Using Historical Source Data to Understand Urban Flood Risk: A Socio-Hydrological Modelling Application at Gregório Creek, Brazil

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Using historical source data to understand urban flood risk: a socio-hydrological modelling application at Gregório Creek, Brazil

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Abstract The city of São Carlos, state of São Paulo, Brazil, has a historical coexistence between society and floods. Unplanned urbanization in this area is a representative feature of how Brazilian cities have developed, undermining the impact of natural hazards. The Gregório Creek catchment is an enigma of complex dynamics concerning the relationship between humans and water in Brazilian cities. Our hypothesis is that social memory of floods can improve future resilience. In this paper we analyse flood risk dynamics in a small urban catchment, identify the impacts of social memory on building resilience and propose measures to reduce the risk of floods. We applied a socio-hydrological model using data collected from newspapers from 1940 to 2018. The model was able to elucidate human–water processes in the catchment and the historical source data proved to be a useful tool to fill gaps in the data in small urban basins.

Keywords urban floods; socio-hydrology; flood risk; social memory of floods; historical data source

Introduction

Floods affect more people worldwide than any other hazard and Brazil has the second-highest flood-loss potential in the world (UNISDR 2015a). To reduce disaster risk and losses, one of the priorities for 'focus actions' set up by the United Nations (UN) Sendai Framework (UNISDR 2015b) was understanding disaster risk and enhancing preparedness.

Risk preparedness is influenced by individual risk perception, which is based on an individual's prior expectations, information about risk and personal vulnerability (Miceli *et al*., 2008; Aerts *et al*. 2018). According to Garde-Hansen *et al*. (2017), for communities to be aware of flooding (and, very importantly, to prepare and take action) as a form of 'socio-ecological resilience', they need to record memories and remember past events in some way.

Memory is a fundamental underpinning of individual and collective life in a place, and thus needs attention in any deliberation of individual and collective resilience (McEwen *et al*., 2017). Memory is an extremely interdisciplinary subject of study. Psychologists, neuroscientists, anthropologists, computer scientists, philosophers, among others, have been discussing this topic for a long time. Over the years, scholars have fractionated memory into various processes and systems according to the objective of their studies (Roediger III and Wertsch, 2008).

In the philosophical field, Hallbwacks (1992) distinguishes two types of memory: individual or personal, and collective or social. In the field of psychology, Atkinson and Shiffrin (1968) divided memory structural components into three features: sensory register; short-term store; and long-term store.

More recently, socio-hydrological research (Sivapalan *et al.,* 2012) has identified memory as an important driver that affects individual values, which are responsible for shifting the feedback between societies and water management. Di Baldassarre *et al*.

(2013) and Viglione *et al*. (2014) proposed a set of differential equations to simulate the dynamics of a floodplain. Viglione *et al*. (2014) identified that collective memory, risk-taking attitudes and trust have a high impact in the process of building a flood risk culture.

Di Baldassarre *et al*. (2015) proposed a simplification of the previous model (Di Baldassarre *et al*., 2013; Viglione *et al*., 2014) to decipher changes in flood risk using high-water levels to estimate relative flood damage, social memory of floods, population density and flood protection level. The model is a mathematical formalization of general, plausible hypotheses about human–flood interactions and does not attempt to perfectly schematize the dynamics of a specific case study, which would be impossible to generalize (Di Baldassarre *et al*., 2015).

Ciullo et al. (2017) applied this model in two real-world case studies. The first one, applied in the city of Rome, used the maximum water level as input in the model, while the second one, applied in the city of Bangladesh, used the flooded area as a proxy for the flood intensity. Since time series might not be available in small basins, alternative sources of data are required to evaluate the magnitude of flood events, such as the possibility to acquire information from photographs. Government-installed cameras or researchers can take these photographs, but a low-cost alternative is using photographs taken by citizens on their cellphones.

In this study, we gathered information from newspaper articles to estimate the maximum water level in several flood events. Our hypothesis is that information provided by the society, such as narratives or photographs, can fill the gap left by the absence of observational networks in small urban catchments.

Having this historical dataset, we applied the model proposed by Di Baldassarre *et al*. (2015) to analyse the flood risk dynamics in the Gregório Creek catchment, located in the city of São Carlos, state of São Paulo (SP), from 1940 to 2018. The aim of this

paper is to understand the role of the social memory of floods in the flood risk variation

and identify what adaptation strategies could be undertaken in order to reduce flood risk.

Case study

The Gregório Creek catchment (Figure 1) is located in the city of Sao Carlos - SP, in

Brazil's southeast region, and has a total area of 18.9 km^2. The flood events in the

catchment are related to convective precipitation (Barros *et al.* 2007).

Urbanization started in the city of São Carlos in the 18th century at the western

part of the Gregório Creek catchment. At the beginning of the 20th century, the Municipal

Market was built on the creek's bank. Since then, this region has been shaped by intense

commercial activity and has been a key area for the city's economic development.

Historical records indicate that this region already suffered from the impacts of floods

during that time (Mendes and Mendiondo 2007).

Mendes and Mendiondo (2007) divided the period after the first flood record into

three stages related to the urbanization rate in the catchment. In the first stage, from 1950

to 1970, the catchment underwent intense urbanization. For the next 10 years, the

catchment experienced an urbanization slowdown, characterizing the second stage. From

1980 to 2002, in the third stage, the urbanized area in the catchment started growing again

as in the first stage. In this study, the third stage was extended to 2004, which shows a

similar urbanization behaviour, and then a fourth stage was introduced, from 2004 to

2018, where the urbanization rate nearly doubled (Figure 2).

Between 1940 and 2018, the urbanized area in the catchment increased from 3 to

14 km^2, approximately 75% of the total catchment area. In terms of inhabitants, the first

stage presented a mean annual growth rate of 0.4%. Despite the stabilization of the urban

area size in the second stage, the mean annual growth rate rose to 2%. In the third stage,

this index reduced to 0.6%, followed by growth in the fourth stage, leading to a value of 2.8%.

Around the middle of the first stage (1950–1970), the new Municipal Market building was opened, also on the bank of Gregório Creek. At the same time, the media depicted the creek as an obstacle to the city's progress, as the flood events damaged commercial activities, indicating the need for structural measures to reduce the occurrence of extreme events (Lima 2017).

