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Resilience of art cities to flood risk: A quantitative model based on depth-idleness correlation

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Abstract
Cultural heritage (CH) is threatened by floods; however, the understanding of exposure and vulnerability is challenging and makes risk and resilience assessment rarely practiced. CH is crucial for post-disaster resilience, especially when the local economy is based on tourism. The work presents a novel framework for evaluating flood resilience, indirect impacts, and associated risk in art cities. The exposure of CH is estimated using the number of visitors as a proxy variable for the social appreciation. A new depth-idleness vulnerability function assigning a reopening time to flood depth is developed from post-event reports. A resilience model is conceived to (i) describe the recovery dynamics, (ii) estimate the indirect impacts in terms of lost visitors to CH for different probabilistic scenarios, (iii) calculate risk, and (iv) identify mitigation actions. The application of the model to the art city of Florence (Italy), a UNESCO site visited by approximately 10 million people a year, shows that a medium recurrence interval flood requires a recovery time of 351 days and causes a loss of 10.5 million visitors. The annual average number of lost visitors is 88,000 approximately. Resilience can be increased by accelerating the reopening and by reinforcing the attractivity of the city.

KEYWORDS
crowd-sourced data, cultural heritage, depth-damage function, flood recovery, indirect impacts, social value, vulnerability

1 | INTRODUCTION

Consequences of natural hazards have been increasing in recent decades (Botzen et al., 2019; Coronese et al., 2019) and floods are among the most frequent and damaging events worldwide. Cultural assets are severely affected by floods and are likely to be increasingly threatened by climate change effects (Cassar & Pender, 2005; Fatorić & Seekamp, 2017; Gizzi, 2021; Marzeion & Levermann, 2014). International disaster risk reduction frameworks (UNISDR, 2015; United Nations, 2005) observe the relationship between different aspects of culture, risk reduction, and resilience, for promoting risk management to preserve cultural assets. Cultural heritage is broadly classified as either tangible, that is, consisting of buildings, historic places, monuments etc., or intangible, that is, referring to oral traditions, performing arts, social practices, rituals etc. (World Bank Group, 2017). Henceforth the term cultural heritage (CH) will refer to tangible CH.

CH plays a fundamental role in post-disaster resilience of communities and art cities (Galloway et al., 2020; Genova et al., 2020; GFDRR, 2020; Jigyasu, 2016; Kumar, 2020). One of the definitions of resilience is "the ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard" (Heinzlef et al., 2020; McClymont et al., 2020; UNISDR, 2015). Post-event recovery is facilitated by the revenues generated from tourism activities, although this depends on the magnitude of impact as well as the efficiency of community participation and governance (Min et al., 2020; Nair & Dileep, 2020; Rosselló et al., 2020).

Quantitative approaches for assessing flood resilience are commonly based on indicators or simulations which evaluate system performances, during or in the immediate aftermath of the event, starting from flood models (Coates et al., 2016; Pregnolato et al., 2016; Schinke et al., 2016). However, conceptual and theoretical frameworks are more popular and highlight difficulties in operationalizing resilience (McClymont et al., 2020). Resilience is often examined for infrastructures (Argyroudis et al., 2020; Joannou et al., 2019; Patel et al., 2020) and urban areas (Chen & Leandro, 2019; Leandro et al., 2020; Sajjad et al., 2021) only to cite a few examples. Recently, machine learning techniques have been adopted to predict climate resilience based on socio-economic indicators (Abdel-Mooty et al., 2021; Feldmeyer et al., 2021) Models which quantify the resilience in terms of medium to long-term recovery dynamics are rarely found in literature especially related to CH (Song et al., 2017). Resilience and risk are strongly linked together, in fact, resilience is related to coping capacity defined as the ability to anticipate, cope with, resist, manage and recover from disasters (UNISDR, 2015).

The commonly accepted approach for risk analysis encompasses hazard, exposure, vulnerability, and capacity assessment (IPCC, 2012; Koks et al., 2015). The quantification of resilience is thus crucial to obtain a complete understanding of risk.

CH is a peculiar asset which poses a challenge in the modeling of vulnerabilities, exposed values, and recovery costs within a "standard" risk assessment procedure. In part, the vulnerability of heritage assets relates to their physical characteristics, including quality of construction and conservation. Firstly, A major difficulty in flood vulnerability modeling lies in linking water depth to a relative or absolute physical loss which is usually described by vulnerability stage–damage curves (Arrighi et al., 2020; Cammerer et al., 2013; Gerl et al., 2016; Molinari et al., 2020). In fact, characteristics like materials, age of construction, finishing levels, etc. are specific for each asset and do not allow a generalization through stage–damage functions (Trizio et al., 2021). The physical contact with floodwaters causes direct damages to CH which can be irreversible or might take decades to be repaired (Bellucci, Ciatti, & Frosinini, 2016). Besides direct impacts to CH, also consequences that occur later in time, that is, indirect (Arosio, Martina, Creaco, & Figueiredo, 2020; Delalay, Ziegler, Shrestha, & Gopal, 2020; Gao, Geddes, & Ma, 2020; O'Donnell & Thorne, 2020), are relevant for the economy based on tourism.

Secondly, cultural heritage has an intangible value which includes the historical, spiritual, esthetic, and social values that constitute the cultural significance of a property (Appiotti et al., 2020; Spennemann & Graham, 2007). Thus, the exposure of cultural heritage is hardly monetizable (Holický & Sýkora, 2010), although significantly related to many profitable economic activities which generate revenues and employment (Bowitz & Ibenholt, 2009; CHCfE, 2015). Then, the definition of replacement cost does not easily apply to CH (Vecvagars, 2006), in fact, when regular infrastructure is affected, repair or reconstruction is usually possible; but impacts on cultural heritage can be irreversible and can also lead to economic losses, including loss of livelihoods (World Bank Group, 2017). The assessment of disaster losses on cultural heritage has not received enough attention so far and is considered quite challenging due to the multidimensionality of the problem (Romão et al., 2020; Romão & Paupério, 2021; UNDP, 2013). Romão and Paupério (2021) reviewed (i) the techniques used in environmental economics to valuate cultural heritage and (ii) the three components of cultural heritage value (extractive use values, non-extractive use values, non-use values).

As a consequence of the difficulties in quantifying exposure and vulnerability, flood risk assessment to cultural heritage has been mostly addressed in a qualitative way by categorizing and ranking assets in terms of vulnerability and performing exposure analysis at national or site scale (Arrighi, Brugioni, et al., 2018; Figueiredo et al., 2019; Garrote & Escudero, 2020; Miranda & Ferreira, 2019; Vojinovic et al., 2016; Wang, 2015). Flood vulnerability models for CH, that is, stage–damage functions are rarely found in literature (Figueiredo et al., 2021), since only recently the Sendai Framework has identified the promotion of resilient CH under the broad priority action areas. Romão and Paupério (2021) proposed an indicator to estimate direct and indirect economic losses to CH after an event based on the expected time to recover, non-extractive use values and non-use values, recovery costs, GDP and gross value added associated to CH sector with an application to the city of Lorca (Spain).

