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1 **The future for Global Water Assessment**

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10

11 *Abstract*

12 The global water cycle is a fundamental component of our climate and Earth system. Many,
13 if not the majority, of the impacts of climate change are water related. We have an imperfect
14 description and understanding of components of the water cycle. This arises from an
15 incomplete observation of some of the stores and fluxes in the water cycle (in particular:
16 precipitation, evaporation, soil moisture and groundwater), problems with the simulation of
17 precipitation by global climate models and the wide diversity of global hydrological models
18 currently in use. This paper discusses these sources of errors and, in particular, explores the
19 errors and advantages of bias correcting climate model outputs for hydrological models using
20 a single large catchment as an example (the Rhine). One conclusion from this analysis is
21 that bias correction is necessary and has an impact on the mean flows and their seasonal
22 cycle. However choice of hydrological model has an equal, if not larger effect on the quality
23 of the simulation. The paper highlights the importance of improving hydrological models,
24 which run at a continental and global scale, and the importance of quantifying uncertainties in
25 impact studies.

26 *Key Words*

27 Water cycle, global, evaporation, river discharge, climate change, climate models

28

29 *1. Introduction*

30 The terrestrial water budget is at the heart of many environmental issues. Water is crucial to
31 agricultural production, carbon budgets (and other biogeochemical cycles), biodiversity,
32 energy generation, industrial production and human health. Extremes play an important role
33 – floods and droughts are pressure points on water scarcity and environmental damage.
34 There is increasing pressures on available water in many regions of the world due to

35 increasing water demand because of a growing population and wealth and this is before the
36 potential impacts of climate change. It is clearly important to develop well founded estimates
37 of future water availability, as well as extremes, to underpin adaptation plans for the future.

38 Floods, droughts, increased water scarcity, reduced food and energy production – many of the
39 key impacts of climate change identified by the IPCC are water related (Bates et al., 2008;
40 IPCC 2007a). From the thermodynamics of the atmosphere we know increasing greenhouse
41 gases are likely to lead to an increase in temperature, and this is already observed. Higher
42 temperatures will increase evaporation, over the oceans in particular and hence water vapour
43 in the atmosphere. This is likely to lead to overall higher rainfall globally and the likelihood
44 of more intense rainfall regionally. Increases in rainfall intensities have been observed in
45 more studies than decreases, although there are wide regional and seasonal variations (Berg et
46 al., 2009; IPCC, 2012; Donat et al., 2012) and there are large areas of the world where there
47 are not sufficiently long records of daily rainfall available to analyse.

48 Climate models continue to suggest increases of rainfall in the northern hemisphere high
49 latitudes and decreases of rainfall in the sub-tropical (generally semi-arid) regions of the
50 world, such as the Mediterranean, southern USA and Central America, south Australia and
51 southern Africa (IPCC, 2007b). In other words wet areas get wetter and dry areas drier.
52 When translated into river flows and available water, future water scarcity is likely to occur
53 in these latter regions but is also likely in China, India and the Middle East, where
54 populations and water consumption are rising fast (e.g. Hagemann et al., 2013; Gerten et al.,
55 2011). The regional details of these changes are, however, very uncertain. The future
56 response of river flows (and hence floods and droughts) at the basin scale will depend not
57 only on the projected changes in rainfall patterns as determined by atmospheric circulation
58 patterns, which are not always well represented in the climate models, but also on the
59 regional-scale basin characteristics (e.g. physiography, land cover, geology, Laize et al.,

60 2010) and human interventions such as dams and water abstraction and irrigation (e.g.
61 Haddeland et al., 2006; Adam et al., 2007; López-Moreno et al., 2009; Biemans et al., 2011).

62 As yet it is difficult to discern an increase in rainfall globally, partly because changes in
63 precipitation in different regions tend to cancel out. There is evidence of increasing
64 precipitation at high latitudes, decreasing precipitation in the subtropical regions and possibly
65 changing distribution of precipitation in the tropics by the shifting position of the
66 Intertropical Convergence Zone (see e.g. Zhang et al 2007). But the regional details of these
67 changes remain very uncertain. There is good evidence that the extremes of rainfall have
68 increased in Europe and worldwide (e.g. Klein Tank and Können, 2003; Zolina et al., 2010,
69 Groisman et al., 2005, IPCC, 2012, Donat et al., 2012). Pal et al., (2011) has been able to
70 conclude that the intense rainfall and floods in the UK in 2000 were significantly more likely
71 due to increased greenhouse gases.

72 Many of the observed trends in the hydrological cycle can be attributed to human activities,
73 but not necessarily to increases in greenhouse gases alone. Wu et al. (2013) argued that both
74 changing greenhouse gases and regionally varying atmospheric aerosol loading has already
75 affected the hydrological cycle. A general decrease in groundwater across the sub-tropics
76 (for example in India, e.g. Rodell et al., 2009; Tiwari et al., 2009 and the mid-west of the
77 USA Rodell et al., 2006) has been observed directly or inferred from GRACE satellite data
78 and is almost certainly due to over extraction for irrigation. Analysis with a global
79 hydrological model shows that in the sub-humid to arid areas the total global groundwater
80 depletion has increased from 126 in 1960 to 283 km³/yr in 2000 (Wada et al., 2010). The
81 latter equals 39% of the global yearly groundwater abstraction. Gleeson et al. (2012)
82 compared the rate of global groundwater depletion against the rate of natural renewal and the
83 supply needed to support ecosystems. They illustrate that humans are overexploiting

84 groundwater in many large aquifers that are critical to agriculture, especially in Asia and
85 North America.

