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Using expert elicitation to strengthen future regional climate information for climate services

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ABSTRACT

Climate change knowledge can inform regional and local adaptation decisions. However, estimates of future climate are uncertain and methods for assessing uncertainties typically rely on the results of climate model simulations, which are constrained by the quality of assumptions used in model experiments and the limitations of available models. To strengthen scientific knowledge for climate services and climate change adaptation decisions, we explore the use of structured expert elicitation to assess future regional climate change. Using the Lower Yangtze region in China as a case study, we elicit judgements from six experts on future changes in temperature and precipitation as well as uncertainty sources, and compare it with climate model outputs from the Couple Model Intercomparison Project phase 5 (CMIP5). We find high consensus amongst experts that the Lower Yangtze region will be warmer in the coming decades, albeit with differences in the magnitude of change. There is less consensus about the direction and magnitude of future precipitation change. Compared with CMIP5 climate model outputs, experts provide similar or narrower uncertainty ranges for temperature change and very different uncertainty ranges for precipitation. Experts considered additional factors (e.g. model credibility, observations, theory and paleo-climatic evidence) and uncertainties not usually represented in conventional modelling approaches. We argue that, in context of regional climate information provision, expert-elicited judgements can characterise less predictable, or less explored, elements of the climate system and expert-elicited reasoning provides additional information and knowledge that is absent from modelling approaches. We discuss the value in bringing together multiple lines of evidence, arguing that expert elicited information can complement model information to strengthen regional climate change knowledge and help in building dialogue between climate experts and regional stakeholders, as part of a more complete climate service.

Practical implications

Scientific knowledge can help decision makers better prepare for the risks and opportunities posed by climate variability and change. Within the field of climate modelling, scientists develop and use computer models to better understand climate processes and estimate future changes under different greenhouse gas concentration scenarios. While knowledge derived from these model outputs has informed national and international climate policy processes, uptake amongst sub-national decision makers in climate-sensitive sectors is limited. Climate services aim to support decision making, through translating climate data into tailored knowledge and products. However, climate services require relevant and reliable information, and estimates of future climate (i.e., climate projections) are inherently uncertain and constrained by model limitations. Climate service providers can therefore benefit from advances in alternative methods for characterising future regional climate knowledge.

In the context of future climate change in the Lower Yangtze region of China, this paper explores the use of structured

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interviewing techniques (elicitations) to capture expert judgements and additional knowledge for climate services. We elicit judgements from six experts on future changes in temperature and precipitation and associated uncertainty sources, and compare them with climate model outputs. Most experts agreed that the Lower Yangtze region will be on average warmer in the coming decades, although there is less consensus about changes in rainfall. Experts also considered additional factors (e.g., model credibility, theory and historical records) and uncertainties not usually represented in conventional modelling approaches.

Key methodological lessons for expert elicitation for regional climate change assessments are identified:

- Expert identification should be based on a systematic review of relevant literature, ideally conducted by scientists with expertise in regional climate and the necessary language skills to review all publications.
- Elicitation protocols should be developed iteratively, informed by best scientific practice and multiple trials with climate scientists.
- Elicitation interviews benefit from being conducted in person to build trust and rapport, ideally in the expert's workplace to allow easy access to relevant literature or data.
- Facilitators should allow time to explain key terms and provide experts with a clear understanding of what is required, without biasing responses.
- Treat all expert judgements as equally valid.
- The approach can be applied iteratively, as part of long-term climate services, allowing experts to update their judgements as new knowledge and evidence emerges.

Raw data on how experts' quantitative judgements agree or differ is unlikely to provide decision makers with clarity and confidence in how regional climate may change. However, our study demonstrates that expert-based information can provide a nuanced understanding of future regional climate that is not well captured in model-based information. It is important to focus on capturing explicit justification and reasoning alongside quantitative judgements. While climate service developers should not rely solely on information from expert elicitations, using this information can complement model information in certain contexts, e.g. when considering risks from low likelihood but high-impact events, such as the response of regional climate to large volcanic eruptions. Highlighting areas of consensus between expert judgements and climate model projections could help improve confidence and support decision makers in implementing adaptation strategies. Combining multiple lines of evidence can also enhance the co-development of engagement devices (e.g. regional climate risk narratives) and stimulate dialogue between diverse stakeholders on the relative plausibility of different climate scenarios for future planning decisions.

In summary, as a proof-of-concept we have demonstrated that expert elicitation methods should be considered within the 'toolbox' of approaches available to climate service developers, recognising their strengths and limitations. The approach outlined is flexible and, as a result, can cater for the diverse and complex demands of climate service developers in different regions and contexts. Yet further efforts are needed to demonstrate the use of expert elicitation in climate services, as well as develop best practice guidance in the design, implementation and evaluation of expert elicitation approaches used in future regional climate applications.

1. Introduction

1.1. Regional climate information for climate services

Scientific knowledge about future climate change is increasingly used to inform local and regional adaptation decisions (Weaver et al., 2013; Hewitt et al., 2020; Ranasinghe et al., 2021). Climate model experiments and projections are extremely useful for informing our understanding of climate processes and how the climate may respond under different greenhouse gas (GHG) concentration scenarios (IPCC, 2021). While, climate model information has informed policy processes (e.g. national adaptation plans (DEFRA, 2018), UNFCCC processes (Mimura, et al., 2014)), the use of projection-based knowledge is limited across wider societal sectors and communities (Kirchhoff et al., 2013; Singh et al., 2018; van den Hurk et al., 2018). To increase the use of climate science and information, the field of climate services has emerged (Hewitt et al., 2020; Ranasinghe et al., 2021). Successful climate services depend on the quality of the underlying scientific information (cf. Baldissera Pacchetti et al., 2021), and as a result systematic knowledge assessment is critical to enhance long-term trust and use of climate information (Otto et al., 2016; Haque et al., 2017).

Regional climate projections are largely based on climate model outputs, and dynamical (Xu et al., 2019) or statistical (Hewitson et al., 2014) downscaling of Global Climate Model (GCM) simulations. However, GCMs and downscaling methods have limitations, such as their inability to capture and accurately represent all key processes that influence climate at regional and local scales (Risbey and O'Kane, 2011; Knutti and Sedláček, 2013; Shepherd, 2014). Regional-scale variables influenced by complex dynamics and small-scale processes (e.g. those associated with precipitation) are particularly challenging to simulate, due to issues of simulation scale and imperfect process understanding. The resulting epistemic uncertainties from model projections are difficult to interpret (Stainforth et al., 2007; Risbey and O'Kane, 2011).

Methods for assessing uncertainty in regional projections (e.g. Monte Carlo analysis, Bayesian approaches) focus on quantifiable dimensions using model datasets, articulated typically as ranges, probabilities or confidence intervals (van der Sluijs et al., 2005). These approaches, whilst widely used (e.g. Qian et al., 2016), are insufficient when applied to climate change risk assessments for societal applications as uncertainty stemming from ignorance and non-independent errors is not easily quantified (van der Sluijs et al., 2005; Dessai et al., 2018). Climate models are constructed and validated based on knowledge and observations of past climate. Using them for long-term climate change projections requires assumptions of stationarity when extrapolating into the future (Stainforth et al., 2007). In addition, particularly at regional and local scales, climate models cannot be expected to capture the full complexity of the land–atmosphere-ocean system, and therefore climate models must be considered imperfect representations of the system which can be misleading in a decision-making context (Frigg et al., 2013). Moreover, they do not consider the quality of the underlying knowledge base and knowledge-making process; i.e. the social practices and cultures that shape models and prediction in climate science (see Mahony et al., 2019). Thus, there have been calls for wider application of expert judgment for the characterisation of uncertainty in future regional and local climate (Dessai et al., 2018; Thompson et al., 2016).

1.2. Expert elicitation

The goal of expert elicitation is to capture expert judgement of uncertain subject matters (Slottje et al., 2008). This can involve eliciting quantitative estimates of uncertain variables, or qualitative insights relevant to a particular scientific issue (Xing and Morrow, 2016). If systematically assessed, these scientific insights based on accumulated experience can make a valuable contribution to decision-making, particularly for local-scale climate variables, like precipitation, that are likely to remain deeply uncertain (Thompson et al., 2016).

A number of approaches to structured expert elicitation (SEE) have been developed, each with accompanying strengths and weaknesses (summarised in Appendix A: Table A1). Elicitations involving face-to-face interactions may encourage experts to think more carefully about their judgements (Knol et al., 2010) while anonymous elicitations (e.g.

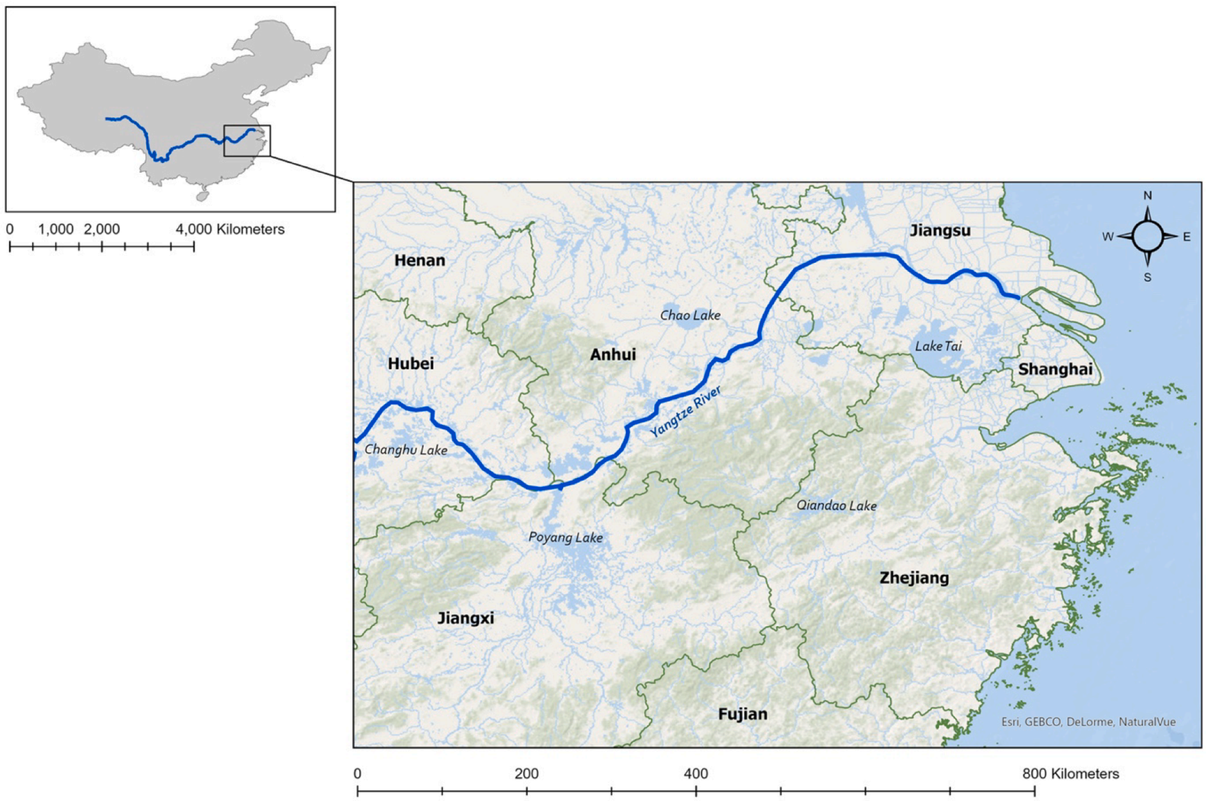

Fig. 1. The Lower Yangtze region of China (27°N to 33°N, 114°E to 123°E). The bold blue lines represent the main channel of the Yangtze River. Green shading represents higher elevation areas.

via surveys, software applications) may limit social desirability biases (Leggett et al., 2003). Individual elicitations work well for targeted investigations but they can be time consuming. Group elicitation, meanwhile, allows experts to share knowledge and consider different perspectives, but may lead to groupthink (Bolger and Wright, 2017) and encourage consensus even when it is not required (Slottje et al., 2008; Knol et al., 2010). Strategies for obtaining consensus judgements, such as the processes used by the Intergovernmental Panel on Climate Change (IPCC) (Mach et al., 2017; Mach and Field, 2017), come with the risk that more influential experts may dominate the process (Knol et al., 2010; Morgan, 2014). Other approaches, such as Cooke's Classical Model (Cooke, 1991), combine individual judgements post-hoc, weighing experts based on their performance on calibration questions. However, this requires a set of expertise-relevant questions where judgements can be compared to actual observations. While this could be applied in contexts such as weather and seasonal forecasting (e.g. using past events), suitable calibration questions are less readily available when it comes to judgements about unprecedented climate change. Moreover, experts can have very different assumptions about underlying mechanisms.

