On inclusion of water resource management in Earth System models – Part 1: Problem definition and representation of water demand

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Abstract

Human activities have caused various changes in the Earth System, and hence, the interconnections between humans and the Earth System should be recognized and reflected in models that simulate the Earth System processes. One key anthropogenic activity is water resource management that determines the dynamics of human–water interactions in time and space. There are various reasons to include water resource management in Earth System models. First, the extent of human water requirements is increasing rapidly at the global scale and it is crucial to analyze the possible imbalance between water demands and supply under various scenarios of climate change and across various temporal and spatial scales. Second, recent observations show that human–water interactions, manifested through water resource management, can substantially alter the terrestrial water cycle, affect land-atmospheric feedbacks and may further interact with climate and contribute to sea-level change. Here, we divide the water resource management into two interdependent elements, related to water demand as well as water supply and allocation. In this paper, we survey the current literature on how various water demands have been included in large-scale models, including Land Surface Schemes and Global Hydrological Models. The available algorithms are classified based on the type of demand, mode of simulation and underlying modeling assumptions. We discuss the pros and cons of available algorithms, address various sources of uncertainty and highlight limitations in current applications. We conclude that current capability of large-scale models in terms of representing human water demands is rather limited, particularly with respect to future projections and online simulations. We argue that current limitations in simulating various human demands and their impact on the Earth System are mainly due to the uncertainties in data support, demand algorithms and large-scale models. To fill these gaps, the available models, algorithms and data for representing various water demands should be systematically tested, intercompared and improved and human water demands should be considered...
in conjunction with water supply and allocation, particularly in the face of water scarcity and unknown future climate.

1 Background and scope

The Earth System is an integrated system that unifies the physical processes at the Earth’s surface. These processes include a wide spectrum of feedbacks and interactions between atmosphere, land and oceans and cover global cycles of climate, water and carbon that support planetary life (e.g. Schellnhuber, 1999; Kump et al., 2010). From the advent of digital computers, Earth System models have been the key to identify past changes and to predict the future of Planet Earth. These models normally include computational components that represent various functions of the land, atmosphere and oceans (Claussen et al., 2001; Schlosser et al., 2007). Land-Surface Schemes (LSSs) are sub-models within Earth System models that represent the land portion of the Earth System. LSSs contain interconnected modules that characterize physical processes related to soil, vegetation and water, over a gridded mesh, and account for their influences on mass and energy exchanges. A LSS, therefore, should either explicitly or implicitly include the dynamics of these physical processes at various temporal and spatial scales (see Trenberth, 1992; Sellers, 1992). There are two general applications for LSSs. First, LSSs are essential components of climate and weather-forecasting models, as they provide the dynamics of surface boundary conditions to the atmospheric models (Verseghy, 1991; Verseghy et al., 1993). Such applications are generally termed in the LSS community as online or coupled simulations (e.g. Entekhabi and Eagleson, 1989; Noilhan and Planton, 1989). A second area of application relates to offline simulations, typically at global, regional or large catchment scales, for assessment of impacts of climate or other environmental changes on land-surface processes. Offline LSSs are computationally much less demanding; they require atmospheric driving variables and simulate land-surface responses to climate but do not represent the effects of land responses on the atmospheric system.
The importance of representing the water cycle in LSSs is well-established (see Pitman, 2003 and references therein) and there has been progressive development of LSSs in representing various components of the hydrologic cycle, such as soil moisture, vegetation, snowmelt and evaporation. As these processes also determine the hydrological response at the catchment and larger scales, LSSs have been applied frequently in offline hydrological modeling (e.g. Liang et al., 1994; Pietroniro et al., 2007; Adam et al., 2007; Livneh et al., 2011) and often compared to large-scale hydrological models, so called Global Hydrologic Models (GHMs) – see Haddeland et al. (2011). In early LSSs, hydrology was conceptualized as a simple lumped bucket model (Manabe, 1969), but this representation has progressively been improved by including more complexity and explicit physics into canopy, soil moisture and runoff calculations (see Deardorff, 1978; Dickinson, 1983, 1984; Sellers et al., 1986, 1994, 1996a; Nicholson, 1988; Pitman et al., 1990). Despite these improvements, major limitations and uncertainties remained in the hydrological simulations of LSSs, causing systematic bias in water and energy balance calculations. These deficiencies have been attributed (in part) to unrealistic assumptions and incomplete parameterizations of catchment response in LSSs (Soulis et al., 2000; Music and Caya, 2007; Sulis et al., 2011). Further attempts, therefore, have focused on including catchment scale runoff generation and routing processes in LSSs. For instance, Pietroniro et al. (2007) combined the streamflow modeling capability of WATFLOOD (Kouwen et al., 1993) with the land-surface parameterizations of CLASS (Verseghy, 2000). Similarly Oleson et al. (2008) improved the representation of hydrology in the 3rd generation Community Land Model (CLM3; Oleson et al., 2004), by including a simple hydrological model inspired by TOPMODEL (Beven and Kirkby, 1979), and a simple groundwater model. The simulation results showed that these developments made significant improvements in representing the global water cycle. Lawrence et al. (2011) further developed the Oleson et al. (2008) land model by including an improved numerical solution for unsaturated soil as well as revised snow and evaporation parameterizations. These modifications resulted in improved simulations of soil moisture dynamics and runoff. Nonetheless, despite a large
body of research, representations of hydrological processes in LSSs remain imperfect and incomplete as current simulations still cannot match past hydrological observations (see Lawrence et al., 2012). Major efforts, therefore, should be made to (1) revisit the assumptions concerning the dominant land-surface processes that determine larger scale hydrological responses; and (2) represent missing processes with efficient parameterizations to improve the description of water cycle in LSSs.

While external forcing, mainly the energy flux from the Sun, is the main driver of the Earth System, internal disturbances such as volcanic eruptions, wildfires and human activities can substantially affect the natural cycles within the Earth System (Vitousek et al., 1997; Trenberth and Dai, 2007; Bowman et al., 2009). In particular, post-industrial human activities from the mid-20th century onwards, have severely perturbed the Earth System (Crutzen and Steffen, 2003; Crutzen, 2006). Recent climate warming and other global changes have raised the consciousness that humans have now become one of the great forces of nature, introducing change to the Earth System (perhaps) more than any other driver (Steffen et al., 2007, 2011). This has initiated a new geological epoch, informally termed the “Anthropocene”, in which it is recognized that the natural processes within the land surface are highly controlled and regulated by humans (see McNeil, 2000). The water cycle is one set of these processes, which also greatly affects livelihoods as well as local, regional and global economies (e.g. Nilsson et al., 2005). During the past century, human water consumption has increased more than 6-fold, with around 5, 18 and 10 times increase in agricultural, industrial and municipal consumption, respectively (see Shiklomanov, 1993, 1997, 2000). Supplying such intensive demands has required large changes in the natural landscape, with respect to both land use and water resource management.

Although some anthropogenic effects such as the emission of greenhouse gases and land-use change have been incorporated in Earth System models (e.g. Lenton, 2000; Zhao et al., 2001; Karl and Trenberth, 2003; Brovkin et al., 2006; Solomon et al., 2009), less effort has been made to represent human–water interactions (e.g. Trenberth and Asrar, 2012; Lawrence et al., 2012; Oki et al., 2013). In current LSS applications, it is
still widely assumed that human effects on the terrestrial water cycle can be ignored. This assumption is highly questionable and can result in the neglect of important land-surface processes (see Gleick et al., 2013). For instance, surface water withdrawals decrease downstream flows, often substantially, and dam operation to supply various human demands considerably changes the timing, volume, peak and the age of natural streamflow (e.g. Meybeck, 2003; Vörösmarty et al., 1997, 2007; Tang et al., 2010). Downstream effects include perturbed flow regimes and reduced inputs to wetlands, lakes, seas and oceans. Vörösmarty and Sahagian (2000) argued that river discharges to internal sinks have decreased remarkably due to the storage, diversion and consumption of water, resulting in seasonal decline in flows of major rivers such as the Colorado River (e.g. Cayan et al., 2010) and extreme effects on lakes and wetlands, such as the death of the Aral Sea (e.g. Precoda, 1991; Small et al., 2001). In parallel, groundwater abstractions are associated with declining groundwater levels, reduced baseflow contributions and loss of wetlands. Current assessments reveal significant groundwater depletion in some areas of the globe, such as Indian peninsula, the US mid-west, and Iran (Giordano, 2009; Rodell et al., 2009; Gleeson et al., 2012). Extensive groundwater pumping is also associated with potential long term contamination, for example by salt water intrusion (Sophocleous, 2002; Antonellini et al., 2008). Water quality impacts, however, remain beyond the scope of this paper.