Few countries have begun cataloging cultural assets, mapping hazard risks, and placing them in the context of historical knowledge and traditions (World Bank Group, 2017). Besides the understanding of risk, preparedness and contingency plans should be prepared to enable rapid response, increase capacity, and ensure an effective recovery. In this context understanding the resilience of a community strongly dependent on cultural tourism is key.

The aim of this work is to investigate the interconnection between resilience, indirect impacts, and risk in art cities exposed to floods, that is, in a context with a high concentration of CH which attracts many visitors and feeds the local economy. Without the ambition of describing the intangible total value of CH and vulnerability in terms of direct losses, since no method is currently able to provide an exhaustive measure of the economic losses to CH (Romão & Paupério, 2021), the work introduces a proxy for socio-economic value of exposure and a new depth-idleness vulnerability function for CH built upon a review of post-flood reports in art cities or cultural attractions. The socio-economic proxy adopted for CH value is correlated to both non-use values, that is, social appreciation, and extractive use values, that is, revenues, and is not fully able to capture other aspects such as spiritual, symbolic, historical values of CH. The depth-idleness function links vulnerability and capacity, since time is an intrinsic factor of resilience. The depth-idleness function is used as input for the resilience model developed in this work, which simulates the recovery dynamic expressed as the number of people coming back to visit cultural attractions. The time required to bounce back to a certain percentage of number of visitors of the pre-event situation is used as a metric for resilience. The number of lost visitors per event and the annual average number of lost visitors are selected as a metric of indirect impact and risk, respectively. A demonstration of the model is provided for the art city of Florence (Italy) which hosts about 370,000 inhabitants and more than 10 million tourists each year before the COVID pandemic restrictions.

The manuscript is structured as follows: Section 2 describes the method including the flood hazard model, the exposure, vulnerability and resilience models; Section 3 introduces the case study; Section 4 describes and discusses the results; Section 5 draws the conclusions of the work highlighting strengths and limitations of the approach and further research perspectives.

2 | METHOD

The method adopted in this study combines (i) a flood hazard model, (ii) an exposure model, (iii) a flood vulnerability model, (iv) a resilience model, (v) the calculation of recovery, indirect losses, and risk metrics. The flowchart in Figure 1 illustrates the connection between the components of the method (white ellipses) and the most significant input/output data in the workflow (gray rectangles). The hazard model provides flood depth map that are the input for exposure model of CH. For each exposed CH, a flood vulnerability model yields the time required to reopen to the public, which feeds a resilience model capable of simulating the temporal dynamics of the number of visitors after the flood event. The comparison between normal and post-event number of visitors allows calculating the loss of visitors during the recovery time span for each flood event. Risk is obtained by combining losses, resilience, and probability of the flood event.

Exposure of CH is here described by the position of the CH with respect to the flooded area and by a proxy value that exemplifies the social appreciation, interest and preference of tourist, that is, the yearly number of visitors (see Section 2.2).

The vulnerability model developed in this study, consists in a depth-idleness function, which assigns to flood depth a damage in terms of time required to reopen again to the public the cultural attraction (see Section 2.3).

In this work, flood resilience is defined as the capacity of the art city to recover and bounce back to the previous state of the system after the shock, that is, the flood. In this study the state of the system is described by the number of open CH buildings and the number of visitors in a time scale of the order of a year after the flood. As shown in Figure 1 the resilience model yields the recovery dynamics which, on the one hand, provides a key metric of resilience itself, that is, the time required to restore normal conditions and, on the other hand provides an input to the assessment of indirect losses and risk. The resilience model is described in detail in Section 2.4.

2.1 | Flood hazard model

The hydraulic model here adopted to simulate the propagation of the event in the floodplain area is HEC-RAS v5.0.7. For this study, a 1D/2D model is set up, where the water profile in the channel is computed through a standard solver of the 1D general equation of unsteady flow and the floodplain is described by 2D shallow water equations (SWE). The SWE describe the motion of water in terms of depth-averaged 2D velocity and water depth in response to the force of gravity and friction. These equations represent the conservation of mass and momentum, and they are solved with the finite-volume method.

