UNIVERSITY OF CALIFORNIA,
IRVINE

A Probabilistic Drought Recovery Assessment Model Using Remote Sensing and Ground-Based Observations

THESIS

submitted in partial satisfaction of the requirements
for the degree of

MASTER OF SCIENCE

in Civil Engineering

by

Charlotte Anne Love

Thesis Committee:
Associate Professor Amir AghaKouchak, Chair
Distinguished Professor Soroosh Sorooshian
Professor Kou-Lin Hsu

2019

TABLE OF CONTENTS

LIST OF FIGURES

ACKNOWLEDGMENTS

Foremost, I would like to express the deepest appreciation to my advisor, Prof. Amir AghaKouchak, for his patient and supportive mentorship. His door is always open for answering questions and providing guidance, and he is always excited and supportive of viable new ideas. His continued mentorship is highly valued as a key component to my current and future success!

I would also like to whole-heartedly thank my committee members, Prof. Soroosh Sorooshian and Prof. Kuo-lin Hsu, for their patient feedback on this thesis work. Additionally, I would like to thank Prof. Sorooshian for his valuable pedagogical contribution to my graduate studies and many, many thanks for making time to help with requests for letters of recommendation.

A huge thanks also goes out to Dr. Ali Mehran and Dr. M. J. Tourian for their fundamental contributions of data for this thesis work. I also owe thanks to the ever-helpful Dr. Shahrbanou Madadgar, who took time to answer my questions in the early stages of data acquisition and clean-up.

Lastly, I would like to thank all of my labmates who were a source of daily encouragement and my family and friends, who were endlessly proud, supportive, and excited for me.

ABSTRACT OF THE THESIS

A Probabilistic Drought Recovery Assessment Model Using Remote Sensing and Ground-Based Observations

By

Charlotte Anne Love

Master of Science in Civil Engineering

University of California, Irvine, 2017

Associate Professor Amir AghaKouchak, Chair

During 2012-2016, California experienced its most extreme drought in recent history due to a combination of record high temperatures and exceptionally low precipitation. Estimates for when a drought is expected to end are fundamental for risk mitigation and water management. A key question is: What is the likelihood of drought recovery given the current drought condition and expected precipitation in the coming wet-season?

A crucial component of drought recovery assessments is the estimation of terrestrial water storage (TWS). Most previous studies have primarily focused on surface-water hydrology (precipitation and/or runoff) for estimating changes in TWS, neglecting the contribution of groundwater to the recovery time of the system. Here I propose a probabilistic model for drought recovery assessments that integrates both ground-based observations and NASA's Gravity Recovery and Climate Experiment (GRACE) data, which comprises all terrestrial water sources. I estimated the probability that meteorological inputs, precipitation minus evapotranspiration and runoff, over three different climate scenarios would balance the September 2015 TWS deficit. My results indicate that the

probability of recovery for an average wet-season is between 33-57%, for an El Niño year it is between 44-54%, and for a year with a 6-month standard precipitation index (SPI) greater than 1.3 (very wet) it is between 70-96%. I conclude that the predicted El Niño conditions for the 2015-16 wet season did not guarantee drought recovery any more than an average year, unless the event was comparable in volume to that of the 1982-83 and 1997-98 El Niño years (i.e., SPI > 1.3).

INTRODUCTION

In the semi-arid western U.S., droughts are a common event that negatively impact water supply and management. Drought assessments are not only relied upon for planning municipal water supply storage, they also are vital for planning agricultural yields and allocating water for the coming growing season. Also included in these water allocations are environmental releases for maintaining healthy aquatic habitats for endangered species and for preventing salt water intrusion in major river deltas.

Many drought assessments are limited to using drought indicators which rely predominantly on surface water hydrology to estimate the changes in water availability within a region. The inclusion of all hydrologic variables, surface water, soil moisture, groundwater, snow cover and ice, is often limited by the lack of direct observations and the complexity of modeling all hydrologic components and their interactions at regional scales (Thomas, Reager, Famiglietti, & Rodell, 2014). Commonly used indicators, such as the Palmer Drought Severity Index (PDSI), are only effective for very specific regions that do not include the western U.S.

Assessing prolonged drought solely using such indices also neglects the contribution of the ongoing loss of groundwater reserves to the recovery time of the system (DeChant & Moradkhani, 2015; Karl, Quinlan, & Ezell, 1987; Thomas et al., 2014). Since the remediation of surface water storage (streams and reservoirs) occurs at a quicker pace than that of groundwater, it is essential to include groundwater to understand a region's long-term vulnerability (Howitt, MacEwan, Medellin-Azuara, Lund, & Sumner, 2015; Thomas et al., 2014). This is especially true of semi-arid regions, such as the southwestern U.S., where surface water supplies are already scarce, and groundwater is relied upon heavily during periods of drought. California, specifically, experienced its most severe drought in over a century during the period of 2012-2016 due to record high temperatures in combination with exceptionally low precipitation (AghaKouchak, Cheng, Mazdiyasni, & Farahmand, 2014; Griffin & Anchukaitis, 2014). Therefore, an assessment of drought duration and termination which includes all components of terrestrial water storage (TWS) is needed for risk mitigation and water management.

Here I present a probabilistic drought recovery assessment for California using gravimetry information from the Gravity Recovery and Climate Experiment (GRACE) mission. This approach involves deriving fluctuations in TWS from changes in the gravity field observed by the GRACE satellites (Rodell & Famiglietti, 1999; Tapley, Bettadpur, Ries, Thompson, & Watkins, 2004; Wahr, Swenson, Zlotnicki, & Velicogna, 2004). I define the TWS deficit for California as the amount of meteorological input (precipitation minus actual evapotranspiration and runoff) required to return the region's TWS level to its historical (2002 - 2014) mean. The probability of receiving meteorological input, which will meet or exceed the TWS deficit over a given timespan, is based upon historic precipitation and runoff observations along with modeled actual evapotranspiration. I provide an assessment based on different meteorological input scenarios; inputs using the entire historic record (1895-2015), the meteorological input of past El Niño years only (1963-2015), and inputs based on high precipitation years only (6-month SPI > 1.3). There is often great emphasis placed on El Niño events in California since the stronger events can bring much needed increases in rainfall to the region (Cayan, Redmond, & Riddle, 1999; Hoell et al., 2016; Schonher & Nicholson, 1989); therefore, I have included additional analysis that projects the expected TWS anomaly given the meteorological input of varying intensities of historic El Niño and La Niña events.