In climate research, expert judgement techniques have been used to estimate climate sensitivity (Morgan and Keith, 1995), sea level rise (Bamber and Aspinall, 2013; Horton et al., 2020), Antarctic ice loss (Oppenheimer et al., 2016) and tipping points in the climate system (Kriegler et al., 2009). They have also been used to characterise regional climate change uncertainty, including a survey-based pilot to explore the added value of evaluating North American regional climate models using expert judgement approaches (Mearns et al., 2017), and a group elicitation workshop to characterise plausible future climate narratives for the Indian Summer Monsoon focused on the Cauvery river basin (Dessai et al., 2018). Expert judgements are also a feature of Regional Climate Outlook Forums determining consensus-based seasonal climate outlooks (Daly and Dessai, 2018). Nonetheless, the use of individual and interview-based SEE in regional climate change assessments remains underexplored.

1.3. Aims

Using the Lower Yangtze region in China as a case study, this paper assesses the contribution of individual and interview-based SEE to regional climate change knowledge. This region was chosen because it is characterised by high uncertainty regarding future climate (particularly for change in the summer monsoon) (Christensen et al., 2013; Gutiérrez et al., 2021), densely populated urban areas and a long history of climate-related disasters (Sun et al., 2019). We use a relatively rapid approach to identifying experts, which can be easily adopted while being sufficiently rigorous. We develop a structured interview protocol, designed to elicit quantitative judgements and qualitative information from leading regional climate experts in China. We then use model outputs from phase 5 of Coupled Model Intercomparison Project (CMIP5) (Taylor et al., 2012) to compare the information provided by experts with results from climate model projections over the study region. This study is guided by the following research questions:

- How is temperature and precipitation in the Lower Yangtze region of China expected to change in the 2040 s and 2080 s?
- What are the key sources of uncertainty in estimating long-term changes in future climate in the Lower Yangtze region of China?
- What is the relationship between the elicited judgements and model results?

Section 2 describes the methods and study region. Findings are presented in Section 3, with Section 4 discussing key lessons and challenges to inform future research. Section 5 concludes by discussing the value in bringing together multiple lines of evidence, including expert judgments, in the context of climate services to support adaptation decisions.

2. Research design and methods

2.1. Case study region: Lower Yangtze region, China

Our case study region encompasses the Lower Yangtze river basin (hereafter the Lower Yangtze region) (Fig. 1). It covers approximately 577,000 km^2 (27°N to 33°N, 114°E to 123°E) across eight provinces of China (Anhui, Fujian, Henan, Hubei, Jiangsu, Jiangxi, Shanghai and Zhejiang). This region has a marine subtropical climate dominated by monsoon winds. The majority of total annual precipitation falls during the hot and humid summer season (JJA) (Xiao et al., 2015). The region is characterised by low, flat floodplains interspersed by numerous rivers and lakes in the north and more mountainous terrain in the south. The Lower Yangtze region has historically experienced extreme climate events and hazards such as storm surges, typhoons, urban pluvial floods and heatwaves (Sun et al., 2019). Climate change and future sea-level rise are expected to trigger more frequent and intense extreme climate events and hazards (Wang et al., 2017; Xie et al., 2018; Ranasinghe et al., 2021).

The north east of the region, often referred to as the Yangtze River Delta economic zone, has rapidly developed into the economic centre of China and one of the largest and most densely populated urbanised areas in the world (Sun et al., 2019). Accounting for ~ 2% of China's land area, the Yangtze River Delta represents ~ 11% of China's total population (~150 million people) and generates ~ 25% of the country's Gross Domestic Product (Yang et al., 2017). Rapid urbanisation has increased exposure and vulnerability to climate risks, with economic losses from climate-related disasters likely to be significant unless society can adapt to current and future climate variability and change (Ge et al., 2013). Improvements in the sharing of high quality information and knowledge across government departments has been highlighted as a critical component of future adaptation efforts in the region (Sun et al., 2019).

2.2. Methods

2.2.1. Structured expert elicitation

Sampling. Relevant experts were identified by systematically reviewing literature on multi-decadal climate projections for the Lower Yangtze region. Using Scopus's TITLE-ABS-KEY field, combinations of the following words were searched: "multi-decadal", "projection", "climat*", and "China". Papers focussing on the Lower Yangtze or Eastern region of China were selected. Those with the highest number of lead author papers and citations provided a list of scientists with relevant substantive expertise in this highly specialised field (n = 24). Most participants were recruited by contacting partners in the Climate Science for Services Partnership (CSSP) China project[1], jointly coordinated by the UK Met Office, China Meteorological Administration (CMA) and Institute of Atmospheric Physics (IAP) at the Chinese Academy of Sciences (Scaife et al., 2021). Due to limited success connecting with scientists outside of the CSSP China network, additional individuals were also recruited based on participants' recommendations of other experts with relevant knowledge, a technique known as snowball sampling. Ultimately, elicitations were limited to 50% of the target experts (n = 12); of these, six completed the elicitation and were included in the analysis. The sample nonetheless falls within the size recommended for expert elicitation (Cooke and Probst, 2006; Gosling, 2018; Bojke et al., 2021). Three experts were employed at the IAP (n = 3) and three at CMA (n = 3).

Elicitation procedure. Elicitations were completed in experts' workplaces to allow access to relevant literature or data, and took between 50 and 145 min (Appendix A: Table A2). The protocol (see Appendix B) was developed iteratively through multiple trials with scientists (cf. Morgan, 2014) at the University of Leeds with expertise in climate but not our case study region. Five elicitations were conducted in English, and one combining English and Mandarin. A map of China with baseline climate data (CN05 gridded observations for 1981 to 2010 (Wu and Gao, 2013)) and definitions of potentially ambiguous terms was provided (see Appendix C).

Elicitations focused on two sets of quantitative judgements: (1) estimates of future temperature and precipitation change, and (2) sources of uncertainty in estimating long-term changes in climate. Throughout, experts were encouraged by the facilitator to consider their responses carefully, provide justification for their judgements in as much depth as possible, and to explain how they had reached estimates and why the estimates could not be higher or lower.

Experts constructed twelve box and whisker plots to represent, as accurately as possible, their knowledge and beliefs regarding future changes in climate averages in the Lower Yangtze region, relative to a historical baseline (1981 to 2010), for mean annual, summer (JJA) and winter (DJF) temperature and precipitation for the 2040 s and 2080 s. Five values were elicited for each: the most extreme plausible upper and lower limits[2], a median and two quartile values. Experts were asked to consider all possible GHG concentration scenarios. Using an online boxplot grapher[3], each value was visually represented to allow experts to reflect on their judgements and, if necessary, revise it. Experts were asked to consider any 'imaginable surprises' that might affect their responses, such as a collapse of thermohaline circulation in the North Atlantic (see Schneider, 2004). During this part of the elicitation, the facilitator repeated judgements back to the participant, challenged its plausibility and (if necessary) revised judgements before recording final values (see Appendix B).

Experts were also asked by the facilitator to identify uncertainty sources and rank them from the largest to smallest contribution to overall uncertainty (in temperature and precipitation change), and finally, assign percentage contributions.

All participants were asked if they would like to meet again with additional time to conduct the elicitation and to reflect on the answers given. Experts 1 and 2 were interviewed on two separate occasions to give them the opportunity to complete the elicitations. On reflection, expert 1 revised their initial judgements and provided further justifications. Any original judgements that were revised were discounted from the analysis presented. Despite not providing median values or interquartile ranges, Expert 6′s judgements were retained since they were able to provide a complete set of maximum and minimum values. In section 4, we reflect further on the selection process, sample size, Expert 1's revised judgements and the potential reasons why some judgements could not be elicited.

2.2.2. CMIP5 analysis

Expert estimates of future climate changes and uncertainty source contributions were compared to the results of GCM simulations conducted for CMIP5. Mean annual, summer (June to August) and winter (December to February) surface temperature and precipitation changes for the Lower Yangtze region were calculated centred on the 2040s (2031 to 2060) and the 2080s (2071 to 2100), relative to a historical baseline (1976 to 2005); the baseline differs slightly to that used in the elicitations but was chosen because it represents the last 30 years of the historical simulations with observed radiative forcings. All available simulations from each CMIP5 GCM, where both precipitation and

[1] https://www.metoffice.gov.uk/research/approach/collaboration/newton/climate-science-for-service-partnership-china.

[2] Anything outside these limits was defined as exceptionally unlikely conditions (<0.01 and >0.99 percentiles).

[3] http://www.imathas.com/stattools/boxplot.html.

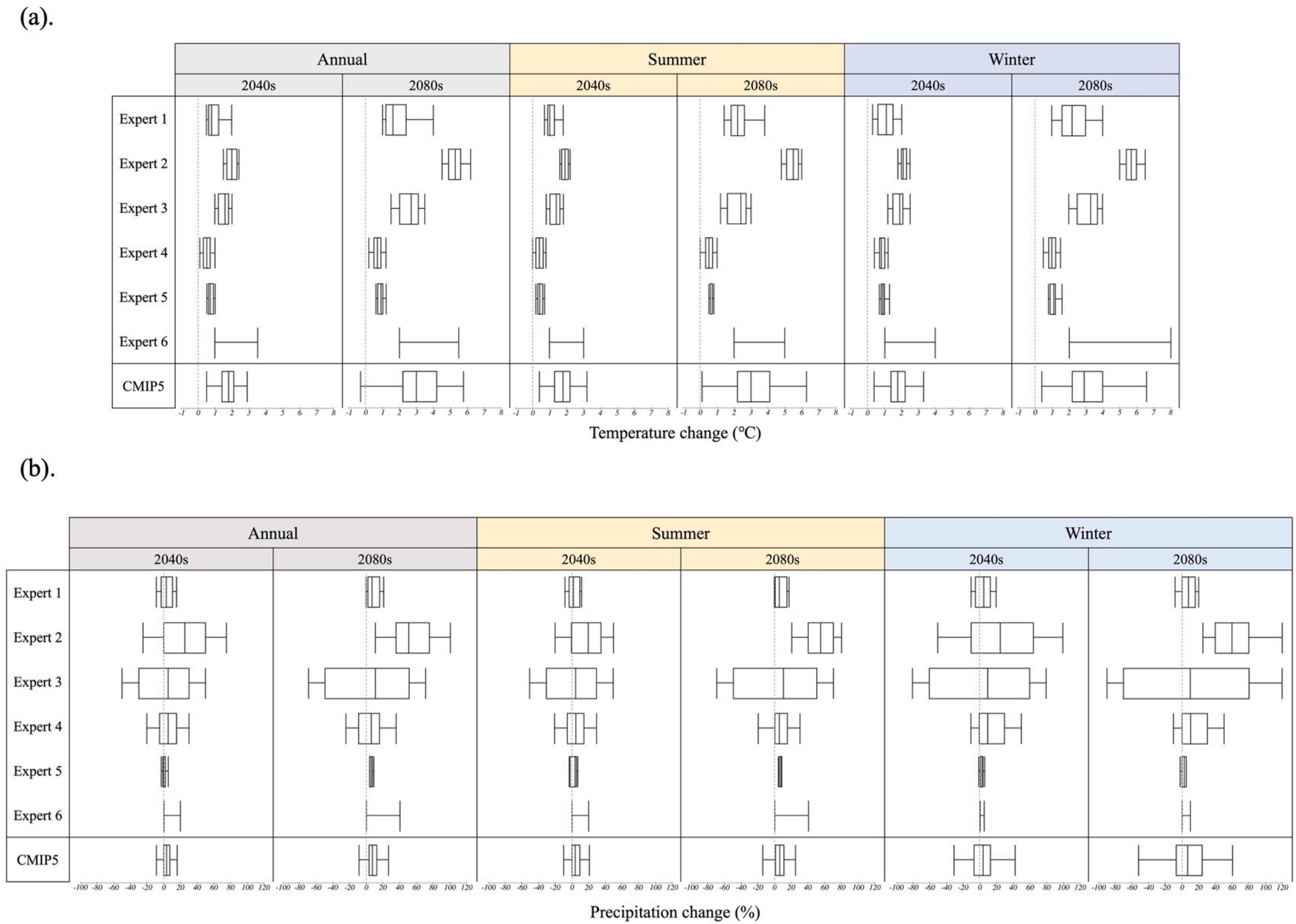

Fig. 2. Boxplots of future climate change in the Lower Yangtze region, China. For each plot, the first line to the left denotes the minimum value; the left vertical line of the box denotes first quartile; the internal vertical line denotes the median value, the right vertical line of the box denotes the third quartile; and the far right of the box denotes the maximum value.

temperature data were available, were included (110 simulations in total) and cover all available Representative Concentration Pathways (RCPs), RCP2.6, 4.5, 6.0 and 8.5 (see Appendix D). Simulations were assumed to be equally likely in our analysis.

