

1 On inclusion of water resource management in Earth System 2 models – Part 2: Representation of water supply and 3 allocation and opportunities for improved modeling

4
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9 10 **Abstract**

11 Human water use has significantly increased during the recent past. Water withdrawals from
12 surface and groundwater sources have altered terrestrial discharge and storage, with large
13 variability in time and space. These withdrawals are driven by sectoral demands for water, but are
14 commonly subject to supply constraints, which determine water allocation. Water supply and
15 allocation, therefore, should be considered together with water demand and appropriately included
16 in Earth System models to address various large-scale effects with or without considering possible
17 climate interactions. In a companion paper, we review the modeling of demand in large-scale
18 models. Here, we review the algorithms developed to represent the elements of water supply and
19 allocation in Land Surface Models and Global Hydrologic Models. We note that some potentially
20 important online implications, such as the effects of large reservoirs on land-atmospheric
21 feedbacks, have not yet been fully investigated. Regarding offline implications, we find that there
22 are important elements, such as groundwater availability and withdrawals, and the representation
23 of large reservoirs, which should be improved. We identify major sources of uncertainty in current
24 simulations due to limitations in data support, water allocation algorithms, host large-scale models
25 as well as propagation of various biases across the integrated modeling system. Considering these
26 findings with those highlighted in our companion paper, we note that advancements in
27 computation and coupling techniques as well as improvements in natural and anthropogenic
28 process representation and parameterization, large-scale models, remote sensing and data

29 assimilation can facilitate inclusion of water resource management at larger scales; however
30 various modeling options should be carefully considered, diagnosed and intercompared. We
31 propose a modular framework to develop integrated models based on multiple hypotheses for data
32 support, water resource management algorithms and host models in a unified uncertainty
33 assessment framework. A key to this development is the availability of regional scale data for
34 model development, diagnosis and validation. We argue that the time is right for a global initiative,
35 based on regional case studies, to move this agenda forward.

36

37 **1 Introduction**

38 The water cycle is fundamental to the functioning of the Earth System and underpins the most
39 basic needs of human society. However, as noted in our companion paper (hereafter referred to as
40 Nazemi and Wheater, 2014a), the current scale of human activities significantly perturbs the
41 terrestrial water cycle, with local, regional and global implications. Such disturbances affect both
42 hydrological functioning and land-atmospheric interactions, and therefore should be explicitly
43 represented in large-scale models. We consider both Land Surface Models (LSMs) and Global
44 Hydrologic Models (GHMs). LSMs generally represent water, energy and carbon cycles, and can
45 be coupled with climate models (i.e. online simulations) for integrated Earth System modeling, or
46 uncoupled from climate models (i.e., offline simulations) for large-scale impact assessment.
47 GHMs are also run in uncoupled mode for impact assessment; however, they focus exclusively on
48 the water cycle. In this survey, we consider the representation of water resources management in
49 these large-scale models and focus on water quantity rather than water quality. We note that while
50 historically the effects of water management have largely been neglected in LSMs and GHMs,
51 there has been increasing interest in recent years in their inclusion and a common first step is to
52 estimate the demand for water, in particular associated with irrigation (see Nazemi and Wheater,
53 2014a). However, in practice water resource systems are often complex, and associated
54 infrastructure may have competing functional requirements and constraints (e.g. flood protection,
55 water supply, environmental flows, etc.), exacerbated during drought. In this paper, we turn to the
56 issues around water supply and allocation and associated representations in large-scale models.

57 Major implications are associated with water allocation from surface and ground water sources.
58 For instance, large dams and reservoirs can significantly modify downstream streamflow

59 characteristics (e.g., Vörösmarty et al., 1997, 2003; Oki and Kanae, 2006; Wisser et al., 2010;
60 Tang et al., 2010; Tebakari et al., 2012; Lehner and Grill, 2013; Lai et al., 2014; Haddeland et al.,
61 2014), with large regional variability (see e.g., Pokhrel et al., 2012a). Considering that almost all
62 major river systems in the Northern Hemisphere (except for the arctic and sub-arctic regions) are
63 dammed (e.g., Meybeck, 2003; Nilsson et al., 2005), it can be argued that accurate simulation of
64 continental and global runoff is impossible without considering the effects of reservoirs. Such
65 hydrologic impacts and associated environmental consequences can be studied through offline
66 LSMs or GHMs. There are, however, important land-surface implications associated with
67 reservoir operation that require online simulations. For instance, it has also been argued that large
68 dams can have important footprints on surface energy (Hossain et al., 2012), with associated
69 effects on land-surface boundary conditions and potential interactions with local and regional
70 climate (MacKay et al., 2009). To understand these effects, online LSMs, i.e. coupled with climate
71 models, are required to provide quantitative knowledge of the extent of such impacts in time and
72 space.

73 Groundwater resources have also been extensively perturbed during the “Anthropocene”. Every
74 year, a large amount of groundwater is pumped to the land-surface for both irrigative and non-
75 irrigative purposes (e.g., Zektser and Lorne, 2004; Siebert et al., 2010). Such extraction has
76 already caused large groundwater depletion in some areas (Rodell et al., 2007, 2009; Gleeson et
77 al., 2010, 2012) and changed the surface water balance due to return flows from demand locations
78 to river systems and ultimately to oceans (e.g., Lettenmaier and Milly, 2009; Wada et al., 2010;
79 Pokhrel et al., 2012b; Döll et al., 2014). In parallel, a considerable proportion of the surface water
80 diverted into irrigated areas may recharge groundwater (Döll et al., 2012). From a broader
81 perspective, groundwater aquifers (particularly shallow groundwater) can also be an important
82 control on soil moisture and wetlands, and thus influence atmospheric surface boundary conditions
83 (e.g., Maxwell et al., 2007, 2011; Fan and Miguez-Macho, 2011; Dadson et al., 2013). These online
84 effects are widely unquantified at the global scale, as the sub-surface processes below the root
85 zone have been generally assumed to be disconnected from the atmosphere (see Taylor et al.,
86 2013).

87 In addition, representing water allocation practice in large-scale models is urgently required to
88 address various emerging water security concerns including (but not limited to) human water
89 supply (e.g. Postel, 1996), ecosystem health (e.g. Vörösmarty et al., 2010), sedimentation (e.g.

90 Syvitsky et al., 2005) and water quality (e.g. Skliris and Lascaratatos, 2004). These latter areas are
91 beyond the scope of this paper, but highlight the need to represent human water allocation in large-
92 scale models for regional and global impact assessments. For instance, the most densely-populated
93 parts of the globe suffer from extremely fragile water supply conditions (e.g., Grey et al., 2013;
94 Falkenmark, 2013; Nazemi and Wheeler, 2014b) and this will be amplified under future climate
95 change and population growth (e.g., Arnell, 2004; Wada et al., 2013b; Rosenzweig et al., 2014;
96 Schiermeier, 2014; Haddeland et al., 2014). While population growth directly affects water
97 demand, indirect effects include changing land and water management, with associated impacts
98 on the aquatic environment. Similarly, climate change is expected to perturb both water demand
99 and supply, as it also results in greater seasonal and inter-annual variability with increase in the
100 risk of extreme conditions (e.g., Dankers et al., 2014; Prudhomme et al., 2014). Looking to the
101 future, Yoshikawa et al. (2013) argued that current sources can only account for 74 percent of the
102 global net irrigation requirements of the 2050s and supply/demand imbalance will cause a major
103 increase in global water scarcity (Alcamo et al., 2007; Hanasaki et al., 2008a, b, 2013a, b; Schewe
104 et al., 2014). In water-scarce conditions, competition for water resources becomes increasingly
105 important and the details of water allocation practice play a key role in the spatial and temporal
106 distribution of water stress. These issues necessitates adaptation strategies to mitigate the effects
107 of water stress and extreme conditions and large-scale models are, therefore, required to assess the
108 effects of various global changes and to examine the impact of alternative management strategies.

109 Representation of water allocation practice introduces a set of issues associated with management
110 and societal preferences, local and regional differences in decision making, complexity of water
111 resources systems (particularly at larger scales), as well as lack of data support. At local and basin
112 scales, water allocation practice is mainly defined as an optimization problem, in which the aim is
113 to minimize the adverse effects of water shortage and/or to maximize the economic benefits of the
114 water resource system. The advent of search algorithms such as Linear Programming (Dantzig,
115 1965), Dynamic Programming (Bellman, 1952) and Genetic Algorithms (Goldberg, 1989) has
116 resulted in a wide variety of operational models for water resource management at small basin-
117 scale (e.g., Rani and Moreira, 2010; Hossain and El-shafie, 2013; see Revelle et al., 1969 for the
118 early developments). These small-scale water allocation models, however, typically do not include
119 processes related to water supply and demand and receive these variables as prescribed inputs.
120 Moreover, small-scale operational models often require detailed information about policy

121 constraints and operational management. This information is not generally available over larger
122 regions and at the global scale. Even if all related information were to be available, the level of
123 complexity within small-scale operational models cannot be supported globally due to high
124 dimensionality in decision variables and computational burdens. These restrictions have resulted
125 in the progressive development of macro-scale algorithms to represent water allocation practice
126 and competition among demands at regional and global scales.

127 The main objective of this paper is to overview the current literature and to identify the state of
128 available methods and applications for large-scale representations of water supply and allocation
129 in LSMs and GHMs, with relevance to both Earth System modeling and regional and global water
130 management. Section 2 addresses the representation of surface and ground water sources. Section
131 3 discusses the linkage between available sources and prescribed demands (see Nazemi and
132 Wheater, 2014a) through macro-scale allocation algorithms. Section 4 reviews current large-scale
133 modeling applications and discusses the quality of available simulations. Section 5 merges the
134 findings of Nazemi and Wheater (2014a) with those obtained in Sections 2 to 4, and highlights
135 current gaps and opportunities from an integrated water resources, hydrology and land-surface
136 modeling perspective. This is finalized by suggesting a systematic framework for model
137 development and uncertainty assessment to guide future efforts in inclusion of water resource
138 management in large-scale models. Section 6 closes our survey and provides some concluding
139 remarks.

140

141 **2 Available representations of water sources in large-scale models**

142 **2.1 Lakes and reservoir**

143 Natural lakes and man-made reservoirs cover more than 2 percent of the global land surface area
144 except for Antarctica and glaciated Greenland (Lehner and Döll, 2004). Lakes and reservoirs are
145 important water sources due to their ability to store and release surface water for human demand.
146 While natural lakes have been historically an important water source for human civilization, man-
147 made reservoirs have been mainly constructed over the last 50 years. Currently, there are more
148 than 16 million reservoirs worldwide (Lehner et al. 2011), retaining around 20 percent of the
149 annual runoff and 10 percent of the total volume of the world's freshwater lakes (Gleick, 2000;

150 Meybeck, 2003; Wood et al., 2011). This makes an important global water resource: Yoshikawa
151 et al. (2013) estimated that reservoirs allocated 500 cubic kilometers just for irrigation during the
152 year 2000, worldwide.

153 From the large-scale modeling perspective, lakes and reservoirs introduce heterogeneity into land-
154 surface parameterizations, with both offline and online implications. To represent these open water
155 bodies, first they should be identified at the grid and sub-grid scales. The availability of basic data
156 for larger lakes and reservoirs is relatively good (see Lehner and Döll, 2004 for a comprehensive
157 list of data sources). For instance, the Global Lakes and Wetlands Database (GLWD;
158 <http://www.worldwildlife.org/pages/global-lakes-and-wetlands-database>) includes more than
159 250,000 lakes globally. In addition, the International Commission of Large Dams (ICOLD;
160 <http://www.icold-cigb.net/>) and Global Reservoir and Dam (GRanD; [http://www.gwsp.org](http://www.gwsp.org/products/grand-database.html)
161 [/products/grand-database.html](http://www.gwsp.org/products/grand-database.html)) databases contain information about the location, purpose and
162 capacity of 33,000 and 7000 large dams, worldwide. However, to estimate evaporation, as well as
163 storage and release, more specific physical characteristics, such as storage-area-depth
164 relationships, are required. These data are generally not available and parametric relationships
165 have been used to approximate these properties based on various assumptions (e.g., Takeuchi,
166 1997; Liebe et al., 2005). Nonetheless, at this stage of model development, reservoir simulations
167 cannot in general be directly verified, due to the lack of observations of reservoir level and storage
168 (Gao et al., 2012). These data limitations may be largely solved in the relatively near future by
169 upcoming satellite missions – see the discussion of Section 5.3 below.

