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Projecting Flood Risk Dynamics for Effective Long-Term Adaptation

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Key Points:

- We present a socio-hydrological model for continuous flood risk projection that captures vulnerability dynamics and quantifies uncertainty
- Our case study highlights the need for effective adaptation to intensifying flood risk and the potential of integrated flood risk management
- The robust flood risk assessment method explores the possibility space comprehensively including adverse feedbacks such as the levee effect

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Flood losses have steadily increased in the past and are expected to grow even further owing to climate and socioeconomic change. The reduction of flood vulnerability, for example, through adaptation, plays a key role in the mitigation of future flood risk. However, lacking knowledge about vulnerability dynamics, which arise from the interaction between floods and the ensuing response by society, limits the scope of current risk projections. We present a socio-hydrological method for flood risk assessment that simulates the interaction between society and flooding continuously, including changes in vulnerability through collective (structural) and private (non structural) measures. Our probabilistic approach quantifies uncertainties and exploits empirical data to chart risk dynamics including how society copes with flooding. In a case study for the commercial sector in Dresden, Germany, we show that increased adaptation is necessary to counteract the expected four-fold growth in flood risk due to transient hydroclimatic and socioeconomic boundary conditions. We further use our holistic approach to identify solutions for effective long-term adaptation, demonstrating that integrated adaptation strategies (i.e., combined structural and non structural measures) can reduce the average risk by up to 60% at the study site. Ultimately, our case study highlights the benefit of the model for robust flood risk assessment as it can capture unintended, adverse feedbacks of adaptation measures such as the levee effect. Consequently, our socio-hydrological method contributes to a more systemic and reliable flood risk assessment that can inform adaptation planning by exploring the possible system evolutions comprehensively including unlikely futures.

Plain Language Summary The rise in flood losses due to climate and societal changes calls for effective strategies to reduce risks. Understanding how floods interact with society and affect vulnerability is crucial in addressing this challenge. However, current flood risk assessments lack this comprehensive insight. We have developed a novel method that integrates floods and society into a single model, enabling us to comprehend how society's vulnerability to floods changes over time. Our approach examines how communities respond to floods, considering both collective (like constructing levees) and private actions (such as individual property precautions). By factoring in uncertainties and utilizing real-world data, we improve our understanding of societal flood adaptation. Using the commercial sector in Dresden, Germany, as a case study, we reveal a potential four-fold increase in future flood risk due to climate and socioeconomic shifts. We propose a combination of collective and private measures, potentially reducing flood risk by up to 60% at the study site. In summary, our method is capable of simulating a wide range of potential futures and uncovering unforeseen challenges that may arise when societies attempt to shield themselves from floods. This aids in robust flood risk management and facilitates better planning for adaptation.

1. Introduction

Global change has sparked an increase in economic river flood losses over the past decades (Barthel & Neumayer, 2012; Bevere & Remondi, 2022). The historic rise in flood losses has mostly been attributed to demographic and economic growth and a concomitant accumulation of exposure in floodplains (Kundzewicz et al., 2014; Paprotny, Sebastian, et al., 2018; Visser et al., 2014). Anthropogenic global warming has not been a dominant control of flood risk change in the past, but its influence might grow in the future due to emerging shifts in flood hazard (Bouwer, 2011; Merz et al., 2021). Continued exposure growth and climate change are going to propel flood risk even further in most regions of the world (Hirabayashi et al., 2013; Jongman et al., 2012). As a result, global average annual flood loss could grow by up to a factor of 10 until the end of the century compared to today under the assumption of constant flood vulnerability (Alfieri et al., 2018; Dottori et al., 2018; Winsemius et al., 2016). The reduction of vulnerability through flood adaptation has proven effective in the past (Jongman et al., 2015; Tanoue et al., 2016) and, hence, is a key element in the effort to offset the expected intensification of impacts (Jongman, 2018; Kinoshita et al., 2018; Winsemius et al., 2016).

Changes in flood vulnerability are difficult to trace as it is a multidimensional quantity that is determined by physical, economic, institutional, and social factors (Merz et al., 2010; UNDRR, 2022), which impedes the collection of continuous and extensive data. Similarly, adaptation measures differ in type (e.g., structural, nature-based), scale (country, object-level), and the implementing actor (government, individual households) (Dottori et al., 2020; Jongman, 2018). Therefore, the dynamics of vulnerability and their effect on flood risk are understood less in comparison to hazard and exposure (Kreibich et al., 2017). This also reflects in prevalent flood risk assessment, where vulnerability changes are usually not considered (Metin et al., 2018). Some modeling studies attempted to bridge this gap by running risk simulations assuming different levels of adaptation (i.e., discrete and constant vulnerability scenarios) (Jongman et al., 2015; Metin et al., 2018; Steinhausen et al., 2022). While this approach goes further than most previous risk analyses, it still cannot capture the continuity of vulnerability change which arises from the constant interplay between flood events and society at different time scales (Sivapalan & Blöschl, 2015). For instance, damaging floods demonstrably trigger adaptation response by the affected society in the aftermath of the event (Di Baldassarre et al., 2015; Kreibich et al., 2017) and, conversely, flood-poor periods might lead to a decay in a societies' risk awareness (Fanta et al., 2019; Viglione et al., 2014). Altogether, limited understanding of the causal factors of vulnerability change and narrowly defined model boundaries do not embrace the complex reality of floodplains (Merz et al., 2015), which becomes even more relevant in a rapidly changing world. Such knowledge is essential for the reliable projection of future adaptation and the quantification of its risk reduction potential (Aerts et al., 2018; Dottori et al., 2018).

Following the call for more systems-thinking in flood risk assessment (Barendrecht et al., 2020; Di Baldassarre et al., 2016; Schröter et al., 2021), recent approaches based on agent-based and socio-hydrological modeling enhance the possibilities of flood risk modeling (Barendrecht et al., 2017). These methods integrate vulnerability as an inherent component in dynamic models and, hence, go a step further than scenario-based approaches (Jongman et al., 2015; Metin et al., 2018; Steinhausen et al., 2022). Haer et al. (2017) developed an agent-based model that incorporates the dynamic flood adaptation by households. It was then extended to governments to study the future evolution of vulnerability and risk under different behavioral scenarios (Haer et al., 2019, 2020). Socio-hydrological system dynamics models are a parsimonious alternative to agent-based models as they only resolve the most essential components and processes on the systems-level (e.g., a floodplain) and focus on the overall co-evolution of human-flood systems (Blair & Buytaert, 2016). Having originated from studies that investigated hypothetical systems (Di Baldassarre et al., 2013; Viglione et al., 2014), these models have recently progressed toward a data-informed solution for quantitative tracing of vulnerability and risk dynamics (Barendrecht et al., 2019; Schoppa et al., 2022). In such models, small-scale variations are treated probabilistically (e.g., via Bayesian methods) rather than being resolved explicitly, which facilitates the efficient exploration of future flood risk projections while including the numerous sources of uncertainty.

Here, we present an efficient socio-hydrological method for continuous flood risk assessment that expands the conventional focus on hazard and exposure changes by explicitly including vulnerability dynamics. The probabilistic approach is calibrated on empirical data and quantifies uncertainties by means of Bayesian inference. In a pilot application for the commercial sector, we (a) project flood risk trajectories until the end of the 21st century accounting for the transient nature of all three risk drivers (hazard, exposure, vulnerability) and (b) assess the effectivity and robustness of adaptation strategies against the background of exacerbating hydroclimatic and socioeconomic boundary conditions. To our knowledge, this is the first time that a socio-hydrological system dynamics model is used in a quantitative projection study of flood risk. Our method helps to link expected large-scale patterns of change (e.g., in climate, demographics, economy) with largely unknown local responses of risk in human-flood systems (Jongman et al., 2015). Moreover, this approach could contribute to unleashing the full potential of societal flood adaptation by enabling the evaluation of competing flood mitigation strategies in comprehensive modeling experiments.