Following Hawkins and Sutton (2009), contributions from three main sources of uncertainty (variability, model and scenario) were calculated for the Lower Yangtze region using the CMIP5 data analysed. For variability uncertainty, the mean standard deviation of results within each initial condition ensemble was calculated (for each model, scenario and time-frame). For model uncertainty, the standard deviation across model simulations for each RCP was calculated and then averaged for each time period (where there was more than one realisation, only the first model realisation was used). For scenario uncertainty, the standard deviation between the average result for each scenario was calculated for each time period. These values were then normalised to provide percentage contributions from each source of uncertainty.

3. Results

3.1. How is temperature and precipitation in the Lower Yangtze region of China expected to change in the 2040 s and 2080 s?

3.1.1. Structured expert elicitation

Figure 2 presents results for our climate variables of interest for the Lower Yangtze region (see also Appendix A: Table A3). Rows 1–6 represent each expert's quantitative judgement of mean annual, summer (JJA) and winter (DJF) surface temperature (Fig. 2a) and precipitation (Fig. 2b) for the 2040 s and 2080 s. The final row represents all available CMIP5 projections for the same variables.

Experts agreed that mean annual, summer and winter temperatures in the Lower Yangtze region would increase, although median estimates varied. For example, for mean annual temperature, Expert 4 estimated a median increase of 0.7 °C by the 2080 s, while Expert 2 estimated a median increase of 5.3 °C. All experts estimated increases in mean winter temperature by the 2040 s and 2080 s equal to or larger than summer or annual temperatures. Uncertainty ranges also varied between experts. Expert 5 estimated an increase in mean winter temperature with a relatively narrow uncertainty range (0.8 to 1.6 °C increase by the 2080 s), while Expert 6 estimated an increase in mean winter temperature with a relatively wide range (2 to 8 °C increase by the 2080 s).

Estimates of precipitation change varied substantially. Expert 4 estimated an increase in mean annual precipitation with relatively narrow uncertainty ranges (3 to 8% increase by 2080 s) while Expert 3 indicated a possibility of both positive and negative future change in mean annual precipitation with very wide uncertainty ranges (−70 to +70% change by 2080s). Experts 1 to 4 estimated that changes in mean winter precipitation will be larger than changes in summer or annual precipitation, while Experts 5 and 6 expected larger changes in the summer.

Experts provided qualitative information elaborating on their responses. Expert 1 provided the most detailed information, particularly in justifying responses for the precipitation variables. For temperature change, Experts 1 and 2 considered the spatial variability in rates of warming across China, with an expectation there would be less warming in the Yangtze compared with Northern China:

> *"In south China, including the Yangtze River* [temperature] *warms slower than the north part."* (Expert 1)

Expert 1 took into account warming that had occurred over recent decades and the difference between global rates of warming compared with warming rates on land:

> *"If you consider temperature change in recent decades, the temperature has increased 1* °C *from pre-industrial period. Over the land, the warming is usually higher than the global warming by 0.2* °C *on average. So in the 2040 s I think, based on my judgement, it can be in the summer 1* °C [increase compared to the present]." (Expert 1)

Expert 4 tempered their estimates of temperature change, reflecting that:

> *"The Yangtze is already very humid, so can't have much change."* (Expert 4)

Expert 6 reported amplified warming due to expected decreases in local aerosol emissions that have, until now, dampened anthropogenic warming and heat wave severity in the Lower Yangtze region.

Expert 1 explained their thought process behind the upper and lower bounds of their temperature estimates:

> *"The upper number is mainly determined by forcing, especially the greenhouse gases… and for the lowest number, internal variability and volcano influences."* (Expert 1)

During the second meeting, Expert 1 elaborated that the long upper tails (median – upper limit) in all of their temperature plots represent uncertainty in future emissions and model sensitivity. Comparing their judgement with historical multi-model ensemble results for the Lower Yangtze region, Expert 1 also explained that the upper limits of their plots were lower than model results to take into account recent advances in our understanding of climate sensitivity:

> *"Model results would give a larger warming* [than my judgement]*… some studies in recent year have reduced the uncertainties of climate sensitivity based on the observational data so I think the uncertainty of the climate sensitivity is not so much as the model told us.. the best estimation is similar to the model mean but the largest maybe not so large as the model… that's why I reduce the highest estimation of the model…* [information users] *should not just use the model data directly."*(Expert 1)

For winter temperature, Expert 6 reported greater uncertainty due to influences from the North Atlantic Oscillation (NAO). Their summer temperature estimates were lower than the annual values, reflecting their expectation that summer warming would be moderated by projected increases in cloud cover and rain in the Yangtze region as a whole. For winter temperature, Expert 1 presented a slight skew to the left of the median (compared with their annual value) to account for high levels of uncertainty in the mechanisms that drive cold surges from high latitudes and an increased likelihood of less warming compared to other seasons:

> *"The winter is more uncertain because it is not only influenced by the systems in the lower latitudes such as the subtropical high but… the variability in some cold surges from the north so the uncertainty in the north.. internal variability is much larger than in lower latitudes. With global warming, Atlantic Multidecadal Oscillation high latitude change will cause larger uncertainty."* (Expert 1)
> *"The range will increase because the lower bound maybe colder."*(Expert 1)

During our second meeting, Expert 1 explained why there was greater uncertainty at the lower end of the winter temperature plots (rather than annual or summer):

> *"In winter, the internal variability will influence more than in the summer… Eastern China is influenced by the cold surge from the north pole. In recent years.. it's not very stable… the polar vortex in the winter…* [so] *it is good to give a large uncertainty for the winter."* (Expert 1)

When revising initial precipitation change estimates, Expert 1 explained that a future increase in precipitation was more likely than a decrease due to higher levels of water vapour in the atmosphere caused by future reductions in aerosols in the region and increased greenhouse gas emissions globally. They explained how during the first elicitation they may have:

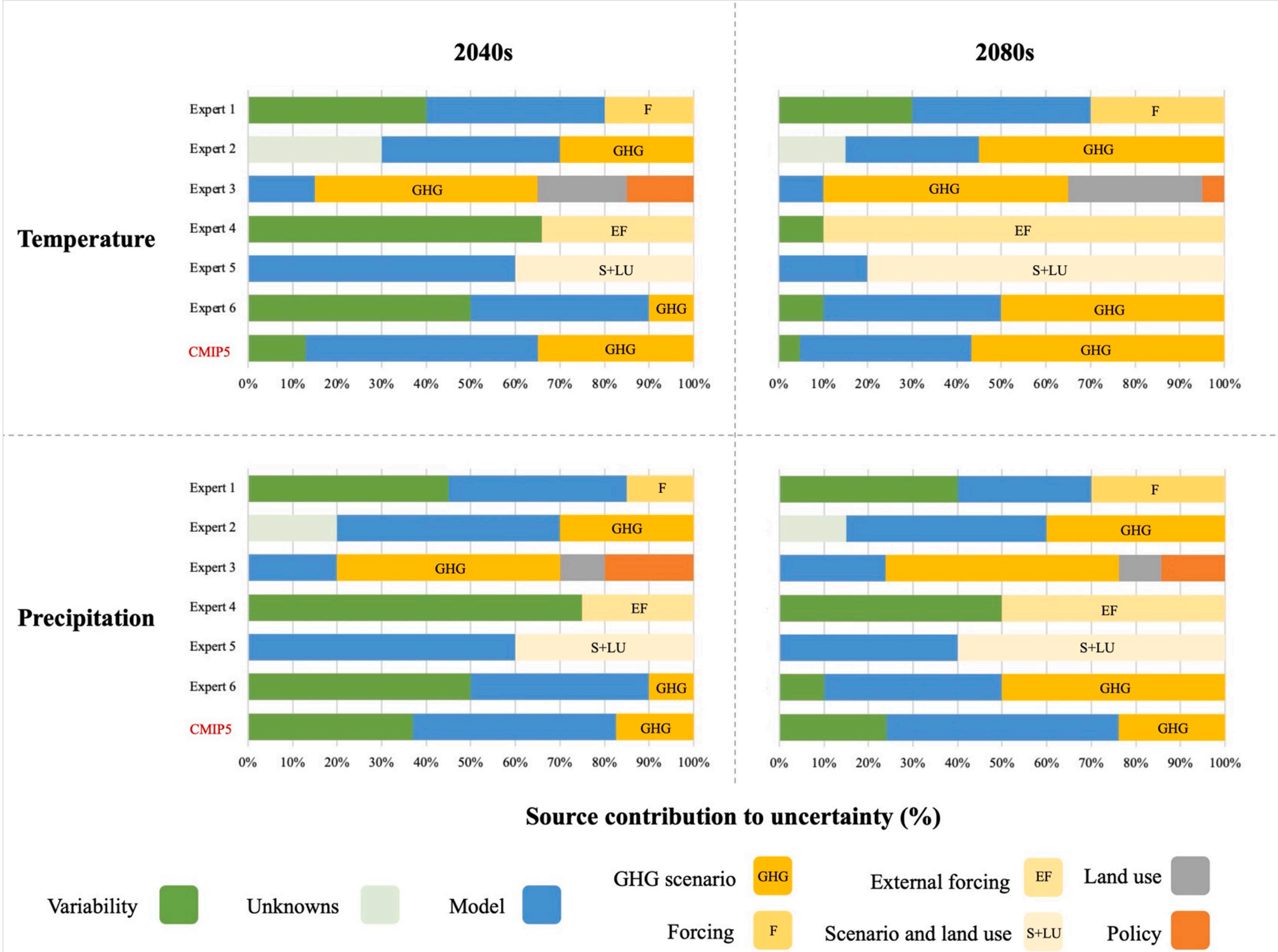

Fig. 3. Expert judgements of the percentage contribution to overall uncertainty when estimating mean annual temperature (top) and precipitation (bottom) for the 2040 s (left) and 2080 s (right) in the Lower Yangtze region, China. Bottom bars represent source contribution to uncertainty calculated using mean annual CMIP5 results for the Lower Yangtze domain.

"… *underestimated the contribution from external forcing, like aerosols and GHGs. In the future in China, the aerosols will decrease to not as much as now… these conditions will provide more water vapour… increasing precipitation.*" (Expert 1)

Expert 1 indicated that revisions were influenced by new model uncertainty emerging for the Yangtze relating to the position of the North West Pacific Subtropical High and an excessive cold bias when modelling the equatorial Pacific. For 2040s estimates, they reported that the sign of change is uncertain because factors related to circulation and internal variability were likely to dominate conditions in the near future compared to the underlying warming trend.

When estimating the upper limits of their precipitation estimates, Expert 1 explained that they should be constrained by warming and subsequent water vapour levels in the Indian Ocean as this is the main moisture source for the Yangtze region. Expert 6 gave upper limit estimates that they believed were higher than CMIP5 results for that region to account for recent convection-permitting model results. Their upper limits were doubled for the 2080 s to account for greater emission forcings, while lower limits remained at 0% to account for an expected reduction in aerosol emissions.

When estimating summer precipitation change for the 2040s, Expert 1 explained that their modest median estimate of 2% represents a significant change in absolute terms given how much rain falls during this season already:

"*The summer [is when] the most rainfall falls so 2% is very large.*" (Expert 1)

As a general comment, Expert 2 reported that other experts may consider their judgements to be controversial as they only take into account two GHG concentration scenarios (RCP 4.5 and 8.5) and are based on simulations from one climate model, considered to more accurately represent current climate in this region. Expert 6 also made an overarching comment that:

" [Future uncertainty in] …*local aerosols from factories is a particularly important factor for Yangtze projections.*" (Expert 6)

Expert 6 referred to relevant sections of IPCC AR5 throughout the elicitation. They were also unable to provide median or interquartile values because they considered local-scale model results too unreliable. These factors and the following statement suggest that this individual felt uncomfortable drawing solely on their experience:

"*Without data, I can see nothing.* [It would be] *just from imagination*" (Expert 6)

3.1.2. The relationship between the elicited judgements and model results

Box plots representing the CMIP5 data show the range of all available projections (across models, realisations and RCPs) for annual, summer and winter temperature and precipitation changes for the 2040s and 2080s (Fig. 2; see Appendix D for the complete dataset).