CHAPTER 1

GRACE-based Equivalent Water Height

GRACE detects changes in Earth's gravity field due to changes in mass. Once changes in atmospheric and oceanic mass are removed the primary signal is due to fluctuations in TWS. In this work, I used 12 years (2002–2014) of GRACE-based equivalent water height anomaly for all of California. This equivalent water height was based on the release 5 datasets from the GeoForschungsZentrum (GFZ) (ISDC: GRACE @ ISDC, 2018). The GRACE spherical harmonic coefficients were processed such that after removing the long-term mean, they describe the monthly anomalies in the geoid (Tourian, Reager, & Sneeuw, 2018). The monthly solutions are contaminated by noise from various sources: aliasing of residual tidal signal (Seo, Wilson, Han, & Waliser, 2008), other signals, and high-frequency noise in the spherical harmonic coefficients due to the orbit geometry and sensor noise. The main tidal constituents were modeled and removed from the GRACE monthly solutions to a large extent. A decorrelation filter was applied to reduce high-frequency noise as suggested by Swenson & Wahr (2006). California is relatively small with respect to the GRACE footprint; therefore, further filtering of the GRACE-derived field was applied using a Gaussian filter with a relatively small radius of 250 km. The filtered monthly solutions were converted to equivalent water heights ΔM on 0.5° × 0.5° grids using (Wahr, Molenaar, & Bryan, 1998):

$$\Delta M(\theta, \lambda; t) = \frac{R\rho_{ave}}{3\rho_w} \sum_{l=0}^{l_{max}} \frac{2l+1}{1+k_l} \sum_{m=-l}^{l} Y_{lm}(\theta, \lambda) \Delta K_{lm}(t) \tag{1.1}$$

where ρ_{ave} is the average density of the Earth (5515 kg/m3), ρ_w is the average density of water (1000 kg/m3), R is the radius of the Earth (6378.137 km), k_l is the load Love number of degree l, Y_{lm} are the normalized spherical harmonic functions of degree l and order m, and ΔK_{lm} are the normalized complex spherical harmonic coefficients after subtracting the temporal mean. The estimated equivalent water heights were aggregated over the Urmia basin via area weighted averaging

$$\Delta M(\chi; t) = \sum_{i=1}^{p} \Delta M(\theta, \lambda; t) \frac{A_i}{A_\chi} \tag{1.2}$$

where χ is the basin index, p is the number of pixels associated with χ, A_i is the area of the grid cell (0.5° × 0.5°) i in χ, and A_χ is the total area of χ. The error envelope was obtained by propagating the calibrated standard deviations provided by GFZ.

Meteorological Input

In this work, I define meteorological input (PER) as an estimate, over varying time spans, of the water volume (precipitation minus actual evapotranspiration and runoff) available to recover the GRACE-derived TWS deficit. Using the terrestrial water budget equation (Swenson & Wahr, 2006; Zeng, Yoon, Mariotti, & Swenson, 2008)

$$\frac{dS}{dt} = P - E - R \tag{1.3}$$

where S is terrestrial water storage, P is precipitation, E is actual evapotranspiration, and R is runoff, such that $P - E - R$ represents the volume of meteorological input required to balance the current deficit in TWS.

