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A service to help insurers understand the financial impacts of changing flood risk in Europe, based on PESETA IV

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ABSTRACT

The European Union PESETA IV project has produced a comprehensive dataset that quantifies the impact of climate change on river flooding and damage in Europe. This data potentially has significant application in the insurance industry, but requires some steps of post-processing, and appropriate delivery mechanisms, before it can be used in practice. The post-processing approach we apply involves statistical modelling of the simulated changes in damage to estimate rates of change of log damage versus global mean surface temperature (GMST). Under linear assumptions, these rates of change can be used to calculate the change in damage between any two time-periods for any GMST scenario. Under further assumptions, these changes can be used to adjust many of the metrics of flood risk used in the insurance industry, such as average annual losses, exceedance probabilities and year loss tables. We deliver these results in two ways to suit different users in the insurance industry. First, the rates of change, and related correlations, are provided as freely available datasets for insurers who prefer to process and apply the data themselves. Second, commercial online software is provided that performs some steps of the processing and application. Many sources of uncertainty affect our results. The results must not therefore be interpreted too literally, but hopefully give a good indication of the sign and rough magnitude of the likely changes in river flood damage due to climate change. Future studies will hopefully reduce the uncertainty.

Practical implications

The insurance industry would benefit from access to better information about how climate change is affecting the possible financial impacts of flooding in Europe. We have written this paper, and created a new data-set and software tools, to meet this need. The dataset is generated from the output of the European union project PESETA IV, which includes the most comprehensive attempt so far to model the financial impacts of climate change on European flood risk. The outputs from PESETA IV are not, however, presented in a form in which they can be used by the insurance industry. We have processed the outputs from PESETA IV to convert them to an appropriate form.

This paper describes the requirements of the insurance industry, our processing of the PESETA IV results, and the ways that our post-processed results can be used to adjust insurance industry metrics.

The dataset consists of estimates of the rate of change of the financial impact of river flooding on current average annual damages, at NUTS2 resolution, for Europe. It also includes a covariance matrix. The variances in the covariance matrix represent the range of results from the different climate models used in the PESETA IV project, at NUTS2 resolution. The correlations in the covariance matrix represent the correlations in damage between all pairs of NUTS2 regions.

This data can be used to estimate the change in average annual damages between a past and future time-period, as is required for insurance risk modelling. The past time-period, or baseline, represents the time-period of the data from which a flood risk model has been built. The future time-period represents the time-period

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of interest. By making appropriate working assumptions, the data can also be used to adjust distributions of maximum and total annual damages, and the damage caused by individual simulated events from a flood risk model.

The software performs the time-period adjustments automatically.

The dataset, and software, may also be of use to others outside the insurance industry, as the information requirements of the insurance industry are rather general.

In due course, we hope to post-process other outputs from the PESETA IV project, for other perils, in a similar way.

Data availability

The data for means and standard deviations by NUTS2 region is available on Zenodo.

Introduction

The risks and consequences of river floods have influenced human activities for many centuries (Paprotny, et al., 2018; Blöschl, et al., 2020; Prettenthaler, et al., 2022). However, because of anthropogenic climate change, some of the risks may now be increasing (Alfieri, et al., 2015; Mentaschi, et al., 2020; Kron, et al., 2019), and methods used to cope with the risk in the past may have started to become less effective (Alfieri, et al., 2016). One way to help manage the problem of increasing risks is to use numerical simulations of river flooding to make estimates of the possible changes in risk due to climate change. One of the most ambitious programs to generate simulations of possible changes in river flood risk due to climate change is the river flooding component of the PESETA IV project (Dottori, et al., 2020). In this project, simulations of climate change from multiple dynamically downscaled climate models were combined with hydrological models for river flooding. The resulting simulations of flooding were then used to drive economic models that determined estimates of possible damage and change in damage. The PESETA IV project covers 34 countries in Europe and surrounding regions.

The PESETA IV river flood results are potentially useful for many of the various groups that are interested in understanding changes in flood risks, although they may need to be converted to different formats, time periods and resolutions for different types of users and different applications. In this article we describe how we have applied the necessary conversion steps to make the PESETA IV results more directly usable in the insurance industry. We also describe how they can be used. One part of using our results is that they need to be scaled according to the required time-period and GMST scenario, and to allow for this the results are being supplied to insurers in two ways. First, as a freely available dataset, for those insurers who wish to apply the scaling themselves. Second, via a commercial software tool that performs the scaling automatically and allows the extraction of scaled results.

The insurance industry has been using computer modelling to quantify the risks of natural catastrophes, including floods, since the 1960s: see the 1972 review by Don Friedman (Friedman, 1972) and textbooks such as Grossi and Kunreuther (2005) and Mitchell-Wallace et al. (2017). The results from these 'catastrophe' models feed into the pricing of insurance and reinsurance, as well as into other aspects of insurance risk management. For river flooding these models are often constructed from statistical simulations of rainfall variability, which are then used as inputs for model components that simulate flooding using dynamical equations. The simulated flood depths are then used, in turn, as inputs for model components that estimate damage to insured properties (Kaczmarska, et al., 2018; Zanardo, et al., 2019). Finally, damage estimates are converted to estimates of losses for insurers. The simulations from catastrophe models are typically created in such a way that they represent *N* different versions of one year of flooding and its impacts, where *N* might take values from 10,000 to 100,000 in order to cover a wide range of possibilities. Losses are derived for each flood event in each of the simulated years, and the loss results are then usually presented as year loss tables (YLTs), with *N* years of simulated losses in them. Various loss diagnostics can be calculated from the YLTs, such as the average annual loss at different spatial resolutions. Results can then be compared with results from fitting statistical distributions directly to historical losses (Prettenthaler, et al., 2017), as a form of validation.

River flood catastrophe models are typically built to match historical measurements of rainfall, river flows, flooding and damage, under the assumption that the climate has been stationary during the period used to make the historical measurements. This period is usually the past few decades for rainfall and river flows, and the past one or two decades for damage measurements. The models are then used to understand present-day risks. In a changing climate, however, the assumption that models constructed in this way represent present-day risks realistically may not be entirely valid. An important challenge is to understand how to adjust the models to account for climate change, and there has recently been some work in this direction (Jewson, et al., 2019; Sassi, et al., 2019).

In this study, we consider how to convert the PESETA IV river flood results to a format in which they could be used to adjust a river flood catastrophe model. The conversion requires three inputs: the first input specifies the period of time that is to be used as a reference, or baseline, representing the period of data on which the catastrophe model was built. The second input specifies the period of time of interest, which would typically be the present day, or some point in the future. The third input specifies a GMST scenario that represents a projection of future climate. We then create a statistical model that allows us to use the PESETA IV results to calculate the percentage change in flood risk between the baseline time period and the time period of interest, for the GMST scenario, using certain assumptions. The multiple climate models used in the PESETA IV project yield multiple alternative sets of results, which allows us to estimate part of the model uncertainty. We describe how to sample from this model uncertainty, incorporating spatial correlations, to create *N* years of samples of possible percentage changes in river flood risk across Europe. These samples can be used to adjust catastrophe model outputs, in ways that we discuss.

In Section 2 we discuss the data we use. In Section 3 we present the statistical model we use to condense and summarize the simulated damages from PESETA IV. In Section 4 we discuss how we apply the statistical model. In Section 5 we describe various ways in which the results can be applied to catastrophe model output. In Section 6 we discuss the uncertainties in the study, and how the methodology compares with other methodologies that can be used to adjust river flood models for climate change. Finally, in Section 7, we conclude.

PESETA IV and GMST data

Peseta IV

PESETA is an EU-funded project to understand some of the possible societal impacts of climate change in Europe and surrounding regions (Feyen, et al., 2020), and follows earlier EU projects such as Impact2C (https://www.atlas.impact2c.eu/en/). In its fourth iteration, known as PESETA IV, impacts due to climate change were calculated for extreme heat and cold, windstorms, water resources, droughts, river floods, coastal floods, wildfires, habitats, ecosystems, agriculture, energy supply and economic activity (https://joint-research-centre.ec.europa.eu/peseta-projects/jrc-peseta-iv_en).

In this article, we only consider the river flood impacts, but may consider other impacts in future projects. We have started with river flood impacts because river flooding is both important, and expected to change significantly under climate change. In the European region covered by PESETA IV, the impacts of severe windstorms and river floods are of similar importance, but the results from the PESETA IV report suggest that the rate of change of windstorm risk under climate change is expected to be low (Spinoni, et al., 2020), while the rate of change of river flood risk is expected to be much higher.

