Abstract

Hydrological extremes, in the form of droughts and floods, have huge impacts on a wide range of sectors including, most prominently, water availability, food security, and energy production, among others. The expectation of heightened drought and flood risk under climate change, coupled with burgeoning population growth and rapid economic development, poses unprecedented challenges for societies to boost resilience to these natural hazards, mitigate their extreme impact, and develop effective and actionable solutions towards sustainable development. The objective of this dissertation is to advance our understanding of these hydroclimate risks and their societal impact in a changing environment through a coupled human and natural system (CHANS).

Chapter 2 and 3 diagnose the changing characteristics of droughts and floods from a climate perspective. Chapter 2 compiles the first Global Drought and Flood Catalogue (GDFC) to provide long-term, consistent and robust estimates of drought and flood hazards. This state-of-the-art catalogue acts as a basis for us to understand current risks and how they may change in the future. Based on GDFC, Chapter 3 develops a novel statistical framework to examine the often overlooked but important risk of coincident droughts and floods.

Chapter 4 and 5 focus on the human dimension of the CHANS. Using a physical framework, Chapter 4 conducts attribution analysis to disentangle how climate variability and human interventions (e.g., water use, irrigation, reservoir operation) intensify or mitigate the recent California drought. Taking a further step, Chapter 5 aims to incorporate human behaviors and decisions – which are currently unrepresented – into a large-scale hydrological model to investigate how individuals’ decisions and their behavioral heterogeneity affect the dynamics of the CHANS. Chapter 6 develops a hydro-economic model to identify possible solutions and optimal development pathways towards better management of water-related trade-offs (i.e., energy produc-
tion and irrigation in California) and environmental sustainability (i.e., groundwater depletion).

The integrated modeling platform developed in this thesis can be used to balance trade-offs among conflicting objectives and quantify the potential space for improving current water management strategies, especially under severe hydrological extremes.
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To my mother.
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Chapter 1

Introduction

1.1 Background and Motivation

Unprecedented droughts and extreme floods repeatedly grab the headlines. In April 2018, Cape Town announced “Day Zero” after a three-year record breaking drought over a century starting from 2015 \cite{Maxmen2018}. The 2017 drought in Kenya forced the country to declare a national emergency, as more than 2.5 million people lacked access to clean water and faced food insecurity \cite{IFRC2018}. In the western coast of the United States, California has been plagued by a multi-year (2011-2016) drought, which caused significant environmental issues (e.g., groundwater depletion, \cite{Famighetti2014} and significantly impacted food \cite{Howitt2014} and energy \cite{Gleick2017} production. On the other extreme side, severe floods hit southwestern Japan and the Indian state of Kerala in the summer of 2018, left more than 200 and 470 people dead, respectively \cite{Witze2018}. On July 21, 2012, Beijing experienced the largest urban flooding event over the past 60 years, which killed 79 people and caused nearly $2 billion in damage. Situation could get even worse when overlapping hazards occur in the same region and within a short interval. For instance, recurrent droughts and floods chronically punctuate Sahel region \cite{IFRC2018}, magnify the
impact of individual flood and drought events, and further increase the vulnerability of populations and ecosystems.

Although there is clear and growing evidence that climate change has likely increased the frequency of these extreme events (e.g., Field, 2012; Hirabayashi et al., 2013; Herring et al., 2015), a comprehensive understanding of drought and flood risk is still lacking, which constrains the potential improvement of the hydrological predictability and therefore makes the disaster preparedness and risk management extremely challenging. Part of the reasons is due to the lack of long-term records, their geographical inconsistencies as well as data uncertainties coming from different products (Trenberth et al., 2014), which make the calculation of extreme statistics less robust. Without improved long-term datasets, we will remain unable to answer the most basic questions regarding trends and variability of these extremes, let alone to tackle current challenges and enhance future resilience.

Moreover, earth systems are inherently linked with human dynamics. On one hand, climate and landscape have been dramatically altered by human activities (e.g., greenhouse gas emissions, engineered water system), which can either compound or inhibit the risk of hydrological extremes. On the other hand, humans are adapting to the changing environment through behavioral changes. A complete understanding of the changing characteristics of hydrological extremes and their associated impact can only be achieved through a coupled human-natural system. Take the recent Cape Town drought as an example. We cannot blame climate change to bear all responsibilities for this record-breaking water crisis in South Africa’s history. It is the increased human water use, poor water management, and ineffective environmental policy that are behind this and many other water shortages (e.g., Muller, 2018). This also holds true for floods occurred in the past five centuries on lower Mississippi, where human engineering (e.g., artificial cut-offs and levee construction) for flood control unintentionally exacerbate the peak flow and make larger floods more de-
structive (Munoz et al., 2018). A better representation of human interventions (e.g., water use, reservoir regulation) in hydrological models is therefore vital to conduct attribution analysis to disentangle how climate variability and human-water interactions influence droughts and floods at multiple scales, as well as to inform possible future changes. Although significant progress has been made in the past decades to represent human-water interface in hydrological models (e.g., Nazemi and Wheater, 2015a,b; Pokhrel et al., 2016; Wada et al., 2017), current modeling frameworks do not explicitly consider the dynamic feedbacks between local human behaviors/decisions and the natural hydrological system, which is not realistic to formulate effective policies for the mitigation and adaptation of natural disasters. A promising avenue to bridge the gap is to apply the agent-based modeling approach and couple it with the highly “disaggregated” process-based hydrological model so that we can have a balanced representation of social, environmental and economic factors. This integrated model also has the advantage to mimic the human-natural system in a probabilistic way by performing different sets of scenarios, which will be useful to policymakers to explore the effectiveness and robustness of different water management strategies to cope with climate change.

Entered into the Anthropocene (Crutzen, 2002; Lewis and Maslin, 2015; Waters et al., 2016), human interventions bring forth a plethora of unprecedented challenges to cope with global issues, such as water scarcity (Vörösmarty et al., 2000; Oki and Kanae, 2006; Kummu et al., 2010; Wada et al., 2011a, 2016a), food security (Godfray et al., 2010; FAO, 2016), and energy security (DOE, 2014). Leveraging the risk amid these challenges under the global change (e.g., climate change in the biogeophysical Earth and social evolution in the World of human societies, Donges et al., 2018) requires an improved and comprehensive understanding of how coupled human-natural systems operate (Sivapalan and Blöschl, 2015; Liu et al., 2007a,b) and how development interventions can elevate these systems for sustainable livelihoods. Given the
fact that water, food, and energy sectors are closely interwoven, collectively achieving the Sustainable Development Goals (SDGs) \cite{UN2015} by 2030 is extremely difficult, as trade-offs exist especially when certain resources are limited. Moreover, policies targeted for one sector may be conflicted with another, further amplifying the difficulty to attain SDGs simultaneously \cite[e.g.,][]{Gao2017, Bryan2018}.

So far, there still exist large knowledge gaps in terms of how human activities \cite[e.g., large-scale water management, individual behaviors, and decisions]{} interact with the natural system across multiple sectors. Lack of such understanding prevents us to create and promote practical solutions to address the above-mentioned nexus security issues. It is therefore imperative to develop an integrated modeling and analysis framework across disciplines and scales to advance our understanding of the overlooked multi-sectoral dynamics. This will allow policymakers to identify portfolios of interventions that minimize trade-offs and maximize positive interactions in space and time towards environmental sustainability.

### 1.2 Dissertation Goals and Overview

This dissertation studies hydrological extremes, in the form of droughts and floods, from natural, human and policy dimensions. The goals are: (1) to advance our understanding of the changing characteristics of hydrological extremes from the climate perspective and under human interventions, (2) to examine their cascading and compounding impacts in a connected, globalizing world using the nexus approach considering the innate interdependencies among water, food and energy, and (3) to discuss potential policy instruments that can increase disaster resilience and environmental sustainability. To achieve these goals, Chapter \ref{ch2} develops a long-term state-of-the-art drought and flood catalogue to quantify and diagnose likely trends and variability of these two extremes. Based on this database, Chapter \ref{ch3} develops a novel statistical
framework to explore the intersection between droughts and floods with a focus on their compounding occurrence. Chapter 4 and 5 bring human dimensions into consideration through a case study of recent California drought. Chapter 6 discusses how to implement nexus approaches to simultaneously examine the trade-offs and synergies among the interconnected water, food, and energy sectors, especially under water scarcity. The last chapter synthesizes the findings and lays forward a path to better manage water-food-energy trilemma in the Anthropocene.

1.2.1 Natural Influences on Drought and Flood Occurrence

• Chapter 2 presents the development of the first global drought and flood catalogue for the 20th and early 21st centuries (1950-2016) by merging the latest versions of *in situ* and remote-sensing datasets with state-of-the-art land surface and hydrodynamic modeling to provide a continuous and consistent dataset of the terrestrial water cycle and its extremes. This catalogue consists of an unprecedented level of detailed information of drought and flood events, regarding their regional spatial-temporal characteristics (i.e., duration, spatial extent, severity) and global risk maps with different return periods. Given the recent impacts of droughts and floods and the expectation for large changes in the future, there is an urgent need to provide improved estimates of past events globally. This catalogue will form the basis for the analysis of the changing risk of droughts and floods that will underscore national and international climate change assessments and will form a key dataset for other studies of climate change and the evaluation of climate models.

• Chapter 3 develops a novel statistical framework to quantify the spatial hotspots and temporal dynamics of the “drought-flood seesaw”, which is defined as the phenomenon of floods following droughts. The seesaw magnifies the impact of individual flood and drought events, yet has not been systematically evaluated, especially at the global scale. An event coincidence analysis is applied to explore
the aggregated seesaw behaviors based on improved and consistent land surface model simulations for the past seven decades (1950-2016). This approach could have practical value as it can inform policy-makers and local stakeholders on the often overlooked but important risk of coincident drought and flood, and therefore help develop more effective water and agricultural management and mitigation plans.

1.2.2 Human Dimensions Come into Play

- Chapter 4 develops a physical framework to conduct attribution analysis to disentangle how climate variability and human interventions (e.g., water use, irrigation, reservoir operation) influence drought occurrence and intensity in the case of recent California drought. The contribution of human water management to the intensification or mitigation of hydrological drought is analyzed using the PCR-GLOBWB hydrological model at 0.5° resolution for the period 1979-2014. This study finds that human activities have increased the occurrence and intensity of hydrological drought in California, especially in the Central Valley. It also underscores the need to take human water management into account for hydrological drought analysis.

- Chapter 5 focuses on the behavioral dimensions of the coupled human-natural system. A coupled hydrological (Community Water Model, CWatM) and agent-based model (ABM) is developed and applied to California’s agricultural sector. Two types of agents are considered, which are (a group of) farmers and government agencies, and assume that their corresponding objectives are to maximize the net crop profit and to maintain sufficient water supply. Through a simulation-based optimization framework, farmers’ daily irrigation behaviors, seasonal choices of crop types and irrigated area, as well as their risk perception to drought, are dynamically incorporated into CWatM. Findings in this chapter demonstrate the potential of using CWatM-ABM as a policy tool to balance trade-offs among conflicting ob-
jectives, design efficient water institutions as well as quantify the potential space for improving the current water management strategies, especially under severe hydrological extremes.

1.2.3 Nexus Approaches to Manage Trade-offs

- Chapter 6 reports on a novel approach in which a macro-scale hydrological model together with the trade-off frontier framework is developed to identify optimal hydropower and groundwater trade-offs under various renewable (i.e., solar and wind energy, SWE) penetration levels, for the case study of the recent 5-year California drought. This chapter identifies development pathways that optimize the economic value of water in competition for energy and food production while ensuring sustainable use of groundwater. This is the first study to quantify the added benefits of SWE in enhancing resilience to hydroclimate shocks, such as droughts, beyond its traditional role of improving air quality and mitigating greenhouse gas emissions. The undiscovered and under-appreciated social value of SWE can help develop impact pathways into policy support and lead to positive practical changes for sustainable water and food security.

1.3 Publications

The core chapters of this dissertation (Chapters 2-6) have been published or (will be) submitted for publication. Below are the full references:

• Chapter 3: **He, X.**, and J. Sheffield, Lagged Compound Occurrence of Droughts and Floods Globally over the Past Seven Decades (in revision), *Geophysical Research Letters*.


Other contributing publications include:


- **He, X.**, and J. Sheffield, Integrated Approaches to Understanding and Reducing Drought Impact on Food Security Across Scales: An Overview (to be submitted), *Current Opinion in Environmental Sustainability*.


Chapter 2

A Global Drought and Flood Catalogue for the Past Seven Decades (1950-2016)

2.1 Introduction

Droughts and floods are two end members of the hydrological spectrum, posing a profound threat to societies and are increasingly making global headlines. Historically, droughts and floods have cost US$596 billion dollars in damages in the early 21st century (2000-2017) (EM-DAT 2018) and have affected more than 3.4 billion people during 1995-2015 (UNISDR 2015). These extremes also have significant impacts on ecosystems (e.g., Palmer et al. 2009; Mora et al. 2018) and could cause humanitarian crises (e.g., migration and conflicts in Syria, Gleick 2014). Looking into the future, these impacts may increase with climate change and economic development. Evidence from climate model projections shows that climate change will lead to increased frequency and intensity of droughts (e.g., Sheffield and Wood 2008a; Orlowsky and Seneviratne 2013; Trenberth et al. 2014) and floods (e.g., Milly et al. 2014).
This poses large challenges for us to develop mitigation and adaptation strategies to cope with climate change as defined in recent global (IPCC, 2018), continental (e.g., the Fourth National Climate Assessment, Wuebbles et al., 2017) and regional (e.g., California’s Fourth Climate Change Assessment) assessment reports.

To this end, there is an urgent need to develop a global catalogue of droughts and floods to gain a coherent picture of how droughts and floods have changed in the past, which acts as a basis for understanding current risk and how it may change in the future. The catalogue should have long-term data records, so that risk quantification is more robust than current existing short-term global drought (e.g., Heim Jr and Brewer, 2012), flood (e.g., Herold et al., 2011; Brakenridge, 2019) and inundation (Pappenberger et al., 2012) products. It also needs to be spatially and temporally continuous and consistent, so that risk can be quantified globally, not only for developed regions (e.g., see recent US flood events compiled by Shen et al. (2017); European drought catalogue by Lloyd-Hughes et al. (2009)), but also for data-poor regions (such as Africa). Moreover, drought and flood risk should be quantified in a consistent way to ensure the comparability between the two (Quesada-Montano et al., 2018). As droughts and floods have interlinked characteristics (e.g., severity, area, duration), co-occurrence of them could contribute to even more extreme and disproportionate impact. Therefore, dependence structures between the contributing variables should be well represented to avoid the underestimation of the compounding impact (Zscheischler and Seneviratne, 2017; Moftakhari et al., 2017; Hao et al., 2018). In fact, the multivariate risk assessment framework has been increasingly recommended by several international guidelines, including the European Parliament and The Council (The European Parliament and The Council, 2007).

Only until recently, the above challenges and concerns can be tackled. This includes recent development in satellite-based measurements (e.g., Lettenmaier et al., 2002; Pall et al., 2011; Field, 2012; Hirabayashi et al., 2013; Arnell and Gosling, 2016).
advances in large-scale land surface and hydrodynamic modelling (e.g., Bierkens 2015) as well as improved risk quantification and event identification approaches (Andreadis et al. 2005). Leveraging on these, this study aims at developing the first global catalogue of drought and flood events: Global Drought and Flood Catalogue (GDFC). The GDFC is generated based on high resolution (0.25°), long-term (1950-2016) and improved land surface simulations driven by quality-controlled and consistent meteorological forcings. Our state-of-the-art catalogue complements existing hazard databases from both the univariate and multivariate perspective, ensures a global scale and more robust quantifications of hazards, and could also be used as ‘benchmark’ to evaluate other datasets and future changes in droughts and floods.

2.2 Overview of Approach

The GDFC builds upon legacy systems developed previously at global (Sheffield and Wood 2007, 2008b) and regional (Sheffield et al. 2014) scales, making use of existing models and datasets, but has been enhanced in the following aspects to provide better estimates of the global terrestrial hydrological cycle and its extremes (Figure 2.1). We first extend the existing long-term global meteorological dataset (Princeton Global Forcings, PGF, Sheffield et al. 2006) from 1950 to near present (2016), which is also enhanced in the spatial resolution (0.25°) through statistical downscaling, and corrected for temporal and spatial inconsistencies (see details in Appendix A.1). This new version (v3) of the PGF is then utilized to drive an updated version of the Variable Infiltration Capacity (VIC) land surface model (see Appendix A.2 for details) to get an improved estimate of the soil moisture and runoff variability that is key to understanding changes in large-scale drought and flood risk. We also implement a newly developed global routing and hydrodynamic model CaMa-Flood.
(Catchment-based Macro-scale Floodplain model) to explicitly represent flood stage (e.g., inundation area and water level) in addition to river discharge for each grid cell (see Appendix A.3 for model details and Figure A.1 for streamflow validation results). Related hydrological variables (e.g., 3-month accumulative precipitation from PGFv3 and monthly soil moisture simulated from VIC) are then transformed to standardized indices (see Appendix A.4) to identify drought and flood events at the pixel level based on the run theory (Appendix A.5). Given the dynamic nature of hydrologic extremes, it is important to characterize the joint spatial-temporal evolution of droughts and floods simultaneously, for instance, how they propagate, merge (two events merging into one) or break up (an event splitting into two or more events separated in space) through time and space. We therefore utilize the Severity-Area-Duration (SAD) clustering algorithm (Appendix A.6) to identify spatially contiguous drought and flood events over six continents (excludes Antarctica) and examine the stationarity of their evolution through the estimation of the time-varying frequency (see Appendix A.7 for details). Characteristics (i.e., frequency, spatial extent, severity) of drought and flood events are synthesized into a catalogue with a particular focus on characterizing the long-term variability in risk from both univariate and multivariate perspectives (Appendix A.8). We establish a publicly-accessible internet data portal and develop an online web interface to enable quick discovery of relevant resources, including the continental drought and flood inventory, drought and flood risk maps, and the underlying global meteorology and hydrological fluxes and states at 0.25° and daily and monthly resolution.
HYDROLOGIC DATA

1. Generating long-term and consistent hydrologic datasets using state-of-the-art physically-based hydrologic modeling platform which includes hybrid meteorological forcings (PGF), improved land surface modeling (VIC), and enhanced hydrodynamic model (CaMa-Flood).

2. Robust quantification of drought and flood risk based on a suite of statistical post-processing procedures, including the statistical transformation of hydrologic data into standardized indices for drought and flood identification, spatial and temporal clustering analysis, and multivariate dependence modeling.

3. Developing a meta-database to deliver products and catalogues (e.g., drought and flood inventory at the continental scale, global risk maps for different types of hydrological extremes, and an online web interface) which enables dissemination of knowledge and data to the wider scientific community.

Figure 2.1: Schematic of the overall framework illustrating three major steps to develop the Global Drought and Flood Catalogue (GDFC).
2.3 Results

2.3.1 Climatology of Drought and Flood Frequency

We use the run theory to estimate the frequency of drought and flood events with different duration categories (short and medium term) and generate both agricultural-type (based on SMPct, Figure 2.2) and meteorological-type (based on SPI3, Figure A.2) global hazard maps (represented by return period). Overall, the spatial distribution of event occurrence is symmetrical between droughts and floods, albeit with slight local differences, indicating a general equal odd of occurrence of these two extremes over a long period (~ seven decades), which is consistent with previous regional studies (e.g., [Bhalme and Mooley 1980]). This pattern is within our expectation as event indices have been standardized and the thresholds which define floods/droughts are symmetrical. Differences will occur spatially and between drought and flood because of differences in the temporal characteristics of individual events. We find that short-duration agricultural-type droughts and floods occur more frequently than medium-duration events over North America, Europe, Central Asia, Southeast China, the northwestern part of South America, southern Africa, and central Australia, where climate is more variable. In contrast, high-frequency medium-duration droughts and floods based on SMPct are mainly found over high latitudes, including northern Canada and Siberia, due to persistent anomalies of soil moisture in cold seasons because of freezing temperatures. These medium-duration agricultural extremes also have high frequency over northeastern and central China, Sahel and western Andes. Such spatial heterogeneity of event frequency is less captured in SPI3-based analysis, highlighting the important role and necessity of accounting for land surface processes in drought and flood hazard assessment.
2.3.2 Stationarity of Spatially Contiguous Drought and Flood Frequency

Acknowledging the dynamic nature of droughts and floods and their interrelated characteristics (e.g., severity, area and duration), it is necessary to investigate their variation and trends at the event-level. We count the occurrence of spatially contiguous droughts and floods using the SAD technique and examine the stationarity of event frequency based on time-varying occurrence rate and associated long-term trends through a nonparametric Gaussian kernel (Figure 2.3). Globally, there are 453/476 short-duration meteorological droughts/floods with a contiguous area larger than 375000 km$^2$ from 1950 to 2016. Fewer (200) medium-duration events are depicted, indicating that prolonged hydrological extremes have less persistence and tend to break into short-term events during their evolution. This is also evidenced by the SMPct-based analysis with a reduced number (179) of medium-duration droughts and consequently an increased number of short-term droughts (570). Among the six
continents, Asia has the largest number of occurrence of both short- and medium-duration droughts and floods, followed by North America, whereas Oceania has the smallest number. This is mainly due to the domain size.

For meteorological extremes (based on SPI3), globally the frequency of short-term droughts has decreased significantly \((p < 0.01)\), from more than 8 events per year in the 1950s to roughly 6 events per year in the 1990s, and then stabilize afterward. There is no statistically significant trend in short-term flood frequency over the whole study period, but it increases slightly in the first half of the study period and decreases dramatically in the second half, with peak occurrence rate around 8 times \(\text{yr}^{-1}\) during the 1980s. Such an out-of-phase relationship in the long-term trend between short-term droughts and floods is also shown in other continents, including North America and Asia, although the decadal fluctuation in event frequency has been dampened due to the large size of the region. Short-term meteorological droughts occur less frequently \((p < 0.05)\) in recent decades over South America, which is consistent with previous studies. In contrast, short-term meteorological floods have a slightly increasing trend over Oceania, although with a reduced degree of statistical significance \((p < 0.1)\). For medium-duration events, droughts and floods occur roughly half as frequently as short-term events and with reduced decadal variability.

We observe that the occurrence of medium-duration floods has become more frequent in recent decades over Europe and South America \((p < 0.05)\), whereas medium-duration droughts occur more frequently over Asia \((p < 0.05)\). Over Africa, the robust increasing trend of medium-duration drought occurrence is coincident with the decreased frequency in medium-duration floods.

Soil-moisture based analysis supplements pure-precipitation based analysis and illustrates a complementary picture of drought and flood occurrence. Compared to the SPI3-based analysis, frequency estimation using SMPct shows an overall reduced decadal variability and a more synchronous and coherent temporal evolution
between droughts and floods, as reflected at both global and regional scales. However, over Africa and Oceania, we find opposite temporal trends between short-duration droughts and floods, with robust decreasing trend in one extreme contemporaneous with robust increasing frequency of the other. Such patterns over Africa show the vulnerability of this region to both dry and wet extremes, due to the high variability in soil moisture that is partly influenced by the ITCZ seasonal footprint (Sheffield and Wood, 2007). Over Oceania, changes in large-scale circulation patterns lead to a wetting trend in soil moisture, resulting in more frequent floods and less frequent droughts. We also find that, at the global scale, the frequency of short-duration extremes has significantly higher magnitude estimated from SMPct compared to that estimated from SPI3, which is mainly attributed to the difference in Asia and North America. Regardless of what event index is used, trend estimation is consistent between SPI3 and SMPct for medium-duration droughts over North America, medium-duration floods over North America and Africa, and short-duration floods over Oceania. This highlights the dominant role of changing precipitation that leads to more frequent meteorological extremes and can translate to agricultural extremes through complicated hydrologic processes. For regions lacking such consistency between SPI3 and SMPct, the complexity of hydrologic processes and how they respond to long-term changes in precipitation needs further investigation to improve our understanding of drought and flood occurrence. In summary, the detected trends of drought and flood frequency are geographically variable and may not be consistent or statistically robust depending on what index is used. Frequency differences between short- and medium-duration extremes highlight the need to improve our understanding of how prolonged events persist or break up under changing atmospheric conditions and changing hydrological processes.
Time Varying Drought & Flood Frequency

Figure 2.3: Time-varying occurrence rates (yr$^{-1}$, bold lines) and 90% confidence bands (shaded area) for spatially contiguous short- ($D_{4-6}$, 4-to-6 months) and medium-duration ($D_{7-12}$, 7-to-12 months) drought (red color) and flood (blue color) events during 1950-2016 identified through the SAD clustering approach using the three-month Standardized Precipitation Index (SPI3, left panel) and soil moisture percentile (SMPct, right panel). Upward/Downward arrow in each panel indicates statistically significant increasing/decreasing trend based on different levels of significance (represented by different numbers of stars). We divide the global land surface (excluding Greenland, Antarctica) into six continents (i.e., North America, Europe, South America, Asia, Africa and Oceania) based on [Sheffield et al. (2009)] and masked out extremely dry regions with annual rainfall less than 100 mm.
2.3.3 Continental Inventory of Drought and Flood Episodes

SAD Analysis of Continental Droughts and Floods

Figure 2.4 show all agricultural drought and flood events with a 3-month duration. For small area extent, SAD curves overlap with each other. Different events tend to have similar severity (these are usually localized events). As fraction area increases, the SAD curves start to divaricate, which is due to the increased spatial variability of soil moisture as drought expands to a larger area. Out of the six continents, droughts and floods identified in Asia generally have smaller fractions of spatial coverage (less than 20%), but the absolute area could be huge given the large domain size. In contrast, extremes occurred in Oceania usually cover a much larger area (e.g., the maximum spatial coverage can be more than 80% of the total area). The reduced number of occurrences in this region is largely due to the small domain size, and the SAD curves are more dispersed compared to other regions. These findings also hold true for SPI3-based analysis (Figure A.3). As expected, longer duration events (6- and 9-month) are rarer, that is why we observe a reduced number of event occurrences (fewer lines in Figure A.4-A.7). However, these longer duration events probably will not stay locally, instead, they will travel and propagate to other places and therefore becomes more spatially extensive (e.g., maximum fraction area in Figure A.6 and A.7 is larger than that in Figure 2.4 and A.3).

To further explore the relationship between droughts and floods, we slice the 2-D SAD curves (Figure 2.4 for example) within a certain window (horizontal or vertical) and calculate the CDF (cumulative distribution function) conditioned upon area and severity for both SMPct- (Figure 2.5 A.8-A.9) and SPI3-based index (Figure A.10-A.12). We group events into large (fraction area ≥ 30%) and small (fraction area ≤ 10%) area as well as high (≥ 0.9) and low (≤ 0.8) severity categories. We conduct the two-sample Kolmogorov-Smirnov (K-S) test to examine whether the CDF between
droughts and floods is statistically significant different. In North America, results show that large area floods are less severe than large area droughts, which holds true for both SMPct- and SPI3-based analysis. However, only SMPct-based results show that smaller area floods are more severe. Moreover, the SMPct-based analysis indicates that low severity floods are usually larger than low severity droughts. However, from the meteorological perspective (based on SPI3), floods usually have smaller spatial extent than droughts (except for the low severity floods with 3-month duration).

In Europe, short-duration floods tend to be less severe than short-duration droughts (e.g., Figure A.10). For longer duration events (i.e., 9-month), large agricultural floods (Figure A.9) and small meteorological floods (Figure A.12) tend to be more severe than droughts. In terms of event size, floods are generally smaller than droughts in this region, but the significance level of the difference varies with duration and severity category. In Asia, meteorological floods are more severe but slightly smaller compared to meteorological droughts for all durations (Figure A.10[A.12]). For agricultural extremes, statistical differences between droughts and floods are only evident.
for 9-month duration event (Figure A.9). For such prolonged events, floods tend to be more spatially extensive and severe than droughts. Floods occurred in South America and Africa are less severe than droughts. With a few exceptions (e.g., 3-month low severity agricultural extremes and 6-month meteorological extremes), floods also tend to cover smaller areas than droughts. Oceania floods extend to larger areas than droughts and also tend to be more severe.

