

1 **Bringing it all together: Science priorities for improved understanding of** 2 **Earth system change and to support international climate policy.**

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72 **Abstract.** We review how the international modelling community, encompassing Integrated Assessment models, global and
73 regional Earth system and climate models, and impact models, have worked together over the past few decades, to advance
74 understanding of Earth system change and its impacts on society and the environment, and thereby support international
75 climate policy. We go on to recommend a number of priority research areas for the coming decade, a timescale that
76 encompasses a number of newly starting international modelling activities, as well as the IPCC 7th Assessment Report
77 (AR7) and the 2nd UNFCCC Global Stocktake. Progress in these priority areas will significantly advance our understanding
78 of Earth system change and its impacts, increasing the quality and utility of science support to climate policy.

79
80 We emphasize the need for continued improvement in our understanding of, and ability to simulate, the coupled Earth
81 system and the impacts of Earth system change. There is an urgent need to investigate plausible pathways and emission
82 scenarios that realize the Paris Climate Targets. For example, pathways that overshoot 1.5°C or 2°C global warming, before
83 returning to these levels at some later date. Earth System models need to be capable of thoroughly assessing such warming
84 overshoots, in particular, the efficacy of mitigation measures, such as negative CO₂ emissions, in reducing atmospheric CO₂
85 and driving global cooling. An improved assessment of the long-term consequences of stabilizing climate at 1.5°C or 2°C
86 above pre-industrial temperatures is also required. We recommend Earth system models run overshoot scenarios in CO₂-
87 emission mode, to more fully represent coupled climate - carbon cycle feedbacks and, wherever possible, interactively
88 simulate other key Earth system phenomena at risk of rapid change during overshoot. Regional downscaling and impact
89 models should use forcing data from these simulations, so impact and regional climate projections cover a more complete
90 range of potential responses to a warming overshoot. An accurate simulation of the observed, historical record remains a
91 fundamental requirement of models, as does accurate simulation of key metrics, such as the Effective Climate Sensitivity
92 and the Transient climate response to cumulative carbon emissions. For adaptation, a key demand is improved guidance on
93 potential changes in climate extremes and the modes of variability these extremes develop within. Such improvements will
94 most likely be realized through a combination of increased model resolution, improvement of key model parameterizations,
95 enhanced representation of important Earth system processes, combined with targeted use of new Artificial Intelligence (AI)
96 and Machine Learning (ML) techniques. We propose a deeper collaboration across such efforts over the coming decade.

97
98 With respect to sampling future uncertainty, increased collaboration between approaches that emphasize large model
99 ensembles and those focussed on statistical emulation is required. We recommend an increased focus on High Impact Low
100 Likelihood (HILL) outcomes. In particular, the risk and consequences of exceeding critical tipping points during a warming
101 overshoot and the potential impacts arising from this. For a comprehensive assessment of the impacts of Earth system
102 change, including impacts arising directly as a result of climate mitigation actions, it is important spatially detailed,
103 disaggregated information used to generate future scenarios in Integrated Assessment Models are available for use in impact

104 models. Conversely, methods need to be developed that enable potential societal responses to projected Earth system change
105 to be incorporated into scenario development.

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107 The new models, simulations, data, and scientific advances, proposed in this article will not be possible without long-term
108 development and maintenance of a robust, globally connected infrastructure ecosystem. This system must be easily
109 accessible and useable by modelling communities across the world, allowing the global research community to be fully
110 engaged in developing and delivering new scientific knowledge to support international climate policy.

111 **1 Introduction**

112 Given the rapidly developing climate crisis, and the negative consequences for planetary habitability and human well-being,
113 there is an increasing need for accurate, reliable, and actionable information encompassing the full spectrum of climate risk.
114 This information is required at global to local scales, near to long timescales, and needs to be tailored to inform critical
115 decision-making related to climate change mitigation and adaptation (e.g., in the context of UNFCCC negotiations, the UN
116 Global Stocktake, IPCC assessments, and the World Adaptation Science Program; WASP), as well as the growing needs of
117 climate service providers. Over the past few decades, coordinated by the World Climate Research Program (WCRP), the
118 international modelling community has worked together to contribute simulations, data and knowledge to support decision
119 making, in particular the cyclical IPCC Assessment Reports (AR). This has been achieved through a suite of interconnected
120 modelling projects and initiatives, with the most important of these listed in Table 1, along with project acronyms and
121 primary citations. Meehl (2023) discusses the synergistic interaction between climate science (particularly Global Climate
122 and Earth system modelling) and the IPCC over the past 4 decades.

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124 With a new IPCC AR cycle (AR7) beginning, it is timely to review how the international modelling community has
125 supported climate policy in the past, including earlier AR cycles, and ask what advances can be made in the overall quality
126 and availability of science to support policy needs. In addition, it is pertinent to review our current understanding of, and
127 ability to model, coupled Earth system change, as well as the societal and environmental impacts associated with this change
128 and ask whether plausible, safe pathways can be developed for the Earth system that avoid the worst impacts of this change.
129 Many of the international projects listed in Table 1, that provide the scientific knowledge on which IPCC reports are based,
130 are beginning new cycles. For example, CMIP7 is starting to take shape, likely running through to ~2030 or beyond. In this
131 paper we outline a number of areas we believe the international modelling community can significantly advance our
132 understanding of, and ability to simulate, past and future Earth system change, including the impacts of these changes.
133 Progress in the proposed areas will also allow an improved investigation of mitigation options for limiting long-term global
134 warming, and its impacts, to acceptable levels. Such developments will deliver enhanced scientific support to international
135 climate policy, during and beyond AR7. The advances we propose assume continued *development, expansion, maintenance,*
136 *and integration* of a robust and interconnected infrastructure ecosystem. Such an infrastructure has underpinned past
137 international modelling collaborations and is a fundamental requirement for realizing the ambitious goals outlined here. The
138 specific science, and science for policy, ambitions, as well as the necessary underpinning infrastructure, are discussed in
139 more detail in subsequent sections. Each proposed focus area can be summarized by the following key goals:

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- 141 • **Provision of a coordinated, internally consistent set of simulations, data, and knowledge to support IPCC**
142 **assessments and international climate policy.** The resulting data sets and knowledge should be based on the most
143 recent and consistent set of Integrated Assessment Model (IAM) scenarios, global and regional Earth system model

144 (ESM) projections and simulated societal and environmental impacts. With consideration of impacts arising both
145 due to the projected Earth system change, and directly from any mitigation actions assumed in the IAM scenarios.

- 146
- 147 ● **Improving understanding and guidance on future Earth system change, allowable emissions, net-zero**
148 **responses, and safe, long-term pathways for planet Earth.** Ensure global and regional ESMs, IAMs, and impact
149 models include the required level of process realism, process interactions, and consistent forcing data to accurately
150 simulate the response of the Earth system and human societies to future socio-economic, mitigation, emission, and
151 land-use scenarios. Develop and analyse a range of future pathways that limit long-term global warming to less than
152 1.5 or 2°C above pre-industrial levels, while minimizing the negative impacts on society and the environment.
153
 - 154 ● **Improving our understanding of, and ability to simulate key climate processes, climate variability, extreme**
155 **events and regional impacts.** Ensure global and regional climate models (GCMs and RCMs) accurately represent
156 key processes, couplings, modes of variability and feedbacks that underpin global to regional climate change. Use
157 these models to deliver robust and detailed projections of regional climate change, including changes in extreme
158 events. Ensure the socio-economic information used to develop IAM mitigation and scenario data is suitably
159 disaggregated and combined with climate projection data to support national to regional scale impact assessment,
160 adaptation planning and climate services.
161
 - 162 ● **Increasing collaboration across approaches to further improve global and regional Earth system and climate**
163 **models.** Ensure strong collaboration across efforts to; increase process realism and coupling in ESMs, increase
164 model resolution and improve physical parameterizations, including ML hybrid-modelling approaches. Ensure
165 these approaches are optimally combined to deliver the best possible development pathway for the next generation
166 of Earth system models.
167
 - 168 ● **Improving model simulations of the observational record and key metrics of climate change.** Ensure
169 improvement in the simulation and understanding of the observed, historical evolution of climate, particularly
170 historical global and regional warming, encompassing the forcings, processes, and feedbacks that determine the rate
171 and pattern of this warming. Improve our ability to constrain and simulate key climate change metrics, such as the
172 Effective Climate Sensitivity (EffCS), Transient Climate Response (TCR), the Transient Climate Response to
173 cumulative carbon Emissions (TCRE) and the Regional Warming to Global Warming ratio (RW/GW)
174
 - 175 ● **Sampling and quantifying future uncertainty.** Develop and apply a hierarchy of models and methods to
176 efficiently explore the range of uncertainty inherent in future Earth system change and its impacts. Ensure regional
177 and national scale adaptation and mitigation is informed by a more complete sampling of the range of potential
178 climate futures, including rare (high impact, low likelihood) outcomes, their local climate signature, and the
179 potential consequences of these for society, the environment and climate policy.
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 - 181 ● **The underpinning technological infrastructure.** Further develop and maintain a robust, globally inter-connected
182 infrastructure ecosystem to ensure efficient co-production and co-exploitation of internally consistent model
183 simulations, via information, data and computational services that enable the rapid and reliable sharing of
184 requirements, knowledge, data, and analysis tools. Such sharing needs to be both within and across multiple
185 modelling projects and user communities, as well as providing suitable support to policymakers, planners, climate
186 services, and the wider international research community.

Acronym	Initiative or project name	Website	Main themes	Citation
IAMC	Integrated Assessment Modelling Consortium	https://www.iamconsortium.org	Future socio-economic pathways, emission and land use scenarios	Moss et al., 2010
WCRP CMIP	Coupled Model Intercomparison Project	https://wcrp-cmip.org/	Earth system and Global Climate modelling	Eyring et al., 2016
ScenarioMIP	ScenarioMIP	https://wcrp-cmip.org/model-intercomparison-projects-mips/scenariomip/	Further develop IAM scenarios into emission, concentration and land-use scenarios for CMIP and CORDEX.	O'Neill et al., 2016
WCRP CORDEX	Coordinated Regional Downscaling Experiment	https://cordex.org	Regional climate downscaling	Giorgi et al., 2009
VIACS AB	Vulnerability, Impacts, Adaptation & Climate Services Advisory Board	https://viacsab.gerics.de/	Advisory body for linking CMIP and CORDEX to the impacts and climate services communities	Ruane et al., 2016
ISIMIP	Inter-Sectoral Impact Model Intercomparison Project	https://www.isimip.org	Global and regional impact modelling for multiple sectors	Frieler et al., 2017
ESGF	Earth System Grid Federation	https://esgf.llnl.gov/	Data curation and distribution system for CMIP and CORDEX	Balaji et al., 2018

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Table 1. Examples of the main international projects contributing to the provision of simulations, data and scientific knowledge to support climate policy, particularly IPCC assessment reports, including a main reference for each activity. CMIP and CORDEX are coordinated by the World Climate Research Program.