As human life and water availability are tightly interconnected (see Sivapalan et al., 2012), current and future changes in the water availability are of major importance to human society, and these issues can be explored to a large extent with offline LSSs or GHMs. Although human water use still accounts for a small proportion of total water on and below the surface (see Oki and Kanae, 2006), it currently includes around 26% of terrestrial evaporation and 54% of surface runoff that is geographically and temporally available (Postel et al., 1996). There are already major water security concerns across highly populated regions of the globe (e.g. Falkenmark, 2013; Schiermeier, 2014) and human demands are growing rapidly, due to increasing population as well as socio-economic development. There are major concerns about how future demand should
be supplied, particularly considering that climate change will likely amplify global water demand and scarcity (e.g., Postel et al., 1996; Arnell, 1999, 2004; Tao et al., 2003; Döll, 2009; Taylor et al., 2013; Hanasaki et al., 2013a, b; Wada et al., 2013; Schewe et al., 2013; Millano et al., 2013; Mehta et al., 2013). Such important threats to water security necessitate a detailed understanding of water availability and demand in time and space; and therefore, large-scale models, including both GHMs and LSSs, are required for impact assessments.

Apart from hydrologic and water security relevance discussed above, anthropogenic activities might have broader implications for the water cycle; although these are to be fully explored, and remain in some cases controversial. For instance, it has been shown that human interventions through irrigation can change soil moisture and hence regional evaporation and near surface temperature. These changes can disturb the “natural” atmospheric boundary conditions and may interact with regional climate through feedback effects (e.g., Sacks et al., 2009; Destouni et al., 2010; Gerten et al., 2011; Pokhrel et al., 2012; Hossain et al., 2012; Dadson et al., 2013). At this stage of model development, the available quantitative understandings about these online implications are limited. To explore these issues it is necessary to include these processes in coupled Earth System models, and this requires explicit representation of human–water interactions within LSS computational schemes.

Due to the importance of anthropogenic activities in determining the future of the global water cycle and human livelihoods, the World Climate Research Programs’ Global Energy and Water Exchanges project (WRCP-GEWEX) has recently identified gaps in describing human–water interactions as one of the grand challenges in Earth System modeling (GEWEX, 2012). The aim of this review is to consider the associated scientific and data challenges, the state of current practice, and directions for future research. We note that human–water interactions include a wide spectrum of land-surface interventions, including land-use change and water resource management. In this paper and a companion paper (hereafter Nazemi and Wheater, 2014), we focus on those activities manifested through water resource management. We consider water
resource management as a set of anthropogenic activities related to storage, abstraction and redistribution of available water sources for various human demands and note that this is subject to operational and policy constraints. Although a fully coupled representation of water resource management in Earth System models is not currently available, important progress is being made, and more generally a body of literature is gradually shaping around describing different aspects of water resource management in offline mode, in particular within the context of GHMs. Nonetheless, there are still fundamental obstacles in including water resource systems within large-scale models even in offline mode.

First, multiple factors affect water resource management at the larger scale, such as climate, hydrology, land-cover and socio-economy as well as land and environment managements. Moreover, real-world management decisions often include cultural values and political concerns. These various influences are so far considered in isolation and the interactions among them are widely unseen (e.g. Beddington, 2013). Second, there is considerable lack of regional and global data concerning the actual use and operation of water resources systems, and therefore, large-scale models cannot be properly tuned or validated. This major limitation has led the research community, for instance, to use estimated demand as a surrogate for the actual use. Lack of data about human operation can also introduce large uncertainty into simulations of terrestrial storage and runoff. For instance Gao et al. (2012) noted that the “...results from global reservoir simulations are questionable” as “there are no direct observations of reservoir storage”. Third, there is a major gap between the scope of local operational water resource models and large-scale applications and research needs. Essentially, the scale at which local water resource management takes place is often within the sub-grid resolution of current large-scale models, which requires narrowing the resolution in large-scale models for explicit representation (see Wood et al., 2011) or adding more sub-grid heterogeneity into grid calculations for implicit parameterization. In addition, there is (and will increasingly be) competition between various water demands which requires allocation decisions. At this stage of model development, however, it
is still unclear how operational policies should best be reflected at larger scales. At the local scale, detailed information on physical and operational systems as well as climate and water supply conditions are available (or can be generated as scenarios; see e.g. Nazemi et al., 2013) and the competition between demands is often reflected as an optimization problem. As the simulation scale moves from local and small basin scales to regional and global scales, the data availability degrades considerably and the high level of calculations within optimization algorithms cannot be maintained, due to computational barriers as well as data availability issues.

Conceptually, water resource management at larger scales can be seen as an integration of two interactive elements, related to water demand as well as water supply and allocation: water demand drives water allocation, which results in extraction from water sources and determines the extent of change in hydrological elements of the land-surface. This has both offline and online implications. For the purpose of our survey, and reflecting the state of algorithm development and data availability, we focus in this paper on the representation of water demand, and in the Nazemi and Wheater (2014) on water supply and allocation. In Sect. 2 we further divide human demand into irrigative and non-irrigative sub-demands and briefly highlight their impacts on the terrestrial water cycle and land-atmospheric feedbacks. Sections 3 and 4 provide an overview of available representations of irrigative and non-irrigative demands at larger scales, respectively. In Sect. 5, we briefly explore state-of-the-art applications and highlight current limitations and uncertainties in estimating current and future water demand and associated online and offline impacts. We further discuss current gaps in Sect. 6 and provide some suggestions for future developments. Finally, Sect. 7 summaries first part of our survey and outlines our main findings with respect to representing human water demand.
2 Types of human demand and their impacts on the water cycle

Human water demands can be divided into irrigative and non-irrigative categories. Irrigation is the dominant human water use and has significantly intensified since the 1950s, due to population growth and technological development (Steffen et al., 2011). This has major importance for global food security, as it produces approximately 40% of the world’s food (Abdullah, 2006). Currently, around 25% of harvested crop area is irrigated (Portmann et al., 2010). This accounts for some 90% of water consumption at the global scale (Döll et al., 2009; Siebert et al., 2010), which is around 70% of the total water withdrawals from surface and groundwater resources (Wisser et al., 2008; Gerten and Rost, 2010). Clearly supplying such a large water demand can severely disturb the “natural condition” by decreasing streamflow volume (e.g. Meybeck, 2003; Gaybullaev et al., 2012; Lai et al., 2014) and groundwater levels (e.g. Rodell et al., 2009; Gleeson et al., 2012; Wada et al., 2010, 2012, 2014). Currently, surface water is the main supplier of global irrigative needs, accounting for 57% of the total consumptive irrigation use at the global scale (Siebert et al., 2010).

Apart from driving hydrological changes, irrigation-induced changes in soil-moisture can affect land surface-atmosphere feedbacks (see Eltahir, 1998). Pokhrel et al. (2012) showed that increased soil water content through irrigation substantially enhances evapotranspiration, and therefore transforms the surface energy balance. Evapotranspiration due to irrigation leads to cooling of the land surface (e.g. Haddeland et al., 2006; Betts et al., 2007; Saeed et al., 2009; Destouni et al., 2010), as well as enhanced cloud cover and chance of convective precipitation (e.g. Moore and Rojstaczer, 2001; Douglas et al., 2009; Harding and Snyder, 2012a, b; Qian et al., 2013). Irrigation may also alter regional circulation patterns due to temperature difference between irrigated areas and neighboring regions (e.g. Kueppers et al., 2007; DeAngelis et al., 2010; Wei et al., 2013). Over highly irrigated regions, this can mask important climate change signals. Gerten et al. (2011), for instance, showed that the irrigation in South Asia has offset the increasing temperature in the region. Agricultural management in irrigated
areas can also have other effects on the water cycle and climate (e.g. Lobell et al., 2006; Kucharik and Twine, 2007). Associated effects of agricultural management, however, remain beyond the scope of this paper.