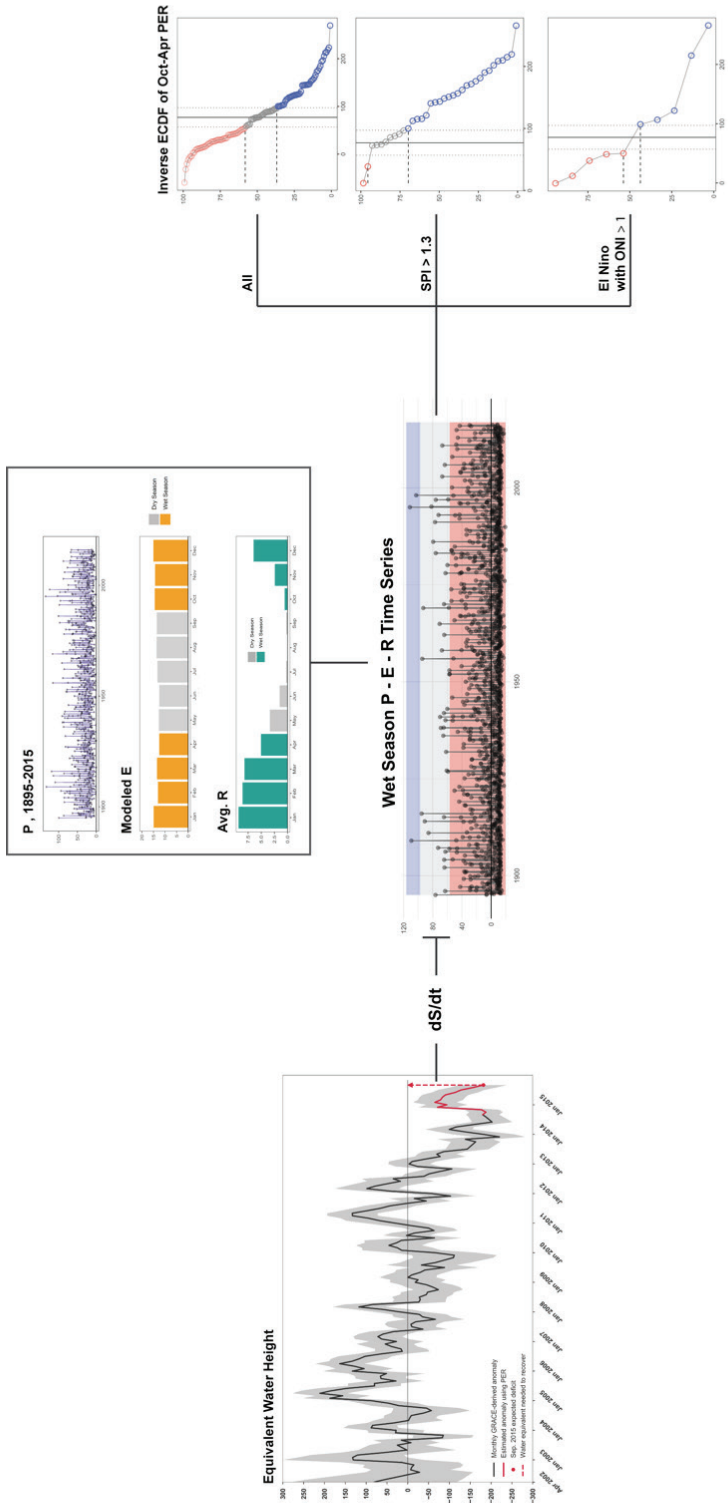

Figure 1.1. Conceptual figure to visually demonstrate the wet season PER time series and the estimation of the probability of meeting or exceeding the TWS deficit (dS/dt).

To calculate monthly PER, I used gauge-based observations of precipitation and runoff, along with modeled actual evapotranspiration. Monthly historical rainfall accumulation for all of California was acquired from National Oceanic and Atmospheric Administration (NOAA National Centers for Environmental information, 2017). The monthly records used cover the period of 1895-2016 and have been adjusted by NOAA to account for instrument changes.

For the combined Sacramento and San Joaquin river delta outflows, I used the California Department of Water Resources (CADWR) Dayflow net delta outflow estimates which account for water exports out of the delta region and tidal effects (Dayflow webpage, 2018). For the remaining runoff data, monthly gauged historical stream flows provided by the United States Geological Survey (USGS) were used.

My runoff calculations consist of all gauged rivers that transport water into or out of California and have data records that extend back to at least 1963. I accounted for both inflow and outflow for California in my runoff calculations; where outflows were denoted as positive runoff values and inflows as negative runoff values. I compared the monthly average volume of all gauged outflowing, or inflowing, rivers to that of just the rivers with a date range 1963 or earlier, with no significant difference. This can be attributed to the fact that most of the inflow and outflow for California belongs to the largest rivers; mainly, the Sacramento/San Joaquin delta, the Colorado River, the Klamath River, and the Eel River. The start year for my observed runoff record, 1963, was chosen due to the start dates for the Klamath and Colorado Rivers streamflow data. Since these two rivers are major sources of outflow and inflow for California, respectively, they could not be omitted from the runoff calculations to extend the date range.

The flows for the Klamath River and the Colorado River are shared with surrounding regions (i.e., Oregon, Nevada, Arizona, and Mexico). To extract the monthly runoff estimates for California only, this exchange of inflows and outflows was accounted for in my calculations. For the Klamath River, the inflow from Oregon measured at the Iron Gate Dam gauge (Fig. 1.2., northernmost yellow dot) was subtracted from the outflow from California measured at the Klamath Falls gauge. The Colorado River calculations are more complicated and involve more uncertainty, since not all extractions from the Colorado River are monitored by USGS or CADWR. To calculate the net flow for the Colorado River relative to California, I used the streamflow just before the California-Arizona border region measured at Davis Dam (inflow; Fig. 1.2., yellow dot), the extractions by Arizona (outflow) via the Central Arizona Project Canal and the Gila Gravity Canal at Imperial Dam, and finally the outflow to Mexico measured at the Yuma gauge at the international border. Assuming the remainder of the flow are the diversions made by California, the result is a relatively large net inflow to the region.