Figure 2.5: Comparison of the empirical cumulative distribution function (CDF) between the 3-month droughts and floods conditioned on area (left panel) and severity (right panel) across six continents using SMPct as the event index. The two-sample Kolmogorov-Smirnov (K-S) test is performed for each pair to examine whether the differences in CDF between droughts and floods are statistically significant. Number of stars represents the level of significance.

Among all the drought and flood episodes, the top five events ranked by duration and spatial extent are summarized in Table 2.1 for each continent. For agricultural extremes, North America has the longest duration (97 months) drought lasting from June 1951 to June 1959, which also turns out to be the most spatially extensive one with peak extent covering 83.2% of the total area. For floods, the top two longest episodes occurred in Asia (i.e., 81 months from 1965 to 1972 and 61 months from 1959 to 1964). The most spatially extensive episode is found in Oceania from April 1973 to November 1974 with the highest coverage up to 92.4%, which also has the longest
duration (20 months) over Oceania. For meteorological extremes, droughts with the longest duration again occur over North America with a similar timing (in the 1950s) compared to the SMPct-based results, but with a much shorter duration (35 months). Longer duration floods are mainly found in Asia during more recent decades (after 2000) compared to those long-lasting episodes occurring in earlier periods (from the 1950s to 1970s) as detected from SMPct. Out of the six continents, Oceania has the largest meteorological droughts and floods, which also tend to cover a larger area than agricultural extremes.

**SAD Envelope Curves of Continental Droughts and Floods**

Based on all individual SAD curves (e.g., Figure 2.4 and A.3, A.7), we extract the maximum bound of severities for a given areal fraction to form a set of SAD envelope curves with different durations (Figure 2.6 for droughts and Figure 2.7 for floods based on SMPct). These envelope curves allow us to construct a continental profile of the most severe droughts and floods. We find that, for prolonged (i.e., 9-month duration) events, severe droughts tend to have larger spatial extent than severe floods for both SMPct- and SPI3-based estimates. For short duration (3-month and 6 months) events, severe droughts have an overall higher severity than severe floods for both agricultural type (except Africa and Oceania) and meteorological type. Comparison between agricultural and meteorological extremes (Figure 2.6, 2.7 vs Figure A.13, A.14) indicates that SMPct-based SAD envelope curves tend to be less stretched out compared to SPI3-based envelope curves, especially for short-duration events. This is also true even for smaller area events, as we can see clear differences in severity across SAD envelope curves with different duration. However, the severity of short-duration events tends to overlap with each other based on SMPct. In addition, SPI3-based SAD envelope curves tend to consist fewer event episodes compared to SMPct, except for droughts in North America and Africa as well as floods in North America.
and Oceania. This implies that meteorological extremes tend to be dominated by single severe episodes affecting larger areas, whereas agricultural extremes tend to be broken up to a few localized severe events that have limited spatial influence and might occur in different periods or regions. In addition, drought and flood envelopes estimated from SPI3 have higher severity, larger extent and shallower gradient compared to those constructed based on SMPct, although with a few exceptions (e.g., all events over North America, 9-month drought over Europe, 3-9 months flood over Europe), indicating a lower decreasing rate of severity with increasing area. This further implies that as droughts and floods develop, meteorological extremes tend to persist over a larger domain while maintaining a higher severity compared to agricultural extremes. Acknowledging the geographical variations, we discuss major drought and flood events for each continent in the following sections.

Figure 2.6: Continental SAD envelope curves for drought events with different durations (3, 6, and 9 months, represented by different markers). For a particular duration (e.g., 3-month), the curve is generated by selecting the maximum bound of severities from all drought events (e.g., left panel of Figure 2.4). Each curve can be made up of different episodes, represented by different colors.
Agricultural Droughts and Floods  In North America, the 1951-1959 drought dominate the 6- and 9-month SAD envelope curves, especially for larger spatial extents, whereas the 1968-1971 and 1976-1977 droughts are the most severe for smaller extents and shorter durations. For floods, most severe episodes occurring in the 1980s dominate the envelope curves. For example, the 1981-1984 flood is the worst for large extents up to 50% fraction, whereas the 1984-1989 flood is the worst for smaller extents. Note the almost identical flood envelopes for 3- and 6-month durations, which indicates that the 6-month events remain high severity as they propagate. In Europe, the 1953-1954 drought is the most severe one for 3-month duration. Almost at the same time (1952-1954), a severe flood occurred and dominates a large proportion of the 3- and 6-month SAD envelope curves. Floods occurred during recent periods (e.g., 2012-2013 and 1998-1999) are the most spatially extensive and can cover up to 60% of the total area. Different from other continents, droughts and floods occurred in Asia are generally inseparable and cover a much smaller fraction with much steeper gradients. Part of this could be due to the large size of the continent, which has more
variable climate and land surface conditions that allow droughts and floods to split more easily and rapidly and potentially more difficult to persist. Notable events include the 1983-1987/2007-2008 droughts, which dominates the SAD envelope curves for smaller/larger extents, respectively. Following the 1983-1987 drought, wet conditions lead to an almost 5-year flood (1987-1991). Although this flood does not have the longest duration (Table 2.1), it is the most severe one in Asia for both smaller and larger extents. In South America, the latest 2015-2016 drought dominates the envelope curve for all durations, especially for large extents. A seven-month drought occurred in 1985 has the highest severity among all the short-duration and small-extent events. For floods, envelope curves are made up of more individual episodes in this region, especially for smaller events. For larger extents, the 1973-1974 flood dominates the 6- and 9-month SAD curves. In Africa, droughts are dominated by events occurred in the 1980s and 1990s, with 1984-1985 drought being the most severe one across almost the full range of spatial extent and for almost all durations. In contrast, severe floods in this region mainly occurred during early 1950s and 1960s-1970s. Compared to other continents, Oceania has the smallest gradient of severity for both floods and droughts, but with the largest possible spatial extent up to 80%. Dominated droughts mainly occur in the 1960s, whereas the 1973-1974 floods contribute almost the entire flood envelopes.

**Meteorological Droughts and Floods** Different from the previous section, this section documented major droughts and floods for each continent from the meteorological perspective (Figure A.13-A.14). In North America, the top two longest droughts (1952-1955, 1955-1958, Table 2.1) contribute to the majority of the SAD envelope curves, especially for large fraction of spatial extent. For smaller extent and short-duration, drought envelopes are mainly made up from the 1976-1977 event. Flood envelope curves in this region are less steep compared to drought, and the
maximum spatial extent is also reduced. The longest duration flood during the 1960s (1961-1962, Table 2.1) dominates the 9-month envelope curve for smaller extent, whereas the 1990s floods (1992-1993 and 1996-1997) dominate the large proportion, which also rank the second and third in terms of spatial extent (Table 2.1). European drought envelope curves are dominated by the top three largest droughts (1953-1954, 1962-1964 and 1976-1977), whose maximum spatial coverage can reach to 75%. As for floods, the envelope curves consist of more events but span a smaller extent compared to droughts. Notable floods include the largest and longest flood (2011-2013) and a more recent episode (2015-2016). In Asia, the most spatially extensive drought (1975-1977) is also the longest, contributing to the tail of the envelopes. The longest and largest flood identified in this region occurs more recently (2012-2016), but this event contributes to the envelope curve only at very small extent. Majority of the flood severity envelopes are made up of the 1966-1967 and 2000-2002 (the second largest) flood. According to the SAD envelope curve in South America, the fourth largest drought (2015-2016) is also the most severe one for almost all the 3- and 6-month droughts. Interestingly, the longest duration flood (1973-1975) dominates almost the entire SAD envelope curves for all durations, except for very small and large extents. In Africa, the largest and longest droughts all occur during the 1980s and 1990s, among which the top three largest ones (1983-1984, 1991-1992) dominate the envelopes. Similarly, flood envelope curves are dominated by the top two longest (1961-1962, 1967-1968) and largest (1961-1962, 1951-1952) episodes. Compared to other continents, severe droughts and floods occurred in Oceania have much larger spatial extent, which can cover up to 90% of the total continents. The 1965 and 1994 droughts dominate short-duration (3- and 6-month) envelope curves, whereas data points on flood envelope curves come almost entirely from the largest and longest flood (1973-1974).
2.3.4 Multivariate Risk of Droughts and Floods

As properties of droughts and floods are inherently and stochastically correlated, frequency analysis should consider their coupled characteristics (i.e., severity, area and duration) and heterogeneous dependence structures with a suitable multivariate setting, instead of using the conventional univariate framework. We perform probabilistic copula analysis (see Appendix A.8) to estimate the joint return period of paired properties of severity and area for droughts/floods with minimum duration of 6 months. This enables us to quantify drought and flood risks as well as accommodate their commonalities and differences in a probabilistic manner and a consistent way. We use two examples over Africa (Figure 2.8) and North America (Figure 2.9) to illustrate the importance of considering the dependence structure of event characteristics for risk assessment. Strong asymmetric and tail dependence is evident, where data points are clustered towards the upper left corner (high severity but small extent, especially in Figure 2.9). As droughts/floods become more spatially extensive, the dependence between severity and area decreases due to increased spatial variability of soil moisture. Such reduced correlation leads to a wider spread of level curves between different return periods (RPs), especially in North America (Figure 2.9). Differences in RP level curves also exist between SMPct- and SPI3-based analysis, indicating that meteorological and agricultural types of extremes have different risks even for events with the same severity, area and duration. This further reinforces the necessity to consider the joint dependence structure between different variables. Results show that SMPct-based RP level curves are generally higher than those based on SPI3, which means agricultural extremes have smaller return periods than meteorological extremes given the same magnitude of severity and area. This implies a higher likelihood of occurrence for agricultural extremes and therefore higher risks. Similar analysis can be applied to examine how risk differs between droughts and floods. In Africa, floods have a lower likelihood of occurrence compared to droughts as can be
seen from the downward shift of flood RP level curves (Figure 2.8). However, such
difference is subtle in North America (Figure 2.9), indicating commensurate risks
between droughts and floods.

Figure 2.8: African droughts (a and b) and floods (c and d) detected from SAD (red
and blue colors) and randomly permuted through Vine Copula (grey color) based on
SMPct (left) and SPI3 (right). Isolines denote the conditional bivariate return periods
(i.e., 5, 20, 100 year) showing a set of possible realizations of area and severity that
share the same probability. All events have a minimum duration of 6 months.

The joint frequency analysis indicates that it is not necessary for all characteris-
tics of droughts/floods to be extreme such that their compound impact is extreme.
For instance, the 1990-91 meteorological drought in Africa (Figure 2.8B) is not the
most severe one if risk is assessed based on either severity or area independently. However, the joint return period of this drought is larger than 100-year indicating a low probability (less than 0.01) of occurrence if severity and area are considered simultaneously. Considering such compound impact, the 1961-62, 1973-74 and 1976 floods (Figure 2.8C) are exceptional with no historical precedent in their severity and area extent. Such events, on average, should occur within an interval of more than 100 years. But in reality they occur shortly afterwards and therefore may cause more devastating impact. Similar pair of events (1976 and 1978 floods) are also identified based on SPI3 (Figure 2.8D). Situation can be even worse if exceptional droughts
and floods follow each other in a short period. For instance, the exceptional 1988 drought in North America (Figure 2.9B) just occurred on the back of the continent’s exceptional 1987 flood, challenging the large-scale water resources planning and management especially for reservoir operations.

2.3.5 Inundation Area Risk

We use CaMa-Flood to simulate floodplain dynamics at the global scale with a particular focus on flood inundation extent (see details in Appendix A.3). We perform the inundation frequency analysis to estimate the fraction of inundation at different recurrence intervals (i.e., return period) based on fitted generalized extreme value (GEV) distributions globally for the annual maximum flooded area (Figure 2.10). Areas of high fractional coverage can be clearly detected from these inundation risk maps, including the lower Mississippi river and the western U.S., Amazon and Parana catchments in South America, the lake Chad, Congo and upper Niger river catchments in Africa, the Indus and Ganges-Brahmaputra-Meghna catchments on the Indian subcontinent, the Yellow, Yangtze and Songhua river basins in China, the Chao Phraya and Mekong river in Southeast Asia, the Murray Darling, Lake Eyre basin and Carpentaria Coast in Australia and the Euphrates and Tigris river catchment in western Asia. As expected, the fraction of flooded area increases with heightened return period. This is especially the case in Amazon, Indus and Ganges-Brahmaputra-Meghna catchments, where more than 50% of the total 25 km by 25 km grid cell can be flooded. The spatial pattern of our inundation hazard maps is consistent with previous modeling studies but with a short period (e.g., Pappenberger et al., 2012). These inundation hazard maps can be combined with demographic and economic data to study other components of the flood risk, such as vulnerability and exposure for impact assessment (Winsemius et al., 2013).
2.4 Deliverables

Communicating results and providing data products, including all aspects of the modeling and diagnostics, is a vital part of this study that will enable dissemination of knowledge and data to the wider scientific community and enable collaboration and feedbacks. We establish a publicly-accessible internet data portal and develop an online web interface to deliver relevant products, including continental drought and flood catalogues, global-scale drought, flood and inundation risk maps, long-term meteorological and agricultural standardized indices, the underlying meteorological forcings and land surface hydrological fluxes and states (Table 2.2). These datasets can be used for climate services (e.g., [Hewitt et al., 2012, Goddard, 2016, Haigh et al., 2018]) to guide large-scale planning and resilience for international organizations (e.g., World Meteorological Organization, World Climate Research, World Bank), intergovernmental agencies (e.g., the United Nations Office for Disaster Risk Reduction, the US Federal Emergency Management Agency, the European Commission), the human-
itarian community (e.g., the International Federation of Red Cross and Red Crescent), and (re)insurance companies.

2.5 Summary and Discussion

This study provides a new panoptic view of both pixel-level and event-level drought and flood risks through the development of the Global Drought and Flood Catalogue (GDFC). Here we only focus on the hazard component of risk, which is fundamental to translate the physical findings for impact assessment by bringing together vulnerability and exposure together. Nevertheless, the following findings are worthy of emphasis and exploration in future work.

2.5.1 Commonalities and Differences between Droughts and Floods

Although numerous studies exist on drought and flood risk, most of them treat drought and flood separately. Development of GDFC enables us to study the commonalities and differences between these two types of extremes in a comprehensive and systematic way. At the pixel level, we find that the long-term drought and flood frequency have symmetric spatial patterns, which is mainly due to the definition of extremes, although geographical difference exists. At the event level, examination of the stationarity of drought and flood frequency depicts a more complex picture, depending on the index type (whether precipitation driven or soil moisture driven), event duration (short-term vs long-term) and geographical location. Globally, the occurrence rate of short-term meteorological droughts has decreased significantly, while there is no robust trend detected for short-term meteorological floods. Agricultural type of these two extremes tends to be more synchronous and temporally coherent with a dampened decadal variability compared to meteorological extremes. Through
a large sample of individual drought and flood episodes, we are able to examine whether droughts are statistically different from floods in terms of area and severity, although conclusions vary across continents. Further consideration of the joint dependence among the multivariate characteristics (i.e., severity, area, and duration) indicates that both droughts and floods have strong and asymmetric dependence between severity and areal extent. Given the same compound impact (e.g., same magnitude of severity and area), floods have a lower chance of occurrence than droughts in Africa, but such difference is subtle in North America. These diagnostic findings together with a large number of event-based drought and flood episodes in GDFC act as a basis and allow us to conduct a more detailed analysis through case studies to advance our understanding of the underlying physical mechanisms that drive the changes of these extremes.

2.5.2 Challenges and Future Directions

As drought and flood hazard risks crystallize with increasing frequency and severity, their impact on societies is likely to further intensity under anthropogenic climate change and human interventions. We need to develop an integrated modeling framework which can bridge the gap between large-scale hazard mapping and local-scale impact assessment. This ultimately requires further development of hyper-resolution land surface models (Wood et al., 2011) together with meteorological forcings that come with a commensurate resolution through dynamical or statistical downscaling methods (e.g., Maraun et al., 2010; He et al., 2016). In addition, it is also vital to validate GDFC with existing hazard database and provide uncertainty information. For instance, current inundation maps can be compared with estimates from other global inundation products either based on observations (e.g., global flood risk maps produced for the 2011 Global Assessment Report on Disaster Risk Reduction, Herold et al., 2011), modeling studies (e.g., Pappenberger et al., 2012) or satellite-derived in-
undation products (e.g., Fluet-Chouinard et al., 2015; Ji et al., 2018). Moreover, since droughts and floods can be interrelated through physical processes (e.g., Dominguez et al., 2009; Dong et al., 2011; Kam et al., 2013) and both of them influence the optimal water resources management strategies (e.g., the conflicting imperatives between releasing/storing water in reservoir when flood/drought occurs), it is necessary to document and compile extreme events that follow each other (e.g., the fast transition from one type of extreme to the other). A recently developed statistical framework (He and Sheffield, 2018) provides a promising avenue to robustly quantify such coincidence risks between droughts and floods, which can be included in the GDFC in future work. Moreover, to facilitate the early warning of future drought and flood hazards, it is imperative to conduct attribution analysis to improve our understanding of how climate change and variability influence drought and flood risks (e.g., Hulme, 2014; Kreibich et al., 2019), and how they interact with human interventions (e.g., He et al., 2017; Wada et al., 2017).

In this study, we focus on large-scale and long-term droughts and floods, as these hydrological extremes tend to have a much larger societal impact, compared to those small-scale and very short events. Further combination of the hazard information with exposure and vulnerability can provide a more complete picture of risk and the associated impact. This is also valuable for society to think of adaptation and mitigation strategies to withstand future elevated drought and flood risk and improve society’s resilience, if more individual and/or multiple pair-event case studies (Kreibich et al., 2017) are conducted. Such efforts can reveal general and transferable conclusions for both developed and developing countries, which have different coping capacities to droughts and floods even when they experience hazards of the same magnitude.
<table>
<thead>
<tr>
<th>Region</th>
<th>SPI-based Duration (months)</th>
<th>Spatial extent (fraction %)</th>
<th>SMPct-based Duration (months)</th>
<th>Spatial extent (fraction %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Africa</td>
<td>1993.09-1994.12 (16)</td>
<td>1981.01-1988.01 (77.9)</td>
<td>1984.01-1985.06 (18)</td>
<td>1984.01-1985.06 (60.9)</td>
</tr>
<tr>
<td>Europe</td>
<td>1962.07-1964.05 (23)</td>
<td>1999.10-2002.04 (43.3)</td>
<td>1958.09-1961.05 (43.7)</td>
<td>1987.11-1999.09 (67.7)</td>
</tr>
<tr>
<td></td>
<td>1956.02-1957.01 (12)</td>
<td>1991.11-2013.07 (62.2)</td>
<td>1956.06-1994.06 (66.7)</td>
<td>2012.05-2013.06 (64.2)</td>
</tr>
<tr>
<td>North America</td>
<td>1955.06-1958.04 (35)</td>
<td>1976.07-1978.05 (67.9)</td>
<td>1951.09-2015.06 (42.7)</td>
<td>1978.04-2015.06 (37.9)</td>
</tr>
<tr>
<td>Oceania</td>
<td>1961.04-1962.11 (20)</td>
<td>1956.06-1994.06 (75.5)</td>
<td>1956.06-1994.06 (51.4)</td>
<td>1951.04-1999.06 (67.9)</td>
</tr>
<tr>
<td>South America</td>
<td>1966.01-1968.09 (22)</td>
<td>1960.03-1992.03 (53.7)</td>
<td>1963.04-1992.03 (53.0)</td>
<td>1951.11-1999.03 (41.8)</td>
</tr>
<tr>
<td></td>
<td>1972.02-1973.01 (12)</td>
<td>1996.05-1997.05 (90.7)</td>
<td>1951.06-1999.06 (97.9)</td>
<td>1951.06-1999.06 (83.2)</td>
</tr>
<tr>
<td></td>
<td>1972.02-1973.01 (12)</td>
<td>1996.05-1997.05 (90.7)</td>
<td>1961.06-1993.06 (25)</td>
<td>1996.07-1998.06 (47.9)</td>
</tr>
<tr>
<td></td>
<td>1975.03-1975.09 (53.7)</td>
<td>1997.04-1997.05 (66.7)</td>
<td>1996.06-1993.06 (25)</td>
<td>1996.06-1998.06 (54.9)</td>
</tr>
<tr>
<td></td>
<td>1967.06-1968.11 (21)</td>
<td>1997.04-1997.05 (66.7)</td>
<td>1975.03-1975.09 (53.7)</td>
<td>2012.03-2013.04 (37.8)</td>
</tr>
<tr>
<td></td>
<td>1995.02-1997.05 (66.7)</td>
<td>1997.04-1997.05 (66.7)</td>
<td>1975.03-1975.09 (53.7)</td>
<td>2012.03-2013.04 (37.8)</td>
</tr>
</tbody>
</table>

Table 2.1: List of top five drought and flood episodes ranked by duration and spatial extent using both SPI-based and SMPct-based event indices. The duration (months) and fraction area (percentage) under drought or flood are given in brackets.
<table>
<thead>
<tr>
<th>Products</th>
<th>Types/Variables/Indices</th>
<th>Data source &amp; Description</th>
<th>Attributes</th>
<th>Format</th>
</tr>
</thead>
<tbody>
<tr>
<td>Catalogue</td>
<td>Drought inventory (Agricultural &amp; Meteorological)</td>
<td>SAD clustering algorithm</td>
<td>6 continents, event ID, date, duration, spatial extent, severity</td>
<td>txt, csv</td>
</tr>
<tr>
<td></td>
<td>Flood inventory (Agricultural &amp; Meteorological)</td>
<td></td>
<td></td>
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<tr>
<td>Hazard maps</td>
<td>Drought frequency (Agricultural &amp; Meteorological)</td>
<td>Return period calculated from VIC-derived indices</td>
<td>0.25°; duration with 1-3, 4-6, 7-12, &gt;12 months</td>
<td>netCDF4</td>
</tr>
<tr>
<td></td>
<td>Flood frequency (Agricultural &amp; Meteorological)</td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>Inundation risk maps</td>
<td>Annual maximum inundation fraction based on CaMa-Flood simulations and GEV distribution</td>
<td>0.25°; 5, 10, 20, 50, 75, 100, 200, 500-year return periods</td>
<td></td>
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<td>Standardized indices</td>
<td>SPI</td>
<td>Precipitation from PGFv3 (1948-2016)</td>
<td>0.25°; SPI1, SPI3, SPI6, SPI12; daily, monthly, yearly</td>
<td>netCDF4</td>
</tr>
<tr>
<td></td>
<td>SMPct</td>
<td>VIC land surface model (1948-2016)</td>
<td>0.25°; daily, monthly, yearly</td>
<td></td>
</tr>
<tr>
<td>Meteorological forcings</td>
<td>Precipitation, 2m temperature, downward surface shortwave radiation,</td>
<td>PGFv3 (1948-2016)</td>
<td>0.25°; 3-hourly, daily, monthly, yearly</td>
<td>netCDF4</td>
</tr>
<tr>
<td></td>
<td>downward surface longwave radiation, 2m specific humidity, surface pressure, 10m wind</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land surface hydrological fluxes and states</td>
<td>Evapotranspiration, runoff, soil moisture at different layers, streamflow, inundation area</td>
<td>VIC land surface model &amp; CaMa-Flood hydrodynamic model (1948-2016)</td>
<td>0.25°; daily, monthly, yearly</td>
<td>netCDF4</td>
</tr>
</tbody>
</table>

Table 2.2: Data products included in the Global Drought and Flood Catalogue.
Chapter 3

Lagged Compound Occurrence of Droughts and Floods Globally over the Past Seven Decades

3.1 Introduction

Weather extremes have been listed as one of the top three global risks for the past five years (2014-2018) (World Economic Forum 2018), among which floods and droughts are the most common and impactful natural hazards globally. They have large impacts on agriculture and food security, water availability, energy production and natural ecosystems (e.g., Gleick 1993, Sheffield and Wood 2011). Globally, drought and flood losses have increased tenfold over the second half of the 20th century, to US$596 billion in the early 21st century (2000-2017) (EM-DAT 2018). A recent study (UNISDR 2015) found that, during 1995-2015, for all weather-related disasters, floods alone affected 2.3 billion people and accounted for 56% of all the weather-related disasters. Drought accounted for 26% of disasters and affected 1.1 billion people. Although a growing body of research has documented that anthropogenic cli-
mate change will increase the frequency and magnitude for floods (e.g., Milly et al. 2002; Pall et al. 2011; Field 2012; Hirabayashi et al. 2013; Arnell and Gosling 2016) and droughts (e.g., Sheffield and Wood 2008a; Orlowsky and Seneviratne 2013) based on climate model projections, historical evidence does not show consistent changes for floods (e.g., Kundzewicz et al. 2014) and droughts (e.g., Sheffield and Wood 2008b; Sheffield et al. 2012; Dai 2013; Trenberth et al. 2014) owing to the lack of observations, use of different metrics, as well as uncertainties from model simulations related to model structure and parameterization schemes.

Although droughts and floods are generally treated separately, there is good reason to analyze their co-occurrence and mechanisms, and manage and mitigate their impacts concurrently for a number of reasons. Firstly, there are many recent examples of coincidental flood and drought events that highlight the compounded impacts of events that follow each other, and are suggestive of the expectation of a more variable climate under climate change. For instance, California recently suffered a multi-year (2011-2016) and intense drought (Diffenbaugh et al. 2015; He et al. 2017), which caused severe environmental issues (e.g., groundwater depletion, wildfires, tree mortality) and economic losses (e.g., Howitt et al. 2014). On the heels of this prolonged drought, the state was hit by severe flooding in February 2017, which triggered a state emergency and an evacuation of 188,000 residents downstream of the Oroville Dam (California’s second largest reservoir) due to its spillway failure (NOAA National Centers for Environmental Information 2018). In September 2015, there was a fast transition from drought to flooding within one week over South Carolina because of the deep tropical moisture connection to Hurricane Joaquin, which brought a once-in-a-thousand-years flood and erased the prevailing drought conditions that had lasted from May to September in 2015. This drought-flood seesaw also happened in the southeast U.S., where Texas experienced its worst drought in recorded history from 2010 until May 2015, which was suddenly ended by a heavy precipitation event.
However, this event caused flash floods, compounded the impacts of the five-year drought which has already changed the landscape and vegetation distribution significantly. The dramatic swing from severe droughts to devastating floods as shown above poses a substantial risk for water management practices, especially for reservoir operation, as there exists a trade-off between short-term flood-control and long-term water-storage imperatives to satisfy water demand. In developing regions, the transition from drought to flood is arguably more impactful because of the compounding effects on population vulnerability. Although floods can sometimes alleviate drought conditions, they can have a significant effect on already impacted and more vulnerable populations (e.g., King-Okumu et al. 2018).

Understanding the coincidence of droughts and floods, and their relationship in a changing environment (see Lins and Slack, 1999; Sheffield and Wood, 2007; Milly et al., 2008) is, therefore, important for fully characterizing natural hazard impacts, and understanding potential mitigation strategies, such as designing more effective reservoir operation rules or agricultural planning. This relies on an improved understanding of the underlying physical mechanisms of hazard risk from both internal variability and external factors (e.g., related to anthropogenic climate change). There is growing evidence that recent warming is leading to more extreme events in general (Peterson et al., 2013) and that flood and drought risk may be linked. For example, flood conditions are often the reason for recovery of drought conditions, such as in the southeast U.S., where tropical cyclones play a major role in drought recovery and alleviation (e.g., Kam et al., 2013; Maxwell et al., 2012, 2013). In the Pacific Northwest U.S., 60-74% of persistent droughts are terminated by atmospheric rivers (Dettinger, 2013). Antecedent conditions (i.e., soil moisture and snowpack conditions) can be related to changing flood risk (Sivapalan et al., 2005), which can also drive drought persistence through reductions in recycled precipitation (e.g., Dominguez et al., 2009).