The river flood modelling procedures used in PESETA IV are described in the PESETA IV technical report (Dottori, et al., 2020). To construct the model, outputs were taken from 5 European global climate models (GCMs). The simulations from the GCMs were downscaled using 5 different regional climate models (RCMs). The 5 GCMs and 5 RCMs were combined in 11 ways, listed in Table 1 (Jacob, et al., 2014). Each of the 11 combined models were used to simulate climate from 1980 to 2100, with greenhouse gas concentrations corresponding to RCP4.5 and RCP8.5 (Meinshausen, et al., 2011), giving 22 model-scenario combinations in total. In PESETA IV, these climate simulations were used to drive the LISFLOOD hydrological model (Van Der Knijff, et al., 2010), and produce future scenarios of river flow including floods (Mentaschi, et al., 2020). River flow simulations were then used in combination with two-dimensional hydraulic simulations (Dottori, et al., 2022) land cover maps (Rosina et al., 2018), GDP maps (Eurostat, 2022a), and flood vulnerability functions (Huizinga, et al., 2017) to calculate economic damage caused by floods. PESETA IV contains projections based on both fixed and varying socio-economic scenarios: we use the projections for fixed scenarios. Validation of the modelled damages is discussed in Dottori et al (2023). In particular, table S18 and Fig. 2 of the supplementary information for that paper compare modelled and reported average annual losses at country level.

For our study, we will use the following outputs from PESETA IV. First, we use annual values of the GMST simulated by each of the 5 global climate models. This data is part of the data that is used to train our statistical model, and we will refer to it as the *training* GMST data. GMST will provide the independent variable in our statistical model. We adjust the training GMST time series with a constant offset so they each have an average of zero during the period 1980–2000. The level of this offset has no impact on our analysis since our methods and results will only depend on changes in GMST. The 1980–2000 baseline is very different from the baselines often used to calculate changes in global temperature due to climate change. For instance, the PESETA IV project uses the baseline period 1881–1910. As a result, changes in GMST that we calculate relative to the 1980–2000 baseline will be considerably smaller than changes relative to earlier baselines. Annual values of the training GMST data are shown in Fig. 1 for the 22 model-scenario combinations, and show differences due to the model and the RCP. Second, we use annual losses simulated from the output from each of the 22 model-scenario combinations, as calculated in the PESETA IV project. This is the other part of the data used to train our statistical model, and provides the dependent variable. The loss data was originally calculated at 5 km resolution, and then aggregated to NUTS2 regions (Eurostat, 2022b). The size of the NUTS2 regions varies, as they follow administrative boundaries. In total, there are 296 NUTS2 regions in our domain, which are visible in Figs. 3 and 4. We will refer to the NUTS2 regions simply as regions.

Table 1
The climate models used in this study, each of which consists of a GCM and an RCM.

GCM	RCM
CNRM-CM5	CCLM4.8–17
EC-EARTH	CCLM4.8–17
MPI-ESM	CCLM4.8–17
EC-EARTH	HIRHAM5
IPSL-CM5	WRF331F
EC-EARTH	RACMO22E
CNRM-CM5	RCA4
EC-EARTH	RCA4
IPSL-CM5	RCA4
HadGEM2	RCA4
MPI-ESM	RCA4

Application GMST data

We will use past and future GMST data to convert the PESETA IV results into percentage changes in flood loss from the temporal baseline to the period of interest. We will refer to this data as the *application* GMST data. We take the application GMST data from Jewson et al. (2021a). The data was created by combining observed GMST values from NASA/GISS (NASA/GISS 2021; Hansen, et al., 2010) from 1880 to 2019 with simulated future GMST values for the four standard RCPs (2.6, 4.5, 6.0, 8.5) created by averaging outputs from all the CMIP5 models, within each scenario separately. We use future GMST based on CMIP5 RCPs rather than the more recent CMIP6 SSPs (Meinshausen et al. (2011)) for our calculations because much of the risk modelling community is still at this point using RCPs to define future climate scenarios. As with the training GMST data, we have adjusted the application GMST data with a constant offset so that the period 1980–2000 has a mean of zero.

The reason we use different data for the training GMST data and the application GMST data is that the training GMST data, and the PESETA IV project as a whole, only considers RCP4.5 and RCP8.0. This is limiting for applications: commentary on the RCPs suggests that RCP6.0 may be more relevant (Sanford, et al., 2014; Harvey, 2020; UNEP, 2021; Hausfather, 2019), and in addition some users may wish to consider the impact of the SSPs. The application GMST data is shown in Fig. 1 in Jewson et al. (2021a).

Statistical model

Model definition

There are various issues that complicate the direct application of the simulated PESETA IV damages to catastrophe model output. The first is that the PESETA IV damages consist of annual values starting in 1980, while catastrophe models are often built using historical data that predates 1980. The second is that the PESETA IV damages are only simulated for RCP4.5 and RCP8.5. Using a statistical model, along with the application GMSTs, allows us to create damage estimates for the other two RCPs, as discussed above. It would also allow us to create damage estimates for the SSPs. The third is that the PESETA IV damage results show large variations from year to year and decade to decade in addition to the climate change signal. These variations are driven by climate variability in the underlying climate models. For our purposes, this variability is not relevant, since the cat models that we want to adjust are based on simulations of many thousands of years of climate variability, and hence already capture climate variability inherently. We will therefore attempt to filter out the climate variability in the PESETA IV results and extract only the climate change signal. The fourth is that the PESETA IV results represent damage rather than loss, where by ‘damage’ we mean physical damage, and by ‘loss’ we mean the losses incurred by an insurance company as a result of the damage, which may be different from the damage for various reasons, including details of insurance coverage. In our analysis, we will equate damage to loss, and will use the words damage and loss as synonyms, but users of our results may wish to adjust the results to render them more appropriate for their specific losses.

To overcome the first three issues given above, we fit a statistical model to the PESETA IV damage results, and then use the output from the statistical model, rather than the results themselves. The statistical model makes the assumption that the logarithm (log) of the flood losses is a linear function of global mean surface temperature (GMST). GMST is the standard index used to measure the rate of climate change, and the assumption that climate change, and the impacts of climate change, are a simple function of GMST is commonly used in the climate community as a first approximation: see, e.g., Knutson et al. (2020). The details of the log-linear model for climate variables as a function of GMST are given in Jewson et al. (2021a). We will investigate the validity of this

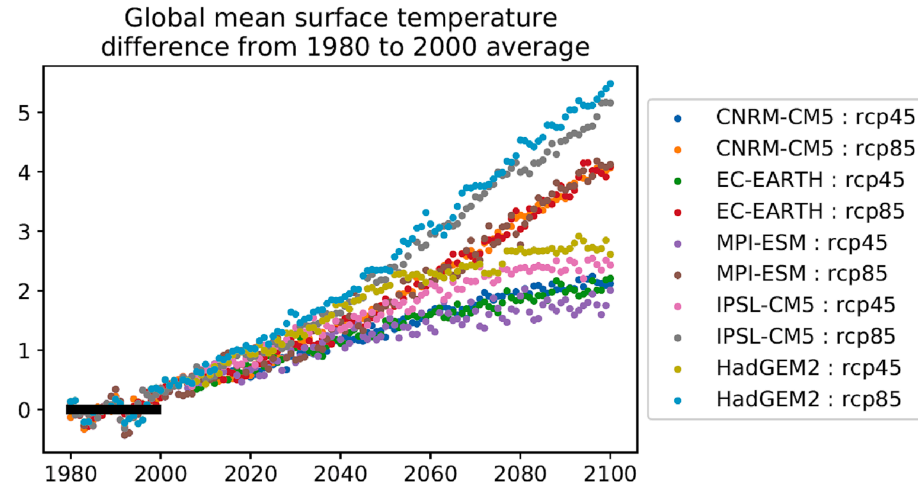

Fig. 1. Simulated global mean surface temperatures from the 5 global climate models used in this study, for RCP4.5 and RCP8.5 in each case. All values are adjusted so that the mean from 1980 to 2000 is zero.