During the second stage (1970–1980), the most substantial structural measures were built in the creek, such as a lining bed and walls and a changing cross-section, which shows that the intense urbanization in the first stage overloaded the catchment's drainage network (Mendes and Mendiondo 2007). In that period, avenues were also built on the banks of the creek (Lima 2017).

The shopkeepers in the region affirmed that flood magnitudes intensified in the third stage of urbanization (1980–2002). However, the sense of belonging to and identifying with a place shows that the shopkeepers consider the city's central area as their place and, because of this, want to stay there despite the flood problem (Marotti *et al.* 2014). Instead of moving to another place, they would rather adopt coping strategies, such as building protective measures (Figure 3), or moving products to higher places in the store.

Marotti *et al.* (2014) interviewed shopkeepers in the area and identified that the notion of place, such as belonging and identity, makes it clear that they regard the centre as their place and, therefore, wish to remain there despite the flood problem. When asked if they would leave the area, some responded that they would not know where to go and others that they would not leave because they love the place.

Methodology

We employed the socio-hydrological equations from Di Baldassarre *et al*. (2015) and adapted them to the case study of Gregório Creek. Although this model is based on simplified equations, we selected it due to the possibility of comparing real-world observations as it uses the floodplain population density instead of community wealth and average distance from the river, as in the previous version of the model. The model is based on a system dynamics framework, which investigates system outcomes and identifies correlations to determine system behaviours (Blair and Buytaert 2016) with a view to modelling human-water dynamics in a floodplain, linking hydrological, demographic, societal and technological aspects.

According to Di Baldassare *et al*. (2015), the model is a simplification of the previous one (Di Baldassarre *et al*., 2013; Viglione *et al*., 2014) and it is a mathematical formalization of general, plausible hypotheses about human–flood interactions. The model does not attempt to perfectly schematize the dynamics of a specific case study, which would be impossible to generalize.

According to Lättilä *et al*. (2010), in system dynamics modelling, leverage points for intervention can be identified fairly effectively. However, this is not possible at an individual level. Top-down approaches, such as this one, are popular because the data are relatively easy to collect and are inherently comparable (Srinivasan *et al.* 2012). For this reason, it is more suitable to apply this approach for studies in small and ungauged watersheds.

Hence, in this study, an analysis of coupled human–water systems with a 'human-in-the-loop' approach is proposed, using photographs made available in physical and online newspapers by members of society, to improve the socio-hydrological model for the Gregório Creek catchment.

Socio-hydrological modelling

The model developed by Di Baldassarre *et al.* (2015) estimates the variation of floodplain density (*D*), societal memory of floods (*M*), flood protection level (*H*), the amount of levee heightening (*R*) and relative losses (*F*) over time using flood magnitude (*W*) as input data. In the case of flooding, the reduction of population density due to displacement of people immediately after an event, as well as the contemporaneous building of societal memory and heightening of levees (for the technological society), are modelled as instantaneous (Di Baldassarre *et al*., 2015). Details of the model are given in Di Baldassarre *et al*. (2013, 2015) and Viglione *et al*. (2014).

$$F \ = \ 1 - \exp\left(\frac{-W}{\alpha_H}\right) \qquad (1)$$

$$\frac{\mathrm{d}D}{\mathrm{d}t} = \rho_D\big(1 - D(1 + \alpha_D M)\big) - \Delta(\psi(t)) \cdot FD_- \qquad (2)$$

$$\frac{\mathrm{d}M}{\mathrm{d}t} = \Delta(\psi(t))FD_- - \mu_S M \qquad (3)$$

$$\frac{\mathrm{d}H}{\mathrm{d}t} = \Delta(\psi(t))R - \kappa_T H \qquad (4)$$

$$R = \varepsilon_T(W + \xi_H H_- - H_-) \qquad (5)$$

where the Greek letters α and ρ and μ represent time-invariant parameters, as presented in Table 1; $\Delta(\psi(t))$, κ_T, ε_T and $\xi_H H$ are, respectively, a nonperiodic Dirac comb, the protection level decay rate, the safety factor for levee heightening and, flood enhancement due to the presence of levees over time. The variables with the underscore represent the value immediately before the flood event. The subscript T stands for the technological equation, which was not used in this study.

The equation that refers to the societal memory of floods (Equation (3)) is calculated based on what Di Baldassarre *et al*. (2015) called "magnitude of psychological

shock experienced by the community", which is calculated based on the proportion of flood damage.

Many studies have recognized that the intensity of individual memory is not a function of exposure to disaster (Sotgiu and Galati, 2007). However, in this study, we assumed that collective memory may be accumulated if more people are affected by flood events. We assumed that, by experiencing a flood event, an individual receives inputs that are transmitted to the short- and long-term store sequentially.

The exposure of individuals to stressful events, such as natural disasters, leads to the secretion of adrenocorticotrophin hormone (ACTH) and, subsequently, the secretion of cortisol into the bloodstream (Shaley, 2000). Some studies have identified that stress-induced cortisol enhances the long-term memory of experiences that have a degree of arousal (Buchanan and Lovallo, 2001; Cahill *et al*., 2003; Jelicic *et al*., 2004; LaBar and Cabeza, 2006).

Flood memories can be considered as a feeling of arousal because people have a strong emotional attachment to their homes and can experience severe distress if their homes are damaged or destroyed (Tapsell and Tunstall, 2008). Based on this, we assume that more intense flood events affect more people and, thereby, increase the number of individuals in the community with enhanced long-term memory due to the release of cortisol during such events.

Fanta *et al.* (2019) divide collective memory into living and distant. The living memory is the memory of witnesses who are still alive in the population; it has an emotional charge and can be passed on through narratives. The distant memory is the one transferred through history textbooks or academic works. In this study, we analyse the memory modelled through equations developed by Di Baldassarre *et al*. (2015) as the living memory of the community.

We assume that living memory increases proportionally to the flood damage because, as more people are affected by the flood, more people will have an enhanced long-term memory in the community and more narratives can be shared to build up the living memory (Figure 4).