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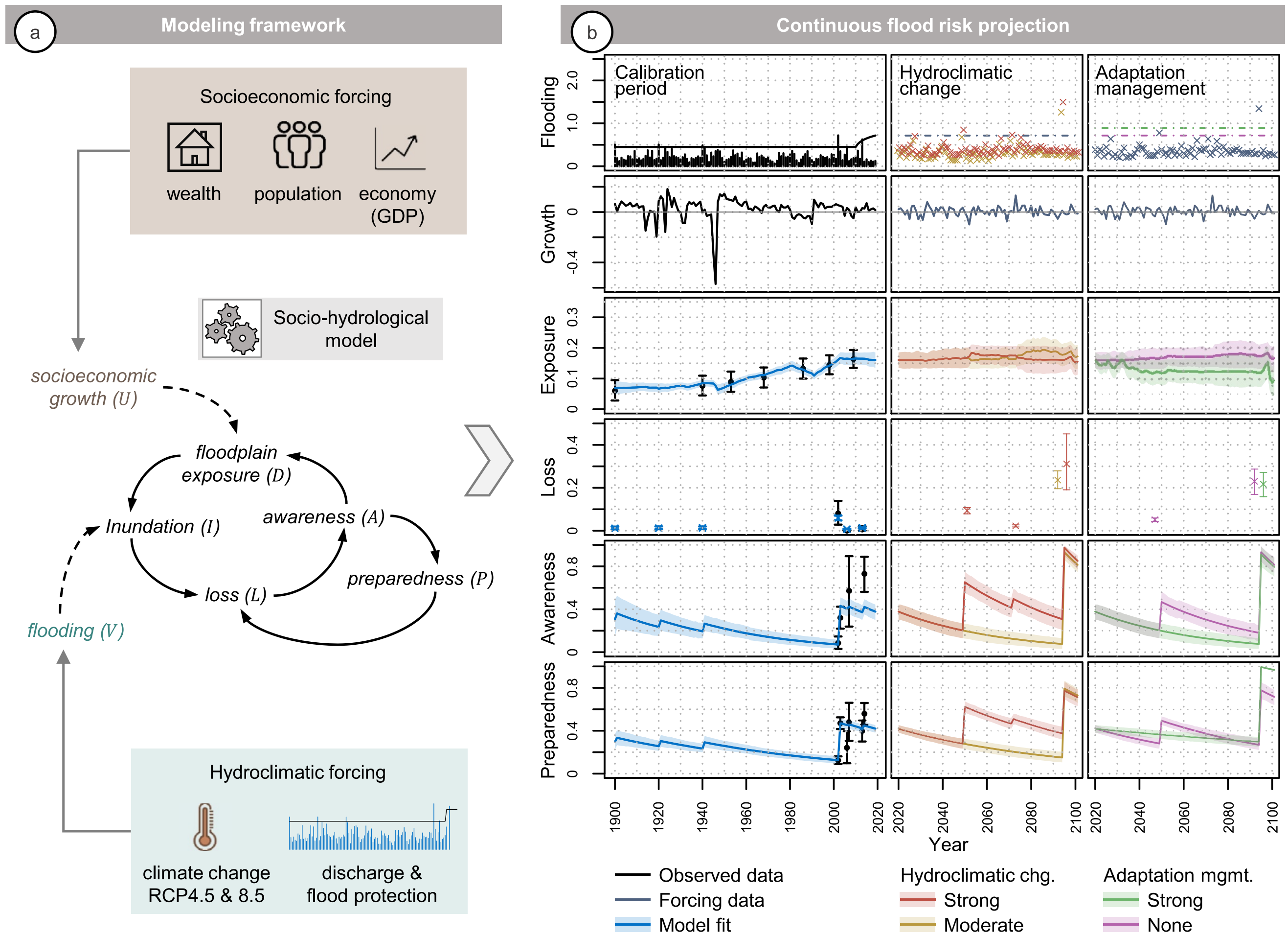

Figure 1. Our method for continuous flood risk projection. The socio-hydrological model, which we previously calibrated to observed data, uses socioeconomic growth and flood forcing data (a) to project continuous flood risk trajectories (b). In simulation experiments, we explore the influence of hydroclimatic change and adaptation management scenarios. We consider a set of adaptation measures (see Table 2) and combine them to identify effective risk reduction strategies; for example, dyke heightening in combination with increasing the longevity of precaution. Depending on the strength of the hydroclimatic change and the adaptation intervention (e.g., moderate or strong), the coupled flood risk system evolves differently. The model is dimensionless so that the internal variables (D, L, A, P) range from zero to one.

2. Methods and Data

2.1. Socio-Hydrological Flood Risk Projection

At the core of the method is a socio-hydrological model (Barendrecht et al., 2019; Schoppa et al., 2022) that captures the temporal interactions between hazard, exposure, and vulnerability in a coupled human-flood system of a given floodplain (Figure 1a). The model is forced by a time series of annual flood maxima V and a socio-economic growth indicator such as gross domestic product (GDP) or population growth rate U. A flood event occurs once the protection level H of the public flood protection infrastructure (e.g., dykes) is exceeded, which causes monetary damage L to the assets in the floodplain and triggers a cascade of reactions by the resident society. Experiencing losses increases the society's flood awareness A which, in turn, enhances its preparedness P through private precaution (i.e., reducing vulnerability) or withdraws from the floodplain and settles in safer locations (i.e., reducing settlement density D and, hence, exposure). These choices affect the exposure and vulnerability in subsequent time steps so that the temporal dependency between flood events and the actions of society are incorporated. Eventually, the model continuously traces the evolution of the settlement density (physical exposure), awareness and preparedness (vulnerability), and flood losses (risk) conditional on the hydroclimatological flood signal (hazard) over the long term (see Table 1).

Table 1
Flood Risk and Its Determinants as Defined by the Intergovernmental Panel on Climate Change (Cardona et al., 2018) and in This Socio-Hydrological Modeling Study

Quantity	General definition	Model representation
Hazard	possible, future occurrence of physical events that may have adverse effects on vulnerable and exposed elements	frequency and magnitude of flood discharge (V)*, inundation (I)
Exposure	inventory of elements (people, assets, etc.) in an area in which hazard events may occur	socioeconomic growth (U)*, wealth* (financial value of assets), floodplain exposure (D)
Vulnerability	propensity of exposed elements to suffer adverse effects when impacted by hazard events	awareness (A), preparedness (P)
Risk	potential for adverse consequences for human or ecological systems	frequency and magnitude of losses in the floodplain (L)

Note. Variables indicated by a star (*) are external to the system dynamics model and used for forcing and scaling of losses.

Mathematically, we describe these processes by a system dynamics model consisting of three coupled differential equations (reformulated into four equations for readability).

$$\frac{dA}{dt} = \tanh(\alpha_A L)\left(1 - \frac{A}{A_{\max}}\right) - \mu_A A \qquad [n_c/n_c] \qquad (1)$$

$$\frac{dP}{dt} = \begin{cases} \tanh\left(\alpha_P \frac{A}{A_{\max}}\right)\left(1 - \frac{P}{P_{\max}}\right) - \mu_P P, & L > 0 \\ -\mu_P P, & L = 0 \end{cases} \qquad [n_m/n_m] \qquad (2)$$

$$\frac{dD}{dt} = U(1 - \alpha_D A)\, D\left(1 - \frac{D}{D_{\max}}\right) \qquad \left[m^2/m^2\right] \qquad (3)$$

$$L = \begin{cases} FL_f = f_F(V,D) f_{L_f}(I,P), & V > H \\ 0, & V \leq H. \end{cases} \qquad [€/€] \qquad (4)$$

For comparability across time and computational advantages, the model variables (D, L, A, P) are scaled from zero to one by dividing them through maximum values representing the system volume. The floodplain system is confined in space by the extent $D_{\max}$ that a flood discharge with a certain return period would cause. In this study we used the 500-year discharge, a common scenario for extreme flooding used in public flood protection planning in Germany (Nones, 2017). The maximum awareness $A_{\max}$ equals the entire society being aware of the flood risk (quantified by the number of households or companies n_c), while the maximum preparedness $P_{\max}$ means that society has exhausted its potential of private precaution (quantified by the ratio of actually implemented to possible precautionary measures n_m). The loss is scaled by the current wealth (i.e., financial value of exposed assets) and computed as the product of the percentage of flooded built-up area F and the loss grade in these inundated areas L_f. The variables F and L_f are estimated in distinct sub-models and depend on the flood return period V and floodplain exposure D and the inundation depth I and preparedness P respectively. The two sub-models for the percentage of flooded area and the loss grade are presented in the Text S1 in Supporting Information S1.

