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To cite this article: A J Pitman *et al* 2022 *Environ. Res.: Climate* **1** 025002

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RECEIVED
25 May 2022

REVISED
27 July 2022

ACCEPTED FOR PUBLICATION
29 July 2022

PUBLISHED
18 August 2022



PAPER

# Acute climate risks in the financial system: examining the utility of climate model projections

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**Keywords:** acute financial risks, regional climate projections, financial stability

## Abstract

Efforts to assess risks to the financial system associated with climate change are growing. These commonly combine the use of integrated assessment models to obtain possible changes in global mean temperature (GMT) and then use coupled climate models to map those changes onto finer spatial scales to estimate changes in other variables. Other methods use data mined from 'ensembles of opportunity' such as the Coupled Model Intercomparison Project (CMIP). Several challenges with current approaches have been identified. Here, we focus on demonstrating the issues inherent in applying global 'top-down' climate scenarios to explore financial risks at geographical scales of relevance to financial institutions (e.g. city-scale). We use data mined from the CMIP to determine the degree to which estimates of GMT can be used to estimate changes in the annual extremes of temperature and rainfall, two compound events (heatwaves and drought, and extreme rain and strong winds), and whether the emission scenario provides insights into the change in the 20, 50 and 100 year return values for temperature and rainfall. We show that GMT provides little insight on how acute risks likely material to the financial sector ('material extremes') will change at a city-scale. We conclude that 'top-down' approaches are likely to be flawed when applied at a granular scale, and that there are risks in employing the approaches used by, for example, the Network of Central Banks and Supervisors for Greening the Financial System. Most fundamental, uncertainty associated with projections of future climate extremes must be propagated through to estimating risk. We strongly encourage a review of existing top-down approaches before they develop into de facto standards and note that existing approaches that use a 'bottom-up' strategy (e.g. catastrophe modelling and storylines) are more likely to enable a robust assessment of material risk.

## 1. Introduction

Climate change represents a risk to the global financial system. Investors have called for information on climate-related risks to be included in the annual financial reports of companies (Reuters 2016, Kerber 2017). Global standard-setters (AASB and AuASB 2019, Anderson 2019, FASB 2021) and corporate and securities regulators (IOSCO 2019, Financial Conduct Authority 2020) have argued that climate-related risks should be presented in financial statements when financially material. The Financial Stability Board's Taskforce on Climate-related Financial Disclosures (TCFD) has developed a framework to help organisations disclose climate-related financial risk (TCFD 2017, TCFD 2021), and governments and security regulators are now mandating such disclosures (HM Treasury 2020, G7 Finance Ministers and Central Bank Governors 2021, Securities and Exchange Commission 2022).

The Network of Central Banks and Supervisors for the Greening of the Financial System (NGFS) comprise 95 central banks and supervisors. It has begun to develop guidelines and/or requirements for the disclosure of climate risks (Ranger *et al* 2022) to support the financial stability monitoring and micro-supervision activities of central banks (NGFS 2021a) and supervisory authorities (NGFS 2021b). The NGFS aims to share best practice and contribute to the development of climate risk management across the financial sector via methods rapidly emerging as the *de facto* standard. There are multiple examples of this trend towards a *de facto* standard including reference to the use of NGFS scenarios in the proposed rule for climate-related disclosures by the US corporate regulator, the Securities and Exchange Commission (2022), the 2021 Bank of England Biennial Exploratory Scenario (Bank of England 2021), the European Central Bank's economy wide climate stress test (Alagoskoufis *et al* 2021), the Climate Vulnerability Assessment conducted by the Australian Prudential Regulation authority (APRA 2021) and the 2021 review of climate scenario analysis methodologies used by banks of the Climate Financial Risk Forum (2021).

The financial sector is exposed to physical climate risks associated with changes in weather and climate (IPCC 2012, Fiedler *et al* 2021). The NGFS (2020) defines 'chronic' (gradual climate change) physical climate risks and 'acute risks', both of which are likely associated with 'extremes'. The Intergovernmental Panel on Climate Change (IPCC) define an extreme as 'the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable' (IPCC 2012). This definition is based on the statistical properties of an event which may, or may not materially affect the financial sector, while a non-extreme event could affect the financial sector. We therefore use the term *material extreme* to describe acute risks that could have a financially material impact on financial institutions, as distinct from climate-derived definitions that reflect statistical properties. Financial materiality is a core principle in financial accounting; the International Financial Reporting Standards Foundation define financially material information as information that could reasonably be expected to influence investors because of its effect on a company by virtue of its financial magnitude or nature (IFRS 2018). We define a material extreme as one that affects the enterprise value (e.g. income, assets) of a financial entity.

Our weather and climate responds to increasing greenhouse gases in the atmosphere in two fundamental ways (Pfahl *et al* 2017). First, via a 'thermodynamic' response, which includes changes in the radiation balance, temperature in the atmosphere, clouds and water vapour all interacting via complex feedbacks. Second, via a 'dynamic' response which includes changes in the atmosphere and ocean circulation. The thermodynamic response alone would lead to a prediction of rainfall intensifying by about 7% per degree of warming (Guerreiro *et al* 2018) all other things being equal. The 'all other things being equal' assumes no dynamical response by the climate, which is implausible. In fact, *globally averaged*, climate models predict a much smaller change in rainfall of around 3% (Allen and Ingram 2002) due to changes in the atmospheric circulation that mitigate against the thermodynamic effects alone (Held and Soden 2006). Predicting and understanding *local* changes in rainfall is particularly complex. Changes in storm tracks, the location of cyclones and many other phenomena will cause rainfall increases much larger than the 7% per degree of warming in some regions, while in other regions reductions in rainfall will be experienced. The sensitivity of a change in an acute physical risk to the dynamical and thermodynamic responses varies with timescale, spatial scale, the nature of the phenomenon and how extreme the event is.