In our case study, the community is assumed to behave as a technological society, as they did not move away from the creek after the flood events and when structural measures were constructed in the creek. However, there is no way to insert the measures adopted in this area in the model because the model assumes the flood protection level to be levee height, which was not the measure adopted here.

We modelled community behaviour assuming that no levees were built (i.e. the amount of levee heightening, R is equal to zero), so there was no amount of flood enhancement due to the presence of levees over time ($\xi_H H = 0$). Hence, Equations (1), (2) and (3) were used in this study.

However, the maximum water levels used as input data in the model consider flood enhancement due to structural measures built in the creek, thus reducing the uncertainty brought about by disregard of the technological equation.

Model parameters

The parameter α_H (see Table 1) for the current state of the basin (without any technological and social solutions applied) was estimated using the definition from Viglione *et al.* (2014): the relationship between the critical distance from the river beyond which the settlement can no longer grow, the mean flood water level and the distance from the settlement centre of mass to the river. The parameter ρ_D is the urbanization rate (km²/year) in this basin, which was obtained through spatial analysis of urbanized area per year. The total urbanized area in each year was divided by the total area of the basin, and the maximum of these values was used.

Parameters α_D and μ_S refer to social aspects, for which we do not have related data. To understand their behaviour, we performed a sensitivity analysis of the model regarding these two parameters and the model showed less sensitivity to parameter α_D. Therefore, we chose to adopt the value established by Di Baldassarre *et al.* (2015) for parameter α_D and to adjust the μ_S parameter so that the values of the population density resulting from the model were adjusted to the observed ones.

Although parameter μ_S does not appear directly in the equation related to the population density (Equation (2)), it is inserted into the equation that models the social memory of floods (Equation (3)), as it is a variable on which Equation (2) is dependent. Considering this, the variation of the parameter μ_S will generate different results for all variables of the model.

Risk estimation

The risk (R) was estimated by adopting the method proposed by Ciullo *et al.* (2017) and is defined by Equation (4). The hazard is assumed to be the probability of the event to occur (f_{w_a}), and the losses are the product of relative losses (F) and floodplain density (D) (Equation (6)). The term f_{w_a} is represented by the generalized extreme value (GEV) probability density function of variable W, which has parameters of shape, scale and location equal to 0.6, 0.06 and 0.02, respectively.

$$\text{Risk} = \text{Hazard} \times \text{Losses} \quad (6)$$

$$\text{Risk} = \int_0^{+\infty} f_{w_a}(W) L(W,D,H) \mathrm{d}W \quad (7)$$

where W is annual high water level.

Data acquisition

The flood water-level dataset used in this work was collected from newspaper articles both by Mendes and Mendiondo (2007) and by the authors of this paper for the periods 1932–2004 and 2005–2018, respectively. The events were divided into four classes according to the water level measurements for each event: (i) no water-level measurements (32 events); (ii) water level below 0.6 m (eight events); (iii) between 0.6 and 1.2 m (three events); and (iv) greater than 1.2 m (one event).

According to the tendency of the occurrence of events, we adjusted an exponential trend line (Figure 5) linking the mean water level of events and the return period of each class. This was done using events only from classes (ii) and (iii), since there was only one event in Class (iv) and it was not possible to estimate its return period. The return period of each class was adopted as the mean time between the events in each class. Hence, the mean water level (0.2 m) was estimated during the events registered in Class (i), which has a mean return period of 1.9 years.

The water level in the streets in the period 2005–2018 was estimated by visual analysis of photographs of these events that are available in local newspaper articles. The water level was estimated by comparison with strategic elements, whose dimensions could be easily identified, such as submerged vehicles (Figure 6).

Concerning data insertion into the socio-hydrological model, the annual maximum values were selected, giving 28 flood events for analysis. The intensity of each event was adopted as the mean water level measurement of its class, and the uncertainty intervals were the values between the maximum and minimum data of its class (Figure 7).

Scenarios

According to Ciullo *et al*. (2017), given the model capability of capturing empirically observed complex human–flood dynamics, the challenge now is to find out how different model components respond according to different possible societal attitudes. Thus, after applying the model to the current scenario of the region, we decided to analyse the model responses to changes related to awareness-raising attitude measures (μ_S variation) and reduced vulnerability (α_H variation).

The first option suggests a decrease in the community vulnerability through an increase in the distance between the creek and the urban settlement from 0.2 m to 1 m, varying the parameter related to the flood depth–damage curve (α_H) from 13 to 67.

The second hypothesis is that it is possible to reduce the risk of flooding by maintaining society's memory higher for a longer period. One way that this could be done is by putting up signs indicating the highest flood water level at different locations. For this purpose, the memory loss rate (μ_S) was changed from 0.5 to 0.01. This new value represents that when a flood occurs, the people remember 99% of what they remembered during the previous flood (Viglione *et al.* 2014).

Results and discussion

First scenario: no interventions

The grey shaded / white areas divide the graph into the four urbanization stages. presents the outcomes of the socio-hydrological model, with the flood magnitude levels (top graph) used as input data, and the normalized observed population density used to calibrate the model. It may be seen from Fig. 8 that the social memory of floods became stronger in the final part of the third stage of urbanization (1980–2004), a period during which the frequency of more intense flood events increased.

The first stage analysed is marked by population density growth in the catchment. With the repeated occurrence of lower magnitude floods, a certain amount of memory remains in the community, but not enough to have an effet on the urbanization trend. In the second stage of urbanization, the mean water level increased and the urbanization trend stabilized, while the main structural measures and the marginal roads were built in and along the creek.

In the third stage of urbanization, a resumption in growth can be identified, which is likely to have been due to greater accessibility as a result of new roads and the perception of safety provided by the structural measures. This dynamic is similar to the so-called "levee effect" described by White (1945) and Di Baldassarre *et al*. (2018). The most significant flood event since 1932 occurred In 1996, leading to a decrease in the population density, and this was followed by the largest recorded event in 1999.

Taking the reduction in the population in the catchment into account, the city authorities began to develop policies to encourage people to return to the area. However, instead of focusing on flood risk reduction or adaptation measures, the target was to revive the historical buildings and build new squares (FUSP 2011). In 2003, the Commerce Square (Figure), popularly known as Beira Rio (Riverside) Shopping, was opened with the aim of organizing and regulating the street hawkers who traded at the front of the Municipal Market; thus, another square was created in 2011.

