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# The benefits of global high-resolution for climate simulation: process-understanding and the enabling of stakeholder decisions at the regional scale.

M. J. Roberts<sup>1\*</sup>, P. L. Vidale<sup>2</sup>, C. Senior<sup>1</sup>, H.T. Hewitt<sup>1</sup>, C. Bates<sup>3</sup>, S. Berthou<sup>1</sup>,

P. Chang<sup>4</sup>, H. M. Christensen<sup>5</sup>, S. Danilov<sup>6</sup>, M.-E. Demory<sup>2,16</sup>, S. M. Griffies<sup>7</sup>,

R. Haarsma<sup>8</sup>, T. Jung<sup>6,9</sup>, G. Martin<sup>1</sup>, S. Minobe<sup>10</sup>, T. Ringler<sup>11</sup>, M. Satoh<sup>12</sup>, R.

Schiemann<sup>2</sup>, E. Scoccimarro<sup>13</sup>, G. Stephens<sup>14,1,2</sup>, M. F. Wehner<sup>15</sup>

<sup>1</sup> Met Office, Fitzroy Road, Exeter. EX1 3PB, UK

<sup>2</sup> National Centre for Atmospheric Science, University of Reading, Reading, UK

<sup>3</sup> University of Exeter, Exeter, UK

<sup>4</sup> Department of Oceanography, Texas A&M University, Texas, USA

<sup>5</sup> Atmospheric, Oceanic and Planetary Physics, University of Oxford, Oxford, UK

<sup>6</sup> Alfred Wegener Institute, Helmholtz Centre for Polar and Marine Research, Bremerhaven, Germany

7 NOAA/GFDL, Princeton, NJ, USA

<sup>8</sup> Royal Netherlands Meteorological Institute, De Bilt, The Netherlands

<sup>9</sup> Department of Physics and Electrical Engineering, University of Bremen, Bremen, Germany

<sup>10</sup> Division of Earth and Planetary Sciences, Faculty of Science, Hokkaido University, Sapporo, Japan

<sup>11</sup> Theoretical Division, Los Alamos National Laboratory, Los Alamos, NM, USA

<sup>12</sup> Atmosphere and Ocean Research Institute, The University of Tokyo, Tokyo, Japan

<sup>13</sup> Fondazione Centro euro-Mediterraneo sui Cambiamenti Climatici (CMCC), Bologna, Italy

<sup>14</sup> Jet Propulsion laboratory, California Institute of Technology, Pasadena, California, USA

<sup>15</sup> Computational Research Division, Lawrence Berkeley National Laboratory, Berkeley, California, USA
<sup>16</sup> Center for Space and Habitability, University of Bern, Bern, Switzerland

\*Corresponding author address: Malcolm J. Roberts, Met Office Hadley Centre, FitzRoy Road, Exeter EX1 3PB, United Kingdom. Email: malcolm.roberts@metoffice.gov.uk

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Capsule summary:

A perspective on current and future capabilities in global high-resolution climate simulation for assessing climate risks over next few decades, including advances in process representation and analysis, justifying the emergence of dedicated, coordinated experimental protocols.

#### Abstract

The timescales of the Paris Climate Agreement indicate urgent action is required on climate policies over the next few decades, in order to avoid the worst risks posed by climate change. On these relatively short timescales the combined effect of climate variability and change are both key drivers of extreme events, with decadal timescales also important for infrastructure planning. Hence, in order to assess climate risk on such timescales, we require climate models to be able to represent key aspects of both internally driven climate variability, as well as the response to changing forcings.

In this paper we argue that we now have the modelling capability to address these requirements - specifically with global models having horizontal resolutions considerably enhanced from those typically used in previous IPCC and CMIP exercises. The improved representation of weather and climate processes in such models underpins our enhanced confidence in predictions and projections, as well as providing improved forcing to regional models, which are better able to represent local-scale extremes (such as convective precipitation). We choose the global water cycle as an illustrative example, because it is governed by a chain of processes for which there is growing evidence of the benefits of higher resolution. At the same time it comprises key processes involved in many of the expected future climate extremes (e.g. flooding, drought, tropical and mid-latitude storms).

33 Introduction

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35 Our capability to perform global climate model simulations suitable to inform 36 societal action is constrained by both available computer resources and the 37 efficiency of the algorithms used in our models. Multi-exaflop computer power 38 would be needed for global climate models to produce multi-member ensemble, 39 multi-century simulations at resolutions capable of resolving macroscopic cloud 40 features and ocean mesoscale eddies. Estimates suggest that such computer 41 power is at least a decade away. Yet, given the enormous scale of 42 supercomputing about to be used for the next Coupled Model Intercomparison 43 Project (CMIP6; Eyring et al. 2016), we feel that this is a particularly important 44 time to review our current status in present-day high-resolution global climate 45 modeling.

46

47 At one extreme, numerous climate model simulations are performed as part of 48 each CMIP cycle (Meehl et al. 2000; Meehl et al. 2007; Taylor et al. 2012; 49 Eyring et al. 2016), organized by the World Climate Research Programme 50 (WCRP). Such models typically include aspects of Earth System complexity such as biogeochemistry, and simulations including several ensemble 51 52 members are usually completed. However, in order to achieve this task, the 53 horizontal resolution has traditionally been compromised, typically to ~150km or coarser in the atmosphere and 1 degree in the ocean. This means that 54 55 important climate processes (such as atmospheric convection, ocean mesoscale boundary currents and eddies) have had to be parameterised rather 56 57 than resolved, and dynamical processes and interactions can be compromised 58 (Collins et al. 2018).