To simulate future climate, the weather and climate science communities developed physical climate models (Randall *et al* 2007, Flato *et al* 2013). On timescales of months to years, these physical climate models provide valuable insights on the thermodynamic and dynamical responses at regional scales and above (Randall *et al* 2007). However, while it is understood that 'weather' (the day-to-day variability) and 'climate' (the average of the day-to-day variability over several decades) are not interchangeable, and despite acute risks being weather related (Ranger *et al* 2022), 'weather and climate' tend to be combined when discussing material risks to the financial sector. Unfortunately, physical climate models do not represent weather-scale dynamical responses or how weather changes the interactions between the thermodynamic and dynamical responses to global warming reliably (Allen and Ingram 2002, O'Gorman 2015). This is linked, in part, to the spatial resolution used by the models (approximately 100 × 100 km pixels) which are too coarse to capture weather-scale processes (Palmer 2013).

Broadly, this introduces a serious limitation in determining future climate risk for the financial sector. Material extremes will almost always be weather-scale phenomena which are least skilfully simulated by existing global climate models. 'Acute risks' highlighted by NGFS (2020) include rare and extreme rainfall events, flooding, tropical cyclones, wildfire, heatwaves and drought (IPCC 2012). However, material extremes could also include events that are not 'extreme' in a statistical sense, especially if they occur concurrently as compound events (Zscheischler *et al* 2018, Ranger *et al* 2021). One example is the possible shift in climate towards long periods of low wind and cloudy conditions—a material extreme to a renewable energy provider and a potential risk to a national economy via disrupted energy supply, a problem that has already occurred in Europe (Bloomfield 2021). The emergence of an awareness of the contribution compound events make, including when climate compounds with non-climate shocks and stresses, to climate related risks is also very relevant (Zscheischler *et al* 2018, Ranger *et al* 2021). None of these are explicitly incorporated in the core NGFS (2021b) scenarios and none of them are likely implicitly captured. Critically, while some weather and climate-related risks are threats to the financial system, current physical climate models can at best quantify the *climate-related* risks while the main driver of material risks to the financial system are more likely *weather-related* risks influenced by a warming climate.

Climate projection using physically-based climate system models is very complex (e.g. Palmer and Stevens 2019). These models were part of the strategy by climate science to understand how much global mean temperature (GMT) would change as greenhouse gases increased in the atmosphere. The focus on GMT enables a hierarchy of modelling approaches to be used to simulate the global and regional response to different greenhouse gas emission scenarios including physically-based global climate models, Earth System Models, Earth System Models of Intermediate Complexity and Integrated Assessment Models (IAMs). IAMs have the considerable advantage over physically-based global models (such as those used in the Coupled Model Intercomparison Project, CMIP) of being able to be run thousands of times to examine probabilistic links between emissions and GMT. The computational efficiency of IAMs and the incorporation of economic modules into IAMs means they can link many emission scenarios, via economic modelling through to economic consequences. However, IAMs are not without problems and most significantly tend to miss the impacts of extreme weather shocks (Stern 2016) which are likely the drivers of material risk.

The methodology recommended by NGFS for assessing climate risk to the financial sector starts with two pre-defined high-level scenarios. The high-risk scenario is presented as a ‘hot-house’ or ‘too little too late’ future that corresponds to the Representative Concentration Pathway (RCP) 6.0 emission scenario and a GMT exceeding 3 °C by 2100. A lower-risk ‘orderly’ or ‘disorderly’ scenario is also defined that corresponds to RCP2.6 and is sub-divided into a 1.5 °C and a 2.0 °C GMT increase. The NGFS methodology uses a wide range of emission scenarios reflecting these two high-level scenarios to calculate a probability distribution of GMT using an IAM that incorporates damage functions that link GMT with impacts on GDP. The assumptions here are legitimate: a larger increase in GMT will lead, on average, to more extreme heat and heatwaves, more intense rainfall and so on (IPCC *et al* 2021) and a smaller increase in GMT will reduce the risk of these impacts (IPCC 2018). Ranger *et al* (2022) discuss the NGFS methodology and the challenges with using IAMs (see also Farmer *et al* 2015, Stern 2016, Pindyck 2017, Hepburn and Farmer 2020) given these models do not reflect the importance of extremes and were not designed to explore uncertainties.

While the NGFS method provides a distribution of GMT it is not reasonable to believe that an increase in GMT of 2 °C is necessarily worse *at a specific local or regional scale* than a GMT of 1.5 °C. Similarly, for a specific region, natural variability can mean that changes are worse in 2040 than 2050, or that there are periods of decadal cooling occurring against a background of century-scale warming (e.g. the warming hiatus, see England *et al* 2014). Similarly, for a specific region, a low emission scenario may lead to worse impacts than a higher emission scenario because, while counter-intuitive, changes in circulation changes may induce a cooling in a region that exceed the warming from greenhouse gas increases in that region. In short, uncertainties stem from different elements of a methodology and these are expressed on different temporal and spatial scales such that the key uncertainties evolve from the physical models on short timescales through to emission scenarios on longer (several decades) timescales (Hawkins and Sutton 2009). Another way to express this is model uncertainty dominates estimates of acute physical risk, but emission scenarios dominate estimates of transition risk.

Additionally to IAMs, the NGFS uses physical climate models from ISIMIP (see Warszawski *et al* 2014) to translate GMT into patterns of changes at a more granular level. This is problematic as physical climate models in general do not represent material extremes well. This is acknowledged in the description of the ISIMIP method where Hempel *et al* (2013) note ‘limitations with regards to the adjustment of the variability persist which may affect, e.g. small scale features or extremes’. If Hempel *et al* (2013) are correct (and we agree they are), and if acute risks to the financial sector are associated with material extremes, the method employed by NGFS does not fully or correctly link our understanding of how emission scenarios connect through GMT to influence risks that are material to the financial sector.