The reaction of the society to flood events is described by socio-hydrological model parameters (Table 2) that characterize the flood coping strategy of the resident society. We assume the parameters to be constant or change at much slower rates than the *socio-hydrological dynamics* (i.e., change in the variables floodplain exposure, loss, awareness, preparedness) which they control. The parameters are calibrated on historic observations of settlement density, awareness, preparedness, and flood loss. We compiled these socio-hydrological training data from heterogeneous data sources such as historic land use maps, surveys using structured questionnaires, published loss reports, and economic and population statistics. The motivation for the structure of the socio-hydrological model and the calibration process are explained elaborately in Barendrecht et al. (2019).

Conditional on previous model calibration and validation on the observed time period, the historic hydro-climatological and socioeconomic forcing time series can be substituted by projection data to drive the model for

Table 2
Parameters in the Socio-Hydrological Model and Their Interpretation

Model variable	Model parameter	Parameter interpretation	Calibrated value (median)	Adaptation measures	Parameter changes
Flood discharge	protection level—H	return period	90 years	levee heightening	100, 150, 200, 300, 500 years
Economic density	risk aversion—α_D	inclination to develop/abandon floodplain	2.89 [-]	relocation, building bans	+25%, +50%, +100%, +200%, +300%
Awareness	anxiousness—α_A	increase in awareness per unit of loss	6.91 [-]	information campaigns, flood drills	
	flood memory—μ_A	half time of awareness	32 years		
Preparedness	activeness—α_P	increase in implemented precautionary measures after a flood	1.17 [-]	building codes, subsidization of precaution	
	longevity of precaution—μ_P	half time of preparedness	50 years		

Note. In the adaptation experiments, we incrementally increased the calibrated parameter values to evaluate the potential of different adaptation measures to reduce flood risk. We estimated the calibrated values from observed data for the period 1900–2019 using Bayesian inference as explained in Schoppa et al. (2022). The listed values refer to the median of the respective posterior parameter distribution.

the future period. This allows for the simulation of continuous trajectories for all system variables into the future, while maintaining the temporal interdependency of flood events and human choices. Figure 1b shows examples of such trajectories. Each trajectory represents one possible future of the flood risk system conditional on the forcing data and the local flood coping characteristic of the society. The model is capable of generating a large number of these trajectories facilitating the quantitative exploration of the possibility space; that is, the set of future outcomes that could emerge from feedbacks between humans and flooding.

Our workflow uses Bayesian inference to capture uncertainties in the observations used for calibration and the estimation of the socio-hydrological parameters. The modular setup also allows for a propagation of the uncertainty in the forcing data as hydroclimatological and socioeconomic projections can be passed to the model in probabilistic form. Consequently, the method can capture, combine, and communicate the different systemic and statistical sources of uncertainty of flood risk projections.

2.2. Application to the Commercial Sector in Dresden

We apply the socio-hydrological method for continuous flood risk projection to the commercial sector in the city of Dresden, Germany, which is situated at the river Elbe. After a comparably long, flood scarce period in the past century, Dresden faced a series of floods in the past 20 years. A major flood in 2002 caused severe losses and induced the society to adapt, which substantially reduced the losses in subsequent events (2006, 2013). Barendrecht et al. (2019) developed the socio-hydrological model described in Section 2.1 to study the historical flood risk dynamics in Dresden for the residential sector. Schoppa et al. (2022) transferred the model to the commercial sector and advanced the loss estimation. For the projection study of this work, we use an updated version of the model by Schoppa et al. (2022) with an improved parameterization and adapted inundation estimation (see Text S1 in Supporting Information S1). The model operates on an annual time step and was calibrated on a socio-hydrological data set that covers the period 1900–2019. Moreover, we validated the model for the flood loss events with available loss reports (i.e., 2002, 2006, and 2013) using leave-one-out cross validation in the previous study.

For this projection exercise, we force the calibrated socio-hydrological model with annual time series of maximum flood return periods (hydroclimatic) from the Elbe and GDP growth rate (socioeconomic) in Dresden for the period 2020–2100. The hydroclimatic forcing data are generated on the basis of projected changes in flood frequency at the representative concentration pathways (RCP) 4.5 and 8.5. The data stem from the European Union's Joint Research Center and were computed by an ensemble of coupled regional climate and hydrological models (Mentaschi et al., 2020). The socioeconomic forcing data is derived from an Eurostat projection of population growth (Eurostat, 2021) and a Markov Chain Monte Carlo projection of GDP per capita for Dresden

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(Steinhausen et al., 2022). Further, we estimate the uncertainty in population growth from the probabilistic country level World Population Prospects 2019 of the UN (UNDESA, 2019).

Beside the physical floodplain exposure, which is captured in the case study through the economic density variable *D* (i.e., share of the floodplain area with commercial occupation), exposure dynamics are also influenced by variations in wealth (i.e., financial value). The socio-hydrological model expresses flood loss as a relative loss ratio; that is, the absolute flood loss divided by the replacement value of the commercial building assets. In this way, the loss estimates are independent of the wealth and can be compared directly between different time periods. For an evaluation of the influence of wealth changes on flood losses it is useful to project the replacement value (i.e., fixed assets) into the future. We assessed the future fixed assets in commercial buildings in the Dresden floodplain from the GDP projections, extrapolated wealth-to-income ratios (Paprotny, Morales Nápoles, & Jonkman, 2018), and regional accounts data (Federal and State Statistical Offices of Germany, 2021). In this way, we assumed the wealth dynamics to be exogenous to the socio-hydrological system but still included them in the analysis of the simulation results. In all calculations that involve monetary units, we used deflated, constant 2015 prices. The supporting information provide further explanation on the raw data sets and the data processing (Text S2 in Supporting Information S1).

2.3. Simulation Experiments

We projected 1000 trajectories of commercial flood risk in Dresden until 2100. To analyze the influence of the flood risk drivers and adaptation measures over time, we subdivided the projection period into three horizons corresponding to the time periods of the hydroclimatological forcing data set: 2020–2040, 2041–2070, and 2071–2100. Moreover, we ran the simulations for RCP4.5 and 8.5 global warming levels using the respective 25%, 50%, and 75% percentiles of the ensemble prediction as hydroclimatic forcing. The ensemble percentiles reflect the uncertainty in the climate and hydrological models. For comparison, we also show simulations for a baseline scenario, which assumes constant hydroclimatic conditions as in the reference period (1981–2010) and wealth as in 2020. This projection study is subdivided into two parts:

In the first experiment, we assume that the flood coping characteristics of the companies in Dresden do not change, which can be considered as a "business as usual" scenario (Section 3.1). This means that we keep the calibrated socio-hydrological model parameters and, hence, the socio-hydrological dynamics fixed during the projection runs. This allows for an assessment of the influence of hydroclimatic and socioeconomic drivers on flood risk changes for the three future periods.

In the second experiment, we alter the socio-hydrological model parameters to quantify the sensitivity of the flood risk system to changes in the companies' coping characteristics through *adaptation* (Section 3.2). The alteration of model parameters should be interpreted as adaptation measures by the government (e.g., increasing protection level, information campaigns) or the companies themselves (e.g., implementation of private precautionary measures, resettling) with the objective of flood risk reduction. For instance, measures that aim at sustaining or increasing the flood awareness of the companies in the floodplain can be considered in the model by increasing the respective flood memory parameter, which controls the decay rate of the flood awareness. Since all model variables have been calibrated to observed data, we can treat the adaptation measures quantitatively and measure their effectiveness. In this example, an increase of the flood memory parameter increases the share of companies that are aware that they are situated in a flood risk area. Empirical evidence on the awareness of companies can be obtained using structured survey data from campaigns or expert interviews. Based on the results of the sensitivity analysis, we finally compare the effectivity of a structural, integrated, and non-structural adaptation strategy in the context of the expected future flood risk.