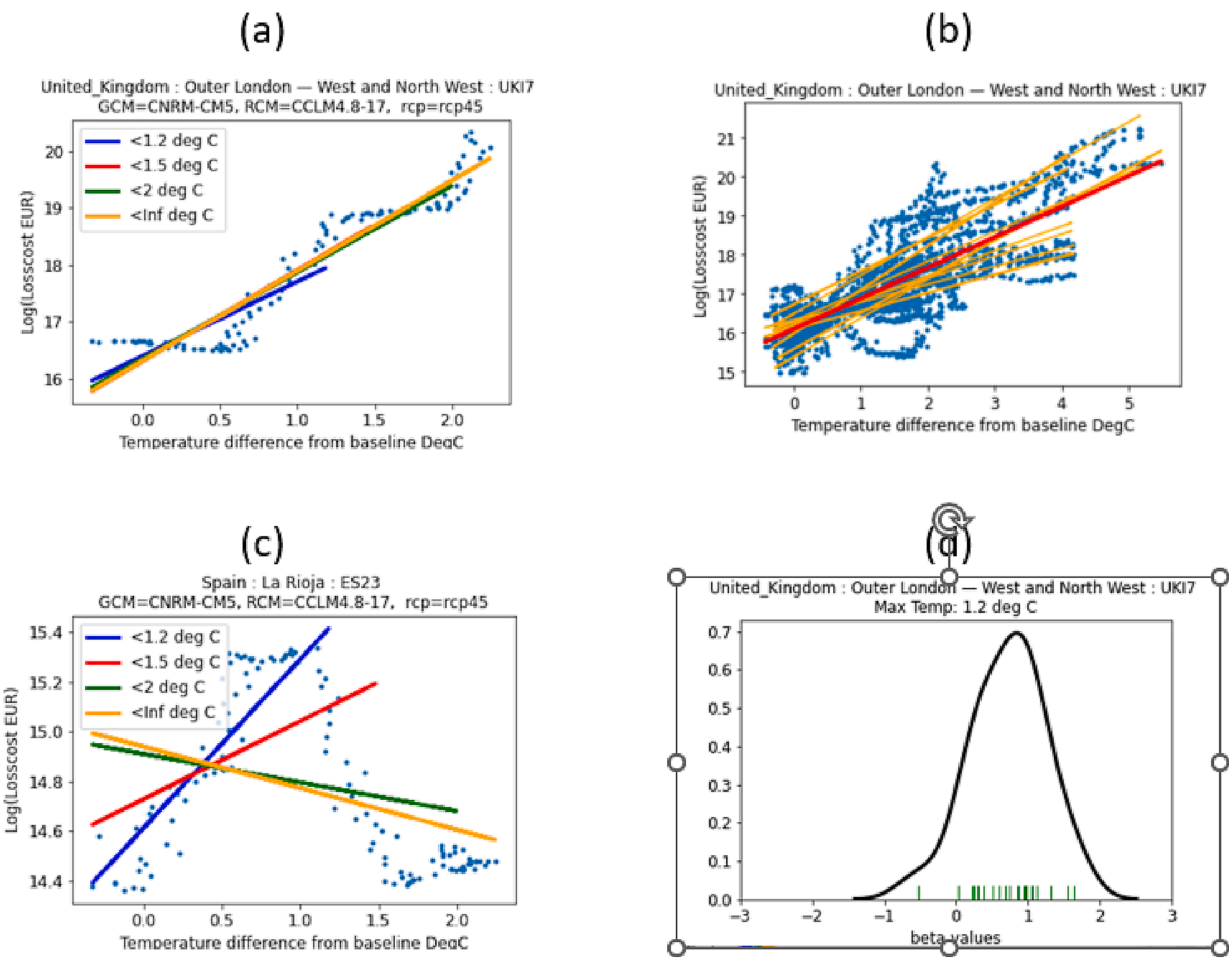

Fig. 2. PESETA IV losses due to river flood. (a) shows the logarithm of simulated losses for one particular NUTS2 region, for one of the 22 GCM-RCM combinations, versus GMST as simulated by the corresponding GCM. Best-fit straight lines are also shown, using GMST ranges up to 1.2℃, 1.5℃, 2.0 °C and the entire range of GMST. (b) shows log losses for the same NUTS2 region, but now as simulated by each of the 22 GCM-RCM combinations, with best-fit straight lines for each of the 22 combinations, and for the entire data-set. (c) is as (a), but for a different NUTS2 region, (d) shows the distribution of slopes from the 22 regression lines derived from the data shown in (b), but fitted to GMST up to 1.2℃.

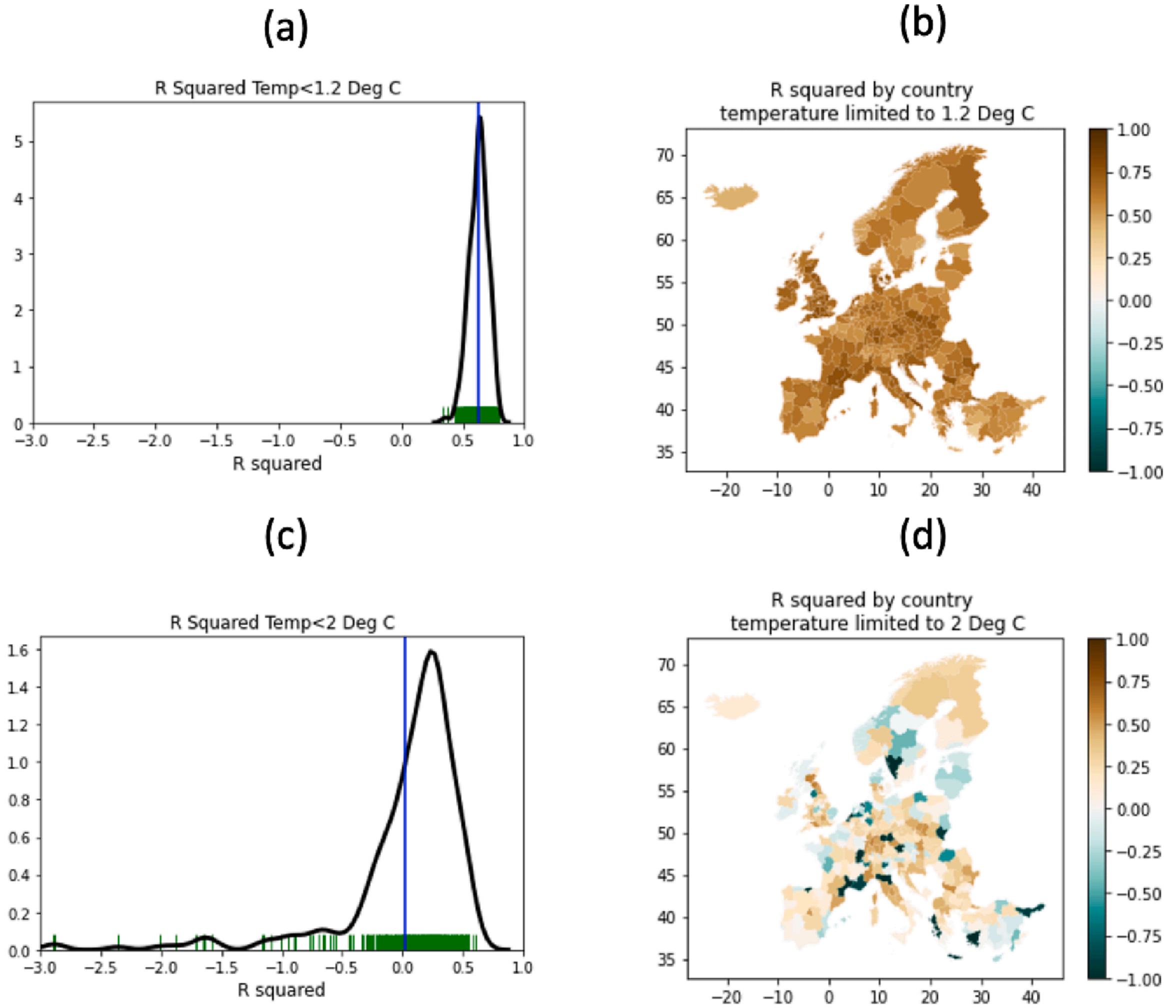

Fig. 3. R-squared values, averaged over 22 model-combinations, for each of the 296 NUTS2 regions covered in the PESETA IV study. (a) and (b) show values for a log-linear model fitted to log loss GMST data up to 1.2°C change in GMST, with the R-squared evaluated using data up to GMST of 1.2°C, while (c) and (d) show values for a model fitted to GMST data up to 2°C, but with the R-squared evaluated using data up to GMST of 1.2°C. (a) and (c) show the distribution of the 296 R-squared values for the 296 NUTSs regions, while (b) and (d) show their geographical distribution.

linear assumption for the log of the PESETA IV river flood losses below.

In this statistical model, we write the losses as L_{ijk}, and the log of the losses as a linear function of the training GMST $T^{training}{}_{jk}$, giving

$$\log L_{ijk} = \alpha_{ij} + \beta_{ij} T^{training}{}_{jk} + residuals \tag{1}$$

where α_{ij} and β_{ij} are free parameters, to be estimated. The subscript i refers to the region, and runs from 1 to 296, the subscript j refers to the model-scenario combination, and runs from 1 to 22, and the subscript k refers to the year, and runs from 1980 to 2100 (121 years). We use a log-linear model for the losses, rather than a linear model, since losses can only be positive, and a linear model would risk that the statistical model could give negative losses for certain values of GMST, which would be meaningless. Fitting the two parameters α_{ij} and β_{ij} to each of the 22 model combinations and 296 NUTS2 regions leads to 6,512 pairs of fitted parameters. The GMST used to fit the parameters in each case is taken from the climate model used in that particular model-scenario combination. The slope parameter in the linear function β_{ij} can be either positive, indicating that losses increase with increasing GMST, as we might expect in regions of increasing rainfall, or negative, indicating that losses decrease with increasing GMST, as we might expect in regions of decreasing rainfall. The intercept parameter α_{ij} is typically non-zero, since we did not subtract the mean log-loss before performing the regression. We will see below that the value of the intercept is, in fact, irrelevant, since we are only interested in changes in damage.