Non-irrigative water demands include municipal and industrial uses, energy-related withdrawals, and other agricultural uses, such as livestock. Non-irrigative demands contribute a lesser proportion to total human water use at the global scale. This proportion, however, has significant spatial variability (Vassolo and Döll, 2005; Flörke et al., 2013) as regional differences in population, income, lifestyle and technological developments can alter the extent of non-irrigative demand significantly (e.g. Alcamo et al., 2003; Flörke and Alcamo, 2004; Hejazi et al., 2013a). However, while irrigation is predominantly a consumptive water use, only a small portion of the non-irrigative withdrawal is consumptive (e.g. Hanasaki et al., 2013a). Non-irrigative withdrawals, therefore, partially or totally return to surface water or groundwater systems with varying degrees of time lag. Still, this can considerably perturb the streamflow regime, quality and temperature (e.g. Maybeck, 2003; Förste and Lilliestam, 2010). Non-irrigative water demands are currently on a rapid incline due to growing population and industrial development. This can increase water stress in both time and space (Hejazi et al., 2013a–d). Recognizing non-irrigative water uses is therefore relevant in terms of possible effects on the terrestrial water cycle and future water security. Also, for some large-scale mining activities, in which the extent of water withdrawals is considerable, the associated changes in soil moisture and land-cover can be potentially relevant to land-atmospheric feedbacks. To the best of our knowledge, online consideration of non-irrigative withdrawals has not yet been explored in the literature.
Available representations of irrigative demand in large-scale models

3.1 Framework and general procedure

Irrigated lands normally introduce heterogeneity into the computational grids of LSSs and GHMs. Such sub-grid heterogeneity can be represented as an additional “tile” similar to forested land, bare soil and snow cover (Polcher et al., 2011). For simplifying our presentation, we classify the current representations with respect to the scale (regional vs. global) and/or mode of simulation (offline vs. online). Tables 1 and 2 summarize representative examples of offline simulations at both regional (Table 1) and global (Table 2) scales. Table 3 presents some online examples. In brief, current online applications have mainly been performed at rather fine temporal and spatial resolutions with shorter simulation periods than offline representations. In contrast, a wide spectrum of host models (i.e. large-scale models in which the irrigation algorithm is embedded), as well as forcing and land-use data, has been used in current offline examples (see Tables 1 and 2). Model resolutions in offline applications can vary from 1 h (e.g. Leng et al., 2013) to 1 day (e.g. Haddeland et al., 2007) in time and few kilometers (e.g. Sibert and Döll, 2010; Nakayama and Shankman, 2013) to few hundred kilometers (e.g. Gueneau et al., 2012) in space. Moreover, offline irrigation demand calculations have been already performed globally under future climate conditions.

Essentially, irrigation algorithms require identifying the extent of irrigated regions and growing seasons. The location and area of irrigation districts and the associated crop types can be extracted from regional and global data sets (e.g. USDA, 2002, 2008; Siebert et al., 2005, 2007; Portmann et al., 2010) and/or remotely sensed data (e.g. Adegoke et al., 2003; Qian et al., 2013). There are two general approaches for identifying growing seasons. The choice of these options depends on the level of detail in the host model. In simpler models, where no energy-balance calculation is available, crops can grow when and where simple temperature- and precipitation-based criteria are met (e.g. Döll and Siebert, 2002). In more detailed models the optimal growing season can be identified based on biophysical conditions of crop growth and/or soil
water, canopy and energy balance conditions to estimate the cropping period that is necessary to obtain mature and optimal plant biomass (e.g. Rost et al., 2008; Pokhrel et al., 2012). This latter approach is applied mainly in the context of global vegetation models and to some extent in LSSs. After the growing season is identified, the irrigation demands (and under some assumptions, actual irrigation withdrawals) at each simulation time step can be calculated. The irrigation demand is the water required for ideal crop growth, in addition to available water. A variety of top-down and bottom-up procedures are available for calculating the irrigation demand in large-scale models and are reviewed further below. If the irrigation demand is completely fulfilled, then the actual evapotranspiration would be equal to crop-specific evapotranspiration under standard conditions (see Allen et al., 1998). In offline applications, the irrigation rate can perturb soil moisture content, evaporation, deep percolation and runoff in irrigated tiles (e.g. Hanasaki et al., 2008a, b; Wada et al., 2011, 2012, 2014). In online applications, the vertical vapor and heat fluxes need to be also considered. The total fluxes for each grid can be then calculated as the sum of the flux contributions from irrigated and non-irrigated portions of the grid (e.g. Haddeland et al., 2006; Pokhrel et al., 2012), and can be further introduced to climate models as coupled surface boundary conditions (e.g. Sorooshian et al., 2011; Harding and Snyder, 2012a, b).

### 3.2 Top-down algorithms for calculating irrigation demand

In top-down approaches, the irrigation demand is not directly calculated, but estimated based on downscaling either historical (e.g. Sacks et al., 2009) or simulated (e.g. Voisin et al., 2013) information, obtained at national or geopolitical scales. Top-down approaches are highly influenced by the availability of global data on water use, such as FAO’s Information System on Water and Agriculture (AQUASTAT; http://www.fao.org/nr/water/aquastat/main/index.stm), which provides annual data on national (and in some cases also sub-national) scales. Downscaling is performed mainly using land-use, technological and/or socio-economic proxies. Current top-down algorithms for calculating irrigation demand are however rather simplistic since annual
irrigation practices are highly variable within a country and a typical year. As a result, calculation of irrigation demand is mainly pursued through bottom-up schemes.

### 3.3 Bottom-up algorithms for calculating irrigation demand

Despite major limitations due to the heterogeneity in soil and crops, bottom-up algorithms try to mimic the optimal crop growth at irrigated sub-grid tiles. These algorithms include a range of modeling assumptions and are heavily influenced by FAO’s guidelines for calculating the irrigation water requirements (see Allen et al., 1998). The key component in the bottom-up approaches that ties different algorithms together is the calculation of potential evapotranspiration, which determines the crop water use in ideal conditions with no water deficit. The calculation of potential evapotranspiration is mainly based on calculating the evapotranspiration for a reference crop and correcting it as a function of crop type and crop development stage using a set of empirical coefficients. Various methods are used to characterize the reference evapotranspiration, such as FAO Penman-Monteith (Allen et al., 1998), Priestley and Taylor (1972) and modified Hargreaves (Farmer et al., 2011) to name a few (see McKenney and Rosenberg, 1993 for more examples). The choice of these formulations has remained rather arbitrary and depends largely on the data availability as well as the level of detail supported in the host model. Here we try to sort and briefly explain the currently available bottom-up algorithms from the most simplistic to most comprehensive algorithm and highlight their strengths and weaknesses.

In the most simplistic bottom-up representations, the irrigation demand at every time step is the water required to bring the soil moisture at the root zone to saturation (e.g. Lobell et al., 2006; Harding and Snyder, 2012a, b), which describes an extreme demand condition and clearly overestimates the actual irrigation water requirement (Sacks et al., 2009). In a more realistic but still naïve representation, the soil moisture requirement during the growing season is considered to be the field capacity (e.g. Nakayama and Shankman, 2013); therefore, the irrigation water need is the water required to bring the soil moisture to field capacity. The description of the
irrigation demand based on the field capacity can also overestimate the actual water requirements, as the evaporation often reaches potential level before the soil reaches field capacity. The threshold at which the evaporation reaches potential evaporation is crop-dependent, but often considered as a constant value in large-scale models. As an offline example, Hanasaki et al. (2008a) assumed that paddy and non-paddy crops require soil moisture content of 100 or 75% of the field capacity at the root zone with constant depth at the global scale. Yoshikawa et al. (2013) later updated the assumption for non-paddy soil moisture requirement and used 60% of field capacity, referring to the requirement for wheat. This is again rather unrealistic as (1) by assuming a constant percentage of the field capacity for all crop types, the diversity in crop water requirement is ignored; and (2) a constant root zone depth at the global scale can result in misestimating the irrigation demand. There are attempts to address these limitations. For instance, Sorooshian et al. (2011) assumed that the required soil moisture content can change in each grid based on the dominant crop. Leng et al. (2013) and Qian et al. (2013) implemented root growth in their irrigation demand algorithm to avoid the overestimation of demand due to a constant root zone. It should be noted that calculating the root growth is also subject to uncertainty; however, associated limitations remain beyond the scope of this paper.

More realistic definition of irrigation water demand would be based on the difference between the crop-dependent potential evapotranspiration and available crop water. This definition has been widely used in global irrigation demand projections (see Table 2). In earlier examples (e.g. Döll and Siebert, 2002; de Rosnay et al., 2003), crop development is described by constant monthly multipliers for potential evapotranspiration and the effective rainfall is used as a surrogate for available crop water. In more advanced algorithms, the correction factors are considered as functions of daily climate, stage of vegetation and root growth. Moreover, actual evapotranspiration or soil moisture content can be used instead of effective rainfall (Haddeland et al., 2006, 2007; Gueneau et al., 2012). There are two key limitations associated with this approach to simulation of irrigation demands. First, FAO’s definition of irrigation water requirement
considers both transpiration from crop and evaporation from soil. It has been noted that this quantification may result in overestimating the irrigation demand and may not properly represent the dynamics of vegetation (Polcher et al., 2011). Second, it is assumed that crop growth is a function of water availability only; therefore, the effects of other drivers such as CO$_2$ on photosynthesis are wholly ignored.