At larger scales, floods and drought are often linked because a shift in circulation
drives flood conditions in one region while causing drought conditions in a neighboring region. For example, the Russian heat wave and Pakistan floods in 2010 were associated by a shift in the jet stream [Lau and Kim, 2012], and the floods in Texas and drought in the southeast U.S. in 2006 were driven by a persistent shift in moisture sources from the Gulf of Mexico [Dong et al., 2011]. At local scales, wet/dry soils can trigger convective precipitation via positive/negative land-atmosphere feedbacks (e.g., Eltahir and Bras, 1996; Taylor et al., 2011, 2012; Guillod et al., 2015).

Nevertheless, studies focused on improving our understanding or even providing basic quantification of transitions between droughts and floods is lacking. The few studies that do exist are either event-based [Seager et al., 2012; Parry et al., 2013] or limited to regional-scales [Dong et al., 2011; Wang et al., 2017; Swain et al., 2018]. A global holistic picture is not available, which is due to: (1) lack of reliable datasets with long-term records, as well as a global coverage to derive robust statistical relationships; and (2) lack of a novel and effective statistical models to better characterize the (lagged) coincidence between droughts and floods. The former can be solved via the use of large-scale hydrological modeling, which is now mature enough to provide reasonable estimates of the large-scale terrestrial water cycle, and there are satellite-gauge combined estimates of precipitation and other meteorological variables to drive these models for multiple decades that are needed to provide robust statistics. Combined these provides the only feasible approach for long-term studies at the global scale. The latter can be addressed through the recent development of event-based coincidence analysis (ECA, Donges et al., 2016; Siegmund et al., 2017), which accounts for both the instantaneous and lagged response between climatic events, such as droughts and floods.

The main objective of this study is to develop a comprehensive understanding of the drought to flood transition (or lagged coincidence), globally over the past seven decades. This can help improve hydrological predictability and risk assessment, and
therefore make disaster preparedness and risk management more effective. Given that empirical evidence, basic theory (e.g., Clausius-Clapeyron), climate model projections, and even public perception, suggest that flood and drought risk are increasing and will continue to do so in the future, we attempt to examine the inter-relationship between droughts and floods, including the geographical hotspots of the seesaw between them and whether this is becoming more prevalent. This is the first global study to quantify this, and may not only shed light on the underlying mechanisms of the flood-drought cycle but also provide useful information to increase society’s resilience to future hydrologic extremes.

3.2 Materials and Methods

3.2.1 Drought and Flood Identification

We focus on large-scale and long-term drought and flood events (equivalent to large-scale and long-term dry and wet spells), as these events usually cause more deleterious impacts and pose more severe risk to water, agriculture, and energy sectors, and therefore deserve special attention. We consider two standardized metrics, which allow comparisons over time and space, as proxies of drought and flood conditions from both the meteorological and agricultural perspectives. The first one is the Standardized Precipitation Index over a one-month period (SPI1, McKee et al. 1993), which is calculated using precipitation from an updated and extended version (v3) of the Princeton Global Forcings (PGF, Sheffield et al. 2006), from 1948 to 2016 at 0.25° spatial resolution. We define meteorological drought at a grid cell if the monthly SPI1 is below the threshold of -1.0 (Svoboda et al. 2012). Similarly, large-scale floods are defined if the SPI1 exceeds 1.0. The other index is the soil moisture percentile proposed by Sheffield et al. (2004a), which is derived from a global off-line simulation of Variable Infiltration Capacity (VIC) land surface hydrological model (Liang et al.)
forced by the PGFv3. Previous versions of this dataset have been analyzed in terms of drought by Sheffield and Wood (2007, 2008b) and Sheffield et al. (2009). The latest version of the simulation analyzed here uses updated soil parameters based on the SoilGrids1km database of soil types and profiles (Hengl et al., 2014), coupled with recently developed pedotransfer functions (Tóth et al., 2015) to estimate model parameters such as saturated conductivity and soil water holding capacities. These are combined with VIC-specific parameter values that were previously calibrated to river discharge measurements from a set of global river basins and evaluated against available in situ and remote sensing hydrological measurements, including soil moisture networks, satellite derived snow cover, water storage and evapotranspiration (Sheffield and Wood, 2007; Pan et al., 2012). We define an area in drought if the monthly soil moisture percentile is below a chosen threshold. The threshold value used to define a deficit is subjective as it depends on the impacted sector. As the objective is to examine drought-flood concurrently, it is necessary to ensure that both extremes have the same long-term occurrence rate. We therefore use the 16th percentile as the threshold to identify the soil moisture drought, as this represents rare events and has the same cumulative probability as the SPI1-based drought threshold (SPI1< -1.0 is equivalent to the 16th percentile). In a similar manner, flood events are defined using a “pluvial” condition, which is measured by the surplus soil moisture above the 84th percentile.

3.2.2 Event Coincidence Analysis

We apply a novel yet conceptually simple method, called event coincidence analysis (ECA, Donges et al., 2016; Siegmund et al., 2017), to investigate the statistical interdependency between droughts and floods (see Figure 3.1). ECA can not only quantify the number of exactly simultaneous occurrences of two extreme events (i.e., floods and droughts in this study), it also allows the consideration of lagged (through
the time lag parameter $\tau$) and time-uncertain (through the window size parameter $\Delta T$) responses between them. In the case of the drought-flood seesaw (defined as the transition from drought to flood), ECA can calculate how frequently droughts are followed by floods with a mutual delay ($\tau$) given a certain temporal window ($\Delta T$) through the calculation of the so-called trigger coincidence rate $r^{D\Rightarrow F}$:

$$r^{D\Rightarrow F}(\Delta T, \tau) = \frac{1}{N_D} \sum_{j=1}^{N_D} \Theta \left[ \sum_{i=1}^{N_F} 1_{[0,\Delta T]}((t_i^F - \tau) - t_j^D) \right]$$

where $\Theta$ is the Heaviside function:

$$\Theta(x) := \begin{cases} 
1 & x > 0 \\
0 & x \leq 0 
\end{cases} ,$$

and $1_{[0, \Delta T]}(\cdot)$ is the indicator function of the selected window $[0, \Delta T]$:

$$1_{[0, \Delta T]}(x) := \begin{cases} 
1 & \text{if } x \in [0, \Delta T] \\
0 & \text{if } x \notin [0, \Delta T] 
\end{cases} .$$

$t_i^F$ and $t_j^D$ represent the flood and drought timing with total number of events $N_F$ and $N_D$, respectively. Here, we chose $\tau = 3$, as this represents a typical (i.e., seasonal) scale at which the large-scale hydrological conditions veer from deficit to surplus, which is critical for long-term water resources management, for example. To further quantify the robustness of the statistical interrelationship between droughts and floods, we conduct an analytical significance test based on the assumption of a Poisson process with the null hypothesis that the lagged coincidence between droughts and floods is randomly distributed.
Figure 3.1: Schematic of the large-scale drought-flood seesaw based on the event coincidence analysis given the time lag ($\tau$) between the drought occurrence timing ($t^D_j$) and flood occurrence timing ($t^F_i$) within a certain window ($\Delta T$). Flood/drought events are detected when the corresponding flood/drought index (i.e., SPI or soil moisture percentile) exceeds/falls below the predefined threshold.

3.3 Results

3.3.1 Climatology of Drought-Flood Seesaw Frequency

At the global scale, we estimate an averaged seasonal drought-flood lagged coincidence frequency of 11.1% and 11.4% for the boreal spring-summer (April-May-June-July-August-September, AMJJAS) and boreal fall-winter (October-November-December-January-February-March, ONDJFM), respectively, during the 1950-2016 period (Figure 3.2 A and B). In other words, about 11% of droughts are followed by floods with a three-month lag after drought onset for the past seven decades. The majority (52.1% for AMJJAS and 55.6% for ONDJFM) of the global land surface (excluding Greenland, Antarctic and desert regions with annual rainfall less than 100 mm) has coincidence rates between 10% and 20%. 12.9/11.6% of the total land surface area has a coincidence rate less than 5% during AMJJAS/ONDJFM, which mainly occurred over Africa. There is a clear shift in these low frequency patterns over Southern
Africa during AMJJAS and over the northern Central Africa (i.e., the transition region between deserts and tropical rainforests) during ONDJFM, which is potentially due to the seasonal movement of the Intertropical Convergence Zone (ITCZ). The climatology of seasonal drought-flood seesaw frequency larger than 30% is virtually non-existent (0.27/0.15% for AMJJAS/ONDJFM). Furthermore, only 5.9% (of the global land surface) of the estimated coincidence rate is statistically significant (with the degree of belief ≥ 90%) during AMJJAS, with spatially organized patterns most prominent outside of the tropics, including western territories of Canada, western coast and central part of the U.S., southeastern Brazil, northwestern Central Africa (CAF), central Democratic Republic of the Congo, the border between Kenya and Somalia, central and northeastern China, central and eastern Australia, and western Siberia (Figure 3.2C). There is a slight increase in the percentage of statistically significant area (∼7.6%) during ONDJFM with robust drought-flood seesaw patterns over Alaska, western Canada, northwestern and central U.S., central and southern Brazil, western Russia, eastern Europe, southern Central Africa, Botswana, Iran, western and southern China (Figure 3.2D). The seasonal difference in the statistically significant clusters over Africa is again likely due to the movement of ITCZ. The scattered patterns found in the western U.S. could be related to the occurrence of atmospheric rivers, which are often associated with drought recovery (Dettinger, 2013), whereas over southern China, the eastern summer monsoon could contribute to the drought-flood seesaw (Ding, 1992; Lau and Yang, 1997; Wu et al., 2006). The robust statistical interdependency between droughts and floods over the southwestern and central U.S., Australia and southern Amazon is in line with previous studies (e.g., Fu, 2015). We further compare the differences for the two periods (Figure 3.2F) for the 10 sub-continent regions (Figure 3.2E). The spatial distribution reveals that the AMJJAS seesaw generally has higher mean values than the ONDJFM seesaw for most regions (except for SAF, OCE, and SSA), and higher spatial variability (based
on the CV) except OCE. For SAF and SNA, there is a clear shift of the distribution, which is also manifested in the spatial pattern (Figure 3.2A and B) as the rainfall band moves, from summer to winter.

### 3.3.2 Epochal Changes in Drought, Flood and Seesaw Frequencies

We next calculate the relative changes in frequency of three hydroclimate extremes (i.e., drought, flood and drought-flood seesaw) during AMJJAS (Figure 3.3) and ONDJFM (Figure B.1 in the supplementary information) between the first (1950-1979) and last 30 years (1987-2016), which reflect any long-term hydrological changes. Globally, the changing frequency for droughts (Figure 3.3A and B.1A) and floods (Figure 3.3B and B.1B) is more organized and spatially coherent compared to that for drought-flood seesaw (Figure 3.3C and B.1C). During AMJJAS, a prominent spatial cluster with increased drought frequency is found over southwestern and southeastern U.S., Colombia, Brazil, western Europe, majority of Africa, India, western Russia, northeast China and eastern Australia (up to five times more frequent for particular pixels). The percentage area with increased drought frequency decreases slightly during ONDJFM compared to AMJJAS, but in general, the area of increased drought frequency is still larger than that of decreased frequency for both AMJJAS and ONDJFM (Figure 3.3A and B.1A). These spatial hotspots are consistent with previous drought exposure (Dilley et al., 2005) and frequency analysis based on long-term historical records of precipitation (e.g., Dai, 2013; Spinoni et al., 2014), Palmer Drought Severity Index (PDSI) (e.g., Dai, 2013) and modeled soil moisture (e.g., Sheffield and Wood, 2008b). Among the 10 sub-continental regions, the probability that droughts become more frequent during AMJJAS in recent decades (Figure 3.3D) is evidenced for more than half of the SAF (53.5%) and SAS (51.8%). The increased drought frequency is even more widespread over EUR (67.4%), SNA (64.8%) and OCE (64.7%),
Figure 3.2: Frequency of drought-flood seesaw for the period 1950-2016. Maps show the lagged trigger coincidence rate, indicating how frequent droughts are followed by floods with a 3-month lag for the boreal spring-summer (AMJJAS) (A) and boreal fall-winter (ONDJFM) (B), and whether the rates are statistically significant based on different levels (90, 95, 99 and 99.9 percent) of significance (C and D). (E) The 10 sub-continental regions (with acronyms for brevity) used to summarize the regional statistics, covering the global land surface excluding Greenland, Antarctica and extremely dry regions with annual rainfall less than 100 mm (E). Ridgeline plots (F) showing the probability distribution of coincidence rate during AMJJAS and ONDJFM for each sub-region with its mean and coefficient of variation (CV).
although the percentage area decreases during ONDJFM (Figure B.1D). Over SNA, 19.5/16.1% of the total land surface area even exhibits frequency ratios of > 3 during AMJJAS/ONDJFM.

Figure 3.3: Maps showing relative changes of drought (A), flood (B) and seesaw (C) frequency in the recent 30 years (1987-2016) compared to the first 30 years (1950-1979) during AMJJAS. The relative changes are represented by frequency ratios, with values larger than 1 indicating events occurring more frequently in the recent period. Regional distributions of these frequency ratios are summarized in ridgeline plots (D, E and F).

Different from droughts, regions experiencing increased flood frequency during AMJJAS in recent decades arise over a large spatial extent of central and eastern U.S., northwestern Amazon (AMZ), southern South America (SSA), Europe, Russia, and the western part of Southern Asia (SAS), especially over the Tibetan regions.
(Figure 3.3B). Similar spatial patterns are found over most of these regions during ONDJFM, with increased flood frequency more pronounced over Europe, western Russia, the Sahel and western Australia. We also observe that for regions with increased flood frequency, the magnitude of frequency ratios is generally smaller than that for droughts, indicating that floods occur less frequently than droughts in recent decades, which is also consistent with the reduced spread of the regional distribution of flood frequency ratios (Figure 3.3E and B.1E). In other words, regions with increased flood frequency have less spatial variability than that for droughts. Similar findings have been reported by previous global (van der Schrier et al., 2013) and regional studies focusing on the U.S. (Kangas and Brown, 2007), Amazon (Marengo and Espinoza, 2016), India (Singh and Ranade, 2010), and Europe (Zolina et al., 2013), albeit with different observational records and metrics. Regional statistics (Figure 3.3E) show that recent decades have experienced an increased probability of floods during AMJJAS for more than two-thirds of SAF (68.4%), more than half of OCE (60.5%) and NNA (61.3%), and for more than four-fifths of the AMZ (83.6%). During ONDJFM, the percentage area with increased flood frequency increases substantially over NAS (54.1%) and SNA (52.3%) compared to AMJJAS (13.1% and 31.6%, respectively). The increased flood frequency during winter months over SNA is consistent with Kangas and Brown (2007), due to higher probability of receiving sufficient moisture.

Compared with droughts and floods, we find less organized spatial structures for the increased seesaw frequency but with much higher ratios (Figure 3.3C and B.1C), suggesting that the seasonal seesaw from droughts to floods has become more frequent in recent decades than either droughts or floods alone. The tendency toward more frequent seesaw is more apparent during AMJJAS (Figure 3.3C) than ONDJFM (Figure B.1C), especially over the sub-tropics and mid-latitudes, which is also revealed from the left-skewed regional distributions (Figure 3.3F and B.1F) with longer tails.
We note an increased seesaw frequency during AMJJAS for nearly half of the SAF (47.2%) and NNA (46.2%). The elevated seesaw frequency during the recent period is particularly high with a threefold increase for more than 10% of OCE and AMZ for both periods. During ONDJFM, nearly one-fifth of the total data points in NNA (18.9%) exhibit ratios of > 3 (Figure B.1F), which is mainly concentrated over the central U.S. (Figure B.1C).

3.3.3 Regional Multi-Decadal Variability of Hydroclimate Extremes

Results in the previous section only consider the two end members of the whole study period. As a complement to the spatial patterns, in this section, we quantify the temporal dynamics using a 30-year moving window (1950-1979 through 1987-2016) to capture the multi-decadal variability. We estimate regional trends based on the non-parametric, pre-whitening Mann-Kendall test (Yue et al., 2002), which is robust and can effectively reduce the influence of autocorrelation. Regional trend tests for AMJJAS (Figure 3.4) and ONDJFM (Figure B.2) suggest that overall there is little change in the seesaw frequency with a few exceptions mostly over NAS, SAS, SAF and OCE. The shading spanning the 25 and 75 percentiles of the regional event frequency indicates that seesaws have the largest spatial variability especially over tropical and Southern hemisphere regions (e.g., CAF, AMZ, SSA, SAF), followed by droughts, and flood frequency has the least spatial variability. Comparison across different regions reveals that SNA and EUR generally have the highest seesaw frequency, whereas Africa has the lowest seesaw frequency (SAF during AMJJAS and CAF during ONDJFM). A few regions (e.g., AMZ, SSA, SAF) show an opposite trend before and after the 1970s, which might be related to the shift in the warm phase of the El Niño Southern Oscillation (ENSO) and the coincidence with increased global mean temperature (Dai et al., 1998).
Figure 3.4: Temporal dynamics of the drought (top panel), flood (middle panel) and seesaw (bottom panel) frequencies calculated from a 30-year moving window with thick lines showing the areal means and shaded areas spanning the 25\textsuperscript{th} and 75\textsuperscript{th} percentiles of grid cell values for each region for drought (red), flood (blue) and seesaw (green). Grey lines show the ensemble of the 10 regional averaged frequencies for comparison. Upward/Downward arrow in each panel indicates that there is a statistically significant increasing/decreasing trend based on different levels of significance (represented by different numbers of stars).

We find that the changing variability of the seesaw behavior is more complex than the changing variability for each individual type of event. The potential that more/less seesaw behavior will accompany increased/decreased drought and (or) flood frequency typically does not hold. For instance, during AMJJAS over the Amazon (AMZ), even though we observe robust declining trends for both drought (-0.02\% yr\textsuperscript{-1}, \(p < 0.01\)) and flood frequency (-0.01\% yr\textsuperscript{-1}, \(p < 0.01\)), no robust trend is identified for
the seesaw frequency (Figure 3.4). Similar patterns are also found over NNA during ONDJFM (Figure B.2). In contrast, albeit that no robust trends are found for either droughts or floods over SAS during AMJJAS and SNA during ONDJFM, increasing trends of seesaw frequency are detected for both regions, although with different degrees of significance ($p < 0.01$ for SAS and $p < 0.1$ for SNA). In another case, only one end of the hydroclimate spectrum (i.e., either flood or drought, but not both) experiences a robust trend, but the trend in seesaw is still statistically significant. This happens over SSA during AMJJAS, where robust increasing trends are only detected for floods (0.06% yr$^{-1}$, $p < 0.1$) and seesaw (0.04% yr$^{-1}$, $p < 0.05$). A similar trait is shared by SAF during AMJJAS, but with robust declining trends for both events. This also happens in Asia (NAS and SAS) during ONDJFM, where a robust trend of seesaw frequency is accompanied by a robust trend of flood frequency, but is essentially zero over NAS for both flood (-0.001% yr$^{-1}$, $p < 0.05$) and seesaw (-0.003% yr$^{-1}$, $p < 0.05$). In contrast, the robust and substantial changing trends of seesaw frequency over AMZ (-0.10% yr$^{-1}$, $p < 0.01$) and OCE (0.13% yr$^{-1}$, $p < 0.01$) during ONDJFM are concomitant with the robust trend of drought frequency. Only few regions experience robust trends for all three types of events. This includes NAS and OCE during AMJJAS, with the former having more pronounced increases in drought occurrence (0.11% yr$^{-1}$, $p < 0.01$), whereas the latter has more pronounced decreases in flood occurrence (-0.08% yr$^{-1}$, $p < 0.01$) compared to the other two events. During ONDJFM, we observe a positive trend of seesaw occurrence (0.06% yr$^{-1}$, $p < 0.01$) over EUR, which coincides with the negative trend of drought occurrence (-0.11% yr$^{-1}$, $p < 0.01$) and positive trend of flood occurrence (0.08% yr$^{-1}$, $p < 0.01$). There has been a decreasing trend of the seesaw from droughts to floods over SAF (-0.04% yr$^{-1}$, $p < 0.05$), mainly due to the negative trend of flood occurrence (-0.12% yr$^{-1}$, $p < 0.01$), albeit with increased occurrence of droughts towards the more recent period (0.03% yr$^{-1}$, $p < 0.01$).
3.4 Discussion and Conclusions

Floods and droughts have been widely studied, yet their interrelationship (the transition from one extreme to the other) has not been systematically examined, especially at the global scale. Using event coincidence analysis we find that globally, about 5.9% and 7.6% of the land surface has experienced statistically significant ($p < 0.10$) drought-flood seesaw during the boreal spring-summer (AMJJAS) and fall-winter (ONDJFM), with an averaged 11.1% and 11.4% of all droughts being followed by floods in the next season, respectively. Although the overall percentage area of seesaw occurrence is small, we identify regional hotspots, mainly in the mid-latitude regions, which have experienced an increase in the frequency of droughts, floods and drought-flood seesaw in the historical period.

Explaining these patterns from a physical standpoint is difficult, given that the mechanisms for individual types of extremes are complex, let alone the intertwined relationship between the two. An understanding of the drought-flood seesaw is therefore difficult to identify, especially at the global scale; the transition from drought to flood is likely case dependent, and influenced not only by climate variability but potentially also by climate change, and therefore difficult to disentangle. Nevertheless, a critical question is whether the identified historic changes in drought-flood seesaw frequency in the regional hotspots are due to climate change and therefore a sign of potential further changes in the future. Numerous studies have demonstrated that with a warming climate, drought risk/frequency could be elevated due to increased evapotranspiration induced by increased temperature. At the same time, the probability of extreme rainfall events is expected to increase, as the atmosphere can hold more moisture from the increased evapotranspiration, which can contribute to increased flood risk. On top of these overall trends, warming-induced changes in global climate variability, such as El Niño/La Niña (e.g., Yu et al., 2017; Fasullo et al., 2018), or Arctic sea ice (e.g., Francis et al., 2017; Coumou et al., 2018) can bring more year-to-
year variability or persistence in weather patterns, substantially influencing regional precipitation and temperature anomalies. Direct human interventions could further exacerbate drought risk (due to increased human water consumption through irrigation and groundwater pumping, \cite{Wada2013, He2017} and flood risk (due to land use changes including urbanization \cite{Yang2013} and agricultural practices \cite{Villarini2014}, as well as levee and dam construction as demonstrated by \cite{Munoz2018} at the local scale). Therefore, it remains to be seen to what extent future seesaw frequency will respond to anthropogenic forcing, internal atmospheric processes as well as human interventions.

Droughts, floods and their transitions are inevitable, but fatalities, infrastructure failure and economic losses are not. The regional hotspots we identified, such as in Africa, generally have high vulnerability to floods and droughts, which can be exacerbated when there is a transition between events, with an already impacted population being even more vulnerable to a subsequent hazard. The framework developed in this study could therefore be of practical value to inform policy-makers and local stakeholders on the potential risks and therefore more effective water and agricultural management policies and robust mitigation plans.
Chapter 4

Intensification of Hydrological Drought in California by Human Water Management

4.1 Introduction

California has endured severe drought since winter 2011 \citep{Seager2015}. This persistent drought has caused $2.2 billion in statewide losses in 2014 \citep{Howitt2014} and piqued wide public interest among the media, scientific communities, policy makers and stakeholders. This is not only due to the reduced productivity of agriculture (with crop revenue loss $810 million), but also due to the lack of water availability for irrigation and hydropower, and the depletion of groundwater storage (with additional pumping cost of $454 million), which has impacted food security \citep{Howitt2014} and caused land subsidence \citep{Amos2014,Farr2015}. Furthermore, on-going urban water restrictions have been made either mandatory or voluntary \citep{Nagourney2015,Mann2015}. This long-lasting, multiyear drought has created extremely low soil moisture conditions, further increasing the risk
of drought induced natural hazards, including landslides, flash floods and mid-winter wildfires (Vardon 2015; Yoon et al. 2015).

California has a typical Mediterranean climate with hot dry summers and mild wet winters. Most of its precipitation falls during the winter time (November to March). The long-term record indicates that 2014 is the third driest year in history and 2012-2014 is the driest consecutive three-year period (Mann and Gleick 2015). Associated with this dry condition are the extremely high temperatures, with 2014 being the hottest year and 2012-2014 being the hottest three years in history (Diffenbaugh et al. 2015; Mann and Gleick 2015). Other significant droughts occurred during the periods 1929-1934, 1976-1977 and 1987-1992 (Cooley et al. 2015).

Previous studies have primarily focused on meteorological drought (deficit in precipitation, Diffenbaugh et al. 2015; Mann and Gleick 2015; Mao et al. 2015; Kam and Sheffield 2016), agricultural drought (deficit in soil moisture, Griffin and Anchukaitis 2014; Williams et al. 2015; Cook et al. 2015) and how the recent severe drought has impacted water resources such as snowpack conditions (Belmecheri et al. 2016; Margulis et al. 2016). There has been a wide debate on the causes of the current California drought. Some studies demonstrate that there is no clear evidence to discern the link between the drought and storm tracks (Funk et al. 2014; Wang and Schubert 2014; Seager et al. 2015). Others hypothesize that climate change has strengthened and changed atmospheric circulation patterns and therefore will increase the frequency and severity of the future drought conditions (Swain et al. 2014). Swain et al. (2014) pointed out the unusual positive geopotential height (termed as “Ridiculously Resilient Ridge”) over the northeastern Pacific Ocean shifted the position of the jet stream to the north and therefore reduced storm activity, which brought less precipitation to California and increased precipitation to the Pacific Northwest. Diffenbaugh et al. (2015) concluded that anthropogenic effects have already increased the risk of unprecedented drought in California through their analysis of the joint prob-
ability of temperature and precipitation anomalies. Other studies have focused on the teleconnection between precipitation and climate phases, including ENSO (Cayan et al., 1999; Haston and Michaelsen, 1994; Mo and Higgins, 1998; Woolhiser et al., 1993), PDO (Cayan et al., 1998; Fierro, 2014; McAfee, 2014), and Madden-Julian oscillation (Jones, 2000).

However, no studies have investigated the direct influence of human water management on long-term changes in the frequency and intensity of hydrological drought (lack of water in the hydrologic system) in California. There is still much to understand about how human activities (e.g., water use, reservoir operations) intensify or mitigate hydrological drought in California (AghaKouchak et al., 2015) and elsewhere. Therefore, the overarching scientific questions in this study are: (1) what are the effects of human water use on California drought?, (2) which regions within California are most heavily affected by human water use?, and (3) how does the human water management alter hydrological drought severity and duration in California?

This study is organized as: Section 4.2 briefly introduces the study area, hydrological model and the experimental design. This section also presents a risk assessment framework to quantify the probability of occurrence for the 2014-magnitude drought event. Results are given in Section 4.3. Section 4.4 summarizes the main findings and points out limitations and further improvements. Methods used to define drought, and to calculate drought characteristics (duration and deficit) are presented in Appendix C.

4.2 Study Area, Model and Methods

4.2.1 Study Area

As the third largest state of the U.S., California has a variety of climate types and therefore can be further classified into seven climate divisions (CDs, Figure 4.1A).
A strong precipitation gradient exists, with higher annual precipitation in Northern California (CD1, CD2 and CD3) and lower precipitation in Southern California (CD6 and CD7). Coastal and southern parts of California (CD1 and CD4) have a Mediterranean climate with dry summers and wet winters. Although CD5 (termed as San Joaquin Drainage) is classified as semi-arid desert, most of the state’s agriculture still grows in this region making the Central Valley one of the most productive agricultural regions in the U.S., with benefits from statewide water transfer projects, including the Central Valley Project (CVP) and State Water Project (SWP). Large dams associated with these two projects also provide flood control during the spring snowmelt season and water supply during the dry summer and autumn. It is therefore necessary to investigate the different characteristics of these 7 CDs as they have very different climate types, and distinctive water resources management activities.