Examples, nonlinearity and truncation of GMST range

Fig. 2a shows an example of the PESETA IV log losses, for a single NUT2s region (in London), and for just 1 of the 22 model-scenario combinations, plotted against the GMST from the corresponding GCM. Fig. 2a also shows best fit straight lines fitted using four different ranges of GMST changes: changes up to 1.2°C, 1.5°C, 2°C and all changes. In this example, the relationship between the GMST and the log losses does appear to be reasonably linear, and the fitted lines shows a good fit to the data and are similar to each other. Variations in the data around the linear fit are mostly due to decadal time-scale climate variability in the climate model, and possibly due to non-linearity in the relationship between GMST and log loss. Fig. 2b shows results for the same NUTS2 region, but now for all 22 model-scenario combinations, along with lines fitted to each (for the complete GMST range in each case). It also shows a single mean line fitted to all the data at once. There is significant spread around the mean line. This spread is due to climate variability in the individual climate models, differences in the response to GMST in the different model-scenario combinations, and possible non-linearity in the climate change response.

Fig. 2a, b give reasonable validation for the use of a linear model for log loss versus GMST. However, not all of the NUTS2 locations give as

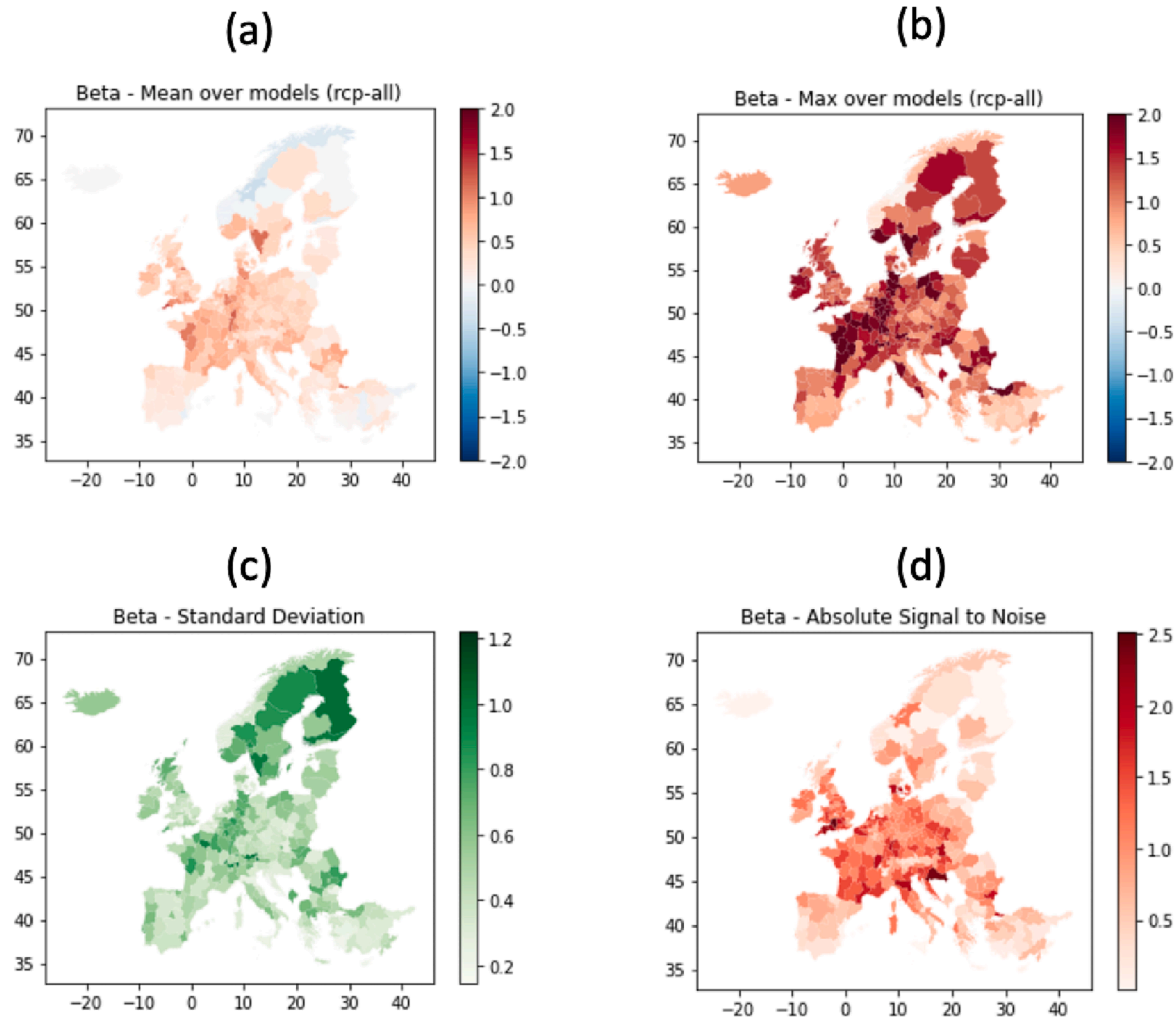

Fig. 4. Diagnostics from best fit straight lines fitted to the PESETA IV log losses vs GMST, using GMST data up to 1.2°C. (a) shows the mean slope parameter, averaged over the 22 model combinations. (b) shows the maximum slope parameter, (c) shows the standard deviation of the slope parameters and (d) shows the signal to noise of the slope parameters.

good a fit. Fig. 2c shows a region (La Rioja in Spain) for which, for this particular model-scenario combination, the variation of loss with GMST is distinctly non-linear, with the loss initially increasing as GMST increases, but then decreasing rapidly beyond 1.2°C of warming. Fig. 2c also shows regression lines fitted to the four different ranges of GMST used in Fig. 2a. The lines now each have very different slopes because of this nonlinearity. The regression line fitted to the whole range of GMST values does not capture the dependency of loss on GMST at all well. Further investigation of this non-linearity shows that it is fairly consistent across the 22 model-scenario combinations, indicating that it is not principally due to climate variability, but is a feature of the loss response to climate change in these models at this location. It also occurs in many other locations.

One way to deal with this non-linear response would be to extend the linear model to include non-linear terms. However, for all purposes for which we envisage our results being used, GMST increases larger than 1.2°C, relative to the period 1980–2000, are not relevant. This is because insurers (and many other potential users of our methods and results) are mainly interested in present day climate, and the climate of the near future (perhaps up to 2035). As a result, we have restricted our regression analysis, for all locations, to just the range of GMST change up to 1.2°C i.e., we use the shortest of the regression lines in Fig. 2a and 2c, over which period the linear assumption is better justified. Under RCP 4.5 / 6.0 / 8.5 a change of 1.2°C, relative to the period 1980–2000, occurs in the years 2045 / 2050 / 2037, respectively. The range of 1.2°C of change relative to 1980–2000 therefore covers our required time period adequately.

Fig. 2d shows the 22 model-scenario combination regression slopes estimated in the case shown in Fig. 2b, but now restricted to a GMST change of 1.2°C. A kernel density has been fitted to the 22 values. We see that most of the slope values are positive, but that there is a range, reflecting the range of values from the 22 model-scenario combinations. This range is an approximate indicator of the model uncertainty in these results. Normal distributions can be fitted to this distribution of regression slopes as a convenient way to summarize this model uncertainty. For fixed GMST, a normal distribution for the regression slope gives a log-normal distribution for the resulting rate of change of loss versus GMST, by Eq. (1).

To validate the choice to restrict to the GMST range to up to 1.2°C, Fig. 3 shows maps and distributions of R-squared values of the linear fit to the log loss time series from using data with GMST values up to 1.2°C and 2.0°C. R-squared values are calculated only for data with GMST up to 1.2°C in both cases. In other words, even when the lines are fitted to data up to 2°C, the R-squared is calculated only on data up to 1.2°C. This is to allow better comparison between the R-squared values in the two cases. The results for 2.0°C show most of the R-squared values are less than 0.5, and many are less than 0, suggesting that the linear model is performing very poorly, as expected from the example shown in Fig. 2c. The results for 1.2℃ show higher R-squared values, mostly above 0.7. This justifies our choice to fit the linear model to data with GMST changes up to only 1.2℃. Using even less data might give an even better fit, but would reduce the precision of the parameter estimates and would limit the applicability of the model to less far into the future.