Some efforts try to overcome these limitations by defining irrigation demand based on potential transpiration instead of potential evapotranspiration (e.g. Wada et al., 2011, 2012) and/or using more comprehensive vegetation schemes. For example Rost et al. (2008) coupled a transpiration deficit algorithm with the Lund–Potsdam–Jena managed Land scheme (LPJmL; Bondeau et al., 2007), which has a detailed vegetation growth module based on carbon and water availability (see Sitch et al., 2003; Gerten et al., 2004). The crop water limitation was calculated based on the atmospheric water deficit, soil moisture, plant hydraulic states as well as the CO$_2$ effects. Considering the effects of both carbon and water in vegetation can provide a basis for explicit linkage between CO$_2$ emission, crop growth and irrigation water requirement. This would be important for future predictions under increasing CO$_2$ effects. Moreover, some recent simulations showed that the irrigation requirement changes if a dynamic growth model is used; and this can improve the partitioning of latent heat flux (e.g. Lu, 2013).

3.4 Projection of irrigative demand

From water and food security perspectives, particularly under various global change scenarios, it is crucial to investigate future irrigation demand and assess various possibilities for irrigation deficit. Climate model projections under IPCC emission scenarios (IPCC, 2000) have been widely used to force bottom-up irrigation demand algorithms (e.g. Arnell, 1999; Wada et al., 2013; Rosenzweig et al., 2013). Efforts have been also made to include intermediate socio-economic scenarios that can match with current climate change scenarios (see e.g. Arnell, 2004; Fischer et al., 2007; Alcamo et al., 2007). For irrigation, intermediate scenarios describe changes in irrigated
areas, irrigation efficiency as well as crop using empirical approaches. For example, Hanasaki et al. (2013a) recently proposed intermediate scenarios based on newly developed Shared Socio-economic Pathways (SSPs; Kriegler et al., 2012; see also Moss et al., 2010), which are consistent with Representative Concentration Pathways (RCPs; Meinshausen et al., 2011; Taylor et al., 2012). Constructing intermediate scenarios using empirical procedures, however, is uncertain as mechanisms that link irrigation expansion to socio-economic factors are not fully known and current empirical relationships can contain large uncertainties. More dynamic linkage between irrigation expansion and socio-economic drivers can be provided by coupled socio-economy-energy-carbon models. One emerging model of such a kind is the Global Change Assessment Model (GCAM; Wise and Calvin, 2009; Wise et al., 2009a, b). GCAM has been recently implemented for simulating the future expansions in irrigation areas and demands (Hejazi et al., 2013b–d) as well as policy implications for irrigation water requirements (e.g. Chaturvedi et al., 2013a, b). Although, these models can represent the dynamic effects of various drivers on irrigation, they remain uncertain as their simulations are rather coarse and they often consider irrigation development only as a function of growths in economy and energy-use; therefore, water availability constraints are widely ignored (Hejazi et al., 2013d).

4 Available representations of non-irrigative demand

4.1 Forms and drivers of non-irrigative demand

Non-irrigative water demands relate to a wide range of municipal, industrial and energy-related uses, as well as other agricultural water needs (e.g. livestock), and include both consumptive and non-consumptive withdrawals. Among these, livestock water demand is assumed fully consumptive, and can be estimated by livestock number and demand per livestock head (e.g. Wada et al., 2011; Strzepek et al., 2012b; Hejazi et al., 2013d). Wada et al. (2014) made a further improvement by estimating daily
livestock requirements at 0.5° × 0.5° spatial resolution using livestock data of Steinfeld et al. (2006). Daily demand was considered as a function of daily temperature.

Municipal, industrial and energy-related water demands are the most dominant forms of non-irrigative uses, and can be considered as complex functions of socio-economic and technological factors, with high variability in time and space. Population is the most significant factor driving these withdrawals (e.g. Alcamo et al., 2003; Hanasaki et al., 2008a; Wada et al., 2014). National Gross Domestic Product (GDP) is also a strong factor (e.g. Gleick, 1996; Cole, 2004; Wada et al., 2011). Hughes et al. (2010) showed that, in general, water uses per capita are more in developing than developed countries due to low-tech water delivery and industrialization. It must be noted, however, that higher GDP may trigger more municipal water use per capita (Alcamo et al., 2007). Strzepek et al. (2010) argued that industrial water use increases with the level of resource industry and decreases when a country moves toward the service sector. Industrial technology is another important factor for non-irrigative use as the extent of both consumptive and non-consumptive uses can significantly change based on the type of technology. Macknick et al. (2011), for instance, provided estimates of total water withdrawals and consumption for most electricity generation technologies within the US. Comparing to recirculating cooling technology, they noted that once-through cooling requires 10 to 100 times more water withdrawal per unit of electric generation. However, the later consumes less than half of the water, consumed by recirculating cooling technology. Climate can be another important factor controlling both consumptive and non-consumptive withdrawals (e.g. Wada et al., 2011, 2013a; Hejazi et al., 2013a; Voisin et al., 2013), but it has been often ignored as an explicit driver of non-irrigative water demand.

4.2 Top-down algorithms for estimation of grid-based non-irrigative withdrawals

Unlike irrigation demand, top-down approaches have been widely used to transfer national or geopolitical data to basin or grid scales. Various downscaling procedures have
been suggested, based on different proxies (see Table 4). These top-down schemes are heavily influenced by the availability of national and global datasets and the downscaling algorithms within the Water – Global Assessment and Prognosis scheme, which is a global water budget and use model (WaterGAP; Alcamo et al., 1997, 2003, 2007). Currently, the availability of different global information sources has provided the opportunity to generate gridded products from different sources. As an example, Hanasaki et al. (2008a) merged the FAO-AQUASTAT data with population distributions and national boundary information from Columbia University (CIAT, 2005) and the consumptive ratios of Shiklomanov (2000) to come up with gridded industrial and municipal water withdrawals and uses at the global scale. More detailed information on various industrial uses resulted in breaking the industrial withdrawals into their components. For instance, Vassolo and Döll (2005) distinguished between industrial water uses related to thermoelectric power generation and manufacturing production. Temporal disaggregation of annual withdrawals, however, has received much less attention. Recently Wada et al. (2011, 2014) and Voisin et al. (2013) developed simple algorithms to disaggregate annual data to monthly and daily estimates (see Table 5).

4.3 Projection of non-irrigative demand

Characterizing the past and future evolution of non-irrigative demands is required to understand the mechanisms controlling water use and water allocation. Current projections have coarse temporal and spatial resolution and describe non-irrigative demands as functions of socio-economic and technological developments (e.g. Davies et al., 2013; Blanc et al., 2013; Hejazi et al., 2013b, d; Voisin et al., 2013). These changes can be characterized by intermediate socio-economic and technological scenarios, as briefly explained above for irrigation expansion (see Sect. 3.4). The projected demands can be further downscaled using various proxy variables, as explained in Sect. 4.2. Table 6 summarizes some representative efforts, which can be classified through explicit and implicit algorithms. In explicit algorithms, changes in water withdrawals are directly described as functions of changes in socio-economy, technology and water price using
simple parametric structures (e.g. Strzepek et al., 2012b; Flörke et al., 2013; Hanasaki et al., 2013a; Hejazi et al., 2013a). The parameters can be assigned using the available global and regional data. In implicit procedures, first the production (or population) is estimated based on integrated economy and population models or prescribed scenarios. By considering the amount of water withdrawal per unit of production (or population) and accounting for technological and/or socio-economic shifts, water withdrawals are consequently projected.

5 State of large-scale modeling applications

The algorithms reviewed in Sects. 3 and 4 have had a wide range of online and offline applications. Comparing to offline applications, online simulations are still under development; they only include irrigation, mainly implemented at regional scale and under current conditions, and present rather contradictory results. Offline applications in contrast include both irrigative and non-irrigative demands, performed under current and future conditions, and provide relatively more consistent results. Here, we briefly summarize the recent applications and highlight the limitations in current simulations.

5.1 Online representation

Recent studies have shown that including irrigation in coupled land-surface schemes can generally improve climate simulations. With respect to regional temperature, for instance, Saeed et al. (2009) showed that representing irrigation activities over north-western India and Pakistan can reduce climate model simulation bias by 5 °. It should be noted, however, that there are still large disagreements in quantifying the effects of irrigation on regional and global temperature (see e.g. Boucher et al., 2004 vs. Lobell et al., 2006), mainly attributed to the difference in the implemented irrigation demand calculations. Sacks et al. (2009) tried to overcome the limitations in demand algorithms by downscaling the AQUASTAT irrigative water use data to the grid scale.
They concluded that irrigation has significant importance for regional temperature, but at global scale the temperature cooling in some regions due to irrigation is cancelled by temperature warming in some other areas due to climate, land-cover and circulation changes. There are, however, some limitations in their study, as the irrigation demand did not vary between years and they applied irrigation only when the LAI is around 80% of the annual LAI. These assumptions can result in large uncertainty.