4.2.2 Model Description

The macro-scale hydrological and water resources model PCR-GLOBWB is utilized for the simulation of the terrestrial water cycle over the period 1979-2014. PCR-GLOBWB runs at a 0.5° spatial resolution at a daily temporal resolution (van Beek et al., 2011; Wada et al., 2014a). The model was forced with the WFDEI meteorological dataset (Weedon et al., 2014). Reference evapotranspiration is calculated based on the Penman-Monteith equation (Allen et al., 1998). In PCR-GLOBWB, runoff (direct runoff and interflow) and baseflow are routed using the kinematic wave approximation of the Saint-Venant equation (Chow et al., 1988). Reservoir operation is considered as four types (water supply, flood control, hydropower generation and others) based on the reservoir data from the GLWD (Global Lakes and Wetlands Database, Lehner and Döll, 2004). Reservoir release is dynamically linked with the routing scheme to meet the local and downstream water demand. Irrigation water demand is estimated based primarily on historical irrigated areas, crop calendar, me-
eteorological conditions, and livestock water demand is based on livestock densities and their drinking water requirements (livestock feed has been included in irrigation if not rain-fed agriculture). To better account for the response of irrigation to model states/fluxes, irrigation water supply is dynamically updated at the daily time step based on the balance and deficit of surface water (for rice) and soil water (for non-rice). Groundwater abstraction is estimated based on the country reported data from the ICGRAC (International Groundwater Resources Assessment Centre) and down-scaled with total water demand and surface water availability. Major water transfer projects in California have not been included in the model simulation due to the unavailable conveyance capacity data and the complex operational and regulatory rules. More details about the model structure and model configuration of human water use can be found in Wada et al. (2014a) and Wada et al. (2016b).

4.2.3 Experiments Design

To investigate how human water use affects drought characteristics, two scenarios are simulated. The first scenario (natural experiment) is configured without any human water management, while the second scenario (human experiment) is conducted taking into account water resources management activities (except water transfers). Through the comparison of these two scenarios, we quantify the relative attribution of human water use in the drought assessment. We focus on hydrological drought, which is usually defined based on negative anomalies of surface and subsurface discharge (Sheffield and Wood, 2011; Van Loon et al., 2016). The commonly used variable threshold level (VTL) method (Hisdal and Tallaksen, 2003; Fleig et al., 2006; Wada et al., 2013; Wanders et al., 2015; Wanders and Wada, 2015) is applied on the simulated daily discharge ($Q$) to derive drought duration (how long the drought lasts) and deficit volume (how severe the drought is) using $Q_{90}$ (monthly 90-percentile flow) as the threshold. In order to quantify the relative contribution of human water use, $Q_{90}$
calculated from the natural scenario over 1979-2014 is used to calculate drought characteristics (duration and deficit volume) for the human scenario. The methodology for calculation of these drought characteristics can be found in Appendix C.

4.2.4 Return Level Analysis for Drought Risk Assessment

To quantify the probability of occurrence or return level for a 2014-magnitude drought event, Extreme Value Theory (EVT) is applied (Swain et al., 2014; Singh et al., 2014; Mastrandrea et al., 2011). The drought magnitude is characterized based on the mean January-December 2014 standardized drought deficit volume (StDef, see Equation C.6 in Appendix C for details) for the entire state and for each individual CD. A parametric distribution is fitted to formulate the relationship between StDef and the return period ($T_r$) over the period 1979-2014 for the two scenarios (natural and human). Parameters of the distribution are estimated using the maximum log-likelihood estimator or L-moments (Hosking, 1990). Given only 36 years of record and the rarity of the 2014 drought event, standard bootstrapping techniques are applied 1000 times to fit the distribution and estimate confidence intervals for the risk assessment.

4.3 Results

4.3.1 Comparison of Drought Severity between Observations and Model Simulation

Figure 4.1 compares the basin-averaged observed and simulated drought deficit volume under natural variability and influenced by human activities (see Figure C.1-C.5 for more validation results). Results from small river basins are variable compared to larger river basins and the addition of water management and consumption does not
improve the simulation over these basins. Improvement is more apparent over larger river basins, where human activities and larger reservoirs play a more important role in intensifying/mitigating drought conditions (overestimating/underestimating drought deficit volume). Overall, the simulated drought deficit volumes considering human activities yields smaller deviations and higher $R^2$ value ($0.68$, $p$-value < $0.0001$) compared to natural conditions ($R^2 = 0.58$, $p$-value < $0.0001$), but the improvement of $R^2$ is not statistically significant at the basin scale according to the analysis of variance (ANOVA), which is probably due to the limited number of data points. We therefore repeated the analysis for each drought event (Figure C.6) instead of the basin average (Figure 4.1) to increase the number of data samples. Tests of line coincidence ($F$-test=$29.23$, $p$-value < $0.0001$) and parallelism ($F$-test=$38.11$, $p$-value < $0.0001$) both indicate that the improvement of $R^2$ is statistically significant. This is consistent with earlier work by Wada et al. (2013), which compared the observed and simulated drought deficit volume based on a large number of drought events over 23 large river basins across the globe that are affected by human water consumption. They found that the improvement of $R^2$ is statistically significant in the human scenario, which demonstrates that for an accurate representation of the regional terrestrial water cycle, physical processes related to human activities should be included in hydrological models.

4.3.2 Time Series of Area in Drought and Drought Deficit

The total area in drought (AID) and StDef have been calculated based on $Q_{90}$ for both scenarios over the whole California (see Appendix C for details). The temporal evolution of these two drought characteristics is given in Figure 4.2A and 4.2B and notable drought events can be detected. For example, two periods, 1987-1992 and 2011-2014, have large values of AID as well as high StDef, indicating severe multi-year droughts. Even though the 1987-1992 drought had a longer duration (5 years)
Figure 4.1: (a) Climatic divisions in California and the USGS stations used for validation and comparison. Size of the dots indicates the relative size of the observed drainage area. (b, c) Comparison between the observed and simulated basin-averaged drought event deficit volume (logarithmic scale) calculated respectively from 22 USGS stations located in major river basins and the collocated grid cells extracted from PCR-GLOBWB under (b) natural variability and (c) including human activities. The points are scaled based on the actual drainage area. See Figure C.1 in Appendix C for the correction of the simulated drainage area.

compared to the 2011-2014 drought and the peak values of the drought characteristics (AID and StDef) are comparable to the recent drought, drought intensity quickly decreases after 1991. While in the 2011-2014 drought event, a long period of high StDef and AID values is found, indicating that the recent drought had a larger spatial extent and a prolonged high impact on the hydrological system. According to the simulation, more than 50% of the total area of California was under drought since late 2012. The temporal evolution of AID under natural conditions (climate variability only) and under human impacts demonstrates that reservoir regulation could reduce the drought area by about 10-20% for normal years, which helped to reduce the impact of short duration drought. Overall, a reduced drought impact is found as a result of reservoir buffering. In terms of StDef, there is no significant difference between these two scenarios for normal years. However, at the beginning of severe drought years (e.g., 1987-1992), human water consumption increases the relative drought intensity. On the other hand, we see a reduced impact as soon as drought recovery starts as a result of reservoir storage that can store excess water and store it for later
use in a drier period. Similar findings are found for the recent drought, where the standardized drought deficit volume under human impacts is smaller than that under natural variability.

Figure 2: Time series of (a) AID and (b) StDef over California from 1979 to 2014 under natural variability (green line), with human activities (red line) and their difference (black line, Human minus Natural). The horizontal dashed line in (a) indicates that 50% of total area in California is under drought.

Figure 4.2: Time series of (a) AID and (b) StDef over California from 1979 to 2014 under natural variability (green line), with human activities (red line) and their difference (black line, Human minus Natural). The horizontal dashed line in (a) indicates that 50% of total area in California is under drought.
4.3.3 Relative Contribution of Human Water Management to Drought Duration and Intensity (During 2014 Drought)

Figure 4.3 shows the spatial pattern of the annual mean drought duration days and deficit for 2014 under the two scenarios, as well as the relative change in drought severity due to human impacts. For drought duration, the overall spatial distribution and the magnitude look very similar under natural variability and with human water consumption. Most parts of California had drought duration greater than 25 days (per month) during this severe drought year. However, the average duration in the eastern part of CD7 is less than 15 days. This is due to the fact that this region has a semi-arid climate and therefore the threshold ($Q_{90}$) calculated from the climatological streamflow to define drought events is also low. Although the spatial pattern looks similar between the two scenarios, there is clear evidence of human impacts on drought duration as indicated from the spatial distribution of the relative increase/decrease. With human impacts, drought duration increases by $\sim 50\%$ for most parts of CD2 and CD3. This is primarily caused by irrigation water consumption, as these two regions have large irrigated areas. The lengthening of drought is also found in CD1, while its magnitude is much milder due to the reduced irrigation water demand.

Similar to the results for drought duration, the intensification of drought deficit (lower panel of Figure 4.3) due to human impacts is obvious in the Central Valley (CD2 and CD5), but the magnitude of the relative increase is much higher (50%-100%) compared to that for drought duration. Although the natural variability is the main driver of the recent drought in this region, human water consumption (water abstraction for irrigation) made the situation much worse by reducing local and downstream water availability. Over the regions where irrigation does not dominate water consumption (CD6 and CD7) and water demand is small, human impacts alle-
viated the hydrological drought by \( \sim 50\% \). The decreased streamflow due to the lack of precipitation could be buffered by the release of reservoirs especially during low flow periods, which are supplies from snowpack.

Figure 4.3: Comparison of drought duration (upper panel, unit: days) and standardized drought deficit volume (lower panel) over California in 2014 under natural variability (left) and with human activities (middle) and the relative contribution (right) due to human activities.

4.3.4 Return Level Analysis

In this section, the EVT is applied for the annual averaged StDef to estimate the return level of the drought. The probability of a 2014 magnitude event and the associated uncertainty in the likelihood estimation are quantified. Five parametric distributions (LogNormal, GEV using L-moments, Pareto, Gamma and Weibull) are tested for the most suitable fit of the statistical distribution. Figure 4.4A and 4.4B (as well as Table C.1) show that the LogNormal distribution best fits the data for both scenarios (only natural variability and with human impacts). In addition, the
LogNormal distribution has the smallest root mean square error between the fitted and the empirical distributions among the five types (see Table C.1). Therefore, this distribution is utilized for the return level analysis.

It is clear to find that 2014 has the largest return period for both scenarios followed by the drought events occurred in the 1990s (Figure 4.4A and 4.4B). The 95% confidence interval of the return period estimated from the bootstrapping method based on the LogNormal distribution indicates that the 2014 drought is between about a 1-in-3 year and 1-in-71 year event under the natural scenario. However, the human scenario has a relatively larger 95% confidence interval of 3-295 years. To better quantify how human activities change the drought risk, we further calculated the likelihood ratio for the return period ($T_{\text{Natural}}/T_{\text{Human}}$). As shown in Figure 4.4C, for the whole of California, there is a 50% likelihood that the probability of the 2014 drought event has at least doubled with human impacts. All the 7 CDs demonstrate that there is >50% likelihood that the 2014 drought event has higher probability under the influence of human water consumption. The most significant impact is found in CD5 (San Joaquin river basin), where there is a 50% chance that the return period is more than 3.5 times larger with human influence than that under natural variability alone. There is even higher confidence (>75%) that the return period becomes 1.5 times larger. This further demonstrates the role of irrigation in the alteration of the hydrological drought. Compared to CD5, which has the largest uncertainty in the estimation of the return period ratio, CD7 (Southeast Desert Basin) has the smallest uncertainty, with the least difference between the natural variability and anthropogenic impacts. These results are consistent with the spatial distribution of the relative increase of the drought characteristics as shown in Figure 4.3.
Figure 4.4: Return level curves fitted by five parametric distributions under (a) natural variability and (b) with human impacts for the entire state over the period of 1979-2014. (c) Box plot showing the distribution of the return period ratio \( \frac{T_{\text{Natural}}}{T_{\text{Human}}} \) using the bootstrapping method for the entire state and each individual CD. The rectangle spans the 25\textsuperscript{th} and 75\textsuperscript{th} percentile and the vertical segment inside the rectangle shows the median. Values larger than 1.5 times interquartile above the 75\textsuperscript{th} percentile are considered as outliers. Colors of the box plot are corresponding to the seven climatic divisions as shown in Figure 4.1A. Return period for the 2014 magnitude drought event is calculated based on the LogNormal distribution.

4.4 Discussion and Conclusions

Few studies have tried to quantify the direct impact of human activities on the recent California drought, and hydrological drought in general. Most studies have focused on
quantifying the likelihood that climate change has impacted meteorological droughts, either through changes in large-scale circulation and teleconnections (e.g., Shukla et al., 2015a, Hoell et al., 2016, Kam and Sheffield, 2016), or local scale thermodynamic forcing and feedbacks via temperature (e.g., Seager et al., 2015). A few studies have looked at the full hydrological cycle based on long-term hydrological simulations (e.g., Mao et al., 2015, Shukla et al., 2015b) but have not examined how human water management has contributed to enhancing or mitigating drought, mainly due to the lack of human representation in modeling frameworks. We show that human activities play an increasingly important role in hydrological drought in California, altering the natural occurrence of hydrological drought as driven by precipitation anomalies, through local scale water use and management that influences the propagation of drought through the hydrological cycle and into changes in streamflow.

Uncertainties in this study are caused by the relatively short period of the model simulation for the risk analysis, but also suffer from the uncertainty in representing human management effects (Wada et al., 2016a). For instance, some human water management modules in the current modeling framework are still configured in a simplistic form or not explicitly considered, such as regulation rules for water use policy, energy production and information on aqueducts or water diversions. This may affect the results in the Central Valley in particular, where large uncertainties may exist in the simulated water availability. Improved estimates of the human impacts could be obtained by a higher resolution representation of reservoir operation, groundwater pumping, irrigation activities as well as more detailed river networks, and particularly specific accounting for water transfers through artificial diversion networks, which in reality can contribute to the supply of irrigation water requirement and may alleviate drought conditions to some extent, especially in the Central Valley. However, we believe that this work provides an appropriate first estimate of the human impact on the 2014 drought. Future research should focus on extending the
simulation to 2015/2016 to examine the impact of the 2016 strong El Niño winter (Wanders et al., 2017). Future work could also focus on a more detailed study of the relative attribution of different types of human activities (groundwater pumping, reservoir operation and irrigation) on changes in drought risk.

This study demonstrates that without considering human water use, the impact of hydrological droughts in California is underestimated. This is especially the case in regions like the Central Valley (Sacramento Drainage and San Joaquin Drainage), where irrigation is the main driver of water consumption. We find that elsewhere in the state water resources management through reservoir operation reduces drought duration and severity. Our extreme value analysis implies that there is high confidence that human water management significantly increases hydrological drought risk over the Central Valley or other areas with a high irrigation water demand. Although this study focuses on the historical perspective, our findings have important policy implications for drought mitigation and management in the context of future climate change. Given that human activities have already worsened the recent drought (as discussed above) and the uncertainty of drought recovery in the near term, water infrastructure in California may face a greater challenge for drought adaptation due to increased water demand (Wada et al., 2013), reduced groundwater storage (Famiglietti, 2014) and declining snowpack (Belmecheri et al., 2016; Margulis et al., 2016).
Chapter 5

Integrating an Agent-based Model into a Large-scale Hydrological Model for Evaluating Drought Management in California

5.1 Introduction

Human activities have dramatically altered the natural environment of the Earth (Hooke, 2000; Wilkinson, 2005), such as deforestation, urbanization, and agricultural expansion. Anthropogenic emissions of greenhouse gases (GHGs) are contributing to global warming, thereby triggering a cascade of side effects, including sea level rise, elevated risk of forest fires, floods and droughts, decreased snow cover and shrinking of ice sheets. In the midst of these alterations, efficient and effective management of the Earth’s fresh water resources has become indispensable. Water management plays a prominent and almost ubiquitous role across the whole spectrum of scales, from local (e.g., abstraction of physical water resources), to regional (e.g., transboundary water
management), and to global (e.g., international food trade and virtual water). The new geological epoch that has ensued from human interventions, i.e., the Anthropocene (Crutzen, 2002; Lewis and Maslin, 2015; Waters et al., 2016), brings forth a plethora of unprecedented challenges to cope with global issues, such as water scarcity (Vörösmarty et al., 2000; Oki and Kanae, 2006; Kummu et al., 2010; Wada et al., 2011a, 2016a), food security (Godfray et al., 2010; FAO, 2016), and energy security (DOE, 2014). Thus, the human component has become an integral and crucial aspect of sustainable development strategies for water resources management. Furthermore, policies designed for stakeholders are also required to integrate cultural, political, and behavioral norms in a coupled human and natural system (CHANS, Liu et al., 2007a,b) to enhance our understanding of the co-evolution of human and natural systems (Sivapalan and Blöschl, 2015).

With time, water policies across different scales have become much more complicated and vital because of the inter-basin, inter-country, and even inter-continental connections in water dependent sectors, such as international food trade (e.g., Dalin et al., 2017), virtual water trade (e.g., Oki and Kanae, 2004; Hanasaki et al., 2010; Oki et al., 2017), and energy systems (e.g., van Vliet et al., 2016). On top of this, climate change poses overwhelming challenges for sustainable development, requiring behavioral changes (Weber, 2015). Certainly, all these changes need to be incorporated while designing usable and cost-effective policies. However, given that our current understanding of the interactions between human behavior and policies lags behind, model experiments arguably are the most cost-effective way to help improve our understanding and reduce the negative consequences of policy inertia when human behavior is not taken into account explicitly. It is, therefore, vital to incorporate human dimensions with the natural system when designing model experiments and conducting scenario analysis. Currently, although a few hydrological and water resources models (e.g., WBMplus, Vörösmarty et al. (2000); Wisser et al. (2010); WaterGAP,
Alcamo et al. (2003a,b); H08, Hanasaki et al. (2008a,b); PCR-GLOBWB, \text{van Beek et al.} (2011); \text{Wada et al.} (2014a, 2016b); MATSIRO, \text{Pokhrel et al.} (2012, 2015); CWatM, \text{Burek et al.} (2017)) consider human water use and management practices (e.g., irrigation, reservoir operation, groundwater pumping), to the best of our knowledge, none of these models includes the dynamics between human behaviors/decisions and water system, especially at the large scale.

As a key component in CHANS, the importance of human activities in the coupled human-water system has caused the rapid development of socio-hydrology of late as an independent field of research (Sivapalan et al., 2012), providing several new avenues to study the interactions between society and water (Pande and Sivapalan, 2017). So far, most socio-hydrology studies only focus on the catchment scale, including the exploration of complex dynamics between humans and floods (Di Baldassarre et al., 2013; Grames et al., 2016), coevolution of irrigated agriculture (Giuliani et al., 2016; Li et al., 2017), flood risk communication and management (Haer et al., 2016), and probabilistic flood warnings (Du et al., 2017a). Development of socio-hydrology itself faces the challenges of how to expand the spatial dimension from small scales (e.g., basin scale) to larger ones (e.g., global scale), and how to better consider the dynamics of interconnectedness across scales (Pande and Sivapalan, 2017). The scaling issue becomes even more vital as the increased pace of globalization is strengthening the inter- and tele-connectedness in the coupled human-water system (Wada et al., 2017). More and more evidence has shown that even piecemeal behaviors/actions can add up to a much larger scale and trigger a cascade of effects (Pande and Sivapalan, 2017). This further points out the necessity to extend the current socio-hydrology framework to larger scales, but with proper treatment of the complexities thereof.

Drawing on the lessons from socio-hydrology, to integrate social and behavioral dimensions into the current large-scale hydrological modeling framework, one effective and promising strategy is to couple process-based models with agent-based models
(ABM) to have an integrated representation of social, environmental, and economic factors by including individual behaviors/decisions within the highly “disaggregated” process-based model. This allows us to have bidirectional interactions and feedbacks between individuals and environmental systems. Benefits of implementing ABM are (Bonabeau, 2002): (1) ABM can capture emergent phenomena; (2) since ABM contains “behaviors” and/or “activities” of agents, the way it describes and simulates human systems is more logical and much closer to the reality as compared to other modeling techniques; (3) ABM has the flexibility to adjust the number of agents and modify the agents’ behaviors; (4) ABM is also able to consider heterogeneity effects. ABM is therefore appropriate in the case of coupled human-water systems because: (1) agent-agent and agent-environment interactions are heterogeneous and complex; (2) behaviors of agents might be changing because of learning and adaptation; (3) individuals have memories. In principle, architectures used to design ABM can be distinguished as two types: heuristic-based/rule-based and optimization-based (Schreinemachers and Berger, 2006). These two approaches have different philosophies: the former attempts to characterize human behaviors from the perspective of psychology and cognitive science, whereas the latter tries to optimize human behaviors based on rationality and utility maximization. Research communities supporting the heuristic-based ABM argue that humans have limited knowledge and their decisions are exposed to many uncertainties, and therefore, it is unrealistic to assume that humans can make optimal decisions. They argue that it is more intuitive to design ABM with heuristic rules instead, which are also straightforward for validation purposes. However, heuristic-based ABM is practically infeasible to handle the heterogeneous production-consumption relationships, and it is mostly redundant to include additional agents and their detailed behaviors. Unlike heuristic-based ABM, which assumes limited human cognition, optimization-based ABM focuses on the inefficiencies in structural factors, such as the failure of institutions, imperfect mar-
kets, limited information or a lack of physical infrastructures (Schreinemachers and Berger, 2006), which are external to decision-makers. From the policy perspective, these structural inefficiencies can be overcome by optimization approaches with policy interventions (Berger et al., 2006). Moreover, optimization can address the trade-offs between economic gain and sustainability in situations where water is scarce and cannot meet all the demands from different sectors. Given the above considerations, we attempt to implement the optimization-based ABM to quantitatively assess how policy interventions in water resources management can affect environmental conditions, especially when the coupled human-water system faces external disturbances (e.g., natural disasters such as floods and droughts), which almost inevitably change human behaviors.

To summarize, the overall objective of this project is to include agents’ behaviors/decisions in a current state-of-the-art hydrological model to have a more realistic representation of the reciprocal interactions and feedbacks between human and natural systems so as to inform policy-making that can cope with natural disasters. Although similar ideas have been proposed before and progresses have been made on the coupling of ABM with hydrological models (Hu et al., 2015; Du et al., 2017b; Noël and Cai, 2017), these coupled modeling efforts essentially focus on small scales (e.g., catchment scale) and are not appropriate for regional to global scales. Our study addresses the issue of designing coupled human-water systems at larger scales. As a case study, we test this integrated model in California focusing on the agriculture sector. California is an appropriate study area as it recently endured record-breaking drought since winter 2011 (Seager et al., 2015). This severe and long-lasting drought also triggered several changes to California’s water policies in the short term (e.g., restrictions on urban water use). It also gave rise to an ongoing debate on future water policy changes to cope with such extreme events, including establishment of
a groundwater banking market, banning water-intensive crops (e.g., almonds) and
efficient water allocation based on the complex water rights \cite{Culp2014}.

The study is structured around the following sections. Section 5.2 introduces the
study area. Section 5.3 presents details of model development including the overall
coupling strategy, the description of the process-based and agent-based models, and
the experimental design. Results are given in Section 5.4. Section 5.5 summarizes
the main findings and discusses policy implications and limitations of this study.

\section*{5.2 Study Area and Problem Description}

We use the integrated model CWatM-ABM to assess the interactions and feedbacks
between farmers’ behaviors and environmental conditions in the state of California.
Being the largest agricultural producing U.S. state, California earned approximately
$47 billion from its agricultural sector in 2015 and contributed 13\% of the U.S. total.
Decreased surface water availability during the 5-year drought from 2011 to 2015
impacted agricultural production of the state. Coping with the water demand resulted
in high pressure on groundwater aquifers, especially in the Central Valley, where
irrigation water supply largely depends on groundwater pumping. As a result, the
area currently faces severe groundwater depletion issues \cite{Famiglietti2014}. The
overdraft of groundwater highlights the need for sustainable development and calls
for fundamental changes of water resources management policies. In 2014, California
passed a legislative water initiative called the Sustainable Groundwater Management
Act (SGMA), which provides a framework for long-term groundwater management
across the entire state. This legislation will change the local stakeholders’ behaviors
in order to achieve groundwater sustainability, which fits well within the scope of
this study, since here we examine the impacts of policy interventions and behavioral
changes on environmental conditions.
Figure 5.1: (a) 7 climatic divisions and 8 U.S. Geological Survey (USGS) stations chosen for calibration and validation in California. Note: Model parameters are only calibrated at USGS station 11523000. (b) Comparison between the observed drainage area from USGS and the corrected drainage area extracted from CWatM.

Figure 5.1A shows the 7 climatic divisions (CDs) in California and 8 USGS stations selected to calibrate the hydrological model. Dividing California into 7 CDs is necessary as they have very different climate types and water resources management activities (see details in [He et al.] 2017). As the selected stations may not be located exactly in the model’s representation of the river network, we manually correct the drainage area by searching for the neighboring grid cells which have the closest drainage area compared to USGS records (Figure 5.1B).

5.3 Methodology

This part describes the overall structure of the integrated model CWatM-ABM and details of the coupling strategy. The process-based hydrological model (CWatM) and an agent-based model (ABM) are also briefly described.
5.3.1 Overall Structure of Coupled Hydrological and Agent-based Model

The overall structure of CWatM-ABM is illustrated in Figure 5.2. Hydrological processes in the natural system and related human interventions are represented in CWatM (as described in Section 5.3.2), whereas social processes in the human system are represented by the agent-based model (ABM, section 5.3.3). CWatM interacts with the ABM via crop profit, which can be estimated based on a crop yield function using the CWatM outputs. The crop profit information will then trigger changes in agents’ behaviors/decisions (e.g., crop mix and irrigation water application rate), which will be sent back to CWatM to update the physical processes. Using this integrated framework, the feedbacks and interactions between the large-scale system dynamics and small-scale individual’s behaviors can be studied in a meaningful way (explained in Section 5.3.3 and 5.3.4). This integrated model can also be used to simulate the human-natural system in a probabilistic manner to explore the effectiveness of different policy interventions (e.g., water management policies) by analyzing different sets of scenarios.

5.3.2 Physical-based Model

Community Water Model (CWatM)

Hydrological processes considering water use and human water management are simulated using the Community Water Model (CWatM, Burek et al., 2017), which is a macro-scale hydrological and water resources model developed by the Water Program at the International Institute of Applied Systems Analysis (IIASA). The main objective of developing CWatM is to facilitate the assessment of the changing pattern of water supply and demand across scales under climate change at different spatial resolutions. In the future, CWatM will be coupled with other existing IIASA mod-
els (e.g., MESSAGE, GLOBIOM, ECHO) to develop an integrated assessment model for nexus issues (e.g., water-food-energy) or hydro-economic modeling. CWatM has a similar structure to PCR-GLOBWB (van Beek et al. 2011; Wada et al. 2014a) and LISFLOOD (Burek et al. 2013), with improved computational efficiency, better interfacing to interact with other nexus models, better allocation schemes to meet water demand, and more accurate characterization of reservoir and lake processes (Burek et al. 2017).