Table 2 lists the socio-hydrological parameters and provides further details on the adaptation experiment. Figure 1b illustrates the two projection experiments and how hydroclimatic change and adaptation management can lead to different evolutions of the flood risk system.

Throughout the experiments, we evaluate the flood risk for the individual projection runs on the basis of risk curves, which are a standard method of quantitative risk assessment in science (Merz & Thieken, 2009; Metin et al., 2018; Priestley et al., 2018) and the insurance industry (Khare et al., 2015; Prettenthaler et al., 2017). Risk curves summarize all projected annual maximum loss events in the simulation period and assign an occurrence exceedance probability to each event. Additionally, we derive three risk metrics from the risk curves, which represent different views on risk (i.e., focus on small and frequent or large and infrequent loss events): the expected annual damage (EAD), which indicates the average loss in any given year and, hence, distributes risk evenly over time; the value at risk (VAR) at a 99.5% confidence level corresponding to a loss event with a 200 years return period; and the tail value at risk (TVAR) at the same confidence level. VAR describes the maximum annual loss at the specified return period, while TVAR characterizes the upper tail of the risk curve by integrating losses beyond this return period (Sairam et al., 2021). The confidence level of 99.5% is the current industry standard for (re-)insurers as prescribed by the European Union Solvency II legislation (European Parliament and European Council, 2009).

Further, we assess the statistical significance of the investigated effects using the continuous, Bayesian "percentage in ROPE" index. It quantifies by how much the posterior distribution of a risk metric has shifted away from a Region of Practical Equivalence (ROPE) due to the effect of hydroclimatic change or adaptation. Here, we computed the ROPE on basis of the risk metric posteriors under a baseline or reference scenario. Depending on the percentage of the risk metric posteriors under the investigated scenario in the ROPE, we classify the scenario effect as: negligible/undecided significance (≥2.5% in ROPE), probably significant (≥1% & <2.5% in ROPE), or significant (<1% in ROPE) (see Text S3 in Supporting Information S1 for details).

3. Results and Discussion

3.1. Projection of Future Flood Risk

Our simulations show that global warming influences the co-evolution of the socio-hydrological flood risk system for companies in Dresden. The hydroclimatic model ensemble projects increasing flood hazard until the end of the century, which propagates through the coupled human-flood system (Figure 2). After an average decline in flood awareness and preparedness until the middle of the century (i.e., increasing vulnerability), awareness and preparedness rise toward the year 2100 (see dashed, black lines). The non-linear development of vulnerability can be explained by the relatively high awareness and preparedness levels at the start of the projection period (shortly after three loss events) and by the intensification of the flood hazard under global warming, which leads to a gradual accumulation of the companies' flood awareness and preparedness. The physical exposure of companies in the floodplain (i.e., economic density) remains nearly constant with only small variations in the median between the RCP4.5 simulations. The exposure is less sensitive to the hydroclimatic forcing than the vulnerability but is rather dominated by the socioeconomic forcing (i.e., GDP growth), which on average is projected to remain relatively stable throughout the century. In general, the projected trajectories across the different ensemble prediction percentiles (25%, 50%, and 75%) reveal that stronger shifts in the flood regime cause more pronounced deviations from the baseline scenario. The development of vulnerability is relatively uncertain and strongly depends on the inherent stochasticity in the flood discharge series, especially the number and temporal succession of loss events. Still, the average tendency toward increased flood adaptation under more severe hydroclimatic forcing is evident. The projected differences in the system evolution between RCP4.5 and 8.5 are hardly distinguishable (see Figure S4 in Supporting Information S1). This is due to the pronounced within-pathway variability of the hydroclimatological forcing data, which masks a possible between-pathway signal in flood change (Mentaschi et al., 2020).

A closer evaluation of the simulated losses via risk curves reveals that flood risk is expected to increase toward the end of the century (Figure 3). We computed risk curves accounting for hydroclimatic change under RCP4.5 and wealth growth (red lines). These risk curves clearly exceed the baseline scenario (gray line) that assumes constant climate and wealth conditions with a growing margin toward the far future (i.e., from left to right plot panel). The growing difference is also reflected by the risk metrics, which increase consistently over time and for all ensemble prediction percentiles. Accounting for changes in climate (RCP4.5 50%) and wealth, the median EAD is projected to double (€2.5 M) in the near future (2020–2040) and quadruple (€7M) approximately until the end of the century (2071–2100) relative to the baseline (€1.1 M and €1.6 M respectively). The relative change in large loss events (VAR, TVAR) is smaller but still increases by approximately a factor of three in the far future (2071–2100). The increase in flood risk in a warmer climate can be explained by more frequent overtopping of the flood protection (risk curves shift toward the left) and higher flood magnitudes causing larger losses (risk curves shift toward the top).

The risk curves show future flood risk considering the superimposed effects and uncertainties of hydroclimatic (flood forcing) and socioeconomic (GDP growth forcing and wealth) change, socio-hydrological model

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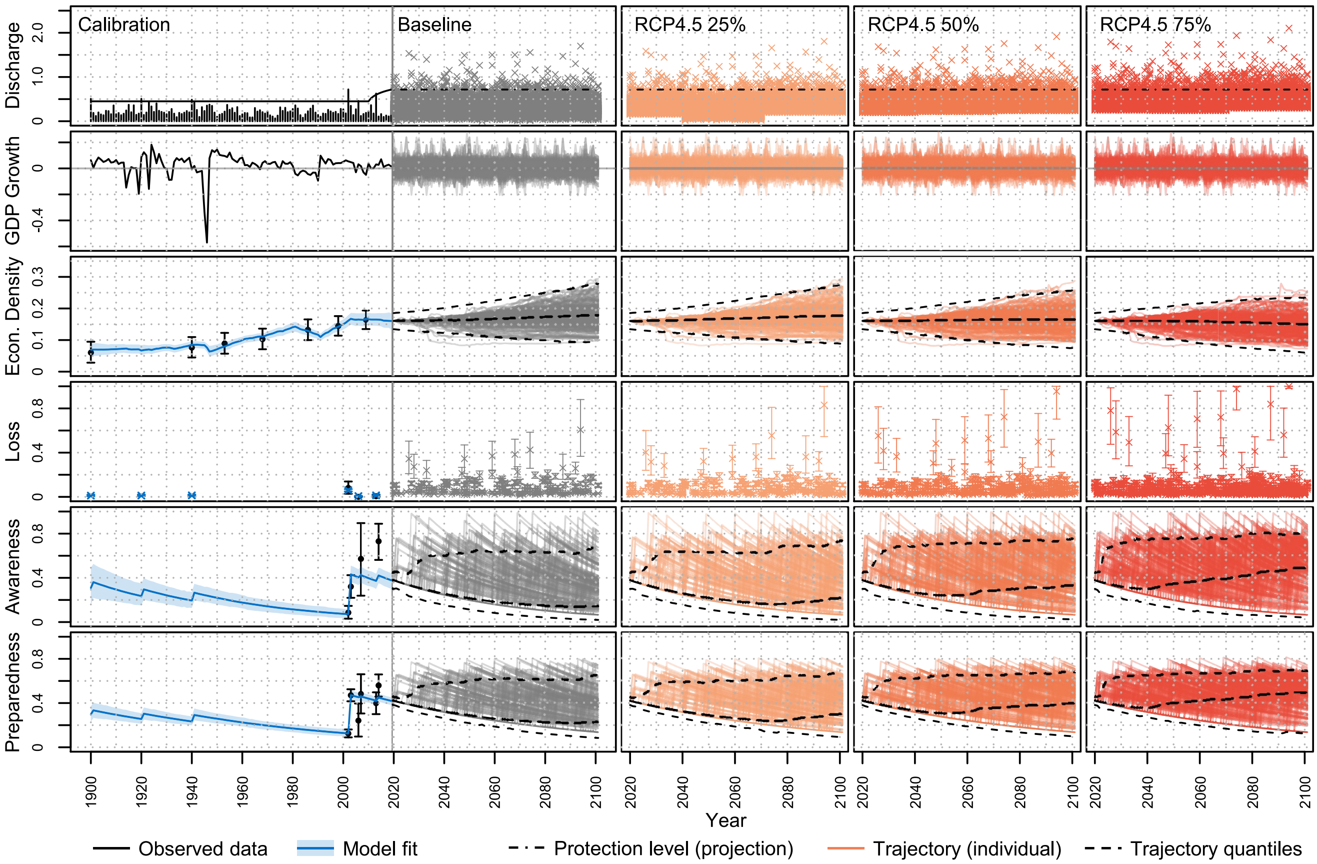

Figure 2. Continuous evolution of the socio-hydrological system for the calibration (1900–2019) and projection (2020–2100) period. The plot visualizes the influence of different hydroclimatic forcing scenarios: baseline with present climate and ensemble percentiles under RCP4.5 climate. For the projections, the colored lines show 200 individual trajectories (median of model uncertainty) and dashed, black lines show the aggregate evolution across all 1000 simulated trajectories (median and 95% highest density interval of projection uncertainty). All variables are dimensionless and range from zero to one. Figure S4 in Supporting Information S1 contains a similar plot for RCP8.5.