Such actions may have been responsible for the renewed growth in population density from 2006, even though at this time the social memory of floods showed the second-greatest peak of the analysed period, a factor that should have stimulated migration away from the floodplain.

Second scenario: environmental interventions

Figure shows the results of memory, flood risk and population density dynamics under the second scenario (with variation in α_H; see Table 1). It may be seen from Fig. 10 that with a slight increase in the distance between the creek and urban settlement, the risk decreased, even with an almost constant population density growth. Although simple, the application of this measure implies moving commercial stands away from Commerce Square, which would bring about cultural and social issues, since the shopkeepers have a sense of belonging with this place.

Third scenario: social interventions

The results of the third scenario are shown in **Figure Figure** . It may be observed that the decrease in rate of memory loss had not brought about any changes in flood risk until the 1970s, a point in time when the structural measures were built in the creek and the flood magnitude intensified.

One factor that may have induced this dynamic is the smaller losses in the first period, a characteristic behaviour of a 'green' society (Ciullo *et al*., 2017). This process has not built up a noticeable level of social memory, as the scale of loss and injury and the impacts of past incidents would have contributed to an increase in the level of physical memory in a system (Bhattacharya-Mis and Lamond 2014).

These results suggest that investment in policies to maintain flood memory in technological societies can reduce the flood risk, but with a smaller effect than the option mentioned in the second scenario. When adopted simultaneously, the environmental and technological measures can complement each other by accepting the limitations of, possibly unreliable, human memories.

According to Di Baldassarre et al. (2015), the presence of flood protection structures leads to a rapid decay in the memory of flooding and, therefore, higher

vulnerability and exposure of societies. However, despite the fact that the society we studied behaved as a technological society, as people did not move away from the creek and built structural measures, the community is constantly experiencing flood events, because the measures adopted do not prevent the water from reaching the ground level.

Thus, the social memory of floods in this community was kept alive during almost the whole of the analysed period, unlike the technological society analysed by Di Baldassarre et al. (2017) and Ciullo et al. (2017), who experienced long periods without living through memories of floods. Thus, a decrease in the parameter related to the rate of memory loss in the Gregório Creek catchment did not significantly reduce the community vulnerability.

Conclusion

This paper shows that information provided by society through narratives and photographs can be a useful tool to fill the information gap in small urban catchments. In addition, combining historical source data and recent modelling techniques can help to understand human–water systems.

The population density growth at the catchment in 2003, stimulated by land-use policies, with a high level of social memory of floods, illustrates people's unreliable memory. This behaviour emphasizes that policies focused on social and environmental memory should be adopted in combination.

Even though the society under analysis showed technological behaviour after the 1970s, it was modelled as a green society because levees were the only type of structural measure that could be adopted in the model used. This assumption may have underestimated the losses, and consequently the flood risk in this period. We recommend that future works include different structural measures in the socio-hydrological modelling. However, we decided to adapt the equations from Di Baldassarre *et al.* (2015)

to the Gregório Creek case to make a comparison across cases where the model has already been applied and to understand what its shortcomings may be when applied to the reality of Brazilian cities.

Even though the structural measures were not considered through the model's technological equation, the water level data used as input to the model carried with it the flood enhancement due to the structural measures built in the creek. This shaped the results differently when looking at periods before and after the construction of these measures. One can observe an increase in the risk in the last three stages of urbanization (illustrated in **Figure 7**) and the fact that the variation in memory loss rate only reduces the risk in this stage; this suggests that policies focusing on maintaining society's memory for a longer period are more effective in technological societies.

Despite the limitations described above, the model employed in this study provided results that helped to understand this community's behaviour and to consider alternatives to improve their quality of life. The output has elucidated some relationships between water and society in the catchment, which will be used as a basis for future in-depth studies.

References

Aerts, J., *et al.* 2018. Integrating human behaviour dynamics into flood disaster risk assessment. *Nature Climate Change*, 1.

Atkinson, R. C., and Shiffrin, R. M. 1968. Human memory: A proposed system and its control processes. In *Psychology of learning and motivation* (Vol. 2, pp. 89-195). Academic Press.

Barros, R., Mendiondo, E. and Wendland, E., 2007. *Cálculo de Áreas Inundáveis Devido a Enchentes para o Plano Diretor de Drenagem Urbana de São Carlos (PDDUSC) na Bacia Escola do Córrego do Gregório.*

Bhattacharya-Mis, N. and Lamond, J., An investigation of patterns of response and recovery among flood-affected businesses in the UK: a case study in Sheffield and Wakefield. ed. *International Conference on Flood Recovery, Innovation and Response*, 2014, 163-173.

Blair, P. and Buytaert, W. 2016. Socio-hydrological modelling: a review asking" why, what and how?". *Hydrology and Earth System Sciences,* 20(1), 443-478.

Buchanan, T. W., and Lovallo, W. R. 2001. Enhanced memory for emotional material following stress-level cortisol treatment in humans. *Psychoneuroendocrinology*, 26(3), 307-317.

Cahill, L., Gorski, L., and Le, K. 2003. Enhanced human memory consolidation with post-learning stress: Interaction with the degree of arousal at encoding. *Learning & memory*, 10(4), 270-274.

Ciullo, A., *et al.* 2017. Socio-hydrological modelling of flood-risk dynamics: comparing the resilience of green and technological systems. *Hydrological sciences journal,* 62(6), 880-891.

Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Salinas, J. L., and Blöschl, G. 2013. Socio-hydrology: conceptualising human-flood interactions. *Hydrology and Earth System Sciences*, 17(8), 3295-3303.

Di Baldassarre, G., et al. 2015. Debates—Perspectives on socio-hydrology: Capturing feedbacks between physical and social processes. Water Resources Research, 51(6), 4770-4781.Di Baldassarre, G., 2017. Socio-Hydrology of Floods.

Di Baldassarre, G., Kreibich, H., Vorogushyn, S., Aerts, J., Arnbjerg-Nielsen, K., Barendrecht, M., ... and Bubeck, P. 2018. An interdisciplinary research agenda to explore the unintended consequences of structural flood protection. Hydrology and Earth System Sciences, vol. 22, num. 11, p. 5629-5637.