86 Terrestrial evaporation has increased through the 1980s and 90s, most probably due to
87 decreasing aerosols (Jung et al., 2011). Since 2000 this increase may have levelled off as
88 evaporation becomes increasingly controlled by soil water limitations rather than the energy
89 available for evaporation. Increasing runoff and decreasing low summer flows in hundreds of
90 near-natural catchments have been observed in Europe (Stahl et al., 2010). Flows in the
91 northern rivers have increased (Peterson et al., 2002), but it is unclear whether this is due to
92 land-cover change, increasing precipitation or indirect effects on water loss from plant
93 transpiration linked to increasing CO₂ levels (see Gerten et al., 2008, Gedney et al., 2006).
94 Gedney et al. (submitted) attributed long-term changes in discharge from large European
95 basins to the combined effects of changing aerosol loading on solar radiation and CO₂ levels
96 on stomatal closure.

97 It is very likely that global warming has influenced river flows, but often either the long-term
98 river-flow data are not available or the natural changes are masked by anthropogenically-
99 driven changes in land cover or water extraction. To reliably assess future water resources
100 collaboration between climate, hydrological and water resource scientists working across a
101 wide variety of scales is thus essential. In recent years considerable advances have been
102 made with the bringing together of a wide variety of data sets and models (see e.g. Weedon et
103 al., 2011, Haddeland et al., 2011, Harding et al., 2011).

104 2. *Global Data Availability*

105 There have been a number of initiatives to collate global precipitation data sets into gridded
106 fields, for example Biemans et al., (2009) identifies seven such datasets. These vary with
107 time step (monthly or daily), time period and spatial resolution. Although some of these

108 datasets incorporate satellite data (for example the Global Precipitation Climatology Project,
109 <http://www.gewex.org/gpcp.html>) and weather forecast analyses (CMAP, Xie and Arkin,
110 1997) all ultimately depend heavily on ground based rain gauge data. While some regions
111 have dense rain gauge networks there are many regions, such as north and central Africa and
112 the high latitudes, where networks are too sparse or the records not sufficiently continuous to
113 provide a thorough assessment of trends and variability (e.g. Groisman et al., 2005).
114 Mountainous regions also present considerable challenges; the networks being inevitably
115 sparse and also biased towards low altitudes. Corrections have only recently been derived for
116 precipitation gauges in mountainous areas (Adam et al., 2006) although the density of gauges
117 and understanding of spatial variations of rainfall in mountainous regions remains inadequate.

118 River discharge is monitored widely around the world. The Global Runoff Data Centre
119 (GRDC, <http://www.bafg.de/>) archives discharge data for almost 9000 gauging stations
120 worldwide, two-thirds of which have daily data. However like the rainfall data the spatial
121 (and temporal) coverage is patchy with large gaps in Africa (excluding South Africa) and
122 Southern Asia. A new dataset of daily streamflow records for 10 countries across Europe,
123 based on an updated version of the UNESCO FRIEND-Water European Water Archive
124 (EWA), is useful for validating model outputs, — (Stahl et al., 2010; 2012, Hannaford et al.,
125 2013). The dataset comprises catchments with minimal anthropogenic disturbances on flow
126 regimes, monitored by gauging stations regarded to have good hydrometric performance with
127 records from 1961 to 2005. The total dataset consists of 579 gauging stations. The
128 distribution of stations over Europe is somewhat uneven with high densities of stations in
129 some areas (e.g., Germany) and limited data in areas that are heavily affected by
130 anthropogenic disturbances (e.g., northern France and the Benelux countries). No data were
131 available across the majority of southern or eastern European countries. The availability of

132 these key river measurements is hampered by the diversity of responsible organisations, a
133 lack of investment and of the political will to share data.

134

135 Evaporation is a difficult quantity to measure and varies with land cover and soil types as
136 well as climate so it is difficult to generalise. There are thus few routine measurements. The
137 nearest we have to a global network is the FLUXNET data set (<http://fluxnet.ornl.gov/>,
138 Baldocchi, 2008). This network consists of over 700 stations but not all the data are available
139 and they cover variable (often short) time periods and are of variable quality. There have
140 been a number of attempts to produce a gridded evaporation product – either based on the
141 FLUXNET data and/or satellite retrievals (e.g. Miralles et al., 2011; Mueller et al., 2013).
142 All these estimates depend on a model to derive evaporation from satellite products and/or
143 meteorology or to extrapolate point measurements spatially and temporally. The mean of the
144 global estimates is 1.56 mm d^{-1} (570 mm yr^{-1}) with a standard deviation of 0.2 mm d^{-1} , or just
145 over 10 percent, regionally the spread can be much larger, of the order of 50% for large
146 basins (Mueller et al., 2011).