(parameter estimation), and inherent stochasticity (randomness in flood series). A decomposition of the different risk drivers for the individual projection horizons (Figure 4) reveals that the uncertainty in hydroclimatic forcing (across and within RCPs) dominates over wealth uncertainty in the near future (2020–2040; panels a, d, g). However, toward the end of the century (2071–2100; panels c, f, i) the growth of fixed assets in company building stock becomes increasingly influential. Predominantly, this applies to the metrics VAR and TVAR (panels d–i) which describe the flood risk for large loss events and therefore are more sensitive to differences in wealth. On the contrary, the hydroclimatic forcing remains comparably important for the average annual risk (EAD; panels a–c) until the end of the century since the frequency of dyke overtopping and, thus, loss events strongly depends on alterations of the flood regime. The projected changes in the risk metrics are statistically significant for the most part although large uncertainties in the wealth forcing and the tail of the risk curve (TVAR) mask robust signals until the far future.

Even though we kept the socio-hydrological parameters fixed in this experiment, the simulations capture the influence of changing physical exposure and vulnerability in form of the economic density, awareness, and preparedness trajectories (Figure 2). Under the baseline simulation with constant hydroclimatic and socioeconomic boundary conditions, all three risk metrics increase over time (Figure 4, gray intervals). This increase of flood risk solely traces back to the internal dynamics of the socio-hydrological system; namely, an average incline of the economic density and decline of awareness and preparedness across the individual trajectories. Yet, compared to the changes in the external hydroclimatic and wealth conditions (red and purple intervals), these socio-hydrological system dynamics only cause small differences in the resulting flood risk.

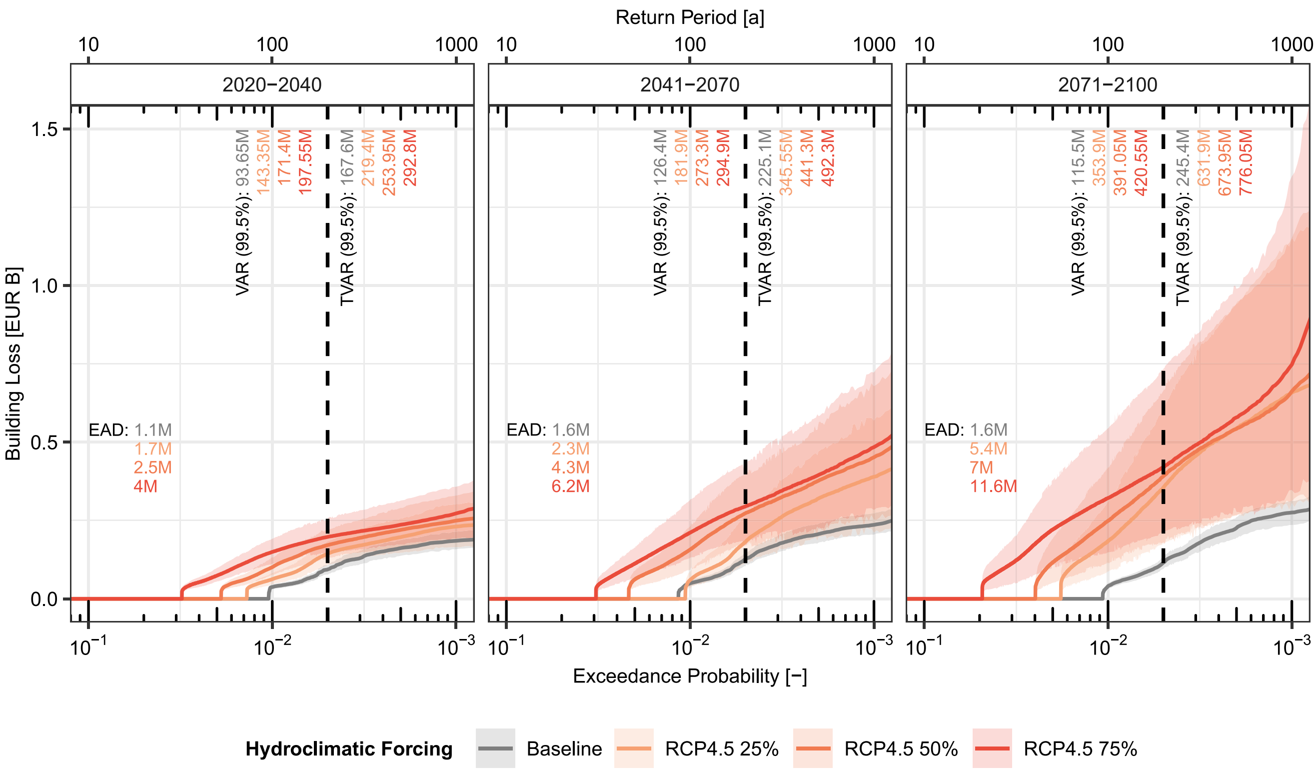

Figure 3. Risk curves (median and 90% highest density interval) and metrics for the three projection horizons considering RCP4.5 climate and wealth growth. For this plot, we multiplied the projected relative losses from Figure 2 with the fixed asset values (i.e., wealth) to receive absolute losses. The individual risk curves reflect the uncertainty in hydroclimatic forcing, while intervals summarize the uncertainty in the wealth projection, flood risk model, and stochastic flood series. The baseline scenario assumes constant hydroclimatic conditions (as in 1981–2010) and wealth (as in 2020). Risk metrics (median): expected annual damage (EAD), value at risk (VAR), tail value at risk (TVAR). Figure S5 in Supporting Information S1 contains a similar plot for RCP8.5.

In summary, the simulations show that the flood risk of the commercial sector in Dresden is likely to increase until the end of the 21st century. This rise is mostly driven by intensifying flood patterns and growing wealth in the floodplain and is in line with projected large scale trends in flood risk (Jongman et al., 2012; Kinoshita et al., 2018; Winsemius et al., 2016). Under the assumption of constant risk coping characteristics of the companies, the influence of socio-hydrological dynamics on the resulting flood risk is almost negligible. This means that the adaptive behavior of companies as in the past century will not suffice to counteract the expected increase in flood risk due to exacerbating hydroclimatic and socioeconomic pressure.

3.2. Effectiveness of Flood Adaptation

The projected positive trends in flood risk from Section 3.1 underline the necessity of effective and optimized adaptation strategies that alter the risk coping behavior (i.e., socio-hydrological parameters) of the commercial sector in Dresden.