170 Depending on their size, lakes and reservoirs can be represented either within channel or sub-grid
171 routing components of host large-scale models. While larger lakes and reservoirs are normally
172 represented within the river routing component and regulate the channel streamflow, smaller
173 bodies are mainly considered within sub-grid parameterizations as an additional pond (e.g., Döll
174 et al., 2003; Wisser et al., 2010). Ideally, natural lakes and reservoirs should differ in their
175 representation due to human management. If human management is neglected, reservoir releases
176 can be represented similar to natural lakes using simple parametric equations that link the reservoir
177 release to reservoir storage (or level) (e.g., Meigh et al., 1999; Döll et al., 2003; Pietroniro et al.,
178 2007; Rost et al., 2008). Lake algorithms, however, have had limited success in highly regulated
179 basins. This is rather intuitive: for natural lakes, the dynamics of lake storage (and hence discharge)
180 are regulated by climate and inflow variability, whereas the dynamics of reservoir discharge (and

181 hence storage) are mainly controlled by pressures of downstream demands and management
182 decisions. Moreover, reservoirs are often multi-functional and deal with competing demands with
183 varying priority in time; therefore, simple lake routing algorithms are unable to fully describe
184 reservoir functionality. Alternatively, macro-scale algorithms for reservoir operation have been
185 suggested, which attempt to link reservoir releases to inflows, storage and prescribed human
186 demands considering water allocation objectives – see Section 3.3.

187 Considering online implications, the effects of dams on near-surface energy and moisture
188 conditions and hence land-atmospheric feedbacks can be important for large reservoirs (Hossain
189 et al., 2012). Addressing this issue using coupled LSMs is currently a major gap in the literature
190 and presents a challenging problem at the grid scale, since the impact of dams on the local climate
191 can be masked by regional climate variability and surrounding land cover (e.g., Zhao and
192 Shepherd, 2011).

193 **2.2 Streamflow diversions and inter-basin water transfers**

194 Streamflow diversions of any magnitude require dams or barrages. At smaller scales, these include
195 within-basin water transfers from local streams to nearby demands. In-basin diversions are often
196 represented in large-scale models by instantaneous abstractions (e.g., Hanaski et al., 2008a, 2010;
197 Döll et al., 2009). Hydrologic routing can be alternatively considered for improved representation
198 (e.g., Wisser et al., 2010). It should be noted that a proportion of the diverted flow normally returns
199 to the river systems. Heuristic algorithms have been advised to mimic the mechanism of diversion
200 based on returning the excess water to the river with some lag. Biemans et al. (2011) for instance
201 represented the dynamics of diverted/return flows for irrigated areas by making water available
202 for consumption for 5 days; if unused, it is released back to the river. This can have important
203 implications for differentiating between the actual use and total withdrawals, in the case where
204 water is over-allocated.

205 Inter-basin water transfers normally involve major infrastructure and can significantly perturb the
206 regional streamflow regime. For instance, proposed South to North water transfer schemes in
207 China (see Liu and Zheng, 2002; Liu and Yang, 2012) would divert 44.8 billion cubic meters of
208 water annually (<http://www.internationalrivers.org/>). The associated hydrological impacts are
209 estimated to be as, or more significant than, land-use and/or land-cover changes (J. Liu et al.,

210 2013). Inter-basin water transfer can be adequately represented by hydrologic routing. Examples
211 are available for some regional applications (e.g., Nakayama and Shankman, 2013a, b; Ye et al.,
212 2013); however, efforts to represent long-distance diversions at the global scale are limited. This
213 is mainly due to data issues regarding the location and specification of diversion channels globally.
214 This could be largely resolved in future due to improvements in remote sensing observations – see
215 the discussion of Section 5.3 below.

216 **2.3 Groundwater**

217 Even large-scale models with detailed water resource management schemes have limited
218 representation of groundwater availability (see Table 1), largely due to the limitations in data
219 related to groundwater storage, withdrawals and sub-surface properties as well as computational
220 difficulties. There have been some efforts to include groundwater in LSMs to describe the aquifer
221 dynamics, land-atmospheric feedbacks and watershed responses, mainly at basin and small
222 regional scales (e.g., Maxwell and Miller, 2005; Maxwell et al., 2007, 2011; Kollet and Maxwell,
223 2008; Ferguson and Maxwell, 2010). These studies consider a physically-based groundwater store,
224 which can be updated at each modeling time step using a 3D representation of groundwater
225 movement, and linked to land-surface calculations through soil moisture dynamics. Such
226 representations are computationally expensive and limited at the global scale, since temporal and
227 spatial domains should be finely gridded for accurate representations of groundwater movement
228 and soil-moisture interactions, particularly in online studies. To the best of our knowledge, no
229 online study, characterizing the feedback effects between groundwater management and climate,
230 is available at the global scale. Offline representation of groundwater management has mainly
231 been performed in the context of GHMs and involves estimation of available groundwater storage,
232 sub-grid groundwater recharge and groundwater withdrawals. In this section, we focus on
233 groundwater availability and recharge and leave the discussion related to groundwater withdrawals
234 to Section 3.2.

235 In current representations, often groundwater availability in general, or the nonrenewable and
236 nonlocal blue water (NNBW) in particular, is assumed as an unlimited local source (e.g., Rost et
237 al., 2008; Biemans et al., 2011; Pokhrel et al., 2012a,b). NNBW is a technical term defined as an
238 "imaginary" source that implicitly accounts for nonrenewable fossil groundwater or other water
239 sources that are not explicitly represented in the model. This can cause major uncertainties in

240 estimation of actual withdrawals (see Section 3.2). Efforts have been made to improve this
241 assumption. For instance, Strzepek et al. (2012) bounded groundwater availability by considering
242 a threshold for groundwater allocation. Wada et al. (2013a) proposed a conceptual linear
243 groundwater reservoir, parameterized globally based on lithology and topography, to estimate the
244 groundwater availability at the grid-scale using the baseflow as a proxy. Although this conceptual
245 representation provides an efficient scheme for global simulations, it ignores the baseflow
246 reduction due to groundwater depletion. In a more recent attempt, Döll et al. (2014) continuously
247 simulated the daily groundwater storage using the difference between groundwater recharge and
248 the sum of baseflow and net groundwater abstraction, with base flow declining with decreasing
249 groundwater storage. Both algorithms, however, do not consider inter-grid lateral groundwater
250 movement, which can have an important impact on water availability across various scales.
251 Although lateral groundwater movement is widely studied in aquifer studies at smaller basin and
252 regional scales (e.g., Ye et al., 2013), it is currently a key missing process representation at larger
253 regional and global scales (Taylor et al., 2013).

254 Groundwater recharge includes the movement of water from the unsaturated soil zone to a
255 saturated groundwater body. There are a number of approaches to represent the vertical water
256 movement in large-scale models, including heuristic methods (e.g., Döll et al., 2003), conceptual
257 “leaky-buckets” (e.g., Wada et al., 2010), or numerical solutions of the physically-based Richards’
258 equation (Best et al., 2011; D. B. Clark et al., 2011). These approaches are based on various
259 assumptions and are subject to large uncertainties. Heuristic schemes relate the recharge rate to
260 surface runoff, using a set of parameters based on catchment, soil and aquifer characteristics. These
261 representations are often simplistic and may result in large estimation errors, particularly in arid
262 and semi-arid regions (Polcher et al., 2011). Conceptual approaches widely assume a steady-state
263 condition and use the unsaturated hydraulic conductivity to represent groundwater recharge with
264 or without considering capillary rise (van Beek and Bierkens, 2008; Wada et al., 2010; van Beek
265 et al., 2011; Wada et al., 2013a; Ye et al., 2013). In a global study, Wada et al. (2012) used this
266 approach to account for additional recharge from irrigated lands based on the unsaturated hydraulic
267 conductivity at field capacity. This can be important for representing the excess water diverted
268 from both surface and groundwater sources. Although conceptual representations are efficient for
269 large-scale studies, still limitations remain in these schemes due to large heterogeneities in soil
270 characteristics, a common assumption of steady-state recharge rate, as well as the inherent

271 uncertainty associated with soil hydraulic properties. The physically-based approaches remove the
272 steady-state assumption; nonetheless as discussed above, they require a detailed numerical scheme
273 for solving a highly non-linear partial differential equation. This is subject to various
274 computational difficulties at larger scales, and invariably there is a gap between the scale for which
275 Richards' equation was developed and the scale at which it is implemented in large-scale
276 groundwater and hydrologic models (Beven, 2006a; Gentine et al., 2012).

277 **2.4 Desalination and water reuse**

278 Water reuse and desalination are currently minor water resources at the global scale and have been
279 widely ignored in large-scale models. Nonetheless, it should be noted that these water sources have
280 local relevance and are important in several water-limited regions (Wade Miller, 2006; Pokhrel et
281 al., 2012a). Wada et al. (2011) estimated that annual desalinated water use is around 15 cubic
282 kilometers globally, of which Kazakhstan uses 10 percent of the total volume. Desalinated water
283 availability can be estimated using a bottom-up approach based on the information available about
284 treatment and water reuse capacity at the grid-scale (Strzepek et al., 2012). These data, however,
285 are limited and uncertain globally. Alternatively, top-down approaches try to downscale
286 countrywide data. Wada et al. (2011, 2013a), for instance, downscaled the countrywide data on
287 water reuse and desalination using a gridded population map. Considering that water reuse and
288 desalination will likely be more important in future due to increased water scarcity at the global
289 scale, we suggest more effort in representing these sources, including data collection to support
290 future algorithm developments – see Section 5.3 below.

291

292 **3 Available representations of water allocation in large-scale models**

293 Water allocation distributes the available water sources among competing demands and should
294 typically include a set of management decisions to systematically (1) link the prescribed demands
295 to available sources of water; (2) determine allocation objectives as well as priorities in case of
296 water shortage; and (3) withdraw the available water based on allocation objectives and
297 management constraints. At this stage of model development, there are limited examples for
298 representation of water allocation at larger scales. These studies are offline and have multiple
299 sources of uncertainty. Table 1 summarizes some examples from the recent literature. In this

300 section, we briefly discuss the main requirements and available algorithms for representing water
301 allocation in large-scale models.

302 **3.1 Main requirements**

303 The first basic requirement is to identify which sources are available to supply the water demands
304 within each computational grid. The majority of current allocation schemes assume that grid-based
305 demands can be supplied from the sources available within the local grid. This assumption is
306 intuitive and easy to implement, however, it naturally ignores long distance water transfers.
307 Various modifications have been proposed to overcome this limitation. Relative elevation and
308 travel time of water from source to demand have been used to condition demands to available
309 sources upstream. For example, Hanaskai et al. (2006) assumed that large reservoirs can supply
310 downstream demands that are located within 1100 km (based on a travel time of 1 month).
311 Similarly, Wada et al. (2011) considered a criterion of approximately 600 km and Biemans et al.
312 (2011) 250 km. These rules are evidently simplistic but can be easily implemented. They also
313 generally assume steady-state conditions, so that the allocated water can be simply abstracted from
314 the source and added at the demand location at the same time step. Alternatively, routing schemes
315 can provide a more accurate basis for representing the water delivery and avoid this limitation –
316 see the discussion of Section 5.5 below.