59

At the opposite extreme, the next major breakthrough in simulation may be reached at scales below 1 km in the atmosphere, as we come close to resolving the largest of boundary-layer eddies, the macroscopic cloud features and convective organisation (Schneider et al. 2017). Several global models (e.g. NICAM; Satoh et al. 2008, 2014) are now able to complete global simulations at sub-km grid spacing (Miyamoto et al. 2014). Such individual simulations are

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66 currently short (<1 year), have only a minimal number of Earth System processes included, and challenge our observational abilities, due to the limited 67 time and space sampling from satellites. However, they can be used to gain 68 69 insights into poorly understood interactions (such as aerosol-microphysics-70 cloud interactions, e.g. Hashino et al. 2013). Such models are also generally non-hydrostatic and hence able to better represent organised convective 71 72 processes and small-scale structures in, for example, tropical cyclones. 73 Considerable uncertainties remain, but such tools are key for future process 74 understanding.

75

76 In between these two fundamental scale boundaries, gradual refinements in 77 resolution might be considered to afford only marginal benefits for our 78 understanding of climate variability and change. However, here we aim to 79 demonstrate that significant improvements in understanding are afforded by 80 global models at intermediate resolutions, which are vital for projections over the next few decades. We show evidence that the large-scale circulation is 81 82 significantly improved in the atmosphere using resolutions finer than 100km, 83 despite the Rossby radius being ~1000km and hence "resolved" in CMIP-type models. For the ocean, the Rossby radius is finer than 100km and hence 84 85 unresolved in most CMIP-ocean models, with potentially important 86 consequences for climate simulation (Hewitt et al. 2017).

87

88 Global NWP models have paved the way for developments in climate modelling 89 and systematically demonstrated the added benefits of enhanced resolution, 90 albeit in the context of initialised forecasts, which also benefit from advances in 91 other components (such as data assimilation, ensemble size, number of 92 observations and other model improvements; Magnusson and Källén, 2013; Bauer et al, 2015). With the advent of seamless modelling approaches (e.g. 93 94 Senior et al. 2009; Brown et al. 2012), NWP and climate models are becoming equivalent in their scientific configurations, and many biases seen in long term 95 96 climate simulations are already evident after days of an NWP forecast (Martin 97 et al. 2010). An example of monitoring progress in NWP, citing resolution as 98 one aspect of improvements in skills scores, in shown in Fig. 10 of Rodwell et

al. (2010). A more general, high-level review of the benefits of resolution inNWP models is provided by Wedi (2014).

101

102 Hence some of the following evidence from climate models is far from unique 103 to them. However, aspects of the hydrological cycle have typically not been a part of NWP skill assessments (which, for example, usually concentrate on 104 105 large-scale quantities that are relevant to users on short-range timescales, such 106 as 500 hPa height, 250 hPa winds and temperature; see references above and 107 Mittermaier et al. 2016). In addition, and more crucially, the NWP modelling systems are typically neither radiatively balanced nor water-conserving, so are 108 109 not well-placed for systematic process studies of water cycle processes on 110 longer time- and space-scales.

111

Regional models are increasingly being used for climate studies at resolutions 112 113 of several kilometres (Kendon et al. 2017). One could argue that this approach 114 mitigates the need for refinements to global model resolutions. Indeed if the 115 requirement is to understand local processes (such as convective precipitation) 116 and extremes in terms of their local impacts, then such models currently 117 represent our best tools. However, the regional models' representation of the 118 large-scale circulation is no better than that of the driving global model (otherwise it would not be well constrained), and this requires the global model 119 120 to credibly represent global modes of variability, dynamic and thermodynamic 121 responses to climate forcing. Hence it is key to make the large-scale circulation 122 as accurate as possible, as this provides critical information needed for the 123 regional downscaling to offer added information. We will argue that it is 124 precisely at these synoptic scales that the new generation of high-resolution global models are showing substantial improvement in the mean state and 125 variability. 126

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We ask in this paper what we can learn from the range of models at global resolutions that are now or will soon become affordable on flagship supercomputers worldwide. In particular we ask what added value such enhanced models provide in terms of the simulated hydrological cycle, and thus

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the trustworthiness and robustness of current climate projections particularlyover the next few decades.

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#### 135

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## 5 The global hydrological cycle

One of the key questions for climate research is how the global water cycle 137 might change in the next few decades. At its most basic, the global water cycle 138 139 describes the movement of water between the different reservoirs in the climate 140 system - in and on the ocean (including sea-ice and ice shelves), over and 141 below the land surface (surface and ground water, land-ice), and the 142 corresponding energy exchanges. It is therefore implicated in many of the 143 impacts that climate change brings - excess water (flooding, tropical and mid-144 latitude storms, atmospheric rivers), lack of water (drought), and intensity of 145 storms (concurrently regulated by energy and momentum exchanges).

146

147 The representation of the global water cycle in coupled climate models, and in particular some of its governing processes, is subject to much larger variability 148 among models than other (thermodynamic) indicators. One can contrast the 149 significant agreement in CMIP5 (Flato et al. 2013), expressed by model 150 151 projections of future warming rates and patterns, against the disagreement in 152 projected precipitation changes, which showed little improvement over the 153 earlier CMIP3 assessment. Although precipitation does not represent the whole 154 water cycle, and our observational record is short and uncertain, such 155 fundamental disagreements do not build confidence in future projections.

156

Part of the reason for this uncertainty is the lack of representation of the 157 158 dynamical aspects of the coupled climate system, and how these are coupled 159 to the physical aspects of model simulation. At the largest scales, on the order 160 of the Rossby radius, model physics (i.e. column processes) dominate the 161 under-resolved dynamics in atmosphere and ocean (Trenberth et al. 2011; 162 Demory et al. 2014). As resolution increases and the synoptic and mesoscales 163 become better resolved, then they both play an important role – perhaps at a minimal resolution of around 50km (Matsueda and Palmer 2011; Delworth et 164 165 al. 2012, Demory et al. 2014). As resolution increase continues towards the 1

166 km-scale, multi-scale dynamics increasingly dominates column physics (see for167 instance the discussion in Vellinga et al. 2016).