Our sensitivity analysis shows that the risk mitigation potential of the different adaptation measures varies across the projection periods and risk metrics. Changes in the parameters protection level, risk aversion, activeness, and longevity of precaution have the largest reduction effect on commercial flood risk in Dresden (Figure 5). Increasing the protection level reduces the EAD most quickly and effectively over the entire projection period (panels a–c). Such structural flood protection can prevent single, severe loss events entirely until a clear return period threshold that depends on the protection level (see VAR; panels d–f), but the risk reduction effect shrinks when considering the entire tail of the risk curve (see discrepancy between VAR and TVAR; panels d–i). Non-structural measures that reduce the economic density (risk aversion) and maintain high levels of preparedness (activeness, longevity of precaution) take until the middle (2041–2070) or end (2071–2100) of the century to unfold their influence and steadily become more significant over time. On the long run, increasing the risk aversion, activeness, or longevity of precaution diminishes flood risk in the tail of the risk curve more effectively

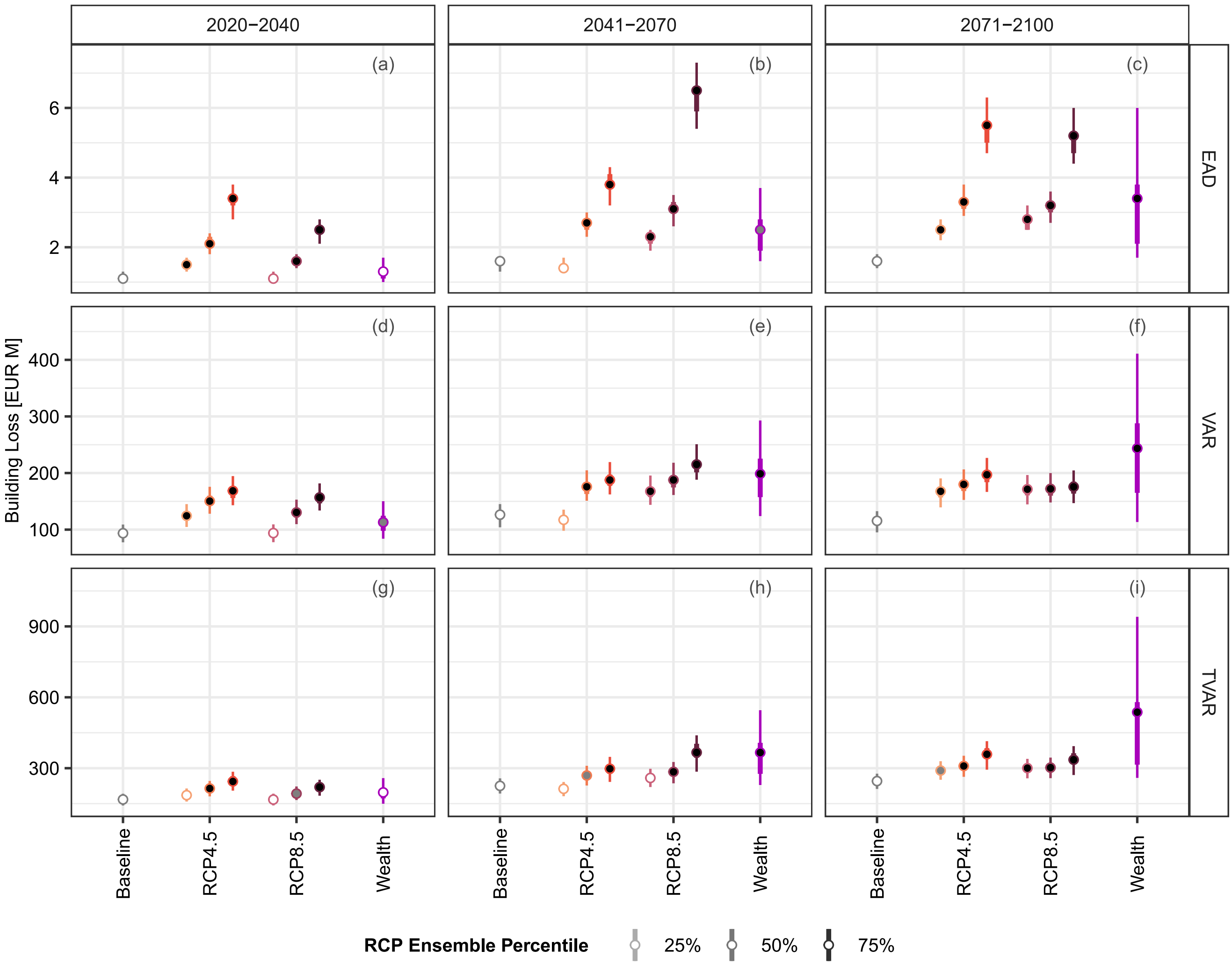

Figure 4. Isolated effect of hydroclimatic and socioeconomic (Wealth) changes on the flood risk metrics relative to the baseline scenario. Each interval plot shows the median, and 50% and 90% highest density intervals across 1000 simulated trajectories. Statistical effect significance is indicated by the points' fill colors: negligible/undecided (white), probably significant (gray), significant (black). Risk metrics: expected annual damage (EAD), value at risk (VAR), tail VAR (TVAR).

than an increase of the protection level (TVAR; panels h and i). The influence of the parameters that affect the companies' flood awareness (anxiousness, flood memory) on the risk metrics is not clearly significant for any projection horizon or metric, which potentially traces back to the indirect link between awareness and loss in the socio-hydrological model (Figure 1).

The plot also reveals that adaptation measures might even lead to unintended feedbacks and increases in risk. For instance, higher flood protection levels reduce the annual loss expectancy (EAD; panel c) but have the opposite effect on large loss events (VAR and TVAR; panels f and i). This 'levee effect' occurs when higher protection standards lead to reduced flood frequency and, in turn, to declining vulnerability and increasing exposure (Di Baldassarre et al., 2015; Montz & Tobin, 2008). Haer et al. (2020) provided quantitative evidence for this effect, and our simulations indicate that this phenomenon also emerges in Dresden in the far future (2071–2100), though the results are only statistically significant in case of the VAR.

The sensitivity analysis shows that the individual adaptation measures have different advantages and drawbacks and, in some cases, only lead to significant risk reduction after strong intervention (i.e., parameter change). Therefore, combinations of adaptation measures could combine the strengths to optimize the risk reduction. We compared the potential of three adaptation strategies to reduce the projected increase in flood risk due to hydroclimatic and wealth changes (Figure 6). A structural strategy (i) that only focuses on a protection level