317 The second important issue is to determine objectives of and priorities for water allocation,
318 particularly during shortage. In the absence of access to local operating rules, this requires defining
319 a set of generic rules to assign the relative preference of each demand and to define the purpose of
320 water allocation. Both irrigative (e.g., Rost et al., 2008; Döll et al., 2009; Wada et al., 2013a) and
321 non-irrigative demands (e.g., Hanasaki et al., 2008a; Strzepek et al. 2010, 2012; Blanc et al., 2013)
322 have been given the highest priority. In cases where multiple demands with the same priority are
323 derived from a unique source of water, the deficit is typically shared proportionately to the
324 demands (e.g., Biemans et al., 2011). Based on priorities and assumptions made regarding water
325 availability, several allocation objectives have been used (see Table 1). It should be noted that
326 water resource management is commonly multi-purpose and allocation objectives and priorities
327 can change within a typical operational year. For example, many reservoirs are designed for two
328 conflicting objectives, i.e. irrigation supply and flood control. To account for this, Voisin et al.
329 (2013a) used rule curves to drop the reservoir storages before snowmelt starts while maintaining

330 the storage in the reservoir to provide releases for irrigation, water supply and hydropower in the
331 remaining part of the year. More specifically, they developed flood control storage targets to
332 complement the irrigation release targets, with mass balance conservation. They showed that this
333 modification can improve the simulation of regulated flow and maintain the spatiotemporal
334 consistency of reservoir levels.

335 Finally, allocation algorithms are required to estimate groundwater abstractions and reservoir
336 releases at each simulation time step based on allocation objectives and priorities. Groundwater
337 abstraction algorithms are generally limited, due to significant gaps in information about
338 groundwater availability and actual groundwater withdrawals at the global scale. Although current
339 data availability for lakes and reservoirs storages is also poor, runoff data are relatively available
340 regionally and globally, which can be used for algorithm development and performance
341 assessment through comparison of simulated and observed discharges downstream of reservoirs.
342 Apart from local or national data, data of the Global Runoff Data Centre (GRDC;
343 <http://www.bafg.de/GRDC/>) have been widely used for validation of macro-scale reservoir
344 operation algorithms.

345 **3.2 Grid-based groundwater abstractions**

346 Groundwater abstractions include both sustainable (renewable) and unsustainable (non-renewable)
347 water uses. While sustainability of groundwater withdrawals is a complex issue, in particular
348 related to environmental impacts of abstraction, the distinction between these for large-scale
349 applications is generally based on the grid-based groundwater recharge, as any abstraction
350 exceeding recharge rate results in groundwater depletion, and therefore, can be considered as
351 unsustainable. So far, groundwater withdrawals have been estimated through either bottom-up or
352 top-down algorithms, both subject to large uncertainty.

353 In bottom-up procedures, the groundwater abstraction is identified using grid-based estimates of
354 surface and groundwater availability as well as the water demand. If the groundwater and/or
355 NNBW is considered as an infinite sources (Rost et al., 2008; Hanasaki et al., 2010; Wisser et al.,
356 2010; Pokhrel et al., 2012a,b), then the groundwater or NNBW abstraction is equal to estimated
357 demand minus estimated water availability at the grid scale. In this case, priorities are not
358 inherently considered; however NNBW has the advantage that it explicitly accounts for the water

359 that should come to the system from outside the modeled domain. If the groundwater availability
360 is bounded at the grid or basin scale, then the maximum groundwater withdrawal cannot exceed
361 the local groundwater availability (e.g. Strzepek et al., 2012; Wada et al., 2013a); however, errors
362 in estimations of surface water availability and water demands can still directly propagate into
363 estimation of groundwater withdrawals.

364 Top-down approaches are based on using recorded regional groundwater withdrawals or
365 downscaling national groundwater abstractions data to finer spatial scales. Siebert et al. (2010)
366 created a global dataset for irrigation water supply from groundwater abstractions based on FAO-
367 AQUASTAT (<http://www.fao.org/nr/water/aquastat/main/index.stm>) and other census and sub-
368 national data. In another effort, Wada et al. (2010, 2012) used the data of the International
369 Groundwater Resources Assessment Center (IGRAC; www.igrac.net) to estimate the countrywide
370 groundwater use for year 2000. These estimates were further downscaled to $0.5^{\circ} \times 0.5^{\circ}$ grids, based
371 on a global map of yearly total water demand. In a countywide study, Blanc et al. (2013) used the
372 groundwater withdrawal data of the USGS for the year 2005 (USGS, 2011) and repeated the data
373 for every year of simulation. These approaches are also limited by the fact that the actual
374 groundwater pumping might be considerably more than the recorded data (e.g., Foster and Loucks,
375 2006; Wada et al., 2012) and groundwater withdrawals can have considerable inter-annual
376 variability. Current and upcoming remote sensing technologies can address some of the issues
377 around groundwater data availability – see Section 5.3 below.

378 **3.3 Macro-scale reservoir operation**

379 Current macro-scale reservoir operation algorithms are designed for offline applications and
380 included in large-scale models for characterizing the impacts of reservoirs on terrestrial water
381 storage, runoff and water supply. These algorithms can be roughly divided into two general
382 categories based on either simulating the reservoir release using a set of prescribed operational
383 rules or using search algorithms to find optimal reservoir release. In brief, simulation-based
384 schemes are based on a set of functional rules that use initial storage as well as inflows and demand
385 pressure during a typical operational period to simulate releases during the operational period. In
386 contrast, optimization-based algorithms search for optimal releases at each time step given an ideal
387 storage at the end of the operational year, storage at the beginning of the year and expected inflows
388 and demands during the year. Naturally, optimization-based algorithms are more computationally

389 expensive; nonetheless, they are more suitable for evaluating competition among water demands
390 and effects of policy change, due to the ability to explicitly include multiple allocation objectives
391 to guide the search for optimal releases. In contrast, simulation-based algorithms are more efficient
392 and can be potentially modified to support online simulations – see Section 5.4. Table 2
393 summarizes some representative examples from the current literature.

394 **3.3.1 Available simulation-based algorithms**

395 Current simulation-based algorithms are heavily influenced by the work of Hanasaki et al. (2006),
396 which was initially proposed for global routing models but extended to GHMs (Hanasaki et al.,
397 2008a, 2010) and LSMs (Pokhrel et al., 2012a,b). The algorithm distinguishes between operational
398 rules for irrigation and non-irrigation purposes. The algorithm also accounts for both inter-annual
399 variability and seasonality in reservoir releases. In simple terms, the total release in a typical
400 operational year is first determined based on the reservoir capacity, initial storage and the annual
401 mean natural inflow to the reservoir. Second, the monthly fluctuations in the reservoir release are
402 parameterized based on annual mean natural inflow, mean annual demand and the prescribed
403 monthly demand. Note that demands are considered as total water withdrawals rather than
404 consumptive uses. Finally, monthly fluctuations are corrected based on inter-annual variability in
405 total reservoir releases (estimated during the first step) to provide actual monthly reservoir
406 releases. The correction, depending on the purpose and size of reservoir, is based on the ratio of
407 initial reservoir storage to total capacity, the ratio of reservoir capacity to annual mean inflow,
408 and/or the monthly mean natural inflows to the reservoir – see Hanasaki et al. (2006) for related
409 formulations.

410 Hanasaki et al.'s algorithm has been widely used in the recent literature as it provides a generic
411 and flexible framework to represent reservoir operation. Döll et al. (2009) implemented this
412 algorithm to represent operation of large reservoirs within the framework of WaterGAP (Alcamo
413 et al., 2003). They considered some modifications to accommodate losses from the reservoir and
414 to characterize the dynamics of demand pressure on reservoirs based on consumptive uses rather
415 than total water withdrawals. Biemans et al. (2011) modified Hanasaki et al.'s algorithm by
416 extracting the reservoir releases using annual and monthly mean regulated inflows (rather than
417 corresponding natural flows), limiting the demand pressure only to irrigation and changing the
418 release rules during high demand periods. These modifications were further added to the Joint UK

419 Land Environment Simulator (JULES; Best et al., 2011, D. B. Clark et al., 2011) for offline
420 simulations (Polcher et al., 2011). Voisin et al. (2013a) made a regional intercomparison between
421 various simulation-based algorithms for the Columbia River Basin and concluded that deriving
422 releases based on withdrawals rather than consumptive uses results in improved simulations of
423 downstream flows. They also indicated that the choice of natural or regulated inflows depends on
424 the severity of the demand pressure and water allocation: If the overall water demand is high with
425 respect to mean annual inflow, it would be better to drive the algorithm with mean monthly
426 regulated inflow; otherwise it is better to use the natural flow, due to large uncertainties associated
427 with water demand estimates, and therefore, regulated flows. Although this study is limited to one
428 region, it provided an assessment of uncertainties in estimating the reservoir releases due to
429 uncertainties in estimating both inflows and water demand – see the discussion of Section 4.

430 Existing simulation-based schemes are not limited to the above algorithms. Efforts have been made
431 to simulate the reservoir releases using parametric functions, in which the parameters can be
432 calibrated using observed downstream flows. For example, Wisser et al. (2010) advised a set of
433 functional rules to parameterize the release from large reservoirs using the actual inflow and the
434 long-term mean inflow to the reservoirs. More recently, Wu and Chen (2012) proposed a new
435 algorithm by explicit consideration of operational rule curves, locally specified for each reservoir.
436 In brief, rule curves are a set of pre-defined reservoir levels that divide the total reservoir capacity
437 into different storage zones. These storage zones can be further associated with demands
438 conditioned on the reservoir using various assumptions. The algorithm considers the reservoir
439 operation at a given day as a deviation from mean releases at that day and represents this by a
440 weighted sum of individual variations as the result of allocation for each individual water demand.
441 Demand-specific allocations can be therefore characterized based on rule curves, the available
442 storage, total capacity as well as the history of inflow to the reservoir. Accordingly the total release
443 at any given day can be defined as a parametric function, in which the parameters can be tuned
444 using observed downstream flows. Although they noted that the operational parameters are
445 inherently time-varying, as the purpose of dam can change with time, a systematic scheme for
446 dealing with non-stationary parametric estimation has not been provided. This remains for future
447 efforts – see Section 5.4.

448 **3.3.2 Available optimization-based algorithms**

449 Optimization-based schemes were initially proposed by Haddeland et al. (2006a) and implemented
450 further in Haddeland et al. (2006b, 2007). These algorithms are heavily inspired by small-scale
451 reservoir operation algorithms within the engineering literature, particularly Dynamic
452 Programming (see Voisin et al., 2013a), and strongly rely on estimates of expected inflow and
453 demand. Therefore, they are not suitable for online simulations, however they can be valuable for
454 integrated impact assessment over large grids and/or assessment regions in offline mode (see e.g.,
455 Strzepek et al., 2010; 2012; Blanc et al., 2013). In brief, the calculation starts by targeting the
456 reservoir storage at the end of a typical operational year based on expected demands. Then, the
457 minimum release at each daily time step is defined based on the expected streamflow at the dam's
458 location to maintain a minimum flow requirement downstream of the reservoir. Accordingly, the
459 maximum allowable daily release is determined based on simulated daily inflow, minimum
460 release, reservoir storage at the beginning of the operational year and the targeted storage at the
461 end of the year. Minimum and maximum releases introduce a feasible release range, where a search
462 algorithm can be used to find the optimal monthly releases that provide the minimum deficit during
463 the year and the least violation from the target storage at the end of the year. Adam et al. (2007)
464 slightly changed this algorithm by considering new thresholds for allowable release and storage
465 and used maximization of hydropower revenue as the objective function for reservoir operation.