In this study, CWatM was forced by the daily meteorological forcing data set WFDEI (WATCH Forcing Data methodology applied to ERA-Interim data, Weedon et al. 2014) at a 0.5° spatial resolution at a daily temporal resolution covering the 34-year simulation period (1979-2012). Precipitation, relative humidity, long- and short-wave downward surface radiation fluxes, maximum, minimum and average 2 m temperature, 10 m wind speed and surface pressure are used as the inputs to drive CWatM. Elevation data used in this study is extracted from the HYDRO1k Elevation
Derivative Database (HYDRO1k; U.S. Geological Survey Center for Earth Resources Observation and Science; https://lta.cr.usgs.gov/HYDRO1K). Soil types are obtained from the FAO Digital Soil Map of the World (FAO 2003). Data used for reservoir operation (water supply, flood control, hydropower generation and others) are obtained from the Global Lakes and Wetlands Database (Lehner and Döll 2004). Crop-specific calendars and growing season lengths are derived from the MIRCA2000 data set (Portmann et al. 2010). For each crop, the crop coefficient at each development stage and the corresponding maximum crop rooting depth are obtained from the Global Crop Water Model (Siebert and Doll, 2010). The original 26 crop types in MIRCA2000 are reclassified into two crop classes, paddy rice and non-paddy crop. Parameters for the non-paddy crop are aggregated by weighting the area of each crop type. Time series of historical (1979-2010) irrigation area are spatially downscaled to 0.5° resolution from the country-level statistics (available at FAOSTAT, http://www.fao.org/faostat/en/#data/RL) based on the distribution of the gridded irrigation area in the MIRCA2000 data set (Portmann et al., 2010). Historical (1979-2010) water demand data in the household and livestock sectors are estimated and corrected based on the FAO statistics, taking into account population growth, and socioeconomic and technological development. Industrial water demand data for 2000 (as baseline) are firstly obtained from Shiklomanov (1996), World Resources Institute (1998) and Vörösmarty et al. (2005), and are then reconstructed by scaling with the time series of water use intensities based on the algorithm developed by Wada et al. (2011b). Details on how to estimate these water demand data can be found in Wada et al. (2014a).

CWatM simulates the water storage and water exchange (i.e., infiltration, percolation, recharge and capillary rise) within two vertically stacked soil layers and one underlying groundwater layer. Water fluxes through the top soil layer and the atmosphere are included in rainfall, evapotranspiration, snowmelt, and canopy interception.
processes. CWatM applies the kinematic wave approximation of the Saint-Venant equation \cite{Chow1988} for runoff (direct runoff and interflow) and baseflow routing. There are four types of reservoir operation rules depending on their purposes. Reservoir release is dynamically linked with the routing scheme to meet the water demand both locally and in the downstream. So far, CWatM has not considered water transfer projects across river basins due to the limited data as well as the complex operational and regulatory rules. As this study focuses on the agriculture sector, in the following, we will only describe physical processes related to irrigation water requirement (IWR), which are directly linked to the crop yield estimation and farmers’ behaviors. More details about the model structure and physical processes can be found in \cite{Wada2014} and \cite{Burek2017}.

CWatM inherits the same irrigation scheme as implemented in PCR-GLOBWB, which separately estimates IWR for paddy and nonpaddy crops. This irrigation scheme can also dynamically link the daily surface and soil water balance with irrigation water, which is more realistic compared to the existing irrigation schemes used in other large-scale hydrological models \cite{Wada2014}. In CWatM, irrigation water for nonpaddy crop fields, $IWR_{\text{nonpaddy}}$ [m], is estimated using the following equation \cite{Allen1998}:

$$IWR_{\text{nonpaddy}} = \begin{cases} TAW - RAW & \text{RAW} < p \times TAW \\ 0 & \text{RAW} > p \times TAW \end{cases}$$\hspace{1cm}(5.1)$$

where $TAW$ (total available water, [m]) is the total soil moisture available to irrigate crops in the soil column and can be calculated as:

$$TAW = \left\{ \left( \theta_{E, FC_{S1}} - \theta_{E, WP_{S1}} \right) \times \left( \theta_{sat_{S1}} - \theta_{res_{S1}} \right) \times \min(SC_{S1}, Z_r) \right\}$$

$$+ \left\{ \left( \theta_{E, FC_{S2}} - \theta_{E, WP_{S2}} \right) \times \left( \theta_{sat_{S2}} - \theta_{res_{S2}} \right) \times \min(SC_{S2}, \max(0, Z_r - SC_{S1})) \right\} \hspace{1cm}(5.2)$$

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and RAW (readily available water, [m]) is the actual soil moisture that is available in
the root zone:

\[
RAW = \left\{ \left( \theta_{E_{s1}} - \theta_{E_{wp_{s1}}} \right) \times \left( \theta_{sats_{s1}} - \theta_{res_{s1}} \right) \times \min(SC_{s1}, Z_r) \right\}
+ \left\{ \left( \theta_{E_{s2}} - \theta_{E_{wp_{s2}}} \right) \times \left( \theta_{sats_{s2}} - \theta_{res_{s2}} \right) \times \min(SC_{s2}, \max(0, Z_r - SC_{s1})) \right\}
\]

(5.3)

where

- \( \theta_{E_{FC}} \): Effective degree of saturation at field capacity [–]
- \( \theta_{E_{wp}} \): Effective degree of saturation at wilting point [–]
- \( \theta_{sat} \): Saturated (volumetric) water content [m³/m³]
- \( \theta_{res} \): Residual (volumetric) water content [m³/m³]
- \( SC \): Storage capacity of the soil layer [m]
- \( Z_r \): Rooting depth [m]
- \( S_1 \): First soil layer [/]
- \( S_2 \): Second soil layer [/]

\( p \) [–] is the fraction of readily available soil water which crops can extract from the
root zone before suffering moisture stress. It can be calculated using the following
empirical formula:

\[
p = \frac{1}{\alpha_p + \beta_p \times ET_0} - 0.1 \times (5 - No_{cg})
\]

(5.4)

where

- \( \alpha_p \): Regression constant (=0.76, \textit{van Diepen et al.}, 1988) [–]
- \( \beta_p \): Regression constant (=1.5, \textit{van Diepen et al.}, 1988) [–]
- \( ET_0 \): Potential evapotranspiration rate [cm/day]
- \( No_{cg} \): Crop group number (=1 to 5, \textit{Doorenbos and Kassam}, 1979) [–]
For paddy crop, we estimate irrigation water requirement ($IWR_{paddy} [m]$) at time $t$ and associated surface water balance using the following equations:

$$IWR_{paddy,t} = \max(0, S_{\max} - (S_{0,t-1} + P_{net,t}))$$

$$S_{0,t} = S_{0,t-1} + P_{net,t} + IWR_{paddy,t} - q_{i,S_0 \rightarrow S_1,t} - EW_{S_0,t}$$

where

- $S_{\max}$: Maximum surface water depth over the paddy fields ($= 0.05$) [m]
- $S_{0,t}$: Surface water layer over the paddy fields at time $t$ [m]
- $P_{net,t}$: Net liquid precipitation [m]
- $q_{i,S_0 \rightarrow S_1,t}$: Infiltration from surface water layer ($S_0$) to first soil layer ($S_1$) at time $t$ [m]
- $EW_{S_0,t}$: Open water evaporation from the surface water layer ($S_0$) [m]

**Crop Model**

The crop yield (CY) can be estimated based on the following yield-ET relationship:

$$CY_{actual} = CY_{max} \times YR$$

$$YR = \min_{i=1}^{4} \left\{ 1 - k_{y}^{i}(1 - \frac{ET_{a}^{i}}{ET_{c}^{i}}) \right\}$$

$$ET_{c} = k_{c} \times ET_{0}$$

where $CY_{actual} [kg/acre]$ is the actual crop yield and $CY_{max} [kg/acre]$ is the maximum crop yield, $YR [-]$ is the yield ratio, $k_{y}^{i} [-]$ is the yield response factor which varies with crop development stage $i$ (4 stages considered in this study), $ET_{a}^{i} [cm/day]$ is the daily actual crop evapotranspiration at stage $i$, $ET_{c} [cm/day]$ is the daily potential crop evapotranspiration without water stress, $ET_{0} [cm/day]$ is reference (potential) evapotranspiration computed from the Penman-Monteith equation ([Allen et al., 1998](#)) and $k_{c} [-]$ is the crop coefficient. Different from the original yield-moisture stress relationship ([Steduto et al., 2009](#)), we decide to use the minimum value of YR among
the four growing stages, as we assume that crop yield is dominated by the worst growing stage if the crop faces severe water stress.

5.3.3 Agent-based Model

As a starting point, the ABM developed in this study consists of two types of human agency: (1) group of farmers; (2) a single regulation agency at the state level. We assume that farmers have rational behaviors and decisions made by them are to maximize the short-term returns. Therefore, they are highly influenced by the short-term information such as the weather forecast and market price of water and crops. In California, farmers’ decisions on crop types and the growing demand of water-intensive cash crops (e.g., almonds) already show considerable impacts on the agricultural landscapes of California. The recent 5 year drought even brought about policy debate on whether farmers should change crop types under water scarcity. Based on the above considerations, farmers’ irrigation activities in terms of irrigation area (e.g., let fallow a certain land area during drought) and the cropping pattern (e.g., change crop types) are included in the ABM. For the regulation agency, we assume that it always aim to achieve a long-term sustainable use of water resources. Therefore, it can adjust reservoir operation policies to meet the minimum requirement of the environmental flow and it can also cease groundwater pumping for irrigation water use to limit aquifer depletion.

Parameters of the ABM are related to each individual agent’s behaviors. For farmers, the key parameters include crop types, irrigation area, and their risk perception to water shortage. In California, the major crops are walnuts, rice, winter wheat, grapes, pistachios, almonds, corn, alfalfa, other hay/non alfalfa, and tomatoes. These crops have distinctive water use levels, with alfalfa being the most water-intensive crop and tomato being the least water-intensive (Cooley 2015). Since the main objective of this study is model coupling, we have not considered perennial crops (e.g., wine
grapes, table grapes, pistachios, walnuts and almonds), which are constrained by the crop types in the hydrological model. We will incorporate these crops in future work (see the Discussion section). In addition, this study only considers paddy rice and non-paddy crops (i.e., corn) because of the structure of CWatM. Note that these simplifications will not necessarily change the overall objectives of this study. In future work, our plan is to conduct simulations with multiple crops reclassified to match the crop types in MIRCA2000 data set ([Portmann et al.](#) 2010 see Appendix D.1).

5.3.4 Coupling Strategy

The main idea for model coupling is to bring different agents’ behaviors and decisions into CWatM across different time scales. For example, farmers make daily decisions on irrigation and seasonal/annual decisions on the crop types and technologies. The regulatory agency makes regulation decisions at the annual time scale. Inspired by the $p$ parameter in Equation 5.1, which characterizes crop’s sensitivity to water stress, and also following the work by [Noël and Cai](#) (2017), we add a new parameter $\alpha$ with positive values in Equation 5.1 to characterize farmers’ sensitivity (or risk perception) to water stress, which directly links CWatM and ABM together through IWR:

$$ IWR_{\text{nonpaddy}} = \begin{cases} \alpha \times TAW - \text{RAW} & \text{RAW} < p \times \alpha \times TAW \\ 0 & \text{RAW} > p \times \alpha \times TAW \end{cases} $$ (5.9)

In the above equation, $\alpha$ has clear physical meaning. If $\alpha$ is larger than 1, then farmers become more sensitive to water stress, which means they tend to irrigate more frequently and withdraw more water for irrigation. In contrast, if $\alpha$ is smaller than 1, farmers are more tolerant to water stress and they tend to take less water and irrigate less frequently. The introduction of $\alpha$ into the physical model also enables
the investigation of the effects of behavioral heterogeneity on system dynamics by assuming that $\alpha$ follows a certain distribution (e.g., normal distribution).

### 5.3.5 Simulation-based Optimization Approach

Section 5.3.4 discusses the conceptual background of coupling the physical model and agent-based model. Mathematically, the overall framework can be summarized as the following simulation-based optimization problem with the objective to maximize the total crop profit $B(S_c)$ given certain constraints:

$$
\text{maximize } B(S_c) = \sum_c [P_c \times CY_c - C_c] \times S_c \\
\text{subject to } WSI_k(S_c) = \frac{W_k(S_c)}{A_k(S_c) - E_k(S_c)} \leq 40\% \\
\sum_c IW \times S_c \leq TAW_{Irri} \\
\sum_c S_c \leq Land_{Irri} \\
S_{paddy} \geq 20\% \\
\text{physical constrains } \in CWatM \text{ (e.g., water balance)}
$$

(5.10)
where

\[ S_c : \text{ Irrigation area for crop c (paddy or nonpaddy) [acre]} \]
\[ B : \text{ Total crop profit [$]} \]
\[ P_c : \text{ Crop price [$/kg]} \]
\[ CY_c : \text{ Crop yield [kg/acre]} \]
\[ C_c : \text{ Production cost [$/acre]} \]
\[ WSI_k : \text{ Water stress index for grid cell k (Wada et al., 2014b) [-]} \]
\[ W_k : \text{ Water withdrawal at grid cell k [m]} \]
\[ A_k : \text{ Water availability at grid cell k [m]} \]
\[ E_k : \text{ Environmental flow requirement at grid cell k [m]} \]
\[ IW_c : \text{ Water used to irrigate crop c [m/acre]} \]
\[ \text{TAW}_{\text{irri}} : \text{ Total available water used for irrigation [m]} \]
\[ \text{Land}_{\text{irri}} : \text{ Total land area for irrigation [acre]} \]
\[ \overline{S}_{\text{paddy}} : \text{ Averaged land area fraction for paddy crop [-]} \]

Procedures to conduct simulations using this simulation-based optimization framework can be further explained by the flowchart (Figure 5.3). Starting from the first year, we sample farmers’ behaviors from a given probability distribution. For agent \( j \), their decisions are passed to CWatM. Combined with the yield-stress relationship, crop profits can be estimated as the economic objective. In the meantime, CWatM calculates the water stress as the environmental objective, which is related to the regulation agency’s decision to meet certain requirements (e.g., keep water stress under certain threshold). We then apply the optimization method to obtain the optimal cropping patterns. If optimal values are not obtained, farmers’ decisions will be updated and the simulation will be rerun. These procedures are repeated for each year until the end of the historical period.
5.3.6 Experiments Design

We run CWatM at 0.5° spatial resolution at the daily time step over California from 1979 to 2012. As a proof of concept, the simulation is conducted for one single year (1981) with initial conditions obtained from the last day of the previous year (1980). To investigate the bidirectional interactions between human behaviors and the system dynamics, two sets of scenarios are conducted. In the baseline scenario, farmers’ irrigation behaviors are not included ($\alpha=1$). For behavior-related scenarios, homogeneous behavior patterns with constant $\alpha$ values characterizing farmers’ high ($\alpha=1.2$) and low sensitivity ($\alpha=0.8$) to water stress are firstly tested in CWatM-ABM. Then, behavioral heterogeneity is included in the coupled system by randomly sampling $\alpha$ in the spatial domain from a normal distribution with unit mean and different standard deviation (i.e., 0.01, 0.02, 0.03, ..., 0.1). As a preliminary attempt, these experiments can help us evaluate how the coupled system will respond to the agent’s behaviors and how individuals will react to the changing environmental conditions.
5.4 Results

5.4.1 Model Calibration and Performance Evaluation of CWatM

We first evaluate the model performance of CWatM to simulate the terrestrial hydrological fluxes. We have calibrated CWatM against streamflow observations from one USGS station (11523000) in the northwestern part of California (see Figure 5.1A). Model calibration is performed using an evolutionary computational framework called DEAP (Distributed Evolutionary Algorithms in Python, [Fortin et al., 2012]). We implement the NSGA-II algorithm ([Deb et al., 2002] in DEAP for single objective optimization. The modified version of the Kling-Gupta Efficiency ([Kling et al., 2012]) is used as the objective function to be maximized:

\[ KGE = 1 - \sqrt{(R - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \]  (5.11)
\[ R = \frac{\sum_{i=1}^{N}(O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{N}(O_i - \bar{O})^2 \sum_{i=1}^{N}(S_i - \bar{S})^2}} \]  (5.12)
\[ \beta = \frac{\bar{S}}{\bar{O}} \]  (5.13)
\[ \gamma = \frac{CV_S}{CV_O} = \frac{\sigma_S/\bar{S}}{\sigma_O/\bar{O}} \]  (5.14)

where \( R \) [-] is the correlation coefficient between simulated (\( S \)) and observed (\( O \)) streamflow, \( \beta \) [-] is the bias ratio, \( \gamma \) [-] is the variability ratio, \( N \) is the number of data points, \( \bar{S}/\bar{O} \) is respectively the average of simulated/observed streamflow, \( CV_S/CV_O \) is respectively the coefficient of variation of simulated/observed streamflow and \( \sigma_O/\sigma_S \) is respectively the standard deviation of observed/simulated streamflow. KGE, \( R \), \( \beta \) and \( \gamma \) have their optimum at unity. We have used a population size of 256 and recombination pool size of 32 with the number of generations set to 30 to calibrate CWatM, which proves to be sufficient to achieve convergence. Specifically, we have
calibrated the model focusing on parameters related to snow, evapotranspiration, soil, groundwater, routing process, lakes and reservoirs. For the full list of calibrated parameters, please refer to Appendix D.2.

Besides $R$ and KGE, the following metrics are also used to evaluate the performance of CWatM:

$$B = \frac{\sum_{i=1}^{N}(O_i - S_i)}{\sum_{i=1}^{N} O_i} \times 100$$

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{N}(O_i - S_i)^2}{\sum_{i=1}^{N} (O_i - \bar{O})^2}$$

where $B$ is the percent bias (Gupta et al., 1999a) and NSE is the Nash–Sutcliffe coefficient of efficiency (Nash and Sutcliffe, 1970). Compared to NSE, KGE measures the Euclidean distance from the ideal point (unity) of the Pareto front and is therefore able to provide an optimal solution, which is simultaneously good for bias, flow variability, and correlation. For more information about the objective function of KGE and its advantages over the often used NSE, consult Gupta et al. (2009).

Time series of observed and simulated streamflow and the associated performance metrics for the calibration period (1991-2010) are shown in Figure 5.4. Results demonstrate that CWatM can well reproduce the streamflow variability and magnitude both at daily and monthly time scale, although for the daily streamflow simulation, CWatM could significantly overestimate or underestimate the flood peak for some events. Overall, the simulation from CWatM is considered to be good based on the streamflow time series and the performance metrics (high KGE, NSE, $R$ and low $B$).

5.4.2 Impacts of Farmers’ Behaviors on System Dynamics

As noted earlier in the experimental design section (Section 5.3.6), we conduct a series of model simulations with varying $\alpha$ values to assess the role of farmers’ behaviors on the coupled human-water system. Here in this section, we examine whether and to
what extent farmers’ behaviors can influence the environmental conditions. Figure 5.5 shows the temporal evolution of the spatially averaged streamflow over California simulated from CWatM-ABM. For all scenarios, we observe that streamflow is more sensitive to farmers’ sensitivity to water stress ($\alpha$) in the early period of the growing season (April to July). Although we only observe small differences in the time series among all three homogeneous scenarios, scenarios with high/low $\alpha$ values generally have higher/lower streamflow magnitude. This is likely due to the fact that if farmers are more sensitive to water stress ($\alpha=1.2$), they tend to irrigate more frequently and withdraw more water for irrigation. In this situation, if surface water is not enough, farmers will pump groundwater for irrigation, which can potentially increase the surface water because of the return flow from irrigation. In contrast, if farmers are less sensitive to water stress ($\alpha=0.8$), they tend to irrigate less frequently and will probably only use surface water for irrigation. In this case, streamflow magnitude is
smaller than the baseline scenario. Different from homogeneous scenarios, we can see increased sensitivity of the streamflow simulation in heterogeneous scenarios, especially for the one with the highest behavioral heterogeneity (i.e., $\alpha$ sampled from the normal distribution with the highest standard deviation). This could be related to the complex upstream-downstream relationship and river networks, which nonlinearity interact with farmers’ irrigation activities through the inclusion of the heterogeneous $\alpha$ value. The underlying physical mechanisms related to catchment properties and hydrological processes explaining this sensitivity still needs further investigation. As a first attempt, we compare the spatial distribution of simulated streamflow from the coupled model for homogeneous (top row in Figure 5.6) and heterogeneous scenarios (bottom row in Figure 5.6) for one particular day (May 24th, 1981). As can be seen, streamflow shows clear-cut spatial variability for all scenarios, with the highest value in Sacramento Drainage basin and the lowest in arid climatic divisions (e.g., South Coast Drainage and Southeast Desert Basin). The overall spatial pattern of streamflow does not seem to be very different among the homogeneous scenarios, although there is a slight difference in the south part of the Sacramento Drainage basin. Including behavioral heterogeneity does not necessarily change the spatial distribution of streamflow compared to homogeneous scenarios, as shown in the bottom row of Figure 5.6. However, there is increased streamflow in San Joaquin Drainage basin in Figure 5.6E. Furthermore, this pattern does not emerge in the scenario with increased heterogeneity (Figure 5.6F), which requires further exploration with more experiments.

As described in Section 5.3.4, farmers’ sensitivity to water stress ($\alpha$) is directly linked with irrigation water requirement, and so we compare the seasonal cycle of water withdrawal for irrigation (Figure 5.7A) and groundwater storage (Figure 5.7B). As expected, in homogeneous scenarios, irrigation water withdrawal increases and groundwater storage decreases if farmers become more sensitive to water stress.
Figure 5.5: Spatially averaged streamflow over California simulated by the CWatM-ABM during the growing season (April to October) in 1981 for scenarios with homogeneous $\alpha$ values ($\alpha=1.0$, farmers’ behaviors are not included; $\alpha=0.8$, farmers have low sensitivity to water stress; $\alpha=1.2$, farmers have high sensitivity to water stress) and heterogeneous $\alpha$ values with different normal distributions (thin gray lines). ($\alpha=1.2$) and vice versa. For heterogeneous scenarios, results indicate that behavioral heterogeneity not only changes the magnitude of irrigation water withdrawal but also tends to push the peak water withdrawal to occur earlier.

5.4.3 Impacts of System Dynamics on Crop Yield

Understanding how farmers’ behaviors influence system dynamics is just one side of the story, the other side is to explore how system dynamics (e.g., environmental conditions) could influence farmers’ crop profit through the interactions and feedbacks between the natural and human system. This is of practical importance for policy making, especially when the system has external disturbances, such as severe drought. Starting from homogeneous scenarios, the spatial distribution of the estimated crop yield for paddy rice and corn in the baseline scenario is shown in the left column of Figure 5.8. Broadly speaking, corn has higher and more uniform geographical distribution of yield production compared to paddy rice. To investigate how system dynamics influence farmers through the interaction with their behaviors, we calculate
Figure 5.6: Spatial distribution of simulated streamflow from CWatM-ABM on May 24th, 1981 for homogeneous scenarios (top row) without considering farmers’ behaviors (left), scenario in which farmers have low sensitivity to water stress (middle) and scenario in which farmers have high sensitivity to water stress (right). Bottom row shows heterogeneous scenarios with increased behavioral heterogeneity (standard deviation of the normal distribution increases from left to right).

Figure 5.7: Seasonal distribution of (left) irrigation water withdrawal and (right) groundwater storage simulated from CWatM-ABM for homogeneous (thick lines) and heterogeneous scenarios (thin grey lines) for 1981.
the relative change (%) of the crop yield for high and low sensitivity scenarios and compare them with the baseline simulation. For the scenario in which farmers are more sensitive to water stress (middle column of Figure 5.8), the rice yield can increase up to $\sim 40-60\%$, especially in the Sacramento Drainage basin. This is because farmers try to irrigate more frequently and take more water for irrigation to ensure the optimal crop growth without or with relatively smaller risk of suffering water stress. The relative increase of yield production also holds for corn, but it expands to a much larger area in the Central Valley. Different from the high sensitivity scenario, opposite spatial patterns can be found in the low sensitivity scenario with decreased rice yield up to $\sim 40-60\%$ in the Sacramento Drainage basin. Similar to the results presented for rice, the relative decrease of yield production for corn due to the reduced irrigation water withdrawal is obvious in the Central Valley, but the magnitude of the relative decrease is smaller ($\sim 20-40\%$). Including behavioral heterogeneity has profound impacts on the relative change of yield production for corn, and the spatial variability generally increases as the variability of $\alpha$ (i.e., standard deviation of the normal distribution) increases (bottom row of Figure 5.9). In other words, the system has more diverse response as the level of behavioral heterogeneity increases. However, this type of response is only significant in the Sacramento Drainage for rice, but not anywhere else (top row of Figure 5.9). Taken together, the results presented in Section 5.4.2 and 5.4.3 suggest that it is important to take into account behavioral heterogeneity when analyzing the bidirectional interactions between the large-scale natural and human systems as it could bring additional sources of uncertainties.

5.4.4 Reconciling Policy Goals

Lastly, we apply the coupled model in the context of policy making to see how to balance the trade-offs if the system has conflicting goals. In this study, the whole system has two conflicting goals corresponding to each agent type. Farmers are trying to
Figure 5.8: Simulated crop yield (left column) for paddy rice and corn in California and the relative change of crop yield (middle and right columns) compared to the baseline scenario (no behavior included in CWatM-ABM).

Figure 5.9: Similar as the percentage change shown in Figure 5.8 but for heterogeneous scenarios with increased level of behavioral heterogeneity from left to right.
maximize their profits in the short term, while the regulation agency is aiming at sustainable water management in the long run. It is therefore important to understand the trade-offs between these two conflicting goals, with the ultimate aim of providing recommendations about optimal and robust solutions for policy makers to decouple the conflicts through policy interventions, such as triggering the behavioral changes of individuals. Figure 5.10 and Figure 5.11 compare crop profit and groundwater depletion calculated from the physical model with and without the ABM coupling. Consistent with previous results, for scenarios with homogeneous human behaviors, the low sensitivity scenario results in lower crop profit and the high sensitivity scenario leads to higher values compared to the baseline simulation (Figure 5.10). However, if CWatM is dynamically coupled with ABM, crop profit can be increased significantly for all scenarios, especially for farmers with low sensitivity, which means even though they do not irrigate frequently, if they have reliable information and make optimal decisions on irrigated areas and crop types, they can still increase their profit substantially. However, the relative increase is not so obvious in the high sensitivity scenario, which is probably due to the constraint on the water availability for irrigation. For the heterogeneous scenarios, the relative increase of crop profit in the coupled model is not linearly correlated with the increasing heterogeneity, although the relative increase is still quite significant. For the sustainability objective, which conflicts with the crop profit, the coupled model can significantly increase the total groundwater storage compared to the uncoupled one (Figure 5.11A). Moreover, the percentage reduction of groundwater depletion can be as high as 80% for the high sensitivity scenario and about 60% for the low sensitivity scenario. Together, these results demonstrate that the coupled model can increase farmers’ profit to a certain extent without compromising groundwater depletion. This can provide important insights for policy makers towards sustainable water management if farmers choose optimal cropping patterns.
Figure 5.10: Crop profit calculated from the physical model with (hatched bar) and without (solid bar) coupling to ABM for homogeneous and heterogeneous scenarios. For heterogeneous scenarios, the normal distribution used to sample $\alpha$ has increased standard deviation from left to right indicating increased behavioral heterogeneity.

Figure 5.11: (a) Seasonal cycle of groundwater storage from coupled (dashed lines) and uncoupled (solid lines) model simulations and (b) the percentage reduction of groundwater depletion for scenarios with homogeneous (thick lines) and heterogeneous (thin lines) behaviors.
5.5 Summary and Discussion

5.5.1 Summary

A coupled agent-based and hydrological modeling framework CWatM-ABM has been developed through a simulation-based optimization framework. To the best of our knowledge, this is the first time that human/behavioral dimensions have been brought into a large-scale hydrological and water resources model. We apply this integrated model to California focusing on the interactions between agricultural activities and water use. The results demonstrate the efficacy of CWatM-ABM to model the role of farmers’ behaviors, which drive the interactions and feedbacks between the coupled human-water system. Numerical experiments with homogeneous and heterogeneous behavioral patterns are compared and indicate that human behavioral heterogeneity can add additional layers of complexity and uncertainties in the model simulation. We also demonstrate that CWatM-ABM offers a potential means for policy makers to balance the trade-offs between an economic objective (e.g., crop profit) and an environmental objective (e.g., groundwater depletion). More broadly, any policy interventions for effective water management with the heightened threat of climate change and anthropogenic activities should most certainly take into account behavioral changes and the associated heterogeneous patterns. Despite the novelty of our approach and potentially useful findings of these initial results, the following issues need to be addressed in future work.