We could consider testing more complex statistical models than Eq. (1) to capture the relationship between GMST and log loss, even for the range of GMST up to 1.2℃. However, given the great uncertainties in the models from which the losses were generated, and the large amount of noise due to climate variability, we feel that this would be over-interpretation. It would imply we understand more about the details of the response to climate change than is really possible to derive from this data given these uncertainties. We can consider the use of a linear model to be giving the first term in a series expansion of the climate change signal. We believe that this will already be useful, since currently there are few or no estimates available even for this first term.

Spatial variability

The analysis described above produces 296 distributions of values for α_{ij} and β_{ij}, for our 296 NUTS2 regions, where each distribution consists of 22 values, from the 22 model-scenario combinations. One such distribution was illustrated in Fig. 2d. We can summarize each distribution using the mean and variance. Fig. 4a shows the spatial variability of the mean values of β_{ij}. We see mostly positive values, indicating increases in losses with increasing GMST, but values close to zero or slightly negative in the north and south of the domain. A value of $\beta_{ij} = 0$ indicates no change in loss as GMST changes. For small values of the term $(\beta_{ij} T^{application}{}_{jk})$, we can linearize equation (1) to give

$$L_{ijk} \approx \exp(\alpha_{ij})(1 + \beta_{ij} T^{application}{}_{jk}) + residuals \quad (2)$$

In this linearized form, a value of β_{ij} of 0.5 indicates a 50% increase in loss per degree C as GMST changes, and a value of β_{ij} of 1.0 indicates a 100% increase in loss per degree C as GMST changes. In many regions the mean value of β_{ij} lies between 0 and 1, indicating changes of damage of between 0% and 100%.

Fig. 4b shows the maximum values of β_{ij} by region. All regions show positive values i.e., all regions show some probability of increase in damage as GMST increases. Fig. 4c shows the standard deviation of values of β_{ij} and Fig. 4d shows the signal to noise ratio, calculated as the ratio of the absolute value of the mean to the standard deviation. We see that for much of the central region, the signal to noise is well above 1 i.e., the signal is larger than the noise, indicating reasonable agreement among the 22 model-scenario combinations. On the margins of the domain the signal to noise is often close zero, indicating significant disagreement among the 22 model-scenario combinations. We do not test for statistical significance of the values of β_{ij}, since statistical testing is not appropriate given that our goal is to get a best estimate of the changes in flood damage rather than accept or reject any hypothesis about the existence of trends. A detailed discussion of the reasons why it does not make sense to use statistical significance testing when creating best estimates is given in Jewson et al. (2021b).

Fig. 5 shows the average β_{ij} values by country. In all countries, average β_{ij} is positive, indicating increasing damages. The largest average β_{ij} value is in France, with a value of over 0.6, corresponding to over 60% increase in damage per degree C (approximately). These average values are simply averages of the numerical values by NUTS2 region, and are not weighted either by the asset values in each region, or by the damage in each region, and so do not necessarily represent the trend in the loss for the country as a whole.

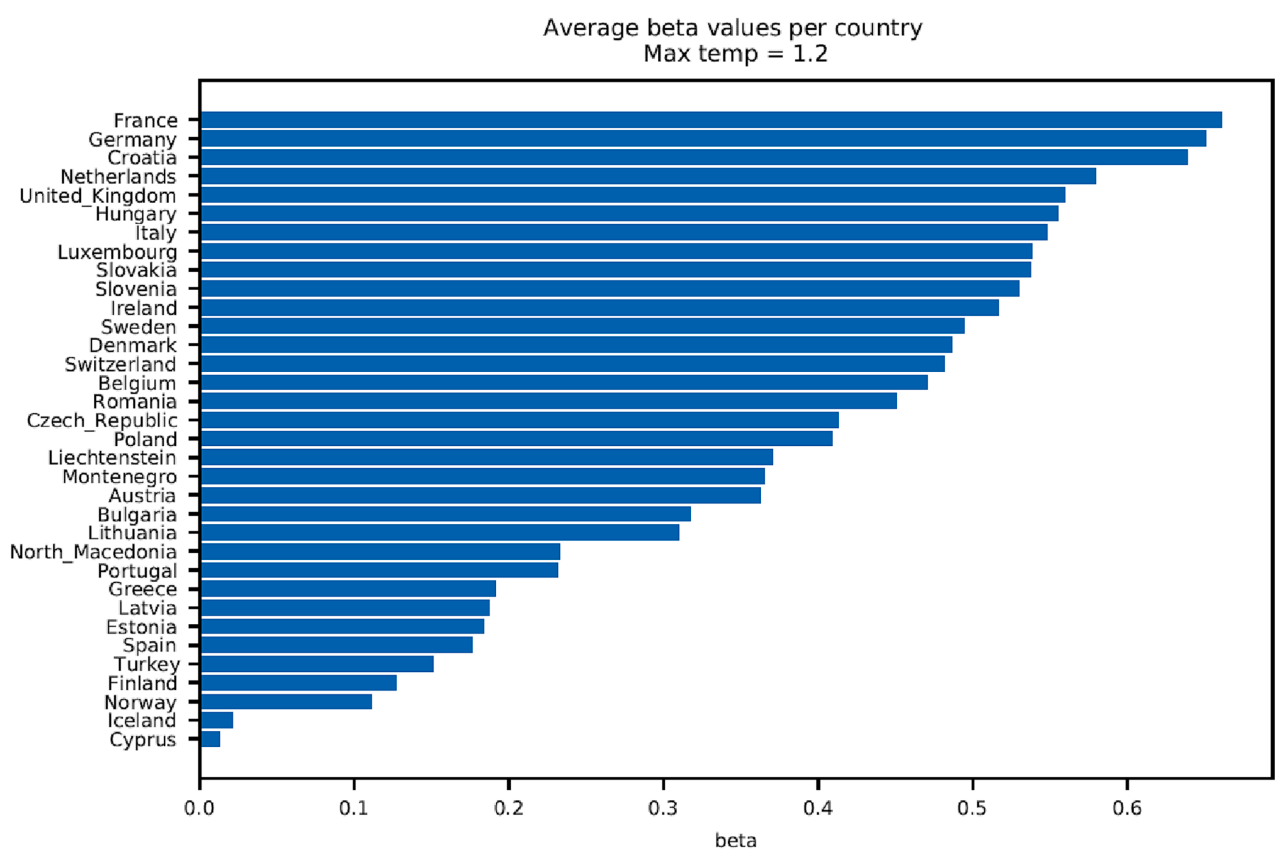

Fig. 5. Average values of the slope parameters shown in Fig. 4a, by country.

Spatial correlations

We can also consider the correlations in space between the 296 distributions for β_{ij}. Modelling these correlations is important for risk modelling, as we discuss in Section 4.3 below. These correlations capture the correlations between the results from the different model-scenario combinations, which we call the model uncertainty correlation. Fig. 6 shows the linear correlation between the 22 estimates of β_{ij} for the Surrey/Sussex (SS) region and for 5 other regions in the UK. Since the correlations are based on only 22 values, they are rather poorly estimated. We see that locally, the estimates of β_{ij} are highly correlated with the SS estimate, while as distance increases the correlations tend to drop. However, the noise around the correlations is large enough that the relative sizes of the correlations do not vary with distance exactly as one might expect. These correlations show that those models that give β_{ij} values at the high end of the range of the 22 model-scenario combinations in the SS region also give estimates at the high end of the range in nearby regions. These positive correlations increase the large-scale risk implied by the results, because they imply, for instance, that in the future scenarios in which SS experiences much more flood damage, much of the UK also experiences much more flood damage. A full representation of the linear correlation structure of the β_{ij} values requires a 296 by 296 correlation matrix, which we calculate.

Application of the statistical model

Single location application

Having fitted log-linear models for loss for each region and model-scenario combination, we can now derive estimates of the change in loss for any period of interest, for each region, and for each model-scenario combination, by using the application GMST time series with the following equation

$$\log L_{ijk} = \alpha_{ij} + \beta_{ij} T^{application}{}_k \tag{3}$$

This is derived from Eq. (1), but with $T^{training}$ replaced by $T^{application}$, and with no residuals modelled, since we are only interested in modelling the climate change related variations in loss. The resulting value for the loss L_{ijk} is then a projection of loss conditional on the application GMST time series. We can apply equation (3) using any of our application GMST values from 1880 to 2100: we are not limited by the period of GMST values used in the training data. However, we are limited to using GMST changes up to 1.2℃, relative to 1980–2000, because the log-linear model fails for larger GMST changes.

As the value of loss calculated by Eq. (3) is based on a single projected GMST value, it does not incorporate uncertainty around the projected GMSTs. GMST projection uncertainty could readily be incorporated, by replacing $T^{application}$ by a distribution of possible future GMSTs. Whether this GMST projection uncertainty should be incorporated or not is a matter of choice, and depends on the definition of the type of projection one wishes to make. To make a projection conditional on the mean GMST from a single RCP, one should not incorporate uncertainty around the GMST. To make a projection conditional on the distribution of GMST values from a single RCP, one should incorporate the uncertainty in the GMSTs from the set of relevant models. To make a prediction based on probabilities of the different RCPs one should include the uncertainties from the GMSTs from each of the different RCPs, appropriately weighted.