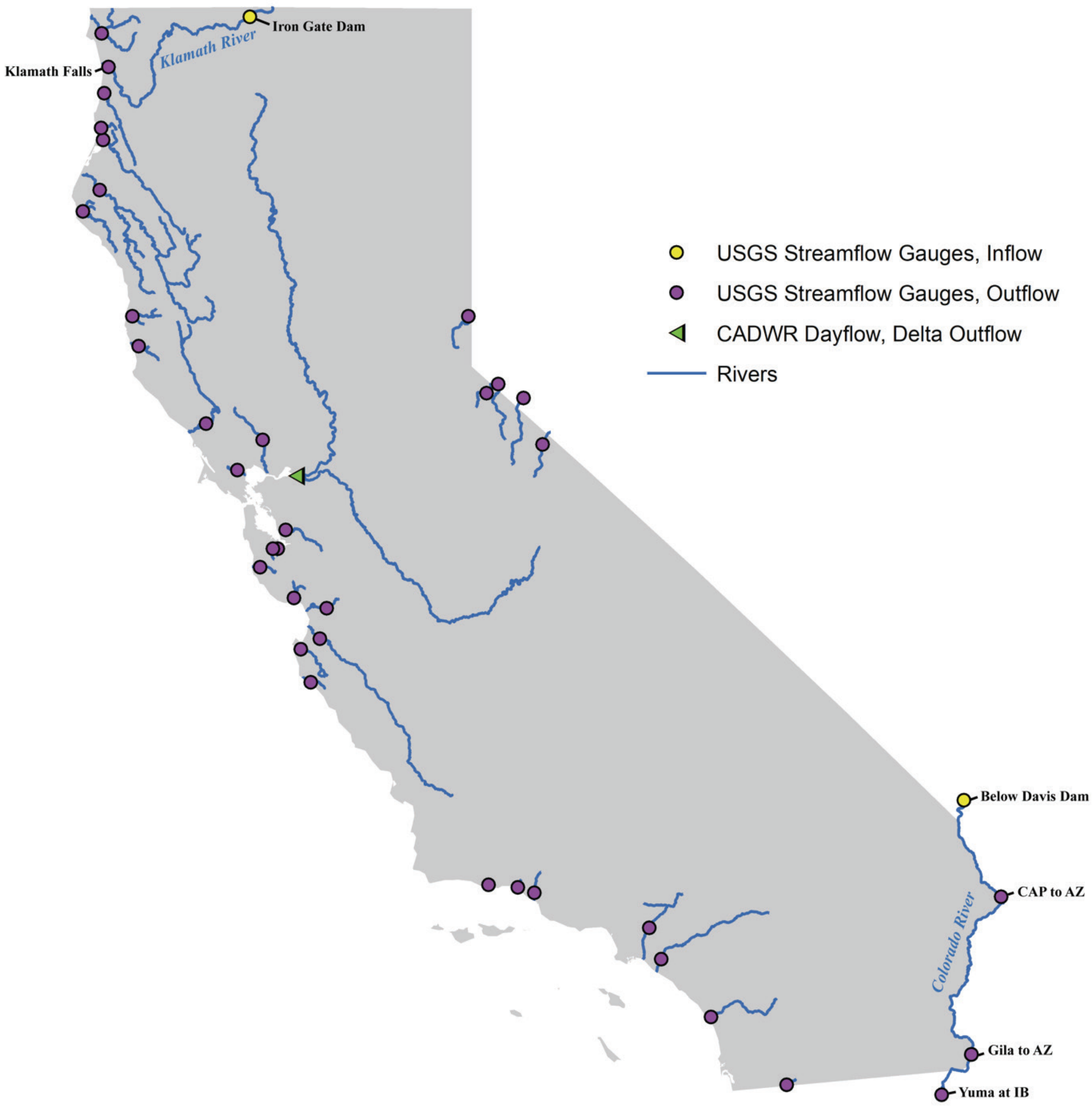

Figure 1.2. Map of California and the major rivers used for runoff calculations. The locations of the USGS streamflow gauges for outflowing runoff (purple dots) and for inflowing stations (yellow dots) used within this study, along with the location of the California DWR Dayflow net Sacramento/San Joaquin delta outflow estimates at Chipps Island (green triangle).

I used modeled monthly actual evapotranspiration (ET) for California, which was output by the hydrologic model developed by Mehran et al. (2017). Initial estimates were determined to be too high after comparing the GRACE-based equivalent water height anomaly with a PER-based expected anomaly over a test period of September 2011 to August 2014 (Figure 1.3). The PER-based expected anomaly was calculated using the cumulative sum of the monthly PER (converted to millimeters of water height equivalent) using the September 2011 GRACE-based equivalent water height as the initial value. I bias-corrected the modeled ET based on annual estimates published by Sanford & Selnick (2013). Comparison of the expected PER-based anomaly using the corrected ET with the GRACE-based equivalent water height produced improved results.

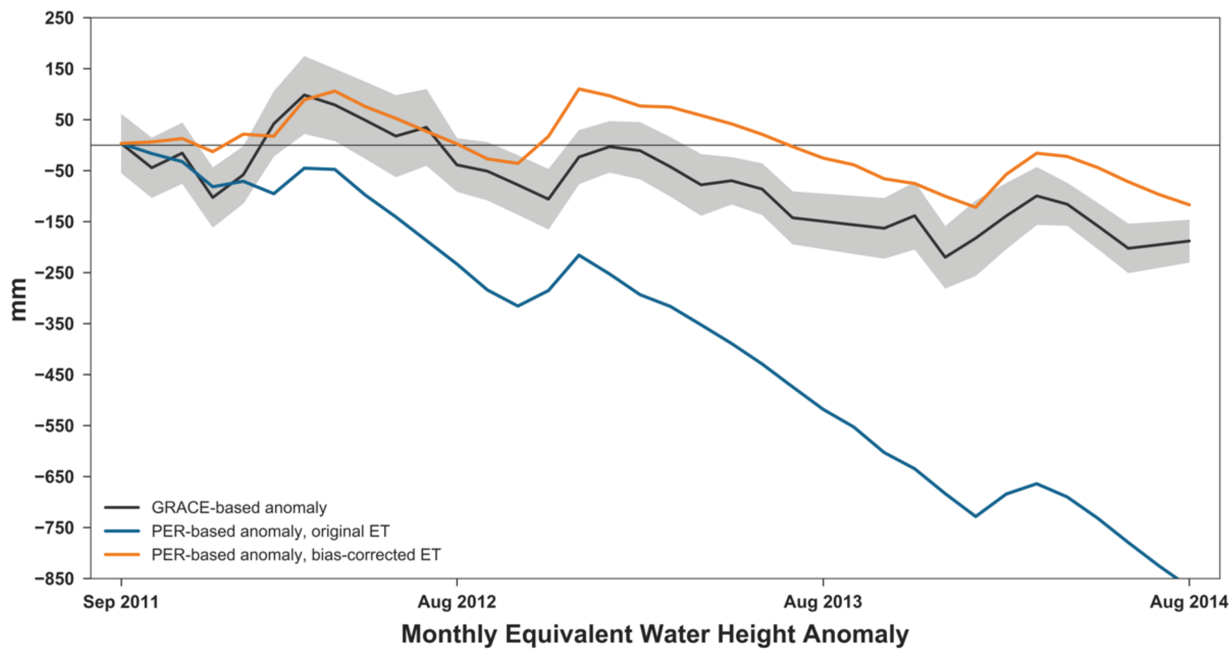

Figure 1.3. Evaluation of actual ET values by comparing the PER-based expected anomaly versus the GRACE-based anomaly. Both PER-based expected anomalies use the same observed monthly precipitation and runoff, only the modeled ET varies between the two lines.

