitive urban and regional policy and planning to promote resilient communities worldwide.

Acknowledgments

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