Irrigation-induced precipitation has been studied for quite some time and has been shown to have a significant footprint on local and regional precipitation patterns (e.g. Barnston and Schickedanz, 1984; Moore and Rojstaczer, 2001). For instance despite regional decline, Tuinenberg et al. (2011) found a positive precipitation trend in climate stations located in the irrigated regions of the Southern Asia. Lucas-Picher et al. (2011) tested four climate models and argued that lack of representing irrigation is the main reason for precipitation bias over Indian Monsoon area. Nonetheless, there are still large disagreements in (1) identifying the dominant mechanisms that drive the irrigation-induced precipitation; and (2) estimating the amount and spatial extension of change in precipitation. DeAngelis et al. (2010) noted that the growing season precipitation increased in the Great Plains of the US during the 20th century as a result of intensive irrigation. Using vapor tracking analysis, they indicated that evaporation from irrigated lands adds to downwind precipitation, which increases as the evaporation increases. Harding and Snyder (2012a, b), however, noted that the extent of effects on precipitation also depend on the antecedent soil moisture. They argued that in low soil moisture conditions, further irrigation can result in suppression of regional precipitation. With respect to the scale of disturbance, Sorooshian et al. (2011) showed that irrigation over California’s Central Valley significantly decreases local temperature and increases local precipitation; however, they argued that the effects of irrigation do not expand far from the place where irrigation takes place. In contrast, Lo and Famiglietti (2013) argued that irrigation in California’s Central Valley intensifies the water cycle in the southwestern US and can increase the flow in the Colorado River.
Online simulations under future climate change are limited and have been performed mainly at regional scales. Gerten et al. (2011) used a nested regional climate model to dynamically downscale the future simulations of a global climate model over the Southern Asia and considered two modes of simulations, with or without irrigation. They concluded that including irrigation can result in roughly half of the temperature increase, predicted without representing irrigation. With respect to future precipitation, simulation with and without irrigation both showed a decrease in precipitation over northern India and increase in precipitation over the southern peninsular; the latter was enhanced with irrigation. They noted that the increase in precipitation cannot be discovered, if the global scale simulations are not dynamically downscaled. This highlights the importance of including irrigation schemes in regional climate models for dynamic downscaling of future climate change scenarios.

In summary despite differences in the host climate and LSS models, irrigation demand algorithms and simulation settings, significant feedback effects are associated with irrigation. Large uncertainties, however, exist in current coupled irrigation–land–surface–climate modeling, which emphasize on the need for more research in this area.

5.2 Offline representation

Offline representation of water demands is more common and a wide variety of GHMs and LSSs in conjunction with different demand algorithms have been used to simulate the dynamics of water demand under both current and future conditions. The available global simulations under current conditions are compared and summarized in Wada et al. (2014) and Chaturvedi et al. (2013a, b) for irrigative demands and in Alcamo et al. (2003) and Hejazi et al. (2013b) for total water consumption. In brief, current simulations are mainly compared at countrywide, continental and global scales, and exhibit large differences in estimates of water demand and use. This can be referred to the differences in data support, demand calculation schemes and host models – see the discussion of Sect. 6 below.
Normally, future projections of water demands include more uncertainty than simulation of current conditions as they are also conditioned on uncertain climate futures and/or socio-economic and technological scenarios. Considering future climate projections, with or without considering irrigation expansion, irrigation demand algorithms have mainly projected increase in irrigation demand under climate change scenarios. As an earlier example, Fischer et al. (2007) estimated irrigation water requirement as a function of both projected irrigated land and climate change from 1990 to 2080. They showed that the impact of climate change on increasing irrigation water requirement could be nearly as large as the changes initiated by socio-economic developments. There are, however, two sets of uncertainty associated with future projections of irrigation demand. First, gridded climate products have significant deficiencies in representing current and future climate, particularly with respect to precipitation (e.g. Lorenz and Kunstmann, 2012; Grey et al., 2013). This can further propagate to estimation of irrigation demand at the sub-grid scale. Second, there are large disagreements between irrigation demand projections with respect to different climate model simulation, irrigation algorithms and host large-scale models. One possible approach to account for these uncertainties would be using multi-model approach as recommended by Gosling et al. (2011) and Haddeland et al. (2011) and implemented to some extent by Wada et al. (2013) and Rosenzweig et al. (2013). Based on the latest IPCC climate scenarios (Taylor et al., 2012), these studies generally concluded that a significant increase in future demand is likely, with possibly one-month or more shift in the peak irrigation demand in mid-latitude regions (Wada et al., 2013), but large uncertainties are associated with the predictions (see Rosenzweig et al., 2013). Moreover, both studies noted that CO₂ increases might have beneficial effects on crop transpiration efficiency, if other factors are not limiting (see also Gerten et al., 2011; Konzmann et al., 2013). Nonetheless, it still remains unclear whether increased transpiration efficiency is cancelled out by increased transpiration due to increasing biomass and plant growth. More studies, therefore, are required in this direction (see Gerten, 2013). This is a context for which LSSs can offer an ideal platform as they have the explicit modules required for...
considering dynamic interactions of carbon, vegetation and water – see the discussion of Sect. 6.

Similar conclusions were obtained with respect to non-irrigative demands. Alcamo et al. (2007) and Hejazi et al. (2013d) showed that increasing domestic and industrial water uses, if not controlled, can be a major threat for water security. There are, however, large discrepancies between different projections of non-irrigative demands (Gleick, 2003), in which the divergence between modeling results becomes more highlighted as the projection horizon increases (see Davis et al., 2013, for electrical demand and associated water use). These uncertainties can be referred to limitations in current data availability for supporting robust and reliable projections, differences in socio-economic and technological scenarios, as well as some underlying assumptions in demand calculation algorithms, which can limit their efficiency in future simulations.

As the current global potential for expanding water demand is rather limited (Rost et al., 2009; Gerten and Rost, 2010), adaptation and mitigation strategies are required to moderate human water demands. In such cases prescribed “policy” scenarios can be introduced into large-scale models for impact assessment. Using this approach, it has been shown that mitigation can significantly decrease future global water demand. For example, Hanasaki et al. (2013a) showed approximately 7-fold and 2.5-fold variation in industrial and municipal demands, depending on the SSP considered. The effects of mitigation, however, have large regional variation. For irrigative demands, Fischer et al. (2007) showed that some regions may be negatively affected by mitigation actions, which depend on specific combinations of CO₂ changes that affect crop water requirement and projected precipitation and temperature changes. Kyle et al. (2013) showed that applying CO₂ mitigation policies can result in high deployment of other high-tech solutions for electrical generation (e.g. solar power) that have low water requirements. Hejazi et al. (2013c) further showed that taxation can be an important factor in mitigating the effect of water scarcity by regulating more water efficient options for irrigation. Hejazi et al. (2013a) further showed the possibility of even a slight decrease in municipal withdrawals in the year 2100 under a high-tech scenario,
despite significant population growth. Davies et al. (2013) showed similar results for electricity water withdrawals if high-tech solutions are employed. Large-scale models also showed that promoting international trade can be a strong adaptation option for controlling regional demand, in which water-limited regions can import water-expensive products from other areas (e.g. Siebert and Döll, 2010; Hanasaki et al., 2010; Konar et al., 2013). Assessment of trade scenarios and water footprinting, however, needs a detailed track of the water cycle (see Chenoweth et al., 2013) and is highly dependent on how reasonable the human demands and production as well as water availability and water allocation are described in time and space. Such a level of accuracy is currently not available and therefore the assessments remain widely uncertain.

In summary, current offline projections agree on large impacts of future change in climate, socio-economy and technology on water demands and the importance of adaptation and mitigation strategies for managing future water security threats. Available projections, however, are rather limited and suffer from major sources of uncertainty, which is revealed by large discrepancies between different simulation products under current and future conditions. We now turn to discuss these gaps in more details and identify the research needs and priorities.