The NGFS methodology implicitly assumes that one can derive a large range of GMT using IAMs and translate that GMT to a more granular-scale physical climate risk via the physical climate models included in ISIMIP. This assumption underpins our three hypotheses below. While NGFS acknowledges that extremes are likely poorly represented and that these physical climate risks are synonymous with material extremes (Hempel *et al* 2013), this has not propagated through the modelling into uncertainty bounds on the impacts on the financial sector assessed. Given the NGFS methodology seems to be emerging as the *de facto* standard to assess physical climate risks, examining the assumptions in NGFS is worthwhile. We therefore raise the following hypotheses which we test for four selected cities that serve as examples for assessing local changes in material extremes:

(a) There is a correlation between GMT and physical climate risk for annual extremes of temperature, rainfall and wind;
(b) There is a correlation between GMT and two compound events (heatwaves and drought, and extreme rain and strong winds);
(c) There is a relationship between emission scenario, time period and changes in the 20, 50 and 100 year return values for temperature and rainfall.

A physical climate modeller might contend that our analysis at the spatial scale of a city (effectively a single climate model grid point) is designed to fail given this is well below the spatial scales global climate models are designed for. However, we are testing the utility of approaches used to link GMT with physical risks, which are already influencing financial decision making and the global scale flow of capital within the financial system via NGFS. For the NGFS method to be applicable, at the scale some within the financial system are now using it, the physical risks at the scale of a city should broadly scale with GMT. If it does, then the GMT obtained from IAMs linked with emission scenarios might contain useful information to predict risk at the scale of a city.

## 2. Methods

The data examined in our analysis is sourced from CMIP6 (Eyring *et al* 2016) and CMIP5 (Taylor *et al* 2012) climate model simulations using the first realization for each model. We use the historical simulations for 1950–2004 and then RCP2.6, RCP4.5 and RCP8.5 for CMIP5 and Shared Socioeconomic Pathways (SSPs) SSP2-4.5, SSP3-7.0 and SSP5-8.5 for CMIP6. Overall, 16 models were available for CMIP6 and 21 models for CMIP5. Using both CMIP5 and CMIP6 simulations as appropriate allows us both to increase the sample size of the simulations available as well as assess whether there any material changes to our conclusions from using either set of simulations.

We select four cities: London (51° N, 0° E), New York (41° N, 74° W), Beijing (40° N, 116° E) and Mumbai (19° N, 73° E) using the closest model land grid box to each city. We calculate two extremes metrics recommended by the CCI/WCRP/JCOMM Expert Team on Climate Change Detection and Indices. The index TXx is the temperature of the hottest day of the year (annual maximum temperature), and R1X is the amount of rainfall occurring on the wettest day of the year (annual maximum precipitation sum).

To calculate the return values corresponding to the 1-in-20, 1-in-50, and 1-in-100 year events a generalised extreme value (GEV) distribution was fitted to the data extracted for RX1 and TXx, model-by-model (for CMIP5 and CMIP6) and for each emission scenario and each city. These data were extracted yearly to create a sample of yearly block maxima required to fit a GEV. Parameters of each distribution were assumed to be stationary and estimated by the likelihood method.

We also considered the compounding, or simultaneous occurrence of a selection of hazards, using only the CMIP6 ensemble. For this we calculated the return periods of the co-occurrence of extreme wind and heavy rain, and extreme heat and drought, using the methodology of Ridder *et al* (2020, 2021, 2022). For each model in the CMIP6 ensemble, GMT was determined as the 20 year mean over the historical period (1961–1990) and four individual 20 year periods under future conditions (2015–2034, 2035–2054, 2055–2074, 2075–2094) following three emission scenarios (SSP1-2.8, SSP2-4.5, SSP5-8.5). The change was then calculated as the future global mean periods minus the historical value (1961–1990). Regression lines were calculated using the linear least-square regression function of the Python SciPy package.

## 3. Results

**Hypothesis 1.** Is there a correlation between GMT and physical climate risk for annual extremes of temperature and rainfall at the scale of selected cities?

We start with two ‘extremes’ that are widely used in climate science, and have been evaluated across CMIP models. Since both occur by definition annually they should be reasonably sampled in a statistical sense. We note, however, that these are not necessarily material extremes for the financial sector, in the sense that experiencing a small change in the hottest day or wettest day of the year is unlikely to impact the sector. Figure 1 shows that there is a positive correlation between TXx and GMT at the scale of a single city in the CMIP6 models. For each city, the simulated value of TXx increases, on average across the ensemble of models, as GMT increases.