466 There are two main issues with the proposed scheme. First, feasible reservoir releases are
467 determined based on forecasted (or expected – Haddeland, 2014; personal communication) flow
468 at dam location; and uncertainties in flow estimates can largely affect the search for optimal
469 releases. Second, a high dimensional search (e.g. 12 releases in the case of a monthly release
470 simulation) must be performed for each operational year, which is computationally demanding.
471 These issues were noted by van Beek et al. (2011). They modified the Haddeland et al. (2006a)
472 algorithm to decrease the complexity and uncertainty associated with the algorithm. First, they
473 defined the expected inflow for each month prospectively as a function of the flow in the same
474 month of the previous years; therefore, they omitted using prognostic flow forecasts. In order to
475 reduce the dimensionality of search, they considered reservoir release as a harmonic function;
476 therefore, only release at beginnings of the release and the discharge periods needed to be
477 determined. As the actual inflow values become available, the release can be consequently updated
478 so that the final storage at the end of release period can meet the predefined target storage. With
479 respect to determining the reservoir inflow based on naturalized or regulated flows, van Beek et

480 al. (2011) noted that either set-ups can be used, depending on how the observed discharge is
481 simulated at the large-scale. This is due to large uncertainties in simulating the regulated runoff –
482 see the discussion below.

483

484 **4 Current large-scale modeling applications**

485 Water supply and allocation schemes reviewed in Sections 2 and 3 have been used in a wide range
486 of offline applications for estimation of human impacts on the terrestrial water cycle. Despite
487 disagreements between different simulation results, the current literature agrees that the effects of
488 water allocation are more pronounced at finer spatial and temporal scales. As an earlier, Haddeland
489 et al. (2007) studied the impacts of reservoir operation coupled with irrigation on continental runoff
490 and argued that water allocation has resulted in 2.5 and 6 percent increase in annual runoff volume
491 in North America and Asia, respectively. This is almost canceled out by increased evaporation due
492 to irrigation. Nonetheless, as the analysis moves from global and continental to regional and large
493 catchment scales, the effects of water allocation become more profound. For instance, while the
494 mean annual runoff decreased in the western US by around 9 percent during a historical control
495 period, the rate of decrement is around 37 percent in the Colorado River during the same period
496 (Haddeland et al., 2006b). The results of the most recent global multi-model intercomparison
497 showed that direct impacts of the water resource management in some regions, e.g., parts of Asia
498 and in the western US, are similar or even more than the climate change effects (see Haddeland et
499 al., 2014). Similarly, the effects of water allocation are more significant at finer time scales. For
500 instance, Adam et al. (2007) noted that reservoirs have a minor effect on annual flows in Eurasian
501 watersheds but have significant seasonal effects by changing the flow timing and seasonal
502 amplitudes (see also Döll et al., 2009; van Beek et al., 2011, Biemans et al., 2011).

503 These simulations, however, are highly uncertain (see e.g., Haddeland et al., 2011, 2014) due to
504 major limitations in algorithms reviewed above, host large-scale models and data support. The
505 efficiency of available water allocation algorithms can be diagnosed by comparing the streamflow
506 obtained from simulations with observations. Currently, macro-scale water allocation schemes
507 cannot fully describe the dynamics of regulated streamflows and there can be major disagreements
508 between the regulated discharges obtained from different reservoir algorithms (Voisin et al.,
509 2013a). It has been shown that calibration can improve the quality of reservoir operation

510 algorithms (e.g. Wu and Chen, 2012); however, calibration is also associated with uncertainty and
511 can potentially hinder model applications for future projections due to possible temporal and
512 spatial variations in optimal parameters. Hanasaki et al. (2006) as well as Döll et al. (2009) showed
513 that simulation-based algorithms can generally provide improved discharge simulations compared
514 to lake routing algorithms. However, it should be noted that simulations still remain substantially
515 biased in highly regulated catchments (e.g. San Francisco River, US; Syr Darya, Central Asia) and
516 in cold regions (e.g. Saskatchewan and Churchill Rivers in Canada), particularly during high flows
517 (e.g. Hanasaki et al., 2008a; Biemans et al., 2011; Pokhrel et al., 2012a). The simulation algorithm
518 of Wu and Chen (2012) was found to be more accurate in simulating both storage and release
519 compared to simple multi-linear regression and the target-release scheme embedded in SWAT
520 (Arnold et al., 1998); however, it was tested only at the local scale and it is not clear how the
521 algorithm can perform in other regions with different climate, level of regulation and allocation
522 objectives. Very similar conclusions were obtained for optimization-based algorithms. Discharge
523 simulations are generally improved compared to the no reservoir condition (e.g., Haddeland et al.,
524 2006a); however, there are still significant deficiencies in simulating highly regulated flows,
525 particularly in mountainous and cold regions such as Colorado River in the US as well as Yukon
526 and Mackenzie Rivers in Canada (e.g., Haddeland et al., 2006b; Adam et al., 2007). This relates
527 in particular to prognostic reservoir inflows, which remain highly uncertain in these environments;
528 this uncertainty contributes to the uncertainty in assigning optimal reservoir releases, often in
529 dynamic and complex manners (Nazemi and Wheeler, 2014c; Muller Schmied et al. 2014).

530 From a broader perspective, the current performance of reservoir operation and water allocation
531 algorithms must be seen in the context of the hydrological performance of the host large-scale
532 models, including how well the water demand has been represented (see Nazemi and Wheeler,
533 2014a). Currently, there are large biases in modeling hydrological processes across various scale
534 and runoff estimates remain widely divergent (e.g., Wisser et al., 2010; Haddeland et al., 2011;
535 Gudmundsson et al., 2012; Hejazi et al., 2013). In particular, it has been shown that current
536 simulations systematically underestimate streamflow in the arctic and sub-arctic regions and
537 overestimate the observations in dry catchments; and reservoir operation algorithms mainly
538 improve the timing of the flow, but not the volume (e.g., van Beek et al., 2011). While there are
539 many potential reasons for this, one key source of this limitation is the quality of gridded
540 precipitation products (Biemans et al., 2009; 2011). Rost et al. (2008) used different precipitation

541 products to simulate the regulated river discharge and found substantial variations in simulated
542 discharge due to the choice of precipitation data. Moreover, they showed that sometimes the total
543 precipitation estimate could be less than the total observed discharge after abstraction and
544 regulation. Upcoming satellite missions can address some of the issues regarding historical forcing
545 (see the discussion of Section 5.3); however, uncertainty in future precipitation (and other climate
546 variables) should be dealt systematically using multiple climate forcing options based on various
547 combinations of concentration pathways, climate models and downscaling procedures.

548 Turning from surface water to groundwater issues, almost all available global studies agree on a
549 significant increasing trend in groundwater withdrawal from the late 20th century onward. As an
550 example, Wada et al. (2013a) argued that from 1990 to 2010, the rate of global groundwater
551 withdrawal increased by around 3 percent a year. These results are in relatively good agreement
552 with major observed depletions in some regional aquifers (see Gleeson et al., 2012). However,
553 various quantified assessments and further conclusions such as regarding groundwater-induced
554 sea-level rise remain highly uncertain and show major disagreements due to crude representation
555 of groundwater availability, recharge and withdrawal, as discussed in Sections 2.3 and 3.2 (see
556 e.g., Wada et al., 2010; Pokhrel et al., 2012b; Döll et al., 2014). This highlights an urgent necessity
557 for improving the representation of human-groundwater interactions at larger scales.

558

559 **5 Towards an improved representation of water resource management in large-** 560 **scale models**

561 **5.1 Ideal representation and remaining gaps**

562 Throughout our survey, we highlighted the importance of including water supply and allocation in
563 conjunction with water demand (see Nazemi and Wheeler, 2014a) in models that are relevant to
564 Earth system modeling and/or are required for understanding the effects of water resource
565 management on the Earth System, with both online and offline implications. From an integrated
566 water resource management and land-surface modeling perspective, water demands can be
567 considered as functions of climate, vegetation and soil-moisture as well as socio-economic and
568 policy variables (see Nazemi and Wheeler, 2014a). As shown in this paper, water supply is driven
569 by water demands but controlled by natural surface and ground water availability, which determine

570 the maximum possible water allocation. Therefore, water demand and water supply should be
571 systematically linked through a feedback loop, represented by water allocation. This integrated
572 water resource system should be then linked to natural land-surface processes at the grid scale.
573 This is rather intuitive: When considered in a typical grid, water allocation perturbs hydrological
574 and land-surface variables within the grid. In parallel, the combined effects of land-surface and
575 hydrological processes govern the variations in surface and ground water availability, which
576 consequently determine water demand (and accordingly water allocation) in the next simulation
577 step. Figure 1 shows a simplified schematic for this integrated modeling framework, in which grid-
578 based calculations of natural and anthropogenic land-surface are further coupled with climate
579 through grid-based land-atmospheric feedbacks.

580 Major gaps remain in representing water resource management in LSMs in the way defined above.
581 First, as also discussed in Nazemi and Wheeler (2014a), the key consideration in Earth System
582 modeling is the conservation of mass, energy and water; however, this is widely violated in current
583 models that include elements of water resource management (see Polcher, 2014). For instance,
584 considering groundwater or NNBW as unlimited water sources necessitates bringing water to the
585 system from outside the modeling domain, breaking the assumption that the Earth System is a
586 closed system. This has particular importance when understanding the effects of human-water
587 interactions on the climate and sea-level rise is sought.

588 Second, water resource management often takes place at the sub-grid resolution of current LSMs
589 used for simulations over large regional and global scales (i.e., 50 kilometers and more). Including
590 the elements of water resource management therefore requires moving towards a
591 “hyperresolution” scale (a few kilometers or less) for explicit representation (see Wood et al.,
592 2011) and/or adding new sub-grid parameterizations related to human-water interactions, as
593 illustrated in Figure 1. However, as the resolutions become finer or more sub-grid parameterization
594 are added, modeling complexity, computational burdens and data requirements increase
595 significantly, particularly in online simulation in which finer modeling resolution and better
596 discretization of soil and vegetation is generally required to capture land-atmospheric feedbacks
597 and possible climate responses (see Sorooshian et al., 2011a).

598 Third, we have noted that all currently available efforts in including water supply and allocation
599 in large-scale models are offline and have been made mainly in the context of GHMs. GHMs

600 provide an efficient platform for algorithm development and testing given the relative lack of
601 computational constraints. However, self-evidently understanding online effects of large reservoir
602 storage and large-scale groundwater pumping needs online simulations using coupled LSMs. At
603 this stage of model development, however, many algorithms originally designed for offline
604 applications might not be suitable for online implementations. An important example is reservoir
605 operation, as both optimization- and simulation-based algorithms have some levels of prognosis
606 that hinder their application in coupled simulations.

607 Fourth, online applications are associated with complexity in representing various feedbacks and
608 time-scaling mismatch among different LSM component and water resource management (see
609 Wang et al., 2004). In addition, current performance of online simulations is limited due to
610 significant biases across different components and propagation of these biases throughout the fully
611 coupled system.

612 Fifth, we have highlighted major limitations even in offline representation of water resource
613 management at larger scales due to various sources of uncertainty. These uncertainties are due to
614 (1) data support, particularly with respect to precipitation, actual water use and land-surface
615 characteristics; (2) water demand, supply and allocation algorithms, particularly with respect to
616 irrigation demand estimation, reservoir operation and groundwater withdrawals; as well as (3) host
617 large-scale models, particularly with respect to those calculations that determine surface and
618 ground water availability. It should be noted that here we only focus on epistemic sources of
619 uncertainty, which needs to be addressed, quantified, communicated and possibly reduced (see
620 Beven and Alcock, 2012). Table 3 summarizes various aspects of uncertainty related to data
621 support, algorithmic procedures and host models, identified for estimation of water demand (see
622 Nazemi and Wheeler, 2014a) as well as water supply and allocation (see Sections 2 to 4) in offline
623 mode. It is often quite difficult to identify the exact source of uncertainty due to complex
624 interconnections between various elements; and currently, a formal framework to test and validate
625 the water resource management components in the face of various sources of uncertainty is not
626 available (see also Beven and Cloke, 2012). In following sections, we briefly focus on these gaps
627 and highlight the opportunities to address them and move towards the integrated representation
628 proposed in Figure 1.