CHAPTER 2
Recovery Scenarios

The GRACE-based equivalent water height anomaly record I used only extends through the 2014 water year, therefore I extrapolated the expected anomaly using PER to obtain an estimate for the September 2015 wet season TWS deficit (Figure 2.1). The PER consisted of observed monthly precipitation, monthly runoff climatology, and modeled monthly ET climatology. The PER was converted from total volume for all of California to equivalent water height, then the cumulative sum was taken each month following the last GRACE anomaly in September 2014. The standard error of the mean (SEM with 95% CI),

$$SEM = \frac{\sigma}{\sqrt{n}}(1.96), \tag{2.1}$$

for the PER was used to propagate the errors of the equivalent water height anomaly. The expected anomaly for September 2015 was then used to calculate the volume of water needed to recover from the drought (the TWS deficit), which is estimated here to be 77 ± 20 km^3. I could then determine the probability of meeting or exceeding the estimated TWS deficit given varying scenarios of historical PER.

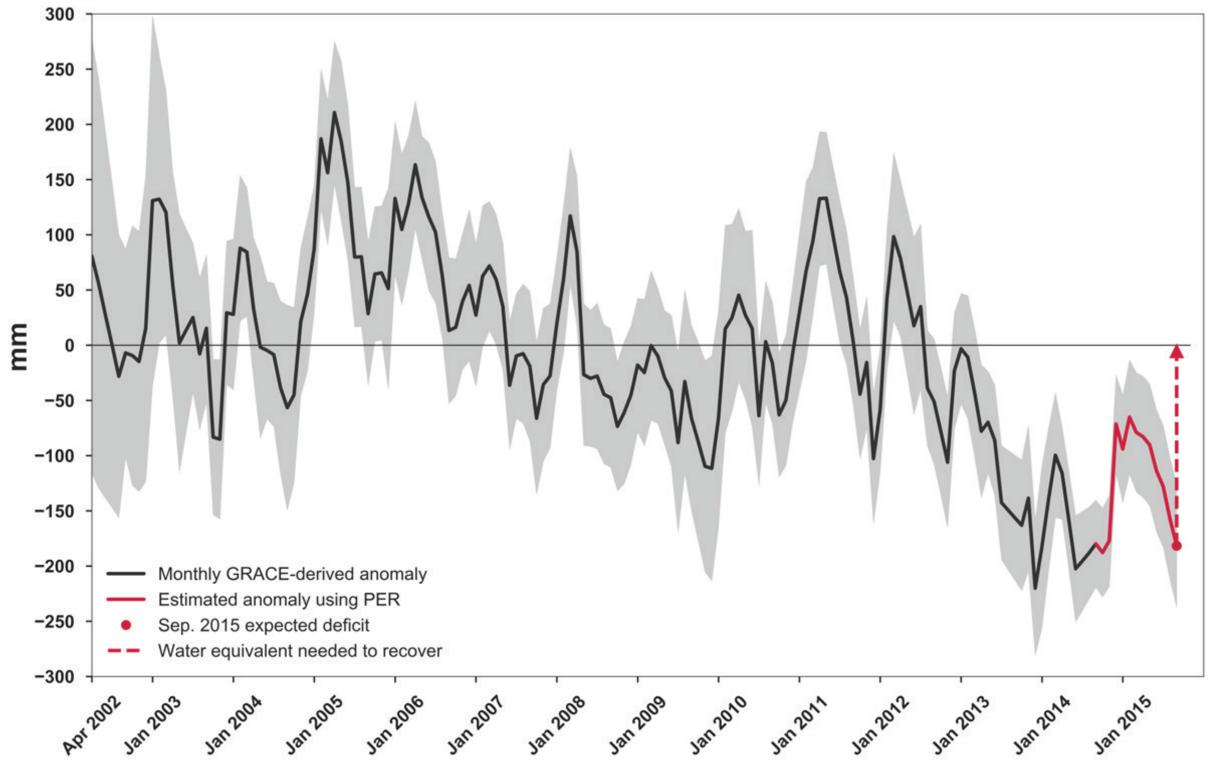

Figure 2.1. GRACE-based equivalent water height anomaly from April 2002 through September 2014 (black line). Expected anomaly using monthly PER for October 2014 through September 2015 (red line) was used to estimate September 2015 TWS deficit (dashed red line) with respect to the mean of the GRACE-based equivalent water height.

The first scenario focuses on the probability of recovery given all historic wet seasons (October – April) from 1895 to 2015. Since the runoff record only extends back to 1963, I used monthly runoff climatology (1963-2015). After calculating the monthly PER from 1895 to 2015, I calculated the total volume of PER for each wet season. The result is a time series of yearly wet-season PER volumes. I then used the inverse empirical cumulative distribution function (ECDF) and Gringorten plotting position (Farahmand & AghaKouchak, 2015),

$$F_n(x)^{-1} = [P_n(X \leq x)]^{-1} = 1 - [(n - 0.12)^{-1}([\sum_{i=1}^{n} I(x_i \leq x)] - 0.44)], \tag{2.2}$$

of the wet-season PER time series to determine the historical probability of any given wet-season meeting or exceeding the calculated TWS deficit volume.

For the second scenario, I wanted to investigate the probability of meeting or exceeding the TWS deficit given an above average wet season. I isolated out the wet seasons that had at least one month which exceeded a 6-month empirical standardized precipitation index (SPI) of 1.3. Water years exceeding a threshold of 1.3 are classified as very wet based on the inverse of the Drought Monitor SPI classifications for dry percentiles (Svoboda et al., 2002). Empirical SPI can be defined as (Farahmand & AghaKouchak, 2015),

$$SPI = \phi^{-1}(p), \tag{2.3}$$

where ϕ is the standard normal distribution function and p is the probability derived using the empirical probability function (inverse of Equation 2.2). Similar to the first scenario, I utilized observed monthly precipitation along with runoff and modeled ET climatology for the monthly PER used in this scenario. After identifying the wet seasons with an SPI greater than 1.3, I then calculated the inverse ECDF to determine the probability of meeting or exceeding the estimated TWS deficit.