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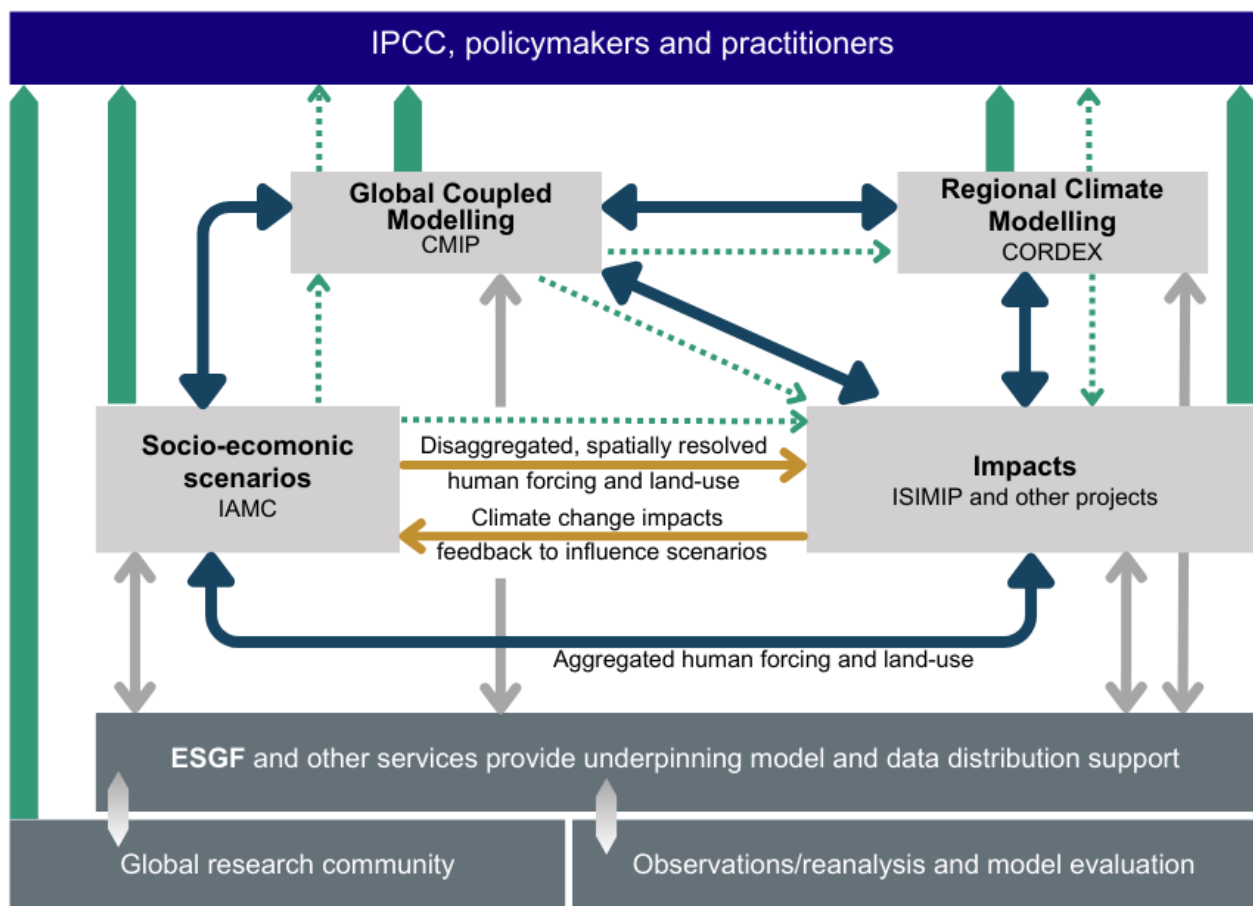
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Over the past few years a number of papers offer important perspectives on future priorities for Earth system and climate modelling, focussing on; the benefits of increased model resolution (Satoh et al., 2019; Palmer and Stevens, 2019; Slingo et al., 2022), the role of AI and ML in model development (Bauer et al., 2023; Eyring et al., 2024b; Schneider et al., 2024), development of Digital Twins (Bauer et al., 2021; Hoffman et al., 2023; Bauer et al., 2024), priority areas for CMIP7 (Dunne et al., 2023; Sanderson et al., 2023), proposals for an operational approach to CMIP (Jakob et al., 2023; Stevens, 2024), and future scenarios to support the IPCC process (Pirani et al., 2024). The recommendations we present here should be viewed in the light of these papers and summarize the views of a group of European scientists who have been engaged in, and in a number of cases led, major international modelling exercises that have delivered critical support to past IPCC assessment cycles. A similar perspective piece, from a number of U.S. climate modelling centres, has also recently been published (Mariotti et al., 2024). Our perspective aims to address the range of activities involved in delivering actionable scientific support to international and national climate policy and therefore encompasses; IAM-based socio-economic, emission and land use scenarios, global and regional Earth system and climate models, regional downscaling and calibration, projection ensembles and emulators, uncertainty quantification, sectoral and environmental impact models, as well as the computational infrastructure necessary to realise and disseminate this complex workflow.

208 **2 Provision of a coordinated, internally consistent set of simulations, data, and knowledge to support IPCC**
 209 **assessments and international climate policy.**

210 The process by which the aforementioned activities have, in the past, delivered data and knowledge into the science and
 211 policy arenas is summarized in Fig. 1. IAMs develop a range of future global pathways, based on narratives for socio-
 212 economic, political, and technological development, as well as climate policy. For methodological reasons these scenarios do
 213 not (yet) consider the impacts of future climate change on human behaviour. The pathways are typically quantified in terms
 214 of highly aggregated information on future population and economic development, energy and food system development,
 215 and environmental consequences. For each pathway, marker anthropogenic emission and land-use scenarios are selected
 216 (van Vuuren et al., 2011; O’Neill et al., 2016; Riahi et al., 2017). These scenarios are combined with observation-based
 217 estimates for the historical past, resulting in a time series of emission and land use data covering ~1850 to 2100 (Hurtt et al.,
 218 2011; Gidden et al., 2019). Using simple climate models (e.g. MAGICC; Meinshausen et al., 2011) and chemistry-climate
 219 models (Lamarque et al., 2011), the emissions are converted into atmospheric concentration time series. The concentration
 220 timeseries, along with the land-use scenarios, are used to “force” ESMs in CMIP to investigate potential changes in the Earth
 221 system arising from each scenario. The ESMs deliver time-varying, spatially discrete estimates of the past and future
 222 evolution of the Earth system, sampling the range of available emission and/or concentration scenarios (Tebaldi et al., 2021).
 223 CMIP simulations are extensively used to inform policymaking addressing global climate change risks. They are also made
 224 available to the international research community via the ESGF, where they are used to increase understanding of the Earth
 225 system and Earth system change, and to highlight areas requiring further model improvement.
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 228 **Figure 1: A schematic illustration of how earlier rounds of IAMC, CMIP, CORDEX and impact modelling activities, such as ISIMIP,**
 229 **have worked together to develop and apply future socio-economic and emission scenarios (IAMC), increase the scientific**
 230 **understanding of, and ability to simulate the coupled Earth system (CMIP and CORDEX), and investigated the impacts of Earth**
 231 **system change on societies and the natural environment (ISIMIP etc). In the figure dark blue lines illustrate the main (generally**

232 two-way) exchanges of scientific knowledge between the different projects. Dotted green lines indicate the main (simulation) data
233 transfer between projects, while grey lines show the main data exchanges outside of these projects (e.g. onto the ESGF for open use
234 by the global research community or into regional or national data distribution sites). Thin orange lines illustrate the new exchanges
235 proposed in Sect. 2 of this paper. Finally, the thick green lines illustrate the main knowledge and data exchange routes between the
236 different projects, the global research community, and the IPCC assessment process, as well as with multiple policymakers,
237 practitioners, and climate service providers around the world.

238
239 CMIP simulations are used extensively as boundary forcing for regional downscaling (e.g. CORDEX) to generate climate
240 information at spatial scales relevant for adaptation policy and climate services, as well as to drive impact model simulations
241 (e.g. crop models in AgMIP (Ruane et al., 2017), fisheries and marine ecosystem models in FishMIP (Tittensor et al., 2018),
242 and a range of impact models that contribute coordinated simulations to ISIMIP (Frieler et al., 2017), addressing impacts
243 such as, biome changes, water resources, human health, energy systems and biodiversity). Regional downscaling follows two
244 main pathways; (i) dynamical downscaling generates high-resolution regional simulations consistent with the ESM boundary
245 condition data (Ruti et al., 2016; Jacob et al., 2020; Teichmann et al., 2021) and (ii) empirical-statistical downscaling
246 (including ML methods) combine observations and models to translate large-scale features simulated by the ESMs to high-
247 resolution, local scale climate information (Gutiérrez et al., 2018; Lange, 2019; Karger et al., 2023). Impact models use both
248 CMIP and CORDEX climate data, as well as socio-economic data and information on mitigation actions from the IAM
249 scenarios (e.g. population distributions and land use patterns that include information on mitigation measures), as forcing to
250 assess the societal and environmental impacts arising from the range of simulated futures (Frieler et al., 2017).

251
252 The combined outcome of this international effort are a set of simulations, data and resulting knowledge covering the past
253 ~175 and future ~100 years (and sometimes longer) that sample; (i) plausible future global socio-economic development
254 pathways, (ii) emission, concentration and land-use scenarios commensurate with these pathways, (iii) global and regional
255 Earth system changes associated with each future pathway and (iv) the societal and environmental impacts arising from the
256 simulated Earth system changes, as well as direct impacts associated with the socio-economic and/or mitigation measures
257 applied in the IAM scenarios.

258
259 There are numerous challenges involved in running the number and variety of model simulations across this range of
260 activities, including cross-project and cross-model dependencies. As a consequence, to date it has not been possible to
261 develop a single, coordinated dataset of forcings, simulations and findings from all four activities (IAMs, CMIP, CORDEX,
262 impact modelling), based on a common set of socio-economic assumptions, scenarios, and driving data, within a single IPCC
263 Assessment cycle. This limitation reduces the overall consistency and utility of information entering the three IPCC working
264 groups (WGs). For example, Global (CMIP) and Regional (CORDEX) simulations are often out of sync, with CORDEX
265 RCMs using boundary data derived from an earlier phase of CMIP. A similar example holds for impact models that often
266 use a mix of global and regional forcing from different phases of CMIP and CORDEX. Furthermore, impact models forced
267 by CMIP/CORDEX climate data, do not include all the socio-economic and climate policy information that underpin the
268 driving IAM emission and land-use scenarios. This is particularly acute with respect to a number of direct human forcings.
269 These forcings are aggregated across multiple sectors and large spatial scales in the IAM scenarios, but need to be
270 disaggregated and harmonized with observed historical data, to more detailed spatial scales and individual sectors, to allow
271 an accurate estimate of their impact on society and the environment, in combination with the impacts due to Earth system
272 change (e.g. see *Direct Human Forcings*, as listed on Table 1, Frieler et al., 2024). An improved accounting of such direct
273 human forcings will be increasingly important as future scenario pathways include major (human) interventions likely
274 required to deliver the negative CO₂ emissions necessary to achieve the Paris Agreement targets. Such interventions
275 themselves can have important direct impacts on food production and biodiversity and therefore need to be accounted for in
276 impact assessments.

278 Partly for methodological reasons, the impacts of climate change (and the potential societal responses to these changes) have
279 not been included in IAM scenarios describing future socio-economic trajectories (i.e. Shared Socio-economic Pathways
280 (SSPs), O'Neill et al., 2020). As climate change is expected to have a considerable impact on society, it is important methods
281 are developed that allow these feedbacks to be included in future scenario development (Pirani et al., 2024). Ideally
282 information on the impacts of climate change would be fed back into the IAMs to iteratively generate new future socio-
283 economic and policy pathways that include the societal responses to both the applied climate mitigation measures and to the
284 impacts of climate change. For example, future land use will need to be adjusted to satisfy global food production, while
285 accounting for the impacts of climate change on crop yields and changes in available land resulting from any land-based
286 climate mitigation measures. These iterative adjustments to future socio-economic scenarios are one way to represent
287 societal adaptation to projected climate change. Given the tight timelines it will not be possible to fully develop such
288 iterative and interactive steps within the IPCC AR7 cycle. Nevertheless, we recommend urgently addressing this link as the
289 envisioned modification of workflows has the potential to significantly improve the overall consistency of future scenarios,
290 integrating important information across socio-economic, Earth system and impact projections.

291

292 The lack of consistency, of both data and knowledge entering IPCC and national climate change assessments, reduces its
293 overall utility and makes the interpretation of uncertainties across the various data sources a challenge. This can lead to
294 inconsistent data and knowledge being used to develop climate policy, with some data being more than 10 years old. We
295 believe the time is right to much more tightly link these key international activities, with more extensive and rapid sharing of
296 simulations, data, knowledge, tools, and personnel, moving such critical *science for policy* work towards an operational
297 footing. Such a change has been proposed earlier (e.g. Jakob et al., 2023; Stevens, 2024). We agree with these proposals but
298 stress the need for “*operationalization*” across the entire workflow involved in developing and delivering robust and useable
299 scientific knowledge. This includes; generation of IAM scenarios and associated forcing data, global and regional Earth
300 system model simulations based on these scenarios, impact model simulations, post-simulation evaluation and analysis,
301 uncertainty quantification, science to policy knowledge translation, and the technical infrastructure needed to support the
302 entire endeavour. To maximize the relevance and utility of the resulting science for policy, we further propose such
303 operational activities employ a co-development and co-exploitation approach, where a cross-section of intended users of the
304 science are involved throughout the process.