FUSP (Fundação de Apoio à Universidade de São Paulo), 2011. *Revisão do Plano Diretor do Município de São Carlos - Produto I.* Fundação de Apoio à Universidade de São Paulo, São Paulo, Brazil.

Garde-Hansen, J., McEwen, L., Holmes, A., and Jones, O. 2017. Sustainable flood memory: Remembering as resilience. *Memory Studies*, 10(4), 384-405.

Halbwachs, M., 1992. *On collective memory*. Chicago, IL: University of Chicago Press.

IBGE, 2018. *Population in risk areas in Brazil.* Rio de Janeiro, Brazil: Brazilian Institute of Geography and Statistics.

Jelici, M., Geraerts, E., Merckelbach, H., and Guerrieri, R. 2004. Acute stress enhances memory for emotional words, but impairs memory for neutral words. *International Journal of Neuroscience*, 114(10), 1343-1351.

LaBar, K. S., and Cabeza, R. 2006. Cognitive neuroscience of emotional memory. *Nature Reviews Neuroscience*, 7(1), 54.

Lättilä, L., Hilletofth, P., and Lin, B. 2010. Hybrid simulation models—when, why, how?. *Expert Systems with Applications*, 37(12), 7969-7975.

Lima, M. C. P. B., Urban processes in São Carlos, SP: two river catchments, two periods. ed. *National Association of Urban and Regional Post-graduate and Research Programs Meeting - ENANPUR*, 2017 São Paulo, Brazil.

Marotti, A. C. B., *et al.* 2014. Historical survey and reports of flooding of the Gregório stream at the central region of São Carlos municipality. *Revista Eixo,* 3(1).

McEwen, L., Garde-Hansen, J., Holmes, A., Jones, O., and Krause, F. 2017. Sustainable flood memories, lay knowledges and the development of community resilience to future flood risk. *Transactions of the Institute of British Geographers*, 42(1), 14-28.

Mendes, H. C. and Mendiondo, E. M. 2007. Histórico da expansão urbana e incidência de inundações: O Caso da Bacia do Gregório, São Carlos–SP. *Revista Brasileira de Recursos Hídricos,* 12(1), 17-27.

Miceli, R., Sotgiu, I., and Settanni, M. 2008. Disaster preparedness and perception of flood risk: A study in an alpine valley in Italy. *Journal of environmental psychology*, 28(2), 164-173.

Roediger III, H. L., and Wertsch, J. V. 2008. Creating a new discipline of memory studies. *Memory Studies*, 1(1), 9-22.

Shalev, A. Y. 2000. Biological responses to disasters. *Psychiatric Quarterly*, 71(3), 277-288.

Sivapalan, M*., et al.* 2014. Socio-hydrology: Use-inspired water sustainability science for the Anthropocene. *Earth's Future,* 2(4), 225-230.

Sivapalan, M., Savenije, H. H. G. and Blöschl, G. 2012. Socio-hydrology: A new science of people and water. *Hydrological Processes,* 26(8), 1270-1276.

Sotgiu, I., and Galati, D. 2007. Long-term memory for traumatic events: experiences and emotional reactions during the 2000 flood in Italy. *The Journal of Psychology*, 141(1), 91-108.

Srinivasan, V*., et al.* 2012. The nature and causes of the global water crisis: Syndromes from a meta-analysis of coupled human-water studies. *Water Resources Research,* 48(10).Tapsell, S. M., and Tunstall, S. M., 2008. "I wish I'd never heard of Banbury": The relationship between 'place'and the health impacts from flooding. *Health & place*, 14(2), 133-154.

UNISDR (United Nations Office for Disaster Risk Reduction), 2015a. *Global Assessment Report on Disaster Risk Reduction.* New York, USA: United Nations Office for Disaster Risk Reduction.

UNISDR (United Nations Office for Disaster Risk Reduction), 2015b. Sendai framework for disaster risk reduction 2015–2030. ed. *3rd United Nations World Conference on DRR*. New York, USA: United Nations Office for Disaster Risk Reduction.

Viglione, A*., et al.* 2014. Insights from socio-hydrology modelling on dealing with flood risk–roles of collective memory, risk-taking attitude and trust. *Journal of Hydrology,* 518, 71-82.

White, G. F., 1945. *Human adjustment to floods: a geographical approach to the flood problem in the United States.* University of Chicago.

Figure Captions

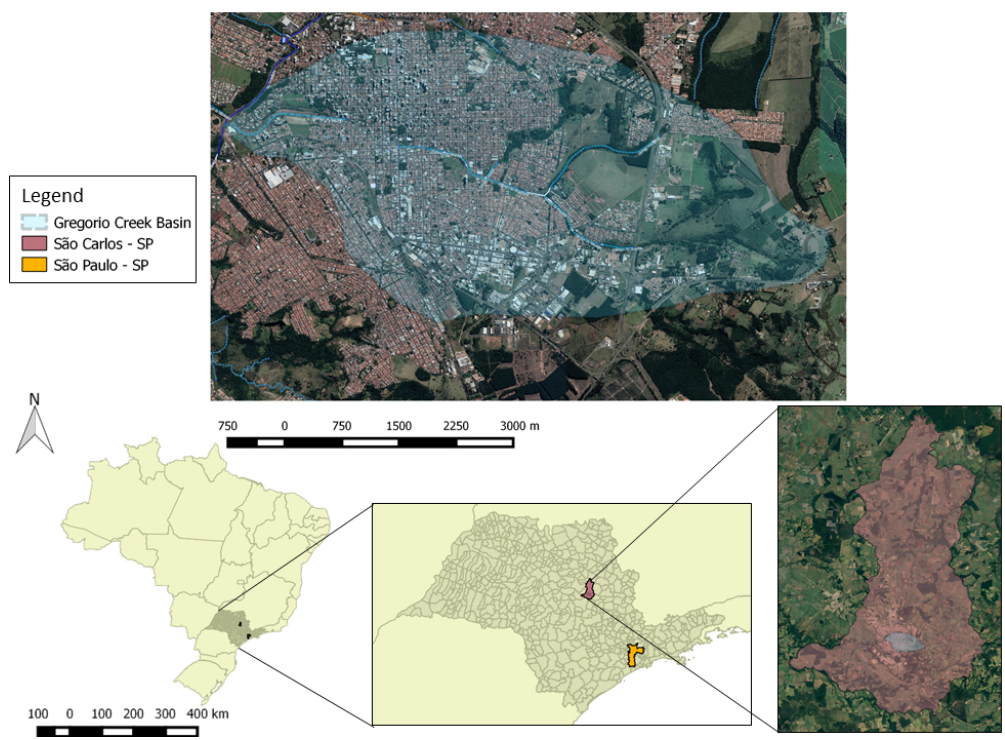**Figure 1.** Gregório creek catchment (highlighted in blue) in the city of São Carlos, Brazil (highlighted in pink).