For the third scenario, I chose to extract El Niño wet-seasons only. This scenario was chosen because NOAA had forecast a strong El Niño for the 2015 wet season (Climate Predicition Center/NCEP/NWS, 2015). El Niño typically brings above average precipitation to southern California (Schonher & Nicholson, 1989); however, above average precipitation is needed in northern California in order to recover the TWS deficit. The strong to very strong El Niño years can produce above average rainfall for both southern and northern California. El Niño years of lesser strength only produced above average rainfall in southern California (Hoell et al., 2016; Schonher & Nicholson, 1989). Therefore, I used the Oceanic Niño Index (ONI) from NOAA to determine which years recorded moderate to very strong El Niño events (ONI ≥ 1) (Dahlman, 2016). The record of moderate to very strong El Niño events is rather sparse, with only ten events occurring during the period of 1963 to 2015. Similar to the other two scenarios, an inverse ECDF was used to determine the probability of any given historic El Niño wet-season meeting or exceeding the estimated TWS deficit.

Uncertainty for the monthly observed precipitation and runoff was determined using the SEM (95% CI) of each month across all years. The error for the modeled ET was based on the SEM of the bias-correction, which was the mean value of the ET ranges for each county within California reported by Sanford & Selnick (2013).

CHAPTER 3
Recovery Probability

Based on the inverse ECDF for all wet seasons from 1895 to 2015, the probability of meeting or exceeding the TWS deficit of 77 ± 20 km^3 is between 33 to 57% (Figure 3.1a). Given wet seasons with a 6-month SPI exceeding 1.3, the probability of recovery is between 70 to 96% (Figure 3.1b). Looking at the El Niño wet seasons only, the probability of recovery is between 44 to 54% (Figure 3.1c). This demonstrates that the probability of recovery for all of California based on El Niño years is similar to the probability of recovery for any given year in the historic record. Therefore, the presence of El Niño conditions is not a guarantee that California will receive enough meteorological input to recover the estimated TWS deficit. The probability of recovery greatly improves when the wet season has an SPI greater than 1.3. For example, the two strongest El Niño years on record (1982-83 and 1997-98) where wet seasons with an SPI greater than 1.3 and their PER exceeds the TWS deficit. Therefore, if the forecasted 2015-16 El Niño were a very strong event and exceeded an SPI of 1.3, there would be a very high probability of recovery.

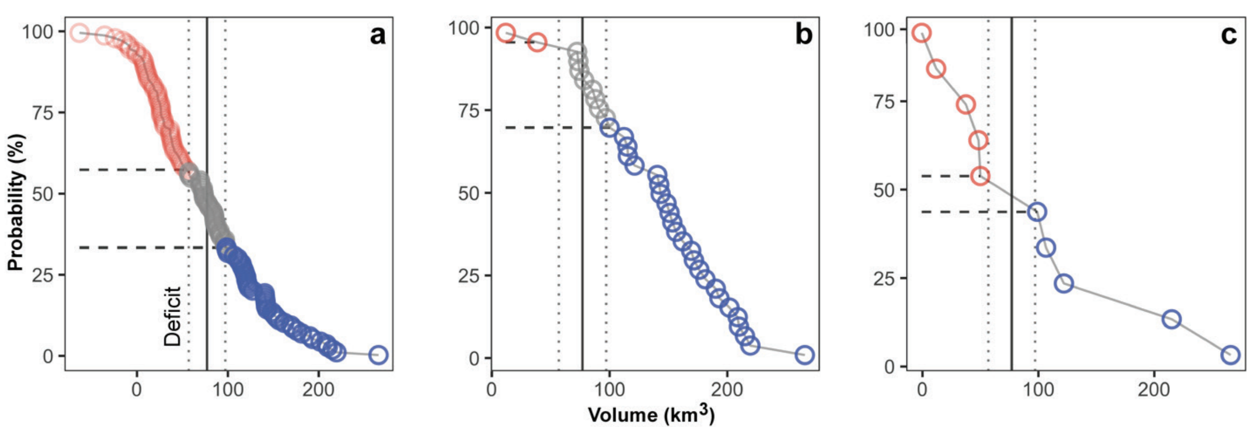

Figure 3.1. Probability of meeting or exceeding the estimated September 2015 TWS deficit (black vertical line) based on historic PER (1895-2015) in varying scenarios. Scenarios

include a) all historic wet seasons; b) all wet seasons with a 6-month SPI exceeding 1.3; c) all wet seasons that occurred during El Niño events. Wet seasons that exceed the TWS deficit are highlighted in blue, those that meet the TWS deficit and its associated error (dotted vertical lines) are shaded with grey, and those that fall short of recovery are highlighted with red. Upper and lower probability bounds are indicated with horizontal dashed black lines.

ENSO Expected Anomaly

Additional scenarios of expected anomalies were analyzed in response to the forecasts by NOAA of an El Niño for the 2015-16 water year (Figure 3.2). I calculated the expected anomaly for the 2015-16 wet season using average historic PER-based on 1) very strong El Niño events, 2) strong El Niño events, and 3) moderate El Niño events. For comparison, I also calculated the expected anomaly for La Niña events using average historic PER-based on water years associated with 1) strong La Niña events, and 2) moderate La Niña events (Figure 3.2b). I included La Niña events here, because Cayan et al. (1999) indicate that there are more complicated regional mechanisms involved with respect to ENSO events than simply northern versus southern California. Cayan et al. (1999) note that there is a higher occurrence of major flooding in the Sierra Nevada during La Niña years, while coastal regions are more prone to flooding during El Niño years.

The results displayed in Figure 3.2a indicate that, based on historic data, a very strong or strong El Niño event would be required to recover the estimated TWS deficit. Figure 3.2b indicates that, historically, La Niña events do not produce enough metrological input to recover the estimated TWS deficit; neither do moderate El Niño events.