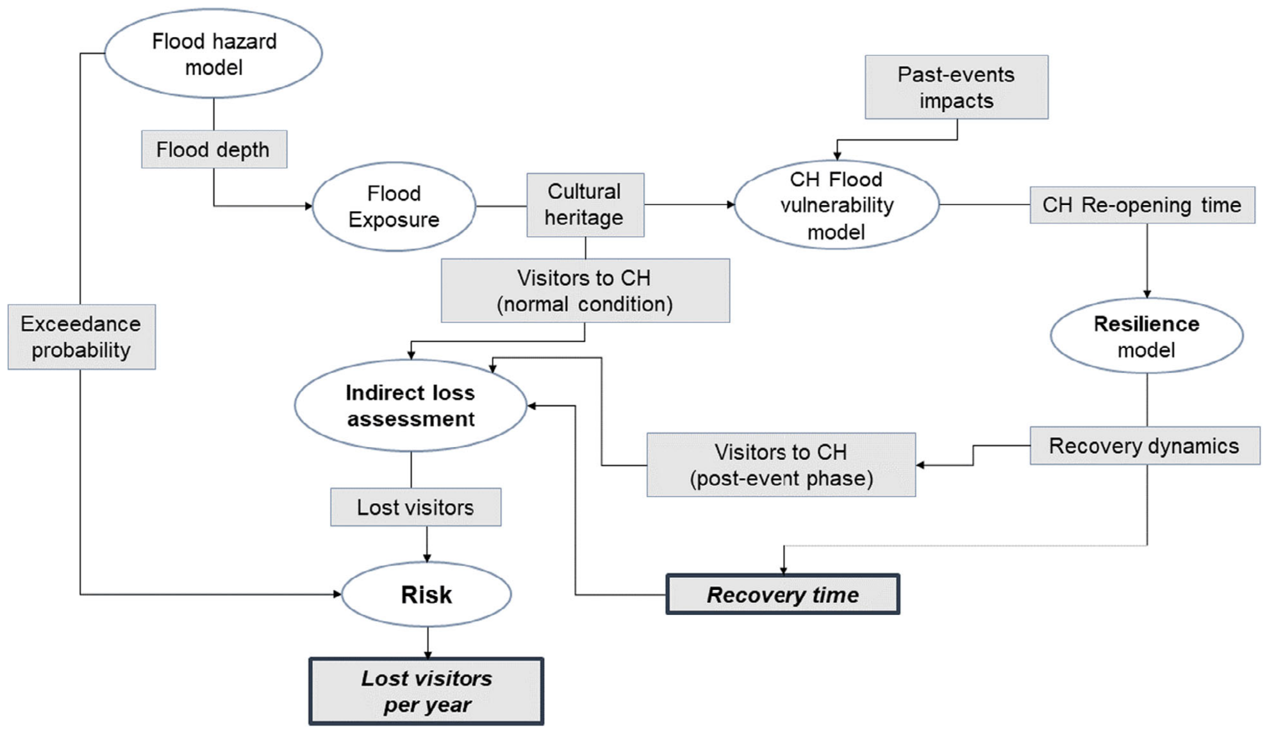

FIGURE 1 Flowchart of the methodology for modeling resilience, indirect impacts and risk to cultural heritage. Ellipses stand for activities; rectangles represent data flow; the two boxes with thick contour are the results of the workflow

The outflow from the riverbanks is modeled through a set of lateral weirs connecting river and floodplain and the flow over structure is determined using the weir equation.

The flood-prone area is discretized into grid cells, where each cell uses the underlying terrain data at 1 m resolution. Buildings are considered as waterproof blocks. For each cell and cell face HEC-RAS generates a detailed hydraulic property table (elevation-volume relationship, elevation-area, etc.). The water can move to any direction based on the given topography and the resistance to the flow controlled by the land use type and associated Manning's coefficient. Four scenarios with exceedance probabilities of 1/30, 1/100, 1/200, 1/500 are simulated. For each probabilistic scenario, the hydrograph duration yielding the largest inundated area has been selected.

The results of the hazard model are the flood depth maps of the study area corresponding to the selected probabilistic scenarios.

2.2 | Crowd-sourced flood exposure model

The exposure analysis is carried out by intersecting flood maps and the polygonal shapefile of CH for each scenario. Exposure is also the value of the asset affected by the flood, for example, for residential buildings the market value or construction cost (Molinari et al., 2020; Paprotny et al., 2021). The value of CH is hardly monetizable, however the social appreciation and value of a cultural attraction, for example, a museum, a noble palace, a church etc. is demonstrated by the number of people visiting it, especially in art cities where tourists have to choose among several possibilities during their stay. Moreover, the number of yearly visitors is not only a proxy of intangible social value of CH (part of non-use values), but also of the economic revenues of tickets and related services, for example, restaurants, accommodations etc (extractive use values). The combination of a degree of loss and the social value of exposure in terms of visitors to CH allows for estimating indirect impacts occurring days/months after the flood (Sections 2.3 and 2.4).

Data about the yearly number of visitors are usually made available by the institutions in charge of managing the cultural attraction. However, some locally managed attractions do not publish the data. A regression analysis is thus used to firstly define the parameters of a function which describes the number of annual visitors based on crowd-sourced review data and secondly to estimate the number of visitors for those attractions without public open data.

Assuming the standard form of a linear equation $V_{i,0} = \alpha \cdot r + \beta$, where r is the independent variable and $V_{i,0}$ the predicted variable, the regression parameters (α

the slope and β the intercept) are obtained by minimizing the sum of squared residuals. In this analysis, r is the annual number of online reviews to cultural attractions and $V_{i,0}$ is the average number of visitors obtained by official reports.

2.3 | Depth-idleness vulnerability model

Against the direct losses to CH which occur because of the physical contact of water and the building/artwork, art cities are often constructing preparedness plans which allow for moving artworks to safe elevations after a flood early warning. Nevertheless, in absence of retrofitting or prevention measures, cultural buildings can be affected and remain idle for the time required to repair/restore the structure. For low water depths, for example, of the order of few centimeters, a deep cleaning and safety check can be enough to reopen the attraction, while for high water depths above 4–5 m, such as in the 2002 Elbe flood in Dresden, the process may take months. A review of flood events occurred in art cities and affecting museums and cultural heritage has been carried out to gather information about the water depths, reopening times and event description. Post-event reports, books and newspapers have been used for the review and sources are available as Data S1. The correlation between flood depth and reopening time is here called depth-idleness vulnerability function and provides a synthetic description of the relationship between vulnerability, that is, potential damage, and capacity, that is, ability to cope with the damages.

A linear regression model is selected to describe the relationship between flood depth h and re-opening time called T_O

$$T_O = T_O(h) = \mu \cdot h \tag{1}$$

where μ is the slope obtained by the least squares method and the intercept is put to zero in the assumption that if the cultural attraction is not flooded, that is, $h = 0$, there is not any forced closure.

2.4 | Resilience model

In this study, indirect impacts are sensitive to the recovery speed of the system, that is, the sooner the attraction reopens the lower the impact expressed in terms of visitors lost. The evaluation of indirect impacts is thus strongly connected to the concept of resilience.

The response of a system to a shock is measured through a state variable versus time. The shock is intended here as the natural hazard (i.e., the flood) which causes the sudden drop of the state variable. In case of an art city with significant cultural heritage, the measures of the state of the system are assumed to be the number of open CH buildings and the number of visitors to CH. Indirect losses can be thus expressed in terms of visitors lost during the time span the systems recovers. In fact, if CH is flooded, although movable artworks can be displaced and saved from damages, it is not accessible to visitors for a certain time (Section 2.3).

The resilience model initializes with the average daily number of visitors $V_{i,0}$ in normal conditions obtained with the method described in Section 2.2 and all CH open to the public. The application of the vulnerability curve (Equation (1)) for each flood scenario provides T_O for each building. The overall number of open attractions at t, $M_O(t)$ in the art city is:

$$M_O(t) = \sum_{i=1}^{n} M_i(t) \tag{2}$$

where i is the *ith* attraction and n is the total number of CH attractions in the site. Each CH attraction can be either open or closed according to the Boolean expression of Equation (3)

$$M_i(t) = \begin{cases} 0 \text{ if } t < T_{Oi} \\ 1 \text{ if } t \geq T_{Oi} \end{cases} \tag{3}$$

However, the willingness to visit the site reduces if only part of the CH is accessible. In other words, there is a sort of delay in coming back after a flood event because the art city loses its attractivity (Dube & Nhamo, 2020; Rosselló et al., 2020). Attractivity $A(t)$ of the art city is here defined as

$$A(t) = \frac{V_{act}}{V_{pot}} \tag{4}$$

where V_{act} is the number of actual visitors at t after the shock, that is, is the sum of the *business-as-usual* visitors $V_{i,0}$ to the open attractions m

$$V_{act}(t) = \sum_{i=1}^{m} V_{i,0} M_i(t) \tag{5}$$

And V_{pot} is the potential number of visitors if all the attractions are open in *business-as-usual* conditions, that is, when m in Equation (5) is equal to n, the total number of CH attractions in the site. The attractivity $A(t)$ is maximum when all CH are open and Equation (4) equals (1), that is, when $V_{act} = V_{pot}$.