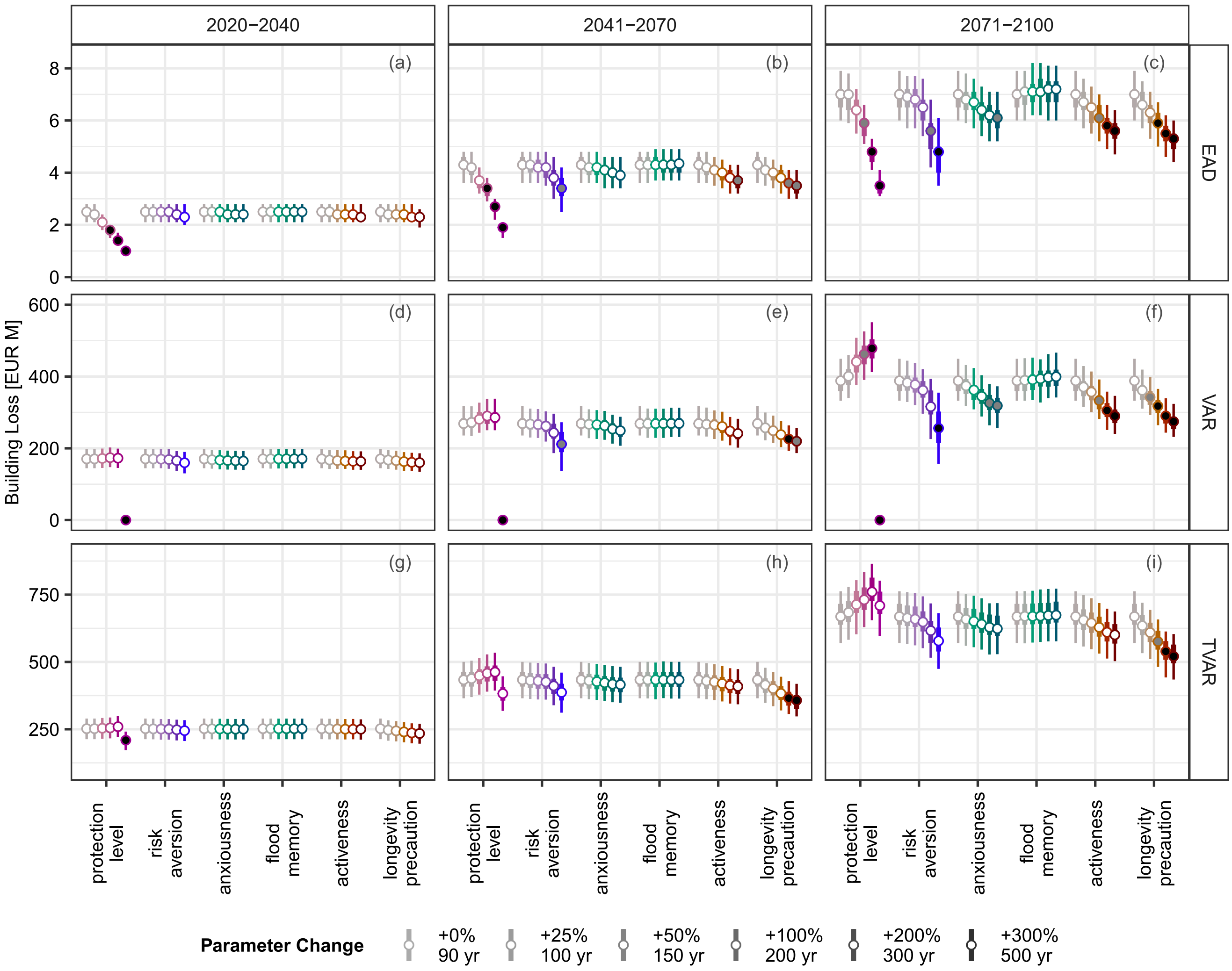

Figure 5. Sensitivity of flood risk metrics toward adaptation measures (i.e., parameter changes). For each interval, we changed the respective parameter while keeping the other parameters fixed at their calibrated value. The interval colors allocate the socio-hydrological parameters to the model variables that they control (pink: protection level, blue: economic density, green: awareness, orange: preparedness). The simulations are based on RCP4.5 (50% ensemble percentile) and median wealth projections (i.e., deflated climate and wealth uncertainty). The strength of the intervention (i.e., parameter change) through a adaptation measure is visualized by the boxplot chroma. Statistical effect significance is indicated by the points' fill colors: negligible/undecided (white), probably significant (gray), significant (black). Risk metrics: expected annual damage (EAD), value at risk (VAR), tail VAR (TVAR). Figure S6 in Supporting Information S1 contains a similar plot for RCP8.5.

increase, an integrated strategy (ii) that combines an increase in flood protection and the longevity of precautionary measures, and a non structural strategy (iii) that only relies on the reduction of physical floodplain exposure and increased preparedness through private precaution.

Across the three adaptation strategies, our simulations show a reduction potential in median EAD of up to 16%–60% in the near, 44%–63% in the middle, and 50%–60% in the long term (panels a–c). The median reduction potential for the VAR ranges from 100% for the structural and integrated strategy to 63% for the non structural strategy (panel d–f). While the projected risk reduction for the EAD and VAR is statistically significant for strong interventions, the effects for TVAR are insignificant due to large uncertainty in both the wealth projections and the tail risk.

The results show that an integrated adaptation strategy is an alternative to a purely structural strategy. While the non structural strategy is less effective than the structural and integrated strategy in the near future, it reduces risk more efficiently by the end of the century. Over time, the structural strategy requires increasing intervention strength (i.e., parameter change) to counteract the adverse consequences of the levee effect. On the contrary, this

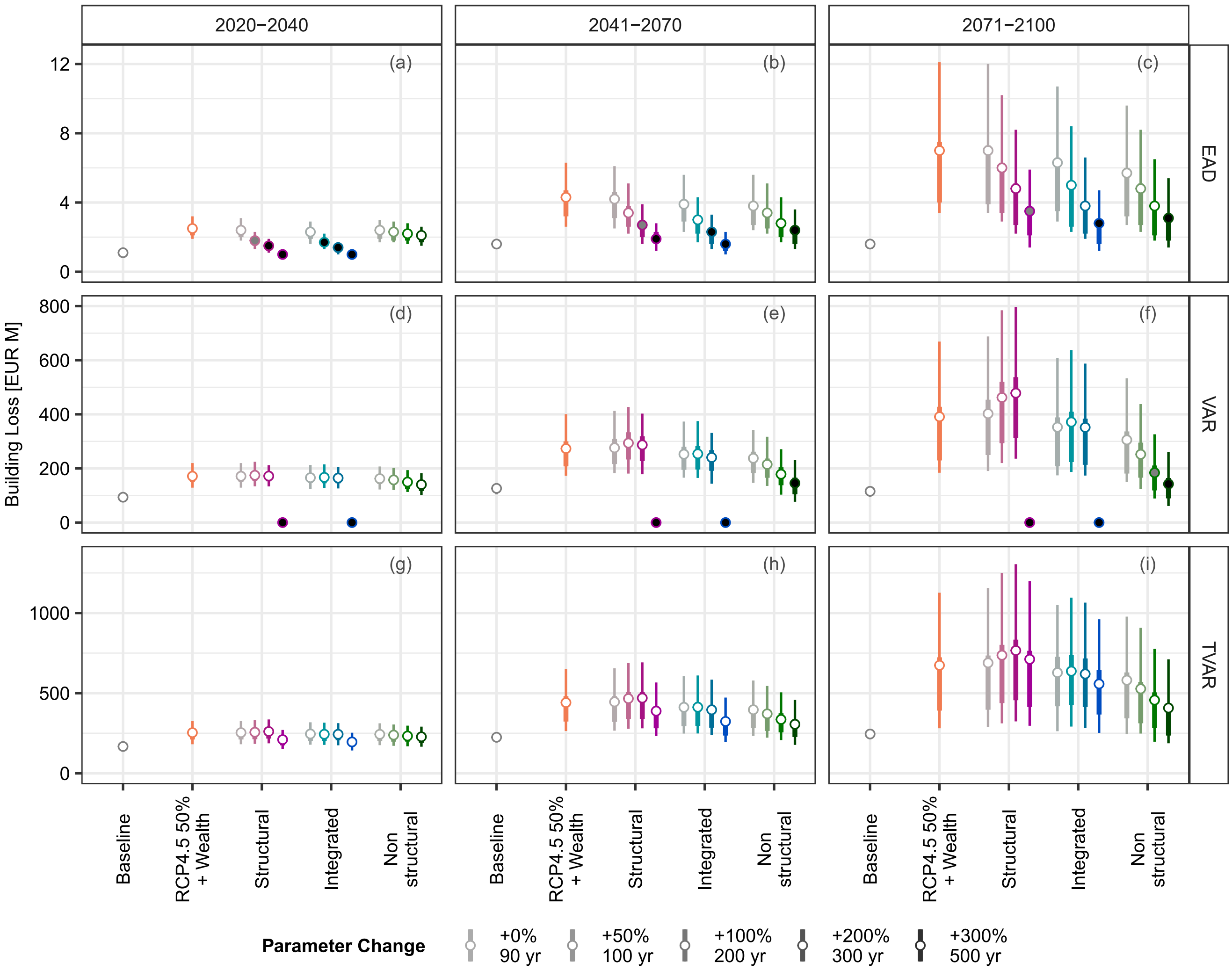

Figure 6. Potential of competing adaptation strategies (structural, integrated, non-structural) to mitigate the expected increase in flood risk. The baseline scenario assumes fixed climate and wealth while the 'RCP4.5 50% + Wealth' scenario assumes hydroclimatic and wealth projections with uncertainty. The interval colors correspond to the color coding from Figures 4 and 5 for same simulation runs (i.e., 'RCP4.5 50% + Wealth' and 'Structural'). The strength of the intervention (i.e., parameter change) through a adaptation measure is visualized by the boxplot chroma. Statistical effect significance is indicated by the points' fill colors: negligible/undecided (white), probably significant (gray), significant (black). Risk metrics: expected annual damage (EAD), value at risk (VAR), tail VAR (TVAR). Figure S7 in Supporting Information S1 contains a similar plot for RCP8.5.

unintended risk increase is attenuated or entirely avoided under the integrated and structural strategy, especially when considering the most severe loss events (VAR and TVAR). Consequently, adaptation strategies that (partially) aim at changing the behavior of society promise more sustainable flood risk reduction and are less prone to unintended feedbacks and adverse consequences.