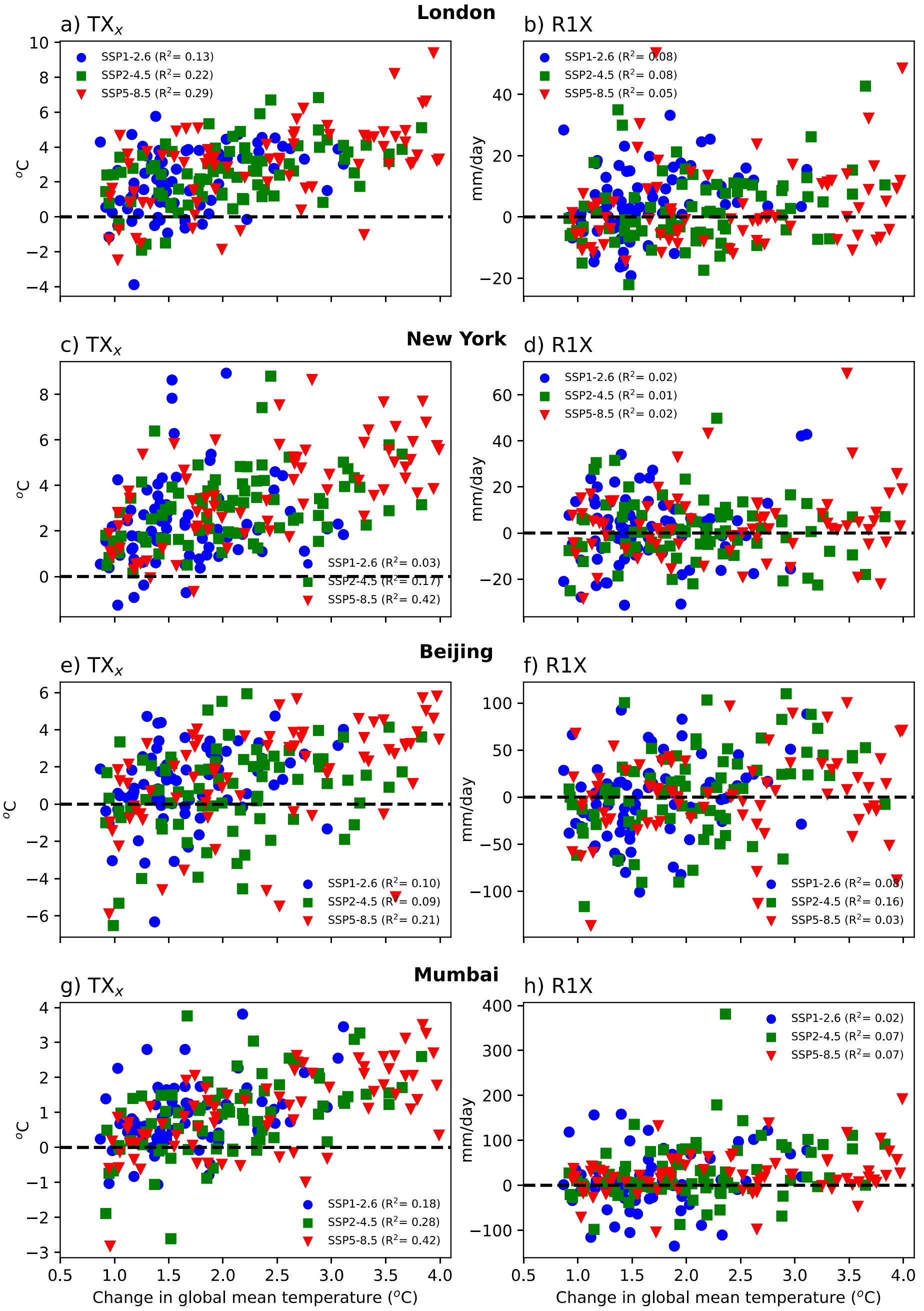


**Figure 1.** Change in TXx (left column, °C) and RX1 (right column, mm $d^{-1}$) as a function of the change in the global mean temperature for three emission scenarios from CMIP6 model simulations (low/SSP1-2.6: blue circles; medium/SSP2-4.5: green squares; high/SSP5-8.5: red triangles). The change in the global mean temperature is calculated for each 20 year period from 2000 to 2100 for each model using the mean over 1961–1990 as baseline. The change in TXx is then calculated for the same 20 year period for a grid point coincident with each city. Since 20 year time periods are used, there are four data points for each model. Note that the scale on the $y$-axis varies between panels.

There are few systematic differences between emission scenarios for the simple reason that results are expressed here as global warming levels (i.e. a given increase in GMT would have occurred earlier in the models under a high emission scenario relative to a low emission scenario). However, while all the changes in GMT are positive, some models suggest the possibility of negative changes in TXx (particularly for Beijing and Mumbai) even as the GMT increase exceeds 2 °C. This highlights that while the thermodynamic response to warming will tend to increase TXx, the dynamic response can lead to a wide range of changes in rainfall, cloud or patterns of circulation that suppress TXx in some circumstances and amplify it in others. That said, there is clearly a tendency for higher GMT to lead to higher TXx (although commonly very weakly, the maximum $R^2$ value is 0.42). The tendency for higher GMT to lead to higher TXx is more apparent when the increase in GMT exceeds the upper limit of the Paris Agreement (2 °C). Below GMT rises of 2 °C, while

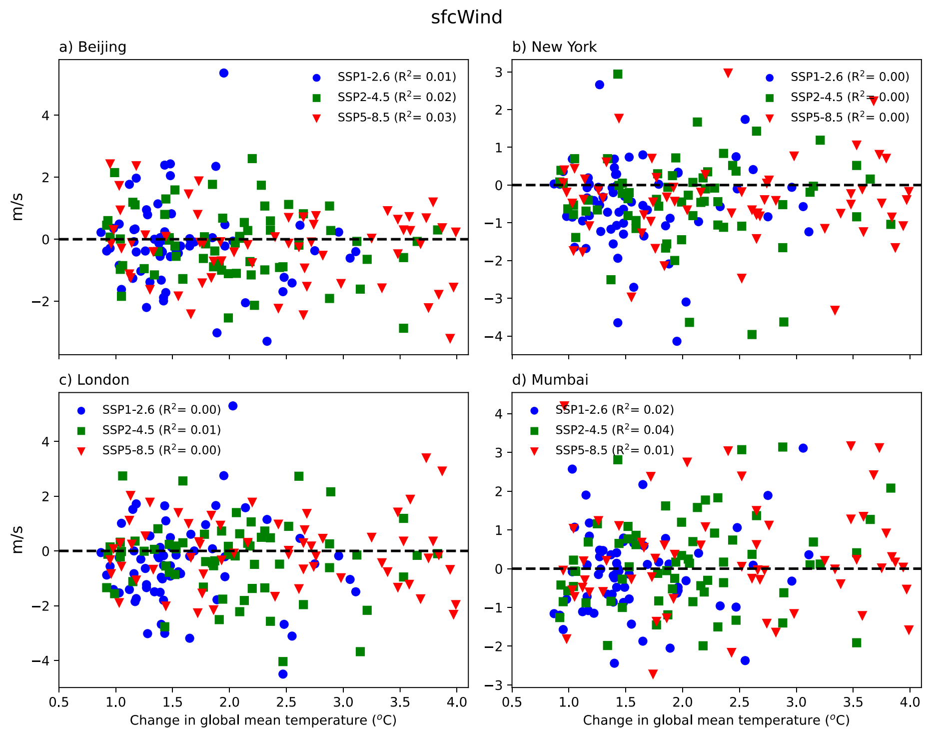


**Figure 2.** As figure 1 but for the annual maximum wind speed (m s$^{-1}$). Note the scale on the $y$-axis varies between panels.

TXx increases with GMT on average, the scatter amongst the CMIP6 models is large and includes both negative and positive changes.