For temperature change, both expert estimates and CMIP5 projections show increases in annual, summer and winter temperatures in the Lower Yangtze region as more probable than a decrease, with an annual median value of 1.8 °C for the 2040 s (expert estimates range from 0.5 to 2 °C) and 3.0 °C for the 2080s (expert estimates range from 0.7 to 5.3 °C) from the CMIP5 simulations. In line with expert estimates, there are only small differences between projected changes in annual, summer and winter temperatures. However, specific aspects of the model results differ from some expert judgements. For annual temperature change, Expert 2 gave a higher median value of 5.3 °C for the 2080s, while Experts 4 and 5 gave lower median judgements of 0.5 °C and 0.7 °C for the 2040s and 0.7 °C and 0.9 °C for the 2080s, respectively. Some upper limit judgements for this variable were also considerably lower than the model-based results (5.8 °C for the 2080s) with Experts 4 and 5 both estimating an upper limit of 1.2 °C for the 2080s. The CMIP5 upper limit of 5.8 °C for annual temperature change in the 2080s is roughly consistent with Expert 2 and 6 estimates. However, in contrast to the entirely positive values elicited from experts, the model projections include a lower limit of −0.3 °C in the Lower Yangtze region (from a simulation under the RCP2.6 scenario). For uncertainty ranges, the model results span a wider range of uncertainty than expert judgements for nearly all six temperature variables of interest, most noticeably for the 2080s. Experts 1 and 6 estimates align most closely with model-based uncertainty range. Experts 4 and 5 estimates are significantly narrower than the model results. For example, for summer temperature change for the 2080 s Expert 5′s estimates range 0.3 °C while the model projection range 6.2 °C.

For precipitation change, both expert estimates and CMIP5 projections show increases in annual, summer and winter precipitation in the Lower Yangtze region as more probable than a decrease, with an annual median value of 3.2% for the 2040s (expert estimates range from no change to 25%), and 7.2% for the 2080s (expert estimates range from 5% to 50%) from the CMIP5 simulations. We found consistency between expert and model-based uncertainty ranges, suggesting that precipitation could decrease in the Lower Yangtze region. However, model projections differ from some expert judgements. For annual precipitation change, Expert 2 gave a higher median value of 25% for the 2040s and 50% for the 2080s, while Expert 5 estimated there will be no change for the 2040 s. The model results for annual precipitation change also indicate a small probability of mean annual precipitation decreasing for the 2080s, while Experts 2, 5 and 6 do not consider it plausible. In terms of uncertainty ranges, the annual model results (24.1% and 35.3% range for the 2040s and 2080s, respectively) sit between Expert 5 (8% and 5% range for the 2040s and 2080s, respectively) with much narrower ranges and Expert 3 with considerably wider ranges (100% and 140% range for the 2040s and 2080s, respectively). In line with Experts 1, 2 and 3, the model results suggest there is greater uncertainty over winter precipitation change than annual or summer change for the 2040s, but in particular for the 2080s. However, this trend is not reflected in the judgements of Experts 4, 5 and 6.

3.2. What are the key sources of uncertainty in estimating long-term changes in future climate in the Lower Yangtze region of China?

3.2.1. Structured expert elicitation

Key uncertainty sources were elicited with the temperature and precipitation change estimates. Expert judgements roughly aligned with established categories from scientific assessments, e.g. Hawkins and Sutton (2009): 'model uncertainty', 'variability' and 'scenario uncertainty'. However, specific terminology and conceptualisations varied and some experts identified uncertainty sources outside of those which are typically quantified using climate model experiments.

All experts apart from Expert 4 cited model uncertainty as a key uncertainty source. Experts 1, 4 and 6 cited internal variability, and all six experts cited either GHG concentration scenario or forcing uncertainty (or a comparable conceptualisation). These last two concepts align well, although forcing may include additional elements such as solar and volcanic activity which are usually assumed constant in climate model experiments. Expert 1 included both anthropogenic and natural forcings within their judgement, emphasising the potential influence of large volcanic eruptions on global climate in the coming decades:

"*If you want to know near-term change or decadal prediction, I think the volcano influence is very important to know how the temperature will change… Volcano is the largest* [natural forcing] *because we expect the solar not to change too much in the next 100 years.*" (Expert 1)

"*The rainfall… is also heavily influenced by the aerosol, both anthropogenic and natural aerosols like volcano emission.*" (Expert 1)

However, Expert 6 preferred to characterise future volcanic activity as exemptions, stating that:

"If there's a big volcano it can dominate… all the projections will be [worth] *nothing…* [but] *we can estimate the climate anomalies associated with a big volcano."* (Expert 6)

Expert 3 disentangled scenario uncertainty from uncertainty in future land use change and future policies related to GHG emissions, stating that:

"Policy uncertainty is different [from scenario uncertainty] *because policy makers make many policies that determine temperature and precipitation change… urbanisation is also very important* [in the Lower Yangtze region]." (Expert 3)

Finally, expert 2 cited 'unknowns' as a distinct and unquantifiable source, by stating that there are:

"Things we don't know." (Expert 2)

In addition to providing key sources, all six experts ranked and assigned percent contributions to overall uncertainty (Fig. 3). Judgements varied between experts, particularly when estimating change for the middle of the century (2040). However, when estimating change for the end of the century (2080), five out of six experts judged scenario uncertainty (or a comparable term) to contribute the most to uncertainty in temperature projections (ranging from 50 to 90%), and four out of six experts gave the same judgement for precipitation projections (ranging from 50 to 60%).

During a second meeting, Expert 1 increased the contribution from model uncertainty by 10% and 5% (while decreasing forcing uncertainty by the same amount) when estimating temperature change for the 2040s and 2080s, respectively. These judgements were revised to take into account additional uncertainties in CMIP6 models compared with CMIP5:

"I know the new [CMIP6] *models have very different sensitivities than CMIP5 models … that means that certainty in climate sensitivity has not improved…the new generation of the models, we know more accurate the physical processes that we didn't know very much before… but other results based on the observational data and techniques shows that climate sensitivities may be closer to the ensemble mean of CMIP5 models… so I think the model uncertainty should be increased* [compared with 1st judgement]." (Expert 1)

3.2.2. The relationship between the elicited judgements and model results

Source contribution to overall uncertainty also varied between experts and CMIP5 outputs (Fig. 3). When projecting mean annual temperature change for the 2040 s, we found substantial disagreement between the experts and the CMIP5 outputs; the latter considering variability to be of less relative importance than any of the experts. For longer-term temperature change (2080 s), we found consistency between experts and the CMIP5 data, indicating that scenario uncertainty (or a comparable term) dominates. When projecting annual precipitation change for the 2040s, we found some agreement between Experts 2 and 5 and the CMIP5 data, considering model uncertainty to be the largest contributor. For longer-term precipitation change (2080s), we found substantial disagreement between the experts and the CMIP5 data; Experts 3, 4, 5 and 6 judged scenario uncertainty (or a comparable term) to be the largest contributor while the CMIP5 data indicated that model uncertainty continues to be the largest contributor, though scenario uncertainty is larger than in the 2040s.

4. Discussion

4.1. Characterising future regional climate over China using structured expert elicitation

Our analysis reveals consistencies and differences between experts, as well as between experts and climate model outputs. Here, we discuss what we have learned about climate change in the Lower Yangtze region, reflecting on the methodological challenges of applying this approach in China.

4.1.1. Future climate change in the Lower Yangtze region, China

We find consensus amongst experts that temperature will increase in the Lower Yangtze region over the 21st century, albeit with differences in the magnitude of change. However, there is less consensus around the direction and magnitude of future precipitation change.

For temperature change, Experts 1 and 6 provided wider uncertainty ranges than other experts. Expert 6′s responses for winter may link to their consideration of the NAO's uncertain role in modulating the region's climate. These experts are in the same research group and have co-authored papers together, meaning similarities may arise from familiarity with the same modelling studies.

For precipitation change, Expert 2′s median values are higher and Expert 3′s uncertainty ranges are wider than other experts. Historical records show that from 1950 to 2000, total summer precipitation over the Lower Yangtze region increased by approximately 12% (Zhang et al. 2005). Some of the very large changes included in the judgements provided by Experts 2 and 3 (exceeding 50% changes) may therefore be implausible and warrant further consideration. Expert 5 provided narrower uncertainty ranges than other experts. However, limited justification was provided only commenting that their 'no change' estimate in annual precipitation for the 2040s was based on multi-model ensemble outputs. Similarly, Expert 2 referenced specific RCP scenarios and simulations from one model when providing estimates.

The qualitative data gathered does not explain all of the differences found. For example, why Expert 4 and 5′s upper temperature limits are so much lower than others, or why Expert 4′s precipitation median values are the same for the 2040s and 2080s.

4.1.2. Uncertainty sources

Judgements on uncertainty sources broadly align with established categories from scientific assessments: 'model uncertainty', 'variability' and 'scenario uncertainty'. However, specific terminology varied between experts. Additional uncertainty sources were identified that are not typically quantified using climate model experiments, including uncertainty in future volcanic activity and other global climate system 'unknowns'. This diversity likely arises from differences in backgrounds, experiences and mental models of uncertainty.

There was agreement that scenario uncertainty (or a comparable term) contributes most to uncertainty for the end of the century (2080s). Experts 1 and 6 highlighted that model projections do not capture the potential influence of large volcanic eruptions on future climate. Few provided explicit justification for a specific 'contribution' value (see 3.2.1). Instead, experts typically referred to region-specific factors that might determine contributions relating to the ability of models to capture topography, future urbanisation, and errors or biases within current observations. They also discussed gaps in current understanding and model disagreement, particularly in relation to the mechanisms influencing monsoon precipitation. Experts often referenced specific models they had helped develop or were familiar with, indicating that experts' specific research backgrounds and experiences played a role in their judgements. For example, Expert 3′s research into urban heatwaves in the lower Yangtze region may explain why they conceptualised land use and policy as distinct sources of uncertainty.

4.1.3. The relationship between the elicited judgements and model results

Experts and model results agree that temperature will increase in the Lower Yangtze region this century, albeit with differences in the magnitude of change. Compared with CMIP5 outputs, experts provide similar or narrower uncertainty ranges for temperature change with most similar ranges provided by expert 6. This suggests that some experts are not taking into account all factors when estimating future temperature change. The similarity between expert 6′s judgements and model results could be due to this expert referring to relevant sections of IPCC AR5 throughout the elicitation.

For precipitation change, the ranges provided by expert 4 are most similar to model results. We find little consensus between expert judgements and model results, though most experts agree with the model results that both increases and decreases in precipitation are plausible. It is possible that familiarity with CMIP5 model results contributed to this relationship. Future studies seeking to compare expert judgements with existing knowledge sources could disseminate a questionnaire before the interview process to ascertain prior knowledge. As mentioned in section 4.1.2, uncertainty sources identified by experts broadly align with the three categories used in our analysis of CMIP5 outputs. However, experts often used different terminology and conceptualisation from scientific assessments, making it difficult to directly compare expert judgements and model results.

4.2. Challenges and lessons learnt from the expert elicitation process

4.2.1. Case study-specific challenges and lessons

Our study identified leading experts in multi-decadal climate projections for the Lower Yangtze region based on a systematic review of English-language articles. Additional researchers who predominantly publish in Chinese journals may have therefore been excluded from our search. Nonetheless, conversations with CMA and IAP researchers indicated that Chinese researchers are heavily incentivised to publish in high-impact international English-language journals accessible via Scopus.

Indigenous socio-cultural concepts and norms are fundamental to professional relationship building in Chinese contexts. Key among them is *Guānxi*, roughly translated as interpersonal relationships characterised by reciprocal benefits and trust-building (Ding et al., 2017; Davison et al., 2018). Without *Guānxi*-based social support networks and extensive in-country time, we found it difficult to gain access to experts and persuade them to participate. Instead, we relied on our colleague's existing relationships and obligations through the CSSP China programme. With only six of the twelve initial participants able to provide a complete set of judgements, a shift towards snowball sampling based recommendations may have skewed the selection process. For example, Chinese colleagues could have recommended individuals they shared *Guānxi* with or those that have high hierarchical status within their network.

Using a non-native language in the elicitation process presents significant barriers to the ability of some experts to convey their thought process and reasoning. Cross-cultural studies, and our own observations, find that compared to native English speakers, native Chinese speakers are less inclined to communicate probabilistically[4] (Phillips and Wright, 1977). Within a Chinese cultural context, individuals who do not share *Guanxi* are less likely to feel "morally and mutually obligated" to exchange knowledge (Farh et al., 1998; Ding et al., 2017; Davison et al 2018). Moreover, collectivist values and a preference for precedent-matching over analytical modes of decision making (Weber and Morris, 2010) may explain why some participants seemed more comfortable relying on model results rather than drawing on their individual accumulated experience.