168

#### 169 *a. Large-scale moisture transports*

170 Studies focusing on the impact of resolution on the simulated global hydrological cycle as a whole remain guite rare (Pope and Stratton 2002; Hack 171 172 et al. 2006; Hagemann et al. 2006; Demory et al. 2014). Demory et al. (2014) 173 find that the simulation of a select few components of the global hydrological 174 cycle is degraded by increasing model resolution, due to an overall excess in net available energy at the surface that is caused by errors in model physics. 175 176 However, they find that the overall hydrological cycle is intensified by global 177 grid refinement, and for consistent reasons, resulting in a strength that compares well with observations (e.g. as in Trenberth et al. 2011). This is 178 179 manifested by less precipitation over the ocean and more precipitation over 180 land, caused by enhanced large-scale atmospheric moisture transport from the ocean to the land, reducing the commonly overestimated precipitation recycling 181 182 over land. At mid-latitudes, this increase in the large-scale atmospheric 183 moisture transport is particularly associated with the storm track regions. Notably, such multi-scale interactions can only be studied with global models. 184 185 Demory et al. (2014) also uncovered a locally asymptotic response of the mid-186 latitude large-scale atmospheric moisture transport, starting at about 60 km grid 187 size, which seems to be within recent observational estimates (Trenberth et al. 188 2011). There are indications that other models show similar sensitivity to 189 resolution (Terai et al. 2017; Vanniere et al., submitted).

190

#### 191 b. Surface water balance and precipitation distribution

192 Precipitation, evaporation, runoff and storage variations characterise the water balance over any land area. All four of these quantities are difficult to observe 193 194 and to simulate by global climate models, and our current ability to close the 195 water balance remains highly unsatisfactory over the global land area and much 196 more so at the scales of continents or large river basins. One example of these 197 uncertainties is illustrated in Figure 1: total global precipitation is remarkably 198 resolution invariant, which points to a very robust constraint provided by global long-wave cooling in all model simulations, producing precipitation estimates 199

200 within the range of significant and persistent observational uncertainty (see 201 estimates by GPCP versus Wild et al. 2015 versus Stephens et al. 2012). 202 Further, increasing the resolution in the HadGEM3 atmospheric GCM (GA3, 203 Mizielinski et al 2014) from about 100 to 25 km changes the model estimate of 204 precipitation partitioning. Land versus sea distribution of precipitation agrees with the findings in Demory et al. 2014; additionally, for the land portion, global 205 206 (rugged) mountain precipitation increases by about 15%, and available 207 observations, which are sparse over complex terrain, are hardly able to assess 208 these model estimates. Precipitation over comparatively small mountain areas 209 is particularly important since it disproportionately contributes to runoff and 210 therefore the generation of so-called blue water which sustains ecosystems and 211 human livelihood.

212

213 Given such uncertainties in global precipitation, it is not surprising that regional 214 distributions are also poorly estimated. Figure 2, reproduced from Wehner et 215 al. (2014), shows an analysis of annual daily total precipitation distributions from 216 three different horizontal resolutions of the Community Atmospheric Model 217 (CAM5.1), for a number of regions. There is some evidence that, at resolutions 218 finer than 25km, grid separation is no longer the limiting factor in reproducing 219 observations (e.g. Hawcroft et al. 2016) and that deficiencies in sub-grid scale 220 parameterisations dominate the model errors (Wehner et al. 2014), particularly 221 when convection is an important contributor to the local atmospheric water 222 budget.

223

Using the same ensemble of GA3 atmospheric model simulations as Demory
et al. (2014) at 130km, 60km and 25km resolution (referred to an N96, N216
and N512 respectively), the precipitation distribution in each IPCC SREX<sup>1</sup>
region is used to determine which model resolution best fits the multiple
observational datasets available over that region (see Appendix A for details).
Figure 3 shows the coarsest best resolution for each region. Several key points
become evident:

<sup>&</sup>lt;sup>1</sup> Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation

- 10

1. In most regions a resolution finer than 130km is worthwhile;

232 2. Globally 60km may be sufficient for this metric, but there are some 233 regions (e.g. Western Africa, South Eastern Asia) which consistently favour 234 25km resolution, often where land-sea contrasts and/or mountainous terrain 235 exist; note also that at latitudes polewards of 50°, the only long-term global 236 observational datasets have resolutions of 110km and hence it not possible to 237 properly assess higher resolution models;

3. There are some regions which are uncertain, either because no model
is clearly better or the observational datasets disagree too much with each other
to assign a best model resolution (i.e. we do not know the climatology well
enough to validate models).

242

243 c. Dynamical processes and moisture transport

Correct attribution of the processes responsible for the global distribution of precipitation is key, because models that produce a reasonable climatology via demonstrably incorrect processes cannot be trusted for climate projections of rainfall.

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### 249 Extra-Tropical Cyclones

250 One likely component driving the sensitivity of simulated moisture transport and 251 precipitation to resolution is the moisture transport effected by dynamical 252 processes such as cyclones (both tropical and mid-latitude). Storms provide a 253 considerable proportion of annual rainfall in many regions of the world 254 (Scoccimarro et al 2014; Guo et al 2017), and as such representing their 255 frequency, variability, position and composition is important. Catto et al. (2010) 256 and Zappa et al. (2013) show that extratropical storm structure and intensity are better represented at resolutions finer than 100km, and hence the moisture 257 transport associated with them. Jung et al. (2012) demonstrate significantly 258 259 improved extratropical cyclone frequency when moving from 130km to 40km 260 resolution, with little change at finer grid spacings.