305

306 Such developments require support across a number of international coordinating bodies, as well as mechanisms to
307 coordinate or pool the significant funding required, for what is inherently an international, multi-institutional and multi-
308 disciplinary endeavour. The building blocks for this do exist, represented by IAMC, CMIP, CORDEX, VIACS, ISIMIP and
309 the ESGF. To date, the bulk of the effort to realize these interconnected projects have been funded through short-term,
310 competitive research grants, with the availability and international coordination of this funding arising partly by chance and
311 often thanks to shared IPCC timelines (Meehl, 2023). While such a development requires significant effort, funding and
312 coordination, the long-term benefits for climate policy are potentially very significant. While moving the policy- and service-
313 oriented aspects of climate projections and impact assessment towards a more operational approach is important, we stress
314 the paramount importance of maintaining a strong science understanding, model improvement, and open data access,
315 approach across all these activities. This will help maintain global participation and ensure continual improvement in the
316 quality of data and knowledge entering the climate policy and service arenas. Fully achieving these goals on the timescale of
317 IPCC AR7 will not be possible. Nevertheless, a first step in this direction is under development as part of the planning for
318 CMIP7, which will operate a dual timescale approach. A set of CMIP7 Fast Track (FT) simulations, specifically intended to
319 support IPCC AR7, is under development. The CMIP7 FT aims for a small set of policy relevant experiments that can be

320 rapidly performed and made available for analysis by early 2027. In addition to the Fast Track, the bulk of CMIP7 will
321 operate on a slower timescale, roughly from 2025 to 2030, with individual science-oriented MIPs (Model Intercomparison
322 Projects) developing and realising a range of experiments and analyses to address outstanding questions and challenges in
323 Earth system modelling.

324

325 Starting to develop a more joined up and efficient workflow across projects, along with increased internal consistency of
326 data and knowledge emanating from these projects, will be an important step towards a durable, more operational approach
327 to delivering scientific support to climate policy and climate services.

328

329 **3 Improving knowledge and guidance on future Earth system change, allowable emissions, net-zero responses, 330 and safe landing pathways for planet Earth.**

331 **3.1 The Paris Agreement: The risk of warming overshoot, allowable emissions, net-zero and negative emissions, 332 and Earth system feedbacks.**

333 The 2015 Paris Agreement (with an aim to limit long-term global warming to well below 2°C above pre-industrial
334 temperatures and pursue efforts to limit warming to 1.5°C; Riahi et al., 2021) focused the attention of policymakers and the
335 public onto the risks and consequences of exceeding these key targets. Partly in response to such policy needs, work
336 accelerated on quantifying allowable carbon emission budgets commensurate with the Paris goals (Millar et al., 2017; Rogelj
337 et al., 2019; Lamboll et al., 2023). It became increasingly clear that to provide accurate guidance on such allowable budgets,
338 Earth system models needed to improve their representation of the carbon cycle and its interaction with physical climate
339 processes. In addition, further improvement was required in representing non-CO₂ climate forcers, such as methane, nitrous
340 oxide and aerosols. Focus also turned to the risk of triggering feedbacks that might push temperatures further from a given
341 target, once the target was exceeded, as well as on the risk of exceeding Earth system tipping points, with potentially major
342 regional impacts. Lastly, recognition that international policy would likely lead to the climate being stabilized at
343 temperatures warmer than pre-industrial or present-day, stimulated work to better quantify the long-term consequences
344 associated with such a stabilized warmer world (King et al., 2021).

345

346 Over the past decade significant progress has led to several ESMs now including a full representation of the carbon cycle,
347 interactively coupled to the physical climate (Arora et al., 2020). This progress has motivated calls for CMIP7 to more
348 strongly focus on CO₂-emission driven simulations, where a more complete representation of future climate – carbon cycle
349 feedbacks can occur (Sanderson et al., 2023). A number of ESMs are also incorporating and coupling other Earth system
350 processes required to properly investigate future emission pathways that realise the Paris Targets, as well as the
351 consequences of long-term stabilization. Developments include; nutrient limitation on terrestrial carbon uptake (Lawrence et
352 al., 2019; Wiltshire et al., 2021), interactive methane cycles with the ability to run in emission-mode for methane (Folberth et
353 al., 2022), interactive treatment of nitrogen and iron cycles (Dunne et al., 2020), interactive permafrost (Burke et al., 2020,
354 Schädel et al., 2024), interactive fires (Mezuman et al., 2020; Teixeira et al., 2021), full atmosphere chemistry (Gettelman et
355 al., 2019; Archibald et al., 2020) coupled to advanced aerosol models (Mulcahy et al., 2020), as well as interactive
356 Greenland and Antarctic ice sheets (Smith et al., 2021; Muntjewerf et al., 2021). Many of these developments, occurring
357 across several ESMs, have either recently entered use in coupled model configurations, or are in an advanced stage of
358 development and planned for use in CMIP7. As a result, the Earth system modelling community are entering a period where
359 simulation of the full Earth system during overshoot, recovery, and long-term stabilization can deliver critical new insights
360 that are urgently required to inform international climate policy.

361

362 An important focus for CMIP7 and ScenarioMIP (O'Neill et al., 2016; van Vuuren et al., 2023) therefore, will be
363 investigation of plausible emission scenarios and global warming pathways that successfully realize the Paris Agreement.
364 Key questions within this activity include; What is the feasibility of actually realizing the Paris targets? Whether a temporary
365 warming overshoot is inevitable? If so, what rate and magnitude of warming is likely to occur, and how sensitive is the Earth
366 system to such factors? Additionally, is it feasible to return to a target warming level on a reasonable timescale once an
367 overshoot has occurred (Bauer et al., 2023)? To provide robust policy guidance on the plausibility and consequences of such
368 pathways, several additional questions need to be addressed: Can accurate predictions of carbon emission budgets (and
369 budgets of other radiatively important greenhouse gases) be made that are commensurate with different warming targets,
370 with or without overshoot (Ramboll et al., 2023)? What is the role of anthropogenic aerosol emissions with respect to future
371 warming and achievability of the Paris targets (Jenkins et al., 2022; Wang et al., 2023) What is the risk of amplifying
372 feedbacks being triggered during overshoot (Melnikova et al., 2022), and is there a risk of exceeding tipping point thresholds
373 in the Earth system, society or the natural environment, during overshoot (Wunderling et al., 2023)? If plausible negative
374 emission pathways do exist, that return the Earth system to an acceptable temperature at an acceptable rate, once overshoot
375 has occurred, what will be the environmental consequences of following these pathways? Furthermore, during the overshoot
376 phase, if major changes or impacts (e.g. ecosystem degradation, population displacement, economic damages) do occur, or
377 tipping points are exceeded (either in society or the Earth system), are these changes reversible when temperatures return
378 back below a target level (Kim et al., 2022; Reed et al., 2023; Santana-Falcón et al., 2023) and how long will such a recovery
379 take (Albrich et al., 2020, Meier et al., 2012)?

380
381 Existing mitigation pathways that rely on negative CO₂ emissions assume a significant stimulation of terrestrial carbon
382 uptake through extensive modifications to land-use (Smith et al., 2016). How the carbon cycle will respond to these
383 interventions is not well quantified. Nor is the actual efficacy of these interventions in reducing temperatures (Schleussner et
384 al., 2023), or the ensuing impacts on the natural world, particularly biodiversity. A dominant part of the negative CO₂
385 emissions in present IAM scenarios is assumed to come from the AFOLU (agriculture, forestry and other land use) sector,
386 through large scale deployment of bioenergy with carbon capture and storage (BECCS). It is of the utmost importance
387 ESMs, with a comprehensive process-based representation of the carbon cycle, are used to assess the efficacy of such
388 AFOLU scenarios in terms of realized negative emissions and temperature response, accounting for interactions with the
389 natural carbon cycle and regional climate. Such major changes to the land surface will likely also lead to significant impacts
390 on water availability, biodiversity and a range of human activities (Séférian et al., 2018; Hof et al., 2018), both directly from
391 the change in land use and indirectly through induced changes in regional climates. Such potential impacts need to be
392 carefully assessed with impact models, with any negative impacts contrasted against the positive impact of the mitigation
393 actions on global warming. New negative CO₂ emissions technologies that encompass marine-based CO₂ removal (mCDR)
394 are increasing in interest. Such approaches aim to increase marine carbon uptake through ocean alkalization (Kwiatowski
395 et al., 2023; Palmieri and Yool, 2024) or increase the storage of ocean carbon via marine afforestation (Bach et al., 2021).
396 These new approaches have the potential to reduce the demand on land-based CDR, reducing the impacts of these techniques
397 on land. However, such ocean techniques can lead to negative consequences for marine ecosystems and organisms, by
398 altering marine nutrients cycles. It is important to emphasise that the full Earth system response to marine CDR is as
399 uncertain as its land counterpart. Uncertainties in its efficacy to remove and store CO₂ remain poorly quantified and
400 estimating the lifetime of CO₂ storage in the water column represents an additional challenge compared to the land-based
401 CDR, due to the complicating role of ocean circulation and potential redistribution of CO₂.

402
403 In addition to negative CO₂ emissions, Solar Radiation Management (SRM) has been proposed as an alternative (or
404 additional) route to limiting global warming to 1.5°C. While there remain concerns around the unintended consequences of

405 SRM (Bonou et al., 2023), as well as the long-term governance of such technology (Pasztor and Harrison, 2021), the
406 international SRM community recently designed a set of scenarios that allow investigation of both the efficacy and potential
407 climate impacts of such technology (MacMartin et al., 2022; Baur et al., 2023; Baur et al., 2024). The same community have
408 proposed an experiment protocol for the CMIP7 Fast Track (Visioni et al., 2024) that targets recovery of the global mean
409 surface temperature to 1.5°C threshold after overshoot. As the world continues to get closer to the 1.5°C threshold, interest in
410 SRM and geoengineering more broadly is likely to increase. The science community will be asked to provide the best
411 possible guidance on the efficacy of SRM, the potential climatic and ecological impacts of SRM, as well as information on
412 the scales (temporal, spatial and quantity) required for this technology to deliver long-term, safe climate stabilization. Such
413 work on climate ‘solutions’ including SRM should be organized under the WCRP Lighthouse Activity on Climate
414 Intervention, which brings together international research communities focussing on both CDR and SRM.
415 Finally, once an “acceptable” warming level is reached, it remains to be established whether the Earth system can be
416 stabilized, long-term at this level (Jones et al., 2019)? And, if so, what the consequences across the Earth system and for
417 society will be from such stabilization (King et al., 2021; Palazzo Corner et al., 2023)? All these questions have major
418 implications for international climate policy. Reliable answers are urgently needed. The international research community is
419 beginning to address such questions, and increasingly has the tools capable of providing answers. We believe the new round
420 of international modelling projects have the potential to make major advances towards delivering robust answers.

421
422 Past CMIP cycles, including the most recent phase CMIP6 (Eyring et al., 2016a), emphasized CO₂-concentration driven
423 simulations, where atmospheric CO₂ concentrations are prescribed and simulated carbon cycle – climate feedbacks cannot
424 influence atmospheric CO₂. This approach was taken largely for pragmatic and inclusivity reasons (i.e. there was only a
425 relatively small number of models with robust and stable coupled climate and carbon cycles). Thanks to efforts such as
426 C⁴MIP (Friedlingstein et al., 2006, Arora et al., 2020), this is no longer the case, with a significant number of ESMs now
427 including advanced carbon cycles coupled to their physical climate (Sanderson et al., 2023). Due to the small remaining
428 carbon budgets involved in realizing the Paris targets, and uncertainty in how the carbon cycle will respond to negative and
429 net zero emissions, it is imperative more ESMs in CMIP7 run in CO₂-emission mode, with full interaction between the
430 physical climate and carbon cycle, including prognostic atmospheric CO₂ (Sanderson et al., 2023; Gier et al., 2024). This
431 will support an improved assessment of feedbacks involving the physical climate and the carbon cycle, addressing
432 consequences for allowable future carbon emissions, the amount of negative emissions required after different overshoot to
433 achieve different stabilization goals, and the associated risks, impacts and potential for irreversible change across the Earth
434 system. Only through such a coupled, prognostic approach can anthropogenic CO₂ emission scenarios, intended to realize
435 key warming targets, be connected with the Earth system response and the impact of these responses on atmospheric CO₂
436 and realized warming/cooling pathways.