147 Similarly there are limited networks of long-term in situ soil moisture measurements,
148 although there are some notable exceptions, for example in the USA, Russia and China (see
149 e.g. Entin et al., 2000). Increasing interest in soil moisture has led to some new
150 measurements and the establishment of the International Soil Moisture Network
151 (<http://www.ipf.tuwien.ac.at/insitu/>, Dorigo et al 2011). An interesting new development is
152 the Cosmic ray soil moisture observing system (COSMOS, Zreda et al., 2012). COSMOS
153 sensors, based on passive detection of scattered cosmic ray neutrons, have the advantage that
154 they average at the field scale, approximately 600m diameter, thus removing much of the
155 smallest-scale spatial variability. The measurement is also non-intrusive, automatic and does
156 not require an internal neutron source for calibration. Despite this increasing activity there

157 are still many regions of the land surface with no soil moisture measurements and even in
158 those where there are the current network is often inadequate to provide representative
159 regional figures.

160 Increasingly satellite products of soil moisture are available (AMSR-E SSM/i , SMOS etc,
161 e.g. Loew et al., 2013;) and more are planned (such as ESA's Sentinel 1) however they
162 monitor only the top few centimetres of the soil rather than the entire soil depth and are often
163 strongly affected by thick vegetation cover. The GRACE (Gravity Recovery And Climate
164 Experiment) satellites provide a unique data set which can retrieve an estimate of the total
165 water storage (groundwater, soil water, snow cover and ice) though at low spatial resolution
166 compared to the microwave satellite sensors. Since 2002 GRACE has provided considerable
167 insights into changing regional ground water levels and seasonal variations of soil water (e.g.
168 Rodell et al., 2009; Famiglietti et al., 2011; Houborg et al., 2012). The solution to these
169 various incomplete measurement systems is almost certainly a data assimilation system
170 combining measurements of different scales with one (or possibly an ensemble) of soil
171 moisture models.

172 We therefore have incomplete measurements of water (and energy) budgets at country,
173 continental and global scales. Given this lack of directly measured components of the water
174 cycle the only way to obtain globally consistent estimates of the stores and fluxes is via
175 hydrological modelling – informed and validated where possible with observations.

176 *3. Uncertainty in estimates of the global terrestrial water budget.*

177 In the last few years the Global Water System Project (GWSP) and the EU funded WATCH
178 project (e.g. Harding et al., 2011) have co-ordinated an inter-comparison of hydrological
179 models globally (WaterMIP, Haddeland et al., 2011). The inter-comparison has made use of
180 a new global data set of meteorological data (the WATCH Forcing Data, WFD, Weedon et

181 al., 2011). This is a combination of reanalysis products (ERA40) with observations (CRU
182 TS2.1 and GPCCv4), thus the models used consistent driving data and a consistent terrestrial
183 grid including a common river routing network. Eleven models were included in the
184 intercomparison, including Global Hydrological Models and stand alone versions of the land
185 surface models commonly used in climate models (Haddeland et al., 2011). The main
186 distinction between these two classes of models is that Global Hydrological Models solve the
187 water balance alone whereas the land surface models solve the energy and water balances
188 (and often have a carbon budget). All but one of the models (WATERGAP) was run without
189 calibration via observed discharge data. The initial analysis was for “naturalised” conditions
190 (Haddeland et al., 2011) - i.e. excluding human influences related to land cover changes,
191 damming, water abstraction and irrigation. Importantly, by concentrating on the late twentieth
192 century, the performance of the hydrological models could be evaluated against observed
193 basin discharge records.

194 The eleven models in WaterMIP showed a significant spread of the partitioning of
195 precipitation into evapotranspiration and runoff. Averaged over the terrestrial surface
196 (excluding Greenland and Antarctica) the average annual global evapotranspiration varied
197 between models from 415 to 586 mm yr⁻¹ and runoff from 290 to 457 mm yr⁻¹. There was no
198 single cause for the spread in model outputs, although the different model treatment of snow
199 was a major factor explaining the different shapes of the simulated annual hydrographs.
200 Most models overestimate total annual runoff in semi arid regions – probably a result of both
201 water extractions not being included in this phase of WaterMIP, and wetland evaporation,
202 typically not being included in these models. Interestingly the runoff for the Brahmaputra
203 was under-estimated – this is probably a result of the underestimate of precipitation in the
204 Himalayan region.

205 Hannaford et al. (2010); Prudhomme et al. (2011), Gudmundsson et al. (2011; 2012a; 2012b),
206 Van Loon et al. (2012), Van Huijgevoort et al. (2013) extended the analysis for a subset of
207 the WaterMIP models to investigate one or both hydrological extremes (floods and droughts).
208 Models were inter-compared, and compared against a precipitation index and against the
209 European streamflow dataset of Stahl et al. (2010; 2012). The analyses concluded that the
210 models generally identify the most extreme events and broadly show the same spatial-
211 temporal resolution evolution of hydrological extremes, but variations in the representation of
212 sub-surface flows and storage between models produce large variations in the simulated
213 dynamics. All models struggle to reproduce the high observed flows –most probably because
214 of the low spatial resolution of the input data ($0.5 \times 0.5^\circ$ or about 50×50 km) and have even
215 more difficulties to simulate low flows.