261

## 262 Tropical Cyclones and African Easterly Waves

There is mounting evidence from many modelling studies that atmosphere resolutions at 50km or finer skilfully represent the interannual variability of 265 tropical cyclones (Zhao et al, 2009; Manganello et al. 2012; Roberts et al, 2014; Kodama et al. 2015). In the Atlantic, much of this improvement can be attributed 266 267 to better global teleconnections (from El Niño, for example, Bell et al. 2014) 268 providing a constraint on the environment, and improved dynamical precursor 269 features such as African Easterly Waves (AEWs). Despite the latter being 270 relatively large-scale dynamical systems, they are poorly represented at ~100 271 km grid scales (Martin and Thorncroft, 2015; Caron et al, 2011). This re-272 emphasises the danger of assuming that representation by at least two grid 273 points is sufficient for resolving features.

274

275 Tropical cyclone importance is not only limited to producing high-impact events: 276 Guo et al. (2017) showed that typhoons in East Asia produce about 50% of 277 precipitation in coastal areas at the peak of the season, but also contribute a 278 sizeable portion of the moisture transport that supports all other types of precipitation further inland. Further, their net contribution to the regional 279 280 moisture budget of China is comparable albeit opposite to that of the monsoon 281 at the time of its recession. Scoccimarro et al. (2014) show a similar result for 282 the North Atlantic tropical cyclones and US precipitation, while Pantillon et al. 283 (2015) show a remote link to Mediterranean rainfall events. These impacts 284 require fidelity in storm characteristics, with Figure 4 (from Manganello et al. 285 2014) illustrating the improvement of storm genesis and track as model 286 resolution is enhanced, while Scoccimarro et al. (2017) demonstrated the additional importance of high frequency coupling between atmosphere and 287 288 ocean.

289

#### 290 Mesoscale Convective Systems

291 In addition to storms influencing the mean precipitation, Vellinga et al. (2014) have shown important scale interactions between large-scale variability and 292 293 smaller scales. Decadal variability in Sahel rainfall is shown to be related to the interaction between the large-scale Atlantic Multi-Decadal Oscillation (AMO) 294 295 and AEWs. Only model resolutions fine enough (at 60km and finer in that study) 296 to represent stronger, self-organised (at the mesoscale) and propagating 297 rainfall events capture the observed decadal trends. There are indications that other CMIP5 models follow this relationship, but analysis is complicated by 298

confounding factors such as different aerosol loadings, indicating a need for amore systematic set of comparable simulations.

301

#### 302 Westerly Wind Bursts

303 Aforementioned dynamical precursor systems such as AEWs are also found to 304 be important in driving variability in other dynamical systems. If they are poorly 305 represented in models, this can significantly bias the simulated mean state, and 306 hence lead to misleading future projections. One example would be the 307 westerly wind bursts (WWBs) in the tropical Pacific that precede El Niño events: in observations the irregular variability of ENSO has been attributed to such 308 309 WWB events (Puy et al. 2017). It may be possible that the inclusion of stochastic schemes (Christensen et al. 2017) enables some of the aspects of 310 311 these precursor systems to be replicated. However development of such 312 stochastic schemes is best informed by models able to simulate the dynamical 313 aspects of these processes, as well as the physics-dynamics coupling.

314

#### 315 Monsoons

316 In the tropics, the monsoon circulations provide a large portion of annual rainfall 317 to many regions. There are many components and individual processes within 318 these circulations (flow reversals, orographic interactions, land-sea contrasts, 319 sensitivity to remote biases), and this may be why increased model resolution 320 does not directly lead to improved monsoon simulation (Ogata et al. 2017; 321 Johnson et al. 2016). Individual components do indicate a resolution sensitivity 322 (such as monsoon depressions, Johnson et al. 2016), but reduction of remote 323 biases to improve the regional mean state may be equally important (Levine 324 and Martin 2017; Martin et al. 2010).

325

#### 326 Atmospheric Blocking

At mid-latitudes, the representation of storm tracks and blocking play important roles in the large-scale dynamics of the water cycle. Dawson et al. (2012) demonstrate a large improvement in the structure of Euro-Atlantic weather regimes in a model run at 16km compared to one run at 150km, while Dawson and Palmer (2015) show a 40km simulation has intermediate regime fidelity. The distribution, frequency and development of European blocking has been 333 shown to be influenced by aspects of atmosphere and ocean resolution 334 (Berckmans et al 2013). Schiemann et al. (2017) showed some improvement 335 in blocking in a multi-model atmosphere ensemble at 25km compared to 336 ~100km, consistent with Jung et al. (2012) results when moving from 130km to 337 40km. Scaife et al. (2011) showed how reducing large-scale model biases in the North Atlantic with a 1/4 degree ocean resolution led to improved frequency 338 339 of European blocking. O'Reilly et al. (2016) studied blocking and extended cold 340 spells over Europe, and showed that the resolution of remote SST fronts was a 341 key factor in reinforcing the blocking anticyclone and hence extending the 342 timescale of the events.

343

#### 344 Ocean dynamics

The impact of resolution on dynamical processes affecting the hydrological 345 346 cycle is not limited to the atmosphere. In particular, the transport of freshwater 347 is related to the stability of the meridional overturning circulation (Drifhout et al. 2013). Since transport of freshwater can take place in narrow currents and 348 349 eddies, this points to an important role for ocean resolution. In the South 350 Atlantic, the transport of freshwater is strongly determined by Agulhas eddies 351 which move salt from the Indian Ocean to the Atlantic Ocean (Drifhout et al. 352 2003). In this region, resolution is key to the simulation of the Agulhas 353 retroflection and the shedding of eddies (Banks et al. 2007; Biastoch et al. 354 2008). In the North Atlantic, ocean resolution is important for capturing the East 355 Greenland current which transports freshwater from both sea ice melt and 356 potential ice sheet melt into the Atlantic (Böning et al., 2016).