These linguistic and cultural factors suggest that, while our Chinese partner's *Guānxi* may have indirectly helped recruitment, the transient and non-reciprocal nature of our relationship with participants (in other words, the absence of *Guānxi*) could have influenced their levels of comfort and engagement in the process, and ultimately, willingness to provide judgements and justifications. However, these limitations are not completely unique to a Chinese context and we would argue that the accessibility of scientists through the CSSP China programme was a strength of our approach.

In addition to the practical and cultural challenges outlined above, our comparatively small sample size results from focussing on a highly specialised research topic. Based on our literature assessment and conversations with experts, we estimate that 50 individuals have sufficient expertise to participate. While a larger sample would have been desirable, the sample of 6 does nonetheless meet most recommended sample size requirements for expert elicitation (Bojke et al., 2021, p. 4–35).

The difference between judgements from experts based at the same institution, and in some cases same research group, reinforces the appropriateness of the decision to conduct individual rather than group elicitations. The elicitation protocol was designed to be completed in 1 h, although all participants were given as much time as they needed. In reality, five of the six elicitations were between 50 and 80 min in duration. The exception was the first meeting with Expert 1, which lasted 145 min. This may have been due to the presence of an additional interviewer stimulating more reflection and discussion. Alternatively, it may reflect Expert 1′s depth of expertise and engagement in the process. Expert 1 was also the only participant to voluntarily revise their initial judgements and provide further justifications. The detailed qualitative information generated during this meeting suggests that a two-stage elicitation process could actually be advantageous, with the gap between meetings allowing for further reflection.

4.2.2. Universal challenges and lessons

In addition to study-specific barriers, we have identified a number of universal challenges and lessons inherent to expert elicitation studies for regional climate change assessments.

The literature review process that informed expert identification was constrained by our level of expertise in regional climate and restricted to English-language journals. Future applications would benefit from drawing on wider expertise and additional language skills during the selection process, and collaborating with in-country partners that are able to review articles written in other languages in the review stage.

Selecting experts based on their number of lead author papers and citations brings limitations but is a practical approach for rapidly identifying individuals with verified expertise. Rather than trying to identify the 'best' experts, the selection process should focus on assembling a sample that represents all major perspectives and responsible interpretations across the field (Morgan, 2014). If time is available, this could be achieved by collaborating with scientists familiar with the broader regional climate literature and sorting potential participants by background and technical perspective. Studies suggest proxies for cognitive diversity (e.g. age, gender, cultural background, life experience and education) should also be prioritised (Page, 2008; Hemming

[4] Phillips and Wright (1977) defined *Probabilistic thinking* as "the tendency to view the world in terms of uncertainty, the ascribing of different degrees of uncertainty to events, and the ability meaningfully to express that uncertainty either verbally or as a numerical probability" (p. 507).

et al., 2018); although, this may be restricted for topics where only a relatively small number of specialists or research groups exist.

While snowball sampling was a practical adaptation in our case, we advise against overreliance on peer recommendations, as people may be more inclined to nominate those with similar opinions, thereby limiting diversity of perspectives (see Bojke et al. 2021). Participant self-selection should also be avoided due to people's inability to recognise their own level of expertise, known as 'the Dunning–Kruger effect' (Kruger and Dunning, 1999). Depending on personality traits, actual competence and cultural context, this can lead to either over or under recognition (Welsh, 2018). For example, studies from Japan have shown that there are cultural incentives to underestimate one's own expertise (Heine et al., 2001). While the inaccessibility or lack of regional climate expertise could limit elicitation studies in some regions, we nonetheless advise against relying on more accessible foreign experts, especially from the Global North, as subsequent information may not be perceived as legitimate by local decision makers (Dessai et al., 2018).

Some experts were unable to provide complete sets of judgements and explicit justification for each of their judgements. It should not be underestimated how unusual, complex and intellectually challenging it must be to take their experience, adapt to a new circumstance and communicate in a non-native language to a non-expert interviewer. To help elicit more qualitative information, we suggest future studies keep other expert judgements on hand so that, if a value elicited is an extreme outlier, they can seek explicit justification. While it is essential to challenge experts to provide reasoning for each of their judgments, interviewers must act impartially and not create doubt in the expert's mind. Power asymmetries between interviewer and participant may also affect the extent to which experts engage in the process. While diversity of expert terminology and conceptualisation is to some extent unavoidable, key terms within the protocol (e.g. uncertainty, plausibility), and the geographical domain in question, should be defined in advance. Despite being encouraged to think about extreme scenarios and draw from their accumulated experience, some experts may still fall back on their memory of model results.

Even if interviewers are skilled and well prepared, the expert's engagement, language proficiency and interpersonal skills determine to a large extent the depth of discussion and duration of elicitations. While the interview protocol should be consistent and participants should be given the same opportunities to respond, it is more important that experts are given as much time as they require to generate additional insights. Future studies could spread the protocol across a longer time period or incorporate multiple breaks. Alternatively, it might be advantageous to repeat the protocol (as mentioned in 4.2.1) after a week or more to allow for reflection and explore the potential significance of introducing new knowledge.

How expert judgements and associated justifications are then interpreted and used depends very much on the primary objective of the elicitation process. Some studies attempt to assess the quality of expert judgements (see Cooke and Goossens, 2008) while others seek to generate a consensus or 'most correct' judgement (Dalkey and Helmer, 1963). However, we argue that, in the context of regional climate information provision, reporting where there is convergence and diversity is itself valuable information for adaptation decision making (Slottje et al., 2008). Expert assessment or 'weighting' would require judgements to be compared with actual observations. Future research could focus on the feasibility of generating suitable calibration questions for long term climate change.

5. Strengthening future regional climate information for climate services

5.1. Expert judgement techniques

Expert judgement techniques offer several advantages when characterising future regional climate for climate services. First, experts can provide a nuanced understanding of regional-scale processes and uncertainties that are not well captured in climate model experiments. In this study, Expert 6 offered insight into the potential impact of decreasing aerosol emissions on future warming and heat wave severity in the Lower Yangtze region (see Li et al., 2016; Wang et al., 2016; Chen et al., 2019). Risk averse decision makers may need to consider high-impact, low-probability events (Taylor et al., 2021), such as the regional climatic impact of large volcanic eruptions. Expert-elicited judgements can characterise these less predictable, or less explored, elements of the climate system that, although common in research contexts (e.g., Paik and Min, 2018; Dogar and Sato, 2019), are not routinely included in such experimental designs as CMIP5, which support global and regional climate projections. Expert justifications (explaining their reasoning behind judgements) are the most valuable outputs from a SEE applied to regional climate change as they provide additional information and knowledge that is absent from modelling approaches.

Nonetheless, expert judgement techniques have limitations and it is important to identify the contexts in which it provides added value. SEE as a method has limited value in a decision making context if experts cannot explain their reasoning behind judgements. Reporting diversity alone provides very little clarity or confidence about how a region's climate might change. In the same way that approaches to selecting the 'best' climate model are flawed (Knutti, 2008), so too are assessments of expertise that attempt to select a 'best' expert. All experts have partial knowledge and use different mental models to make their judgement (Morgan et al. 2002). Analogous to the benefits of using a 'multi-model' approach, consulting multiple experts will help in contrasting judgements and understanding areas of agreement and disagreement. Expert 1′s second meeting demonstrates that judgements are not fixed; they are likely to change as new knowledge emerges and expertise evolves. Therefore, in the same way as the evolution of climate modelling experiments in the CMIP programme, judgements may be updated over time based on new science and understanding.

5.2. Multiple lines of evidence

Given the strengths and weaknesses of modelling approaches and expert judgements, it is worth considering what can be gained by combining approaches and taking into account multiple lines of evidence. We argue that SEEs have the potential to provide a richer, more nuanced understanding of climate change in a particular region. These approaches also bring to light sources of uncertainty that are either not included or not well represented in model experiments. However, because information provided by experts is not constrained (as is the case for dynamical climate models), further interrogation may reveal some judgements to be implausible (e.g., potentially ranges provided by experts 2 and 3 for precipitation change in our study). We therefore discourage decision makers from applying expert judgement in isolation. Considering model outputs alongside expert information can sometimes provide clarity. For example, where expert and model values and ranges converge, more robust scenarios and adaptation strategies can be developed. On the other hand, divergence may demonstrate a need to consider other lines of evidence before making potentially maladaptive decisions.

SEE should be seen as a method available to climate service providers to go beyond the reliance on climate model information, enrich knowledge and understanding, and to provide qualitative information that can support climate service users in interpreting and applying model information (see Doblas-Reyes et al., 2021 for a more detailed discussion). In fact, SEE's value extends beyond climate services to other decision making contexts where uncertainty is high. In our study, Expert 1 provided much needed nuance by explaining that, as a result of recent advances in our understanding of climate sensitivity, the upper limit of temperature estimates should be lower than previous model results suggest. This expert also recommended that climate service users interested in future temperature change in the Lower Yangtze do "*not just use the model data directly*" (Expert 1). This type of insight could be useful for climate service users when trying to assess the likelihood of low or high magnitude projections.

It may also be useful as a way to combine quantitative and qualitative information to form narratives or storylines, to help engage broader and non-scientific audiences (Dessai et al., 2018; Shepherd et al., 2018; Jack et al., 2020). By bringing together diverse stakeholders in regional climate (experts, service providers, decision makers and civil society) with the results from model and elicitation approaches, a dialogue can help to unpack contradictions between expert judgements and assess the plausibility and likelihood of future climate scenarios to support future planning decisions.

5.3. Concluding remarks

In this study, we explored the value of characterising future regional climate knowledge through SEE. Amongst leading experts in regional climate change in the Lower Yangtze region we find high consensus amongst experts that mean temperatures will increase in the region over the 21st century, albeit with differences in the magnitude of change. However, there is less consensus around the direction and magnitude of change for future precipitation and contributions from different sources of uncertainty. Our findings indicate the potential to move beyond the current practice of relying solely on model information to develop regional climate projections, which are subject to poor or incomplete characterizations of some known uncertainties (e.g., impacts of volcanic eruptions, or aerosol emission changes).

Our analysis builds on previous studies highlighting the potential value of eliciting otherwise hidden expert knowledge through careful elicitation (Oppenheimer et al., 2016). To further advance this area, we urge future studies to clearly document what has and has not worked. It would also be interesting to examine whether and how scientific training, cultural background, and mental models of uncertainty influence expert judgements. Our findings clearly show that scientific practices (e.g., climate modelling and prediction) are shaped by local epistemic, institutional and political cultures (Mahony et al. 2019). Subsequent elicitation studies should contribute to scholarly work on how climate knowledge is produced and validated, and uncertainties "perceived, negotiated and controlled", in different cultural contexts (Heymann et al., 2017). Future research could also focus on developing strategies to integrate and present these different knowledge types in a way that engages local and regional adaptation decision makers.

As a proof-of-concept, this work demonstrates that SEE, used alongside modelling approaches, can contribute to a richer understanding of regional climate knowledge for use in climate services. When elicitations are carefully planned and facilitated, and participants are comfortable with the process, rich and useful qualitative information can be elicited from experts. The approach is flexible and can be conducted relatively quickly (e.g., compared with running and analysing climate model simulations), therefore catering for the diverse and complex demands of regional climate services providers. Elicitation methods should be considered within the 'toolbox' of approaches available to climate service providers, recognising their strengths and limitations in different contexts. These types of knowledge assessments have the potential to engage a broader set of stakeholders and open model assumptions up to closer scrutiny, thereby improving the usability and credibility of future regional climate information for adaptation decisions.

CRediT authorship contribution statement

Sam Grainger: Methodology, Investigation, Writing – original draft, Visualization. **Suraje Dessai:** Methodology, Writing – review & editing, Supervision, Funding acquisition. **Joseph Daron:** Investigation, Writing – review & editing. **Andrea Taylor:** Methodology, Writing – review & editing, Project administration, Funding acquisition. **Yim Ling Siu:** Funding acquisition, Writing – review & 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.

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Appendix A:. Additional figures

Table A1
Advantages and disadvantages of different structured expert elicitation approaches (adapted from Bojke et al., 2021).