437
438 We propose other important aspects of the coupled Earth system, at risk of rapid change, should also be run in a more
439 *coupled and prognostic* manner in CMIP7. Assessment of coupled interactions and risks across the entire Earth system,
440 including potential tipping point risks (Ritchie et al., 2021), is severely lacking in earlier IPCC Assessment Reports. Giving
441 greater emphasis to coupled and prognostic interactions across the Earth system (particularly those thought to play a major
442 role in determining the magnitude of future change) in an internally consistent framework will allow a more complete
443 assessment of Earth system change, beyond that focussed solely on the physical climate. In addition, we emphasize the need
444 to assess the impact of specific and targeted human actions (designed to mitigate future climate change or to adapt to
445 expected future change) on regional climate, as well as on other aspects of the coupled Earth system, including resilience of
446 the natural environment, biodiversity, and consequences for other human activities (e.g. food security, energy production or

447 air quality). The current scientific priorities with respect to such interactions, along with (in italics) the key phenomena,
448 feedbacks and consequences such coupled simulation would enable improved assessment of, are listed below:

449

- 450 (i) Water, vegetation and biogeochemical cycles of carbon, nitrogen, phosphorous; *improved estimates of vegetation*
451 *change, terrestrial carbon uptake, regional water cycles and ecosystem tipping risks.*
- 452
- 453 (ii) Climate, vegetation, and fire: *improved assessment of future fire risk and interactions with carbon uptake,*
454 *atmospheric composition and ecosystem tipping risks.*
- 455
- 456 (iii) Permafrost, climate, vegetation, and carbon: *stability of permafrost under warming and long-term warming*
457 *stabilization, carbon/methane release from thawing permafrost, ecosystem expansion into thawing permafrost zones.*
- 458
- 459 (iv) Climate, ice sheets, and sea level: *improved assessment of potentially irreversible loss of Antarctic and Greenland ice*
460 *mass and consequences for sea level rise, ocean circulation and ocean heat uptake.*
- 461
- 462 (v) Climate, atmospheric composition, and air quality: *internally consistent assessment of regional radiative forcing,*
463 *climate change and air quality.*
- 464
- 465 (vi) Ocean physics, biogeochemistry and ecosystems: *assessment of ocean warming, marine carbon uptake and long-term*
466 *storage, ocean acidification and impacts on marine ecosystems.*
- 467
- 468 (vii) Human-Earth System interaction: *assessment of the direct impact of human activities on the Earth system, regional*
469 *climate, society, and the environment. e.g. Mitigation actions designed to address air quality and/or climate change,*
470 *such as major land use change, nature-based solutions, climate interventions (geoengineering). Adaptation measures*
471 *designed to address regional to national scale climate risk.*
- 472
- 473 (vii) The interplay between global change, regional climate variability, changes in climate and weather extremes, and
474 resulting impacts across the Earth system.

475 **3.2 Regional Earth system change; assessing societal and environmental impacts.**

476 In addition to changing how global ESMs are run, we propose that regional downscaling (for example dynamical
477 downscaling or Regional Climate Modelling, as used in CORDEX) also advance their representation of key regional Earth
478 system processes (beyond the physical atmosphere-land system; Giorgi and Prein, 2022; Nabat et al., 2020; Sevault et al.,
479 2014). Here we refer to regional climate modelling or dynamical downscaling in the broadest sense, encompassing any
480 physics-based dynamical model targeting a fine-scale representation of the climate over a specific region of the world. This
481 includes limited-area models (LAM), variable-resolution GCMs (VRGCM) and, more recently, regional earth system
482 models, convection-permitting regional models, and two-way coupled systems. In addition, atmosphere-land only global
483 models are beginning to run for decadal timescales (and likely longer in the coming decade) and can be driven by sea surface
484 temperatures and sea ice derived from ESM projections, providing a global downscaling option for coupled ESM
485 projections. Whatever the technical choices used to perform such dynamical downscaling in future projection mode, forcings
486 from global ESMs and GCMs will be required, either as lateral, surface, or inner model boundary condition data. Similarly,
487 we use the term statistical downscaling in a very broad sense, covering established statistical methods for transferring

488 simulated large-scale climate data to local scales, as well as the increasing range of machine learning (ML) techniques,
489 including recent deep learning applications (Gerges et al., 2023; Soares et al., 2024).

490

491 To better sample the uncertainty range of global projections, dynamical and statistical downscaling should preferentially use
492 CO₂ emission-driven ESMs as boundary forcing and employ an efficient (as automated as possible) method to select an ESM
493 ensemble for a given region and rapidly generate the required boundary condition data. The resulting combination of global
494 emission-driven ESMs, regional ESMs, and advanced statistical/ML-based downscaling, running in a tightly linked
495 framework, will allow a more complete assessment of potential changes across the global and regional environment at scales
496 required by policymakers and planners. Given the rapid development of a diversity of dynamical, statistical and ML-based
497 methods to generate high-resolution regional data, it is important a common evaluation framework is developed that is
498 applicable across global to local scales (and across the implied model resolutions) as well as being agnostic to the methods
499 employed, so different downscaling approaches can be objectively evaluated against each other, region by region and
500 application by application.

501

502 We further recommend impact models use a coordinated, multi-model ensemble of (global and regional) simulation-data,
503 based on the CMIP7 CO₂-emission driven ESMs, that capture a representative fraction of the uncertainty space of global and
504 regional projections. In addition, impact models should aim to sample multiple members of individual ESMs, and the
505 downscaling of these ESMs, to better quantify the importance of internal (natural) variability in regional climate impacts.
506 Forcing impact models, either directly by global ESM output or by appropriately downscaled data, themselves driven by the
507 same ESM simulations, will ensure global consistency of the impact simulations and comparability of impacts resulting from
508 global and regionally downscaled forcing over the same region. In addition to coordinated forcing from ESM and
509 downscaled data, a more complete, disaggregated set of IAM scenario data describing socio-economic development and
510 potential mitigation or adaptation measures will ensure greater coherency between global and regional impact assessments
511 and the underpinning IAM, ESM and regional forcing data. The resulting global models and downscaling combinations can
512 also be used to assess the efficacy and potential impacts associated with different regional climate change mitigation or
513 adaptation actions, offering scientific assessment of such proposed climate solutions.

514 **4 Improving our understanding of, and ability to model key climate processes, climate variability, extreme** 515 **events and regional impacts.**

516 **4.1 Improving key phenomena and couplings in global climate models.**

517 Some of the key uncertainties in Earth system model projections relate to errors in simulating important regional climate
518 processes and phenomena, including interactions across spatial scales and regions. For some of these phenomena, model
519 resolution has been shown to be a key factor. Hewitt et al. (2022) showed that increasing ocean model resolution, in
520 particular better resolving the ocean mesoscale, is important for accurately representing a number of key processes,
521 including; ocean eddies in the Southern Ocean and North Atlantic (*with implications for simulated marine heat and carbon*
522 *uptake, ice sheets and sea-level rise*), ocean deep water formation in the Labrador and Nordic Seas and on the Antarctic shelf
523 (*with implications for the global ocean overturning circulation and heat uptake*), the Atlantic Meridional Overturning
524 Circulation (*with implications for heat and carbon uptake, as well as regional climate*), ocean upwelling regions (*with*
525 *implications for marine carbon uptake, productivity and fisheries*). Increased resolution, in both the atmosphere and ocean, is
526 also important for simulating large-scale hydrological processes (Vannière et al., 2019) (*with important implications for*
527 *regional water cycles, water availability and food security*), as well as modes of climate variability, such as the El Niño
528 Southern Oscillation (ENSO) and associated teleconnections (*with implications for the rate of ocean heat uptake and*

529 *regional climate variability*). While increased model resolution (to better resolve the meso- or the synoptic scales) is an
530 important component of reducing several systematic biases in coupled models, it is equally important to improve key
531 parameterization schemes for processes that continue to be unresolved, even at horizontal resolutions of $\sim 10\text{km}/0.1^\circ$ in
532 coupled models. In particular, it is critical to ensure further improvement in parameterizations at the heart of uncertainty in
533 the simulated Effective Climate Sensitivity (EffCS), Transient Climate Response (TCR) (Meehl et al., 2020) and aerosol-
534 cloud forcing (see Sect. 6 of this paper).

535

536 Upscale effects from many small-scale processes can be important. For example, oceanic mesoscale eddies tend to drive
537 atmospheric mesoscale storms in the extra tropics (Liu et al., 2021), while at larger scales the atmosphere can drive ocean
538 variability (Frankignoul, 1985). These effects are apparent only in coupled systems and their large-scale consequences, such
539 as the preferred location and orientation of the jet stream, mid-latitude storm tracks, and related air-sea fluxes, can only be
540 captured in large-domain models with mesoscale or better resolution (Seo et al., 2023). Furthermore, couplings between the
541 heat, water, and carbon cycles, means improving the representation (and parameterization) of physical processes will deliver
542 important benefits for simulating the carbon, and other biogeochemical, cycles. In addition to the large-scale impacts, higher
543 resolution models also offer an improved simulation of climate variability, in particular weather extremes such as; tropical
544 cyclones (Roberts et al., 2020), extreme precipitation (You et al., 2023), atmospheric rivers (Liang and Yangyang, 2023), jet
545 streams and atmospheric blocking (Schiemann et al., 2020) with consequences for the frequency and location of extreme
546 weather (Athanasiadis et al., 2022), which both depend on SST realism delivered by resolving the ocean mesoscale. All these
547 events have important impacts across the coupled Earth system, including upscale effects, e.g. drying of the atmospheric
548 column by tropical cyclones over the Maritime Continent, with impacts on ENSO (Scoccimarro et al., 2021). Similarly, in
549 the ocean increased resolution can improve the representation of important dynamical phenomena, such as marine heatwaves
550 (Plecha and Soares, 2020) the representation of bottom water formation (Heuzé, 2021) and mixed layer eddies (Calvert et al.,
551 2020).

552

553 Increasing model resolution alone does not guarantee improvement in all simulated metrics and leads to significant
554 challenges related to model spin-up, model equilibration, calibration, and uncertainty quantification. Simulation
555 improvements are often best realized through a combination of increased model resolution and targeted improvement to key
556 parameterization schemes. While the compute cost increases considerably as model resolution is increased, recent studies
557 suggest increased resolution can deliver important insights into some long-standing model biases, and perhaps reconcile
558 mismatches between simulated and observed historic trends. For example, Rackow et al. (2022) show that resolving the
559 ocean mesoscale improves the simulation of Antarctic sea-ice trends, Chang et al. (2023) illustrate increased realism in
560 ocean upwelling as model resolution is increased, and ongoing work suggests higher resolution simulations can better
561 capture recent observed trends in the Eastern Pacific that are not captured in CMIP6 models (Seager et al., 2022). Such
562 improvements will increase confidence in future model projections and have important implications for predicting future
563 extreme events, such as tropical cyclones, floods, droughts, and heatwaves.