5.5.2 Further Improvement of ABM

Farmers’ Sensitivity to Water Stress

Currently, the coupled model CWatM-ABM is developed through a top-down approach. The model is described at the aggregate level because of the coarse resolution (0.5°) of the physical model to reflect the large-scale dynamics. This is also part of
the reason why we use a lumped parameter $\alpha$ to characterize the averaged behaviors for a group of farmers in terms of their risk perception to water stress. However, we could also combine a bottom-up approach to decompose this lumped parameter to other factors, not only hydro-climatic variability, but also related to farmers’ income, past experience, cultural norms, social safety nets, internal characteristics, and adaptation strategies to natural disasters. We can then parameterize farmers’ behaviors using a multi-layer and multi-scale approach through a hierarchical structure with nested scales starting from the local farmers and then upscale to the pixel scale ($\sim 50 km$) to match the resolution of the physical model. However, the challenge is to find appropriate data to calibrate and validate the $\alpha$ parameter at different scales, which becomes even more difficult if we want to consider the temporal evolution of $\alpha$ due to farmers’ realistic learning and adaptation. However, it seems to be promising to link human behavior/attitude to risk with the coping capacity as proposed by Wada et al. (2016a) if the model is scaled to the global scale.

Besides the scaling issue, heterogeneity effects in this study are considered by assuming that farmers’ sensitivity to water stress follows the normal distribution. However, this may not be always the case and data are needed to validate this assumption. Moreover, the idea of sampling $\alpha$ from a particular probability distribution is to include stochasticity or “randomness” with the assumption that we lack certain knowledge about the distribution of farmers’ behaviors. In reality, farmers’ behaviors and associated heterogeneity are certainly a function of various factors as discussed above, which will be much more complex and difficult to parameterize.

**Agent-Agent Interactions and Agent-Environment Interactions**

As mentioned in the Methodology section, one of the main advantages of ABM is its unique ability to model agent-agent interactions and agent-environment interactions. However, this could be very challenging to include in the model. For example, ground-
water depletion in California could reduce surface flows, but the current version of
the hydrological model does not simulate this hydrological connection (there are no
groundwater-surface water interactions). Therefore, this type of agent-environment
interaction in the ABM (i.e., farmers experiencing reduced surface flows and respond-
ing in some way) is not currently possible, which needs further model development in
future work. In terms of agent-agent interactions, a variety of interactions between
different agents can exist, with associated challenges in how to model them: farmers
and farmers, farmers and government agencies, upstream and downstream agents, and
agents across different sectors. These interactions can be possibly modeled through a
diffusion model, such as the BASS model (Bass, 1969) or through role-playing games.

5.5.3 Further Improvement of Optimization

In this study, ABM is coupled with CWatM using an optimization framework, which is
based on the assumption that farmers have rational behaviors. Although this might
not be realistic from the perspective of the full social behavior and psychological
characteristic of agents, it turns out to be very helpful to conceptualize the coevolution
of human and water (Sivapalan and Blöschl, 2015). Nevertheless, we could apply a
combined optimization and heuristic-rule based ABM and couple it with CWatM
for future model development to increase the realism. It should also be noted that
there is still a lot of room for improvement of the optimization framework. For
example, this study only considers two types of crops as a proof-of-concept to test
the overall coupling strategy. It would be more realistic to consider more crop types
and even perennial crops, which would provide more adaptation options for farmers.
Furthermore, the water availability constraint based on the water stress index (WSI)
in the optimization is considered at the annual time scale. WSI has a strong seasonal
cycle and it would be more realistic to add a monthly constraint for WSI instead of
the annual constraint. We also do not account for the pricing of water, as we assume
that crop price is constant and the production cost is also constant, which in reality fluctuate and can influence individual’s behavior.

5.5.4 Policy Implications

Water infrastructure in California is already facing great challenges in coping with drought due to increased water demand \cite{Wada et al., 2013}, reduced groundwater storage \cite{Famiglietti, 2014} and declining snowpack \cite{Belmecheri et al., 2016; Margulis et al., 2016}. Human footprints have further worsened the recent drought \cite{Diffenbaugh et al., 2015; He et al., 2017} and are adding another level of uncertainty to drought recovery in the near term. Therefore, including the influence of human behavior is imperative for drought adaptation policy making. The integrated framework CWatM-ABM developed in this study could empower water managers and local governments with a new tool, which combines physical hydrological modeling with human decision-making. This framework can guide policymakers in the design of effective strategies for coping with water management under the risks of climate change, and facilitate decision-making on optimal drought adaptation options for water infrastructure investment. In particular, we can \textit{ex-ante} simulate the impact of policy interventions on the system level dynamics through a set of scenarios: (a) baseline scenarios that maintain the current management options and policies; (b) regulation scenarios that constrain groundwater pumping and ensure minimum environmental flow; (c) water market scenarios that consider the changes of crop types and the water price; (d) policy adaptation scenarios considering new technology for irrigation water saving, downstream water allocation based on actual and changing pattern of irrigation water demand, and negotiation of water allocations among different agents. These scenarios can help us explore the effectiveness of different water management strategies for drought adaptation. In addition to these scenario-based analyses, the
optimization framework itself provides a unique opportunity to assess the trade-offs between competing goals in our study.
Chapter 6

Solar and Wind Energy Enhances
Drought Resilience and
Groundwater Sustainability

6.1 Background and Motivation

As the central element of the water-food-energy (WFE) nexus (Perrone and Hornberger, 2014; Scanlon et al., 2017; Cai et al., 2018), effective management of water resources, especially for regulated river basins, is key to meet societal needs, including irrigation supply for food production and reservoir water release for hydropower generation. However, current water management strategies are often carried out independently for each sector, leading to competition for water resources (Hurford and Harou, 2014; Conway et al., 2015). This is likely to be exacerbated by the potential for increasing severity of drought under climate change (Sheffield and Wood, 2008a) and growing demand for limited water resources (Wada et al., 2011b, 2014a). For example, globally, 54% of hydropower plants compete with irrigation water use (Zeng et al., 2017), and this competition between food production and hydropower generation has
been increasing with several hot spots identified around the world. The competition usually happens between upstream and downstream sources. For instance, upstream hydroelectric power plants tend to store more water to increase and maintain the hydraulic head for power generation, even during the dry season. In contrast, downstream users need water released from upstream reservoirs to irrigate crops with a different timing (e.g., during the growing season). In some cases, a lack of available surface water puts a burden on groundwater, which also acts as a buffer to alleviate drought, leading to groundwater depletion ([Wada et al., 2010, 2012, Dalin et al., 2017, Marston and Konar, 2017], given the slow process of groundwater recharge to aquifers ([Taylor et al., 2013]). Meanwhile, increased water scarcity ([Vörösmarty et al., 2000, Schewe et al., 2014] and shifts in the timing of streamflow ([Barnett et al., 2005, Stewart et al., 2005] could further strain the WFE nexus and exacerbate the conflicts or trade-offs between irrigation and hydropower. For instance, traditional reservoir operation rules without consideration of the non-stationarity ([Milly et al., 2008]) of hydroclimate may no longer be efficient enough to navigate the trade-offs due to the seasonal imbalance between water supply and demand.

Here, we argue that these trade-offs, and their future evolution, can be potentially solved by consideration of integrated management tools and the fast increase of low-carbon energy generation, such as solar and wind energy (SWE). Given the fact that SWE deployment is accelerating and is particularly substitutable for hydropower if they are paired with energy storage facilities (e.g., thermal storage, batteries), energy systems are becoming less reliant on hydropower, as well as fossil fuels, especially for developed regions. Consequently, water used to drive turbines for hydropower generation can be saved for irrigation purposes to ensure food production, whilst reducing groundwater usage thereby increasing groundwater sustainability especially under drought. Here we emphasize the social value of SWE for environmental sustainability, which remains poorly understood in the scientific community and policy
circles, through a case study in California. We first examine how water scarcity, as well as SWE, influences decisions surrounding the optimal and sustainable allocation of water for hydropower generation and food production. We then estimate the unrecognized and under-appreciated value of SWE beyond its role in the traditional energy sector and the synergies between SWE and groundwater to enhance drought resilience and environmental sustainability. Our analysis can help develop and integrate impact pathways into policy support for positive practical changes for sustainable water and food security.

6.2 Solar and Wind Energy Help Secure a Sustainable Future of Groundwater

California recently endured a record-breaking drought after 2012 (Diffenbaugh et al. 2015; He et al. 2017), which significantly impacted food production (Howitt et al. 2014), reduced hydropower generation (Gleick 2017) and caused severe environmental issues (e.g., groundwater depletion, wildfires, tree mortality, land subsidence). As the largest agricultural producing state in the U.S., California earned approximately $47 billion from its agricultural sector and contributed to 13% of the U.S. total in 2015 even during the drought. The maintenance of crop revenue and overall resilience of the agricultural sector largely relied on the unsustainable groundwater overdraft, which effectively offset the drought impact, but contributed to severe groundwater depletion (∼3.7 km³/year, Faunt and Sneed 2015). In the energy sector, during this driest year of the drought, decreased surface water availability sent the in-state hydropower generation plunging to 7% of the total electricity generated, substantially below the state’s long-term average of around 18% (Gleick 2017). This power deficit was offset by electricity generated through the rapidly growing solar and wind fleet, as well as from increased use of natural gas and electricity purchased from out-
of-state sources (Gleick, 2017). Furthermore, for the first time, in 2012, solar and wind electricity generation exceeded hydropower in California (Gleick, 2017) due to the declining cost of wind turbines and solar photovoltaic (PV) in conjunction with the popularity and stringency of the Renewables Portfolio Standard (RPS), which mandates a certain proportion of renewables in the energy production.

The penetration of SWE not only offset some of the decreases in hydropower but has implications beyond the energy sector given the inextricable links among food, energy and water. This added value can be derived by considering the sustainability trade-offs within the WFE nexus. In general, there is a direct trade-off between hydroelectricity production and irrigation of crops in how surface water is allocated between the two. There is also an indirect trade-off between hydroelectricity production and groundwater abstraction, as groundwater can substitute for reduced surface water availability during a drought, which in the case of the recent California drought allowed crop production to generally be unaffected. Given relatively low groundwater recharge rates and increasing risk of drought, this indirect trade-off highlights potential sustainability challenges for groundwater.

We adopt the trade-off frontier (TF) (also called production possibility frontier, see Perrone and Hornberger, 2016 and Appendix E.1 for details) to investigate the compromise between hydroelectric generation and groundwater abstraction in California given a set of surface water constraints (gray solid lines in Figure 6.1) varying from a dry to a wet year. We use a calibrated and physically-based hydrological model with water management options to simulate the surface water availability for hydropower production as well as the irrigation water requirement (including both surface water and groundwater) for food production. We then estimate how surface water and groundwater can be optimally allocated to maximize the total economic revenue ($R$). Efficient surface water allocation strategies are represented by the TF curve, while it is inefficient/unattainable if strategies fall inside/outside of the TF.
A strategy is inefficient if surface water is not fully used for hydropower (production is lower than potential) and agriculture (irrigation is less than crop demand), and groundwater is used for irrigation instead. A strategy is unattainable if the water demand for both hydropower production and irrigation exceeds the surface water availability, and the shortfall in irrigation demand cannot be satisfied by the current groundwater abstraction rate. Iso-revenue curves (green dashed lines in Figure 6.1) connect points of equal economic profit with different quantities of hydroelectricity production, economic cost of groundwater pumping and revenue loss due to crop failure (see Appendix E.2 for details on revenue calculation). Crop revenue may be reduced if water demand is not met by surface water allocation and the current rate of groundwater abstraction. Iso-revenue curves are convex given the law of diminishing marginal utility. The point of tangency between the TF and the iso-revenue curve (black point in Figure 6.1) indicates the optimal (or economically efficient) condition where efficient water allocation and maximum revenue could both be achieved through appropriate policy instruments, such as SWE penetration and groundwater abstraction caps as discussed later. Externalities or market failure may distort the iso-revenue curve, and social and technological constraints (e.g., cropping decisions, lack of infrastructure for water storage and diversion) may cause the allocation to be unattainable. On top of these factors, hydroclimate variability will shift the TF inwards and outwards for low (lower surface water availability in a dry year) and high inflow (higher surface water availability in a wet year) conditions, respectively. Connecting the optimal points under different surface water availability conditions forms a so-called expansion path (EP, pink lines in Figure 6.1, see Appendix E for algorithms applied to find EP). The EP informs policymaking by identifying the optimal water allocation to secure food production while balancing hydroelectric generation and groundwater abstraction as surface water availability changes.
Figure 6.1: Trade-off frontiers (gray solid lines) for three inflow conditions (dry, normal and wet year), the corresponding iso-revenue lines (green dashed lines) and expansion paths (red solid lines) for optimal water allocation given different penetration ratios of SWE (from 17% to 40%) and different groundwater pumping lift ($\Delta h$). Light green shaded area represents unsustainable zone, where more groundwater is abstracted for irrigation as less surface water is available due to its use for hydroelectric generation. Pink shaded area is the safe and just zone, where optimal points can be achieved. Light blue shaded area represents uneconomical zone, where we sacrifice the revenue from hydropower production in order to maintain the groundwater sustainability.

To examine the added value of SWE in reducing sustainability trade-offs, we use this framework to quantify how optimal strategies maximizing hydroelectricity and agricultural income, whilst avoiding groundwater depletion, are altered by the penetration of SWE. California has seen sustained growth of solar and wind power, which account for 17% of statewide electricity generation in 2016 (data from California Energy Commission). By 2030, solar and wind are projected to generate 35-40% of total electricity (Brinkman et al., 2016) to achieve the goal of 50% renewables together with hydropower (State Bill No. 350). Given this target, we consider two penetration scenarios to examine how future penetration of SWE (40%) would in-
fluence the hydroelectricity-groundwater trade-offs compared to the current situation (17%) under different surface water availability conditions. Penetration of SWE influences the shape and position of the iso-revenue lines and therefore changes the position of the optimal point (Figure 6.1). Iso-revenue lines in the current penetration scenario have smaller curvature than those in the future penetration scenario, indicating smaller marginal revenue of hydroelectricity. This implies that as more SWE is deployed and the hydroelectricity price goes down, to maintain the same revenue, one unit of abstraction of groundwater requires more hydroelectric generation to compensate the pumping cost. This in turn shifts the EP rightward (more sustainable for groundwater), favoring surface water allocation for irrigation and reducing groundwater abstraction. This happens because hydropower is displaced by solar and wind, surface water, which would otherwise generate hydroelectricity, is conserved and can now be used for irrigation. As indicated by the horizontal part of the EP, the initial allocation of surface water is targeted for crop production with higher priority until surface water availability surpasses a certain threshold. This is especially the case when surface water becomes scarcer during a drought, and the cost of pumping groundwater to the surface becomes higher than the revenue gained from hydroelectricity generation. As surface water becomes abundant, it starts to be allocated to both hydropower generation and irrigation with equal marginal water allocation efficiency (see Appendix E.4 for details) as shown in the diagonal part of the EP.

The sustainability value of SWE is, however, tempered by groundwater depletion. If groundwater is abstracted at unsustainable rates (abstraction exceeds recharge, as is currently happening in the Central Valley of California) then the value of SWE in reducing surface water allocation trade-offs also decreases. Groundwater depletion results in higher pumping lift ($\Delta h$) and costs, which therefore further exacerbates the trade-offs between groundwater abstraction and hydroelectric generation. Conse-
sequently, this pushes the socially optimal EP together with the “safe and just zone” further to the right (Figure 6.1B compared to Figure 6.1A) suggesting less groundwater is abstracted. However, given the increased groundwater depletion ($\Delta h = 20 \text{ m}$), any additional groundwater abstraction could make the groundwater aquifer less sustainable (increased unsustainable zone in Figure 6.1B). We also note the enhanced length of the horizontal EP (Figure 6.1B), which implies that groundwater depletion further reduces the marginal revenue of hydropower during drought periods. As groundwater becomes scarcer and more expensive, hydropower should be reduced to save water for irrigation. This leads to the shrinkage of the uneconomical zone, as groundwater pumping costs are saved with a higher magnitude compared to the magnitude of the revenue loss due to the reduced hydropower.

### 6.3 Taking into Account Groundwater Sustainability Policies

The TF-EP framework envisions the optimal pathway to balance the trade-offs between hydroelectric generation and groundwater abstraction, which in reality is over-optimistic and may not be achievable owing to a set of physical, political and economic constraints. One possible constraint comes from regulation policies, which could act as a barrier to achieving the social optimum, such as the recently passed Sustainable Groundwater Management Act (SGMA) in California. Such quantity-oriented regulations set the limit for groundwater abstraction ($g_w$) (see the schematic illustration in Figure 6.2A), under which the “optimal” point can only fall into the shaded area. For years with relatively low surface water availability, this groundwater cap ($g_w^{\text{Cap}}$) reduces efficiency even with high penetration of SWE, as the optimal condition is not attainable (that is, the optimal point $O_C/O_F$ moves to $A$). As water availability further increases, imposing limitations via regulations may not influence
the optimal point under future penetration of SWE (as \( O'_F \) is still in the shaded area), whereas under current penetration the “optimal” point is shifted from \( O'_C \) to \( A' \). Limiting groundwater use in turn increases the risk of crop failure and therefore reduces the crop revenue. To quantify this, we define the relative revenue loss (\( \delta \)) as:
\[
\delta = 1 - \frac{R(g_w \leq g_w^{\text{Cap}})}{R(g_w \leq \infty)},
\]
which has a range from 0 to 1, with 0 indicating zero revenue loss and the optimal point still achievable. Intuitively according to Figure 6.2A, this implies that control on groundwater abstraction is not stringent enough to move the optimal point out of the shaded area, which means regulation policies do not exert any impacts on the optimal water allocation and therefore the total revenue is not influenced. As \( \delta \) increases, we face higher revenue loss either because we have a stricter groundwater cap, or there is lower surface water availability. With fixed surface water availability (Figure 6.2B), \( \delta \) monotonically decreases as \( g_w^{\text{Cap}} \) increases for both current penetration \( (P_1^C \rightarrow P_2^C) \) and future penetration \( (P_1^F \rightarrow P_2^F) \). In other words, as we loosen the limit on groundwater use, the relative loss will be reduced. This further implies that groundwater sustainability is put at risk for economic revenue.

Groundwater pumping lift (\( \Delta h \)) adds another layer of complexity to the relative revenue loss (\( \delta \)). Higher pumping lift indicates higher pumping cost associated with more severe groundwater depletion. In the plane with zero revenue loss, higher pumping lift would require more stringent groundwater regulations \( (P_2^C \rightarrow P_3^C) \) in order to achieve the optimal trade-offs as described in Figure 6.1. We note that future penetration of SWE pushes the boundary towards a smaller groundwater cap \( (P_2^C \rightarrow P_3^C) \), which implies that we can set relatively strict regulations for groundwater sustainability with a higher percentage mix of SWE in the energy portfolio. Ideally, society would like to move towards the black point in Figure 6.2B with lower revenue loss and higher groundwater storage recovery (smaller pumping lift). Our results highlight the difficulty in recovering groundwater storage \( (P_4^C \rightarrow P_1^C) \) once it has depleted to a certain extent even with extremely strict regulations (e.g.,
Figure 6.2: (a) Schematic illustration of how groundwater abstraction cap shifts the optimal point for groundwater-hydropower trade-offs. $O_C/O_C'$ and $O_F/O_F'$ represent the trade-offs optimal point given current (17%) and future (40%) penetration of SWE in the normal/wet year. The vertical dashed line sets the limit of groundwater abstraction to meet certain regulations. “Optimal” point with water constraint can only fall into the shaded area. (b) Changes of the relative revenue loss ($\delta$) as a function of groundwater pumping lift ($\Delta h$) and groundwater abstraction cap ($g_{\text{Cap}}^w$) with different penetration ratios of SWE (17% and 40%). Revenue loss zones are represented by the wedge-shaped area enclosed by the orange lines. Dot represents the ideal situation.

zero allowance). This is because a small reduction of pumping lift (slightly recovery of groundwater storage) would result in a significant increase in revenue loss (i.e., $\delta$ increases dramatically along $P_C^1 \rightarrow P_C^1$ with a slight decrease of $\Delta h$); and given that people tend to be loss averse and prefer to make decisions based on losses rather than gains (Kahneman and Tversky, 1979), the system will tend to move back to its initial state of larger pumping lift with lower revenue loss (moving towards $P_C^1$ rather than $P_C^1$). In addition to these effects, even when groundwater storage is recovered ($\Delta h$ reduces), the reduced groundwater pumping cost will create incentives for people to extract more groundwater (EP in Figure 6.1B is shifted to the left in Figure 6.1A), which again will eventually exacerbate groundwater depletion. This
implies that once we are trapped in the situation with severe groundwater depletion, it will be difficult to move out of it. However, this negative effect can be potentially offset to some degree with higher penetration of SWE, which shifts $P_C^1 \rightarrow P_C^1$ down to $P_F^1 \rightarrow P_F^1$. Our results further demonstrate that if groundwater use is not regulated and the depletion keeps getting worse (pumping lift increases), then the benefits of higher SWE penetration is limited as the distance between the two wedge-shaped surfaces ($P_C^1P_C^4P_F^1P_F^4$ and $P_F^1P_F^2P_C^3P_C^4$) decreases. This suggests that the combined effect of more stringent control on groundwater abstraction plus SWE penetration is key to ameliorate revenue loss as well as benefit groundwater recovery. In summary, the results indicate that groundwater depletion can potentially diminish the added sustainable outcomes of SWE and we cannot merely assume that the positive effect of solar and wind penetration will persist indefinitely. Policy makers therefore have to take the long-term outlook of groundwater depletion into consideration when planning further deployment of SWE.

6.4 The Unrecognized and Under-appreciated Social Value of Solar and Wind Energy beyond the Energy Sector

The recent severe and long-lasting drought in California triggered reforms to California’s water policies in the short term to restrict water use (e.g., restrictions on urban water use). It also elevated an ongoing debate on future water policy changes to cope with such extreme events, such as establishing a groundwater banking market, banning water-intensive crops (e.g., almonds) and implementing quota-based water rights for efficient water allocation ([Culp et al., 2014]). During the drought, the fast deployment of SWE helped compensate for the electricity deficit caused by the re-
duction of hydropower generation. Previously, SWE has only been recognized to facilitate air pollution mitigation and carbon emission reductions. Using the trade-off frontier method and expansion path, this study provides new insights into the under-appreciated social value of SWE from the perspective of food security and environmental sustainability. The theoretical framework we have proposed can inform decision makers to design policies that can shift optimal water allocation towards the target of ensuring food security with the aid of SWE. Furthermore, the high penetration of SWE has additional value to increasing the society’s resilience to drought given the following considerations. Electricity generated from SWE is intermittent and can be curtailed when it destabilizes power grids or becomes too abundant, especially as penetration level increases. Energy storage is therefore needed to enable excess electricity to be used and reduces the impact of SWE intermittency to the grid, enabling high penetration of SWE ([Barton and Infield] 2004; [Denholm et al.] 2010). The deployment of energy storage provides co-benefits beyond the operation of the electricity grid. By using electricity stored from peak SWE generation, power systems would reduce reliance on hydropower, making both power generation and food production more resilient to drought. Furthermore, drought-tolerant SWE is substitutable for hydropower: less rainfall during a drought is associated with clearer skies and increased solar power generation. For example, state-wide solar power generation in California increased by 27 percent during the driest winter from November 2011 to March 2012 compared to the average generation in previous years (according to Clean Power Research).
6.5 Synergies between SWE and Groundwater Enhance Drought Resilience and Environmental Sustainability

The recent severe drought in California has acted as a catalyst to regulate unconstrained groundwater use, which has chronically lagged behind surface water regulations. In our study, we examine one possible groundwater regulation, which is to impose limits on groundwater abstraction, and analyze how it potentially feeds back to the social (i.e., water sustainability) value of penetrating SWE. We find that a groundwater abstraction cap could potentially reduce crop irrigation and cause revenue loss, despite its benefit for environmental sustainability. Nevertheless, our results show that more stringent groundwater limitation (lower cap) would render less relative loss as SWE penetrates, and that SWE would largely alleviate the relative loss due to the increase of pumping lift. These findings highlight the co-benefits between the energy and environment in the sense that maintaining environmental (e.g., groundwater) sustainability can partially offset the impact of groundwater regulations on revenue loss. This is of critical importance for long-term policy making as we should not wait until groundwater further depletes to penetrate SWE. Otherwise, the added value of SWE in the future to balance the hydropower-groundwater trade-offs would be largely diminished. Our results suggest that it is beneficial to simultaneously deploy SWE and impose regulations on groundwater use earlier rather than later, since these two policies, when working together, facilitate each other to provide a greater combined benefit than either individual policy.
6.6 Applicability and Generalization to Regional Nexus Challenges

Although the particulars of the WFE nexus in each state or country differ, the method that we have framed should be applicable more generally to other regions outside of California. For instance, the TF-EP framework can help collectively achieve the United Nations’ SDGs for water security (SDG 6), food security (SDG 2) and energy security (SDG 7). Instead of treating all the SDGs in isolation, our method provides insights to systematically considering co-benefits and trade-offs of various policies for the WFE nexus, especially in regions vulnerable to climate change. While we focus on trade-offs between hydropower and groundwater, the general concept of TF-EP framework can be extended to a spectrum of sectors (e.g., domestic, industrial) and scales (e.g., from local to regional to global, and from the hourly basis of the electricity market to the seasonal basis of reservoir operation to the yearly basis of various water rights regimes). Despite this general applicability, we note that the trade-offs and associated sustainability discussed here depend on the strong substitutability of SWE to hydropower in California. Lack of such substitutability may reduce the efficacy of this framework to balance the trade-offs and manage resource sustainability. For instance, in developing regions such as much of sub-Saharan Africa, hydropower still has price advantages compared to other forms of renewables. Unless stringent environmental regulations are imposed, the optimal solution to manage food energy trade-offs may not be obtainable under such a weak substitutability. Nevertheless, our approach can facilitate decision making processes. For instance, given the complexity of upstream-downstream relationships in river basins, policy could be focused on creating incentives for upstream hydropower plants to release water for downstream irrigation. Such incentives could be in the form of government subsidies to operators of upstream hydropower plants using taxes paid by farmers in the downstream area
if they are assured of water supply for irrigation. Alternative policy instruments can be designed to better price surface water based on experiences from Spain (Fuentes 2011) and the European Water Framework Directive (WFD) or implement market-based systems to manage groundwater resources based on lessons drawn from the Murray-Darling Basin in Australia or Edwards Aquifer in Texas (Wheeler et al. 2016), which can assist California water agencies to meet the mandates of SGMA.

