DEVELOPMENT AND APPLICATION OF A PARSIMONIOUS WATER BALANCE MODEL FOR MEDITERRANEAN CLIMATE CONDITIONS

By

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A dissertation submitted in partial satisfaction of the requirements for the degree of

Doctor of Philosophy

in

Engineering – Civil and Environmental Engineering

in the

Graduate Division

of the

University of California, Berkeley

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Summer 2017
ABSTRACT

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The annual water balance is an important indicator of the hydrologic function and utility of a watershed, and yet there has been relatively sparse research of the special considerations that control the yearly partition of precipitation in a Mediterranean climate (MC) like that of California. In particular, there is a gap in empirical characterization of the annual water balance over a broad collection of watersheds spanning the diverse climate and landscape conditions of the state. This research develops and applies a top-down, parsimonious, physically interpretable water balance model that explicitly accounts for seasonality, a critical climate factor for MC regions.

The research was motivated by the observation of a straightforward, linear relationship between total annual precipitation and streamflow for watersheds in the Russian River Basin of northern California. A dataset of monthly water balance variables was developed to meet the criteria of accurate estimations, geographic contiguity, and temporal longevity, continuity, and consistency. Inspection of the long-term water balance for 159 watersheds in the state led to a more general form of the precipitation-streamflow relationship, a segmented linear model. Model parameters were estimated for each watershed via regression of water balance observations using a structural probabilistic model that was resilient to uncertainties in the input data.

Model parameter estimates displayed aggregate clustering by prevailing wetness conditions, as well as geographic regionalization. The average predictive uncertainty for gaged watersheds ranged from 50 to 125 mm per year in terms of area-normalized streamflow. Modeled streamflow residuals were used to evaluate historical changes in the water balance, revealing a decreasing trend in the streamflow of most California watersheds during the onset of the climate change era, controlling for precipitation. Sensitivity analysis showed that changes in the seasonality of precipitation and potential evapotranspiration have an order-of-magnitude larger impact on the water balance relative to other climate drivers. Spatial proximity correlation and watershed feature regression both showed promise as methods for estimation of model parameters in ungaged watersheds. The model was also contextualized with regards to the influential Budyko curve.

This research demonstrated that a parsimonious and interpretable model was capable of describing the annual water balance for the diverse hydrologic conditions across California. By focusing on the analysis of many watersheds over long timeframes it was possible to characterize and interpret broad trends and patterns that influence the water balance in MC regions.
DEDICATION

This work is dedicated to the memory of Professor James Hunt, a mentor and friend, who taught me to seek simplicity. And to Karen, whose encouragement, patience, and support made it possible to have it all, together.
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INTRODUCTION

1.1 SUMMARY

California hydrology is a densely woven patchwork of natural and human-made systems; a drop of rain near the Oregon border might be used to wash dishes in San Bernardino, making its journey via subsurface channels, surface streams, concrete viaducts, massive pumps, water treatment facilities, and municipal distribution pipes. Hydrology conditions in the state are famously varied, ranging from lush rain forests to alpine snowfields to dry scorching heat. Water management in the state is likewise complicated and contentious due to Byzantine bureaucracy, over-allocation of resources, and short-sighted development [Hanak et al., 2011]. The result is a water system stressed beyond any reasonable capacity to support the many natural and human needs, leaving no margin for adaptation to any changes in water supply. And yet the most important factor for that supply, climate, is indeed changing. Overall, this points to a need to characterize and understand broad patterns and trends in the California water supply.

The general approach to understanding the effect of changing inputs to a system is to model that system and then vary inputs to the model to see what happens. Mechanistic models are ideal for this purpose because they account for dynamic interactions of the various components in a system, and there are various such models that have been applied to provide insights about California hydrology. But a significant challenge of mechanistic approaches is that uncertainties in model parameters can have an outsized impact on outcome uncertainties, and accurate estimation of hydrology parameters is notoriously difficult for watersheds and even more so for regional studies.