We can convert the changes given by Eq. (3) into fractional changes F_{ij} between two years $k = m$ and $k = n$ using the following equation:

$$F_{ij} = \frac{L_{ijn} - L_{ijm}}{L_{ijm}} = \frac{e^{\alpha_{ij}+\beta_{ij}T_n} - e^{\alpha_{ij}+\beta_{ij}T_m}}{e^{\alpha_{ij}+\beta_{ij}T_m}} = \frac{e^{\beta_{ij}T_n} - e^{\beta_{ij}T_m}}{e^{\beta_{ij}T_m}} = e^{\beta_{ij}(T_n-T_m)} - 1 \tag{4}$$

We see that the fractional change only depends on β_{ij}, as α_{ij} has now cancelled. For these fractional changes, the β_{ij} parameters encapsulate all the information we need to capture from the results from the PESETA IV study.

Equations (3) and (4) give loss for a single model-scenario combination and so ignore model uncertainty. Loss projection distributions that incorporate the model uncertainty can be generated in two alternative ways, which we refer to as non-parametric and parametric methods. In the non-parametric method the 22 values of β_{ij} for a given location can each individually be converted into loss projections, using equations (3) and (4), giving 22 loss projections, the range of which encapsulates the model uncertainty. In the parametric method normal distributions fitted to the 22 values of β_{ij} can be used in place of β_{ij} in Eq.

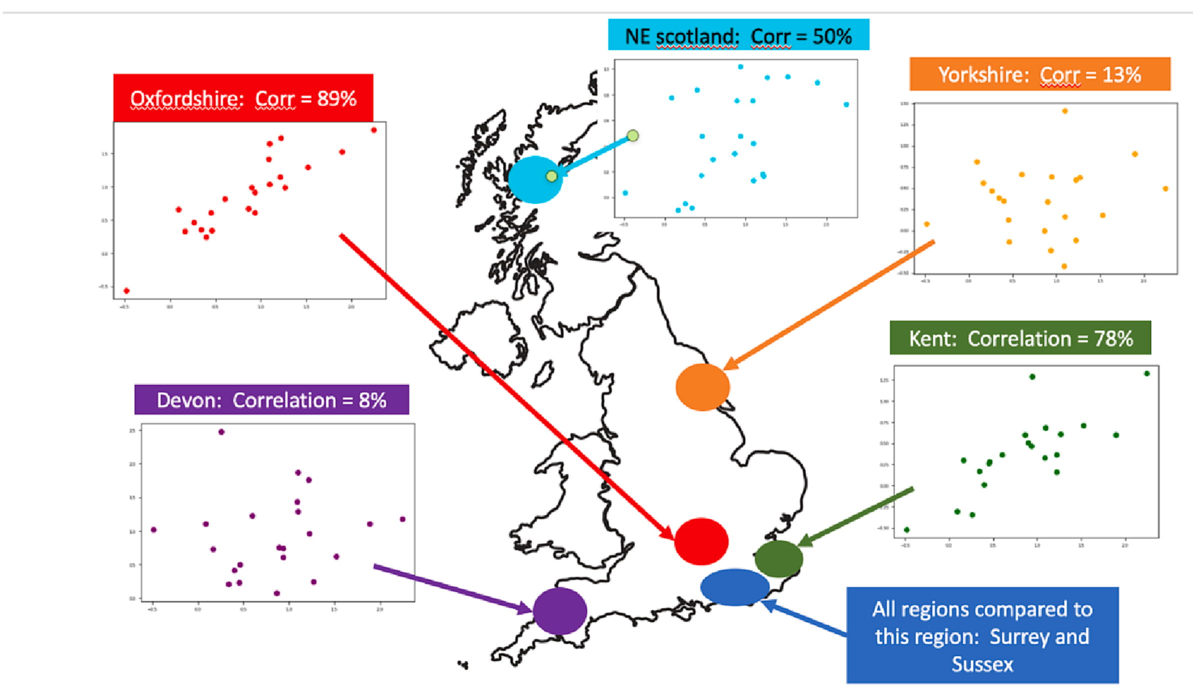

Fig. 6. Correlations between slope parameters from the 22 model combinations, for 5 locations in the UK with one location in the South East UK.

(3) or (4). This gives log-normal distributions for the loss, for each value of GMST. Using the parametric method has the possible advantage that it will extrapolate the tails of the distribution, relative to just using the 22 fitted values. If a large number of samples of the possible loss are required, either the normal distributions for β_{ij}, or the log-normal distributions for loss, can be sampled.

Multi-year period application

We can also calculate estimates of percentage changes in loss between any two multi-year periods. This is essential for our application to catastrophe models. Consider a catastrophe model built using observed rainfall data from 1970 to 2019. Without further adjustment, the model represents the climate of this historical period. Suppose then that the user wishes to understand how climate change may change the results from this model by the period 2025–2030. The change required is now a change between these two multi-year periods. Based on Eq. (3), changes between two multi-year periods P_1 and P_2, of lengths N_1 and N_2, with mean losses M_{ij}^1 and M_{ij}^2, are given by

$$F_{ij} = \frac{M_{ij}^2 - M_{ij}^1}{M_{ij}^1} = \frac{\frac{1}{N_2}\sum_{i \in P_2} e^{\beta_{ij}\ T_i} - \frac{1}{N_1}\sum_{i \in P_1} e^{\beta_{ij}\ T_i}}{\frac{1}{N_1}\sum_{i \in P_1} e^{\beta_{ij}\ T_i}} \quad (5)$$

Once again, α_{ij} has cancelled.

Single location example

Fig. 7 gives an example. Fig. 7a shows 3 GMST projections, derived from the CMIP5 model ensemble. The projection baseline has been adjusted so that the projections are zero over the period 1950 to 2019, although the choice of projection baseline makes no difference to the results we derive below since it is only the change in the GMST that matters. Fig. 7b uses Equation (5) to derive fractional changes in the AAL for one particular NUTS2 region (region 65844949, Burgenland in Austria), based on the mean value of β_{ij} that we have derived for this region. In Fig. 7c we apply these fractional changes to a value for the baseline AAL for this region. For the baseline AAL value, we use the AAL estimate for this region from the first of the GCMs listed in Table 1, using results for the period 1980 to 2022. The period 1980 to 2022 therefore forms the period P_1 in Equation (5). We define period P_2 multiple times, using an 11 year sliding window around every year from 1970 onwards. We are thus modelling climate change driven variations in AAL both backwards and forwards in time using our model. This leads to negative values for the fractional change before the year 2000 (which is roughly the midpoint of the AAL baseline from 1980 to 2022) and hence values