This study reveals some challenges which deserve further considerations. Firstly, our proposed framework focuses on the annual timescale without considering the intermittency of SWE. On short time scales (e.g., diurnal), the reduction of hydropower during a severe drought may result in a deficit between power supply and demand especially during peak demand hours and therefore jeopardize grid stability. To meet demand and cover shortfalls, either backup power such as natural gas plants needs to be ramped up or additional electricity needs to be imported from neighboring grids. This is vital for regions whose baseload power source is hydropower, for example North Carolina, where additional regulation policies are required to control price volatility enhanced by large reductions of hydropower generation due to drought. In addition, the production function of hydroelectricity depends on the output from hydrological models, which work well at coarse scale resolution but may not capture the small-scale variability, especially for small hydropower plants. Besides, the spatial-temporal variability of groundwater depletion is not considered as we have focused on the state level. Related to this, the current economic analysis can be extended beyond the private cost (i.e., pumping cost). Instead, we can incorporate the social welfare (i.e., scarcity rent associated with reducing the stock of the depletable nature of groundwater aquifer) by calculating the present value of current and future revenues of groundwater uses based on the Hotelling model (Hotelling 1931). Last, but not least, electricity imports from other regions outside of California are not included in the framework. These issues should be addressed in future work.
Even though this study highlights the value of SWE in helping ensure food security and maintain groundwater sustainability, SWE is no panacea for solving the WFE trilemma. Differences in RPS policies (in the U.S.), energy sources, hydroclimate variability, upstream-downstream relationships, and political and social constraints are likely to increase the complexity of rigorously managing the WFE nexus further than the archetype in this study. Complexity of the real world brings further challenges to the scientific community in terms of how to incorporate the trade-off framework into large-scale hydrological or hydro-economic models. In models that these trade-offs are not considered, such exclusions can potentially influence the robustness of policies and the adaptability of the society to the changing environment. In this regard, previous work by Connor et al. (2015) and its recent application to Australian land-sector sustainability (Gao and Bryan, 2017) is an example of how this might be achieved. However, downscaling the trade-offs from large scales (e.g., state level) to small scales (e.g., county scale or grid scale) requires further investigation into complex topological networks of renewable power plants and their relationship with other sectors, which can be potentially simplified using computable general equilibrium (CGE) models.
Chapter 7

Synthesis

7.1 Summary and Conclusions

Droughts and floods are two of the most common and devastating natural hazards, affecting a wide range of sectors including water, agriculture and food security, energy production, infrastructure, and ecosystem health. This dissertation aims to quantify and understand the historical changes of these two water-related natural hazards and their societal impact through the lens of the coupled human and natural system (CHANS). Given the current data disparity, model deficiencies, and the complex biophysical and socio-economic processes, it is imperative to study CHANS through an integrated modeling framework across scales and disciplines. Throughout the dissertation, this framework has been developed with each chapter emphasizing one particular aspect. Specifically, Chapter 2 and 3 formulate a statistical framework to robustly quantify and diagnose the likely trends and variabilities in drought and flood risks, the intersection between these two phenomena, and their cascading, compounding impacts, that has resulted in the first global drought and flood catalogue. From the physical point of view, Chapter 4 develops an attribution framework to disentangle how climate change, variability and human interventions (e.g., irrigation,
reservoir operation, groundwater pumping) influence droughts at the regional scale. A coupled hydrological and agent-based model is further designed in Chapter 5 for the purpose of formulating effective mitigation and adaptation policies for natural disasters, through the incorporation of human behaviors and decisions. Finally, in Chapter 6, a hydro-economic model is developed to identify possible solutions and optimal development pathways towards better management of water-related trade-offs (i.e., energy production versus irrigation) and environmental sustainability (i.e., groundwater depletion) within the framework of water-food-energy nexus. Following is a summary of each chapter with the main findings.

Chapter 2 develops the first global catalogue of large-scale droughts and floods for the 20th and early 21st centuries (1950-2016) by merging the latest versions of *in situ* and remote-sensing datasets with state-of-the-art land surface and hydrodynamic models to provide a continuous and consistent dataset of terrestrial water cycle and its extremes. These datasets are analyzed to quantify the spatial-temporal characteristics (including severity, spatial extent, and duration) of large-scale drought, flood, and inundation events with a particular focus on characterizing the long-term variability in risk from both univariate and multivariate perspectives. The catalogue facilitates our understanding of the changing behavior of these hydrologic extremes and can be used for analysis of individual events, their drivers and impacts, risk assessment of different types of events, and as a benchmark for model evaluation, which can lead to improvements in disaster preparedness and mitigation, provision of climate services and evidence for policymaking.

Chapter 3 investigate how often droughts have been followed by floods (defined as “drought-flood seesaw”) in the past seven decades through a novel yet mathematically simple approach. Results demonstrate that globally, about 5.9% and 7.6% of the land surface has experienced statistically significant ($p < 0.10$) drought-flood seesaw behavior during the boreal spring-summer and fall-winter, with an average 11.1% and
11.4% of all droughts being followed by floods in the following season, respectively. Although this global frequency pattern is modest, the occurrence of drought-flood seesaw has become more frequent than either droughts or floods alone in the last three decades, with regional hotspots mainly occurring over the sub-tropics and mid-latitudes.

The contribution of human water management to the intensification or mitigation of hydrological drought over California is examined in Chapter 4. Results demonstrate that during the severe 2014 drought, water management alleviated the drought deficit by ~50% in Southern California through reservoir operation during low-flow periods. However, human water consumption (mostly irrigation) in the Central Valley increased drought duration and deficit by 50% and 50-100%, respectively. Return level analysis indicates that there is more than 50% chance that the probability of occurrence of an extreme 2014 magnitude drought event was at least doubled under the influence of human activities compared to natural variability. This impact is most significant over the San Joaquin Drainage basin with a 50% and 75% likelihood that the return period is more than 3.5 and 1.5 times larger, respectively, because of human activities.

Chapter 5 applies the agent-based modeling (ABM) approach and couples it with a large-scale hydrological model (i.e., Community Water Model, CWatM) to investigate how individuals’ decisions and their behavioral heterogeneity affect the dynamics of the coupled human-natural system. This chapter focuses on the agricultural sector in California and consider two types of agents, which are (a group of) farmers and government agencies, and assume that their corresponding objectives are to maximize the net crop profit and to maintain sufficient water supply. Farmers’ behaviors are linked with local agricultural practices, such as cropping patterns and deficit irrigation, through a lumped parameter, which characterizes farmers’ management practice to soil water deficit towards crop water stress. This parameter enables us
to incorporate farmers’ decisions into CWatM across different time scales, ranging from daily irrigation amount to seasonal/annual decisions on crop types and irrigated area. Results demonstrate the efficacy of the integrated model CWatM-ABM to model the important role of farmers’ behaviors in the coupled human-water system. Scenario analysis with homogeneous and heterogeneous behavioral patterns indicates that human behavioral heterogeneity can add an additional layer of complexity and uncertainty in the model simulation. Application of this integrated framework to the pilot study of California can be useful to define drought mitigation policies and adaptation planning as well as quantify the potential space for improving the current water management strategies.

Anchored on the California drought work (Chapter 4 and 5), water-related sustainability and trade-off issues are further discussed in Chapter 6 through a nexus approach, with a particular focus on the fast penetration of renewables in the form of solar and wind energy (SWE). Previously, the benefits of SWE are usually assessed in terms of fossil fuel replacement and air pollution reduction. However, there are other under-appreciated benefits of SWE within the water-energy-food-nexus that are poorly understood, but have implications for optimizing trade-offs between energy and food production, and improving resilience to drought and sustainability of water resources. This chapter develops a trade-off frontier framework to identify development pathways that optimize the economic value of water in competition for energy and food production while ensuring sustainable use of groundwater. Results indicate that in the long term, SWE penetration creates a beneficial feedback for the WFE nexus: SWE enhances drought resilience and benefits groundwater sustainability, and in turn, maintaining groundwater at a sustainable level increases the added value of SWE to energy and food production. The proposed framework can be applied to other nexus trade-off challenges and facilitate progress towards the United Nations Sustainable Development Goals (SDGs).
7.2 Future Directions

There are several exciting avenues now open to further research. First of all, to manage drought and flood risk and reduce their impact, we should implement both top-down (supply-oriented, focusing on water availability) and bottom-up (demand-oriented, focusing on sectoral water use) approaches. The former will involve a better understanding of the underlying physical mechanisms which lead to changes in hydroclimate, such as large-scale drivers (e.g., sea surface temperature, sea ice), regional and local scale feedbacks (e.g., land-atmosphere coupling), and natural variability (e.g., El Niño Southern Oscillation). This can help increase the hydrological predictability and reduce the forecast uncertainty. Integrating such knowledge into the operational and monitoring system (e.g., [Sheffield et al., 2014] will be the next step, as this can further improve the risk management and deliver useful information for impact studies that are relevant to stakeholders and policymakers. In the meantime, it is vital to continue diagnosing how human interventions alter the drought and flood risk from the bottom-up perspective. This requires a more realistic understanding and prediction of how water demand will dynamically respond to the changing climate and changing human behaviors (e.g., water conservation during drought and the post-drought rebound, social memory). This can be achieved by tailoring the coupled CWatM-ABM to more local and policy-relevant scales to solve local community challenges. Combined with the top down approaches, we will be able to solve a much larger picture problem across the human-environment interface.

Moreover, recent years have seen major strides in the development of biophysical Earth System Models (ESMs) and socio-economic Integrated Assessment Models (IAMs), both of which have been widely adopted to investigate the water-food-energy nexus ([Calvin and Bond-Lamberty, 2018]). However, they either emphasize biophysical dynamics (most ESMs) or socio-economic processes (most IAMs), with the other end of the spectrum being stylized instead of process-based. The few models that do
incorporate socio-economic and policy dimensions into ESMs are usually static in the sense that policies are prescribed and do not dynamically feedback into the climate (Gao and Bryan 2017; Bryan et al. 2018), therefore failing to consider deep climate and policy uncertainties. In addition, these models are usually small-scale and case-dependent, therefore lacking certain capabilities to be generalized across scales and regions. Harnessing the advantages of both ESMs and IAMs paves a promising avenue to complement each other’s strengths and to represent the coupled human-natural system in a more realistic way. This requires close collaboration with multidisciplinary scientists and practitioners in the fields of hydrology, climate, agricultural, energy, social, economic and computer science.
Appendix A

Supporting Information for
Chapter 2

A.1 Enhanced Global Meteorological Forcings

We have developed an updated and extended version (v3) of the meteorological forcing dataset, Princeton Global Forcing (PGF, [Sheffield et al., 2006]), from 1948 to 2016 at 3-hourly temporal resolution and 0.25° spatial resolution. PGF is a hybrid dataset of meteorological data derived from the National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) reanalysis and a suite of global observation-based products. Compared to the original PGF, precipitation in PGFv3 is scaled to match updated monthly products of the Climate Research Unit (CRU) TS3.24 that has fixed some of the wet biases observed in earlier versions ([Trenberth et al. 2014]). Corrections are also made to the reanalysis rain day statistics which have been found to exhibit a spurious wave-like pattern in high-latitude wintertime ([Sheffield et al. 2004b]). Precipitation is disaggregated in space to 0.25° by statistical downscaling using relationships developed with the Global Precipitation Climatology Project (GPCP, [Adler et al. 2003]) daily product.
Disaggregation in time from daily to 3-hourly is accomplished similarly, using the TMPA 3-hourly real-time dataset. Other meteorological variables (downward longwave radiation, specific humidity, and surface air pressure) are downscaled in space accounting for changes in elevation. Surface air temperature is scaled to match the CRU dataset in terms of monthly means and diurnal range. The reanalysis downward short- and longwave radiation products are adjusted for systematic bias using the NASA Langley Research Center Surface Radiation Budget (SRB) remote sensing based dataset (Gupta et al., 1999b) and spurious trends in the shortwave radiation are corrected using relationships with cloud cover. These data are available from http://hydrology.princeton.edu.

A.2 Enhanced Land Surface Model Simulations

The Variable Infiltration Capacity (VIC, Liang et al., 1994, 1996; Cherkauer et al., 2003) land surface model (LSM) is utilized for the offline simulation of the terrestrial water cycle over the period 1948-2016 covering the global land area except for Antarctica. In this study, we use version 4.0.5 of VIC (an older but parallelized version), and run it in a water balance mode with a daily time step at a 0.25° spatial resolution. The model is forced with daily precipitation, maximum and minimum temperature, and wind speed obtained from the above updated PGF meteorological data. The VIC model requires a number of distributed parameter datasets as input. These include physical soil and vegetation parameters as well as a number of model specific parameters that generally require calibration. In this study, values of these parameters have been updated to take advantage of the recent Soilgrids global dataset of soil texture and properties (Hengl et al., 2014) and using new generation pedotransfer functions (Tóth et al., 2015). The distribution of vegetation cover is taken from the AVHRR-based, 1 km, global land cover dataset of Hansen et al. (2000), which uses
the University of Maryland (UMD) classification scheme, by calculating the fractional area of each vegetation type within each 0.25° grid cell. Vegetation parameters such as height and stomatal resistance are specified for each of 12 vegetation classes and are taken from Nijssen et al. (2001). Values of leaf area index (LAI) are specified for each vegetation type that exists in each grid cell by resampling the dataset of Myneni et al. (1997), which is based on AVHRR normalized difference vegetation index values. The LAI values are specified for each month but do not vary from year to year. We are currently in the process of updating these to the latest MODIS based land classifications and to use the inter-annually varying GIMMS-AVHRR LAI dataset, and incorporating a new global depth to bedrock datasets (Shangguan et al., 2017).

The land-sea mask and grid cell elevations are taken from the National Geophysical Data Center (NGDC) ETOPO 2-min global elevation and bathymetry dataset (US Department of Commerce, 2006). The elevations are also used to define the elevation sub-grid tiling used in the VIC model.

A.3 Enhanced Routing Model

The physically-based hydrodynamic model CaMa-Flood (Catchment-based Macroscale Floodplain, Yamazaki et al., 2011) is utilized in this study to simulate continental-scale river discharge and flood inundation. CaMa-Flood offers several distinct advantages over existing routing models (e.g., Lohmann et al., 1998) due to its explicit representation of flood stage (e.g., water level and inundation area) in addition to river discharge for each grid cell, and more realistic hydrodynamic processes (e.g., backwater effects, bifurcation channels), yet still maintain high computational efficiency through the discretization of the entire river network into unit-catchments. River network maps in CaMa-Flood are generated by the Flexible Location of Waterway (FLOW, Yamazaki et al., 2009) algorithm using high-resolution hydrography.
datasets including HydroSHEDS for below 60°N and Global Drainage Basin Dataset (GDBD, [Masutomi et al., 2009]) for above 60°N. Flow direction has been modified to be consistent with a satellite-based river width dataset (Global Width Database of Large Rivers, GWD-LR, [Yamazaki et al., 2014]). CaMa-Flood calculates river discharge and flow velocity using the local inertial equation proposed by [Bates et al., 2010] and is forced by gridded daily runoff simulated from VIC LSM at the 0.25° spatial resolution. Model spin-up is repeated twice with the same year (1948) of runoff forcing to reach steady state conditions. We exclude the first two years (1948-1949) from the analysis to avoid any spurious effects.

### A.4 Standardized Indices

We identify large-scale hydrological extremes from both meteorological and agricultural perspectives based on two widely used indices: Standardized Precipitation Index (SPI, [Svoboda et al., 2012]) and soil moisture percentile (SMPct, [Sheffield et al., 2004a]). SPI measures the standard departure of precipitation from the long-term climatology for an aggregated period (e.g., monthly, seasonal, annual). Calculation of SPI involves two steps. The first step is to fit precipitation time series at each grid cell with a Gamma distribution:

\[
f(P; \alpha, \beta) = \frac{\beta^\alpha P^{\alpha-1}e^{-\beta P}}{\Gamma(\alpha)}
\]  

(A.1)

where \(P\) is the running series of aggregated precipitation; \(\alpha\) is the shape parameter and \(\beta\) is the scale parameter, both of which can be estimated through the maximum likelihood estimation (MLE) method; \(\Gamma(\cdot)\) is the gamma function. The second step is to transform the cumulative probability of the fitted Gamma distribution to a standard normal distribution (with mean zero and variance one). For an observed \(P\) at a given time scale, SPI is calculated as the number of standard deviations away from
the median \( P \) with negative and positive values representing precipitation deficit and surplus, respectively. Following the widely used classification category (McKee et al., 1993), we define drought and flood at a grid cell if the SPI is below or above the threshold of -1.0 and 1.0, respectively. Albeit the advantage of convenient computation, SPI only reflects a corner of the whole hydrologic picture (i.e., precipitation) and ignores other important hydrologic processes including evapotranspiration (ET) and runoff (R). Soil moisture (SM) based indices can complement this, as SM reflects the aggregated behavior of land-surface water balance among \( P \), ET and R, and is closely related to agricultural activities (e.g., plant growth) (Sheffield et al., 2009). We aggregate the simulated daily SM from the VIC model to a monthly time scale and calculate SMPct at each grid after fitting an empirical distribution. Transforming SM into a percentile space enables us to compare the deficit and surplus of SM relative to its seasonal climatology across locations with different climate conditions (Sheffield et al., 2004a). A threshold of 20\(^{th}\) percentile is used to define drought conditions, as suggested by the U.S. Drought Monitor. On the flip side and analogous to large-scale wet extremes, floods are defined in a conceptual way for grid cells with SMPct exceeding the 80\(^{th}\) percentile threshold.

### A.5 Run Theory to Estimate Drought and Flood Frequency

We use the run theory to estimate the event (drought or flood) frequency at the pixel level (Yevjevich, 1972; Sheffield and Wood, 2007) for different duration classes \( (D_c) \),
which are defined as follows:

\[
D_{4-6}, \text{short-term } 4 \leq D \leq 6 : \begin{cases} 
SI \leq SI_D^0 & \text{for drought} \\
SI \geq SI_F^0 & \text{for flood}
\end{cases} 
\quad (A.2)
\]

\[
D_{7-12}, \text{medium-term } 7 \leq D \leq 12 : \begin{cases} 
SI \leq SI_D^0 & \text{for drought} \\
SI \geq SI_F^0 & \text{for flood}
\end{cases} 
\quad (A.3)
\]

where SI is the standardized index (either SPI or SMPct, see details in A.4), SI_D^0/SI_F^0 is the event threshold for drought/flood. We count the total number of runs (defined as consecutive time series of SI below/above the threshold SI_D^0/SI_F^0 for drought/flood) in the study period (1950-2016) to calculate the frequency of occurrence for short- \(D_{4-6}\) and medium-term \(D_{7-12}\) duration events. We then inverse the frequency to get the corresponding return periods.

### A.6 Clustering Algorithm for Drought and Flood Identification

We implement an existing and well-tested approach for tracking spatially contiguous drought and flood events and quantifying their characteristics in time and space based on the severity-area-duration (SAD) algorithm (e.g., [Andreadis et al., 2005][Sheffield et al., 2009][Zhan et al., 2016]). SAD has the advantage to track how each individual event cluster merges or breaks at each time step. It links multivariate event characteristics (i.e., severity, spatial extent, duration) through the following equation:

\[
S = 1 - \frac{\sum_{D} \text{SI}}{D}, \quad \text{SI} \in \{\text{SPI, SMPct}\} \quad (A.4)
\]
where $S$ is severity, SI is the standardized index (either SPI or SMPct, see details in A.4) to define hydrological extremes (e.g., drought or flood), and $D$ is the duration in months. At each time step, the maximum spatial extent ($A$) is reached by repeatedly adding surrounding pixels with a constant increment (80 model pixels) to the center of the cluster until all contiguous pixels exceeding the threshold are included (see details in Andreadis et al. 2005, Sheffield et al. 2009). For a given duration, the maximum severity under each spatial extent forms the SAD curve. The upper bound delineated from all SAD curves forms the SAD envelope curve, which characterizes the event severity over an area given the specified duration. Two critical thresholds have to be predefined in SAD to identify the spatial clusters, including the index threshold to detect the pixel-level extremes (see details in A.4) and a minimum cluster size threshold ($N_{\text{grids}}$) to ensure a reasonable number of spatially connected pixels. In this study, we set $N_{\text{grids}}$ to be 150 grids (approximately $3.75 \times 10^5 \text{ km}^2$), a value suggested by the original SAD algorithm (Andreadis et al. 2005) and is recently tested by Zhan et al. (2016).

**A.7 Stationarity of Drought and Flood Events**

We estimate the time-varying occurrence rate ($\lambda_t$) of drought and flood events through a nonparametric Gaussian kernel technique (Mudelsee et al. 2003; Mudelsee 2014) based on the following equation:

$$\lambda_t = \frac{1}{h} \sum_{i}^{N} K\left(\frac{t - T_i}{h}\right)$$  \hspace{1cm} (A.5)

where $h$ is the band width, $T_i$ is the occurrence date for the event (drought or flood) $i$ ($i = 1, 2, 3, ..., N$), and $K$ is the Gaussian kernel to weigh the observed event dates. We select a bandwidth of 10 years for kernel smoothing to reflect the decadal variability. To reduce the bias of estimating $\lambda_t$ near boundaries, we generate pseudodata
outside of the original time series with a time interval of $3h$ for both left and right boundaries, yet still maintain the same empirical distribution based on the “reflection” rules suggested by Cowling and Hall (1996). Confidence intervals of $\lambda_t$ are estimated using a bootstrap technique by randomly sampling the event occurrence dates 2000 times with replacement. We calculate the Cox-Lewis statistic (Mudelsee et al. 2003) to test whether $\lambda_t$ exhibits a monotonic trend with the null hypothesis of constant $\lambda_t$ over the study period (1950-2016).

### A.8 Copula-based Risk Analysis

Risk assessment of droughts and floods can be greatly enhanced if the dependence structure of severity ($S$), area ($A$) and duration ($D$) can be well represented. However, such high dimensional dependence modeling becomes inflexible due to the “curse of dimensionality”. In addition, dependence structures between different pairs of variables can be very different. For instance, one pair may have tail dependence (extreme dependence) and other pairs may have symmetric or asymmetric dependence. Recent development of vine copulas (pair-copula constructions) can overcome these limitations as it can decompose the multivariate copulas into pair copulas based on the hierarchical graphical models (Bedford and Cooke 2002, Kurowicka and Cooke 2006, Cooke et al. 2015). Given these advantages, Vine Copula has been widely applied in hydrology recently (e.g., Hao and Singh 2016, Wanders et al. 2017, Bevacqua et al. 2017). In this study, we utilized the R package VineCopula to optimize the vine structure (either C-vine or D-vine) through the determination of the most appropriate bivariate copula family and its corresponding parameters (see details in Schepsmeier et al. 2012). We test seven parametric distributions (exponential, Gamma, generalized extreme value, Generalized Pareto, lognormal, Weibull minimum, and Weibull maximum) to find the most suitable fit of the marginal distribution for $S$, $A$ and
As $D$ is discrete (integer values with the unit of month) and has repeated values (called “ties”), rank of data points is not unique anymore, making the multivariate analysis ambiguous (e.g., fit the marginal distribution). To overcome this issue, we add random noise (called “jittering”) to the original discrete data sets and generate 200 continuous pseudo samples following the procedures suggested by [Michele et al. (2013)]. For each random sample, we first identify the best-fitted distribution and count how many times each distribution is selected. Distribution with the highest selection frequency is then identified as the best-fitted distribution for $D$. After fitting the three-dimensional joint distribution function using Vine Copula, the joint non-exceedance probability between $S$ and $A$ conditional on $D$ can be calculated as:

$$p_{SA|D} := \mathbb{P}[S > s, A > a \mid D > d] = 1 - F(S \leq s, A \leq a \mid D > d)$$

$$= 1 - \frac{C_{SA}(u_s, u_a) - C_{SAD}(u_s, u_a, u_d)}{1 - u_d}$$

(A.6)

where $u_s, u_a, u_d = F_S(s), F_A(a), F_D(d)$ are marginal distributions for $S$, $A$ and $D$; $C_{SA}$ and $C_{SAD}$ are copula functions fitted from Vine Copula. Different from the conventional univariate return period (RP), here we calculate the so-called Kendall’s return period (KRP) $T_{SA|D}$, to ensure the mathematical consistency for multivariate events as suggested by [Salvadori et al. (2011)]:

$$T_{SA|D} = \frac{\mu}{1 - \overline{K}_C(\overline{q})}$$

(A.7)

where $\mu = \frac{N}{n}$ is the average interarrival time; $N =$ number of years; $n =$ number of events, $\overline{K}_C(\overline{q}) := \mathbb{P}[p_{SA|D} \geq \overline{q}]$ is the Kendall’s survival function and $\overline{q}$ is the survival Kendall’s quantile. For any return period $T_{SA|D}$ (e.g., 100-year), $\overline{q}$ can be calculated
through the inversion of $K_C$ from Equation A.7:

$$\bar{q} = K_C^{-1} \left( 1 - \frac{\mu}{T_{S|A|D}} \right)$$  \hspace{1cm} (A.8)

Substitute $\bar{q}$ into Equation A.6 and calculate the quantiles of $S$ and $A$ based on their marginal distributions, we can get a bundle of isolines, which represent a combination of realizations of $S$ and $A$ that share the same KRP$\text{s \cite{Salvadori et al. 2013}}$. 

135
Figure A.1: Streamflow validation results based on KGE (Kling-Gupta Efficiency). Only gauges with drainage area larger than 5000 km$^2$ are selected. Streamflow observations are obtained from the Global Streamflow Indices and Meta data archive (GSIM, Do et al. 2018; Gudmundsson et al. 2018).

Figure A.2: Same as Figure 2.2 but droughts and floods are identified based on SPI3.
Figure A.3: Similar as Figure 2.4, but drought and flood events are detected using SPI3.

Figure A.4: Similar as Figure 2.4, but for 6-month drought and flood events.
Figure A.5: Similar as Figure A.4 but drought and flood events are detected using SPI3.

Figure A.6: Similar as Figure 2.4 but for 9-month drought and flood events.
Figure A.7: Similar as Figure A.6, but drought and flood events are detected using SPI3.

Figure A.8: Similar as Figure 2.5, but for 6-month events.
Figure A.9: Similar as Figure 2.5, but for 9-month events.

Figure A.10: Similar as Figure 2.5, but drought and flood events are detected using SPI3.
Large area droughts & floods
Small area droughts & floods
High severity droughts & floods
Low severity droughts & floods

6-month Events (based on SPI3)

Figure A.11: Similar as Figure A.10, but for 6-month events.

9-month Events (based on SPI3)

Figure A.12: Similar as Figure A.10, but for 9-month events.
Figure A.13: Similar as Figure 2.6 but drought events are detected using SPI3.

Figure A.14: Similar as Figure A.13 but for flood events.
Appendix B

Supporting Information for Chapter 3

Figure B.1: Same as Figure 3.3, but for ONDJFM.
Figure B.2: Same as Figure 3.4 but for ONDJFM.
Appendix C

Supporting Information for

Chapter 4

C.1 The Binary Sequence of Hydrological Drought Occurrence

Let

\[ S(t,n) = \begin{cases} 
1 & \text{if } Q(t,n) < Q_{90}(t,n) \\
0 & \text{if } Q(t,n) \geq Q_{90}(t,n) 
\end{cases} \]  \quad (C.1)

where \( \{S(t,n)\} \) is the binary discrete time series of the drought state at daily time scale, which only include two integers 0 and 1, with 0 means normal conditions and 1 indicates that drought occurs at location \( n \) at a given time \( t \). \( Q(t,n) \) is the simulated daily streamflow and \( Q_{90}(t,n) \) is the threshold.
C.2 Drought Duration and Area in Drought (AID)

Drought duration $D(t, n)$ for each event $m$ at grid cell $n$ can be defined as:

$$D_{m}(n) = \sum_{t=T_f}^{T_i} S(t, n)$$  \hspace{1cm} (C.2)

where $T_f$ and $T_i$ are the first and the last time step when $S(t, n) = 1$. The total area in drought (AID) at time $t$ measures the percentage of the drought area, which can be calculated as:

$$AID(t) = \frac{\sum_{n=1}^{N} D(t, n)}{N}$$  \hspace{1cm} (C.3)

where $N$ is the total number of grid cells. The range of AID is within 0 and 1, with 0 indicating no grid cells are in drought and 1 indicating that all the area is in drought.