357

#### 358 d. Land-Atmosphere coupling strength

The asymptotic behavior with resolution uncovered by Demory et al. (2014) and 359 discussed earlier is directly relevant to the correct representation of land-360 361 atmosphere coupling in GCMs: at scales finer than 50km, the systematic 362 overestimation of the contribution of land evaporation to precipitation starts to 363 be mitigated by realistic simulation of atmospheric moisture convergence. 364 However, observational evidence indicates that we must also simulate 365 mesoscale circulations generated by landscape heterogeneity, at horizontal scales of 10km or less. For instance, Taylor (2012) showed that precipitation 366

367 over the Sahel occurs over dry land patches, but coarse GCMs preferentially produce precipitation over moist patches, where convective parameterisation 368 369 responds to surface moist static energy. This is because they do not represent 370 the mesoscale horizontal transports of moisture between different land patches. 371 The phase of the diurnal cycle of precipitation over land can also impact landatmosphere coupling, and is almost uniformly poorly simulated in GCMs (Slingo 372 373 et al. 1992; Bechtold et al. 2004; Clark et al. 2007; Ackerley et al. 2015) with 374 implications for surface energy and moisture budgets. Recent convective 375 parameterisations (e.g. Bechtold et al. 2014) have improved the diurnal cycle phase, while Birch et al. (2015) demonstrated similar capability by disabling 376 377 convective parameterisation at around 10km resolution.

378

#### 379 e. Air-sea interactions

The ocean's mesoscale influence on the atmosphere in the extra tropics has 380 381 been known from observational analyses for some time, both near-surface 382 (e.g., Chelton et al. 2004; Xie 2004) and in the free troposphere via precipitation, clouds and upward winds (e.g., Minobe et al. 2008; 2010; 383 384 Tokinaga et al. 2009; Frenger et al. 2013; Ma, J. et al. 2015, Smirnov et al. 385 2015). However, it has required deployment of models with sufficient resolution 386 in both the atmosphere and ocean in order to study and understand such 387 interactions at the process level (Small et al. 2008; Chelton and Xie 2010, Kwon 388 et al, 2010; Ma, J. et al.; 2015; Ma, X. et al. 2016).

389 Coupled simulations demonstrate fundamental changes in the character of 390 atmosphere-ocean coupling once they admit the ocean mesoscale (Bryan et al. 391 2010; Roberts et al 2016), with modelling confirming that SST forces the local 392 winds at frontal- and mesoscales, as observed (Chelton et al. 2001). In contrast, when the ocean model uses a coarse grid (1.0° or coarser), the opposite is 393 found (Kirtman et al. 2012). These results point to the high possibility that 394 395 frontal- and mesoscale air-sea interactions are poorly represented in CMIP5 models, consistent with the CMIP3 analysis by Maloney and Chelton (2006), 396 397 with potential consequences for the fidelity of simulations of the hydrological 398 cycle.

400 Atmospheric resolution is also important to capture coupled responses. For example, the salient feature of the Gulf Stream rain band (Minobe et al. 2008; 401 402 2010) is captured by an atmospheric GCM of about 50km grid-spacing (Minobe 403 et al. 2008; Kuwano-Yoshida et al. 2010; Scher et al. 2017). By direct 404 comparisons between high-resolution and low-resolution regional atmospheric model simulations (Willison et al. 2013; Ma, X. et al. 2016; Hawcroft et al. 2017), 405 406 it is shown that latent heat release associated with extratropical cyclone development is fundamentally important for realistic winter storm simulations, 407 408 and it is only when the model has sufficient resolution to resolve small-scale 409 diabatic heating that the full effect of mesoscale air-sea interactions on 410 extratropical cyclogenesis can be correctly simulated.

411

412 The remote atmospheric response to oceanic fronts and eddies, in comparison 413 to the local response, is generally more difficult to identify using direct 414 observations (Frankignoul et al. 2011; O'Reilly and Czaja, 2015), hence most existing studies are based on high-resolution model experiments. A particularly 415 416 useful experimental strategy for this type of study is a set of twin atmospheric 417 model simulations, one of which is forced by observed SSTs and the other by spatially smoothed SSTs (Xie et al. 2002; Minobe et al. 2008; Kuwano-Yoshida 418 419 et al. 2010; Small et al. 2014b; Piazza et al. 2015; Ma, X. et al. 2015 and 2016). 420 These studies reveal how fine scale ocean features influence storm density 421 (Minobe et al. 2008; Piazza et al. 2015), fronts (Masunaga et al. 2015; Parfitt et al. 2016); jet-stream shifts (Piazza et al. 2015; Ma, X. et al. 2015 and 2016; 422 423 O'Reilly et al. 2017), storm-track strength (Small et al. 2014b) and remote 424 rainfall response along US West Coast to Kuroshio eddies (Ma, X. et al. 2015 425 and 2016; Kuwano-Yoshida and Minobe 2016).

426

#### 427 f. Hydrological extremes

Global models are useful for studying extremes in order to account for both teleconnected events and for events governed by the large-scale environment. For example the Russian heat wave of 2010 was part of the same wave train that led to the devastating Pakistan floods (Lau and Kim 2010; Watenabe et al. 2010), while Atlantic tropical cyclones have been shown to affect Arctic sea ice cover (Scoccimarro et al. 2012). Assessing model skill in tropical cyclone 434 landfalling, where the large-scale steering flow is key, is in its infancy (e.g.
435 Camp et al. 2015; Murakami et al. 2016), but this is clearly an important metric
436 for impacts.