Figure 2. Population density values with time in the different periods mentioned in Mendes and Mendiondo (2007).

Figure 3. Adaptive measures in a jewellery store in the Municipal Market area. Highlighted areas indicate the floor level enhancement (yellow) and the supports for the flood barrier (red).

Figure 4. Representation of the construction of the living memory[2]. SR: sensory register; ST and LT: short- and long-term storage, respectively. Notes: [1]Atkinson and Shiffrin (1968); [2]Fanta et al. (2019); [3]Hallbwacks (1992).

Figure 5. Number of events (bars) and mean flood water level per class (red dots), classified according to the mean return period and their tendency (dotted blue and dot-dashed red lines, respectively).

Figure 6. Submerged cars in a street during the 2018 flood event. The silver car in the right side of the picture was used to estimate the flood water level (G1, 2018).

Figure 7. Annual maximum water levels represented by their associated uncertainty intervals. The mean return periods are 2, 10 and 18 years (black, green and yellow markers, respectively). The grey shaded / white areas divide the graph into the four urbanization stages.

Figure 8. Socio-hydrological model input data (flood magnitude, in black) and outcomes (red, with uncertainty shown as shaded areas), with the observed population density (yellow dots). The grey shaded / white areas divide the graph into the four urbanization stages.

Figure 9. Section of Gregório Creek showing Commerce Square on the right bank.

Figure 10. Memory, risk and population density according to the actual (black, $\alpha_H = 13$) and lower (blue, $\alpha_H = 67$) vulnerability conditions. The grey shaded / white areas divide the graph into the four urbanization stages.

Figure 11. Risk variation for the actual ($\mu_S = 0.5$, blue line) and minimum ($\mu_S = 0.01$, red line) memory loss rate values.

Table 1. Description of parameters and their adopted values..

Parameter	Description	Unit	Adopted value
α_H	Parameter related to flood depth–damage curve [a]	L	13 [a]
ρ_D	Maximum relative growth rate [a]	1/year	0.009 [a]
α_D	Ratio between preparedness and awareness [a]	-	5 [a]
μ_S	Memory loss rate [a]	1/year	0.5 [b]

[a] Di Baldassarre *et al.* (2015).

[b] Defined for this specific study.

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Figure 1: Gregorio creek catchment (highlighted in blue) in the city of São Carlos – Brazil (highlighted in pink).
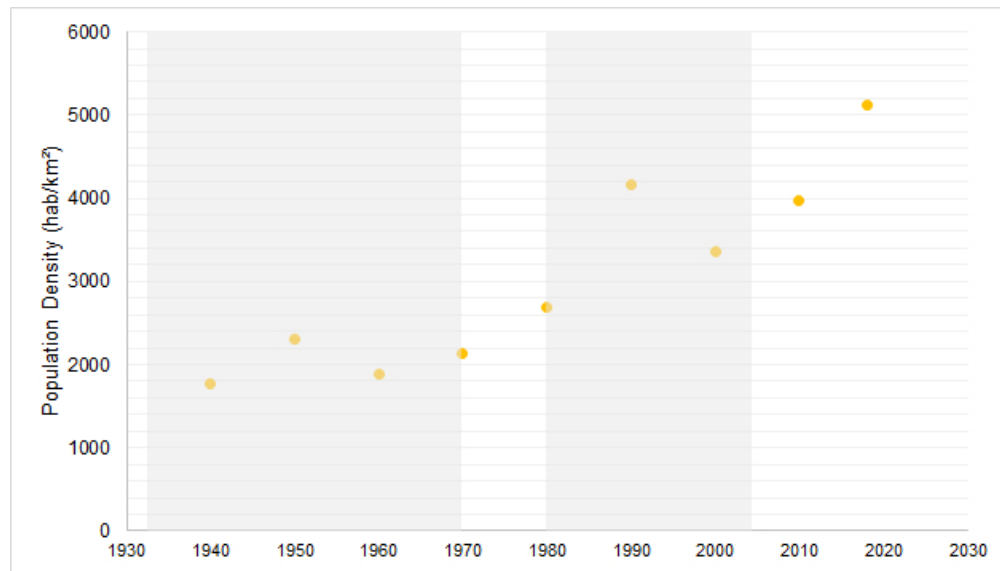
Figure 2: Population density values with time in the different periods mentioned in Mendes and Mendiondo (2007).

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Figure 3: Adaptive measures in a jewellery store in the Municipal Market area. The floor level enhancement is highlighted in yellow, and the supports for the flood barrier are highlighted in red.
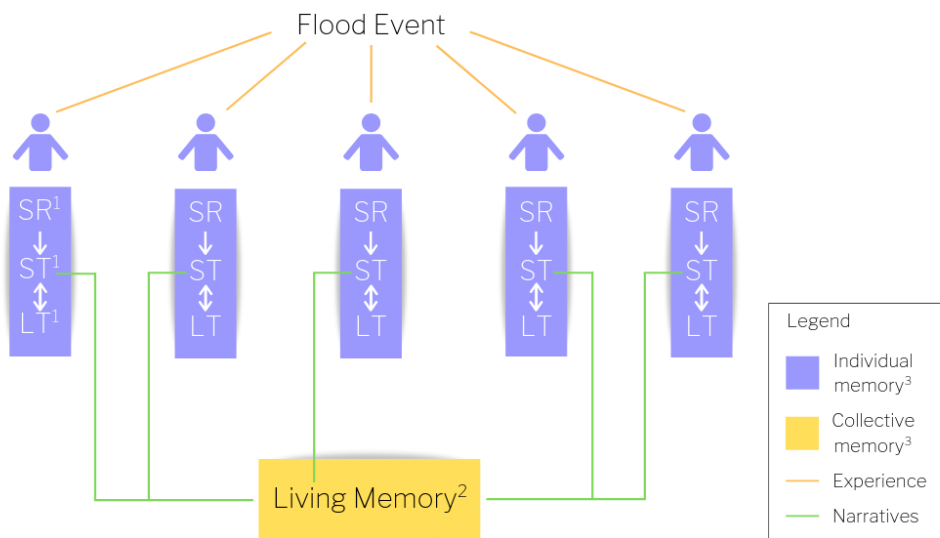
Figure 4: Representation of the construction of the Living Memory[2]. SR is Sensory Register, ST and LT are the Short- and Long-Term storage, respectively. [1] Atkinson and Shiffrin (1968), [2]Fanta et al., (2019), [3] Hallbwacks (1992).