Figure 1 demonstrates no strong link between GMT and the amount of rainfall on the wettest day of the year (RX1). For London, the largest increases occur under the lowest emission scenario, and none of the regression lines are statistically significant (the highest $R^2$ value is only 0.08). Results are very similar for the other cities. Note, for each city, increases in GMT can be associated with *decreases* in RX1 for many of the models, and the sign of the change does not become clear for any emission scenario until GMT exceeds 2 °C. Similar to TXx this is likely associated with the local-scale balance of the thermodynamic and dynamic responses to elevated $CO_2$. For GMT increases below 2 °C, knowing GMT provides no clear guidance on whether RX1 will increase or decrease at the scale of a city. While RX1 will increase in the future, on average, at global and continental scales this does not mean that it will increases at a specific geographic location.

Similar to RX1, there is no correlation between the annual maximum wind speed and GMT (figure 2). There is also no correlation between emission scenario and the sign of the change in wind.

Overall therefore, there is some association at the city scale between GMT and TXx but not for RX1 or the annual maximum wind speed. Our results show that knowing the change in GMT does not provide much insight on the change in these quantities at the scale of these cities. It is therefore possible that the NGFS strategy might have some value for those financial entities and systems vulnerable to the annual hottest day of the year. However, if the material risks are associated with extreme wind or rain, the NGFS methodology systematically underestimates the uncertainty and scale in how these extremes influence the financial sector, and in some cases, the direction (positive or negative).

**Hypothesis 2.** Is there a correlation between GMT and two compound events (heatwaves and drought, and extreme rain and strong winds) at the scale of selected cities?

Compound events tend to lead to higher risks than an intense rainfall event or a very hot day that occurs in isolation (Zscheischler *et al* 2018, Ridder *et al* 2020). We analyse changes in compound events via the use of return periods. Figure 3 shows the results for two compound events—wet and windy, and hot and dry. There is no relationship between the return periods of wet and windy compound events and GMT. There is an apparent relationship between hot and dry events and GMT but this is because part of the compound event responds directly to temperature and since the GMT is increasing, there is an offset for this compound event. However, note that the reduction in the return intervals (that is, an increase in the risk of an event) does not scale with the increase in the GMT for Beijing and Mumbai and the strength of the correlations are very weak

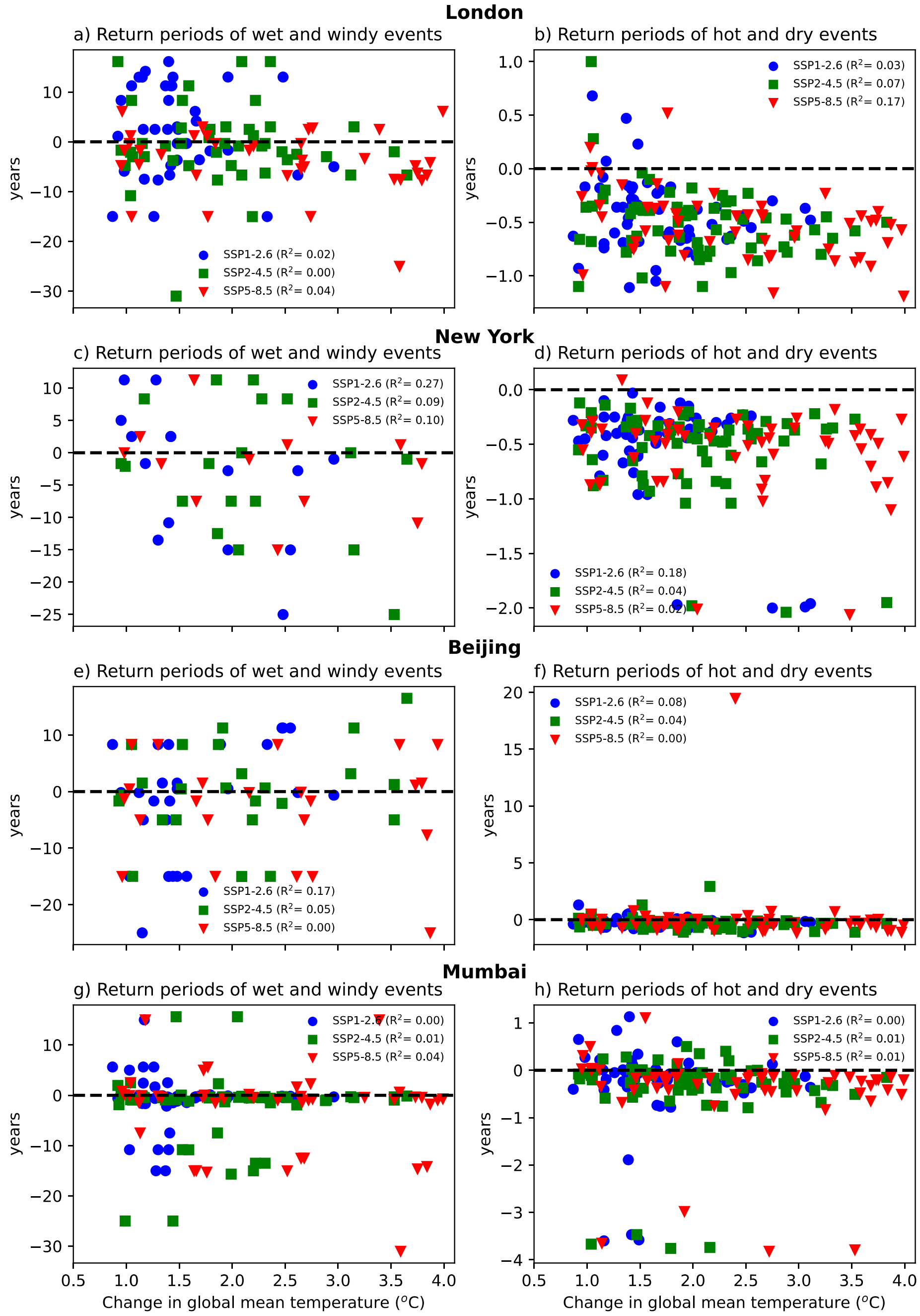


**Figure 3.** As figure 1 but for the change in the return periods for wet and windy events (left column) and hot and dry events (right column). Note, a reduction in the return period means an event of given magnitude occurs more often. Note the $y$-axis varies between panels. We chose not to omit anomalous values because we did not wish to hide the range of model projections.

for London and New York. Note also that the slopes of the regressions are generally steeper for a median emission scenario (SSP2-4.5) than for a high scenario (SSP5-8.5). This does *not* mean that high emissions offer lower risk, rather this result simply highlights deep uncertainty in model projections of these types of events.