6 Discussions

Major gaps remain in the current capability in modeling water demands and understanding their online and offline impacts on the Earth System and human livelihood. These gaps are partially due to inherent complexity in modeling Earth System processes, which is more significant in coupled simulation modes. Apart from various computational barriers, one main challenge in online simulations is the uncertainty associated with coupling land and atmospheric models, as given a unique land-surface boundary condition, the simulations obtained by different climate models can be divergent (Koster et al., 2004; Pitman et al., 2009; Dadson et al., 2013). Another major challenge for coupled irrigation–land–surface–climate simulations is the choice of
appropriate temporal and spatial resolutions, in which the relevant physical processes and feedbacks between land and atmosphere should be represented and described. Ideally, the optimal modeling resolution should be identified based on physical realism; nonetheless, the choice of resolution in coupled simulations is mainly constrained by computational resources and data availability. If these are not limiting factors, it has been shown that finer temporal and spatial resolutions can improve online representation of irrigation. For instance, using six different combinations of temporal/spatial resolutions, Sorooshian et al. (2011) concluded that spatial and temporal resolution in coupled irrigation–land–climate models can significantly change both temperature and precipitation simulations over irrigated grids and a fine level of detail is required for representing the physical processes controlling the feedbacks between irrigation and atmosphere. The effects of fine modeling resolution seem to be in general less significant in offline runs. Compton and Best (2011) conducted offline global simulations and showed that fine spatial resolution has little importance on long-term modeling of evaporation and runoff; however, the temporal resolution does change the mean evaporation/runoff balance. The issues around modeling resolution are explored more in Nazemi and Wheater (2014).

Large uncertainties are also associated with offline human water demand simulations under current and future conditions. Lissner et al. (2012), for instance, noticed significant difference in terms of water demand per capita between the simulated products of WaterGAP and reported AQUASTAT data. These uncertainties are mainly related to (i) available data support, (ii) demand calculation algorithms and (iii) host models. These sources are widely connected and cannot be easily addressed and quantified independently. Here we briefly discuss these sources and propose few directions for future developments.

1. Uncertainty in current data support: major uncertainties are associated with the data required for executing demand calculation algorithms. Siebert et al. (2005) noted that even the locations of irrigation districts are uncertain in many regions and sub-grid variability of crops within irrigated are not generally available. Wisser
et al. (2008) argued that major uncertainties are associated with forcing, irrigation and crop maps and this can result in large differences between simulations of irrigation water requirement. The issues around data support applies to non-irrigative demands as well. For the case of water use for electricity generation in the US, Macknick et al. (2011) noted that “federal data sets on water use in power plants have numerous gaps and methodological inconsistencies”. Data uncertainty can propagate into structural and parametric identification during model development and can further extend to future projections. The availability of different sources of global and regional data has resulted in emergence of various datasets, with varying degrees of quality, which can potentially support demand calculation algorithms. At this stage of research, the various datasets are not systematically compared with respect to their uncertainty and the associated effects on demand simulations. This is a major need for future exploration.

2. Uncertainty in demand calculation algorithms: this includes both irrigative and non-irrigative demands.

a. Irrigative demand: limitations in current algorithms mainly include the uncertainty in describing the crop moisture requirements in time and space. Current bottom-up algorithms do not appropriately consider plant-specific water requirements at the sub-grid scale due to missing soil and crop diversity. This can result in misestimating the irrigation demand. Moreover, widely-used irrigation demand estimates based on FAO guidelines often require several input variables (see e.g. Farmer et al., 2011 and Hejazi et al., 2013b for simplifications), and given the need for downscaling of climate variables for future simulations, these can be outperformed by simpler models (e.g. Vörösmarty, 1998; Oudin et al., 2005; Wisser et al., 2010). At current stage of research, different methods for calculating reference evapotranspiration and corresponding demand simulations have not yet been fully analyzed and compared to identify appropriate algorithms with respect to region,
climate and type of crops. This can be considered as an important need for further research. Another avenue for future development can be improving the demand simulations using data assimilation and model calibration. These opportunities will be discussed further in Nazemi and Wheater (2014).

b. Non-irrigative demand: the current modeling capability is temporally coarse and available downscaling and projection algorithms mainly do not account for seasonal variations in water demand. There are also parametric and structural uncertainties in functional mappings that link water demand to socio-economic and technological proxies. At this stage, it is not fully understood how these uncertainties propagate into future projections. This is an important avenue for future exploration. Developing robust downscaling and projection algorithms for non-irrigative demands is another important need for future development. Future developments should consider limitations in available data and future scenarios as well as the diversity and spatiotemporal variability in non-irrigative demands.

3. Uncertainty in host models: host models can add substantial uncertainty to demand simulations, particularly for irrigation. As noted in Sect. 3, the calculation of irrigation demand involves solving the soil water balance at every simulation time step and this is determined by how the relevant natural processes, such as actual evapotranspiration and soil moisture are parameterized in the host model. Haddeland et al. (2011) showed major differences in the global simulations obtained from six LSSs and five GHMs due to differences in underlying assumptions, process representations, and related parameterizations. It is also shown that considering feedback effects between irrigation and atmosphere can considerably change potential evaporation (e.g. Blyth and Jacobs, 2011; Lu, 2013); therefore offline irrigation demand simulations based on GHMs might be biased as they inherently ignore climate feedbacks. Moreover, GHMs often cannot represent important processes such as the effects of increased carbon concentration on irrigation demand. This limitation may result in major deficiencies in simulating
climate change scenarios as CO\textsubscript{2} increases can significantly change vegetation dynamics (e.g. Prudhomme et al., 2013), which can further alter the evaporation and runoff regimes (Gerten et al., 2004). From this perspective, it can be concluded that online LSSs are superior to GHMs with respect to simulations under increasing CO\textsubscript{2} concentration and future water stress, as they often include many of the required computational components for investigating interactions between climate, carbon, vegetation and water cycles. Efforts are however needed to transfer recent demand calculation algorithms developed in the context of GHMs into LSSs. In addition, although it has been argued that the uncertainties in host models are more significant than in climate forcing (e.g. Wada et al., 2013), uncertainties in irrigation algorithms and large-scale host models have not been fully disjointed and distinguished. This requires “mix and match” multiple demand algorithms with multiple host models to conduct a systematic intercomparison and sensitivity analysis. This can be considered as an important research direction.

7 Summary and concluding remarks

The terrestrial water cycle has been greatly affected in time and space by human activities during the recent past, to the extent that the current geological era has been named the “Anthropocene”. Anthropogenic activities, therefore, are required to be represented in models that are used for impact assessments, large-scale hydrological modeling and land–atmosphere feedback representations. Current human–water interactions are mainly manifested through water resource management, which can be further broken down into two interacting components, related to water demand as well as water supply and allocation. In this paper we considered the representation of water demand in large-scale models. Water demand was further divided into irrigative and non-irrigative categories. We summarized current demand calculation algorithms based on type of demand, modeling procedure and underlying assumptions. Current applications were overviewed; and limitations in knowledge are identified and discussed.
Considering current gaps in representing the anthropogenic demands in large-scale models, three main directions are suggested for future developments. These include (1) systematic intercomparisons between different datasets, demand algorithms and host models and associated uncertainties with respect to different geographic regions as well as various socio-economic and climate conditions; (2) developing improved algorithms for calculating both irrigative and non-irrigative demands in time and space considering data limitations as well as diversity and spatiotemporal variability in human demand; and finally (3) transferring the algorithms developed in the context of GHMs to LSSs for (a) improved irrigation demand calculation under increasing CO₂ effects; and (b) further coupled studies with climate models to address various scientific questions with respect to interactions between carbon, irrigation and climate under climate change conditions. Apart from these immediate research needs, efforts are also required to link with socio-economic and energy models to have a full understanding of the dynamic interactions between natural and anthropogenic drivers of human water demand and consumption (Calvin et al., 2013). This seems to be more of a long-term development due to the limitations in current demand algorithms, LSSs as well as socio-economic and energy models.

As a final remark, it must be noted that the effects of water demand on both terrestrial water cycle and water security cannot be fully studied unless considered in conjunction with water supply and allocation, which determine the extent of human intervention in water cycle. This is particularly important for future predictions, as the increasing water scarcity is a major limiting factor for water demand and can substantially increase competition over available water sources. In Nazemi and Wheater (2014), we review how water supply and allocation have been represented at larger scales and been integrated with various water demands and natural land-surface processes at grid and sub-grid scales.

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Italy, available at: https://www2.uni-frankfurt.de/45218039/Global_Irrigation_Map (last access: 6 May 2014), 2007.