564

565 There is strong evidence a coordinated set of simulations for CMIP7, with resolutions enhanced over those typically used
566 (e.g. 10-20 km in the atmosphere and $\sim 0.1^\circ$ in the ocean), can deliver an improved simulation and understanding of key
567 regional climate processes and a more robust assessment of future changes in many of these processes, with benefits for
568 impact and adaptation planning. Chang et al. (2020) demonstrated that CMIP-length simulations, with an equilibrated
569 coupled model, are now possible at resolutions of $\sim 10\text{-}20\text{ km}/0.1^\circ$. Many groups produced simulations following the CMIP6
570 HighResMIP protocol (Haarsma et al., 2016), though generally with very limited ensemble sizes. Given increased model
571 efficiency and available compute resources, CMIP7 provides an opportunity to further investigate the benefits of increased

572 coupled model resolution, alongside increased ensemble size, longer simulation length, methods for improved model
573 equilibration and initialization, and enhanced process realism. Given current structural limitations of coupled climate
574 models, of whatever resolution, sampling model diversity, through multi-model CMIP-style exercises, remains critical for
575 providing robust estimates of projection uncertainties and risks (see Section 7). This is particularly the case with respect to
576 regional climate change, where processes may be resolution-dependent (e.g. Moreno-Chamarro et al., 2022) and therefore
577 sensitive to biases common across lower resolution models. A diversity of enhanced resolution coupled models thus needs to
578 be promoted, but also optimized across the competing demands for delivering future projection data that is of maximum
579 quality and utility both for the science and policy communities.
580

581 **4.2 Increased model resolution from global to regional scales for regional impact assessment and adaptation.**

582 Like their global counterparts, Regional Climate Models have also increased in resolution, with a growing set of models now
583 running at convection-permitting resolutions (~1-3km resolution; Ban et al., 2021; Hohenegger et al., 2023). In addition to
584 an improved simulation of the convective scale, high-resolution itself brings direct benefits, by delivering climate
585 information closer to impact and adaptation relevant scales and by better resolving local climate in regions of strong
586 orographic forcing, complex land-sea-lake structures, or heterogeneous land surface types. Moreover, explicitly resolving
587 convective events, including the self-organization and self-intensification of these events, brings physical grounding to
588 simulated precipitation extremes (Kendon et al., 2021; Caillaud et al., 2024), including the ability to evaluate models against
589 observations at common spatial scales (Caillaud et al., 2021). A growing set of regional projections, employing convection-
590 resolving models (Pichelli et al., 2021; Chapman et al., 2022; Kawase et al., 2023; Kendon et al., 2023), is shedding new
591 light on the interaction between future climate change and regional hydrological responses. Convective-scale regional
592 models can also be deployed for shorter, targeted purposes. For example, by focusing downscaling onto event sets where
593 such high regional resolution is expected to add value to coarser scale models, or by sub-selecting global projections that
594 allow a broad range of climate hazards, needed for robust adaptation, to be simulated regionally at high resolution.
595

596 While the combination of high-resolution coupled global climate models (~10-20 km in the atmosphere and ~0.1° in the
597 ocean) and convection-permitting regional climate models (~1-3 km) is computationally demanding, the potential to deliver
598 radically new findings and policy support, at scales required by national and regional planners, means they are an
599 increasingly important input to national climate scenarios and climate services. This is particularly the case with respect to
600 extreme weather events. In the next phase of CMIP and CORDEX, we propose increased collaboration, as well as increased
601 data and knowledge sharing, between high-resolution global climate models, convection-resolving regional models, and
602 statistical/ML-based downscaling, with the goal of producing a coordinated ensemble of state-of-the-art, high-resolution
603 global and regional projections. We further recommend the resulting (global and regional) projections are used to drive a
604 range of impact models (e.g. in ISIMIP, AgMIP and FishMIP). As the future impacts felt by natural and human systems is
605 not only dependent on climate change, but also on the direct human forcing of climate arising from the underpinning
606 scenarios themselves, it will be important to also represent these drivers at high spatial resolution. The resulting set of
607 climate change and impacts data will be of enormous value to national climate change impact assessments, adaptation
608 planning and climate services. To maximize the quality and consistency of this multi-scale, multi-method data set, it is
609 important systems are developed and employed to support careful evaluation of the cascade of information across methods,
610 scales, and regions, as well as from climate to impacts, highlighting both value-added and consistency-lost across the entire
611 chain.
612

613 **4.3 Global Storm Resolving models and the path to global km-scale**

614 Global models with grid spacing in the range 1-10km are often referred to as Global Storm Resolving Models (GSRMs, e.g.,
615 Hohenegger et al., 2020; Judt et al., 2020; Caldwell et al., 2021). GSRMs running at ~3-5km global resolution currently
616 achieve a throughput of ~0.5 simulated years per day (SYPD), with an aim to reach 1 SYPD in the coming years. GSRMs
617 originated within the international DYAMOND initiative (Stevens et al., 2021) and the GRSM community are currently
618 designing year-long experiment protocols (Takasuka et al., 2024, submitted). In addition, within the EU-sponsored
619 Destination Earth (DestinE; Wedi et al., 2022) two coupled GCMs have run a reduced HighResMIP experiment (for the
620 period 1990 to 2040) with grid spacing of 5km.

621
622 Examples of scientific highlights realised by GSRMs include; a realistic representation of the interannual frequency of
623 Tropical Cyclones (TC) in major basins, comprising a realistic distribution of all severity categories (Judt et al., 2020), as
624 well as realistic representation of the rate of TC intensification, possible as resolutions reach 3km or better. Recent
625 comparative studies among km-scale ocean models show large-scale features that affect the storm tracks and air-sea coupling
626 (e.g., Gulf Stream separation) are more consistent in these models than in coarser resolution ocean models. Internal
627 variability is also substantially larger in eddy-rich models (Chang et al., 2020; Jüling et al., 2021), including stronger SST
628 responses to AMOC variations. In terms of coupled phenomena, realistic representation of the North Atlantic storm track has
629 been shown to be sensitive to resolution of the ocean mesoscale, including instantaneous (eddies) and climatological features
630 (western boundary currents) (Moreno Chamorro et al., 2022). Representation of the full spectrum of precipitation processed
631 by cyclones, including their frontal structures, organised convection, such as Mesoscale Convective Systems and squall lines
632 are generally more realistic as model resolution is increased (Vellinga et al., 2016).

633
634 Many of these achievements have been in the realm of convection-permitting Regional Climate Models (see section 4.2) for
635 the past ~5 years. GSRMs offer the additional value of being able to simulate upscale effects from small scales onto larger
636 scales, e.g. how the Hadley and Walker circulations are affected, including meridional transports of energy, as well as
637 implications for global teleconnections, mediated by atmospheric wave propagation. Many of these achievements were
638 realised thanks to the development of new dynamical cores capable of reducing the total number of computations, by use of
639 uniformly spaced global grids, or by models running more efficiently through advanced numerical schemes in time and
640 space, and by exploiting multiple parallelisation paradigms on the latest supercomputers, including those equipped with
641 GPUs. With the advent of even more powerful new classes of GPU, such as the NVIDIA Hopper or AMD MI300 series,
642 completing a selection of typical CMIP6 experimental protocols at ~3km resolution, with a total turnaround of order of one
643 year, will soon be possible.

644
645 Data output and analysis constitutes a major challenge at these resolutions: output of order petabytes per day are
646 commonplace, and storing multiple ensemble members for centennial-scale simulations is not feasible. Multiple approaches
647 are being tested to alleviate this problem, such as performing the most data-intensive and multi-variate analyses while the
648 models are running, reduced data precision, or holding data on fast disks for very brief time periods to allow immediate
649 consumption by users. Other approaches include the use of hierarchical data layers, which can be output and handled in
650 parallel, with incremental expense, as exemplified by the HEALPIX standard. An ambitious vision for addressing such data
651 challenges, including co-design, co-production, and global access, is provided in the Earth Virtualisation Engines concept
652 (Stevens et al., 2024).

653

654 **5 Increasing collaboration across approaches to improve global and regional Earth system and climate models.**

655 The accuracy of numerous simulated Earth system and biogeochemical phenomena strongly depends on the quality of
656 simulated physical climate drivers (Doney et al., 1999). Examples of such dependencies include, but are not limited to; (i)
657 vegetation growth/loss, terrestrial carbon uptake, and the simulated water cycle; (ii) wildfires and simulated precipitation,
658 soil moisture and winds; (iii) marine productivity and the dynamics of ocean upwelling, (iv) mass loss from marine ice

659 sheets and regional ocean circulation; (v) global ocean heat and carbon uptake, and representation of deep water formation,
660 (vi) regional air pollution and modes of atmospheric circulation. Conversely, in the real-world, carbon cycle – climate
661 feedbacks (as well as other Earth system feedbacks) change the fraction of anthropogenic CO₂ (and other gases, such as CH₄
662 or N₂O) that remain in the atmosphere to cause warming, thereby influencing the magnitude of physical climate feedbacks
663 (e.g. water vapour, lapse-rate, cloud or sea ice feedbacks). Furthermore, while an accurate simulation of the mean climate (in
664 time and space), as well as trends in this measure of climate, are important, an accurate representation of variability (in both
665 time and space) of the underpinning physical climate can often be as important for simulating the Earth system response to a
666 changing climate. Such variability is also a critical driver of the impacts of climate change. Regional climate variability,
667 particularly the width of the distribution of such variability (i.e. the extreme tails of future climate distributions), is generally
668 better represented as resolution is increased, both in global and regional models (Wehner et al., 2014; IPCC, Doblus-Reyes et
669 al., 2021; Ban et al., 2021).

670

671 High-resolution coupled global climate models can be viewed as the physical core of the next generation of Earth system
672 models, offering an improved simulation of the driving physical climate, including climate variability and extreme events.
673 Collaboration across the development of high-resolution physical climate models, and Earth system models that emphasize
674 enhanced process-realism, needs to deepen both in CMIP7 (with respect to global models, Dunne et al., 2023) and CORDEX
675 (with respect to regional models). Such collaboration can benefit from, and feed into, ongoing efforts under the WCRP LHA
676 Explaining and Predicting Earth System Change (<https://www.wcrp-climate.org/epesc>), and offers an unprecedented
677 opportunity to bring advances from both areas together to support development of the next generation of Earth system
678 models. Such a meeting point between these two model development paths offers a unique testbed for assessing
679 technological advances (e.g. hybrid-resolution ESMs, Berthet et al., 2019; AI-based emulation approaches, Son et al., 2024),
680 as well as conceptual challenges in Earth system modelling (e.g. quantifying and optimizing the benefits and trade-offs
681 between resolution, complexity and ensemble size). AI/ML-based approaches also have the potential to improve model
682 parameterizations, while potentially also increasing computational efficiency, enhancing the overall projection capability of
683 these models. This needs to be further explored (Eyring et al., 2024a), with increased sharing of methodologies and findings
684 across ML-based, and more traditional (process-based) approaches to model development (Schneider et al., 2024). Increased
685 collaboration and knowledge sharing across these efforts can lead to a step change in our overall ability to provide robust
686 climate information at scales that meets the needs for mitigation and adaptation decision-making (Eyring et al., 2024b).

687

688 A number of initiatives are beginning to develop “Digital Twins of the Earth” (DTEs, Bauer et al., 2021; Hoffman et al.,
689 2023), (e.g. the WCRP Digital Earth LHA, <https://www.wcrp-climate.org/digital-earths>) targeting an optimal fusion of Earth
690 system modelling and observations, to deliver fit-for-purpose and actionable information to society. These approaches
691 combine forward modelling, data assimilation, and machine learning tools with user models designed to answer specific
692 questions. A number of (global and regional) DTEs are beginning to provide samples of km-scale information, with the
693 majority of DTEs to-date being atmosphere-land only models. For application to future climate change, such models
694 presently require sea surface and sea ice boundary condition data (or atmospheric boundary conditions) derived from
695 coupled ESM projections. As DTEs further develop to include other components of the Earth system (e.g. oceans,
696 cryosphere, carbon cycle etc) it will be important they are carefully evaluated against existing approaches to deliver high-
697 resolution future climate information (either via uninitialized projections or observation-initialised predictions). It will also
698 be important to document the uncertainties in DTE projections/predictions arising from different modelling choices, different
699 external forcings and emission scenarios, as well as from internal variability. This is particularly important with respect to
700 predicted or projected changes in future extreme weather events, which by definition are rare occurrences, with low
701 predictability.

702

703 Only a few efforts to date are trying to develop two key aspects of digital twins; linking inputs to observations and outputs to
704 human systems. In Europe, Destination Earth (<https://destination-earth.eu/>) experiments with weather and climate twins,
705 down to resolutions of 2.5 km, and aims to make its experimental design respond to user needs, so models store a minimal
706 amount of data, but are re-run on a regular basis, incorporating the latest data requests in each update. In the US, the
707 Department of Energy has tested combining physical models (e.g. the Energy Exascale Earth System Model, E3SM (Golaz
708 et al., 2022)) with human system models, including Integrated Assessment or Energy Grid models. In addition, ultra-high-
709 resolution global storm-resolving models (GSRMs, Stevens et al., 2019; Lee and Hohenegger, 2024) run at 1-5 km
710 resolution may provide further understanding and insights into biases, complementing CMIP7/CORDEX simulations.
711 Increased sharing across the range of modelling communities will benefit all strands of work, improving our combined
712 ability to model the Earth system and deliver robust and actionable information to policymakers and society.