The real dynamic of visitors $V(t)$ is thus a function of $A(t)$ according to a power law,

$$V(t) = V_{pot}A(t)^k \tag{6}$$

where k is an exponent determining the weight of the attractivity factor.

The loss in terms of visitors at each time step $V_{loss}(t)$ is then the difference between V_{pot} and $V(t)$

$$V_{loss}(t) = V_{pot} - V(t) \tag{7}$$

The overall impact $L(T_R)$ of a scenario with annual exceedance probability $1/T_R$, that is, return period T_R, depends on the overall recovery time in the integral form:

$$L(T_R) = \int_{T_{shock}}^{T_{end}} V_{loss}(T_R, t)\,dt \tag{8}$$

where T_{end} is the time where the number of visitors bounces back to pre-shock conditions, that is, the end of the recovery phase. T_{shock} is the time when the flood occurs. The analysis described above may be repeated for several flood scenarios corresponding to assigned probability levels. If the estimation of the overall impact is carried out for scenarios with different T_R the risk expressed as *annual average number of visitors lost* can be estimated as

$$Risk = \int_0^1 L(T_R)\,d\left(\frac{1}{T_R}\right) \tag{9}$$

Since the model cannot easily be validated without specific post-event data, a sensitivity analysis of the estimated risk with respect to the parameters μ (slope of the vulnerability function) and k (attractivity) is performed.

Although resilience and risk are strictly connected in the model, the number of resilience curves which yields the same value of $L(T_R)$ and risk are infinite. Resilience is not only the capacity of recover and bounce back to previous normal conditions, but to achieve this goal in a timely manner, that is, the slope of the resilience curve matters. Synthetic indicators for the recovery speed in this work, besides the total recovery time t_{end}, are $t_{30\%}$, $t_{60\%}$, $t_{90\%}$ which represent the time (days) required to bounce back to 30%, 60% and 90% value of the state variable in normal conditions, that is, the pre-event number of visitors. Partial recovery time indicators are considered crucial for supply chain systems, especially those where competitors in the market offer similar products, for example, other art cities. In fact, visitors may be less loyal to the system when a disruptive event diminishes the system's capability to satisfy their demand. Visitors may need to cancel their stay should their demand, that is, a sufficient number of open attractions, not be met in a timely fashion (Ni et al., 2018).

3 | CASE STUDY

The method is applied to the city of Florence (central Italy). The historical city center of Florence has been listed as a UNESCO World Heritage since 1982. The last important flood event in the area was the 1966 flood which caused 38 casualties, severe damage to many of its most precious art works and threatened the economic and social viability of the city and its residents (Galloway et al., 2020) causing a great emotional impact in the whole international community (Kumar, 2020; Nencini, 1966). Before the restrictions imposed by the pandemic, the city was yearly visited by about 10 million tourists, with negligible seasonal fluctuations. The study area hosts 175 buildings classified as CH that are provided as a shapefile by the District of the Northern Appennines, the authority in charge of flood risk mapping in the Arno river catchment.

The District Authority also provides the river cross section including bridges and weirs needed for the 1D hydraulic modeling of the urban reach and the scenario hydrographs used as upstream boundary conditions. The floodplain is described by a 1 m resolution, 0.15 m vertical accuracy, LiDAR derived, Digital Terrain Model freely available in the regional cartographic data portal. Manning's coefficient in the riverbed is in the range 0.03–0.04 m$^{-1/3}$/s. In the floodplain it has been set to 0.14 and 0.09 m$^{-1/3}$/s for dense and sparse urban areas respectively, according to Land Use Land Cover data. The computational grid counts 800 thousand cells with a size of 8 m.

The data about the number of annual visitors $V_{i,0}$ is retrieved for 48 out of 175 attractions for the year 2018 from the reports by the Regional Authority (Regione Toscana, 2019). The online reviews sources for the fitting are TripAdvisor and Google Maps.

4 | RESULTS AND DISCUSSION

The results of the application of the method to the case study of Florence are presented into three sub-sections.

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Section 4.1 presents the visitors-reviews regression curve, Section 4.2 shows the vulnerability curve for CH and Section 4.3 describes the results of flood hazard, resilience model and the estimation of indirect impacts.

4.1 | Flood exposure

The flood exposure model provides the annual number of visitors in *normal* conditions based on online reviews for all CH excluded by the annual report (Regione Toscana, 2019). From the analysis of the sources of online reviews to CH, the best fit was obtained by using the annual number of TripAdvisor reviews ($R^2 = 0.87$). The use of Google Maps and the sum of Google Maps and TripAdvisor reviews yielded a determination coefficient of 0.71 and 0.80, respectively, thus they were not used. Figure 2 shows the obtained visitors-reviews regression curve. Circles represent the couples annual visitors-reviews for the CH with available official data; the dashed line is the regressed model used to estimate the number of visitors for those CH without data. The most visited museum with 2 million visitors and about 5000 reviews in 2018 is the Uffizi Gallery. The regression model is sensitive to the most visited CH attractions (three upper right points of Figure 2). If those points are removed from the analysis, the function sharply increases its slope and the number of visitors for the most visited CH attraction is overestimated of about 60%. Other proxies for the number of visitors to CH and or other functional forms should be possibly tested and validated in further research.

4.2 | Flood vulnerability

In this work, the vulnerability model for CH is represented by a depth-idleness linear function which assigns a time needed for re-opening T_O to the value of flood depth, based on the analysis of post-event reports and newspapers (Supporting Information of Figure 3). Figure 3 shows the empirical curve obtained with $R^2 = 0.90$, whose equation is

$$T_O = 93.46 \cdot h \tag{10}$$

For each meter of flood depth, the model estimates about 3 months, that is, 93 days, to reopen the attraction. The data represented with a cross refers to the Ca′ Pesaro Museum in Venice affected by an exceptional high tide in 2019 and the Albertinum Fine Arts Museum in Dresden, affected by the Elbe river flood in 2002. The first has been excluded because the inundation triggered a fire which slowed down the recovery. The latter has been excluded from the regression because after the flood, the museum underwent extraordinary renovations and re-organizations already planned before the event which took 72 months. Taking advantage of “forced” closure to execute extraordinary maintenance works and renovations is a common behavior which has been observed in Venice after exceptional high tide events and also during the 2020 Covid pandemic restrictions in Florence.