629 **5.2 Outstanding challenges – closing the water balance and online simulations**

630 At this stage of research, issues around closing the water balance and online simulations are the
631 most fundamental challenges in representing water resource management in Earth System models.
632 Closing the water balance requires considering all the sources of human water withdrawals and
633 uses in the system and integrating them into the host large-scale models. One major gap in
634 representing the water sources is groundwater, which is ignored or crudely represented in most
635 current models. In parallel, as noted above, performing online simulations requires moving
636 towards finer spatial and temporal scales and handling various sources of bias within the integrated
637 system. Although providing an extensive discussion on issues around integrating groundwater
638 models with LSMs as well as online Earth System modeling remains beyond the scope of this
639 paper, here we attempt to briefly point to the main challenges and highlight a few opportunities
640 for future developments.

641 Technically, the issues around coupling LSMs with groundwater and/or climate models are rather
642 similar. In principle, (1) both require couplers to build an integrated model from independent
643 models; (2) both require refining temporal and spatial resolutions; (3) both substantially increase
644 the complexity of calculations; (4) both need research in terms of improving and adding new
645 algorithms for process representations; and finally (5) both require handling various sources of
646 uncertainty. Research on coupling individual models in an integrated Earth System modeling
647 framework is ongoing and currently there are various coupling strategies available (e.g., Dunlop
648 et al., 2014). One challenge in coupling the elements of water resource management with climate
649 is the mismatch between temporal scales of water resource management and natural cycles in the
650 Earth System (Wang et al., 2004; Michetti and Zampieri, 2014). For instance, capturing the online
651 effects of evaporation from reservoirs requires running the climate model with fine temporal
652 resolution; although the reservoir evaporation is mainly a function of reservoir temperature and
653 area, which vary slowly. Research, therefore, should be done to compare and optimize existing
654 coupling strategies to handle such inconsistencies in time scaling.

655 One major need for representing groundwater and for online simulations is the necessity for
656 moving towards finer spatial resolutions. This can result in various challenges. First, even if the
657 spatial resolution increases, several sources of heterogeneity would still be ignored, as current
658 LSMs do not consider them. For instance, LSMs usually define plant species based on Plant
659 Functional Types (PFTs), within which all parameters are identical. However, current LSMs
660 recognize only limited PFTs and hence they typically ignore much of the biodiversity (Sato et al.,

661 2014). Improvement in LSMs in terms of adding more detail into land-surface parameterization
662 can provide opportunities to represent such sources of heterogeneity. Second, going toward finer
663 modeling resolutions requires improved data support at finer scales. Although, fine resolution data
664 are becoming more and more available (e.g., for soil properties – see Sato et al., 2014), such
665 datasets are normally obtained from multiple independent sources, which differ in terms of their
666 quality (see S. Liu et al., 2013). More efforts towards producing standardized and accurate data
667 sources can support future fine-grid Earth System modeling. Finally, moving towards finer scales
668 requires a new set of process representations and parameterizations (Hurrell et al., 2013). There
669 are new developments along scale-aware parameterizations (e.g., Hurrell et al. 2009) that can help
670 refine parameterizations for finer spatial scales.

671 One important issue with online simulations and groundwater modeling is the computational
672 complexities compared to offline surface water simulations (e.g. Hill et al., 2004; Kollet et al.,
673 2010; Wood et al., 2011). Wehner et al. (2008) suggested opportunities to address computational
674 burdens, including hardware design (i.e., building enhanced computer processors for a specific
675 application) and use of distributed and grid systems. A wide range of applications exists for grid
676 and cloud computing systems (see Schwiegelshohn et al., 2010; Lecca et al., 2011; Fernández-
677 Quiruelas et al., 2011). Improved computational power can also provide a basis to explore various
678 model resolutions to identify critical scales for process representations (see Gentine et al., 2012)
679 and to support computationally expensive offline calculations, such as groundwater processes,
680 dynamic crop growth, river routing and model calibration (e.g. von Bloh et al., 2010;
681 Rouholahnejad et al., 2012; Wu et al., 2013).

682 Understanding and handling various sources of uncertainty requires activities towards evaluating
683 model performance against observations, which includes new diagnostics for systematic
684 assessments of the modeling system. One key challenge is the fact that LSMs are run over large
685 grids, whereas validation data for land-surface variables and groundwater can be only obtained at
686 local scales. There are several attempts to overcome this issue. For instance, FLUXNET
687 (daac.ornl.gov/FLUXNET/fluxnet.shtml) coordinates regional and global analyses of observations
688 from micrometeorological tower sites to fill validation gap for online LSMs. As Sato et al. (2014)
689 indicated, such observation networks can facilitate diagnosing the LSMs efficiency and sources of
690 errors over large geographical scales. Moreover, a large number of combinations of model
691 configurations should be tested to ensure reliability and performance of individual components

692 and characterize the bias propagation from one component to others (Hurrell et al., 2013). For that
693 purpose, it should be noted that increased modeling complexity does not necessarily result in an
694 improved precision (see Sato et al., 2014; Smith et al., 2014); therefore, a systematic approach is
695 required to test, intercompare and falsify modeling options in the light of validation data available.
696 This will be discussed in more detail in Section 5.6.

697 **5.3 Data support**

698 As noted through our survey, major data limitations exist in representing various aspects of water
699 resource management, which are related to forcing, parameterization, calibration and validation of
700 water demand, supply and allocation algorithms (see also Table 3). At this stage of research, major
701 gaps are noted in spatial and temporal quality and coverage of the data related to climate,
702 hydrology, socio-economy, policy and water resource management that are required to drive or to
703 support large-scale models (see Wood et al., 2011; Gleick et al., 2013; Oki et al., 2013).

704 One important opportunity to improve data support is the use of remote sensing technology, which
705 can provide a synoptic view of the state of land-surface and atmospheric variables (see Sorooshian
706 et al., 2011b; Asrar et al., 2013) and a reliable data support for dynamic forcing, parameter
707 estimation as well as evaluation of large-scale models (see Dijk and Renzullo, 2011; Trenberth
708 and Asrar, 2012). For instance, Landsat missions (<http://landsat.gsfc.nasa.gov>; see Williams et al.
709 2006) have captured long-term variations in global land-cover with a temporal resolution of 16
710 days and spatial resolution of up to 30 meter, which can help to parameterize anthropogenic
711 activities such as crop growth and reservoir area. More recently, passive MODerate Resolution
712 Imaging Spectroradiometer (MODIS; <http://modis.gsfc.nasa.gov>; see Savtchenko et al., 2004)
713 provide a wide range of land-surface information and have already been applied for various large-
714 scale modeling studies, including validation of online models (Sorooshian et al., 2011a), high
715 resolution parameterization (Ke et al., 2012) and monitoring storage in large reservoirs (Gao et al.,
716 2012). Assimilation of MODIS land measurements with meteorological data and the Penman-
717 Monteith equation has also provided 8-day, monthly and annual evapotranspiration estimates at 1
718 km resolution globally (Mu et al., 2007, 2011). This can provide a basis to evaluate simulated
719 evapotranspiration over land-surface (see Section 5.4). Another important product is the Gravity
720 Recovery and Climate Experiment (GRACE; <http://www.csr.utexas.edu/grace/>; see Tapley et al.,
721 2004), measuring changes in the total terrestrial water storage at rather coarser resolutions.

722 GRACE data have already been used in studies related to regional groundwater depletion (e.g.,
723 Rodell et al., 2007, 2009), model calibration (e.g., Sun et al., 2012) and validation of large-scale
724 simulations (e.g., Pokhrel et al., 2012a,b; Döll et al., 2014).

725 Upcoming satellite missions can further support representation of water resources management.
726 For instance, precipitation is a key limitation in hydrological modeling in general, but is also
727 important for irrigation demand and scheduling. The upcoming Global Precipitation Measurement
728 mission (GPM; <http://gpm.nasa.gov>) will collect data at 10km resolution, every 3 hours, globally.
729 The upcoming Soil Moisture Active Passive mission (SMAP; see Entekhabi et al. 2010) will
730 provide improved global soil moisture measurements every 24 hours without sensitivity to cloud
731 cover. This can be considered as an important data support for irrigation demand algorithms.
732 Another upcoming remote sensing mission is the Surface Water and Ocean Topography mission
733 (SWOT; see Fu et al., 2009; Biancamaria et al., 2010; Durand et al., 2010), which will provide
734 fine-scale measurements of various surface water stores, including reservoirs as well as natural
735 and man-made channels. Such information at the global scale has the potential to revolutionize
736 representation, calibration and validation of algorithms related to estimation of inflow to
737 reservoirs, reservoir releases and inter-basin water transfers.

738 There are also important improvements in sharing ground-based data and simulation results,
739 including some inspiring grass-root data collection efforts. For example, the International
740 Groundwater Resources Assessment Centre (IGRAC; www.un-igrac.org) assigns an associate
741 expert to each one-degree grid cell to submit monthly groundwater levels. Such data can be a
742 critical source for testing groundwater withdrawal algorithms. Similar grass-root efforts could be
743 made to record other water resource management data, particularly with respect to actual (rather
744 than licensed) water uses, local management policies and water technologies. We also note that
745 sharing of gridded climate forcing and simulation results is important and provides a basis for
746 consistent model intercomparison efforts. One example is the recently finished EU-WATCH
747 program (<http://www.eu-watch.org/>), which provides forcing and simulation results of WATCH's
748 Model Intercomparison Project (WaterMIP; <http://www.eu-watch.org/watermip>).

749 **5.4 Water resource management algorithms**

750 Computational algorithms for representing the elements of water resource management have
751 various sources of uncertainty (see Table 3) and improving the related representations and reducing
752 the modeling uncertainty can be considered as an important avenue for future developments. Some
753 important opportunities include enhancing the simulation-based reservoir operation algorithms for
754 online applications and various applications of calibration, data assimilation and system
755 identification techniques.

- 756 • One crucial limitation of current reservoir operation algorithms, as noted above, is in
757 online applications. Simulation-based schemes provide a basis to move forward, however,
758 modifications are required to relax prognostic inputs and to represent the thermal and
759 evaporative functions of reservoirs for online applications. Modeling schemes have been
760 already developed for representing energy balance of natural lakes at sub-grid scale (e.g.,
761 MacKay, 2011; MacKay and Seglenieks, 2013) and can be merged with improved
762 simulation-based reservoir operation algorithms to simultaneously characterize reservoir
763 release, storage and evaporation as well as land-atmospheric feedbacks. However, an
764 important question remains in how to address substantial biases in estimation of reservoir
765 release due to the uncertainty in estimation of reservoir inflows, particularly in online
766 simulations. This issue can be partially handled using data assimilation frameworks; but
767 substantial uncertainty remains in future simulation, where assimilation is not possible.
768 Therefore, efforts should be made to represent reservoirs in a robust manner that can handle
769 the inflow biases.
- 770 • Calibration using observed, simulated or assimilated system behavior can be used to
771 implicitly represent management and sub-grid heterogeneity. One example would be to
772 address diversity in irrigation demand by finding “representative parameters” that match
773 the assimilated evaporation over a typical irrigated grid. Calibration with ability to identify
774 time-varying parameters could also be used to improve the performance of reservoir
775 operation algorithms and provide a basis to account for variations in water allocation
776 practice in time and potentially in space by considering functioning of multiple reservoirs.
- 777 • Another opportunity is to improve functional mappings of system response and demand
778 through system identification techniques. These techniques can range from statistical
779 regression models to more sophisticated machine-learning techniques such as artificial
780 neural networks (e.g., Nazemi et al., 2006a) and genetic symbolic regression (e.g.,

781 Hassanzadeh et al., 2014). One example would be building functional relationships for
782 estimation of irrigative or non-irrigative water demands and/or uses. Another would be to
783 represent reservoir operations through transfer functions and enhanced rule-based models
784 as well as building different decision support systems for handling operations taking place
785 at different time scales (i.e. hydropower with a 5-minute market, floods with sub-hourly to
786 hourly time step, and monthly seasonal water supply). This can provide an interesting
787 prospect to extract operational rules from observed data and to incorporate soft variables
788 such as social values and expert insights into modeling water resource management (e.g.,
789 Nazemi et al., 2002). This can provide various opportunities, for instance for describing
790 the operation of multiple reservoirs at the basin scale, which is widely ignored in the current
791 large-scale reservoir operation schemes.