216 *4. Prediction of future flows*

217 In order for future impacts of climate change to be assessed correctly it is essential that
218 driving data are as realistic as possible. Current GCMs have substantial biases in their
219 rainfall simulations. Most models overestimate precipitation, particularly over areas of
220 complex topography and underestimate high intensity precipitation (see e.g. Mehran et al.,
221 2012). For example for ECHAM6 model overall the precipitation is overestimated by 10%,
222 with up to 5 mm day^{-1} in the tropics and 2 mm day^{-1} in mid latitudes (Stevens et al., 2012). In
223 fact the errors in GCM daily precipitation are evident in the entire intensity spectrum, with
224 too much low intensity drizzle and an underestimate of high precipitation events (see e.g.
225 Piani et al., 2010b). Hydrological models involve thresholds and other non-linearities which
226 result in incorrect trends and incorrect changes in extremes given the wrong input data. Most
227 studies, therefore, use off line calculations of runoff flowing some degree of bias correction
228 of the original GCM output (e.g. Hempel et al., 2013). This procedure has the added
229 advantage of allowing the intercomparison of multiple climate and hydrological model

230 combinations, thus providing an estimate of uncertainty in the hydrological sub-models. It
231 has the disadvantage of neglecting and feedbacks between the land surface and atmosphere
232 (Dadson et al., 2013) and introduces inconsistencies between the land surface model of
233 the GCM and the hydrological model. Given that it is unlikely that the biases in GCM
234 outputs will be substantially reduced in the near future some sort of bias correction is
235 inevitable if realistic driving data are to be provided to the hydrological models (Allen and
236 Sollen, 2008; Lenderink and Van Meijgaard, 2008).

237 The WaterMIP process (Figure 1) was the first stage in a comprehensive multimodel analysis
238 of the 20th and 21st C terrestrial water cycle. The initial runs for the 21st C have performed
239 made with the outputs from the AR4 runs (Hagemann et al., 2013) for which only a limited
240 set of GCMs stored outputs suitable to run the full set of hydrological models. All climate
241 models have biases in their precipitation (and other fields) – these biases are in both the mean
242 and day-to-day variability. These biases have a substantial impact on runoff, when translated
243 through the modelling chain (Sharma et al., 2007, Hansen et al., 2006 and Hagemann et al.,
244 2011). Within the multi-model impacts framework described in Fig. 1, prior to the
245 hydrological model runs a statistical bias correction of the GCM driving data based on
246 quantile mapping was used to adjust both daily precipitation and daily temperature (Piani et
247 al., 2010a; 2010b). Recently the WaterMIP study has been extended using the CMIP5 runs
248 for the twenty first century (Taylor et al., 2012) within the ISI-MIP (Schiermeier, 2012;
249 Dankers et al., 2014; Prudhomme et al., 2014).

250 The bias correction methodology mentioned here has many advantages – for example it
251 corrects both the mean and the variability. However, by breaking the daily correlations
252 between temperature and rainfall and failing to bias correct other associated hydrological
253 drivers – such as humidity and radiation (Haddeland et al., 2012) - additional errors can
254 therefore be introduced during bias correction. This methodology also fails to correct the

255 sequencing of wet and dry days within a month which may be critical in determining the
256 probability of floods and droughts (Zolina et al., 2010). Thus the introduction of bias
257 correction may be necessary, given the current state of climate simulations globally and
258 regionally, but does introduce additional uncertainties in estimates of future climate impacts
259 (see e.g. Ehret et al., 2012).

260 5. *Influence of bias correction*

261 A number of studies have described the use of bias corrected GCM output to simulate river
262 flows (Haerter et al., 2011; Hagemann et al., 2011; Chen et al., 2011). Below we explore the
263 impact of a bias correction by comparing model outputs based on both bias-corrected and
264 uncorrected forcing. We use a single large catchment (the Rhine) using two
265 hydrological/land surface models and the outputs from a single climate model (IPSL). The
266 model outputs for 1960-2001 are compared with daily observed naturalised discharge data.

267 The two land surface/hydrology models are:

268 a) JULES – the land surface model of the UKMO climate model (Best et al., 2011) simulates
269 the water and energy budgets of the land surface at a sub-hourly time step. Evaporation is
270 modelled using a modified Penman/Monteith equation coupled to a photosynthesis/surface
271 conductance model. A multi-layer soil model generates surface and sub-surface runoff which
272 is then routed through the river network using a linear routing model (Oki et al., 1999).

273 b) The Simple Synthetic Hydrology Model (SSHM) - is a transient soil-water balance model
274 that is combined with a conceptual groundwater model. It uses daily precipitation,
275 temperature and reference evaporation as forcing data, and it was applied to simulate time
276 series of daily snow melt, snow storage, actual evapotranspiration, soil moisture storage,
277 groundwater recharge and discharge (Van Lanen *et al.*, 1996; 2013). Land use and soil data

278 characterise the physical catchment structure. SSHM is based upon the FAO approach to
279 compute actual evapotranspiration (Allen et al., 1998) and the widely-used HBV model (e.g.
280 Seibert et al., 2000).

281

282 The models were run for 1960 to 2000 using climate model output (1960 to 2000) that was
283 bias corrected using a technique which corrects the mean and probability distributions of the
284 daily average air temperature and precipitation (Piani et al. 2010a; 2010b). The outputs are
285 compared with daily naturalised discharge data from the GRDC (Figures 2 and 3).