Re-opening time estimated with this depth-idleness vulnerability function is affected by significant uncertainties. First, the use of flood depth, which is a relatively simple flood parameter but still not easy to estimate

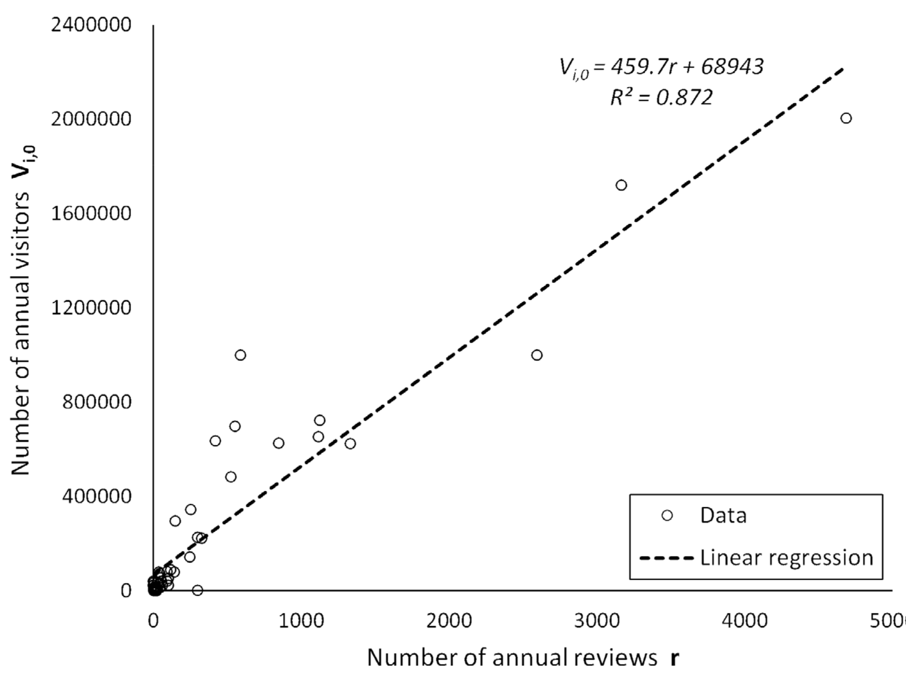

FIGURE 2 Crowd-sourced exposure model. The regression allows estimating the number of yearly visitors to CH without official data

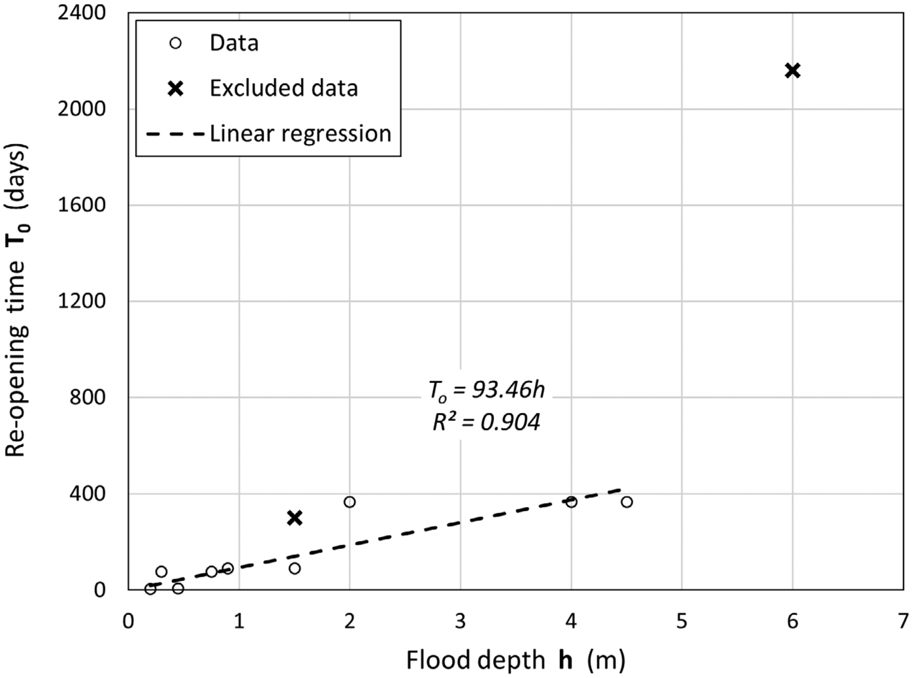

FIGURE 3 Depth-idleness vulnerability function for cultural heritage. Two points have been excluded from the regression

without uncertainty. Then, other economic, social and political aspects play a crucial role in post-disaster recovery such as resonance of the event, availability of funding, insurance capabilities, bureaucracy etc. Moreover, the limited number of available data for the regression does not allow to draw exhaustive considerations. More data from real events would be needed to validate the depth-idleness vulnerability function.

4.3 | Resilience, indirect impacts, and risk

The 2D hydraulic simulation of four hazard scenarios provides flood maps with different return periods, that is, 30, 100, 200, 500 years. The 500 years scenario represents the hydrologic magnitude of the historical 1966 flood. These maps represent water depth at 1 m resolution in the domain. Since buildings have been considered as waterproof blocks in the simulation, a buffer of 2 m around the CH building polygon has been drawn in order to calculate the mean flood depth per building per scenario. In this study, the presence of elevated ground floors in CH buildings, which might reduce the actual exposure has not been considered and quantified, but on-site surveys to the 176 cultural buildings could be carried out to have a more accurate understanding. Flood depth is used as input for Equation (10). Figure 4 shows the 500 years flood scenario for Florence, the CH buildings used to estimate the impacts and the location of historical marble plates which identify the water depths reached in the 1966 flood. In the map of panel (a), flood depths in the historical city center span from about 0.5 m in the most ancient roman district (center of the map) up to 4–5 m in the eastern portion of the city. Figure 4(b) is the scatter plot of simulated versus recorded flood depths. Simulated flood depths underestimate the 1966 event depths with a bias of 0.5 m. In fact, if the same hydrologic event affected the city nowadays, the flood depth would be lower thanks to the prevention actions undertaken in the last 50 years which reduce the inundation volume of about 70 Mm^3 (Arrighi, Rossi, et al., 2018; Autorità di bacino del Fiume Arno, 1999; Galloway et al., 2020).

Figure 5 shows the results of the resilience model in terms of open CH (a) and number of visitors (b) with the attractivity parameter $k = 3$. For the 30 years recurrence interval the city is not affected by the flood. For the 100 years scenario, downstream neighborhoods are flooded. The inundated area is 7.2 km^2 with an average flood depth of 1.3 m, only three CH buildings are affected with a maximum reopening time for one of those buildings of 30 days. The visitors come back to pre-event conditions in 36 days with an estimated loss of about 30 thousand visitors (Table 1).