713 **6 Improving model simulations of the observational record and key metrics of climate change**

714 To increase confidence in future projections it is important models accurately reproduce the observed historical record. This
715 requirement encompasses multiple variables and timescales, with long-term trends in global mean surface air temperature
716 (GMSAT), including the forcings and feedbacks controlling these trends, of first order importance. In CMIP6 a number of
717 ESMs exhibited EffCS values (of 5°C or greater) that are higher than the 5-95% range, as assessed by multiple lines of
718 evidence (Sherwood et al., 2020). Some of these models also simulated global warming rates over recent decades (~1980 to
719 2014) greater than seen in observations (Tokarska et al., 2020), leading to suggestions these “hot models” were unrealistic
720 and should be filtered out from climate impact assessments (Hausfather et al., 2022).

721

722 Cloud feedbacks are the largest contributor to uncertainty in EffCS. Perhaps surprisingly, CMIP6 ESMs with high EffCS
723 often evaluate better against observations for present-day clouds than earlier or lower EffCS models (Bock and Lauer, 2024;
724 Kuma et al., 2023), and also accurately reproduce recent trends in cloud-radiation when driven by observed sea surface
725 temperatures (SSTs, e.g. Loeb et al., 2020). These ESMs also represent a number (though not all) cloud feedback processes
726 more accurately than earlier models, particularly those related to mixed phase clouds over the Southern Ocean (Jiang et al.,
727 2023). Nevertheless, studies continue to highlight problems across the majority of CMIP6 models with respect to Southern
728 Ocean clouds (Schuddeboom and McDonald, 2021) and, in particular, low-level tropical marine clouds (Konsta et al., 2022),
729 with observation-based constraints of the latter cloud type suggesting an EffCS closer to 3°C (Myers et al., 2021). It is
730 therefore possible some high EffCS CMIP6 models improved one cloud feedback (e.g. mid-latitude, mixed phase clouds
731 leading to a less negative cloud phase feedback) that exposed other feedback errors (e.g. too positive low-level, tropical
732 marine cloud feedback) that previously compensated each other with respect to the total cloud feedback. Such one-sided
733 improvement can result in an increased positive total cloud feedback and high EffCS. Continued improvement in the
734 representation of cloud processes and feedbacks across all relevant cloud types, including exploitation of new observational
735 data and analysis methods, will be crucial for better constraining EffCS in CMIP7 and improving the simulation of historical
736 climate and rates of global warming.

737

738 While a number of high EffCS models in CMIP6 simulated too strong global warming over the period ~1980 to 2014,
739 establishing a direct link between EffCS and historical warming is not straightforward. This is mainly due to the
740 confounding role of aerosols, as well as the important role played by natural variability. In CMIP7 historical forcings are
741 planned to be extended to 2022 (i.e. 8 years longer than in CMIP6). Recent studies suggest anthropogenic effective radiative
742 forcing (ERF) has become more positive, by ~50%, between the decades 2000-2009 and 2010-2019, mainly due to a

743 reduction in the negative aerosol ERF (Jenkins et al., 2022; Hodnebrog et al., 2024). This change has been accompanied by
744 almost a doubling of the GMSAT warming trend between these two decades. Jenkins et al. (2022) suggest that while some of
745 the increased GMSAT trend is very likely due to reduced aerosol cooling, long-term variability in ENSO may also
746 contribute. Modelling studies by Wang et al. (2023) further suggest that decreasing aerosol emissions may outweigh
747 decreasing CO₂ emissions in terms of their impact on warming and climate extremes during the path to global net-zero
748 carbon emissions. Kang et al. (2023a, b) suggest the SST pattern observed in the Pacific between ~1979 and 2013, which
749 induces a negative cloud feedback term (that is not captured in most coupled ESMs), is linked to cooling SST trends in the
750 Southern Ocean over this period (also not captured in coupled ESMs). They suggest that as Southern Ocean SSTs begin to
751 warm, the tropical Pacific SST pattern may decay, resulting in a more positive cloud feedback and potentially an increased
752 rate of global warming. Understanding and simulating the drivers of such SST trends, as well as their interaction with
753 climate feedbacks and global warming, will be crucial to increase confidence in future projections.

754
755 Constraining future feedbacks and evaluating model processes controlling these feedbacks is a difficult challenge. Emergent
756 Constraints, which use a multi-model ensemble to identify relationships between observable Earth System variations and
757 projected future changes, are an attractive way to constrain future feedbacks based on observations (Hall et al., 2019; Nijssen
758 et al., 2020) and thereby reduce uncertainty in future projections. To date, assumed emergent relationships are often simple
759 linear regressions. Machine Learning techniques are a promising route for identifying multi-dimensional, non-linear
760 relationships between contemporary observables and the future state of the Earth System (Schlund et al., 2020) and may
761 therefore improve the constraints on future feedbacks and even allow an evaluation of model processes controlling these
762 feedbacks. An improved simulation of the historical past, combined with improved constraints on key feedbacks and the
763 processes controlling these feedbacks, will increase confidence in ESM projections and improve estimates of key climate
764 change metrics such as EffCS, TCR and TCRE with implications for estimates of allowable carbon emissions commensurate
765 with different policy targets.

766
767 Both global and Regional ESMs struggle to accurately represent observed regional climate trends, as underlined for Western
768 Europe by recent literature (Ribes et al., 2022; Schumacher et al., 2023; Vautard et al., 2023). This may be partly linked to
769 poor quality lateral and surface boundary conditions (e.g. most recently from CMIP6 ESMs), but may also be a result of
770 missing, or poorly represented, regional forcings and/or feedbacks in the RCMs themselves (Nabat et al., 2014; Boé et al.,
771 2020; Taranu et al., 2022, e.g. the representation of aerosol-climate interactions or the simulation of regional/coastal SST
772 trends). For RCMs, too short evaluation runs, and lack of adequate calibration strategies may also contribute to these
773 problems. Tackling such weaknesses, combined with development of an evaluation system applicable across the scales and
774 downscaling methods involved, will be important for increasing trust in high-resolution, regional projections that are used in
775 numerous national climate scenarios and impact assessments.

776 **7 Sampling and quantifying future uncertainty**

777 Multi-model ensemble projections (MME), such as those from CMIP and CORDEX, sample a number of plausible IAM
778 emission and land-use scenarios. The MMEs often include a small number of ensemble members per individual model, each
779 sampling internal variability (as represented by that model). The MME approach, to a limited extent, also addresses
780 structural modelling uncertainty. The degree this aspect of uncertainty is sampled is ultimately constrained by the resolution
781 and process realism of the models involved, and by the degree of commonality of approaches to representing unresolved and
782 uncertain model processes (Merrifield et al., 2023).

783 7.1 High Impact Low Likelihood (HILL) outcomes.

784 While such MMEs sample a fraction of the uncertainty in future Earth system change, this sampling is far from complete,
785 particularly with respect to the extreme, low-likelihood end of potential Earth system change. Such responses are referred to
786 as HILL (High Impact, Low Likelihood) outcomes (Wood et al., 2023). While HILL outcomes have a low likelihood of
787 happening, there remains a small chance they will occur. One example would be if the Earth's equilibrium climate sensitivity
788 (ECS) turned out to be $\sim 5^{\circ}\text{C}$. While this outcome is highly unlikely (IPCC AR6 quotes the *very likely range* (5-95%
789 probability) of ECS as between 2°C and 5° ; see Fig. 7.18, in IPCC, 2021, Ch7, Forster et al. 2021), if it did occur the impacts
790 on society would be extremely large.

791
792 HILL events may also occur at lower levels of warming (Armstrong-McKay, 2020) and impact numerous parts of the Earth
793 system across a range of regions and timescales. For example, a HILL event may be triggered if a threshold of Antarctic ice
794 loss is exceeded, which may then accelerate and become irreversible, with consequences for sea level rise and coastal
795 communities (Garbe et al., 2020; Taherkhani et al., 2020). Similar, poorly quantified, and poorly understood, risks exist for
796 other potential Tipping Points in the Earth system, such as collapse of the Atlantic Meridional Overturning Circulation
797 (AMOC, Klose et al., 2023), dieback of the Amazon rainforest (Parry et al., 2022), or rapid permafrost thaw (Turetsky et al.,
798 2020). Tipping points also exist in the natural environment and in society and may be triggered at modest levels of warming.
799 Examples include climate driven species loss already occurring at today's levels of global warming (e.g. first species
800 extinction attributed to climate change; IPCC 2023 SPM), mass mortality in coral reef ecosystems (Donner et al., 2017;
801 Hughes et al., 2018; Hughes et al., 2019), shift from kelp- to urchin-dominated coastal communities (Rogers-Bennett and
802 Catton, 2019; McPherson et al., 2021). HILL events, both in the natural Earth system and society are not only sensitive to
803 changes in the mean climate, but also to changes in climate variability. Increased inter-annual variability can have major
804 impacts on society and ecosystems (von Trentini et al., 2020). Systematic shifts, even in sub-seasonal climate can
805 significantly impact society (e.g. changes in the frequency distribution of hot summer days and nights, and human mortality;
806 Schär et al., 2004).

807
808 The signal of natural variability (in models expressed as internal variability across a model ensemble) increases in
809 importance, relative to the signal of human forced climate change, as spatial and temporal averaging scales decrease, and
810 projection timescales become shorter (Hawkins and Sutton, 2009). A consequence of this is that larger ensembles are
811 required to reliably detect a forced climate change signal from an extreme realization of natural variability. The shorter
812 duration and/or rarer the event, the larger the ensemble size likely required to be confident a (forced) signal is outside the
813 range of natural variability. This is important information for reliable and cost-effective adaptation to potential future climate
814 risks. Several groups have produced large ensembles covering the historical past and future (Olonscheck et al., 2023; Maher
815 et al., 2021; Deser et al., 2020), using 50 to 100 realizations, often started from different initial conditions taken from the
816 model's pre-industrial simulation. Such large ensembles are ideal for detecting forced regional changes (as simulated by that
817 particular model) from internal (natural) variability (also as simulated by the particular model). Due to the high
818 computational cost involved, to date such large ensembles are generally based on relatively low-resolution models that do
819 not carry the process complexity of full ESMs. This can limit their overall utility. For example, low resolution models
820 struggle to simulate intense weather events, such as tropical cyclones or extreme precipitation. As a result, their utility for
821 investigating changes in extreme weather is limited, although this limitation could be addressed, for specific regions at least,
822 by building ensembles consisting of both Global and Regional models run in tight coordination.

823
824 Recently, single model initial condition large ensembles (SMILEs) have been combined to form multi-model ensembles of
825 SMILEs (Lehner et al., 2020), increasing the sampled uncertainty beyond internal variability to also encompass (to some

826 degree) structural model uncertainty. Techniques have been developed to optimally combine individual SMILEs, with
827 different ensemble numbers, to produce an unbiased multi-model SMILE that also considers present-day model performance
828 in its design (Merrifield et al., 2020). New Machine Learning techniques offer the potential for a more efficient and
829 comprehensive assessment of the future projection uncertainty space and can be used to guide, and in some cases realise, the
830 creation of large ensembles, including ones targeted onto extreme event risks (Eyring et al., 2024a).