286

287 *i) Simulation of Rhine discharge*

288 The MBE (Mean Bias Error as the percentage difference of an average variable, e.g. average
289 modelled discharge, from the observed average, Weedon et al., 2013) for precipitation shows
290 that the IPSL-corrected precipitation matches the WATCH Forcing Data precipitation within
291 the error margins (Fig. 3). Since the bias correction is based on the WFD this small MBE
292 confirms that the bias correction was correctly applied. On the other hand, the original raw
293 IPSL precipitation for 1960-2000 is close to double the WFD precipitation (MBE circa 100%,
294 Fig. 3).

295 Comparison of the observed- and modelled-daily discharge MBE (Figure 3) provides an
296 indication of the long-term (multi-year) water balance. The discharge MBE for both JULES-
297 WFD and SSHM-WFD are significantly positive compared to the observed discharge
298 indicating that both models discharge too much water overall – this is particularly true of
299 SSHM and is presumably due to inadequacies in the evaporation formulations (too little net
300 evaporation annually). Use of the corrected IPSL forcing for both JULES and SSHM
301 substantially improved discharge MBE compared to using the WFD forcing. The overall

302 corrected IPSL precipitation is essentially the same as the WFD precipitation. Thus changes
303 in discharge MBE relate to differences between other atmospheric forcing variables such as
304 net radiation, wind speed and humidity that are not affected by the bias correction method of
305 Piani et al.(2010a and b).

306 The discharge MBE for JULES forced with the un-corrected IPSL data is larger than for
307 forcing with either the WFD or the corrected-IPSL data. A component of this over-estimation
308 must be the excessive un-corrected IPSL precipitation (indicated by the precipitation MBE).
309 By contrast, SSHM discharge MBE is slightly under-estimated given the uncorrected IPSL
310 forcing rather than over-estimated for the other forcing. As the uncorrected IPSL
311 precipitation is about double both the WFD precipitation and corrected IPSL precipitation,
312 the underestimation of SSHM discharge when forced with uncorrected IPSL data implies too
313 much modelled evaporation.

314 *ii) Annual cycles in Rhine discharge.*

315 Spectrally the largest identifiable component of the daily discharge variability is the strong
316 annual cycle (observed or modelled with any forcing). Focussing discussion on the annual
317 scale makes it easier to interpret the reasons for differences between model output and
318 observations and between different forcings. The amplitude-ratio and phase (or timing) of
319 modelled discharge at the annual scale is used for comparison with the GRDC naturalised
320 discharge observations (for methodology see Weedon et al., submitted). Note that for the
321 WFD-forced model output the short-term (sub-annual) variability should ideally match the
322 GRDC record hence the observed discharge (red) is plotted on top of the JULES-WFD
323 discharge (black) and SSHM-WFD discharge (black, Fig. 2a). However, for the IPSL data
324 derived from a GCM run, the specific meteorological evolution is not expected to match the
325 actual meteorological history of 1960-2000. Thus the comparison is restricted to comparing

326 the average characteristics of the annual cycles in modelled discharge with the annual cycles
327 in the observed discharge (Figs 2b and c and 3 b and c).

328 Forced with the WFD, JULES has an annual cycle in discharge that is too large (Figs 2a and
329 3b), but with the correct timing (phase, Fig. 3c). While summer JULES-WFD and GRDC
330 discharge are similar (Fig 2a) the JULES-WFD baseflow in winter is too large. This is
331 probably because of the underestimation of overall evaporation (MBE about
332 +20%). However, SSHM forced with the WFD has an annual cycle with approximately the
333 correct amplitude and timing (within error) despite an MBE of about +60%. Thus SSHM-
334 WFD correctly represents the variations (amplitude and phase) of the baseflow, but
335 underestimates the overall evaporation so the MBE is too high. Visual inspection of Figure 2a
336 shows that in terms of sub-annual discharge variations linked to precipitation events JULES-
337 WFD reproduces the large sub-annual variability seen in the GRDC data pretty well.
338 However, SSHM has only muted short-term discharge events compared to observations
339 perhaps linked to limited surface runoff modelling.

340 Using the corrected IPSL forcing JULES has an annual cycle in discharge that is too large
341 compared to observations and slightly larger than under WFD forcing, but still with the right
342 timing (Fig. 3). Since the overall discharge in JULES-IPSL-corrected is lower than JULES-
343 WFD (MBE about +10%), the larger amplitude annual cycles may reflect more evaporation
344 in the summer compared to JULES-WFD - as supported by the lower average baseflow in the
345 summer (Fig. 2b).

346 The SSHM annual discharge cycle is too large when forced by the IPSL-corrected data - and
347 is much larger than for SSHM-WFD (Fig. 3b). As the discharge MBE is lower overall (about
348 +10% versus +60%) the large annual cycles may reflect much larger amounts of evaporation

349 in the summer as reflected by the substantially lower baseflow compared to the SSHM-WFD
350 run.

351 JULES-not-corrected-IPSL has very large annual cycles in discharge (Figs. 2c and 3). This at
352 least partly relates to the large uncorrected precipitation input as reflected by the much higher
353 baseflow in winter than the other JULES runs. However, in addition summer baseflow is
354 lower than for JULES-WFD and JULES-corrected-IPSL so apparently summer evaporation is
355 larger than before - adding to the amplitude of the annual cycle.