Choices in eliciting expert judgement	Advantages	Disadvantages	Example
Elicit at individual level	Reduces risk of judgement biases and groupthink arising from social influences.Promotes individual ownership of judgements and enables comment rationale for judgements.	Experts unable to reflect on and revise judgements based on relevant information raised by other experts.Can be time consuming to perform separate elicitations.	Cooke's classic method (Cooke, 1991)
Elicit at group level	Experts are able to consider and integrate information from others when forming judgments.Enables consensus judgements to be reached.	Risk of groupthink, with more senior (or more vocal) individuals dominating the discussion and therefore subsequent consensus judgements.	IPCCClimate Outlook Forums (see Ogallo et al., 2008)
Elicit at the individual and group level	Allows experts to generate independent judgements, before considering, reflecting and revising them based on information provided by other experts in an iterative way to build a consensus judgement.Some combined approaches such as Delphi, limit direct interactions that could introduce social biases.	Procedure can be time consuming, requiring experts to commit to several iterations.When anonymity is preserved clarification cannot be directly sought from other experts.Any direct interaction between experts carries the risk of introducing social biases.	Delphi (Rowe and Wright, 1999) SHELF (Oakley and O'Hagan, 2010)IDEA (Hemming et al., 2018)
Weight experts based on calibration questions	Identifies experts who are good at making probabilistic judgements and gives greater weight to their judgements.	Calibration questions require that judgements be compared with actual observations. While this may be feasible for weather and seasonal climate forecasting. For long term climate change suitable calibration questions may not exist.	Cooke's classic method (Cooke, 1991)
Mathematically aggregate judgements	Useful in cases where the goal is to create a single distribution, without having a group consensus.	Less useful when one is principally interested in identifying areas of consensus and disagreement.Ignores qualitative considerations about why particular judgements were made.	Linear pooling (Soares et al, 2018)

Table A2
The dates and duration of the structured expert elicitations selected for analysis.

Expert	Date	Duration
1	29/11/17	2hrs 25mins
	01/04/19	1hr 20mins
2	08/12/17	10mins
	18/04/18	1hr 05mins
3	29/03/18	55mins
4	19/04/18	50mins
5	02/05/18	55mins
6	01/04/19	1hr 15mins

Table A3
Quantitative judgements on future climate change in the Lower Yangtze region, China. Numerical summary of values elicited for annual, summer, winter temperature and annual, summer, winter precipitation projections for the 2040 s and 2080s.

Variable of interest	Expert 1					Expert 2					Expert 3					Expert 4					Expert 5					Expert 6					CMIP5				
	Min	Q2	Med	Q4	Max	Min	Q2	Med	Q4	Max	Min	Q2	Med	Q4	Max	Min	Q2	Med	Q4	Max	Min	Q2	Med	Q4	Max	Min	Q2	Med	Q4	Max	Min	Q2	Med	Q4	Max
Annual temperature change (°C) by 2040s	0.5	0.6	0.8	1.2	2.0	1.5	1.7	2.0	2.3	2.4	1.0	1.2	1.6	1.8	2.0	0.1	0.3	0.5	0.7	1.0	0.5	0.6	0.7	0.9	1.0	1.0				3.5	0.5	1.4	1.8	2.1	2.9
Annual temperature change (°C) by 2080s	1.0	1.2	1.6	2.4	4.0	4.5	4.9	5.3	5.6	6.2	1.5	2.0	2.7	3.1	3.5	0.2	0.5	0.7	0.9	1.2	0.6	0.7	0.9	1.0	1.2	2.0				5.5	−0.3	2.2	3.0	4.2	5.8
Summer temperature change (°C) by 2040s	0.7	0.9	1.0	1.3	1.8	1.6	1.7	1.9	2.1	2.2	0.8	1.0	1.4	1.6	1.8	0.0	0.2	0.4	0.6	0.8	0.2	0.3	0.4	0.6	0.7	1.0				3.0	0.4	1.3	1.8	2.2	3.2
Summer temperature change (°C) by 2080s	1.4	1.8	2.2	2.6	3.8	4.8	5.1	5.5	5.8	6.0	1.2	1.6	2.4	2.7	3.0	0.0	0.3	0.5	0.7	1.0	0.5	0.6	0.7	0.7	0.8	2.0				5.0	0.1	2.2	3.0	4.1	6.3
Winter temperature change (°C) by 2040s	0.3	0.6	1.1	1.5	2.0	1.8	2.0	2.1	2.3	2.5	1.2	1.5	1.9	2.1	2.5	0.4	0.7	0.8	1.0	1.2	0.7	0.8	0.9	1.0	1.3	1.0				4.0	0.4	1.4	1.8	2.2	3.3
Winter temperature change (°C) by 2080s	1.0	1.6	2.2	3.0	4.0	5.0	5.4	5.7	6.0	6.5	2.0	2.5	3.3	3.7	4.0	0.5	0.8	1.0	1.2	1.5	0.8	0.9	1.1	1.2	1.6	2.0				8.0	0.4	2.2	2.9	4.0	6.6
Annual precipitation change (%) by 2040s	−9	−3	3	10	15	−25	0	25	50	75	−50	−30	5	30	50	−20	−5	5	15	30	−3	−1	0	2	5	0				20	−9	0	3	7	16
Annual precipitation change (%) by 2080s	−1	1	6	15	20	10	35	50	75	100	−70	−50	10	50	70	−25	−10	5	15	35	3	3	5	7	8	0				40	−9	3	7	12	26
Summer precipitation change (%) by 2040s	−8	−3	2	10	12	−20	0	20	35	50	−50	−30	5	30	50	−20	−5	5	15	30	−3	−2	4	6	7	0				20	−10	0	4	9	21
Summer precipitation change (%) by 2080s	−1	0	5	14	17	20	40	55	70	80	−70	−50	10	50	70	−20	0	5	15	30	4	5	7	8	8	0				40	−14	1	6	11	25
Winter precipitation change (%) by 2040s	−10	−5	5	13	20	−50	−10	25	65	100	−80	−60	10	60	80	−10	0	10	30	50	−1	1	3	4	6	0				5	−31	−7	4	13	42
Winter precipitation change (%) by 2080s	−8	0	8	16	20	25	40	60	80	120	−90	−70	10	80	120	−10	0	10	30	50	−2	0	3	5	5	0				10	−52	−7	7	24	61

Appendix B:. Expert elicitation protocol

Introduction checklist

- Firstly, thank the participant for their time.
- Ask if they have done anything like this before?
- Introduce protocol
  - We will start with questions about your expertise and key sources of uncertainty for multi-decadal projections of temperature and precipitation change. During the second part of the elicitation, we will elicit quantitative estimates of future changes in specific climate variables. This will be your professional judgement, based on your expertise and interpretation of the evidence. Please tell us if you haven't reflected upon the topic in question or feel it is too far outside your area of expertise.
- In reporting the results of this study, you will be listed but not associated with your specific responses.
- Seek informed consent for participation and having their responses recorded.

START OF PROTOCOL

I. Opening questions

- For the record, what is your scientific background and area of expertise (inc. timescales/regions of interest)?

II. Characterisation of uncertainty

1. For the Lower Yangtze region, what are the key sources of (contributors to) uncertainty when trying to estimate long-term future changes (30-year averages) in [insert variable]? (Encourage them to explain/elaborate on theory & literature, if necessary)

2. Out of these, what are the largest uncertainties?
   a) Can you rank them from the relative largest to the smallest?
   b) Could you divide them into % contributions over time?
   c) Can you think of any other/surprise categories?

Repeat for temperature change in the 2080s and precipitation in the 2040s and 2080s.

III Quantitative elicitation

- Introduce change of approach at this stage.
- The objective of this elicitation is to construct a box and whisker plot to represent, as accurately as possible, your knowledge and beliefs regarding future changes in climate in the Lower Yangtze region.
- Very quickly run through an example e.g. Can you estimate how far is it between London and Exeter? Plausible limits? Median? Quartiles?

Plausible limits*:

3. What are the most extreme (yet plausible) conditions in terms of changes in [insert variable]?
4. Could you put a value on this lower limit?
   a) Challenge/revise (if necessary) the value – is it <u>exceptionally unlikely</u> that the value would lower than this?
5. Could you put a value on this upper limit?
   a) Challenge/revise (if necessary) the value – is it <u>exceptionally unlikely</u> that the value would higher than this?

Therefore, you are almost certain that the true value will lie between the lower limit and the upper limit given? Any value outside this range is, in your judgement, not plausible? (Note value and draw the range on a piece of paper to aid participants).

Median:

6. Could you give a median value?
   a) Challenge/revise (if necessary) the value – is it <u>equally likely</u> for the true value to be above or below this Median?

Quartiles:

7. Could you give a first quartile value?
   a) Challenge/revise (if necessary) the value – is it <u>equally likely</u> for the true value to be between this value and your lower limit, than between this value and your median?
8. Could you give a third quartile value?
   a) Challenge/revise (if necessary) the value – is it <u>equally likely</u> for the true value to be between this value and your upper limit, than between this value and your median?

* Anything outside these limits would be exceptionally unlikely (<0.01 and >0.99 percentiles).

Input 5 values into web tool and:

9. Challenge/revise (if necessary) their estimates.
10. Can you provide some justification for this box plot? E.g., How have you come up with this value?
11. Now considering surprises, would you change any of the values provided?

Variables of interest
By the 2040s, what will be the change in **mean annual temperature (°C)** compared to 1981–2010?
By the 2040s, what will be the change in **mean summer temperature (°C/JJA)** compared to 1981–2010?
By the 2040s, what will be the change in **mean winter temperature (°C/DJF)** compared to 1981–2010?
By the 2040s, what will be the change in **mean annual precipitation (mm)** compared to 1981–2010?
By the 2040s, what will be the change in **mean summer precipitation (mm/JJA)** compared to 1981–2010?
By the 2040s, what will be the change in **mean winter precipitation (mm/DJF)** compared to 1981–2010?
By the 2080s, what will be the change in **mean annual temperature (°C)** compared to 1981–2010?
By the 2080s, what will be the change in **mean summer temperature (°C/JJA)** compared to 1981–2010?
By the 2080s, what will be the change in **mean winter temperature (°C/DJF)** compared to 1981–2010?
By the 2080s, what will be the change in **mean annual precipitation (mm)** compared to 1981–2010?
By the 2080s, what will be the change in **mean summer precipitation (mm/JJA)** compared to 1981–2010?
By the 2080s, what will be the change in **mean winter precipitation (mm/DJF)** compared to 1981–2010?
Thank participant for their time. If participants wish to withdraw from the study after taking part, they can do so within two weeks by emailing us (give contact details).
END OF PROTOCOL

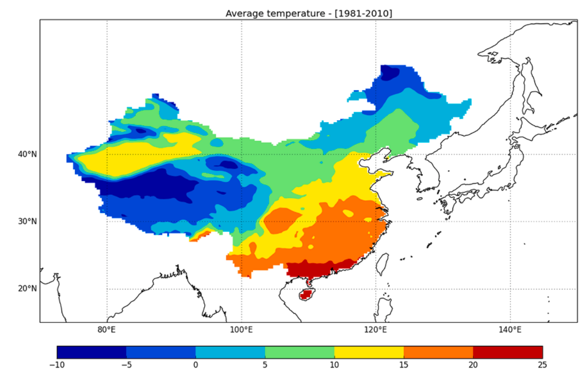
Appendix C:. Additional information pack for elicitation participants

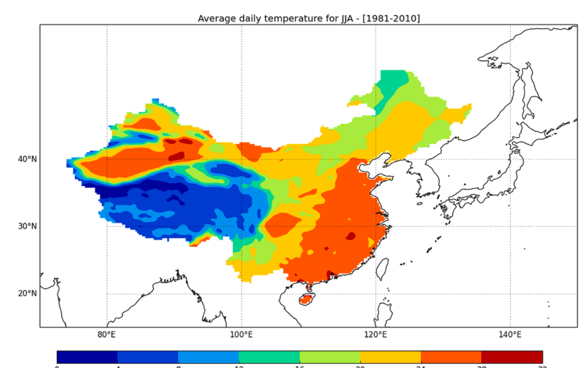
Definitions

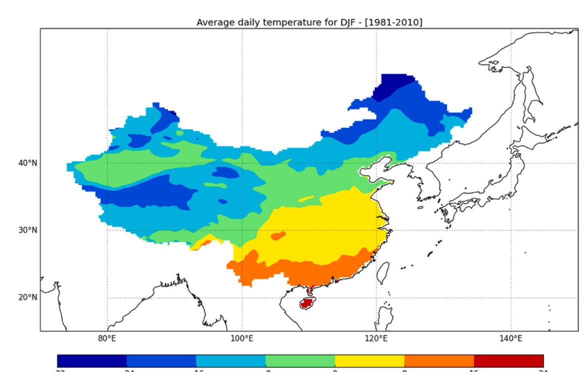
Uncertainty
A state of incomplete knowledge that can result from a lack of information or from disagreement about what is known or even knowable. It may have many types of sources, from imprecision in the data to ambiguously defined concepts or terminology, or uncertain projections of human behaviour. Uncertainty can therefore be represented by quantitative measures (e.g., a probability density function) or by qualitative statements (e.g., reflecting the judgment of a team of experts). [source: IPCC AR5 WG1 glossary].
Exceptionally unlikely
<0.01 and >0.99 percentiles [source: IPCC AR5 WG1].
Surprises
Low-probability, but high-consequence extreme (i.e. rapid, nonlinear) climatic events such as a collapse of the ‘‘conveyor belt’’ circulation in the North Atlantic Ocean or rapid deglaciation of polar ice sheets. This could be caused by an imaginable but unanticipatable event (e.g. Asteroid hitting the earth) or an event or process never before imagined [source: Schneider 2004].