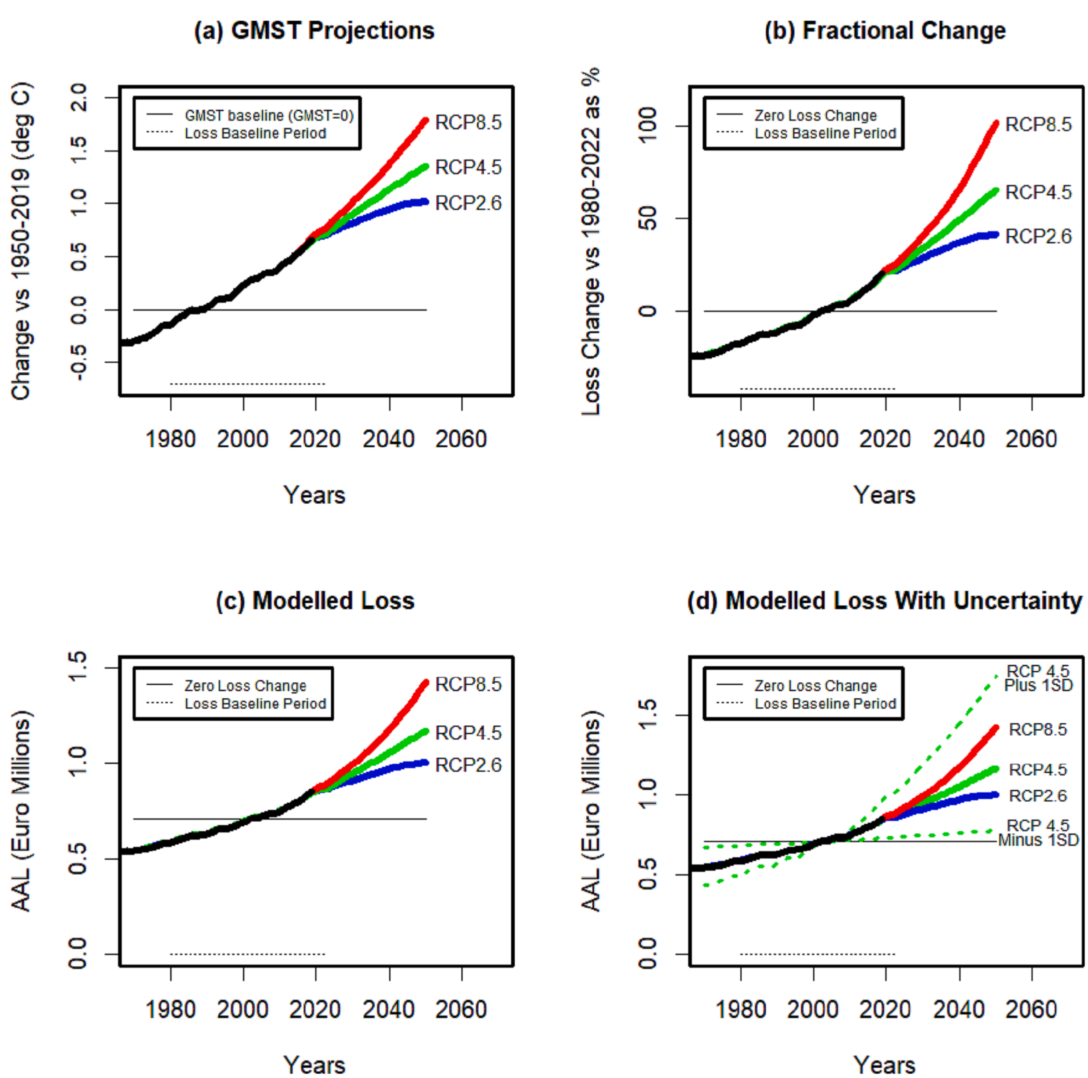

Fig. 7. An example of the application of the methodology we describe, for a single NUTS2 region. (a) shows GMST projections for 3 RCPs. (b) shows fractional changes in damage derived from the GMST projections, relative to a damage baseline of 1980–2022. (c) shows full modelled losses, generated by applying the fractional changes to an estimate of the average annual loss, based on modelling for the period 1980–2022 and (d) shows the same as (c) but with plus and minus 1 standard deviation shown around the RCP4.5 modelled losses.

for the modelled AAL which are below the baseline AAL. However, it is the modelled AAL values from 2023 onwards which are of the most interest, and these show positive values for the fractional change and increases in the AAL relative to the baseline. Fig. 7d shows the same as Fig. 7c, but now with additional lines that show plus and minus one standard deviation of the AAL, for the RCP4.5 scenario only. We see that, for this NUTS2 region, the uncertainty range is wide, and wider than the range due to choice of RCP.

Multi-location application

In addition to generating loss scenarios for individual locations, we can create spatially distributed loss scenarios that take into account the spatial correlations between the different model-scenario combinations. This can be done in two ways, corresponding to the non-parametric and parametric methods described above for creating loss scenarios for a single location. In the non-parametric method, one could generate a spatial loss scenario by using Eq. (3) 296 times, with the 296 β_{ij} values for the 296 regions, but from just one of the 22 model-scenario combinations (i.e., by varying i but fixing j). This would then be repeated for the other 21 model-scenario combinations (by varying j), to create 21 further spatial loss scenarios. The 22 resulting spatial loss scenarios naturally incorporate the spatial correlations present in the β_{ij} values.

In the parametric method, one could simulate a large number of realisations of the set of 296 β_{ij} values, using a multivariate normal distribution based on the normal distributions fitted to the β_{ij} values at each location, and the correlations between the locations discussed in Section 3.4 above. Using this method, one could, for instance, simulate N realisations of the set of 296 values, where N corresponds to the number of years of simulation in a YLT. This is then convenient for some of the methods one might use for adjusting catastrophe model results, as discussed below.

Adjusting catastrophe model output

We now discuss how the above results might be applied to different forms of output from a catastrophe model. Given the proprietary nature of the catastrophe models used by the insurance industry, we are unable to give any quantitative examples.

Assumptions

We start by discussing the assumptions we need to make to bridge the gap between the PESETA IV results and typical catastrophe model results.

Assumptions with respect to assets modelled

The first set of assumptions relates to the fact that the underlying set of assets being modelled is likely not the same for the PESETA IV changes and for any catastrophe model analysis. Therefore, to apply the PESETA IV results to a catastrophe model analysis we have to make the assumption that the impacts of climate change on the damage for the two different sets of assets, when expressed as a fractional change, will be similar. The PESETA IV project modelled the overall economic impacts of river flooding. A typical catastrophe model analysis might model the impact of river flooding on databases that attempt to represent the set of buildings insured by the whole insurance industry, or the smaller set of buildings insured by one insurance company. Assuming that the impact of climate change would be the same on these different sets of assets is a bold assumption. However, it may not be unreasonable, as a first way to generate an estimate of the impacts of climate change, given the wider context. Little or no information is currently available about the details of the possible impacts of climate change on river flood damage, and there are large uncertainties involved in all aspects of both the PESETA IV project and catastrophe model analyses.

Assumptions with respect to modelling resolution

The second set of assumptions relates to resolution. The PESETA IV damages were originally calculated at 5 km resolution, and were then aggregated to NUTS2 resolution. Catastrophe models often calculate damages at much higher resolutions, perhaps of 10 m or 50 m, in an attempt to get close to resolving individual buildings. However, the catastrophe models certainly do not simulate all the factors that are relevant for understanding the details of flood risk at these scales. The catastrophe model results are often then aggregated to lower resolutions, particularly to either HR-CRESTA or LR-CRESTA regions, both of which are higher resolution than NUTS2 (CRESTA regions are a proprietary set of region definitions used in the insurance industry: see https://www.cresta.org). The most consistent way that the PESETA IV results could be applied to catastrophe model results, in terms of resolution, would be for the catastrophe model results to be aggregated to NUTS2 resolution, so that they are at the same resolution as the PESETA IV results. Alternatively, the PESETA IV results at NUTS2 resolution could be applied to catastrophe model results at higher resolutions, such as LR-CRESTA or HR-CRESTA regions, or even to results for individual buildings, by assuming that the percentage changes in loss are constant across each NUTS2 region. This assumption of constant percentage change within each NUTS2 regions is likely unrealistic in detail, but can be used as a working assumption.

We have not calculated our results directly on CRESTA regions since the definitions of the CRESTA regions are proprietary and not available to us at this point. We may be able to obtain the CRESTA region definitions in future: for now, to apply these results to CRESTA regions one would have to assume that the changes are constant across each NUTS2 region as discussed above.

Assumptions related to the impacts on individual flood events

The third set of assumptions relates to the application of the PESETA IV results to individual flood events. The PESETA IV results we have used as input are changes in the annual average loss due to river flooding. Annual average losses are the average of losses from many individual flood events, large and small. In the PESETA IV results, there is no indication as to which of the individual event losses are changing, only that the annual mean across all types of events is changing. The most consistent way to apply the PESETA IV results is therefore to apply them to results for average annual losses from catastrophe models.

However, insurers are also interested in the changes in individual events. To apply the PESETA IV results to individual events, or metrics related to individual events, one would have to make additional assumptions. The simplest assumption would be to say that losses for all events are increasing by the same percentage change. This is a working assumption: there is little evidence at this point to prove or disprove this assumption. However, it is likely not true in detail. For instance, if the most extreme rainfall events are increasing more rapidly than other events, that may lead to the most extreme flood events increasing more rapidly than smaller events.

Given these assumptions we can now consider how PESETA IV results could be applied to catastrophe model output of different types.

Adjusting average annual losses

One of the most commonly used metrics in insurance risk modelling is the average annual loss (AAL). AAL can be calculated from historical losses or from a catastrophe model, and at different resolutions ranging from individual buildings to a large globally distributed portfolio of buildings. When calculated for individual buildings, it is an important input into insurance pricing. The PESETA IV results could be used to adjust AAL results at any scale, subject to the assumptions discussed above. We will consider application at the NUTS2 scale.

For any individual NUTS2 region, catastrophe model AALs could be adjusted in a number of different ways using our PESETA IV-derived results. Most simply, the mean percentage change in loss for that region, calculated as the mean of the 22 individual loss changes from the 22 model-scenario combinations, could be applied to the catastrophe model AAL, to give an adjusted AAL. This method, however, ignores the model uncertainty in our results. To capture the model uncertainty non-parametrically, the 22 changes for that region could be applied separately to the catastrophe model AAL, to give 22 new values for the AAL. To capture the model uncertainty parametrically, N simulated values for the loss changes for that region could be applied to the catastrophe model AAL, to give N adjusted values for the AAL. Finally, if the unadjusted AAL itself already has an associated uncertainty, the two distributions of uncertainty could be convoluted together to create the new distribution of uncertainty.