437

438 Despite improvements in simulation of tropical cyclones in CMIP5 (Walsh et al. 439 2013), only a handful of global models showed any TCs reaching category 1 440 hurricane/typhoon intensity. More recently the grid spacing in state of the art 441 global models has become sufficiently fine (order of 10-30 km) to realistically 442 represent TCs, even in terms of intensity (Manganello et al. 2012; Wehner et 443 al. 2014; Wehner et al. 2015; Murakami et al. 2015; Walsh et al. 2015; 444 Scoccimarro et al. 2016a; Scoccimarro et al. 2017), up to the maximum category 5. Our current understanding of future changes to frequency and 445 intensity (Walsh et al. 2015) is based on these relatively few capable models, 446 447 hence indicating a more systematic and multi-model study is required to 448 increase our confidence in such interpretations.

449

450 The higher gradients of moisture and temperature simulated in high horizontal 451 resolution global climate models are also important beyond the tropics, and projected to become more important in the future. The simulation of extra-452 453 tropical transition of tropical systems, and robust future projections thereof, show substantial sensitivity to resolution (Haarsma et al. 2013) thus 454 455 representing new challenges and opportunities for the prediction of the 456 changing risks posed by extreme precipitation, winds and storm surge 457 impacting Europe.

458

#### 459 Future prospects and challenges

460 There are an increasing number of modelling groups able to push our current modelling capability to the next level. This includes using km-scale global 461 462 atmosphere and eddy-rich ocean simulations. Different methods are being tried 463 to overcome the many associated technical challenges, ranging from more 464 efficient algorithms to novel numerical methods. One factor that has so far been lacking is a large multi-model, multi-resolution ensemble of global simulations 465 466 using a common experimental design to enable coordinated analysis. This is 467 the goal of the CMIP6 HighResMIP project (Haarsma et al 2016), which 468 proposes a simple experimental design with the primary goal of assessing the 469 robustness of projections across a multi-model ensemble, as a response to 470 changes in the representation of climate processes with model horizontal 471 resolution.

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Using the CMIP6 HighResMIP protocol to create a multi-model reference
dataset, work within the EU Horizon 2020 PRIMAVERA<sup>2</sup> project and with
collaborators will also assess the costs and benefits of other advances:

476

477 1. Stochastic parameterisation schemes, which attempt to represent the 478 variability of unresolved, sub-grid scale processes (Palmer 2009), offer a 479 complementary approach to increasing model resolution. Due to nonlinearities 480 in the system, including a zero-mean noise into a GCM leads to systematic shifts in the climate that can reduce model biases (Jung et al. 2005; Williams 481 482 2012; Berner et al. 2015; 2017), and improve variability (Lin and Neelin 2000, 2003; Dawson and Palmer 2015; Christensen et al 2015, 2017), often 483 analogous to refining model resolution (e.g., Berner et al. 2012; Watson et al. 484 485 2017)). As model resolution increases, stochastic approaches will become more valuable, as representing the interaction of the resolved scales with the 486 487 sub-grid through purely deterministic schemes becomes harder to justify 488 (Dorrestijn et al. 2013);

489

2. Global cloud-system resolving models are a particularly important tool for 490 491 understanding multi-scale structures, such as the large-scale and synoptic 492 environment of tropical cyclogenesis (Nakano et al. 2017; Yamada et al. 2017), 493 or large-scale sea breezes and convection initiation (Birch et al. 2015). They also demonstrate the potential of models in complementing and enhancing 494 observations, for example the discovery by Miyakawa et al. (2012) of the three-495 496 fold structure of convective momentum transport associated with MJO, using the high-resolution data by Miura et al. (2007); 497

<sup>&</sup>lt;sup>2</sup> <u>https://www.primavera-h2020.eu</u>

499 3. Eddy-rich ocean models: the majority of CMIP5 climate projections were undertaken using coarse (1° or coarser) ocean model components (typically 500 501 with meridional refinement near the equator). At this grid spacing, the first 502 baroclinic Rossby radius is resolved only near the equator (Hallberg, 2013). 503 Hewitt et al. (2017) reviewed the improvements found in going towards eddypoor/eddy-rich regimes  $(1/4^{\circ} - 1/10^{\circ})$ , with important consequences for large-504 505 scale biases (McClean et al. 2011; Delworth et al. 2012; Small et al. 2014a; Hewitt et al. 2016), heat uptake (e.g. Griffies et al. 2015; Kuhlbrodt et al. 2015) 506 507 and ocean marine ecosystems (Saba et al. 2016; McKiver et al 2015; Stock et al. 2010). Coupled simulations with ocean resolutions up to 1/16 degree will 508 509 enable investigation of the impact of eddies on the mean state and variability of 510 the coupled system;

511

4. Unstructured meshes: an alternative approach to globally uniform increases 512 513 in resolution is offered by a new generation of models for the atmosphere, ocean and sea ice, formulated on unstructured meshes (e.g., Danilov 2013; 514 Ringler et al. 2013; Zarzycki et al., 2014; Sein et al. 2016). Unstructured 515 516 meshes provide multi-resolution capacity, that is, they have the flexibility to 517 enhance resolution where required. Several of the more mature unstructured 518 mesh models (Finite Element Sea Ice-Ocean Model (FESOM), Wang et al. 2008; Wang et al. 2014; Danilov et al. 2017; Model for Prediction Across Scales 519 520 (MPAS), Skamarock et al. 2012; Ringler et al. 2013), will participate in aspects of CMIP6 (specifically OMIP and HighResMIP). CMIP6 will thus provide an 521 522 excellent opportunity to assess and contrast such approaches within a large 523 multi-model framework;

524

525 5. Improved physical parameterisations - particularly those that are designed to 526 work at multiple scales (e.g. Arakawa et al. 2016; Fox-Kemper et al. 2013) - are 527 being developed for all components of the climate system, but these efforts 528 need resources and skilled people (Jakob 2014). Such schemes enable 529 seamless modelling across space and timescale with less parameter tuning, 530 albeit requiring the highest resolution global models for testing their efficacy.