### Table 1. Representative examples for including regional irrigation in large-scale models (offline mode).

<table>
<thead>
<tr>
<th>Reference</th>
<th>Irrigation data</th>
<th>Irrigation demand</th>
<th>Region</th>
<th>Host model</th>
<th>Forcing</th>
<th>Temporal resolution</th>
<th>Spatial resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>de Rosnay et al. (2003)</td>
<td>Döll and Siebert (2002)</td>
<td>Difference between effective rainfall and FAO potential evapotranspiration (Allen et al., 1998) without considering irrigation efficiency.</td>
<td>Indian Peninsula</td>
<td>ORCHIDEE (Ducoudré et al., 1993)</td>
<td>ISLSCP-I (Sellers et al., 1996b)</td>
<td>24 h</td>
<td>1° × 1°</td>
</tr>
<tr>
<td>Haddeland et al. (2006)</td>
<td>Döll and Siebert (2002)</td>
<td>Difference between current soil moisture content and minimum of FAO Penman–Monteith crop-specific evapotranspiration and soil moisture content at field capacity.</td>
<td>Colorado (USA) and Mekong (east Asia)</td>
<td>VIC (Liang et al., 1994)</td>
<td>Adam and Lettenmaier (2003); Maurer et al. (2002)</td>
<td>3 h</td>
<td>0.5° × 0.5°</td>
</tr>
<tr>
<td>Gueneau et al. (2012)</td>
<td>GAEZ (IIASA/FAO, 2012); FRIS (USDA, 2006)</td>
<td>Difference between current soil moisture content based on CLM4CNcrop crop growth model of CLM4 (Levis and Sacks, 2011; Levis et al., 2012).</td>
<td>USA</td>
<td>CLM3.5 (Oleson et al., 2004, 2005)</td>
<td>NCC (Ngo-Duc et al., 2005)</td>
<td>6 h</td>
<td>2.5° × 2.5°</td>
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<td>Leng et al. (2013)</td>
<td>MODIS (Ozdogan and Gutman, 2008); NASS (USDA, 2002)</td>
<td>Difference between current and ideal soil moisture content based on CLM4CNcrop crop growth model of CLM4 (Levis and Sacks, 2011; Levis et al., 2012).</td>
<td>Contiguous USA</td>
<td>CLM4 (Lawrence et al., 2011)</td>
<td>NLDAS (Cosgrove et al., 2003)</td>
<td>1 h</td>
<td>0.125° × 0.125°</td>
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<tr>
<td>Nakayama and Shankman (2013)</td>
<td>Liu (1996, in Chinese; see Liu et al., 2010)</td>
<td>Difference between current soil moisture content and soil moisture at the field capacity.</td>
<td>Changing, Yellow River basins (China)</td>
<td>NICE (Nakayama et al., 2011)</td>
<td>ECMWF (<a href="http://www.ecmwf.int/products/data/">http://www.ecmwf.int/products/data/</a>)</td>
<td>6 h</td>
<td>10 km × 10 km</td>
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<tr>
<td>Voisin et al. (2013)</td>
<td>Crop area projections in Chaturvedi et al. (2013a, b).</td>
<td>Downscaling GCAM model estimations (Wise and Calvin, 2009; Wise et al., 2009a) using methods of Hejazi et al. (2013a), Siebert and Döll (2008) and Hansakasi (2013a, b).</td>
<td>US mid-west</td>
<td>SCLM-MOSART (Lawrence et al., 2011; Li et al., 2013; Tesfa et al., 2014)</td>
<td>CASCade (<a href="http://cascade.usgs.gov">http://cascade.usgs.gov</a>)</td>
<td>1 h</td>
<td>0.125° × 0.125°</td>
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</table>
### Table 2. Representative examples for including global irrigation in large-scale models (offline mode).

<table>
<thead>
<tr>
<th>Reference</th>
<th>Irrigation data</th>
<th>Irrigation demand</th>
<th>Host model</th>
<th>Forcing</th>
<th>Temporal resolution</th>
<th>Spatial resolution</th>
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<tbody>
<tr>
<td>Hanasaki et al. (2006)</td>
<td>Döll and Siebert (2000)</td>
<td>Similar to Döll and Siebert (2002). Reference evaporation is based on FAO Penman Monteith.</td>
<td>TRIP (Oki and Sud, 1998)</td>
<td>ISLSCP-I (Sellers et al., 1996b)</td>
<td>24 h</td>
<td>0.5° × 0.5°</td>
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<tr>
<td>Wisser et al. (2008)</td>
<td>Siebert et al. (2005, 2007); GIAM (Thenkabail et al., 2009)</td>
<td>Similar to Haddeland et al. (2006) using Allen et al. (1998) procedure.</td>
<td>WBM (Vörösmarty et al., 1998)</td>
<td>CRU TS 2.1 (Mitchell and Jones, 2005); NCEP (Kalnay et al., 1996)</td>
<td>24 h</td>
<td>0.5° × 0.5°</td>
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<tr>
<td>Rost et al. (2008, 2009)</td>
<td>Siebert et al. (2007)</td>
<td>Difference between available plant-moisture and an updated Priestley and Taylor (1972) potential evapotranspiration based on potential canopy conductance of carbon and water (Sitch et al., 2003).</td>
<td>LP,jmL (Bondeau et al., 2007)</td>
<td>CRU TS 2.1 (Mitchell and Jones, 2005)</td>
<td>24 h</td>
<td>0.5° × 0.5°</td>
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<tr>
<td>Hanasaki et al. (2008a, b)</td>
<td>Döll and Siebert (2000)</td>
<td>Difference between current and 75 % of field capacity. Irrigation applied 30 days prior to planting. Detailed crop growth representation based on SWIM (Krysanova et al., 1998).</td>
<td>H07 (Hanasaki et al., 2008a, b)</td>
<td>NCEP-DOE (Kanamitsu et al., 2002); GSWP-2 (Zhao and Dirmeyer, 2003)</td>
<td>24 h</td>
<td>1° × 1°</td>
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<tr>
<td>Siebert and Döll (2010)</td>
<td>MIRCA2000 (Portmann et al., 2010)</td>
<td>Difference between actual and crop-dependent reference evapotranspiration computed according to Priestley and Taylor (1972). Crop coefficients obtained from Allen et al. (1998).</td>
<td>GCWM (Siebert and Döll, 2008)</td>
<td>CRU TS 2.1 (Mitchell and Jones, 2005)</td>
<td>24 h</td>
<td>0.08° × 0.08°</td>
</tr>
<tr>
<td>Wada et al. (2011, 2012)</td>
<td>MIRCA2000 (Portmann et al., 2010)</td>
<td>Difference between actual and potential transpiration according to van Beek et al. (2011), using Priestley and Taylor (1972) crop-specific and transpiration (Allen et al., 1998).</td>
<td>PCR-GLOBWB (van Beek et al., 2011)</td>
<td>CRU TS 1.0 (New et al., 1999, 2000)</td>
<td>24 h</td>
<td>0.5° × 0.5°</td>
</tr>
<tr>
<td>Pokhrel et al. (2012)</td>
<td>Siebert et al. (2007)</td>
<td>Procedure of Hanasaki et al. (2008a, b). Crop calendar is based on Potential evapotranspiration (Allen et al., 1998).</td>
<td>MASTIRO (Takata et al., 2003)</td>
<td>Kim et al. (2009); GPC (Rudolf et al., 2005)</td>
<td>6 h</td>
<td>1° × 1°</td>
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<tr>
<td>Wada et al. (2013a)</td>
<td>MIRCA2000 (Portmann et al., 2010)</td>
<td>Constant 50 mm surface water depth for paddy Irrigation until 20 days before harvesting. For non-paddy areas, the difference between current and ideal plant available moisture at field capacity with dynamic root zone.</td>
<td>PCR-GLOBWB (van Beek et al., 2011)</td>
<td>ERA-interim (Dee et al., 2011); MERRA (<a href="http://gmao.gsfc.nasa.gov/merra/">http://gmao.gsfc.nasa.gov/merra/</a>)</td>
<td>24 h</td>
<td>0.5° × 0.5°</td>
</tr>
</tbody>
</table>
Table 3. Representative examples for including irrigation in coupled land-surface models (online mode).