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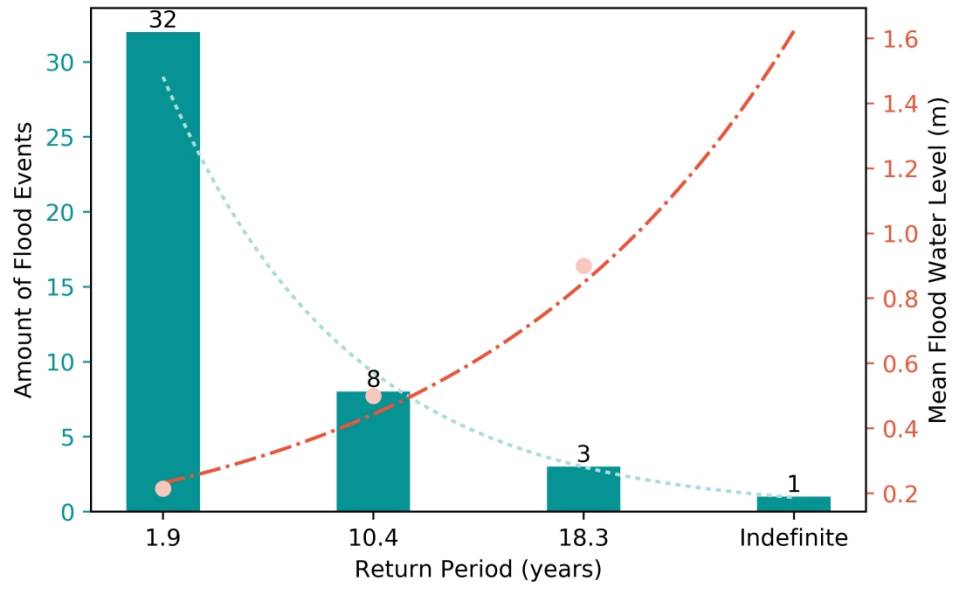
Figure 5: Number of events occurred (bars) and mean flood water level (red dots) per class (divided based in the mean return period) and their tendency (blue dotted and red dashed line, respectively).

Figure 6: Picture of submerged cars in a street from the 2018 flood event. The car highlighted in orange was used to estimate the flood water level (G1, 2018).

347x238mm (72 x 72 DPI)

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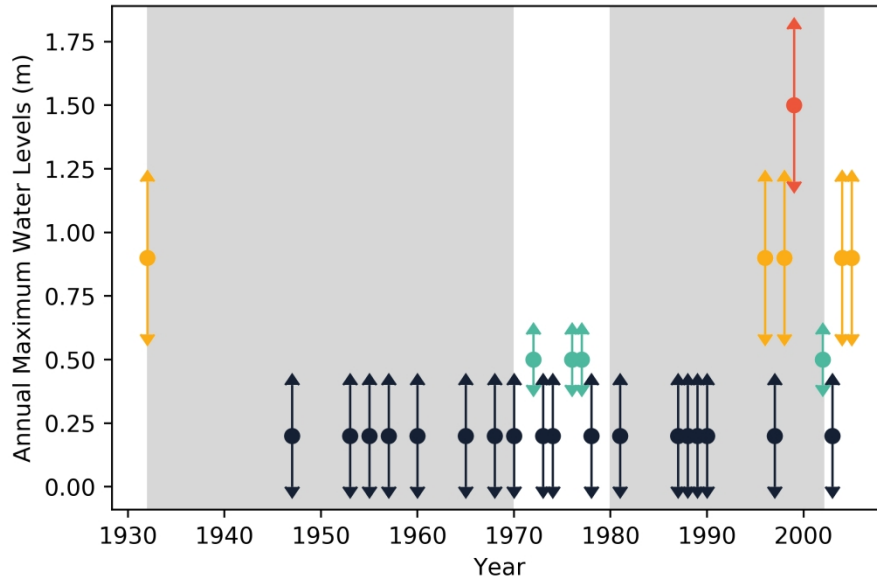14
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Figure 7: Annual maximum water levels represented with their associated uncertainty intervals. The mean return periods are two, ten and eighteen years for the black, green and yellow markers, respectively. The grey and white areas represent the first and third and second and fourth urbanization stages, respectively.