In short, figure 3 shows that there is no association between either compound event and GMT for the cities examined here. We again note that this does not mean that physical climate models cannot simulate changes in compound events (see for example Ridder *et al* 2020). Rather, our results mean that knowing GMT, or the change in GMT, does not allow for a robust estimate of how these compound events will change at the spatial scales of a city.

**Hypothesis 3.** Is there a relationship between emission scenario, time period and changes in the 20, 50 and 100 year return values for temperature and rainfall at the scale of selected cities?

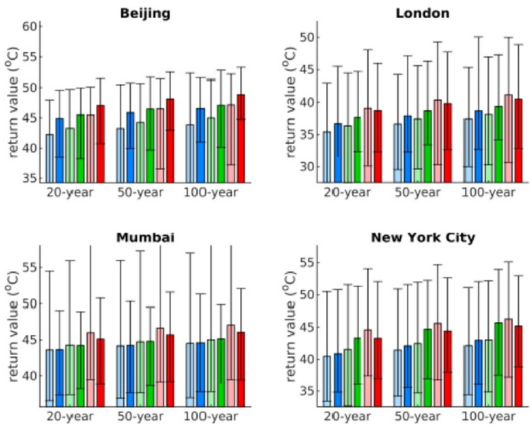


**Figure 4.** The actual return values (20 year, 50 year and 100 year) for annual maximum temperature (TXx) for four cities simulated for 2100. The lighter colour shows CMIP5 and the darker colour shows CMIP6 simulations for low (blue), medium (green) and high (red) emission scenarios. The coloured bars show the ensemble mean and the error bars show the ensemble range.

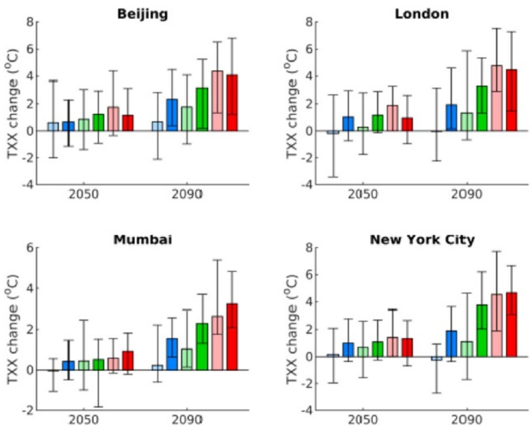


**Figure 5.** The change in the annual maximum temperature (TXx) for four cities for low (blue), medium (green) and high (red) emission scenarios for CMIP5 (the lighter colours) and CMIP6 (the darker colours). The coloured bars show the ensemble mean and the error bars show the ensemble range. Two periods are shown, 2050 represents a 20 year period (2040–2060) and 2090 represents a 20 year period (2080–2100).

While TXx and RX1 are commonly reported extremes within the climate community, much rarer and more extreme events are more likely to be material extremes. This is understood by the insurance industry (Ranger *et al* 2022) who use the 1% (1 in 100 year) or even more extreme events to calculate risk.

Figure 4 examines the change in the 20, 50, and 100 year return values for the four cities using low, mid and high emission scenarios (for both CMIP5 and CMIP6). First, note the expected result that the return value of TXx increases less under a low emissions future and more under a high emissions future (for each city the blue bars are lower than the red). However, figure 4 includes estimates of uncertainty (thin bars) and note that the uncertainty for TXx under a low emission future is very large such that it includes most of the range for TXx under a high emissions future. This means that the impact of the emission scenario is relatively small compared with the uncertainty within the CMIP5 and CMIP6 ensemble. That said, the *change* in the return periods between 2030 and 2050, and between 2030 and 2090 (figure 5) are on average positive as expected, and increase strongly into the longer-term future for all cities. However, even by 2090 some models in both CMIP5 and CMIP6 predict *decreases* in TXx by 2090 as seen in the full uncertainty range shown in figure 4. As noted earlier, this relates to the local expression of the changes in the thermodynamic and dynamic responses, as well as natural variability.

Rainfall return values (figure 6) show that on average the amounts increase weakly as a function of emission scenario but with very considerable uncertainty. This is highlighted in figure 7 where the sign of the change in rainfall for all four cities is clearly uncertain. The ensemble average of all models tends to suggest an increase (most coloured bars are positive) but the ensemble range illustrated by the thin bars is most commonly centred on 0.0 for 2050. That is, it is not the magnitude of the change in rainfall that is uncertain

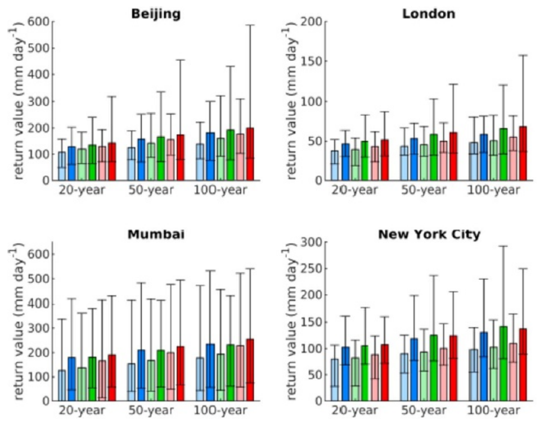


**Figure 6.** The actual return values (20 year, 50 year and 100 year) for annual maximum rainfall (RX1) for four cities simulated for 2100. The lighter colour shows CMIP5 and the darker colour shows CMIP6 simulations for low (blue), medium (green) and high (red) emission scenarios. The coloured bars show the ensemble mean and the error bars show the ensemble range.