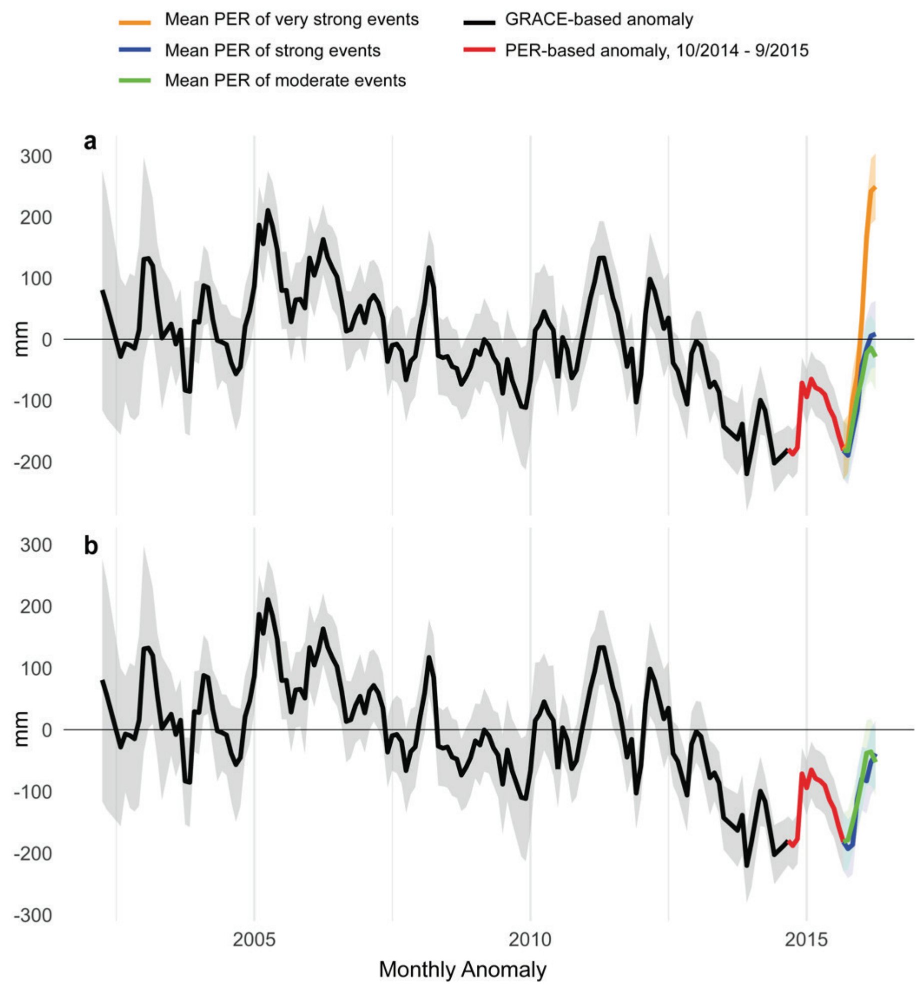

Figure 3.2. Comparison of various ENSO scenarios for a 2015-16 wet season based on historic (1963-2014) a) El Niño events, and b) La Niña events. The expected anomalies for the various ENSO scenarios use observed precipitation, average historic runoff, and modeled ET. The red line for the PER-based anomaly uses the observed precipitation and observed runoff for October 2014 to September 2015, along with modeled ET.

CHAPTER 4

Conclusions

Estimates for when a drought is expected to end are fundamental for risk mitigation and water management. California experienced its most extreme drought in recent history during 2012-2016 due to a combination of record high temperatures and exceptionally low precipitation. The big question then is, what is the probability of drought recovery given the current drought conditions and expected precipitation in the coming wet-season?

A crucial component of drought recovery assessments is the estimation of terrestrial water storage (TWS). Here I constructed a probabilistic model for drought recovery assessments that integrates both ground-based observations and NASA's Gravity Recovery and Climate Experiment (GRACE) data, which comprises all terrestrial water sources including surface reservoirs and lakes, rivers and streams, soil moisture, groundwater, snow water, and ice. I estimated the probability of receiving a total wet-season (October-April) meteorological input which will meet or exceed the September 2015 TWS deficit for California, based upon historic precipitation and runoff observations along with modeled actual evapotranspiration. I provide a probabilistic assessment based on different meteorological input scenarios; inputs using the entire historic record (1895-2015), inputs of past El Niño years (1963-2015) with an Oceanic Niño Index (ONI) greater or equal to 1.0, and inputs based on high precipitation years only (6-month SPI > 1.3).

I found that the probability of meeting or exceeding the estimated TWS deficit of 77 ± 20 km^3 during an El Niño year, between 44 to 54%, is similar to the probability of recovery based on the scenario containing all historic wet-seasons (1895-2015), between 33 to 57%. This demonstrates that an El Niño year does not guarantee recovery any more than an average historic year, most likely due to the fact that not all El Niño years result in high precipitation for all of California.

The results for the high precipitation years (6-month SPI > 1.3), with a probability between 70 to 96%, indicates that it is historically possible to meet or exceed the volume required to recover the estimated September 2015 TWS deficit in only one wet-season. The two strongest El Niño years have a 6-month SPI over 1.3 and meteorological input volumes that are sufficient to recover the 77 ± 20 km^3 TWS deficit estimated. However, the record only contains two very strong El Niño events, making it difficult to affirm whether additional very strong El Niño events would also have a 6-month SPI over 1.3. There is still a chance that a strong El Niño wet-season could produce enough to meet the TWS deficit, however a moderate El Niño or a La Niña wet-season would likely not, based on historical events. Given that El Niño conditions were forecast, there was a 44-54% chance of drought recovery during the California 2015-16 wet-season.