The 200 years scenario has an inundated area of 18.7 km^2 (1.4 m average flood depth) and affects 118 out of 176 CH buildings. For this hazard scenario the time needed to come back to a normal status is less than 1 year, that is, 351 days, with an estimated loss of visitors of about 1 million (Table 1), which is about 10% of the annual number of visitors in 2018. For the 500 years

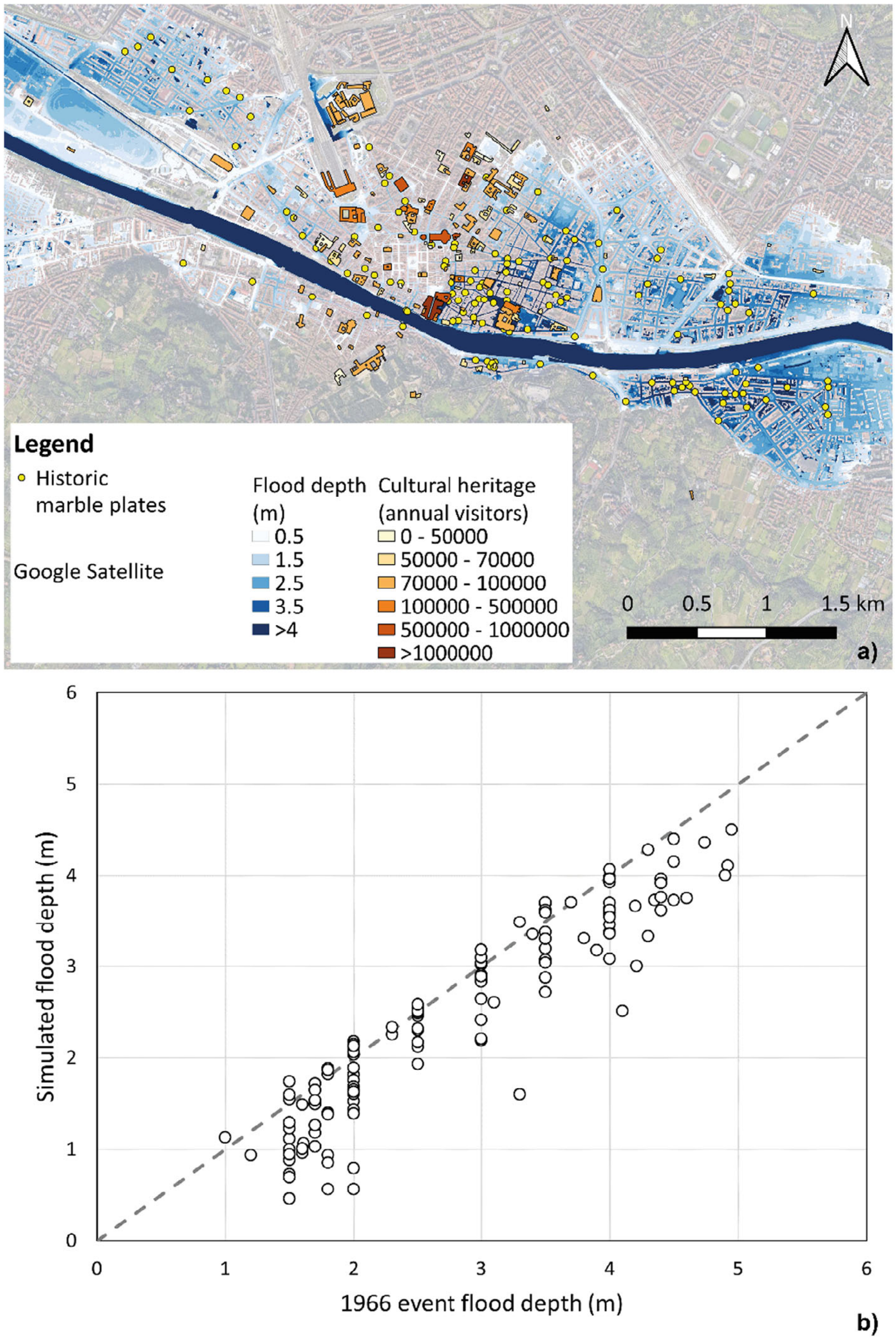

FIGURE 4 Flood hazard results. (a) 500 years flood depths, CH exposure and location of historical marble plates, (b) validation of flood hazard model against the historical flood depths

flood, the worst scenario considered, the inundated area reaches 24.7 km^2. One hundred and forty three CH buildings are affected, and 393 days are needed to restore the normal situation, the number of visitors lost is about 1.3 million (Table 1). From the comparison of panels (a) and (b) of Figure 5 it is possible to see that the dynamics of reopening of attractions is smoother than the dynamics of the number of visitors. This is due to the attractivity of the site, driven by a relatively small number of CH which have millions of visitors each year (The Uffizi Gallery, the Cathedral, the Gallery of Accademia). In fact, when the Uffizi gallery reopens (2 m flood depth for $T_R = 500$ years, 188 days of closure) the number of visitors in the city has a sharp increase.

The application of Equation (9) provides the risk in terms of annual average loss, which is equal to 87,564 lost visitors, about 0.9% of the visitors recorded in 2018. Although the estimated loss seems negligible, if we consider that each visitor spends about 150 € per day in Florence (IRPET, 2019), the indirect economic loss is about 13 M€/year, that is, 25% of the risk estimated for the city by considering only direct tangible losses to residential buildings and commercial activities (Arrighi, Brugioni, et al., 2018).