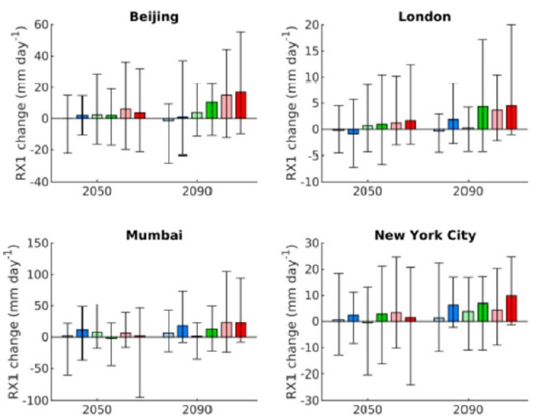


**Figure 7.** The change in the annual maximum rainfall (RX1) for four cities for low (blue), medium (green) and high (red) emission scenarios for CMIP5 (the lighter colours) and CMIP6 (the darker colours). The coloured bars show the ensemble mean and the error bars show the ensemble range. Two periods are shown, 2050 represents a 20 year period (2040–2060) and 2090 represents a 20 year period (2080–2100).

at this scale, it is the *sign* of the change which is uncertain and depends crucially on the models selected in forming any ensemble.

## 4. Discussion and conclusions

We welcome the initiatives within the global financial system to examine acute risks associated with physical climate change and we strongly concur that acute risks associated with weather and climate threaten elements of the financial system. Using physical climate models to examine large-scale risks or as guides for scenario or storyline planning is useful, and using reduced complexity models such as IAMs to develop large ensembles of how GMT responds to emission scenarios is well established. Our analysis is not examining whether acute risks are material, rather we examine the assumption, within methodologies including but not limited to NGFS, that large ensembles of GMT can be used to inform acute climate risk at spatial scales well below the sub-regional scale.

The NGFS methodology links large ensembles of GMT, via ISIMIP, to local and regional-scale climate risk. The methods used by NGFS to create large ensembles of GMT are not in question, nor are the climate models used in ISIMIP which have considerable validity for the large-scale assessment of impacts of climate change. The issue is the link implied within the NGFS methodology that translates GMT, through ISIMIP, to a granular level of physical climate risk which, in reality, is generated through climate-induced weather-scales and weather-related extremes. This link depends on the patterns simulated by the ISIMIP models, balancing the thermodynamic and dynamic responses, and their capacity to reflect the correlations between GMT and material extremes at a granular scale.

Our results show that irrespective of the capacity to derive a distribution for possible changes in GMT, and however well this distribution samples uncertainty, the methods used to link GMT to local, i.e. city-scale, annual extremes of rainfall and wind, or the return periods of two compound events, or the 1 in 20, 1 in 50 and 1 in 100 year rainfall or temperature extremes is deeply uncertain. Whether the ISIMIP models, or CMIP models are used, the translation of GMT into spatial expressions of extremes leads to uncertainty not merely in the *magnitude* of change, but in the *sign* of many changes. The uncertainty dwarfs any signal from emission scenarios, at least over the next 50 year. There are strategies to reduce the apparent uncertainty in projected extremes by sampling climate models according to skill or independence, but whether this reduces actual uncertainty, thereby enabling more robust decisions on managing risk, is unknown. Before we continue, we emphasise that the conclusion that there is no useful link between GMT and material risks *does not mean* that climate models have no role to play in assessing the impact of climate change on financial risk.

One of the advantages of physical climate models, including those used in ISIMIP, is that they provide easily accessible and quantitative information. Within CMIP6 for example, which include newer models than ISIMIP, a multi-petabyte store of open access climate change information exists. This is obviously very attractive to groups seeking to build approaches, or undertake analyses, that can be applied anywhere in the world. However, there are two fundamental principles to consider in using any physical climate modelling system. First, accuracy and precision are not the same thing; physical climate models are very precise, but not necessarily accurate and may not be accurate for problems they were not designed for. Second, uncertainty cannot be ignored; deep uncertainty exists in climate projections (Lempert *et al* 2013) and affects both the magnitude and sign of the change in most physical risks and very probably most material risks. This cannot be ignored because the consequences are not easy to predict. Ranger *et al* (2022) describe, for example, the stress testing run by the Bank of England (2020), noting that the input data is largely sourced via the NGFS methodology and that no uncertainty information is provided. From a physical climate projections perspective this is simply flawed. Refer to figures 2(d) and 3(a) and take any value of GMT and select the associated wind speed change or return period. Depending on which CMIP6 model and emission scenario is selected, increases, decreases or no change can be obtained. It is deeply misleading to select a single value from the ranges shown in figures 2 and 3 without also accounting for the uncertainty. Further, despite claims within NGFS (Bertram *et al* 2021) that the IAM used (MAGICC6) is designed 'to capture the full GMT uncertainty for different emissions scenarios', and accepting MAGICC6 is a legitimate tool to use, it is misleading to suggest it captures the full range of uncertainty. It is not known, and it is probably unknowable, to what degree any IAM captures the full range of uncertainty. The ISIMIP project is not designed to select global models that capture uncertainty, or independence (Abramowitz and Bishop 2014), or particularly good or bad models. It is simply an ensemble of opportunity (Tebaldi and Knutti 2007) with strengths and weaknesses. The ISIMIP models are legitimate tools to use, but they are quite old model versions, quite coarse in terms of spatial resolution and only six models complete the ensemble. Referring to the uncertainty bars shown in figures 4–7, selecting six CMIP models would reduce the *apparent* uncertainty because of the smaller sample size, but it would not reduce the *actual* uncertainty. It is noteworthy here that even the full CMIP6 ensemble, which now includes over 50 models, samples an unknown fraction of the true uncertainty. We also note that assessing material risks using CMIP6 (with SSPs) is unlikely to lead to more robust conclusions that using CMIP5 (with RCPs). While climate models are improving, at the spatial scales of individual cities and on time scales of decades both CMIP5 and CMIP6 provide projections that cannot be clearly differentiated.