531

532 Observational requirements

533 It is also important to exploit global observations that can both assess GCMs 534 and explore independent ways to improve process representation, including 535 their global teleconnections, in these models. An example is provided by the 536 NASA Gravity Recovery And Climate Experiment (GRACE) satellite mission for 537 the global water cycle (Böning et al. 2012), which is able to provide simultaneous assessment of water storage in different components of the 538 539 climate system. The evolution of high-resolution GCMs represents an important 540 and as yet unmet challenge to develop observational products at matching 541 resolutions: no observational counterparts to the spatially complete and 542 physically consistent GCMs exists, capable of supporting the study of multi-543 scale interactions. Instead, a wide range of instruments and methods, each with 544 characteristic strengths and limitations, need to be employed. A combination of high resolution modeling and observational datasets are key to WCRP's Global 545 Water and Energy Exchanges (GEWEX) project focus on improved 546 547 understanding of the relevant geophysical processes of water and energy 548 variability and change on regional to local scales.

549

550 At global resolutions affordable over the next decade, the representation of 551 atmospheric convection remains a huge challenge. While it plays a fundamental 552 role in the climate system, the poor quality of current simulations calls into 553 guestion all processes dependent on it (including all Earth System complexity). 554 This lack of simulation skill is also enveloped in many of the largest 555 uncertainties in climate projections, such as climate sensitivity, in particular due 556 to uncertainties in future cloud changes. However, even once model resolutions 557 should become so refined that we may consider removing convective 558 parameterisation, we would move into regimes in which poorly observed and understood interactions (multi-scale, aerosol-cloud-microphysics processes, 559 air-sea and land-atmosphere interactions) will produce similar uncertainties. 560 561 The number of ensemble simulations would also be severely limited, due to the huge computational expense. Hence there is no known threshold beyond which 562 563 we would expect simulations to become independent of parameterisation 564 choices, and therefore we need to continue to develop a manifold of global 565 modelling practices, not limited to exploiting peak resolution.

566

567 Summary

568 Society requires robust information about climate risks over the next few 569 decades in order to make good financial decisions about adaptation strategies, 570 as well as mitigation decisions.

571

572 We have shown that enhanced resolution capabilities in global climate 573 modelling have the potential to:

- 574
- 575

• provide improved, globally consistent information about climate hazards and impacts, as shown by examples pertinent to the global water cycle

- highlight future areas where more investment is required (High
   Performance Computing, better algorithms, suitable observations)
- use a common simulation protocol to enable deeper understanding
- 579

580 Tackling climate model uncertainty (measured by variability, or range of future 581 projections) from different perspectives can potentially reveal limitations in any framework. We are moving forward with a suite of complementary efforts, 582 583 spanning uniform grid refinement across the globe in CMIP-class models; improved dynamical mesh designs providing the foundations for cloud-system 584 585 resolving simulations; unstructured mesh and stochastic approaches. We are 586 implementing these changes at the present time, as part of CMIP6, and continued, albeit accelerated evolution should enable our future models to be 587 588 significantly less dependent on still-unresolved processes, such as convection. 589

The computational and analysis cost of this new generation of simulations, in 590 591 terms of HPC, storage, network speed and analysis platform, is clearly large. 592 New collaborative paradigms will be needed to efficiently address some of 593 these challenges, including use of central analysis platforms, incorporating both 594 data storage and compute, so that algorithms can be moved to the data rather 595 than vice versa. Better coordination of experimental design and collaboration 596 can help to form multi-model datasets to ameliorate the cost of single model ensemble simulations, and greatly enhance the scientific understanding from 597 598 community analyses of such datasets, using common tools. A current example 599 of such good practice is CMIP6 HighResMIP.

601 APPENDIX A

602 Methodology to choose best model resolution

603 The methodology used to construct Figure 3 is based on the GA3 ensemble of 604 global simulations (Mizielinski et al 2014), with five ensemble members at 25km and 130km resolution, and three members at 60km. Four observational 605 606 datasets are used: Tropical Rainfall Measuring Mission 3B42 product, version 7 (TRMM; Kummerow et al., 1998a; Huffman et al., 2007, 2010) and Climate 607 608 Hazards Group InfraRed Precipitation with Station data (CHIRPS; Funk et al. 2015) over 50°S-50°N, both at 25km grid resolution; Global Precipitation 609 610 Climatology Centre (GPCC; Schneider et al. 2008) and the Global Precipitation Climatology Project (GPCP; Huffman et al. 2009), both globally at 110km. All 611 data are initially regridded to a common 130km grid. For each region, a 612 histogram of daily precipitation is constructed in two ways; a) using equally-613 614 spaced intensity bins, b) using a non-linear distribution of bins following Martin et al. (2017) to show the relative importance of precipitation events in a given 615 616 intensity bin to the total precipitation. The root mean square difference (RMSD) 617 between a reference histogram (TRMM in the tropics, GPCP in mid-high latitudes) and all other datasets is calculated across all bins using a logarithmic 618 619 scale, and illustrated in Figure 5. Figure 3 is then determined by using the 620 RMSD for each histogram type, to determine the coarsest best resolution model 621 to fit the observations. When using different bins to calculate the RMSD 622 produces contradictory results, or in regions where the observational datasets 623 span a wider range than the model resolution differences, the "uncertain" 624 category is used.