Eventually, the exact risk figures of this projection are of secondary importance compared to the overall response of the flood risk system over time, for example, the direction and relative magnitude of risk change. Our results support the finding of a study at European scale by Haer et al. (2019) that optimized adaptation on the governmental and private level carries the potential to outweigh the flood risk increase due to climate and exposure change (RCP4.5 50% + Wealth). However, while Haer et al. (2019) report that the risk reduction potential of structural measures grows over time relative to private adaptation (e.g., precautionary measures), we observe opposite trends. While this discrepancy might originate from differences in study scale, model configuration, or considered risk metric, it highlights that further research on the interplay between governmental and private adaptation is necessary.

3.3. Potential and Limitations of Socio-Hydrological Flood Risk Projection

The proposed socio-hydrological method addresses current challenges in flood risk assessment such as narrowly defined system boundaries (Merz et al., 2015) or the lack of holistic modeling solutions for small-scales (Jongman et al., 2015). As shown for the study site Dresden, the method can translate transient, large-scale hydroclimatic and socioeconomic boundary conditions into a response of a local, coupled flood risk system (e.g., continuous trajectories, changes in risk metrics). The approach also expands the system boundary by incorporating physical exposure (economic density) and vulnerability (awareness, preparedness) as intrinsic system components capturing potentially adverse non-linearity and feedbacks such as the levee effect. Additionally, it enhances the temporal scope (i.e., centuries) and considers temporal dependencies (continuous simulation) in the analysis, revealing the different time scales at which adaptation measures act. The parsimonious design of the underlying system dynamics model makes the approach an efficient solution for the exploration of the possibility space. Conditional on suitable calibration data, our method is transferable to other study sites or could be used with different socio-hydrological model configurations; for example, to investigate systems that are exposed to both flooding and drought (Mazzoleni et al., 2021).

A crucial aspect for the added value of the method is its usability in practice, for instance for adaptation planning. While the applicability of socio-hydrological methods is often limited due to high demands toward data or a lack of variable interpretability (Sivapalan et al., 2012; Troy et al., 2015), the proposed method relies on a fully quantitative modeling framework, where variables and parameters are informed by empirical evidence. This enables the monitoring of changes in the flood risk system with benchmark data that is collected through remote sensing (e.g., physical floodplain exposure) or structured surveys (e.g., awareness). Such monitoring could reveal whether flood risk, quantified in form of regularly updated risk curves and metrics, is actually developing as projected after the implementation of adaptation measures, or whether amendments to the risk reduction strategy are necessary. Further, in the Bayesian framework of the proposed method, newly available observations can be included in the inference facilitating ongoing updates of the calibrated model parameters and uncertainty estimates (Schoppa et al., 2022).

Nevertheless, the practical value of the adaptation experiment is limited as it does not consider the tangible and intangible costs and feasibility of the competing adaptation strategies. Differences in the implementation cost of protective or preventive measures (e.g., levee heightening, relocation) might make an adaptation strategy more favorable although its risk reduction potential is inferior, or measures might fail due to the resistance of the resident society. Thus, the combination of the presented method with economic instruments such as cost benefit analysis or expected utility theory (Dottori et al., 2020; Haer et al., 2019), could enhance the informative value of the simulations. Moreover, given the considerable uncertainties in the projections, it might be necessary to switch the adaptation strategy at certain points in the future. Risk-based decision making such as dynamic adaptive policy pathways (Haasnoot et al., 2013; Kwakkel et al., 2015) could be combined with socio-hydrological flood risk projection to deal with this deep uncertainty (Merz et al., 2021) and leverage the potential of adaptation even further.

While our method expands the systemic and temporal scope of flood risk assessment, it has its own limitations. The lumped approach explores the possibility space efficiently (Aerts et al., 2018), but lacks detail in representing spatial variation. Representing model variables in aggregate, probabilistic form might overlook developments that alter the functioning of the human-flood system such as a spatial redistribution of assets in the floodplain. From a hydrological perspective, the floodplain topography is only implicitly considered in the lumped inundation submodel, potentially masking local hydraulic effects. In addition, the lack of appropriate data makes it difficult to adequately validate all components of the system dynamics model. In particular, the vulnerability dynamics would require additional validation, but consistent data series of sufficient length on awareness and preparedness are scarce. The bounded rationality of human actions adds further complexity to the modeling of adaptive behavior (Haer et al., 2017; Loucks, 2015). As a result, the quantified uncertainty in the model projections likely underestimates the full range of possible system evolutions.

To overcome these shortcomings, systemic flood risk assessment should employ alternative data sources and synergies between competing modeling principles. Modern data acquisition via social media or longitudinal surveys has the potential to alleviate the scarcity of validation data. Joint modeling experiments using system dynamics and agent-based models could combine data-driven inference with behavioral theory to provide new insights into flood adaptation.

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4. Conclusions

Converging global dynamics of flood hazard and exposure are intensifying flood risk at the local scale and necessitate holistic decision-support tools for flood adaptation planning. The presented method for socio-hydrological flood risk assessment represents a systemic and yet efficient solution for the long-term projection of flood risk dynamics. Our case study for the commercial sector in Dresden confirmed that greater efforts on flood adaptation are required to offset the expected four-fold increase in flood risk (i.e., EAD) due to hydro-climatic change and accumulating wealth. We demonstrated that our continuous simulation method can identify effective adaptation strategies that are robust to unintended feedbacks such as the levee effect. According to our simulations, an integrated adaptation strategy, which combines levee heightening with an enhancement of private precaution, could reduce the average annual flood risk by up to 60% at the end of the century. By expanding the system boundary of conventional risk assessment by vulnerability dynamics, this approach can explore a wide range of probable outcomes instead of only the most plausible futures. This raises the chance of detecting risky system states before catastrophes occur.

Nevertheless, the enhanced perspective and computational efficiency comes along with process simplifications and spatial aggregation. Therefore, socio-hydrological flood risk assessment is particularly useful in combination with established risk assessment practices. We see clear advantages of a flood risk assessment workflow that combines coarse and holistic with detailed and focused modeling solutions. For instance, a socio-hydrological flood risk model could first identify effective and robust adaptation strategies from a large set of possible adaptation measures, considering potentially adverse consequences or the factor of surprise. Afterward, spatially explicit risk assessment, including hydraulic or object specific loss modeling, could be used for further optimization or a selection process among the subset of efficient adaptation scenarios.

Data Availability Statement

The historical data for the calibration of the socio-hydrological model can be obtained from the following sources: The discharge time series can be downloaded from the Global Runoff Data Centre (BfG, 2021). The flood loss survey data for companies are distributed via the German flood damage database HOWAS21 under a community-based use concept (GFZ, 2021). Economic data (GDP and assets values) are contained in the HANZE data set (Paprotny, Morales-Nápoles, & Jonkman, 2018) and its updated version (Paprotny, 2023; Paprotny & Mengel, 2023). The remaining data were shared with the authors upon request by the data owners; that is, the inundation maps by the Environmental Agency of the city of Dresden (Nuremberg Institute of Technology, 2019), the water level time series by the German Federal Institute of Hydrology (WSV, 2021), the historical land use maps by the Leibniz Institute of Ecological Urban and Regional Development (Gruner, 2012), and the flood loss records at the municipal level by the Saxonian Relief Bank (SAB, 2007).

The data that we used for the projections are available at the following sources: The regional population projections are distributed via the Eurostat database (Eurostat, 2021), while the probabilistic country level population projections can be obtained from the UN (UNDESA, 2019). National accounts data are available via the German statistics portal (Federal and State Statistical Offices of Germany, 2021) and data on the spatial wealth distribution and wealth to income ratios are contained in the HANZE data set (Paprotny, Morales-Nápoles, & Jonkman, 2018). Spatial data on the current flood protection in Dresden are available at the open data portal of the city of Dresden (City of Dresden, 2018). The projections of flood discharge change belong to the Joint Research Centre and were shared with the authors upon request (Mentaschi et al., 2020).

All our computations and analyses were carried out with the software packages R (R Core Team, 2020), QGIS (QGIS Development Team, 2020), and Stan (Stan Development Team, 2021).

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