AghaKouchak, A., Cheng, L., Mazdiyasni, O., & Farahmand, A. (2014). Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought. *Geophysical Research Letters*, *41*(24), 2014GL062308. https://doi.org/10.1002/2014GL062308

Cayan, D. R., Redmond, K. T., & Riddle, L. G. (1999). ENSO and Hydrologic Extremes in the Western United States*. *Journal of Climate*, *12*(9), 2881–2893. https://doi.org/10.1175/1520-0442(1999)012<2881:EAHEIT>2.0.CO;2

Climate Predicition Center/NCEP/NWS. (2015). Climate Prediction Center: ENSO Diagnostic Discussion. Retrieved July 10, 2015, from http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/enso_advisory/enso disc.html

Dahlman, L. (2016). Climate Variability: Oceanic Niño Index. Retrieved November 30, 2018, from https://www.climate.gov/news-features/understanding-climate/climate-variability-oceanic-ni%C3%B1o-index

Dayflow webpage. (2018). Dayflow. Retrieved November 30, 2018, from https://water.ca.gov/Programs/Environmental-Services/Compliance-Monitoring-And-Assessment/Dayflow-Data

DeChant, C. M., & Moradkhani, H. (2015). Analyzing the sensitivity of drought recovery forecasts to land surface initial conditions. *Journal of Hydrology*, *526*, 89–100. https://doi.org/10.1016/j.jhydrol.2014.10.021

Farahmand, A., & AghaKouchak, A. (2015). A generalized framework for deriving nonparametric standardized drought indicators. *Advances in Water Resources*, *76*, 140–145. https://doi.org/10.1016/j.advwatres.2014.11.012

Griffin, D., & Anchukaitis, K. J. (2014). How unusual is the 2012–2014 California drought? *Geophysical Research Letters*, *41*(24), 2014GL062433. https://doi.org/10.1002/2014GL062433

Hoell, A., Hoerling, M., Eischeid, J., Wolter, K., Dole, R., Perlwitz, J., … Cheng, L. (2016). Does El Niño intensity matter for California precipitation? *Geophysical Research Letters*, *43*(2), 2015GL067102. https://doi.org/10.1002/2015GL067102

Howitt, R., MacEwan, D., Medellin-Azuara, J., Lund, J., & Sumner, D. (2015). *Preliminary Analysis: 2015 Drought Economic Impact Study* (Report for the California Department of Food and Agriculture). University of California, Davis. Retrieved from https://watershed.ucdavis.edu/files/biblio/2015Drought_PrelimAnalysis.pdf

ISDC: GRACE @ ISDC. (2018). Retrieved November 30, 2018, from http://isdc.gfz-potsdam.de/grace-isdc/

Karl, T., Quinlan, F., & Ezell, D. S. (1987). Drought Termination and Amelioration: Its Climatological Probability. *Journal of Climate and Applied Meteorology*, *26*(9), 1198–1209. https://doi.org/10.1175/1520-0450(1987)026<1198:DTAAIC>2.0.CO;2

Mehran, A., AghaKouchak, A., Nakhjiri, N., Stewardson, M. J., Peel, M. C., Phillips, T. J., … Ravalico, J. K. (2017). Compounding Impacts of Human-Induced Water Stress and Climate Change on Water Availability. *Scientific Reports*, *7*(1). https://doi.org/10.1038/s41598-017-06765-0

NOAA National Centers for Environmental information. (2017, December). Climate at a Glance: U.S. Time Series. Retrieved December 2, 2015, from http://www.ncdc.noaa.gov/cag/

Rodell, M., & Famiglietti, J. S. (1999). Detectability of variations in continental water storage from satellite observations of the time dependent gravity field. *Water Resources Research*, *35*(9), 2705–2723. https://doi.org/10.1029/1999WR900141

Sanford, W. E., & Selnick, D. L. (2013). Estimation of Evapotranspiration Across the Conterminous United States Using a Regression With Climate and Land-Cover Data1. *JAWRA Journal of the American Water Resources Association*, *49*(1), 217–230. https://doi.org/10.1111/jawr.12010

Schonher, T., & Nicholson, S. E. (1989). The Relationship between California Rainfall and ENSO Events. *Journal of Climate*, *2*(11), 1258–1269. https://doi.org/10.1175/1520-0442(1989)002<1258:TRBCRA>2.0.CO;2

Seo, K. W., Wilson, C. R., Han, S. C., & Waliser, D. E. (2008). Gravity Recovery and Climate Experiment (GRACE) alias error from ocean tides. *Journal of Geophysical Research: Solid Earth*, *113*(B3), B03405. https://doi.org/10.1029/2006JB004747

Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., … Stephens, S. (2002). The drought monitor. *Bulletin of the American Meteorological Society*, *83*(8), 1181–1190. https://doi.org/10.1175/1520-0477-83.8.1181

Swenson, S., & Wahr, J. (2006). Post-processing removal of correlated errors in GRACE data. *Geophysical Research Letters*, *33*(8), L08402. https://doi.org/10.1029/2005GL025285

Tapley, B. D., Bettadpur, S., Ries, J. C., Thompson, P. F., & Watkins, M. M. (2004). GRACE Measurements of Mass Variability in the Earth System. *Science*, *305*(5683), 503–505. https://doi.org/10.1126/science.1099192

Thomas, A. C., Reager, J. T., Famiglietti, J. S., & Rodell, M. (2014). A GRACE-based water storage deficit approach for hydrological drought characterization. *Geophysical Research Letters*, *41*(5), 2014GL059323. https://doi.org/10.1002/2014GL059323

Tourian, M. J., Reager, J. T., & Sneeuw, N. (2018). The Total Drainable Water Storage of the Amazon River Basin: A First Estimate Using GRACE. *Water Resources Research*, *54*(5), 3290–3312. https://doi.org/10.1029/2017WR021674

Wahr, J., Molenaar, M., & Bryan, F. (1998). Time variability of the Earth's gravity field: Hydrological and oceanic effects and their possible detection using GRACE. *Journal of Geophysical Research: Solid Earth*, *103*(B12), 30205–30229. https://doi.org/10.1029/98JB02844

Wahr, J., Swenson, S., Zlotnicki, V., & Velicogna, I. (2004). Time-variable gravity from GRACE: First results. *Geophysical Research Letters*, *31*(11), L11501. https://doi.org/10.1029/2004GL019779

Zeng, N., Yoon, J.-H., Mariotti, A., & Swenson, S. (2008). Variability of Basin-Scale Terrestrial Water Storage from a PER Water Budget Method: The Amazon and the Mississippi. *Journal of Climate*, *21*(2), 248–265. https://doi.org/10.1175/2007JCLI1639.1