We acknowledge that many of these issues are clearly highlighted in the literature. Bertram *et al* (2021) notes that 'findings from the Climate Impact Explorer should thus be used to supplement rather than replace national or regional risk assessments'. They further note that 'uncertainty in the climate sensitivity is sampled by considering four different GCMs', and that several impact models are used to sample the uncertainty'. Bertram *et al* (2021) also notes:

> *Following established approaches in the scientific literature (see e.g.* James *et al* 2017*), we assess impact indicators as a function of the GMT level. This means we assume that a given GMT level will on average lead to the same change in that indicator even if it is reached at two different moments in time in two different emission scenarios. This assumption is generally well justified and differences are small compared to the spread across changes projected by different models (*Herger *et al* 2015*).*

We strongly agree with these statements and emphasize the 'on average' and 'generally well justified'. The problem is, however, that while these approaches are well justified on average, the acute physical risks and the material extremes associated with regional-scale and finer scale climate change are not well described by averages. After all, the financial sector seeks to know *which specific* regions are most at risk, not that a fraction of the globe is at increased risk. If financial risk is aggregated to a continent, systematic errors associated with these assumptions might be averaged out, but the NGFS methodology is being used at a granularity well below that examined in this paper. This involves very significant uncertainties and determining whether climate change results in a *material extreme* is country, economy and business specific. At these scales, and in the context of material extremes associated with climate-induced weather-scale phenomenon, the ways in which the NGFS methodology are being employed is very likely misleading. There is a key implication here that is deeply concerning:

> *If all Central Banks (or the over 100 members of NGFS) use a methodology that is systemically biased, this could itself lead to a major systemic risk to the global financial system.*

The current NGFS scenarios do not represent the range of plausible climate outcomes possible at a country level—a systematic bias—and most banks, insurers and investors are using these scenarios *without fully accounting for uncertainty.* Misuse or misunderstanding of what climate models tell us, and assumptions that products like NGFS have utility at sub-national scales could make the risks we are trying to avoid through the NGFS scenarios worse. Rectifying this is important and requires an open collaboration between banks and the scientific community to develop scenarios appropriate for stress testing.

The most fundamental issue with assessing financial risk associated with acute physical risk relates to the acknowledgement that these risks are associated with weather, usually locally, and usually (but not necessarily) statistically extreme. The use of global climate models, which do not resolve weather-scales, are not appropriate for local scales and may not capture material extremes, is highly questionable. While using the quantitative information from climate models is tempting and provides a considerable amount of apparently precise information, failure to fully represent uncertainty leads to false confidence. By contrast, there are well-known ways to decouple assessments of acute physical risks from climate model quantitative information. Using climate models to inform scenarios, storylines (Shepherd 2019, Jack *et al* 2020) and stress testing, or using climate models to modify the statistics represented in current-day catastrophe modelling can all help break the false assumption that the numerical precision in climate models equates to accuracy at a granular level. In many ways, this echoes guidance from Schinko *et al* (2017) to consider models as tools to explore a system as distinct from predicting a system, or Saravanan (2022) who explores the need to take climate models seriously, but not literally. Given the material risks from climate change are commonly the tail risks, more use of catastrophe modelling might lead to decision making that builds more resilient systems. However, some material risks are likely associated with long periods of drizzle, or of high cloud cover and still winds. These are events associated with persistence which climate models are known to capture with relatively low skills (see for example Kumar *et al* 2013).

The relative ease with which large ensembles using IAMs can be generated and linked to acute risk at sub-regional scales is understandably attractive for large financial institutions, central banks and financial regulators. It is therefore unlikely that these will be wholly replaced by an alternative approach. This relative ease, however, hides immense uncertainty that is likely material, and that risks misleading an institution or regulator, exposing entities to litigation, and directly challenging centuries of accounting and assurance practice. We suggest three immediate actions:

(a) the NGFS method is likely misleading in determining granular level acute or material risks to the financial sector and we strongly advise that it is openly critiqued and does not become a *de* facto standard by default.
(b) no products or methods should be employed that fail to properly account for uncertainty, and how uncertainty is estimated needs very carefully consideration. There is no evidence that merely adding more climate models, or more estimates of GMT reduces uncertainty.
(c) there is a rich history of assessing risk at the local scale (Ranger *et al* 2022). This 'bottom-up' assessment can utilize historical climate data, existing risk estimates, analysis of the vulnerability of an entity to these acute physical risks, stress testing of investment portfolios and so on. The historical data can be perturbed using expert judgement based on multiple lines of evidence, including climate models. A financial institution should confront the 'top-down' methodologies proposed by regulators with bottom-up assessments of their acute physical risks and review how different the resulting estimates are.

Perhaps the single most important point here is that while the 'top-down' approach is likely to become the *de facto* standard for assessing a financial institution's exposure to climate change, this should only be done in conjunction with alternative 'bottom-up' methods.

Finally, we note that climate science and the science of climate projections is evolving rapidly. Further, regulation and disclosure linked with climate risk is developing rapidly. A company with the ability to undertake, at least to some degree, a bottom-up assessment of material risks, and to engage with external parties from a position of understanding, will be well positioned as climate projections change. A company with internal capability will be more able to ask the right questions, avoid buying risk advice that is misleading, and be able to identify opportunities associated with climate change more quickly. While building some internal capability might seem confronting and expensive, building future strategies on information that is not understood and is potentially misleading is likely more so, and quite possibly exposes the global financial system to systemic risks of its own making.

## Data availability statement

No new data were created or analysed in this study.

## Acknowledgments

The research was funded by the Australian Research Council Centre of Excellence for Climate Extremes (CE170100023). We are grateful to the National Computational Infrastructure at the Australian National University and the Earth System Grid Federation for making the CMIP6 model outputs available. We acknowledge the World Climate Research Programme, which, through its Working Group on Coupled Modelling, coordinated and promoted CMIP6. We thank the climate modelling groups for producing and making available their model output, the Earth System Grid Federation (ESGF) for archiving the data and providing access, and the multiple funding agencies who support CMIP6 and ESGF. We thank Philipp Aglas for help in providing some of the figures. Nicola Ranger acknowledges financial support from the UK Natural Environment Research Council (NERC Grant NE/V017756/1).

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