Baseline climate data (Source: CN05 gridded observations for 1981 to 2010 (Wu and Gao, 2013))

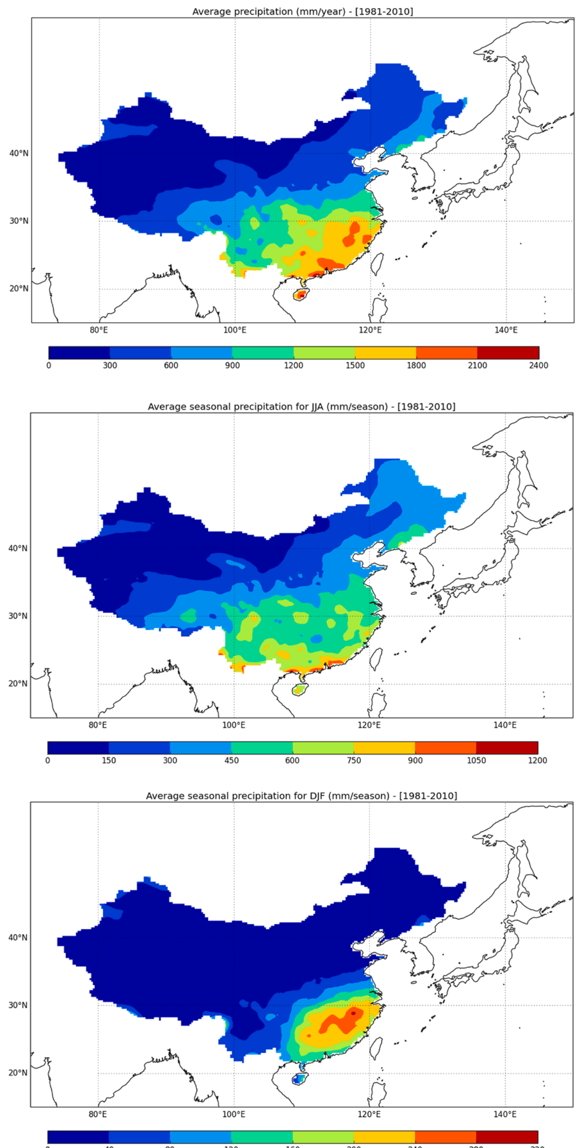
Mean temperature







Mean precipitation



Appendix D:. CMIP5 model simulations and projections data

Period	RCP scenario	Model	Realisation	Annual-mean temperature change (°C)	DJF-mean temperature change (°C)	JJA-mean temperature change (°C)	Annual-mean-total precipitation change (%)	DJF-mean-total precipitation change (%)	JJA-mean-total precipitation change (%)
2040s	2.6	bcc-csm1-1	r1i1p1	1.29	1.32	1.19	5.13	14.91	−0.16
		bcc-csm1-1-m	r1i1p1	1.38	1.39	1.37	1.66	−18.4	4.4
		BNU-ESM	r1i1p1	1.36	1.27	1.35	2.11	−1.41	4.93
		CanEMS2	r1i1p1	1.65	1.51	1.64	4.32	7.9	12.21
		CCSM4	r1i1p1	1.03	1.18	1.02	3.45	12.55	8.62
			r2i1p1	1.13	0.96	1.23	−0.25	−8.08	−0.1
		CNRM-CM5	r1i1p1	1.02	0.73	1.09	0.95	−3.42	−3.15
		CSIRO-Mk3-6-0	r1i1p1	1.72	1.69	1.83	8.9	−1.87	6.93
		FIO-ESM	r1i1p1	0.24	−0.03	0.43	1.06	−11.06	6.3
		HadGEM2-ES	r1i1p1	2.34	2.86	2.26	10.37	19.72	12.48
		IPSL-CM5A-LR	r1i1p1	1.67	1.78	1.48	−3.58	−13.31	−1.12
		IPSL-CM5A-MR	r1i1p1	1.48	1.31	1.46	−4.91	−17.71	1.63
		MIROC-ESM	r1i1p1	2.05	1.86	1.94	2.14	11.77	−5.59
		MPI-ESM-LR	r1i1p1	1.19	1.63	0.94	1.08	4.25	2.47
		MRI-CGCM3	r1i1p1	0.72	0.94	0.73	3.54	8.76	9.61
	4.5	ACCESS1-0	r1i1p1	2.09	2.18	2.22	6.88	1.15	3.7
		ACCESS1-3	r1i1p1	1.61	1.5	1.55	7.08	12.2	9.08
		bcc-csm1-1	r1i1p1	1.59	1.49	1.64	3.18	7.52	4.34
		bcc-csm1-1-m	r1i1p1	1.71	1.55	1.94	−1.76	−15.57	0.76
		BNU-ESM	r1i1p1	1.46	1.18	1.44	−1.33	−6.12	3.41
		CanEMS2	r1i1p1	1.89	1.82	1.93	5.56	13.5	11.58
			r2i1p1	2.05	2.15	2.12	8.08	7.38	8.01
			r3i1p1	1.83	1.51	1.82	6.23	−3.83	19.32
			r4i1p1	1.75	1.55	1.67	7.47	−10.12	16.13
			r5i1p1	1.86	1.51	1.81	4.17	−0.55	8.47
		CCSM4	r1i1p1	1.19	1.15	1.09	4.38	7.11	11.47
			r2i1p1	1.14	1.05	1.08	6.39	4.48	4.62
		CMCC-CM	r1i1p1	2.18	2.74	1.95	−2.16	−15.81	−3.48
		CMCC-CMS	r1i1p1	2.44	3.41	1.63	−2.02	−10.22	4.83
		CNRM-CM5	r1i1p1	1.32	1.16	1.35	−1.02	0.14	−4.78
		CSIRO-Mk3-6-0	r1i1p1	1.89	2	1.94	9.13	12.97	3.58
			r2i1p1	2.06	2.29	2.27	2.6	19.61	−5.69
			r3i1p1	1.82	1.8	2.01	1.16	25.55	−4.08
			r4i1p1	1.94	1.94	2.16	9.57	41.69	3.19
			r5i1p1	1.91	2.01	3.25	9.95	32.89	−0.82
			r6i1p1	1.77	1.86	1.97	9.76	2.14	5.4
			r7i1p1	1.92	1.84	2.15	4.8	30.97	3.72
			r8i1p1	1.69	1.79	1.93	2.83	29.73	−6.71
			r9i1p1	1.98	1.82	2.38	7.5	4.15	3.76
			r10i1p1	1.84	1.93	1.97	6.84	13.94	1.41
		FIO-ESM	r1i1p1	0.75	0.61	0.85	1.61	−13.89	5.64
		HadGEM2-ES	r1i1p1	2.3	2.22	2.52	4.22	16.77	1.48
			r2i1p1	2.6	3.46	2.42	6.01	−3.6	8.81
			r3i1p1	2.03	2.12	2.42	0.25	19.95	−0.48
			r4i1p1	1.9	2.37	2.08	5.3	10.08	3.73
		HadGEM2-CC	r1i1p1	1.98	1.94	2.19	7.6	9.89	−3.87
		inmcm4	r1i1p1	0.5	0.4	0.55	2.21	4.94	3.46
		IPSL-CM5A-LR	r1i1p1	2	2.08	2.03	3.11	−1.36	2.98
			r2i1p1	2.04	2.43	1.73	1.71	−22.11	14.85
			r3i1p1	2.27	2.59	1.93	−1.79	−14.25	11.45
			r4i1p1	1.75	1.67	1.81	1.6	−4.93	8.33
		IPSL-CM5A-MR	r1i1p1	1.67	1.22	1.63	−3.05	−31.26	7.1
		IPSL-CM5B-LR	r1i1p1	1.39	1.54	1.32	1.15	−4.8	5.92
		MIROC-ESM	r1i1p1	2.31	2.01	2.26	−1.56	15.19	−13.65
		MPI-ESM-LR	r1i1p1	1.38	1.85	1.17	10.5	10.15	14.85
			r2i1p1	1.39	1.51	1.27	−1.67	1.17	−4.35

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Period	RCP scenario	Model	Realisation	Annual-mean temperature change (°C)	DJF-mean temperature change (°C)	JJA-mean temperature change (°C)	Annual-mean-total precipitation change (%)	DJF-mean-total precipitation change (%)	JJA-mean-total precipitation change (%)
			r3i1p1	1.39	1.75	1.19	1.46	0.95	3.72
		MRI-CGCM3	r1i1p1	1.25	1.67	1.09	1.31	−2.29	0.63
	6.0	bcc-csm1-1	r1i1p1	1.26	1.23	1.21	3.57	−0.42	4.88
		bcc-csm1-1-m	r1i1p1	1.36	1.47	1.31	−3.14	−17.8	3.49
		CCSM4	r1i1p1	1.35	1.58	1.22	−0.55	−7.13	5.05
			r2i1p1	1.09	1.24	1.05	9.24	5.34	8.96
		CSIRO-Mk3-6-0	r1i1p1	1.34	1.55	1.23	0.4	4.15	−0.03
		FIO-ESM	r1i1p1	0.67	0.51	0.95	1.54	−16.25	6.27
		HadGEM2-ES	r1i1p1	1.89	2.04	2.01	5.77	17.61	6.47
		IPSL-CM5A-LR	r1i1p1	1.53	1.28	1.53	−2.38	−10.64	4.05
		IPSL-CM5A-MR	r1i1p1	1.32	1.14	1.21	−7.94	−25.47	−2.76
		MIROC-ESM	r1i1p1	2.05	1.67	1.85	−3.19	−3.27	−10.34
		MRI-CGCM3	r1i1p1	0.78	1.1	0.62	4.98	−9.92	3.6
	8.5	ACCESS1-0	r1i1p1	2.28	2.06	2.62	7.35	4.49	−1.6
		ACCESS1-3	r1i1p1	2.12	1.92	2.06	8.14	13.65	8.82
		bcc-csm1-1	r1i1p1	1.81	1.64	1.88	3.74	8.27	0.97
		bcc-csm1-1-m	r1i1p1	2.05	2.14	2.02	0.9	−24.85	8.17
		BNU-ESM	r1i1p1	2.09	2.13	1.84	0.69	−8.42	9.52
		CanEMS2	r1i1p1	2.13	1.9	2.33	3.23	14.37	9.51
			r2i1p1	2.43	2.29	2.54	9.22	11.84	9.03
			r3i1p1	2.18	1.9	2.21	10.53	−8.9	20.46
			r4i1p1	2.2	2.08	2.18	13.23	5.92	20.37
			r5i1p1	2.17	1.53	2.24	3.61	−2.88	10.89
		CCSM4	r1i1p1	1.7	1.89	1.74	3.24	6.03	10.72
			r2i1p1	1.73	1.7	1.82	5.5	−7.12	9.43
		CMCC-CESM	r1i1p1	2.46	2.94	1.78	−2.4	−5.05	13.5
		CMCC-CM	r1i1p1	2.79	3.37	2.42	−0.75	−17.15	2.92
		CMCC-CMS	r1i1p1	2.86	3.99	1.88	−1.42	−9.09	−2.2
		CNRM-CM5	r1i1p1	1.57	1.51	1.6	−1.21	−0.92	−4.59
			r2i1p1	1.17	1.17	1.2	1.59	−1.34	6.27
			r4i1p1	1.02	1.04	1.15	6.88	6.23	6.36
			r6i1p1	1.49	1.31	1.27	1.37	−6.39	0.85
			r10i1p1	1.32	1.13	1.11	4.39	2.53	2.87
		CSIRO-Mk3-6-0	r1i1p1	2.3	2.5	2.53	4.96	13.02	−1.57
			r2i1p1	2.08	2.34	2.27	8.12	20.49	4.47
			r3i1p1	2.25	2.25	2.42	1.65	14.3	−5.56
			r4i1p1	2.15	2.19	2.26	9.39	30.94	1.43
			r5i1p1	2.17	2.24	2.32	9.82	27.25	6.84
			r6i1p1	2.1	2.08	2.33	6.27	30.32	−1.88
			r7i1p1	2.19	1.97	2.46	7.07	39.09	6.1
			r8i1p1	2.09	2.15	2.38	7.51	30.1	−4.04
			r9i1p1	2.02	1.92	2.33	7.01	3.72	2.34
			r10i1p1	2.28	2.48	2.53	15.67	52.81	−2.41
		FIO-ESM	r1i1p1	1.14	1.02	1.24	2.64	−18.49	8.77
		HadGEM2-ES	r1i1p1	2.76	2.76	2.91	9.14	18.78	13.78
		HadGEM2-CC	r1i1p1	2.72	2.8	2.86	7.39	6.71	4.28
		inmcm4	r1i1p1	0.91	0.97	0.89	0.49	7.03	2.81
		IPSL-CM5A-LR	r1i1p1	2.5	2.48	2.39	−0.21	−21.41	8.41
		IPSL-CM5A-MR	r1i1p1	2.23	1.92	2.35	−8.52	−26.76	1.41
		IPSL-CM5B-LR	r1i1p1	1.82	2.03	1.75	−1.69	−6.23	7.86
		MIROC-ESM	r1i1p1	2.78	2.55	2.74	0.01	18.6	−14.5
		MPI-ESM-LR	r1i1p1	1.67	1.87	1.38	5.1	14.38	9.56
			r1i1p1	1.42	1.36	1.38	0.2	−5.47	−5.9