792 **5.5 Host models**

793 Limitations in host models can introduce a wide range of uncertainties (see Table 3). This is due
794 to the fact that water resource management algorithms are fully embedded within the host models
795 and interact with calculations related to land-surface process at the grid scale (see Figure 1). For
796 instance, estimation of antecedent soil moisture affects estimation of irrigation demand. Similarly,
797 estimates of inflows to reservoirs govern the calculations related to reservoir releases and storage.
798 Currently, there are major limitations in representing soil moisture, snow cover, permafrost,
799 evapotranspiration, deep percolation and runoff in large-scale models and they cannot be
800 represented without large uncertainty (Lawrence et al., 2012; Trenberth and Asrar, 2012; Oki et
801 al., 2013). Moreover, host models often contain missing processes. For instance, current host
802 models often ignore the effects of increased CO₂ concentration on irrigation demand. This may
803 result in large uncertainties under climate change effects (see Wada et al., 2013b).

804 While an extensive review of these issues goes beyond the scope of this paper, we note that
805 substantial efforts continue to be made to include missing processes and to improve current
806 parameterizations of natural and anthropogenic processes in large-scale models, particularly in the
807 context of LSMs. For instance, the Community Land Model (CLM; Oleson et al., 2004; 2008;
808 Lawrence et al., 2011) has been recently improved by new algorithms for representing permafrost
809 (Swenson et al., 2012), agriculture (Drewniak et al., 2013) and irrigation (Levis and Sacks, 2011;
810 Levis et al., 2012). Another important development is the vector-based river routing algorithms

811 (e.g. Li et al., 2013a,b) that can improve the representation of natural and anthropogenic channel
812 processes such as reservoir stores, streamflow diversions and inter-basin water transfers (see
813 Lehner and Grill, 2013). Another key opportunity is the application of data assimilation and/or
814 calibration techniques to reduce parametric uncertainty and to improve prediction capability. Some
815 systematic frameworks for calibration and parameterization of land-surface processes are
816 suggested (Rosolem et al. 2012, 2013). We expect improvements in process representations and
817 parameterizations related to LSMs will increase in near future due to the need that has been already
818 recognized (e.g., Wood et al., 2011; Lawrence et al., 2012; Trenberth and Asrar, 2012; Gleick et
819 al., 2013; Oki et al., 2013; Dadson et al., 2013).

820 **5.6 A framework to move forward**

821 Several improvements need to be made in order to appropriately represent the elements of water
822 resource management in Earth System models. We noted that moving towards including the
823 elements of water resource management in a way described in Figure 1 requires continuous
824 developments in water resource management algorithms, host LSMs, online land-atmospheric
825 coupling and data support. We pointed to the main gaps and provided a brief overview on the
826 opportunities for overcoming these limitations. As far as the algorithms related to representing
827 water resource management are concerned, Table 4 summarizes improvements that need to be
828 made before we can properly represent human-water interaction in Earth System models, along
829 with targeted temporal and spatial resolutions. Modeling resolutions can vary across various
830 elements of water resource managements due to the difference in how different elements affect
831 water and energy balance at the land-surface. For instance, irrigation and crop growth directly
832 affect both energy and water balance at the sub-grid scale, with substantial difference between
833 crop function during a day. Therefore, irrigation should be represented at a fine temporal and
834 spatial resolution to capture potential climate responses. Reservoirs also affect water and energy
835 balance; however, as noted above reservoir area and surface temperature vary slowly and therefore
836 there is no need to approach a finer time-scale than the scale needed for representing the water
837 balance and downstream releases.

838 As noted throughout our survey, a variety of modeling options for representing key elements of
839 water resource management at larger scales is currently available and new details about natural

840 and anthropogenic processes are continually being added to Earth System models. Nonetheless,
841 major limitations exist in current data, algorithms and host models, which induce major biases
842 within components and complicate uncertainty quantification and model tractability. At this
843 juncture, a primary task for model development should be to test and compare different data and
844 modeling alternatives in an integrated system. This requires considering model hierarchy and the
845 links between different components and exploring individual and integrated model space with
846 respect to accuracy, identifiability and capability for generalization. This, in turn, can direct where
847 future attempts should be focused to reduce uncertainties further (see also Smith et al., 2014;
848 Michetti and Zampieri, 2014). Guidelines are available for (1) considering multiple working
849 hypotheses for supporting and representing relevant sub-processes and modeling component; (2)
850 constructing different simulations based on various combinations of the considered options and
851 (3) rejecting them if they fail to describe new data, violate their underlying assumptions and/or can
852 be equally described by simpler models (M. P. Clark et al., 2011; see Popper, 1959). Modular
853 systems, such as the recently released WRF-Hydro (Gochis et al., 2013), are particularly suitable
854 for building such a framework as they provide a tool for constructing/falsifying different
855 hypotheses for process representations, parameterizations and data support in a unified
856 computational platform.

857 To address this and to move towards the integrated representation of water resource management
858 in LSMs, suggested in Figure 1, we propose a systematic framework for improving the
859 incorporation of water resource management through building, testing and falsifying various
860 modeling options. Figure 2 shows this framework based on the links between different modeling
861 components. In brief, Figure 2 divides the model development into six components, related to (A)
862 modeling set-up and data configuration, (B) climate modeling, (C) land-surface modeling, (D)
863 water resource management representation, (E) calibration and parametric identification, as well
864 as (F) testing and falsification. The framework starts with prior knowledge (A), coming from the
865 modeling purpose, current modeling capabilities and limitations and the knowledge obtained from
866 previous modeling attempts. According to the prior knowledge and emerging advancements, a
867 range of modeling scales can be selected and multiple working hypotheses can be configured to
868 represent the data and modeling options in (B) to (E). Depending on the mode and period of
869 simulation, climate data or more generally climate models (B) are required to force or to be coupled
870 with land-surface processes. The land-surface component (C) includes relevant sub-modules

871 related to natural processes, water supply and allocation and irrigative and non-irrigative
872 withdrawals. The anthropogenic activities are controlled by the water resource management
873 component (D), which requires inputs from land-surface and climate components to determine
874 water availability and to estimate various demands with the aid of these and/or other proxies (piori
875 knowledge). Rules for prioritizing, partitioning and allocating water demands are reflected in a
876 management decisions sub-module that further drives water allocation in the land-surface
877 modeling component. Sub-modules within (C) and (D) often contain unknown parameters that
878 need to be identified through prior knowledge or calibration. As a result, calibration and parameter
879 identification algorithms (E) with capability for further uncertainty assessment are a key
880 requirement. Population-based optimization algorithms are particularly suitable for parameter
881 identification as they provide a range of behavioral parameters, which can be analyzed through
882 advanced visualization schemes and provide valuable insights into modeling uncertainty,
883 identifiability and multiple performance measures (e.g. Nazemi et al., 2006b, 2008; Pryke et al.,
884 2007). Moreover, population-based algorithms can provide methodological linkage to uncertainty
885 assessment through various diagnostic tests. Guidelines are provided to test and falsify models
886 through various evaluation criteria such as parametric identifiability (e.g. Beven, 2006b), Pareto
887 optimality (Gupta et al., 1998), predictive uncertainty (Wagener et al. 2004) and limits of
888 acceptability (Beven and Alcock, 2012).

889 Due to the current stage of model development, there is a need to approach the framework
890 suggested in Figure 2 with a sequential workflow, as certain improvements should be made first
891 before we can improve others. Figure 3 divides the suggested framework into four sequential
892 working packages. First, various options for data support, water resource management (WRM)
893 algorithms and host models should be benchmarked, tested and intercompared individually to
894 highlight their relative suitability in further offline simulation. This would naturally result in
895 falsifying some of the working hypotheses. The selected options then should be mixed-and-
896 matched in an offline mode. The offline simulation efficiency should be then explored and
897 intercompared between various integrated settings to assess the biases propagated across the
898 system and examine the robustness of the individual components in an integrated offline
899 simulation. The non-falsified options in this stage can be further improved and configured for
900 online simulation, which can be then coupled with climate models in a way described in Figure 2.

901 A key requirement for implementing the suggested framework is the availability of suitable data,
902 at an appropriate scale, for algorithm development and intercomparison. Although global studies
903 are important to improve our knowledge of the Earth System and global water supply, our ability
904 to conduct a comprehensive global study as proposed in Figure 2 is currently limited due to
905 methodological, computational and funding barriers. We argue that a network of regional case
906 studies, however, could provide access to local data, and a sample of comparative examples to
907 support algorithm intercomparison and further development. We note, for example, the success of
908 model intercomparison projects such as MOPEX (Duan et al., 2006) for hydrological modeling,
909 and suggest that the time is right to develop a similar initiative for the incorporation of
910 anthropogenic effects in hydrological models. One possibility is to draw on the resources of the
911 set of Regional Hydroclimate Projects (RHPs) supported by the Global Energy and Water
912 Exchanges (GEWEX) initiative of the World Climate Research Program (WCRP). As an example,
913 our home river basin in western Canada, the 340,000 km² trans-boundary Saskatchewan River
914 Basin (SaskRB), is a GEWEX RHP, embodies a complex large scale water resources system
915 (Nazemi et al., 2013), and poses globally-relevant science and management challenges (see
916 Wheater and Gober, 2013). These require improved representation of water resource management
917 at larger scales to diagnose the changes in the regional discharge, climate and water security as the
918 result of current and future water resource management and climate change. Such RHPs could
919 provide a basis for model development and intercomparison to support inclusion of water resource
920 management in Earth System models for fully coupled global simulations. We have already started
921 to explore various modeling options and the ways of improving individual algorithms (i.e. stage 1
922 of sequential model development protocol illustrated in Figure 3) throughout the SaskRB. For
923 instance, we have benchmarked several reservoir operation algorithms using observed inflows and
924 assessed the possibility of improving simulation using calibration. We have realized that the
925 efficiency of reservoir operation algorithms can be considerably improved if the assumption of
926 fixed model parameterization is relaxed and the algorithm parameters are identified through
927 calibration against observed reservoir level and discharge. We are about to finalize this study and
928 will present our findings through a technical paper in near future.

929

930 **6 Summary and concluding remarks**

931 Human water supply and allocation have intensively perturbed the water cycle. We noted that the
932 inclusion of these anthropogenic activities in Earth System models poses a new set of modeling
933 challenges and progress has remained incomplete. Despite some major developments, we noted
934 that current limitations significantly degrade the modeling capability at larger scales, particularly
935 with respect to future conditions, and neglect potentially-significant sources of change to land-
936 atmospheric system. We highlighted important deficiencies related to representing groundwater
937 stores and withdrawals as well online implications of large reservoirs. We also noted that current
938 water allocation algorithms have considerable limitations in representing streamflow in regulated
939 catchments. We argued that these limitations are attributed to uncertainties in data support, water
940 allocation algorithms and host large-scale models.

941 We identified four opportunities for improvements. These are advancements in (1) high
942 performance computing and coupling techniques; (2) remote sensing, data collection and data
943 sharing; (3) calibration algorithms, system identification techniques and assimilation products; and
944 (4) ongoing improvements in host models including both process representation and parameter
945 identification. As there are several options available for data support, water resource management
946 algorithms and host models, we proposed a modular framework for testing various modeling and
947 data options, which can be configured by multiple working hypotheses and implemented in a
948 unified and fully integrated modeling framework. The selected working hypotheses can be tested
949 and falsified on the basis of available information, intercomparison and/or various model diagnosis
950 frameworks. Similar to other recent commentaries (e.g., M. P. Clark et al., 2011; see also Beven
951 et al., 2012), we believe that such a systematic framework is essential for improving current
952 modeling capability in both offline and online modes and can be pursued using regional case
953 studies, before aiming for fully coupled global simulations. WCRP RHPs are one source of suitable
954 examples to move this agenda forward.