Adjusting annual loss distributions

Other commonly used metrics in insurance risk modelling are the probabilities that the maximum loss in a year will exceed a certain level, and the probability that the total loss in a year will exceed a certain level. For some applications in insurance, particularly risk management, capital allocation and reinsurance design and pricing, these metrics are as important, or more important, than AAL. As discussed above, the PESETA IV results we have described apply to annual average losses, and contain no direct information about the distribution of individual losses in a year. If one is willing to assume that the changes apply equally to individual events, then they could, nevertheless, be applied as percentage changes to the maximum and annual total losses, giving changes in the distributions of these quantities. This may be better than nothing in the absence of any other information about how those distributions may change. As in the previous Section, the changes could be applied by using just the mean of the 22 model-scenario combinations. To capture model uncertainty, one could apply them non-parametrically by using the 22 values separately, or parametrically by using N simulated values of loss changes from a distribution fitted to the 22 values.

Adjusting single region year loss tables

Our PESETA IV results could also be used to adjust the losses in year loss tables, if again one is willing to assume that losses for different events all change by the same percentage change. For a single NUTS2 region, the simplest way to do that would be to ignore model uncertainty and apply the mean percentage changes to the loss for every event in every year. To capture model uncertainty, one could apply the 22 values separately to different years in the YLT, or use N simulated values and apply different samples to every year. This latter methodology is perhaps the most consistent with the overall catastrophe modelling approach of sampling all possible uncertainties in every year of simulation.

Adjusting multi location YLTs

Since our results cover multiple regions, they could also be applied to simulated losses for multiple regions. All the methods described above generalize to adjustments for multiple regions at once, and would correctly propagate model uncertainty and model correlation into the final multi-region loss results. This is the most general way to apply our results.

Discussion

Uncertainties

It must be emphasized that the components of this study, and the data on which it depends, each involve many uncertainties, and in combination the uncertainty in the final results is large. The sources of uncertainty in the PESETA IV study and resulting outputs include:

1) Climate projection uncertainty: climate models only give imperfect representations of current and future climate. It is possible that the behaviour of future climate lies outside the range of the climate simulated by any of the 11 models used in the PESETA IV study.
2) Flood model uncertainty: models for river flooding only give imperfect representations of real flooding, even if forced with realistic climate forcings, due to limitations in the input data, including topographic data and soil data, and limitations in the models themselves, including challenges related to the modelling of flood protection.
3) Damage model uncertainty: models for the damage caused by flooding only give imperfect representations of what the actual future damage may be, even if forced with realistic floods.

In addition, our linear model for log-loss as a function of GMST is an approximation. Other sources of approximation and hence uncertainty have been discussed in Section 4.1 (uncertainty related to future GMSTs) and Section 5.1 (uncertainty related to mismatches in the set of assets, spatial scales, and assumptions about whether the results can be applied to individual events). Furthermore, catastrophe models are themselves built using many approximations and have many uncertainties, even before adjustment with the PESETA IV results.

Some of the overall uncertainty is quantified in our calculations. For instance, the spread of the results from the 22 climate model-scenario combinations gives an estimate of the climate projection uncertainty. However, many of the sources of uncertainty are not quantified in our calculations, and hence the ranges of results we derive are likely to underestimate overall uncertainty.

These uncertainties do not invalidate our attempts to produce estimates of the impact of climate change: it is important to estimate the impacts of climate change using the best methods we can at this point in time. At the time of writing, we are not aware of any other publicly available information which would give as much information about the possible economic impacts of climate change and river flooding in Europe as we are providing in this study. However, the uncertainties do affect the interpretation and application of the results. Our perspective on the impacts of the uncertainties is that we believe our results may well capture the correct sign of the impacts of climate change on loss in most regions. They certainly suggest that the changes are not zero. They may also give a first estimate of the rough magnitude of the size of the impacts. They likely do not give good estimates of the differences in impacts between regions with similar impacts. Whether information that is this uncertain is valuable or not and depends on the application, and ultimate decisions about whether and how to use this uncertain information lie with the user.

Comparison with other methods for incorporating climate change into catastrophe models

We have discussed the possibility of adjusting the results from river flood catastrophe models by taking changes in losses from the PESETA IV project and using them to adjust loss results from the catastrophe model. This approach could be argued to take advantage of the strong points of both catastrophe models and climate models, in that the catastrophe model is used to generate detailed high resolution flood losses, while the climate model results are used to capture the changes due to climate change. However, this method has many limitations (the possible sources of uncertainty have been discussed above), and there are various other methodologies that one could consider using to adjust a river flood catastrophe model to account for climate change. We briefly describe some of the alternatives below.

A second methodology would be to rebuild the catastrophe model using rainfall simulated by climate models. A third methodology would be to rebuild the catastrophe model using rainfall simulated from statistical models, but adjusted to account for climate change. A fourth methodology would be to extract projected changes in rainfall from climate models and use them to make adjustments to an existing catastrophe model, without rebuilding the model, by applying weights to the years of simulation (see Sassi et al. (2019)).

These four approaches each have pros and cons, and none of these four approaches is remotely close to what one would ideally do, which is to connect an extremely high resolution highly realistic climate model to highly realistic flood and damage models and run the combined model for many thousands of years. However, this ideal approach is not possible at this point in time, and may not be possible for many decades in the future. Our approach, and the other three approaches described above, are therefore compromises that allow us to approximate the ideal approach in some way. Which of the four approaches gives the most realistic results is extremely difficult to say.

Conclusions

Flood risk is changing because of climate change, and information about how it may be changing could potentially help design responses that mitigate any negative impacts of the changes. For instance, one idea that has been suggested for mitigating the negative impacts of flooding is the formation of a state-run cross-border risk pooling mechanism (Prettenthaler, et al., 2017). Any mitigation efforts require analysis of the possible impacts of climate change on flooding. Perhaps the most comprehensive publicly available analysis of the impacts of climate change on flood risk in Europe has been produced as part of the PESETA IV project (Dottori, et al., 2020; Feyen, et al., 2020). The PESETA IV results have many possible applications: we have considered their application to insurance industry flood risk modelling. The insurance industry estimates flood risk using catastrophe models, and the PESETA IV results could potentially be used to adjust the output from those models. However, for the PESETA IV results to be used to adjust catastrophe models, they first have to be converted in various ways. We have described such a conversion process, involving three steps. First, we have used PESETA IV output consisting of simulated annual values of damage, at NUTS2 resolution, to estimate the rate of change of damage versus global mean surface temperature (GMST) in a log-linear model. This step smooths the variations in the PESETA IV output due to internal climate variability. The implicit assumption in this step is that the rate of change of log loss versus GMST is constant with time, which only turns out to be a reasonable assumption for the data we analyze up to around 1.2 deg C change in GMST, relative to 1980–2000. Second, we have described how the rate of change of log loss versus GMST can then be used to estimate the percentage change in damage between the historical baseline period of a catastrophe model (the time period of the data on which the model was built and calibrated) and any other point in time, for any RCP, subject to the limitation that the GMST change should be less than 1.2°C relative to 1980–2000. Third, we have described how a multivariate normal distribution can be fitted to the rate of change of the log loss, which allows for an arbitrary number of years of spatially correlated changes to be simulated. We have then also described how the percentage changes in damage calculated in this way can be applied to the different outputs from a catastrophe model, as well as the various assumptions that one must make for such adjustments to be valid. We deliver our results to the insurance industry in two ways. For those companies who wish to perform the scaling by time-period and GMST themselves, we provide the results as a freely available dataset. For other companies, a software tool is available that can be used to perform this scaling and extract the scaled results.

There are extremely large uncertainties involved in our analysis, and in any results derived from our analysis using catastrophe models. These include the uncertainties inherent in the climate models, flood models and damage models used in the PESETA IV project and uncertainties related to our assumptions of a log-linear relationship between GMST and damage. They also include uncertainties related to the need to assume that changes in damage for all physical assets, as calculated in PESETA IV, can be applied as changes in damage to subsets of the full set of physical assets, as required. Nevertheless, given the general lack of quantitative information about the impacts of climate change on flooding and damage in the public domain at this point in time, we hope that our results will prove useful as first estimates of the rate at which climate change is leading to changes in the damage caused by flooding. They may, at least, give reasonably robust indications of the regions in which damage may be increasing or decreasing, and rough estimates of the size of the changes.

Data availability

A dataset containing the results for the estimated rates and correlations of the climate change impact on log damage due to river flooding for different regions in Europe will be freely available on Zenodo at publication.

An online software tool that scales this data as a function of time-period and GMST scenario is commercially available.

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CRediT authorship contribution statement

Stephen Jewson: Conceptualization, Methodology, Project administration, Writing - original draft, Writing - review & editing. **Trevor Maynard:** Visualization, Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing - review & editing. **Francesco Dottori:** Data curation, Writing - review and editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data for means and standard deviations by NUTS2 region is available on Zenodo.

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