<table>
<thead>
<tr>
<th>Reference</th>
<th>Irrigation data</th>
<th>Irrigation demand</th>
<th>Region</th>
<th>Host LSS</th>
<th>Climate model</th>
<th>Temporal resolution</th>
<th>Spatial resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adegoke et al. (2003)</td>
<td>LandSat (<a href="http://landsat.gsfc.nasa.gov/">http://landsat.gsfc.nasa.gov/</a>)</td>
<td>Target soil moisture deficit (difference between actual and saturated Soil moisture).</td>
<td>High Plains (USA)</td>
<td>LEAF-2 (Walko et al., 2000)</td>
<td>RAMS (Pielke et al., 1992)</td>
<td>30 s nested in 1 min</td>
<td>10 km × 10 km nested in 40 km × 40 km</td>
</tr>
<tr>
<td>Sacks et al. (2009)</td>
<td>FAO-AQUASTAT (<a href="http://www.fao.org/nr/water/aquastat/main/index.stm">http://www.fao.org/nr/water/aquastat/main/index.stm</a>)</td>
<td>AQUASTAT irrigated water uses applied at constant rate when LAI exceeds 80% of the maximum annual value.</td>
<td>Global</td>
<td>CLM3.5 (Oleson et al., 2008)</td>
<td>CAM (Collins et al., 2004, 2006)</td>
<td>20 min</td>
<td>2.8° × 2.8°</td>
</tr>
<tr>
<td>Sorooshian et al. (2011)</td>
<td>CIMIS-MODIS (<a href="http://www.cimis.water.ca.gov/cimis">http://www.cimis.water.ca.gov/cimis</a>)</td>
<td>Target soil moisture deficit (Irrigation starts when the soil moisture drops below a maximum depletion threshold beyond which the plant in stressed (a percentage of field capacity, depending on the crop) and continues to field capacity).</td>
<td>California Central Valley (USA)</td>
<td>Noah (Ek et al., 2003)</td>
<td>NCAR-MM5 (Chen and Dudhia, 2001a, b)</td>
<td>30 min</td>
<td>4 km × 4 km 12 km × 12 km 36 km × 36 km</td>
</tr>
<tr>
<td>Harding and Snyder (2012a, b)</td>
<td>MODIS (Friedli et al., 2002; Ozdogan and Gutman, 2008; NASS, USDA, 2002)</td>
<td>Target soil moisture deficit (difference between actual and saturated soil moisture at depth of 2 m).</td>
<td>Great Plains (USA)</td>
<td>Noah (Ek et al., 2003)</td>
<td>WRF (Skamarock et al., 2005)</td>
<td>30 s and 25 s</td>
<td>10 km × 10 km</td>
</tr>
<tr>
<td>Qian et al. (2013)</td>
<td>MODIS (Ozdogan and Gutman, 2008; Ozdogan et al., 2010)</td>
<td>Similar to Sorooshian et al. (2011). Based on Ozdogan et al. (2010), moisture threshold is fixed at 50% of filed capacity. Roots grow based on the greenness index.</td>
<td>Southern Great Plains (USA)</td>
<td>Noah (Ek et al., 2003)</td>
<td>WRF (Skamarock et al., 2005)</td>
<td>3 h</td>
<td>12 km × 12 km</td>
</tr>
</tbody>
</table>
Table 4. Representative examples for calculating grid-based non-irrigative demands using downscaling coarse scale estimates.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Estimated demand</th>
<th>Downscaling procedure</th>
<th>Data support</th>
<th>Targeted resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alcamo et al. (2003)</td>
<td>Domestic</td>
<td>Distributing country-level withdrawals based on population, ratio of rural to urban population (constant for each country) and percentage of population with access to drinking water.</td>
<td>Population (van Woerden et al., 1995); Access to drinking water (WRI, 1998)</td>
<td>0.5° × 0.5° (Global)</td>
</tr>
<tr>
<td></td>
<td>Industrial</td>
<td>Downscaling county-wide industrial withdrawals based on proportion of urban population.</td>
<td>Population (van Woerden et al., 1995)</td>
<td></td>
</tr>
<tr>
<td>Vassolo and Döll (2005)</td>
<td>Thermoelectric</td>
<td>Calculating the gridded data for power production based on downsampling global estimates. Allocating constant flow to each unit of production according to type of cooling system.</td>
<td>World Electric Power Plants Data Set (<a href="http://www.platts.com">http://www.platts.com</a>).</td>
<td>0.5° × 0.5° (Global)</td>
</tr>
<tr>
<td></td>
<td>Manufacturing</td>
<td>Estimating country-wide sectoral production volumes along with water intensity for each unit of production in each sector. Downscaling total demand to the grid-scale based on city nighttime light.</td>
<td>Industrial production volumes (UN, 1997; CIA, 2001); Sectoral intensity (Shiklomanov, 2000; WRI, 2000); Night city light pollution (US Air Force, <a href="http://www.ngdc.noaa.gov/dmsp">http://www.ngdc.noaa.gov/dmsp</a>)</td>
<td></td>
</tr>
<tr>
<td>Hanaskai et al. (2008a)</td>
<td>Domestic and industrial</td>
<td>Countywide data downscaled to grid scale by weighting population and national boundary information, further converted to water consumption estimates.</td>
<td>AQUASTAT countrywide withdrawals, Population and national boundaries (CIAT, 2005); ratio of consumption to withdrawal (Shiklomanov, 2000).</td>
<td>1° × 1° (Global)</td>
</tr>
<tr>
<td>Hejazi et al. (2013b)</td>
<td>Municipal and industrial</td>
<td>Demand estimates of GCAM model (<a href="http://wiki.umd.edu/gcam">http://wiki.umd.edu/gcam</a>) downscaled as a function of population. Population density assumed static in time.</td>
<td>Global population density data based on WWDR-II and methodology of Wada et al. (2011, 2013a)</td>
<td>0.5° × 0.5° (Global)</td>
</tr>
</tbody>
</table>
Table 5. Representative examples for disaggregating annual non-irrigative demand into monthly estimates.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Estimated demand</th>
<th>Disaggregation procedure</th>
<th>Data support</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voisin et al. (2013)</td>
<td>Electrical</td>
<td>Dividing electrical use into industry, transportation and building sectors. Assuming uniform distribution for industry and transportation uses and capturing the monthly fluctuations in building use based on heating/cooling degree days.</td>
<td>CASCaDE (<a href="http://cascade.wr.usgs.gov">http://cascade.wr.usgs.gov</a>)</td>
</tr>
</tbody>
</table>

References


Voisin et al. (2013) Electrical Dividing electrical use into industry, transportation and building sectors. Assuming uniform distribution for industry and transportation uses and capturing the monthly fluctuations in building use based on heating/cooling degree days. CASCaDE (http://cascade.wr.usgs.gov)
Table 6. Representative examples for projection of non-irrigative water demands using socio-economic variables.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Simulated demands</th>
<th>Simulation procedure</th>
<th>Temporal resolution</th>
<th>Spatial resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alcamo et al. (2003a)</td>
<td>Domestic and industrial</td>
<td>Explicit simulation of change in industrial and domestic withdrawal as functions of usage intensity and technological change. Usage intensities are functions of GDP.</td>
<td>Annual</td>
<td>Countrywide</td>
</tr>
<tr>
<td>Strzepek et al. (2012b)</td>
<td>Municipal and industrial</td>
<td>Explicit simulation of change in municipal water use as a function of population and per capita income. Industrial water use considered as a function of water use per capita and GDP considering growth rate and climatic and water availability factors.</td>
<td>Annual</td>
<td>Assessment sub-regions (global)</td>
</tr>
<tr>
<td>Davies et al. (2013)</td>
<td>Electrical</td>
<td>Implicit simulation – changes in regional cooling system shares estimated based on shift from wet to dry cooling technologies. Reductions in water withdrawal and consumptions estimated based on level of technological change.</td>
<td>Annual</td>
<td>Geopolitical regions (global)</td>
</tr>
<tr>
<td>Hanasaki et al. (2013a)</td>
<td>Industrial and municipal</td>
<td>Explicit simulation of industrial withdrawal as a function of electricity production and water intensity which decreases linearly in time. Municipal water use calculated as a function of population and change in municipal intensity, varying based on GDP.</td>
<td>Five year interval</td>
<td>Countrywide</td>
</tr>
<tr>
<td>Blanc et al. (2013)</td>
<td>Electrical, domestic, industrial and mining</td>
<td>Electrical demand projected implicitly using ReEDS (Short et al., 2009) and integration with USREP model (Rausch and Mowers, 2013). Water withdrawal and consumption to meet electrical demand estimated using Strzepek et al. (2012a). Other demands categorized into three groups: public supply, self-supply and mining supply and simulated explicitly. Public supply considered as a function of population and GDP per capita. Self-supply considered as function of sectoral GDP. Mining supply considered as a function of mining's GDP.</td>
<td>Annual</td>
<td>Assessment sub-regions (US)</td>
</tr>
<tr>
<td>Hejazi et al. (2013a)</td>
<td>Municipal</td>
<td>Withdrawal per capita explicitly determined as a function of GDP per capita, water price and technological development. Technological development considered as a function of operational efficiency, which further determines extent of water use.</td>
<td>Annual</td>
<td>Geopolitical regions (global)</td>
</tr>
<tr>
<td>Hejazi et al. (2013b,d)</td>
<td>Industrial</td>
<td>Manufacturing water demand is explicitly simulated based on population and GDP. Water demand for primary energy scaled by amount of fuel production and water demand for secondary energy.</td>
<td>Annual</td>
<td>Geopolitical regions (global)</td>
</tr>
<tr>
<td>Wada et al. (2013a)</td>
<td>Industrial and municipal</td>
<td>Industrial and municipal withdrawal taken from WWDR-II dataset (Shiklomanov, 1997; Vörösmarty et al., 2005) and backcasted explicitly using economic and technological proxies. Net municipal water demand calculated as a function of fraction of urban to total population and recycling ratio.</td>
<td>Annual</td>
<td>Countrywide (global)</td>
</tr>
</tbody>
</table>