955 It should be noted that filling current gaps in the inclusion of water resource management in Earth
956 System models requires substantial efforts across a wide range of disciplines, from social and
957 policy sciences to economics and water management, from natural sciences to engineering and
958 mathematical modeling, and from remote sensing to hardware technology and computer science.
959 Interdisciplinary research efforts, therefore, are important. Moreover, for various reasons including
960 funding limitations, the community needs to fully recognize the role of collaboration and explore

961 various opportunities to share data and resources for efficient model developments and for
962 consistent intercomparisons.

963 Finally, it should be indicated that our survey considered water resource management from a water
964 quantity perspective. Water quality concerns are increasingly associated with growing human
965 water demand and can also impact water supply and allocation. Coupling water quality and
966 quantity in Earth System models is however very much in its infancy and much future effort will
967 be required to fill this gap. We hope that our survey will trigger more attention towards the
968 necessity for improving current Earth System modeling capability to respond to the needs and
969 challenges of the “Anthropocene”.

970

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979

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Table 1. Examples of available representations of water supply and allocation in large-scale models

Reference	Water supply				Water allocation		
	Diversions	Reservoirs	Groundwater store	Desalination and reuse	Supply-demand dependency	Priorities in demands	Operational objectives
Haddeland et al. (2006b)	In- and inter-grid abstraction	Macro-scale operation ¹	N/A	N/A	Reservoir can supply up to 5 grids downstream ²	Irrigation, flood control, hydropower, others	Minimize deficit, maximize hydropower
Hanasaki et al. (2008a)	In- and inter-grid abstraction	Macro-scale operation	N/A	N/A	Reservoir can supply up to 10 grids downstream	Municipal, industrial, irrigation	Allocate available water
Rost et al. (2008)	Local abstraction	Lake routing	NNBW assumed unlimited ³		Local grid	Irrigation only	Meet demand using available water
Döll et al. (2009)	In- and inter-grid abstraction	Macro-scale operation	N/A	N/A	Reservoir can supply up to 5 grids downstream	Irrigation, non-irrigation	Meet total demand ⁴
Hanasaki et al. (2010)	Local abstraction	Macro-scale operation/local abstraction	NNBW assumed unlimited		Local grid	Irrigation and livestock only	Meet total demand using unlimited NNBW
Strzepek et al. (2010)	Local abstraction	Macro-scale operation ⁵	Countrywide estimates	N/A	Local basin	Domestic, industry, livestock, irrigation	Maximize profitability
Wisser et al. (2010)	In-grid hydrologic routing	Macro-scale operation	Unlimited local source ⁶	N/A	Local grid	Irrigation only	Meet total demand using unlimited groundwater
Biemans et al. (2011)	Local abstraction, Heuristic routing	Macro-scale operation	NNBW assumed unlimited ⁷		Reservoir can supply up to 5 grids downstream	Irrigation only	Proportional allocation of available water
Wada et al. (2011)	In- and inter-grid abstraction	Macro-scale operation	Countrywide estimates	Countrywide estimates	Reservoir can supply up to 600 km downstream	Irrigation, flood control, hydropower, others	Minimize deficit, maximize hydropower
Pokhrel et al. (2012a)	Local abstraction	Macro-scale operation	NNBW assumed unlimited		Local grid	Irrigation, non-irrigation	Meet total demand using unlimited NNBW
Strzepek et al. (2012)	Local abstraction	Macro-scale operation ⁵	Basin-scale threshold	Function of capacity	Local basin	Non-agricultural, Agricultural	Minimize groundwater use and spill
Blanc et al. (2013)	Local abstraction, Heuristic routing	Macro-scale operation ⁵	Basin-scale threshold	N/A	Local basin	Non-agricultural, Agricultural	Minimize groundwater use and spill
Hanasaki et al. (2013b)	Local abstraction	Macro-scale operation	N/A	N/A	Local grid	Municipal, industrial, irrigation	Allocate available water
Voisin et al. (2013a,b)	In- and inter-grid abstraction	Macro-scale operation	N/A	N/A	Reservoir can supply up to 200 km downstream	irrigation, flood control, hydropower and others	Allocate available water
Wada et al. (2013a)	In- and inter-grid abstraction	Macro-scale operation	Conceptual reservoir	Countrywide estimates	Reservoir can supply up to 600 km downstream	Irrigation, non-irrigation	Allocate available water

¹ Simultaneous operation of multiple dams in a river basin was not considered.

² See Haddeland et al. (2006a).

³ Simulations without assuming unlimited groundwater store were also performed.

⁴ Demand that cannot be allocated in any given day is allocated later in the year or in the next year, when water is available.

⁵ A virtual reservoir is considered for each basin.

⁶ Shallow groundwater is represented as a runoff retention pool, which delays runoff before it enters streams.

⁷ Simulations with considering only surface water availability were also performed.

Table 2. Representative examples of available macro-scale reservoir operation algorithms implemented in large-scale models

Reference	Host model	Routing algorithm	Type of operation	Reservoir data	Validation discharge data
Hanasaki et al. (2006)	N/A	TRIP (Oki and Sud, 1998)	Simulation-based	WRD98 (ICOLD)	GSWP (Dirmeyer et al., 1999; Oki et al., 2001)
Haddeland et al. (2006a,b, 2007)	VIC (Liang et al., 1994)	Linearized Saint-Venant (Lohmann et al., 1996, 1998)	Optimization-based	ICOLD; Vörösmarty et al. (1997, 2003)	USGS(http://waterdata.usgs.gov) USBR (http://www.usbr.gov) GRDC (http://www.bafg.de/GRDC/)
Adam et al. (2007)	VIC (Liang et al., 1994)	Unit hydrograph and Linearized Saint-Venant (Lohmann et al., 1996, 1998)	Optimization-based	ICOLD; Vörösmarty et al. (1997, 2003)	Adam and Lettenmaier (2008)
Hanasaki et al. (2008a)	H08 (Hanasaki et al., 2008a,b)	TRIP (Oki and Sud, 1998)	Simulation-based	WRD98 (ICOLD)	GRDC (http://www.bafg.de/GRDC/)
Döll et al. (2009)	WaterGAP (Alcamo et al., 2003)	HBV (Bergström and Singh, 1995)	Simulation-based	GRanD (Lehner et al., 2008)	GRDC (http://www.bafg.de/GRDC/)
Wisser et al. (2010)	WBMplus (Vörösmarty et al., 1998)	Muskingum-Cunge (Ponce and Changanti, 1994)	Simulation-based	ICOLD	UNH-GRDC (Fekete et al., 1999, 2002)
Biemans et al. (2011)	LPJmL (Gerten et al., 2004; Rost et al., 2008)	Linear reservoir model (Huggins and Burney, 1982)	Optimization-based	GRanD (Lehner et al., 2011)	GRDC (http://www.bafg.de/GRDC/)
Van Beek et al. (2011)	PCR-GLOBWB (van Beek and Bierkens, 2009)	Kinematic Saint-Venant (Chow et al., 1998)	Optimization-based	GLWD1 (Lehner and Döll, 2004)	GRDC (http://www.bafg.de/GRDC/)
Wu and Chen (2012)	SWAT (Arnold et al., 1998)	SWAT (Arnold et al., 1998)	Simulation-based	Wu et al. (2007)	Chen and Wu (2008) ¹
Pokhrel et al. (2012a)	MASTIRO (Takata et al., 2003)	TRIP (Oki et al., 2001)	Simulation-based	WRD98 (ICOLD)	GRDC (http://www.bafg.de/GRDC/)
Voisin et al. (2013a)	VIC (Liang et al., 1994)	MOSART (Li et al., 2013a,b)	Simulation-based	GRanD (Lehner et al., 2011)	USGS(http://waterdata.usgs.gov) USBR (http://www.usbr.gov) GRDC (http://www.bafg.de/GRDC/)
Voisin et al. (2013b)	SCLM (Li et al., 2011; Lawrence et al., 2011)	MOSART (Li et al., 2013a,b)	Simulation-based	GRanD (Lehner et al., 2011)	USGS(http://waterdata.usgs.gov) USBR (http://www.usbr.gov) GRDC (http://www.bafg.de/GRDC/)

¹ Discharge data used for calibration as well

Table 3. Uncertainties in current offline representations of water resource management in large-scale models

Component	Type of activity	Specification	Data uncertainty	Algorithm uncertainty	Host model uncertainty ¹
Water demand (Nazemi and Wheeler, 2014a)	Irrigative demands	Irrigation	Climate forcing; soil, crop, land-use and land management including sub-grid heterogeneities; actual diversions; socio-economy and technological variables; agricultural management	Characterizing the potential evapotranspiration and crop water demand; representing the sub-grid crop diversity, irrigation expansion, crop change, return flows	Estimation of actual evapotranspiration, soil water movement, runoff and canopy losses; considering CO ₂ effects
		Industrial uses	Location, diversity and capacity of uses; actual diversions; downscaling proxies; socio-economy and technological variables	Seasonal variations in industrial water needs; structural and parametric uncertainty in estimation and projection of industrial demand.	N/A
	Non-irrigative demands	Energy-related uses	Location, diversity and capacity of uses; actual diversions; downscaling proxies; socio-economy and technological variables	Seasonal variations in energy-related water needs; structural and parametric uncertainty in estimation and projection of industrial demand.	N/A
		Municipal Uses	Population; diversity in uses; actual diversions and uses; downscaling proxies; socio-economy and technological variables	Seasonal variations in municipal water needs, structural and parametric uncertainty in estimation and projection of municipal demand	N/A
		Livestock uses	Heads; socio-economy	Seasonal variations in livestock water need; return flows	N/A
		Environmental flows	Habitat and ecosystem needs in time and space	Over-simplicity of demand calculation	Hydrological processes upstream
Water supply	River diversion	Location of diversion; capacity, slope and other properties of diversion networks	Diversion losses, return flows	Channel routing	
	Lakes and reservoirs storages ²	Precipitation; reservoir location and characteristics; actual storage; small dams	Crude representation of reservoir releases using representations of natural lake, losses from reservoir	Hydrological processes upstream of dams, channel routing	
	Inter-basin transfer	Location of diversion; capacity, slope and other water transfer properties; management policies; actual water transfer.	Diversion losses, simplicity of heuristic algorithms	Channel routing, calculation of demands	
	Reused water	Location, capacity and actual desalinated water supply	Limited representations	N/A	
	Groundwater storage	Soil properties, groundwater movement	Crude representation of groundwater availability, ignoring inter-cell lateral groundwater movements	Estimation of groundwater storage, recharge and discharge, calculation of demand.	
Water allocation (see Sections 2 to 4)	Operational objectives	Management policies and local constraints	Limitations of common objective functions; Temporal and spatial variations in operational objective	Estimation of water demand and supply	
		Demand-Supply dependency	Management policies and local constraints, topography, diversion channels	Steady-state assumption	Estimation of water demand and supply
	Priorities	Management policies and local constraints	Temporal and spatial variations in priorities	Estimation of water demand and supply	
	Reservoir operations	Management policies and local constraints	Simplicity of operational rules in simulation-based approaches, complexity of optimization-based algorithms, prognosis of both approaches	Operational objectives, inflow to reservoirs, water demand	
	Groundwater withdrawal	Wells location, groundwater management, actual pumping capacities	Crude representation of groundwater withdrawals based on both top-down and bottom-up algorithms	Groundwater storage, surface water availability, grid-based water demands	

¹ Uncertainties from host-model also include the uncertainties that can extend from other algorithms, related to water resource management, embedded in host models (see Figure 1).

² See also reservoir operations.