356 The SSHM run with the uncorrected IPSL data has an annual cycle that appears to be too
357 small in amplitude - though it is within error (95% confidence interval) of agreeing with
358 observations. Since the discharge MBE is lower than expected there may be too much
359 evaporation overall. However, the summer baseflow is very similar to the winter baseflow on
360 average so the summer evaporation appears to be far too low.

361 The message from this analysis of the case study is that in order to obtain realistic discharge
362 estimates, as judged against observations, bias correction is necessary and has an impact on
363 the mean flows and their seasonal cycle. However choice of hydrological model has an
364 equal, if not larger effect on the quality of the simulation. This conclusion supports that of
365 Hagemann et al. (2013).

366 6. *Conclusions*

367 Water resources are already under considerable pressure in many parts of the world. These
368 pressures will increase with global changes – particularly increasing population and affluence
369 leading to increasing water extraction and land cover change. Climate change will also add
370 to these pressures with dry areas getting drier and an increasing proportion of precipitation
371 falling in extreme events, also leading to longer dry spells. Any adaptation measures must be

372 strongly underpinned by a good knowledge of the current regime and an understanding of
373 possible future regimes. This can only be obtained by a combination of models and data.
374 Considerable progress has been made in recent years in the compilation of global data sets
375 and in our understanding of model errors.

376 The substantial spread found between hydrological models commonly used for impact
377 analysis suggests a single impact model should be used with great care (Haddeland et al.,
378 2011; Stahl et al., 2012; Van Huijgevoort et al., 2013; Hagemann et al., 2013). This study
379 also suggests that improvements to hydrological models used at large scales could and should
380 be made, in particular in the high and low flow domain. Obvious examples are the
381 improvement of evapotranspiration and snowfall components of models, to improve the
382 overall water balance, and the inclusion of additional hydrological processes, such as ground
383 water, permafrost and wetlands, to improve the low and high flow representation. The use of
384 calibration via spatially-aggregated local observations is an additional aspect which should be
385 carefully considered. Calibration can undoubtedly improve radically the simulation within a
386 single basin; however, it can hide structural weaknesses within a particular model. It may
387 also reduce the global applicability of a model – it is clear that the modelling suite used must
388 be considered carefully against its purpose.

389 Global climate models still show persistent regional biases in precipitation and a tendency to
390 produce too much light rain (see e.g. Perkins et al., 2007). Regional climate models fare a
391 little better but still have considerable biases (e.g. Rawlins et al., 2012). Mean runoff can be
392 seen as a residual of the precipitation after subtraction of the evaporation so any bias in the
393 precipitation is likely to be amplified, in percentage terms, in the runoff. In addition many of
394 the runoff processes are strongly non-linear, thus the variability (in time and space) is
395 important. While simulations of precipitation are improving progress is slow and there is
396 little prospect of dramatic advances in the next few years. In the meantime society needs

397 regional and local assessments of the impact of climate change and this cannot wait for the
398 advance of climate models. The need for the correction of biases in the GCM outputs to
399 provide realistic estimate of runoff (and changes in runoff) is demonstrated in this paper. It is
400 also clear that the current state-of-the-art bias-correction methodologies need further
401 refinements. Hempel et al. (2013) have developed the bias correction methodology of Piani
402 et al. (2010a) to include other variables, such as radiation, but problems with cross
403 correlations still persist.

404 Estimations of the water cycle for the future contain many uncertainties – GHG scenarios,
405 climate model uncertainties, hydrology/climate feedbacks, bias correction, imperfect large-
406 scale hydrological models, water use/exploitation scenarios. We need a new framework for
407 impact model assessment which should include: common driving data, common (and
408 explicit) land use and extraction scenarios, ensembles of climate and hydrological models and
409 uncertainty description. The new ISI-MIP approach is a useful step towards an integrated
410 inter-sectorial approach in impact assessment (Piontek et al., 2014).