831 **7.2 Internal variability, parameter uncertainty and model structural uncertainty.**

832 An additional approach for investigating modelling uncertainty is the Perturbed Parameter Ensemble (PPE) (Murphy et al.,
833 2007). In the PPE approach uncertain, often difficult to constrain, model parameters are varied within reasonable limits,
834 where possible constrained by observations (Booth et al., 2017). The resulting PPE members can be further filtered to retain
835 only skilful members in terms of present-day climate and/or historical trends (e.g., Sexton et al., 2021; Peatier et al., 2022).
836 Recent advances in model calibration (e.g., Hourdin et al., 2021, 2023) will be instrumental in better designing future PPEs.
837 Using the PPE approach, it is sometimes possible to mimic key measures of future projection uncertainty (e.g. the range of
838 climate feedbacks and ECS in a CMIP MME) using only a single model (Collins et al., 2011). Applying the PPE approach
839 across multiple global and regional model systems allows probabilistic regional climate projections that sample a significant
840 fraction of the future projection uncertainty (Evi et al., 2021). Such approaches support an assessment of regional impacts
841 sampling uncertainty in the future driving global and regional climate, including changes in climate and weather variability.
842

843 In addition to physically based models, advanced statistical methods such as emulators (Meinhausen et al., 2011; Leach et
844 al., 2021) and Machine-Learning (ML) (Watson-Parris, 2021; Eyring et al., 2024a) are increasingly being used to more fully,
845 and rapidly, investigate uncertainty in future Earth system change. Emulators and ML methods can be trained either on an
846 individual model or an ensemble of historical and future projections made by ESMs (Beusch et al., 2020; Nath et al., 2022)
847 or RCMs (Doury et al., 2022, 2024) and used to investigate a large range of future emission and land-use scenarios, or to
848 focus on specific aspects of projection uncertainty (e.g. high ECS futures). Process understanding and observations can also
849 be brought into the emulation process, enabling the resulting emulators to mimic the behaviour of the more complex ESMs
850 (Séférian et al., 2024), while weighting this behaviour towards better performing models (Beusch et al., 2020; Sanderson et
851 al., 2017). Statistical emulation approaches are also used to assess the sensitivity of ESMs to uncertain model parameters
852 (expanding the PPE approach), both for parameterization development (Silva et al., 2021; Rasp et al., 2018) and for
853 developing and selecting ESMs that combine acceptable present-day performance with constraints on their future response
854 (e.g. constraining ECS to lie within a specified range (Peatier et al., 2022)). Emulators were used extensively alongside
855 global and regional projections in IPCC AR6 to deliver observation-constrained future projections (Nicholls et al., 2022).
856 Emulators and ML tools can enhance the provision of climate information (Pfleiderer et al., 2024) and support
857 interdisciplinary integration, allowing direct coupling to IAM scenarios and thus supporting cross-working group
858 collaboration in IPCC AR7 and beyond.

859 **7.3 Assessing uncertainty across all the steps in providing actionable climate information.**

860 The new round of international modelling projects presents an opportunity to bring together the range of approaches and
861 methods used to assess and quantify uncertainty across IAM models and scenarios, global and regional models (considering
862 internal model variability, parameter uncertainty and structural model differences), and impact models (both in terms of the
863 climate forcing used and uncertain impact model parameters). This collaboration should also extend to communities
864 developing, improving and applying emulators and simple climate models (Séférian et al., 2024). Collaboration across
865 communities and activities will help increase the range of uncertainty space that can be analysed, and lead to a more
866 systematic and coordinated approach to uncertainty assessment across the full suite of modelling activities delivering

867 knowledge and data to climate policy and services. We further recommend significant effort be devoted to the
868 communication of uncertainty and conversely, communication of what is expected to occur in the future, and the level of
869 certainty/confidence that can be attached to these outcomes, with the target audiences being climate change policymakers,
870 planners, and practitioners.

871
872 Going forwards, a key demand on the international modelling community, with respect to supporting IPCC AR7 and the
873 UNFCCC Global Stocktake, will be the development and analysis of realizable future pathways that limit global warming to
874 the targets of the Paris Agreement. These pathways are likely to include an overshoot of the warming targets and therefore
875 the need for negative CO₂ emissions (i.e. active removal of CO₂ from the atmosphere). How these negative emissions will be
876 realized in practice and what magnitude is feasible, remain open questions. A thorough analysis and quantification of the full
877 cascade of uncertainty associated with such pathways is an important demand on the science community. This analysis needs
878 to encompass uncertainty in; how the necessary negative CO₂ emissions will be realized (i.e. the mitigation actions
879 themselves), the response of the carbon cycle to decreasing atmospheric CO₂, the efficacy of any CO₂ removal in reducing
880 global temperatures, and the regional climate responses that may arise from such cooling pathways. In addition,
881 uncertainties in the (expected) reduction in the societal and environmental impacts of Earth system change, as global
882 warming is reduced, need to be assessed, and the impacts avoided compared to any impacts arising directly from the
883 mitigation actions themselves. Along the entirety of this chain of events and responses there is deep uncertainty. The science
884 community needs to analyse, quantify, and communicate this uncertainty as thoroughly and clearly as possible.

885
886 Robust climate adaptation requires information on the range of potential future changes (which represent the climate hazard
887 in risk decision frameworks). While progress has been made in quantifying global and large-scale impacts arising from a
888 range of climate change drivers, this has only been partially successful with respect to translating these impacts to the scales
889 needed to develop local to national adaptation plans. CMIP7 offers an opportunity to more fully include and propagate the
890 wider CO₂-emission driven uncertainties through to local-scale climate information (as outlined in Sect. 3.2). An equally
891 important dimension is the role natural variability plays in climate change, especially on the timescale of the next 10 to 40
892 years (that frames many adaptation decisions). On these timescales and at the local scale, natural variability typically
893 dominates the forced climate change signal, for example for precipitation and temperature. This information is ever more
894 critical as society adapts to climate change in a mitigating world, where such mitigation aims to limit the climate change
895 signal. Large initial condition ensembles are a key tool for understanding and quantifying the role natural variability plays.
896 The expense (computational, data storage) of generating and sharing Lateral Boundary Conditions (LBCs) required to drive
897 Regional Climate models has limited the availability of LBC data, and hence the potential for regional scale simulations
898 (such as CORDEX) to sample the role of regional natural variability in the context of the wider climate hazard space, at
899 impact relevant scales. Commitments for new LBCs are often made before a simulation's credibility can be assessed and
900 before any understanding of where the realisation of variability plus feedbacks places a particular simulation in the wider
901 potential projection space. There will be value, therefore, in exploring iterative approaches between ESM and regional
902 modelling groups to identify optimal ESM simulations to be rerun for LBC generation.

903
904 Statistical downscaling may provide the most effective route to link wider ESM projections to what they imply at the local
905 level (Gutiérrez et al., 2019), as these approaches are not restricted by the limited availability of LBCs. Emerging Neural
906 Network Machine Learning techniques trained on existing regional (RCM and Convection Permitting RCM (CPM))
907 simulations, are showings promise in capturing spatial and temporal climate change, at local scales, based on large scale
908 drivers simulated by ESMs (Baño-Medina et al., 2021; Doury et al., 2022). Whilst there is still work to be done (e.g.
909 achieving multi-variate coherence (González-Abad et al., 2023), transferability to other ESMs (Baño-Medina et al., 2024),

910 and building frameworks to verify ML downscaled results), their emergence is likely to transform how the science
911 community provides local scale climate Information, as they allow the production of this information to be determined by
912 realisations that can inform on the range of local scale climate hazard (bottom up) rather than the limited availability of Earth
913 system model LBCs (top down). ML-based downscaling therefore has the potential to translate coarse-scale Earth system
914 model output directly to spatial scales of utility for impact models, impact assessment and local adaptation planning (Eyring
915 et al., 2024b). Such developments can be transformative in other senses, too. For example, given adequate prior ESM to
916 RCM/CPM training data, CMIP7 has the potential to be downscaled almost as soon as the ESM simulations are completed,
917 something which could help inform, for the first time, IPCC AR7 with consistent global and regional projection data, and
918 associated impact simulations (see Sect. 2). Similarly, ML may offer ways to address the prohibitive storage costs of
919 conventional high resolution local data by enabling the availability of such data on demand based on large scale variables
920 (which are much cheaper to store). Ultimately, incorporating Machine Learning into the production of high-resolution
921 regional climate information is likely to open further benefits due to the flexibility such tools enable. For example, ML
922 downscaling will be amenable to approaches that use observations to bias correct the regional data, directly. Similarly, as
923 insights from new modelling (e.g. resolving convective scales, interactive atmosphere-shelf sea-wave models) come online,
924 ML downscaling tools may be able to produce new high resolution regional climate data reflecting these insights, if
925 modelling experiments are designed to inform the required ML training.

926 **8 The underpinning technological infrastructure**

927 The ambitious science and science for policy aims discussed in this paper cannot be realized without a state-of-the-art
928 underpinning computational and data infrastructure, supported by experienced personnel. Our recommendations require the
929 co-design of certain experiments, followed by the production, quality-control and sharing of numerous datasets from a
930 diverse range of modelling systems, between producers and a heterogeneous set of consumers separated in time and space. An
931 aspiration for IPCC AR7, as described earlier, is to deliver a coordinated and coherent set of data from across the most recent
932 IAM scenarios, global projections (CMIP7) and regional downscaling (CORDEX), as well as impact model results based on
933 these scenarios and climate forcing. To achieve this will require more efficient and rapid sharing of both requirements and
934 data across all communities, including where feasible user communities. We therefore stress the need to improve the
935 underpinning infrastructure ecosystem that supports these modelling efforts to enable the co-development of suitable
936 experiment protocols, followed by the production, evaluation, and exploitation of datasets, which themselves can be used as
937 input to other simulation workflows, with different production, validation, and exploitation cycles. This will need to be
938 realized for far more numerous and larger volume datasets, and across a broader and more disparate set of requirements and
939 communities than was previously the case.

940
941 CMIP6, like CMIP5, benefited from a globally coordinated data infrastructure, the Earth System Grid Federation (ESGF),
942 linked to a large array of other important and necessary services (Balaji et al., 2018). The CMIP6 ESGF is now more than a
943 decade old, largely not maintained and is therefore not fit for the scale of the challenge outlined above. The array of services
944 linked to the ESGF include: standards-based data, model and experiment descriptions; citation and errata services for
945 simulation data and derived products; and data quality control procedures (addressing the presence of required data,
946 standards compliance etc, not to be confused with procedures for assessing the scientific quality of the data). The data
947 infrastructure itself needs to support systematic (and efficient) simulation evaluation, and support replication of data from
948 source to “super-nodes” that can host large volumes of multi-model data and provide sufficient local computational resource
949 to allow analysis with minimal requirement for data movement (Eyring et al., 2016). Local computing services will need to
950 include both specific “well known” computational services such as those necessary to generate on-demand statistics, and

951 those necessary to support user-generated analysis pipelines that may include AI and ML techniques. To realize the
952 ambitions outlined in this paper, the volumes of data that will need to be hosted at such super-nodes will be significantly
953 larger than for CMIP6, and the services will need to be easier to navigate for a more heterogeneous community, extending
954 beyond the modellers and analysts of earlier CMIP cycles.

955

956 There are several activities underway that aim to address some of these requirements. Notable amongst these are the
957 development of reusable evaluation and analysis workflows such as ESMValTool (Eyring et al., 2020; Righi et al., 2020)
958 with the goal of fully integrating these into the CMIP publication workflow (Eyring et al., 2016b), the democratisation of the
959 use of cloud computing via Pangeo (Abernathy et al., 2021), the use of new data formats such as HealPix (Chang et al.,
960 2023), and the development of new technologies aimed at a future ESGF (Hoffman et al., 2022). However, there are also
961 significant areas where little or no development is underway. These include enhanced documentation, errata, and citation
962 services, many of which are relying on best efforts and need dedicated investment and effort in new techniques and modes of
963 deployment. Considerable work will be required to bring all of these strands together into a coherent system that can be
964 deployed and supported world-wide and sustained throughout the next IPCC cycle (and beyond).

965

966 This new ecosystem will need to support and coordinate efficient methods for data reduction and sharing, cross model
967 analysis and evaluation, with an emphasis on bringing together existing and new observational and reanalysis datasets,
968 models, emulators, and advanced analysis tools for rapid and in-depth analysis and exploitation. The new system will need to
969 interface with other major data holdings, for example those of the WCRP Lighthouse activities¹ (Flato et al., 2023), the
970 Destination Earth² data holdings, the existing ISIMIP data repository³, the Copernicus Climate Change Service (C3S)⁴ and
971 new data holdings that may arise from the EVE (Earth Visualization Engines)⁵ initiative. It will need to conform to FAIR
972 (*Findable, Accessible, Interoperable, and Reusable*) principles (Wilkinson et al., 2016) and meet the needs and requirements
973 arising not just from CMIP7, but from the range of communities involved in IAMC, CORDEX and VIACS/ISIMIP.
974 Critically, the system will need to be fully supported by dedicated data managers, capable of addressing community
975 questions pertaining to data quality, model and data documentation, as well as supporting users of embedded infrastructure
976 tools to facilitate the rapid use and reuse of data and tools across communities. It is this rapid use and reuse that will deliver
977 the internal consistency, across models and research communities, that is key to the transformative impact expected for
978 international climate policy from the science and modelling efforts proposed in this article.