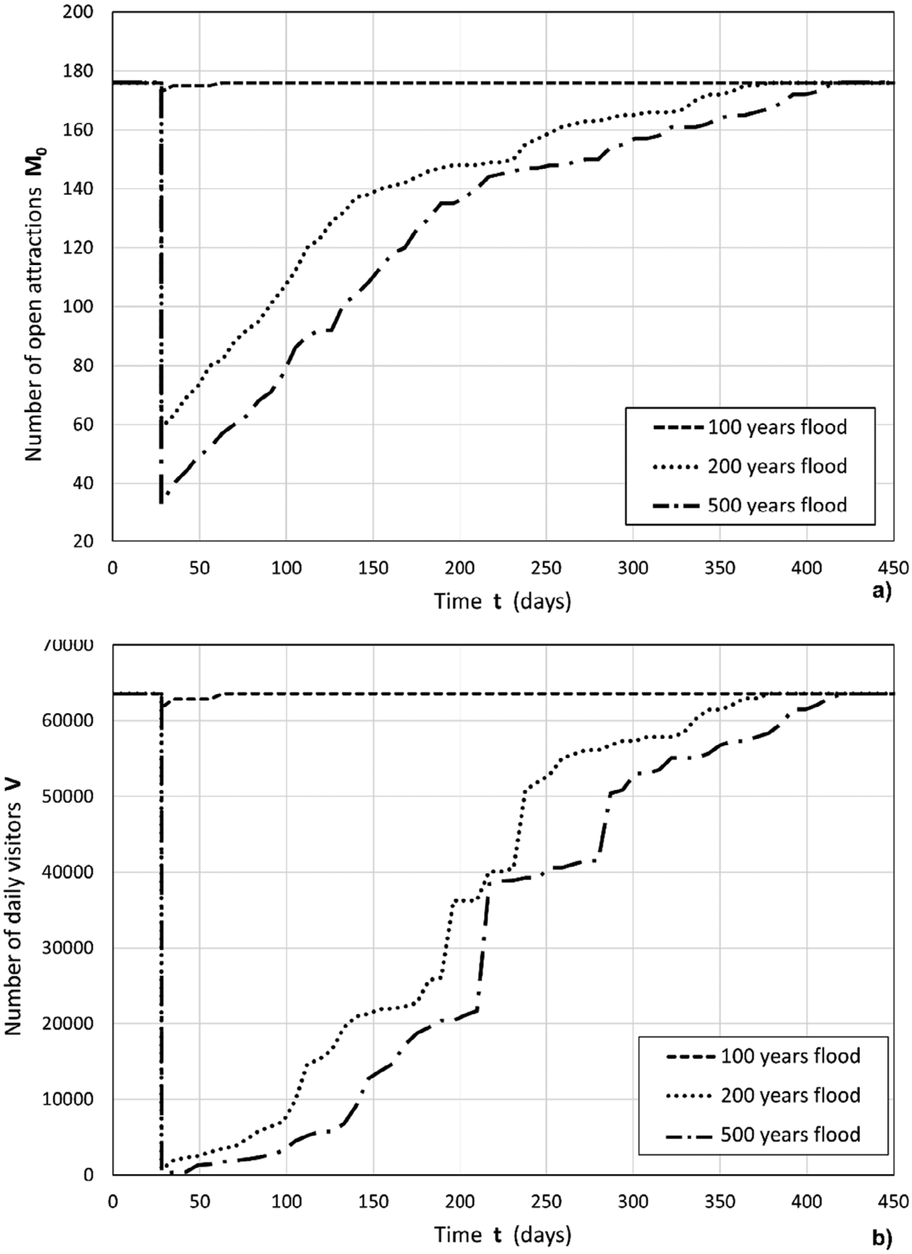

FIGURE 5 Results of the resilience model for the three hazard scenarios affecting CH. Number of open CH attractions M_O after the flood event (a); number of visitors V after the flood (b)

TABLE 1 Estimated number of lost visitors $L(T_R)$, time required to reach partial recovery of the system 30%–60%–90% and time required for total recovery come back to normal status t_{end} for the simulated flood hazard scenarios

Return period T_R (years)	Visitors lost $L(T_R)$	$t_{30\%}$ (days)	$t_{60\%}$ (days)	$t_{90\%}$ (days)	t_{end} (days)
30	0	0	0	0	0
100	32,252	5	8	34	36
200	10,462,373	106	187	267	351
500	12,930,684	153	190	329	393

Although validation of flood risk models is widely acknowledged as a fundamental step, it is particularly challenging for cultural heritage assets due to the lack of post-event data and the difficulties in valuing monetary costs. In this work the depth-idleness vulnerability function has been empirically derived, however the slope parameter μ is affected by the quantity and quality of available data. Moreover, the resilience model includes the attractivity parameter k which delays the recovery.

A sensitivity analysis has been carried out to understand how the estimated risk and recovery time are modified when μ and k are perturbed one at a time. The results are shown in Figure 6 in terms of number of visitors V after the 200-years flood event, with the slope of depth-idleness vulnerability curve $\mu \pm 15\%$ (dots) and with the attractivity parameter $k \pm 15\%$ (line).

A decrease of 15% in the slope of the vulnerability curve reduces t_{end} of about 50 days, with an almost symmetric behavior for the 15% increase. The variation of k does not modify t_{end} but modifies the number of visitors at t. As can be observed by comparing the two sensitivities, the change in μ causes a horizontal shift of the resilience curve, towards the right or left side of the graph when μ increases or decreases, respectively; while the change in k causes a vertical shift of the resilience curve, upward or downward directed when k decreases or increases, respectively. Moreover, the sensitivity to k decreases with time, since the attractivity of the art city tends to one when the number of visitors increases (Table 2). On the contrary, the sensitivity to μ is less significant in the first 100 days after the flood event and then increases.

The variation of risk in terms of annual average number of lost visitors to CH and total and partial recovery times with the perturbed parameters are summarized in Table 2. The slope of the depth-idleness curve μ is the most sensitive parameter for the estimated risk, in fact the elasticity, that is, the ratio between variation of the parameter and variation of risk is almost 1, while the elasticity to k is 0.4. The partial recovery time $t_{30\%}$ is particularly sensitive to a change in the parameter k, which is on the contrary negligible for t_{end}. The partial recovery times $t_{60\%}$ and $t_{90\%}$ are particularly sensitive to the parameter μ.

The significant influence of the parameters μ and k on the estimated recovery time, indirect scenario impacts and risk highlights two key actions to be undertaken by local stakeholders and institutions in the aftermath of a flood. The first one is to speed up the reopening of CH attractions, especially those attracting large amounts of visitors to reduce t_{end}. The second one, is to increase the attractivity by inviting people to visit the city in order to contribute to the recovery. In this sense, the parameters μ and k do not have a constant value, but depend on the capacity of the art city to recover, that is, its coping capacity and resilience, which depend on the amount of resources available, the priorities of stakeholders and on the worldwide resonance of the event (e.g., crowdfunding, insurance reimbursement), as occurred in Florence after the 1966 flood (Kumar, 2020). The sensitivity analysis also suggests that working on increasing the attractivity, that is, by reducing k, in the immediate aftermath of the flood and then focus on a fast reopening is the best resilience strategy.