411

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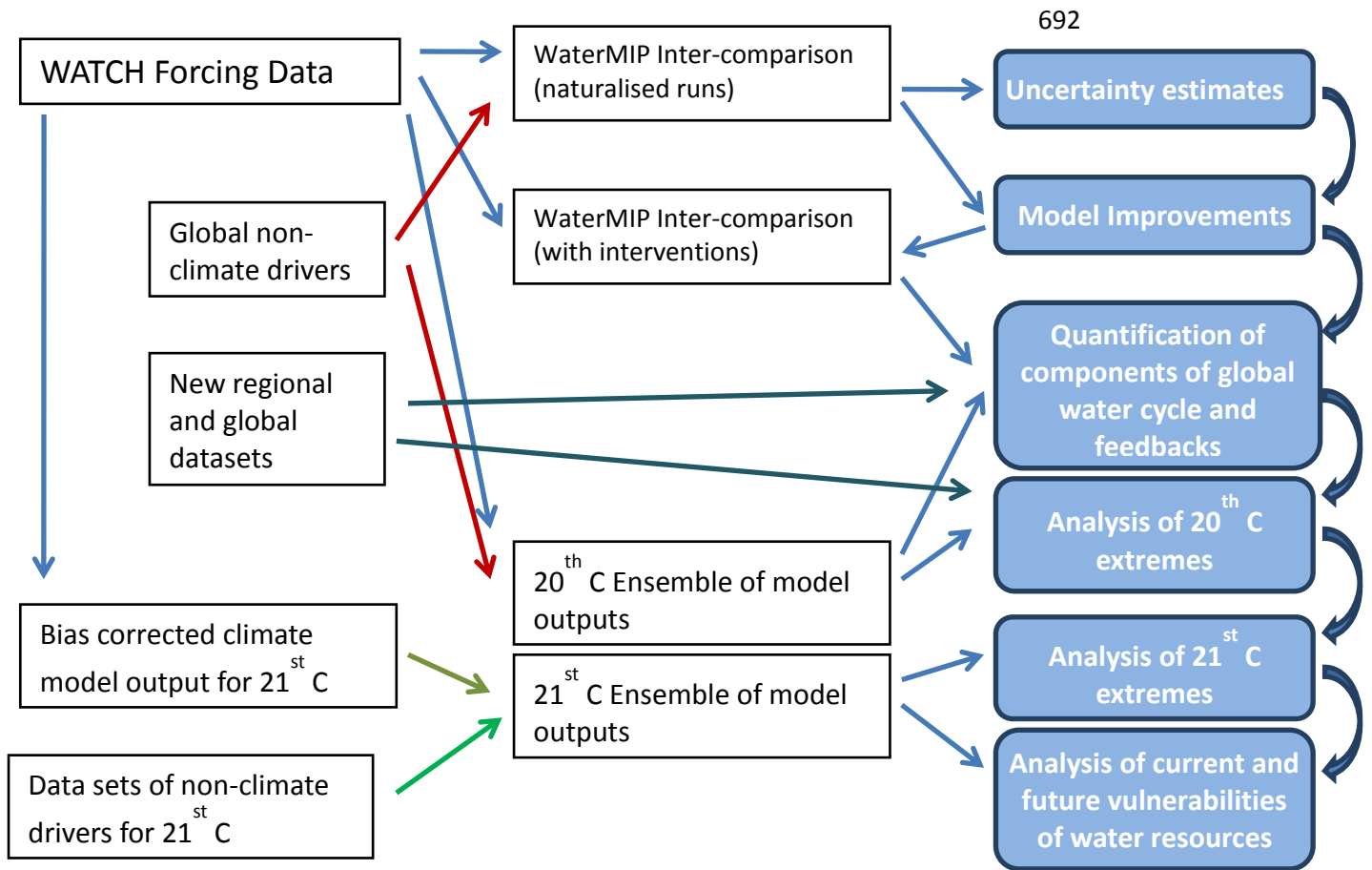
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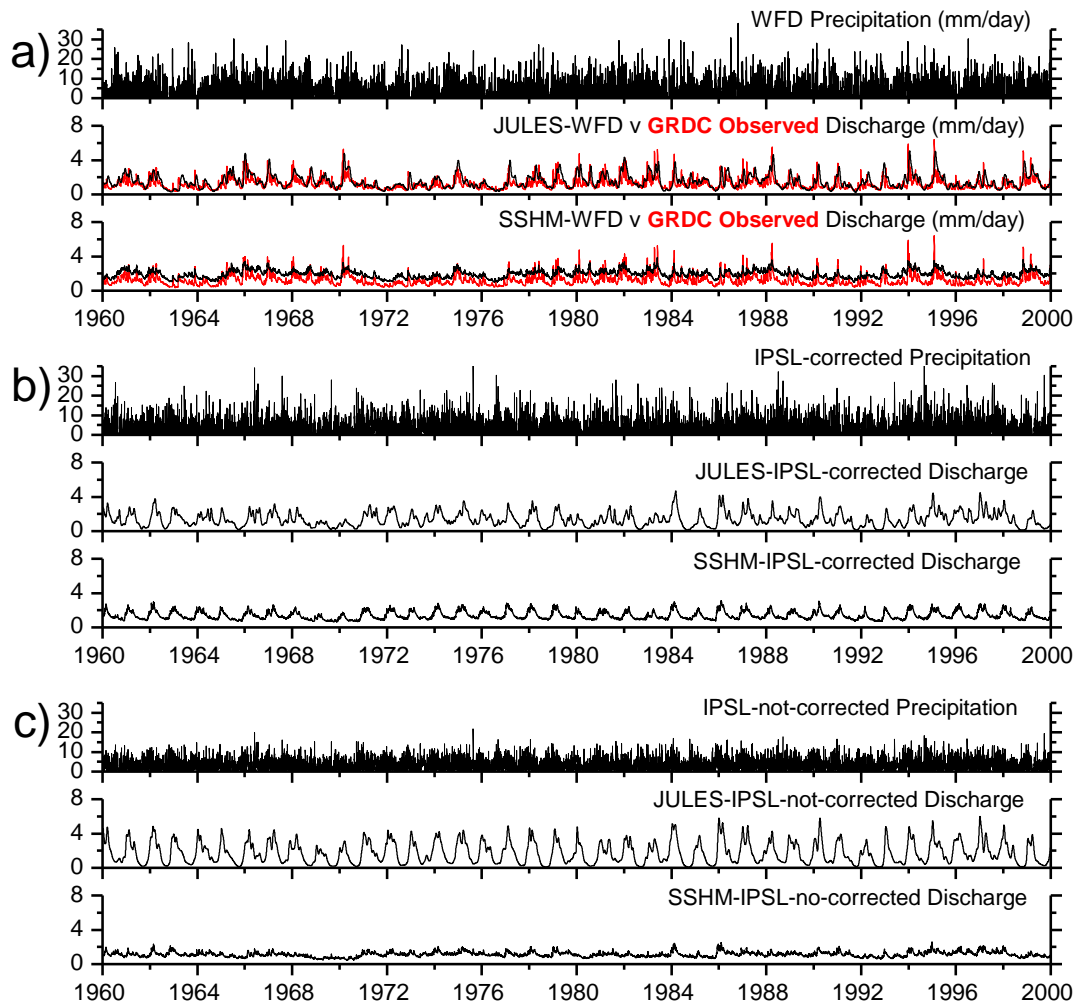
695 Figure 1. Analysis scheme of the WaterMIP intercomparison.