Table 4. Required developments to include the elements of water resource management in Earth System models (see also Table 3)

Water resource management component	Required algorithmic improvements	Targeted spatial scale	Targeted temporal scale	Data support for parameterization and validation
Irrigation demands	Improving the calculation of crop-specific water demand considering the effect of CO ₂ , considering soil-water movement and other losses	Hyperresolution and sub-grid scale	Sub-daily/sub-hourly (for online simulations)	Crop and soil diversity, measured or assimilated evaporation over irrigated lands
Non-irrigative human demands	Improving the mapping relationship, representing the diversity of non-irrigative demands	Large grids with the ability to be downscaled into finer resolutions using socio-economic and climate proxies	Yearly and monthly with the ability to be downscaled into finer scales using socio-economic and climate proxies	Water use data, gridded climate and regional socio-economic data
Environmental flow needs	Improving the demand approximation considering the diversity in the aquatic life	Catchment scale	Monthly and less	Aquatic biodiversity and water use, climate information, water temperature, water quality
Lakes and reservoirs	Improving the representation of release and storage, linking hydrologic representation with energy-balance components	Grid and sub-grid	Daily	Reservoir storage and water level, release downstream of reservoirs, storage-area-elevation relationships, operational objectives
Water diversions	Representing in-grid and inter-grid water diversions including losses	Grid and inter-grid	Daily	Water distribution specifications, location of abstractions
Groundwater	Improving the representation of groundwater storage and recharge	Grid	Daily (shorter in online simulations)	Soil properties, well locations, pumping capacities
Water reuse and desalination	Improving the representation of water reuse and desalination and the annual dynamics of water supply from each facility	Grid	Yearly with the ability to be downscaled into finer time scales using climate and socio-economic proxies	Location and capacity of facilities, gridded climate, regional socio-economic data

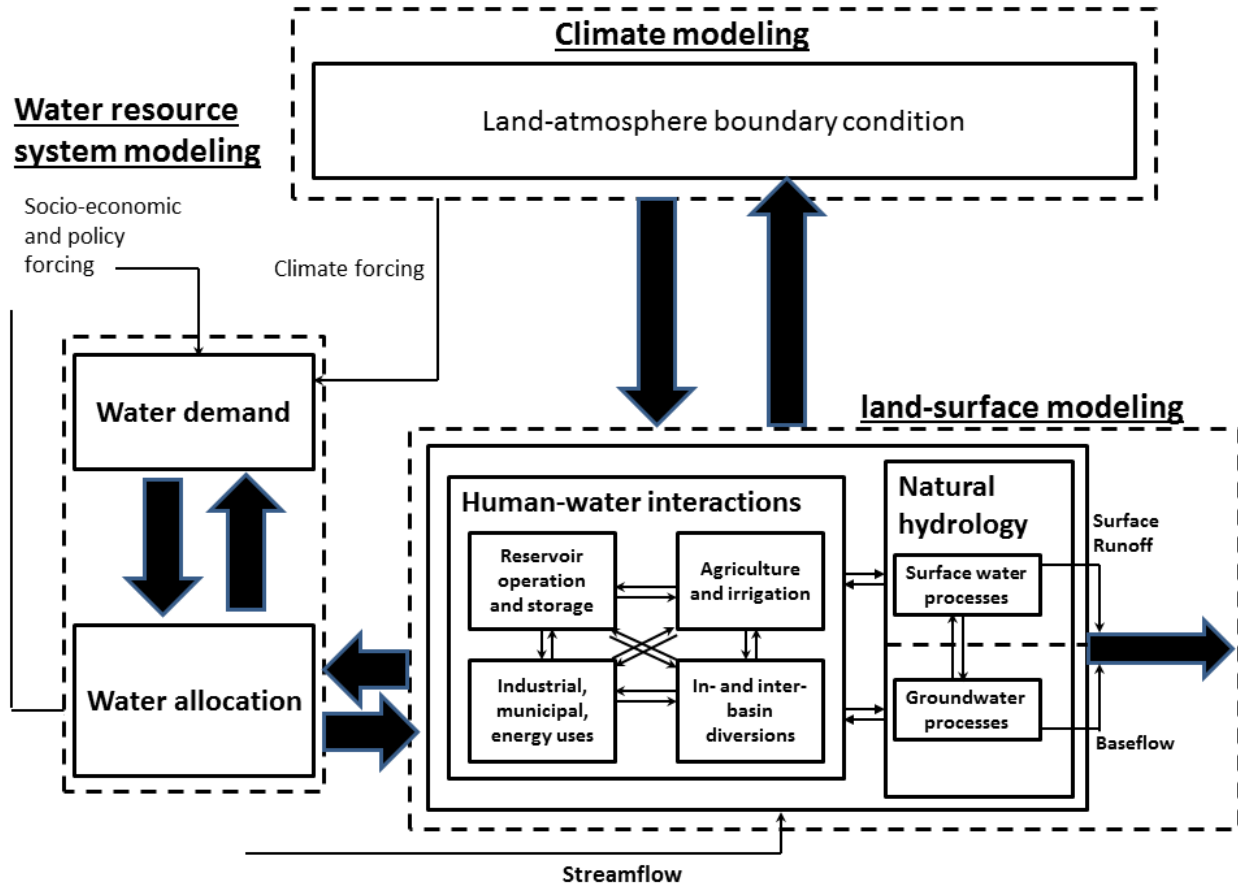


Figure 1. A fully coupled framework for inclusion of water resources management in a typical LSM grid

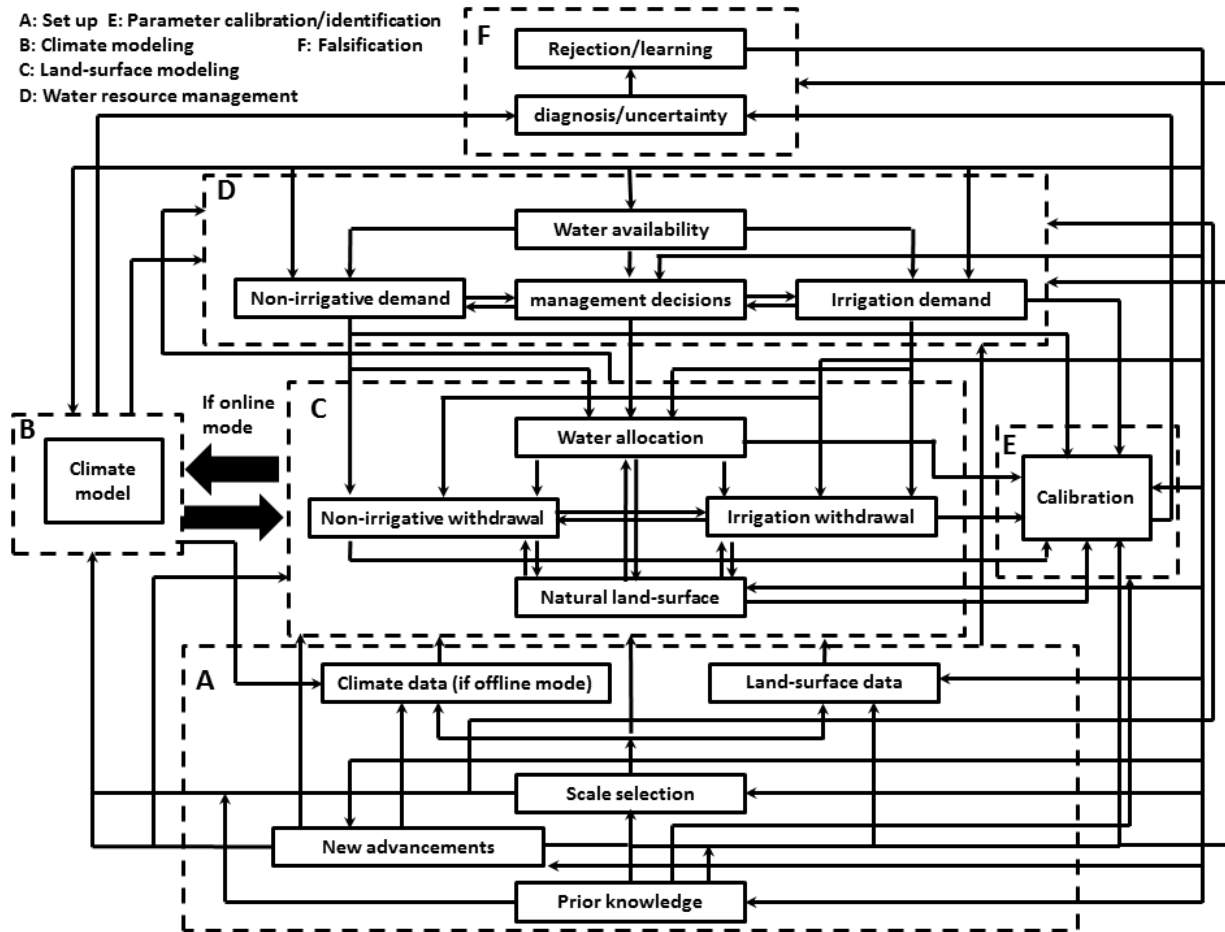


Figure 2. A modular framework for improving the inclusion of water resource management in LSMs through building, testing and falsifying multiple working hypotheses

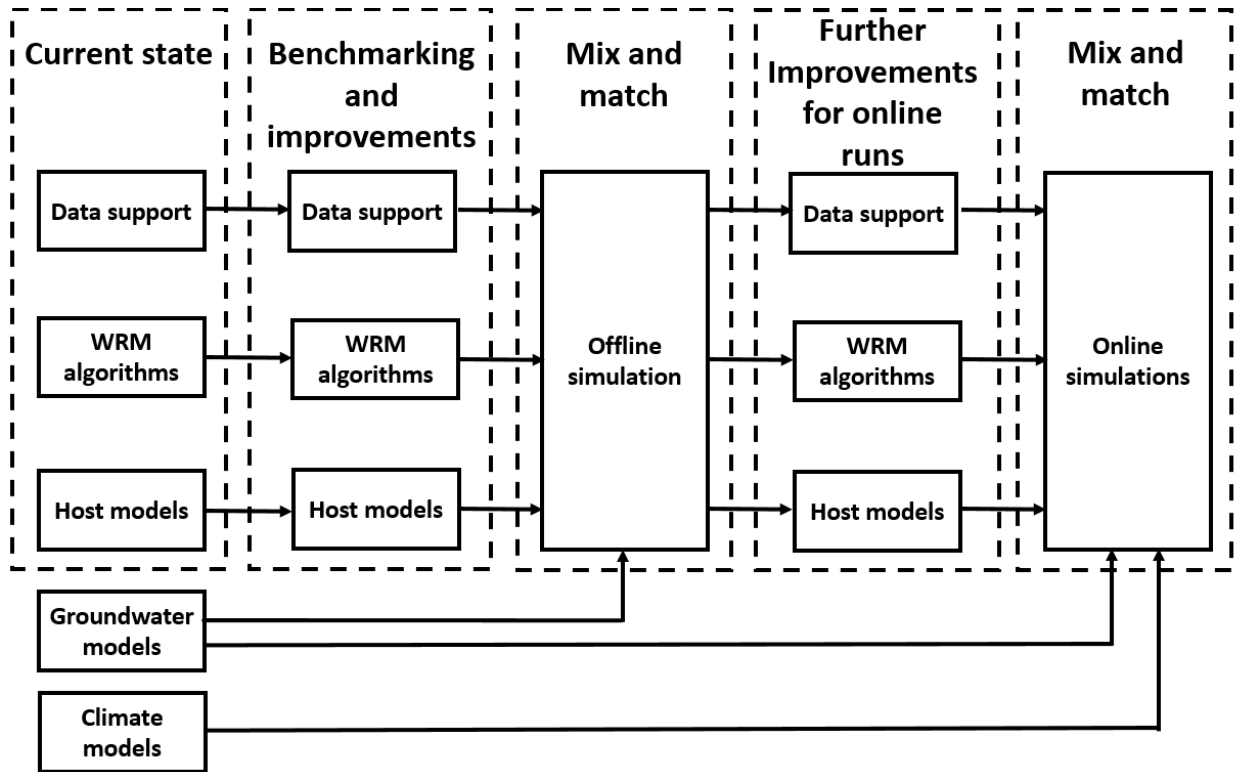


Figure 3. A sequential workflow for benchmarking, improving and including the elements of water resource management into offline and online Earth System simulations