625

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1357 Figure captions

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1359 Figure 1: Long-term mean precipitation estimates from different sources over the ocean, flat terrain and mountainous terrain (see inset, mountainous area is 1360 25% of total land area). Bar chart labels: N96, N216, N512 are 130km, 60km, 1361 1362 25km resolution simulations respectively using HadGEM3-GA3 (Mizielinski et 1363 al. 2014); N480, "N480, N96 orography" are GA6 (Walters et al. 2016) 1364 simulations at 27km resolution, the latter with orography degraded to N96 (130km) resolution; N96\*, N216\*, N512\* are the same N96, N216, N512 as 1365 1366 above, but with estimates scaled by the global surface net shortwave radiation bias; Observation-based estimates: GPCP (GPCP v2.2, Adler et al. 2012); Wild 1367 et al. (2015) (uncertainties not shown); Wild et al. (2013); Stephens et al. 1368 1369 (2012); Trenberth et al. (2009).

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1371 Figure 2: Comparisons of the annual probability density distributions (y-axis) of daily precipitation (mm day<sup>-1</sup>, x axis) between the models and location specific 1372 gridded observations as indicated by the dataset name in parentheses. a: 1373 1374 Global land and ocean (GPCP), b: Global land only (UW-Global), c: Tropical land and ocean, 20S-20N (TRMM), d: CONUS (UW-CONUS), e: Asia 1375 1376 (APHRODITE), f: Europe (E-OBS). Red, blue, green and black lines 1377 respectively represent the 2° CAM5.1, 1° CAM5.1, 0.25° CAM5.1. Observations are represented by the black line in Figure 2a and by gray shading in Figures 1378 2b-2f, indicating the range of available data sets. Daily precipitation was 1379 1380 remapped onto the 2° grid before computing the distributions in all cases. Any precipitation rates larger than 100 mm/day are assigned to the last bin for 1381 1382 normalization purposes that sometimes results in an uptick at the end of the 1383 plot. Reproduced from Wehner et al. (2014).

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Figure 3: Map showing the lowest best resolution model for each region as defined in the Appendix by comparing daily precipitation histograms. N512=25km, N216=60km, N96=130km mid-latitude resolution. Uncertain implies either no model is clearly better, or that observational uncertainty is too large to determine a best model.

Figure 4: North Atlantic Ocean (left) genesis and (right) track densities as number density per season per unit area equivalent to a 5° spherical cap for (a), (f) IBTrACS (Obs) and IFS simulations at (b), (g) T2047, (c), (h) T1279, (d), (i) T511, and (e), (j) T159 resolutions. Reproduced from Manganello et al. (2012) with permission by the authors.

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Figure 5: Illustration of comparing Root Mean Square Difference (RMSD) values (see Appendix A for details) from models and observations, with uncertainty in observations and model ensemble spread both indicated as shading, and here RMSD is normalized to one dataset (TRMM in this example). One model is clearly best in case a), two models cannot be split in b) due to overlap in spread, while in c) the observations disagree too much to assign a best model.

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Figure 1: Long-term mean precipitation estimates from different sources over the ocean, flat terrain and mountainous terrain (see inset, mountainous area is 25% of total land area). Bar chart labels: N96, N216, N512 are 130km, 60km, 25km resolution simulations respectively using HadGEM3-GA3 (Mizielinski et al. 2014); N480, "N480, N96 orography" are GA6 (Walters et al. 2016) simulations at 27km resolution, the latter with orography degraded to N96 (130km) resolution; N96\*, N216\*, N512\* are the same N96, N216, N512 as above, but with estimates scaled by the global surface net shortwave radiation bias; Observation-based estimates: GPCP (GPCP v2.2, Adler et al. 2012); Wild et al. (2015) (uncertainties not shown); Wild et al. (2013); Stephens et al. (2012); Trenberth et al. (2009).





1431 Figure 2: Comparisons of the annual probability density distributions (y-axis) of 1432 daily precipitation (mm day<sup>-1</sup>, x axis) between the models and location specific 1433 gridded observations as indicated by the dataset name in parentheses. a: Global land and ocean (GPCP), b: Global land only (UW-Global), c: Tropical 1434 land and ocean, 20S-20N (TRMM), d: CONUS (UW-CONUS), e: Asia 1435 (APHRODITE), f: Europe (E-OBS). Red, blue, green and black lines 1436 respectively represent the 2° CAM5.1, 1° CAM5.1, 0.25° CAM5.1. Observations 1437 are represented by the black line in Figure 2a and by gray shading in Figures 1438 2b-2f, indicating the range of available data sets. Daily precipitation was 1439 remapped onto the 2° grid before computing the distributions in all cases. Any 1440

1441 precipitation rates larger than 100 mm/day are assigned to the last bin for

1442 normalization purposes that sometimes results in an uptick at the end of the1443 plot. Reproduced from Wehner et al. (2014).



AMZ

N512

NEE

1449 1450

Figure 3: Map showing the coarsest best resolution model for each region as
defined in the Appendix by comparing daily precipitation histograms.
N512=25km, N216=60km, N96=130km mid-latitude resolution. Uncertain
implies either no model is clearly better, or that observational uncertainty is too
large to determine a best model.

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WAR

N216

EAF

N96

SAF

NAU

Uncertain

SAD







Figure 4: North Atlantic Ocean (left) genesis and (right) track densities as number density per season per unit area equivalent to a 5° spherical cap for (a), (f) IBTrACS (Obs) and IFS simulations at (b), (g) T2047, (c), (h) T1279, (d), (i) T511, and (e), (j) T159 resolutions. Reproduced from Manganello et al. (2012) with permission by the authors.



Figure 5: Illustration of comparing Root Mean Square Difference (RMSD) values (see Appendix A for details) from models and observations, with uncertainty in observations and model ensemble spread both indicated as shading, and here RMSD is normalized to one dataset (TRMM in this example). One model is clearly best in case a), two models cannot be split in b) due to overlap in spread, while in c) the observations disagree too much to assign a best model.

GPCC

25km

GPCP