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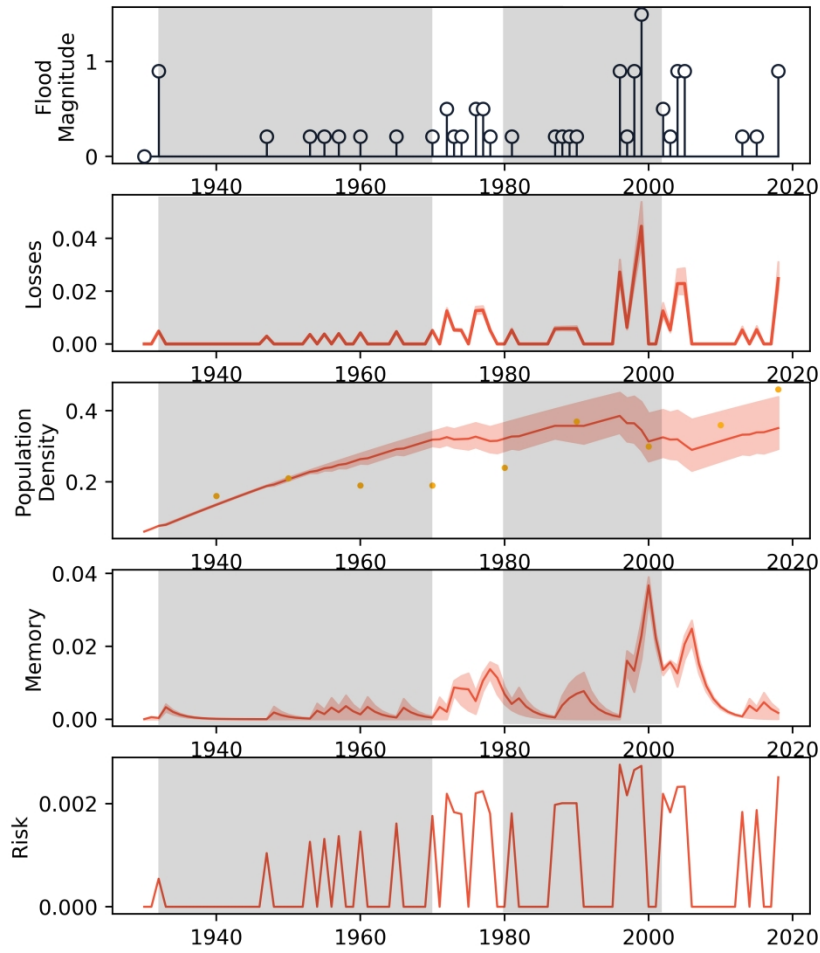44
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Figure 8:

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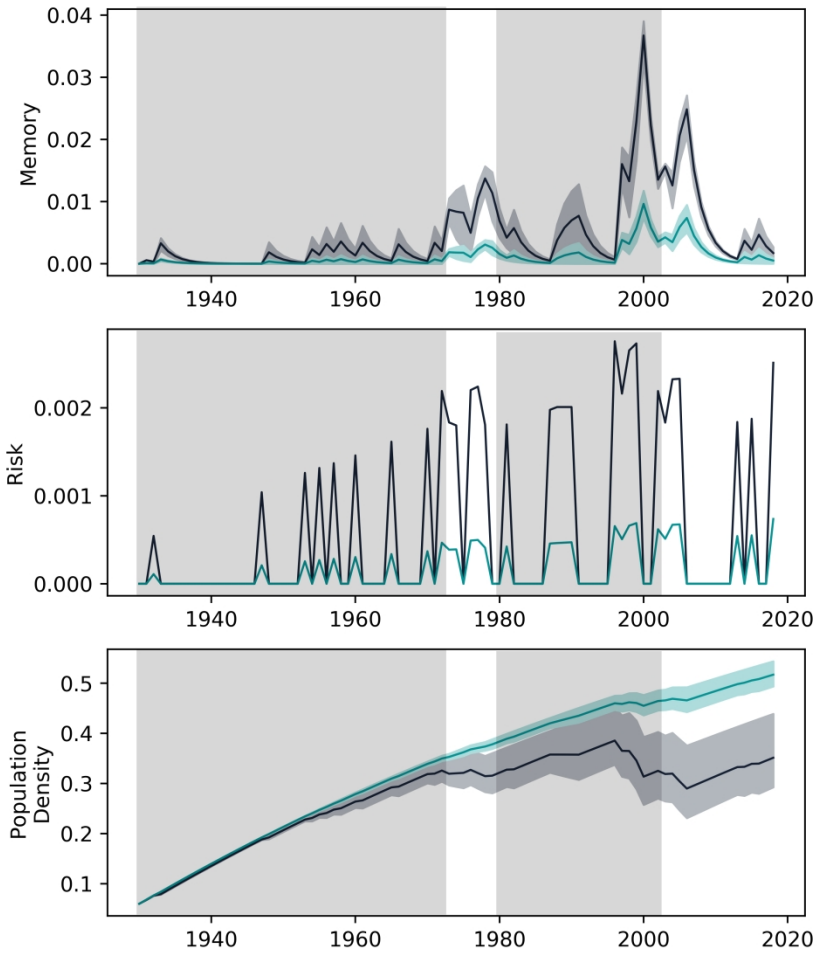Figure 9:

1456x819mm (72 x 72 DPI)

Figure 10:

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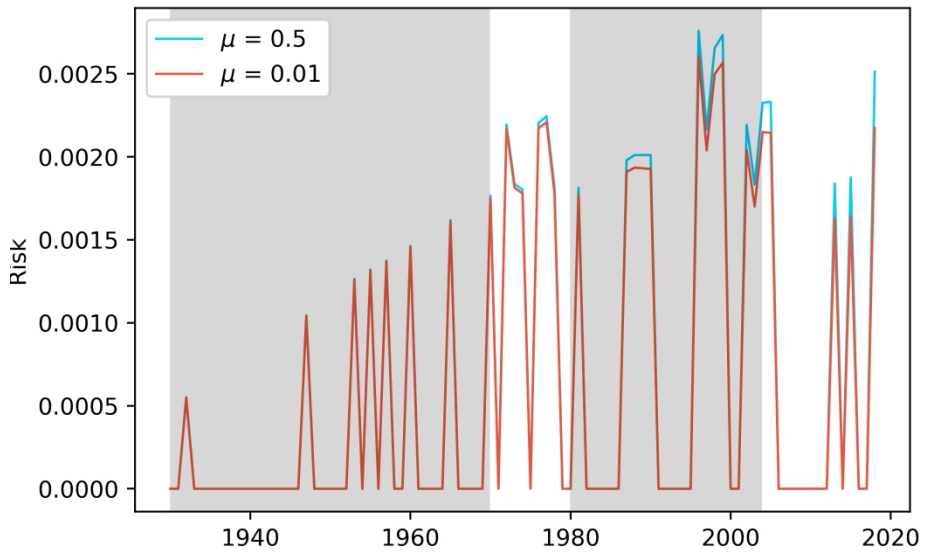41
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Figure 11: respectively.