In our model we assumed that the integration interval to estimate risk ends at t_{end}, however an art city can be

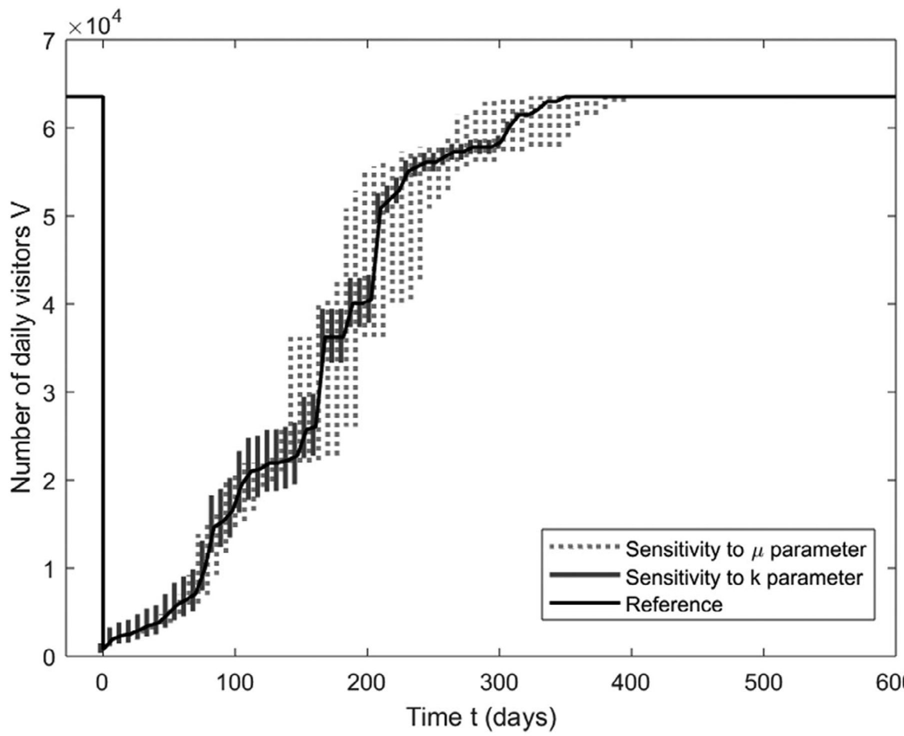

FIGURE 6 Sensitivity of the resilience model for $T_R = 200$ years to the parameters μ (dots) and k (lines)

	$\mu = 93.46$		$k = 3$	
	$\mu + 15\%$	$\mu - 15\%$	$k + 15\%$	$k - 15\%$
Risk sensitivity				
Annual average number of lost visitors	+15.14%	−14.74%	+5.49%	−6.53%
Resilience sensitivity				
t_{end}	+13.96%	−15.95%	0.00%	0.00%
$t_{30\%}$	+18.55%	−13.99%	+36.75%	−7.71%
$t_{60\%}$	+14.97%	−14.97%	+9.25%	−9.90%
$t_{90\%}$	+13.14%	−15.71%	11.50%	−4.38%

TABLE 2 Risk sensitivity and resilience sensitivity for the scenario $T_R = 200$ years with respect to the parameters μ and k

able to reach a new final state in which the number of visitors exceeds the pre-shock conditions, thus the indirect losses reduce in a longer time span ($t > t_{end}$).

5 | CONCLUSIONS

Flood impacts to cultural heritage are rarely addressed in literature although their social and economic relevance is widely recognized. This work developed a new methodology for assessing the resilience to floods, indirect impacts and risk in art cities with a demonstration in the city of Florence, a UNESCO World Heritage hosting 176 cultural heritage buildings and millions of visitors each year.

The adopted methodology follows the common approach of combining hazard, vulnerability, exposure, and capacity to assess risk, but with a quantification of resilience, indirect impacts and an original declination of the concepts of exposure and vulnerability. With respect to existing works that examined flood risk to CH by combining hazard maps and heritage typologies as main parameter for a qualitative vulnerability classification at national or regional scale (Figueiredo et al., 2019; Garrote & Escudero, 2020), this work focuses on the intermediate scale of site where numerous CH is present, that is, an art city. The resilience model here introduced allows to quantify the system dynamics which is crucial to evaluate the time needed to recover after an event, this aspect has been rarely investigated for CH. In the work by Romão and Paupério (2021), recovery time is assumed based on post-earthquake understanding of structural damages to CH, as well as recovery costs which are based on the municipal Master Plan. The application to the city of Florence also provides a quantitative demonstration of the interconnection between indirect impacts, resilience and risk, which is often addressed by means of conceptual and theoretical frameworks rather than with operational models (McClymont et al., 2020). The use of the number of visitors to each CH to approximate the social appreciation of each CH attraction, never used before for flood impact assessment, although not exhaustive of the different components of CH value (Romão & Paupério, 2021), provides a metric of intangible value well correlated with both non-use values (e.g., social value) and extractive use values (e.g., tourism revenues). The depth-idleness flood vulnerability function, which assigns to flood depth a re-opening time, is again a novel aspect of this research which might complement recent approaches of ultra-detailed stage–damage functions developed for a single cultural building (Figueiredo et al., 2021). The conclusions that can be drawn from the application to the case study are:

i. A flood event like the historical 1966 flood would cause an estimated loss of 12.9 million visitors and a total recovery time of 393 days.
ii. The estimated risk in the study area is 87,564 lost visitors per year (0.9% of 2018 visitors). This value can be turned into a monetary risk of about 13 M€/year, if the average daily expenses of visitors are considered.

iii. Resilience can be increased by accelerating the re-opening of CH attractions and by increasing the attractivity of the art city, as highlighted by the sensitivity analysis.

The main limitations of the proposed method which should be addressed by future research are:

i. The estimation of the number of visitors to CH by means of the regression against reviews, which are subject to changes in time, such as in case of restriction to travels or site promotion can be well correlated to revenues but less correlated to social value, that is, a decrease of visitors does not imply a loss of CH non-use value. Moreover, the regression model here obtained is site specific, although the method could be transferred to other case studies. Nevertheless, the number of visitors is a good state variable to simulate the recovery dynamics in the resilience model.

ii. The depth-idleness vulnerability function is obtained by a limited number of post-event data and is affected by several sources of uncertainty besides the hydrologic ones, such as funding availability, prioritization, and allocation following a disaster. More data would be necessary to validate the model and other variables could be taken into account to estimate re-opening times.

Further studies should also focus on the estimation of direct impacts to CH and on more detailed exposure analysis at single building scale to detect elevated ground floors in order to obtain a better understanding of direct/indirect flood risk. Prolonging the resilience model after the final recovery time would also allow for simulating adaptive art cities capable of bouncing back to better pre-event conditions.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the folder "Data_Resilience_of_art_cities_to_flood_risk:_A_quantitative_model_based_on_depth-idleness_correlation" at https://drive.google.com/drive/folders/1VYwug0TcTvhET4V_wVqsQ3qGwoDZoE1B?usp=sharing. The river cross section data and CH building shapefile that support the findings of this study are available upon request from Autorità di Bacino Distrettuale dell'Appennino Settentrionale.

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