979 **9 Summary and recommendations for the way forward**

980 Over the past three decades, internationally coordinated modelling projects have delivered a wealth of simulations, data, and
981 scientific knowledge to support policy actions addressing climate change mitigation and adaptation. As a new round of these
982 projects start up, and a 7th IPCC assessment cycle begins, we have reviewed how these projects collectively have delivered
983 science support to international climate policy. We propose a number of science, technology and collaboration priorities that
984 we believe these projects should jointly focus on over the coming decade. Progress in these areas will increase the quality
985 and utility of science support to climate policy, while also increasing our understanding of Earth system change, including
986 the impacts on society and the natural world, as well as our ability to model such future changes and the associated impacts.
987

¹ <https://www.wcrp-climate.org/lha-overview>

² <https://destination-earth.eu/>

³ <https://data.isimip.org/>

⁴ <https://cds.climate.copernicus.eu/>

⁵ <https://eve4climate.org/>

988 One key proposal is for the involved modelling communities, spanning integrated assessment, scenario generation, global
989 and regional Earth system modelling, regional downscaling, and impacts modelling, to work much more closely together
990 during the next round of projects, with an aim to deliver a coordinated set of scenarios, projections and impact assessments
991 all based on the same underpinning socio-economic and mitigation scenarios and using the most up to date model
992 configurations. This will significantly improve the quality and consistency of scientific knowledge available to the upcoming
993 (AR7) and future IPCC assessments, as well as to the 5-yearly UNFCCC Global Stocktakes. Building on interactions
994 developed over the past 5-10 years, and proposals for simulations supporting international climate policy to become more
995 operational in structure, the time is right to actively develop a tighter and more efficient set of links across the relevant
996 modelling projects. Realizing this ambition within the AR7 timeframe is likely not possible. Nevertheless, significant effort
997 to achieve such internal consistency and efficient sharing of data, knowledge, and personnel, will lead to future workflows
998 better suited to fully realizing this ambition. In addition, we highlight the need for impact models to receive more detailed
999 information (disaggregated, spatially and by sector) on the socio-economic assumptions underpinning the IAM scenarios.
1000 Conversely, increased effort is required to allow knowledge of projected future climate impacts, and the likely societal
1001 responses to these impacts, to be iteratively incorporated into the generation of emission and land-use scenarios. Thanks to
1002 CMIP5 and CMIP6 cycles, there is an increasing set of well-established links between IAM scenario production teams, Earth
1003 system modelling groups, CORDEX downscaling teams, and impact modellers, with the majority of the modelling in these
1004 activities using a common data infrastructure system. These established connections and shared infrastructure make the
1005 potential for a more efficient, inter-connected workflow across all these activities a real possibility in the coming years.
1006

1007 The programme of work we outline addresses numerous key knowledge gaps, several of which were highlighted in IPCC
1008 AR6 (IPCC, 2021). Given the increasing number of ESMs capable of running in CO₂-emission mode, including simulation
1009 of the coupled climate and carbon cycle, as well a range of other Earth system phenomena, combined with an increasing
1010 number of coupled GCMs running for centennial timescales at ~10km resolution, we believe many of these knowledge gaps
1011 can be successfully addressed over the coming decade. Exploitation of CMIP6 was identified as limited in AR6, pointing to
1012 a need to support and better focus coordinated international modelling projects, including links between projects. Plausible
1013 overshoot scenarios that return to the Paris Climate targets by the end of the century or later (e.g. by 2130), were limited in
1014 CMIP6 and need to be a greater focus in CMIP7. To address this, it is crucial ESMs are extended to allow a more thorough
1015 assessment of the efficacy of proposed land and marine CO₂ removal techniques in reducing atmospheric CO₂ and driving
1016 global cooling, while accounting for potential Earth system feedbacks (IPCC 2021; Canadell et al., IPCC 2021). ESMs need
1017 to be capable of assessing both CO₂ and non-CO₂ feedbacks during overshoot (e.g. a changing efficiency of CO₂ uptake by
1018 natural reservoirs as CO₂ is removed from the atmosphere, or methane release into the atmosphere from wetlands or
1019 permafrost (Canadell et al., IPCC 2021)), as well as the potential for, and consequences of, rapid change in key Earth system
1020 components during overshoot, such as ice sheet loss or forest dieback (Canadell et al., IPCC 2021; Fox-Kemper et al., IPCC
1021 2021). In addition, interactions between CO₂ warming and trends in aerosol emissions need to be thoroughly assessed, so the
1022 impact of decreasing aerosol emissions on the near-term rate of global warming and achievability of the Paris targets can be
1023 better quantified. Such analysis needs to be complemented by analysis of the (societal and environmental) impacts of a
1024 warming overshoot, the degree of reversibility of these impacts once cooling to a target level is achieved, and the impacts
1025 resulting from long-term stabilization at a target warming level (assuming it is warmer than today). The majority of IAM
1026 scenarios, designed to realize the Paris Agreement, assume extensive deployment of land-based (and in a very limited
1027 number of cases, marine-based) atmospheric CO₂ removal technology. The direct impact of these mitigation actions on
1028 society and the environment needs to be assessed and contrasted with the impacts avoided from the resulting reduction in
1029 global warming. An additional set of approaches to limit the magnitude of future warming, referred to as geoengineering, are
1030 increasingly discussed in policy circles and the media. The most widely known being Solar Radiation Management (SRM;

1031 Lawrence et al., 2018; Vioni et al., 2023). While there remain concerns around the safety and governance of such actions, it
1032 is increasingly important the research community actively assesses the efficacy of these approaches, including the risks and
1033 potential consequences of deployment of this technology at the scales required. Projections beyond 2100 were not
1034 comprehensively covered in CMIP6 (Chen et al., IPCC 2021). This is important for understanding committed changes and
1035 the consequences of long-term stabilization at temperatures warmer than today. This is particularly acute with respect to sea-
1036 level rise (Fox-Kemper et al., IPCC 2021), with Antarctic and Greenland ice sheets representing the largest uncertainty in
1037 future sea-level projections. It is vital these systems are better modelled in CMIP7 and beyond.

1038
1039 More accurately simulating the observed, historical evolution of the climate system (i.e. reducing systematic model biases),
1040 including the representation of the forcings and feedbacks driving the observed warming, is crucial for increasing confidence
1041 in model projections and for maximizing the use observations in model improvement. Associated with this, we advocate the
1042 use of new approaches (for example, combining Machine Learning and Emergent Constraint techniques) to enable more
1043 extensive use of observations to constrain model projections and future feedbacks. A key requirement remains improved
1044 constraints on key metrics of Earth system sensitivity (e.g. EffCS, TCR, TCRE and the Regional to Global Warming ratio)
1045 and that models accurately simulate these metrics, including the processes underpinning them.

1046
1047 Due to their exceptional impact, we highlight the need for improved knowledge of, and ability to simulate, extreme weather
1048 events, including potential future changes in such events. We further stress the importance of assessing the impact of
1049 extreme events on society and the environment, considering the level of uncertainty inherent in projections of such rare
1050 events. This requirement also extends to the modes of climate variability that extreme events develop within (including
1051 natural variations, future changes and extreme realizations of these modes). Looking towards the next generation of Earth
1052 system and climate models, we propose significantly increased collaboration across communities investigating enhanced
1053 Earth system process realism, those working on increased model resolution, and improved physical parameterizations, as
1054 well as groups working on ML-based hybrid modelling. Increased collaboration across these communities will optimize
1055 findings from each approach for development of the next generation of Earth system models. This recommendation holds
1056 equally for global and regional models, including collaboration between these communities.

1057
1058 With respect to uncertainty, in future emission scenarios, in Earth system change, and in the impacts, we propose extensive
1059 collaboration across the range of approaches addressing these issues. Wherever possible work should assess, quantify, and
1060 emulate uncertainty as it propagates through the stages of IAM scenarios, ESM projections, regional downscaling, and
1061 impact simulations, so a more complete assessment of total uncertainty can be provided to policymakers. An additional
1062 consideration is to better quantify what can be predicted (based on model predictions started from observed initial
1063 conditions) versus projected (changes in future climate statistics relative to past or present statistics resulting from external
1064 forcing). An important challenge in this area is to accurately quantify the level of predictability at different time and spatial
1065 scales, for different variables and regions. We highlight the need for improved modelling and assessment of potential High
1066 Impact Low Likelihood (HILL) outcomes, with the possible exceedance of tipping points in the Earth system, in the
1067 environment, or in society, being of critical importance. Given there will always be some level of uncertainty in the future
1068 climate, it is important to focus on the communication of this uncertainty, or possibly more importantly, communication of
1069 what is expected in the future and with what level of confidence. This is a key area in the science-policy interface.

1070
1071 The transformative goals outlined in this paper require the support of a robust, efficient, and internationally connected
1072 infrastructure. While components of such an infrastructure exist, much work is needed to design, build, deliver and sustain
1073 an integrated system that meets the objectives outlined here, and maximises the benefits of existing initiatives and

1074 investments. The resulting infrastructure must exploit common tools and standards and be designed and delivered with both
1075 a long-term perspective and a well-trained workforce. It will need to handle increasing volumes of data, support the use of
1076 new techniques for data analysis (such as remote analysis of big data using ML and AI techniques), and facilitate the easy
1077 exchange of data, knowledge, and analysis tools. Without such an infrastructure, many of the aims outlined in this paper will
1078 not be met in a timely manner, if at all.

1079
1080 Finally, to expand the reach and benefits of international modelling, including the uptake and use of model simulations, to a
1081 more global scale and thus deliver underpinning scientific support for global climate policy, there is an urgent need for
1082 increased involvement of Global South scientists. WCRP leads a number of important efforts in this area. These need to be
1083 ramped up significantly and put on a sound long-term footing. Given the global nature of the climate crisis, that the impacts
1084 are, and will continue to be, most strongly felt by Global South countries, a globally inclusive response is a necessity. This
1085 makes both scientific sense (to draw on local expertise for understanding and predicting local Earth system change and its
1086 impacts), as well as political sense (climate policy is generally better tailored to a specific country's needs if it is based on
1087 local expert advice that is accessible over the long-term). We (a group of European scientists) encourage our governments
1088 and funding agencies to provide sufficient, long-term support to further develop and maintain a strong and globally inclusive
1089 scientific collaboration over the coming decades.

1090 **Author contribution**

1091 All co-authors provided ideas and comments to the manuscript. CJ, HJ, SJ, BNL, RS, TK, KF, BS, BB, SS, DVV, HH, EOR,
1092 FA, MR, PF, PLV, VE and PC conceived and developed the original ideas and recommendations in the paper. CJ and HJ wrote
1093 the paper, with regular input from the 17 other people listed in the first 19 co-authors and periodic input from all other co-
1094 authors.

1095 **Competing interests**

1096 Two co-authors are on the ESD editorial board: Roland Seferian and Richard Betts.

1097 **Acknowledgements**

1098 CJ, RS, BS acknowledge funding from the European Union Horizon 2020 project ESM2025 (grant number 101003536). BN,
1099 SJ, FA, VE acknowledge funding from the EU Horizon 2020 project IS-ENES3 H2020 project (grant number 824084). TK,
1100 CJ, KF and HJ acknowledge funding from the Horizon Europe project OptimESM (grant number 101081193). PC, VE and
1101 PF acknowledge funding from the European Union Horizon 2020 project 4C (grant number 821003). MJR, PLV DVV and
1102 HH acknowledge funding from the European Union Horizon Europe project EERIE (grant number 101081383), SS
1103 acknowledges funding from the Horizon Europe project IMPETUS4CHANGE (grant number 101081555), VE
1104 acknowledges funding from the Horizon 2020 European Research Council (ERC) Synergy Grant USMILE (Grant
1105 Agreement No. 855187). BBBB and HH were supported by the UK Met Office Hadley Centre Climate Programme funded
1106 by BEIS and Defra. NSF is funded by National Institute for Health and Care Research award NIHR204850 and Natural
1107 Environment Research Council grant number NE/Y503319/1. Discussions that led up to and supported the development of
1108 this paper occurred in all of the above projects, as well as in the COST Action CA19139 PROCLIAS (PROcess-based
1109 models for CLimate Impact Attribution across Sectors), supported by COST (European Cooperation in Science and
1110 Technology; <https://www.cost.eu>).

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