C.3 Drought Deficit Volume

Drought deficit volume ($V$, $m^3/s$) measures how severe the drought is compared to the normal streamflow conditions. It can be defined as:

$$V(t, n) = max(0, \; Q_{90}(t, n) - Q(t, n))$$  \hspace{1cm} (C.4)

The total drought deficit volume for each drought event $m$ at grid cell $n$ is the accumulation of the consecutive deviation of the streamflow from the threshold over the drought duration period:

$$V_{m}(n) = \sum_{t=T_f}^{T_i} V(t, n)$$  \hspace{1cm} (C.5)
To allow the comparison among different climatic divisions, standardized drought deficit volume (StDef) is utilized, which is normalized by the mean of $V_m(n)$:

$$\text{StDef}(t, n) = \frac{V(t, n)}{\frac{V_m(n)}{T_f - T_i}} = (T_i - T_f) \frac{V(t, n)}{V_m(n)} \quad \text{(C.6)}$$
Table C.1: Root mean square error (RMSE) used to evaluate the goodness-of-fit between the empirical and fitted cumulative distribution function (CDF) of the standardized drought deficit volume from 1979 to 2014.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Natural scenario</th>
<th>Human scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>LogNormal</td>
<td>0.051</td>
<td>0.038</td>
</tr>
<tr>
<td>GEV_LM</td>
<td>0.057</td>
<td>0.081</td>
</tr>
<tr>
<td>Pareto</td>
<td>0.073</td>
<td>0.094</td>
</tr>
<tr>
<td>Gamma</td>
<td>0.189</td>
<td>0.064</td>
</tr>
<tr>
<td>Weibull</td>
<td>0.153</td>
<td>0.097</td>
</tr>
</tbody>
</table>
Figure C.1: Streamflow validation metrics for 22 selected USGS stations including Kling-Gupta efficiency (KGE), coefficient of determination ($R^2$), mean absolute error (MAE, $m^3/s$) and root mean squared error (RMSE, $m^3/s$).
Figure C.2: Time series of monthly observed and simulated discharge (top panel) at USGS station 11523000 and the corresponding scatter plots (bottom left: Natural scenario; bottom right: Human scenario).
Figure C.3: Similar as Figure C.2 but for USGS station 11520500.
Figure C.4: Similar as Figure C.2 but for USGS station 11274000.
Figure C.5: Similar as Figure C.2 but for USGS station 11452500.
Figure C.6: Similar as the middle and right panels of Figure 4.1 but the deficit volume is calculated for selected drought events.

Figure C.7: Comparison between the observed drainage area from USGS and the drainage area extracted from PCR-GLOBWB model. As the selected USGS stations may not be located exactly in the river network of PCR-GLOBWB, we manually correct the drainage area between the model and observations.
Appendix D

Supporting Information for

Chapter 5

D.1 Reclassification of Crop Types in California based on MIRCA2000 Dataset

Table D.1: Top 10 major crops in California and the corresponding ID in MIRCA2000 data set.

<table>
<thead>
<tr>
<th>Major crops in California</th>
<th>Crop ID in MIRCA2000</th>
<th>Crop name in MIRCA2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walnuts</td>
<td>24</td>
<td>Other perennial</td>
</tr>
<tr>
<td>Rice</td>
<td>3</td>
<td>Rice</td>
</tr>
<tr>
<td>Winter wheat</td>
<td>1</td>
<td>Wheat</td>
</tr>
<tr>
<td>Grapes</td>
<td>20</td>
<td>Grapes</td>
</tr>
<tr>
<td>Pistachios</td>
<td>24</td>
<td>Other perennial</td>
</tr>
<tr>
<td>Almonds</td>
<td>24</td>
<td>Other perennial</td>
</tr>
<tr>
<td>Corn</td>
<td>2</td>
<td>Maize</td>
</tr>
<tr>
<td>Alfalfa</td>
<td>25</td>
<td>Fodder grasses</td>
</tr>
<tr>
<td>Other hay/Non alfalfa</td>
<td>25</td>
<td>Fodder grasses</td>
</tr>
<tr>
<td>Tomatoes</td>
<td>26</td>
<td>Other annual crops</td>
</tr>
</tbody>
</table>
## D.2 CWatM Calibration

Table D.2: Hydrological processes and related parameters used to calibrate CWatM.

<table>
<thead>
<tr>
<th>Category</th>
<th>Parameter and its physical meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Snow</strong></td>
<td>Snowmelt coefficient as a degree-day factor</td>
</tr>
<tr>
<td><strong>Evapotranspiration</strong></td>
<td>Crop factor as an adjustment to crop evapotranspiration</td>
</tr>
<tr>
<td><strong>Soil</strong></td>
<td>Soil depth factor: a factor for the overall soil depth of soil layer 1 and 2</td>
</tr>
<tr>
<td></td>
<td>Preferential bypass flow: empirical shape parameter of the preferential flow relation</td>
</tr>
<tr>
<td></td>
<td>Infiltration capacity parameter: empirical shape parameter $b$ of the ARNO model</td>
</tr>
<tr>
<td><strong>Groundwater</strong></td>
<td>Interflow factor: factor to adjust the amount which percolates from interflow to groundwater</td>
</tr>
<tr>
<td></td>
<td>Recession coefficient factor: factor to adjust the base flow recession constant (the contribution from groundwater to baseflow)</td>
</tr>
<tr>
<td><strong>Routing</strong></td>
<td>Runoff concentration factor: a factor for the concentration time of runoff in each grid-cell</td>
</tr>
<tr>
<td></td>
<td>Channel Manning’s $n$ factor: a factor roughness in channel routing</td>
</tr>
<tr>
<td><strong>Reservoir and lakes</strong></td>
<td>Normal storage limit: the fraction of storage capacity used as normal storage limit</td>
</tr>
<tr>
<td></td>
<td>Lake A factor: factor to channel width and weir coefficient as a part of the Poleni weir equation</td>
</tr>
<tr>
<td></td>
<td>Lake and river evaporation factor: factor to adjust open water evaporation</td>
</tr>
</tbody>
</table>
Appendix E

Supporting Information for
Chapter 6

E.1 Trade-off Frontier and Expansion Path

The trade-off frontier (TF) and expansion path (EP) can be solved within an optimization framework. The objective is to maximize the total revenue ($R$) by solving the following non-linear optimization problem under a set of linear water constraints:

$$\begin{align*}
\text{maximize} & \quad R(s_{\text{Hydro}}^{w}, s_{\text{Crop}}^{w}, g_{w}) = B_{\text{Hydro}}^{w}(s_{\text{Hydro}}^{w}) - C_{\text{Pump}}^{w}(g_{w}) - D_{\text{Crop}}^{w}(s_{\text{Crop}}^{w}, g_{w}) \\
\text{subject to} & \quad s_{\text{Hydro}}^{w} + s_{\text{Crop}}^{w} = s_{w} \\
& \quad s_{\text{Crop}}^{w} + g_{w} = IWR \\
& \quad 0 \leq s_{\text{Hydro}}^{w}, s_{\text{Crop}}^{w} \leq s_{w} \\
& \quad 0 \leq g_{w} \leq \min\{g_{\text{Cap}}^{w}, IWR - s_{\text{Crop}}^{w}\}
\end{align*} \tag{E.1}$$

where $B_{\text{Hydro}}^{w}$ [$\$] is the economic profits from hydroelectric generation, $C_{\text{Pump}}^{w}$ [$\$] is groundwater pumping cost, $D_{\text{Crop}}^{w}$ [$\$] is the damage due to crop failure, $s_{\text{Hydro}}^{w}$ [$m^3$] is the surface water allocated for hydroelectric generation, $s_{\text{Crop}}^{w}$ [$m^3$] is the surface
water allocated for crop irrigation, \( s_w \) [\( m^3 \)] is the total available surface water that can be allocated between hydropower production and irrigation, \( g_w \) [\( m^3 \)] is groundwater withdraw for crop irrigation, \( g_{w \text{ Cap}} \) [\( m^3 \)] is the groundwater cap due to regulations and IWR [\( m^3 \)] is the irrigation water requirement calculated from the hydrological model (see details in Section E.3).

### E.2 Economic Revenues and Costs

Economic profits from hydropower (\( B_{\text{Hydro}} \) [\$]) can be calculated as:

\[
B_{\text{Hydro}}(s_{\text{Hydro}}) = \min \{ Q_e^{\text{Total}} \times (1 - \text{pct}^{\text{SWE}}) - Q_e^{\text{Base}}, Q_e^{\text{Hydro}} \} \times p_{s_{\text{Hydro}}} \tag{E.2}
\]

Estimation of \( B_{\text{Hydro}} \) requires to carefully price \( s_{\text{Hydro}} \). Here we do not use the levelized cost of electricity (LCOE) for hydropower, instead we attempt to calculate its shadow price (\( p_{s_{\text{Hydro}}} \) [\$/GWh]) given the fact that when water is limited (e.g., during drought), we must make a choice between water used for agriculture or water used for hydropower. At the annual time scale, the reduction of hydropower should be made up by natural gas according to the dispatch curve. Therefore, \( p_{s_{\text{Hydro}}} \) should depend on the fluctuation of natural gas price (\( p_{\text{Gas}} \) [\$/GWh]) and can be calculated as:

\[
p_{s_{\text{Hydro}}} = p_{\text{Gas}} \times [1 - f(\frac{Q_e^{\text{SWE}}}{Q_e^{\text{Total}}}) \times g(\frac{Q_e^{\text{Hydro}}}{Q_e^{\text{Total}}})] \tag{E.3}
\]

where \( f(\frac{Q_e^{\text{SWE}}}{Q_e^{\text{Total}}}) = e^{-\frac{\alpha_1 \times Q_e^{\text{Total}} \times (1 - \text{pct}^{\text{SWE}})}{Q_e^{\text{Total}}}} \) is the downward adjustment of \( p_{\text{Gas}} \) due to the penetration of SWE (in other words, SWE has price advantage compared to hydropower). \( g(\frac{Q_e^{\text{Hydro}}}{Q_e^{\text{Total}}}) = e^{-\frac{\alpha_2 \times Q_e^{\text{Hydro}}}{Q_e^{\text{Total}}}} \) is the downward adjustment of \( p_{\text{Gas}} \) due to the reduction of hydropower (in other words, hydropower has price advantage compared to natural gas). \( Q_e^{\text{Total}} \) [GWh] is the total electricity demand for California, \( \text{pct}^{\text{SWE}} \) [-] is the percentage mix of SWE in the energy portfolios (i.e., 17% for 2016 and
∼40% by 2030), $Q_{e}^{\text{Base}}$ [GWh] is the base load (e.g., nuclear), $Q_{e}^{\text{Hydro}}$ [GWh] is the hydroelectricity generation and is estimated using a linear function of annual averaged streamflow (Bartos and Chester 2015; Perrone and Hornberger 2016; Gleick 2017). $\alpha_1 (=1)$ and $\alpha_2 (=1.1)$ are scaling factors of price elasticity. It should be noted that our analysis is conducted at the annual time scale. Therefore, it is not necessary to consider the intermittency of hydropower, solar and wind energy, which in reality can be problematic to be dispatched. Nonetheless, the objective here is to examine the cumulative effects of the penetration of solar and wind on the water-food-energy nexus in a long term, which we argue that the intermittency will not influence the final results.

Groundwater pumping costs ($C_{\text{Pump}}$ [\$]) are estimated using the following form based on Knapp et al. (2003):

$$C_{\text{Pump}}(g_w) = (k + c\sigma)g_w + g_w c\Delta h + \frac{c g_w^2}{A s_y} \frac{\Delta h}{2}$$  \hspace{1cm} (E.4)

where $k$ [\$/m$^3$] is the average cost per unit of groundwater withdrawal related to equipment use, $c$ [\$/m/m$^3$] is pumping costs per unit lift of extracted groundwater, $\sigma$ [m] is drawdown, $\Delta h$ [m] is pumping lift, $A$ [m$^2$] is the aquifer area and $s_y$ is the specific yield of the aquifer. Parameter values are obtained from Table A1 in Knapp et al. (2003) with unit conversion and adjustment for $A$ and $s_y$.

Crop damages ($D_{\text{Crop}}$ [\$]) can be estimated as:

$$D_{\text{Crop}}(s_w^{\text{Crop}}, g_w) = B^{\text{Crop}} \times \left(1 - \frac{s_w^{\text{Crop}} + g_w}{IWR}\right)$$  \hspace{1cm} (E.5)

where $B^{\text{Crop}}$ [\$] is the averaged revenue of field crops based on the estimation from Cooley et al. (2015).
E.3 Hydrological and Water Resources Model

Irrigation water requirement (IWR) is simulated with the Community Water Model (CWatM, Burek et al., 2017), which is a macro-scale hydrological and water resources model developed by the Water Program at the International Institute of Applied Systems Analysis (IIASA). In this study, CWatM was forced by the daily meteorological forcing dataset WFDEI (WATCH Forcing Data methodology applied to ERA-Interim data, Weedon et al., 2014) at a 0.5° spatial resolution and daily temporal resolution covering the 34-year simulation period (1979-2012) (meteorological forcings and key parameters are described in Chapter 5). CWatM inherits the same irrigation scheme as implemented in PCR-GLOBWB (van Beek et al., 2011; Wada et al., 2014a), which can separately estimate IWR for paddy and nonpaddy crops classified from the original 26 crop types in MIRCA2000 (Portmann et al., 2010). The irrigation scheme dynamically links the daily surface and soil water balance with irrigation water, which is more realistic compared to the existing irrigation schemes used in other large-scale hydrological models (Wada et al., 2014a). Details on the calculation of irrigation water for paddy and nonpaddy crops are provided in Chapter 5.

We calibrated and validated CWatM against streamflow observations from eight USGS stations in California. Model calibration is performed using an evolutionary computational framework called DEAP (Distributed Evolutionary Algorithms in Python, Fortin et al., 2012). The modified version of the Kling-Gupta Efficiency (KGE, see equations in Kling et al., 2012) is used as the objective function to be maximized. We have used a population size of 256 and recombination pool size of 32 with the number of generations set to 30 to calibrate CWatM, which proves to be sufficient to achieve convergence. Specifically, we have calibrated the model focusing on snow, evapotranspiration, soil, groundwater, routing process, lakes and reservoirs. Besides the correlation coefficient ($R$) and KGE, we also use percent bias ($B$, Gupta et al., 1999a) and Nash–Sutcliffe coefficient of efficiency (NSE, Nash and Sutcliffe, 1970).
1970) to evaluate the performance of CWatM. Time series of observed and simulated streamflow and the associated performance metrics for the calibration and validation periods can be found in Appendix E.5. Results demonstrate that CWatM can well reproduce the streamflow variability and magnitude both at daily and monthly time scale.

E.4 Pseudocode for Trade-off Analysis

To find the optimal water allocation (solid point in Figure 6.1) given the water constraint, we first calculate the water allocation efficiency (WAE) for hydropower (WAE\textsuperscript{Hydro}) and crop (WAE\textsuperscript{Crop}) using the following equations:

\[
\text{WAE}_{\text{Hydro}} = \frac{R(s_{w}^{\text{Hydro}} + \delta s_{w}^{\text{Hydro}}, s_{w}^{\text{Crop}}, g_w) - R(s_{w}^{\text{Hydro}}, s_{w}^{\text{Crop}}, g_w)}{\delta s_w}
\]

\[
\text{WAE}_{\text{Crop}} = \frac{R(s_{w}^{\text{Hydro}}, s_{w}^{\text{Crop}} + \delta s_{w}^{\text{Crop}}, g_w) - R(s_{w}^{\text{Hydro}}, s_{w}^{\text{Crop}}, g_w)}{\delta s_w}
\]

Water allocation decisions will be made based on the relative value of WAE\textsuperscript{Hydro} and WAE\textsuperscript{Crop}. Assume that at the initial stage, WAE\textsuperscript{Crop} is larger than WAE\textsuperscript{Hydro}, then within a certain range of water availability, water will only be allocated for irrigation purpose. However, as the water availability increases, WAE\textsuperscript{Crop} decreases. When WAE\textsuperscript{Crop} reaches to the same value as WAE\textsuperscript{Hydro}, water will start to be allocated for both crop irrigation and hydropower. When we implement this algorithm, we do not have to explicitly calculate the value of WAE\textsuperscript{Hydro} and WAE\textsuperscript{Crop} as we may face numerical stability problems if \(\delta s_w\) is very small. Instead, we just need to compare \(R(s_{w}^{\text{Hydro}} + \delta s_{w}^{\text{Hydro}}, s_{w}^{\text{Crop}}, g_w)\) and \(R(s_{w}^{\text{Hydro}}, s_{w}^{\text{Crop}} + \delta s_{w}^{\text{Crop}}, g_w)\) as we can get rid of \(R(s_{w}^{\text{Hydro}}, s_{w}^{\text{Crop}}, g_w)\) and \(\delta s_w\) if we let WAE\textsuperscript{Hydro} = WAE\textsuperscript{Crop}. In the following, we consider two cases to solve the nonlinear optimization problem with and without consideration of groundwater cap.
**Algorithm 1** Using implicit gradient descent approach to find the optimal point (No groundwater cap)

**Input:**
- $s_w$: surface water availability
- $\delta s_w$: step size
- $\varepsilon_0 (<1)$: accuracy limit
- IWR: irrigation water requirement

**Output:**
- $s_{Hydro}^w$: surface water for hydropower
- $s_{Crop}^w$: surface water for crop irrigation
- $g_w$: groundwater withdrawal

```plaintext
function FindOptimalPoint($s_w$, $\delta s_w$, $\varepsilon_0$, IWR)
1: \[ s_{Hydro}^w = s_{w,0}^w = 0, s_{w,0}^w = s_w - s_{Hydro}^w - s_{w,0}^w, g_{w,0} = \text{IWR} \] /* Initialize water allocation */
2: \[ s_{w,0}^w > 0 \] do
3: \[ WAE_{k}^{\text{Hydro}} = R(s_{w,k}^w, s_{w,k}^w, g_{w,k}) \] /* Calculate allocation efficiency for hydropower */
4: \[ WAE_{k}^{\text{Crop}} = R(s_{w,k}^w, s_{w,k+1}^w, g_{w,k+1}) \] /* Calculate allocation efficiency for crop */
5: \[ \gamma_{k+1} = \gamma_k + 2^{-k-1} \] /* Adjust the allocation */
6: \[ \gamma_{k+1} > 1 \] then
7: \[ \gamma_{k+1} = \gamma_k \] /* Increase the iteration number */
8: \[ \varepsilon = |WAE_{k}^{\text{Hydro}} - WAE_{k}^{\text{Crop}}| \] /* Calculate the error */
9: \[ k = k + 1 \] /* Re-initialization */
10: \[ s_{w,0}^w = s_{w,0}^w - \delta s_w \] /* Change the remained surface water */
11: \[ s_{w,0}^w = s_{w,0}^w - \delta s_w \] /* Find the optimal solution */
12: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Initialize the iteration number $k$ and allocation parameter $\gamma_k$ */
13: \[ s_{w,0}^w = s_{w,0}^w \] /* While the result is not precise, keep this loop */
14: \[ s_{w,0}^w = s_{w,0}^w \] /* Allocate water to hydropower */
15: \[ s_{w,0}^w = s_{w,0}^w \] /* Allocate water to hydropower */
16: \[ s_{w,0}^w = s_{w,0}^w \] /* While the result is not precise, keep this loop */
17: \[ s_{w,0}^w = s_{w,0}^w \] /* Allocate water to hydropower */
18: \[ s_{w,0}^w = s_{w,0}^w \] /* Re-initialization */
19: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
20: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
21: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
22: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
23: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
24: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
25: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
26: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
27: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
28: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
29: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
30: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
31: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
32: \[ s_{Hydro}^w, s_{Crop}^w = s_{w,0}^w, g_w = \text{IWR} - s_{w,0}^w \] /* Re-initialization */
```
```
Using implicit gradient descent approach to find the optimal point (With groundwater cap)

**Input:**
- \( s_w \): surface water availability
- \( \delta s_w \): step size
- \( \varepsilon_0 < 1 \): accuracy limit
- IWR: irrigation water requirement
- \( g_w^{\text{Cap}} \): groundwater cap

**Output:**
- \( s_{\text{Hydro}} \): surface water for hydropower
- \( s_{\text{Crop}} \): surface water for crop irrigation
- \( g_w \): groundwater withdrawal

**Algorithm 2**

```plaintext
function FindOptimalPointWithCap(s_w, \( \delta s_w \), \( \varepsilon_0 \), IWR, \( g_w^{\text{Cap}} \))

1. Initialize water allocation
2. Allocate water step by step
3. While the result is not precise, keep this loop
4. Re-initialization
5. Find the optimal solution
end function
```

/* Initialize water allocation */

```plaintext
s_{\text{Hydro}} \times \text{Crop} = s_{\text{Hydro}} \times \text{Crop} = (s_{\text{Hydro}} \times \text{Crop} - s_{\text{Crop}})
```

/* Allocate water to crop */

```plaintext
s_{\text{Crop}} = s_{\text{Crop}} + s_{\text{Hydro}} \times \text{Crop}
```

/* Allocate water to hydropower */

```plaintext
s_{\text{Hydro}} = s_{\text{Hydro}} + \delta s_w
```

/* Increase the iteration number */

```plaintext
k = k + 1
```

/* Re-initialization */

```plaintext
s_{\text{Hydro}} = s_{\text{Hydro}} \times \text{Crop} = s_{\text{Crop}}
```

/* Find the optimal solution */

```plaintext
s_{\text{Hydro}} \times \text{Crop}, g_w
```

/* Calculate the error */

```plaintext
\varepsilon = |WAE_k^{\text{Hydro}} - WAE_k^{\text{Crop}}|
```

/* Calculate allocation efficiency for hydropower */

```plaintext
WAE_k^{\text{Hydro}} = R(s_{w,k+1}^{\text{Hydro}} - s_{w,k+1}^{\text{Cap}})
```

/* Calculate allocation efficiency for crop */

```plaintext
WAE_k^{\text{Crop}} = R(s_{w,k+1}^{\text{Crop}} - s_{w,k+1}^{\text{Cap}})
```

/* Adjust the allocation */

```plaintext
\gamma_{k+1} = \gamma_k + 2^{-k-1}
```

/* If the allocation efficiency differs */

```plaintext
\gamma_k + 1 > 1 then
```

/* Initialize the iteration number */

```plaintext
k = 0, \gamma_0 = 1, \varepsilon = 1
```

/* Initialize the iteration number */

```plaintext
k = 0, \gamma_0 = 1, \varepsilon = 1
```

/* If water allocation to crop is over the total demand */

```plaintext
if \( s_{w,0} > \text{IWR} \) then
```

/* Set error to be 0 */

```plaintext
\varepsilon \geq \varepsilon_0 do
```

/* While the result is not precise, keep this loop */

```plaintext
\text{IWR}, \varepsilon \geq \varepsilon_0 do
```

/* Increase the iteration number */

```plaintext
k = k + 1
```

/* Change the remained surface water */

```plaintext
s_{w,0} = s_{w,0} - \delta s_w
```

/* Re-initialization */

```plaintext
s_{\text{Hydro}} = s_{\text{Hydro}} \times \text{Crop} = s_{\text{Crop}}
```

/* Find the optimal solution */

```plaintext
s_{\text{Hydro}} \times \text{Crop}, g_w
```

/* Calculate the error */

```plaintext
\varepsilon = |WAE_k^{\text{Hydro}} - WAE_k^{\text{Crop}}|
```

/* Increase the iteration number */

```plaintext
k = k + 1
```

/* Change the remained surface water */

```plaintext
s_{w,0} = s_{w,0} - \delta s_w
```

/* Re-initialization */

```plaintext
s_{\text{Hydro}} = s_{\text{Hydro}} \times \text{Crop} = s_{\text{Crop}}
```

/* Find the optimal solution */

```plaintext
s_{\text{Hydro}} \times \text{Crop}, g_w
```

/* Calculate the error */

```plaintext
\varepsilon = |WAE_k^{\text{Hydro}} - WAE_k^{\text{Crop}}|
```

/* Increase the iteration number */

```plaintext
k = k + 1
```

/* Change the remained surface water */

```plaintext
s_{w,0} = s_{w,0} - \delta s_w
```

/* Re-initialization */

```plaintext
s_{\text{Hydro}} = s_{\text{Hydro}} \times \text{Crop} = s_{\text{Crop}}
```

/* Find the optimal solution */

```plaintext
s_{\text{Hydro}} \times \text{Crop}, g_w
```
E.5 Streamflow Calibration and Validation Results

Figure E.1: Calibration results for USGS gauge 11074000.

<table>
<thead>
<tr>
<th>Obs.</th>
<th>Sim.</th>
</tr>
</thead>
<tbody>
<tr>
<td>KGE</td>
<td>0.806</td>
</tr>
<tr>
<td>NS</td>
<td>0.631</td>
</tr>
<tr>
<td>NSlog</td>
<td>0.176</td>
</tr>
<tr>
<td>R2</td>
<td>0.870</td>
</tr>
<tr>
<td>Bias</td>
<td>11.35%</td>
</tr>
<tr>
<td>RMSE</td>
<td>8</td>
</tr>
<tr>
<td>MAE</td>
<td>4</td>
</tr>
<tr>
<td>Mean</td>
<td>11</td>
</tr>
<tr>
<td>Min</td>
<td>3</td>
</tr>
<tr>
<td>5 %</td>
<td>4</td>
</tr>
<tr>
<td>50 %</td>
<td>7</td>
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<td>95 %</td>
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<tr>
<td>99 %</td>
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</tr>
<tr>
<td>Max</td>
<td>100</td>
</tr>
<tr>
<td>133</td>
<td></td>
</tr>
</tbody>
</table>
Figure E.2: Validation results for USGS gauge 11074000.
Figure E.3: Calibration results for USGS gauge 11150500.
Figure E.4: Validation results for USGS gauge 11150500.
Station: USGS 11274000

Figure E.5: Calibration results for USGS gauge 11274000.
Station: USGS 11274000

Figure E.6: Validation results for USGS gauge 11274000.
Figure E.7: Calibration results for USGS gauge 11303500.
Figure E.8: Validation results for USGS gauge 11303500.
Figure E.9: Calibration results for USGS gauge 11390500.
Figure E.10: Validation results for USGS gauge 11390500.
Station: USGS 11467000

(a) Streamflow time series for calibration period

(b) Scatterplot for calibration period

<table>
<thead>
<tr>
<th></th>
<th>Obs.</th>
<th>Sim.</th>
</tr>
</thead>
<tbody>
<tr>
<td>KGE</td>
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<tr>
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<td></td>
<td>0.590</td>
</tr>
<tr>
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<td>-0.260</td>
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<tr>
<td>R2</td>
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<td>0.915</td>
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<td>Bias</td>
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<td>MAE</td>
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<tr>
<td>Mean</td>
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<td>529</td>
</tr>
<tr>
<td>Max</td>
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</tr>
</tbody>
</table>

(c) Monthly Q climatology cal. period

(d) KGE evolution

Figure E.11: Calibration results for USGS gauge 11467000.
Station: USGS 11467000

(a) Streamflow time series for validation period

KGE = 0.28, NSE = 0.58, R2 = 0.92, B = 27.37 %

(b) Scatterplot for validation period

<table>
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<tr>
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<tr>
<td>MAE</td>
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<tr>
<td>99 %</td>
<td>559</td>
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<tr>
<td>Max</td>
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</table>

(c) Monthly Q climatology val. period

Figure E.12: Validation results for USGS gauge 11467000.
Station: USGS 11477000

(a) Streamflow time series for calibration period

(b) Scatterplot for calibration period

(c) Monthly Q climatology cal. period

(d) KGE evolution

Figure E.13: Calibration results for USGS gauge 11477000.
Figure E.14: Validation results for USGS gauge 11477000.
Figure E.15: Calibration results for USGS gauge 11523000.
Figure E.16: Validation results for USGS gauge 11523000.
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