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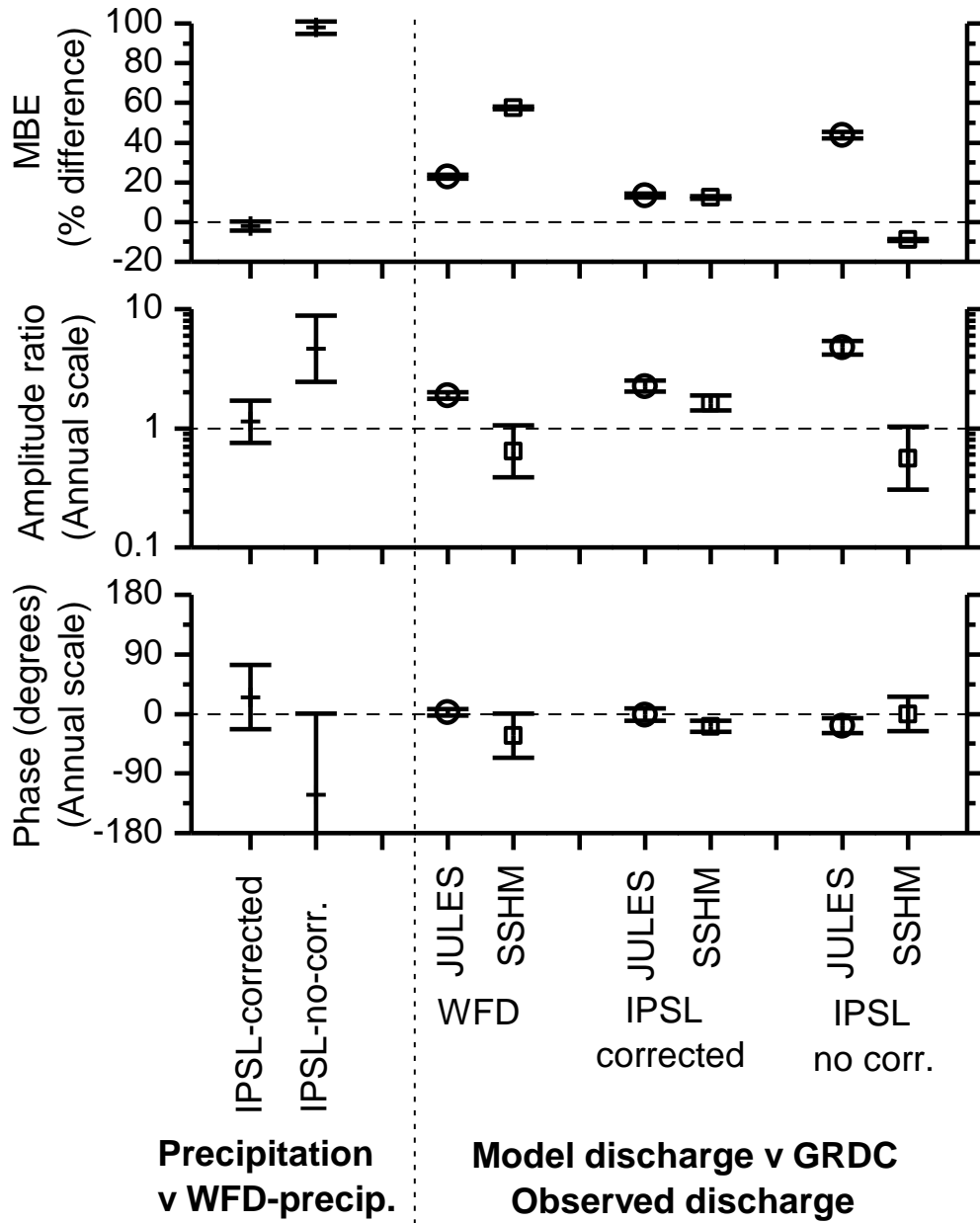
699 Figure 2. Time series of precipitation inputs, discharge and model runs, as described in text.



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702 Figure 3. Mean Bias Error (MBE), annual amplitude and phase for model runs. Bars indicate the 95%
 703 confidence interval.



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