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Period	RCP scenario	Model	Realisation	Annual-mean temperature change (°C)	DJF-mean temperature change (°C)	JJA-mean temperature change (°C)	Annual-mean-total precipitation change (%)	DJF-mean-total precipitation change (%)	JJA-mean-total precipitation change (%)
		MRI-CGCM3							
		MRI-ESM1	r1i1p1	1.5	1.52	1.63	4.76	3.53	0.99
2080s	2.6	bcc-csm1-1	r1i1p1	1.17	1.15	1.18	9.06	16.06	7.37
		bcc-csm1-1-m	r1i1p1	1.37	1.47	1.5	0.59	−10.75	5.33
		BNU-ESM	r1i1p1	1.35	1.16	1.39	3.54	−3.66	1.87
		CanEMS2	r1i1p1	1.58	1.44	1.58	4.62	6.79	9.55
		CCSM4	r1i1p1	0.94	1.19	0.81	8.92	11.17	11.48
			r2i1p1	1.01	1.07	0.9	7.35	4.11	7.33
		CNRM-CM5	r1i1p1	1.24	1.36	1.14	−2.65	−1.86	−4.23
		CSIRO-Mk3-6-0	r1i1p1	2.04	2.12	2.08	11.21	19.79	5.01
		FIO-ESM	r1i1p1	−0.32	−1.06	0.12	0.66	−11.46	3.36
		HadGEM2-ES	r1i1p1	2.44	2.48	2.56	6.06	17.27	0.92
		IPSL-CM5A-LR	r1i1p1	1.61	1.7	1.47	−3.92	−18.89	6.93
		IPSL-CM5A-MR	r1i1p1	1.35	1.05	1.26	−5.45	−20.8	3.53
		MIROC-ESM	r1i1p1	2.41	2.04	2.63	2.54	12.9	−11.88
		MPI-ESM-LR	r1i1p1	0.78	1	0.52	6.25	12.17	5.95
		MRI-CGCM3	r1i1p1	1.13	1.13	1.15	8.38	−1.07	4.96
	4.5	ACCESS1-0	r1i1p1	3.16	3.04	3.35	11.63	8.13	2.67
		ACCESS1-3	r1i1p1	2.79	2.5	2.91	12.6	20.82	8.32
		bcc-csm1-1	r1i1p1	2.01	1.98	1.98	4.81	2.32	6.41
		bcc-csm1-1-m	r1i1p1	2.1	2.12	2.18	6.71	-8.44	10.53
		BNU-ESM	r1i1p1	2.25	2.23	2.17	5.6	−2.48	7.77
		CanEMS2	r1i1p1	2.55	2.19	2.67	3.01	7.49	9.52
			r2i1p1	2.6	2.52	2.6	12.61	0.21	20.34
			r3i1p1	2.61	2.32	2.59	10.44	1.49	23.63
			r4i1p1	2.57	2.49	2.43	11.75	12.45	19.67
			r5i1p1	2.35	1.85	2.17	7.57	−4.68	24.58
		CCSM4	r1i1p1	1.74	1.84	1.74	5.37	7.24	14.54
			r2i1p1	1.79	1.85	1.84	11.42	15.41	5.05
		CMCC-CM	r1i1p1	3.18	3.95	2.77	3.04	−4.35	1.66
		CMCC-CMS	r1i1p1	3.51	4.65	2.54	1.87	−6.18	−0.06
		CNRM-CM5	r1i1p1	2.06	1.91	2.1	1.78	6.96	−2.72
		CSIRO-Mk3-6-0	r1i1p1	3.17	3.39	3.46	9.77	39.84	−5.96
			r2i1p1	2.84	2.99	3.13	13.55	37.87	4.25
			r3i1p1	2.88	2.52	3.37	8.56	23.49	−1.79
			r4i1p1	3.1	3.39	3.21	15.84	36.48	0.9
			r5i1p1	3.25	3.35	3.5	14.45	41.07	1.14
			r6i1p1	2.99	2.99	3.33	14.93	34.06	11.21
			r7i1p1	3.27	3.29	3.55	7.2	53.65	−0.66
			r8i1p1	2.82	2.68	3.24	12.52	43.44	−3.2
			r9i1p1	2.73	2.68	3.12	12.95	29.28	2.58
			r10i1p1	3.1	3.31	3.21	11.67	39.03	1.06
		FIO-ESM	r1i1p1	0.59	0.36	0.94	7.01	−13.04	13.69
		HadGEM2-ES	r1i1p1	3.53	3.85	3.46	17.08	27.51	18.89
			r2i1p1	3.43	4.06	3.33	8.03	0.48	11.27
			r3i1p1	3	2.94	3.41	6.76	27.61	−1.4
			r4i1p1	3.07	3.52	3.11	13.78	30.31	2.34
		HadGEM2-CC	r1i1p1	3.06	3.07	3.25	14.77	25.76	6.32
		inmcm4	r1i1p1	1.07	1.03	1.04	1.91	−6.93	9.15
		IPSL-CM5A-LR	r1i1p1	2.77	2.89	2.67	2.94	-19.88	10.25
			r2i1p1	2.82	2.84	2.66	−0.12	−22.44	11.17
			r3i1p1	2.88	2.92	2.76	−3.22	−24.88	10.07
			r4i1p1	2.78	2.79	2.68	5.58	−13.13	13.23
		IPSL-CM5A-MR	r1i1p1	2.72	2.48	2.79	−11.93	−35.89	−2.66
		IPSL-CM5B-LR	r1i1p1	2.03	2.25	1.94	5.50	8.89	10.08

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Period	RCP scenario	Model	Realisation	Annual-mean temperature change (°C)	DJF-mean temperature change (°C)	JJA-mean temperature change (°C)	Annual-mean-total precipitation change (%)	DJF-mean-total precipitation change (%)	JJA-mean-total precipitation change (%)
		MIROC-ESM	r1i1p1	3.26	2.88	3.2	6.68	40.56	−13.61
		MPI-ESM-LR	r1i1p1	1.8	2.14	1.57	4.73	18	8.31
			r2i1p1	1.93	2.28	1.87	3.39	11.32	1.53
			r3i1p1	1.85	2.08	1.78	3.96	−1.87	10.72
		MRI-CGCM3	r1i1p1	1.77	2.04	1.8	10.79	−0.41	15.25
	6.0	bcc-csm1-1	r1i1p1	2.42	2.4	2.4	3.81	1.25	7.64
		bcc-csm1-1-m	r1i1p1	2.63	2.52	2.6	−0.24	−24.95	5.74
		CCSM4	r1i1p1	2.35	2.58	2.31	2.52	−11.89	11.57
			r2i1p1	2.35	2.48	2.28	7.62	−17.33	9.94
		CSIRO-Mk3-6-0	r1i1p1	2.93	2.89	3.01	6.28	21.27	−1.05
		FIO-ESM	r1i1p1	1.01	0.72	1.38	2.07	−15.39	7
		HadGEM2-ES	r1i1p1	3.87	3.8	4.14	8.13	20.96	2.08
		IPSL-CM5A-LR	r1i1p1	3.15	3.04	3.13	−7.24	−22.06	1.28
		IPSL-CM5A-MR	r1i1p1	2.92	2.37	2.99	−14.53	−36.21	−3.66
		MIROC-ESM	r1i1p1	3.72	3.61	3.37	3.41	15.61	−7.62
		MRI-CGCM3	r1i1p1	2.05	2.53	1.91	12.37	12.02	13.88
	8.5	ACCESS1-0	r1i1p1	5.21	4.74	5.84	10.19	7.55	0.06
		ACCESS1-3	r1i1p1	4.53	4.21	4.43	10.89	14.42	10.46
		bcc-csm1-1	r1i1p1	3.87	3.66	4.16	7.29	8.6	3.22
		bcc-csm1-1-m	r1i1p1	4.18	4.06	4.55	0.5	−36.41	2.06
		BNU-ESM	r1i1p1	4.31	4.25	4.12	4.31	−17.16	2.28
		CanEMS2	r1i1p1	4.29	3.7	4.58	9.33	11.43	19.82
			r2i1p1	4.55	4.24	4.74	14.35	5.02	22.89
			r3i1p1	4.42	3.68	4.67	11.78	−1.77	29.93
			r4i1p1	4.28	3.87	4.34	16.65	5.54	30.22
			r5i1p1	4.5	3.82	4.67	9.26	1.17	20.77
		CCSM4	r1i1p1	3.73	3.65	3.79	7.53	−3.73	11.52
			r2i1p1	3.7	3.45	3.76	8.07	−20.46	15.46
		CMCC-CESM	r1i1p1	4.86	6.04	3.67	4.68	−3.11	24.49
		CMCC-CM	r1i1p1	5.15	6.07	4.6	2.51	−11.98	−0.03
		CMCC-CMS	r1i1p1	5.29	6.56	4.2	4.5	−1.8	−1.73
		CNRM-CM5	r1i1p1	3.18	2.96	3.07	6.79	8.01	2.32
			r2i1p1	2.96	2.76	2.8	4.27	3.59	12.03
			r4i1p1	2.76	2.79	2.79	13.25	16.32	21.07
			r6i1p1	3.21	3.06	2.94	8.9	3.29	5.19
			r10i1p1	3.25	2.81	2.93	4.16	4.41	1.79
		CSIRO-Mk3-6-0	r1i1p1	4.8	5.07	5.11	16.21	45.44	−1.57
			r2i1p1	4.67	4.92	5.1	15.79	75.06	−5.03
			r3i1p1	4.66	4.73	4.97	17.41	48.47	9.11
			r4i1p1	4.95	5.31	5.27	13.54	75.6	0.63
			r5i1p1	4.83	5.19	5.32	25.91	83.31	2.33
			r6i1p1	4.63	4.76	5.05	22.68	56.77	5.21
			r7i1p1	4.74	5.02	5.12	12.15	89.66	−2.66
			r8i1p1	4.66	4.72	5.16	16.09	60.81	−3.47
			r9i1p1	4.51	4.53	4.94	19.62	58.22	8.82
			r10i1p1	4.88	5.22	5.22	4.27	18.59	−5.39
		FIO-ESM	r1i1p1	2.52	2.44	2.73	0.84	−23.06	8.25
		HadGEM2-ES	r1i1p1	5.78	5.67	6.17	13.29	36.34	10.55
		HadGEM2-CC	r1i1p1	5.55	5.23	6.25	15.53	30.83	0.66
		inmcm4	r1i1p1	2.19	2.04	2.15	−2.5	−19.6	6.08
		IPSL-CM5A-LR	r1i1p1	5.37	5.31	5.27	−9.42	−41.73	4.35
		IPSL-CM5A-MR	r1i1p1	5.37	4.8	5.66	−20.74	−51.61	-10.08
		IPSL-CM5B-LR	r1i1p1	4.16	4.47	3.86	−0.87	−16.13	7.0
		MIROC-ESM	r1i1p1	5.82	5.73	5.82	2.24	32.06	−18.99

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Period	RCP scenario	Model	Realisation	Annual-mean temperature change (°C)	DJF-mean temperature change (°C)	JJA-mean temperature change (°C)	Annual-mean-total precipitation change (%)	DJF-mean-total precipitation change (%)	JJA-mean-total precipitation change (%)
		MPI-ESM-LR	r1i1p1	3.8	4.28	3.67	10.9	15.56	9.68
		MRI-CGCM3	r1i1p1	3.45	3.71	3.16	13.79	−8.38	20.07
		MRI-ESM1	r1i1p1	3.43	3.58	3.24	20.66	41.11	21.93

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