Given this difficulty, there is an opportunity to contribute to understanding of statewide water patterns and trends via a straightforward analytical framework with modest data requirements, broad applicability, useful accuracy, and physically-interpretable parameters. This research proposes and applies such a framework, the Mediterranean Climate Water Balance (MCWB) model. The salient features of the MCWB are that it is:

- An approach for estimating annual runoff $R$ in a watershed as a function of a two broadly available climate variables: precipitation $P$, and potential evapotranspiration $PET$.
- Tailored to the seasonality of a Mediterranean climate by explicitly accounting for seasonality of $P$ and $PET$.
- Parameterized by three physically-interpretable landscape factors:
  - Two coefficients that describe the amount of subsurface water retention vs. seepage for mid-range and wet conditions, $a_{\text{mid}}$ and $a_{\text{wet}}$.
  - A threshold describing the transition between mid-range and wet conditions, $S^*$
- Data-driven and parsimonious, only as complex as necessary to capture the observed hydrological behavior.

The remainder of this introduction provides overview descriptions of the study area, the importance of the annual water balance, research philosophy and scope, challenges specific to this work, and a preview of the document structure.

1.2 STUDY AREA

The study region for this research is the state of California, a choice motivated by a number of considerations. Pragmatically, water data is relatively abundant and accessible, with records maintained by the United States Geological Survey (USGS), the U.S. National Oceanographic and Atmospheric Administration, the California Department of Water Resources, and numerous local
jurisdictions. Furthermore, the University of California offers special resources for the study of California water, including the Water Resources Collection and Archive, and the special collections of the Bancroft Library at UC Berkeley, both of which provide historical context for water resource development. More generally, the past, present, and future of California water is a rich and compelling topic. From historical accounts of dramatic power struggles and monumental engineering efforts [Reisner, 1987; Hundley, 2001], to fictional interpretations of real events [Polanski, 1974], to local microcosms of the complexities of water usage [Moran, 2012], there are few other places where water plays such a prominent role in the identity and narrative of a region as it does for California’s forty million residents.

Given the importance of water in California, it is perhaps surprising that the special considerations of hydrology in the state, in particular the prominent role of the region’s Mediterranean climate, are generally underrepresented in research about broad patterns and emergent behavior in the water cycle (§ 2.10). For example, the often-used Model Parameter Estimation Experiment (MOPEX) watershed dataset [Schaake et al., 2006], curated for the purpose of historical analysis of natural conditions, includes only 17 California watersheds, too few to represent the diversity of conditions across the state. It is not unreasonable to focus on the most general findings of continental- or global-scale research at the expense of the outlier considerations of Mediterranean climate regions (MC regions), but it does diminish its usefulness for California. A more recent reference dataset [Newman et al., 2015] includes broader coverage of California but has not yet been extensively cited in annual water balance research.

In addition to benefits to hydrology within the state, California-centric research is largely extensible to other MC regions. Furthermore, explicit consideration of MC factors like climate seasonality can be expected to generalize well to non-MC regions, though this is not explored in this research.

On balance, California is not only a compelling region for water study, but there are unmet needs for hydrology research. The particular strengths and challenges of water research at the statewide scale are discussed next.

California is in some ways an ideal region for water study. Physically, the state is largely self-contained within a natural water boundary, with very few natural inflows or outflows from bordering jurisdictions. This means California-centric resources for water research are generally sufficient, reducing the burden of data collection and contextual research. Additionally, the state encompasses an extraordinary diversity of hydrological conditions, as illustrated in Figure 1. Average annual precipitation ranges from over 2 m per year in the coastal rainforests and alpine snowfields in the north of the state, to less than 20 cm in the central valley and southwestern desert. The geospatial pattern of average potential evapotranspiration is essentially the inverse, such that average aridity, the ratio of PET to P and one of the most important drivers of the annual water balance, indicates extreme energy surpluses for over one third of the state and water surpluses for another third, leaving relatively little of the state with balanced energy-water conditions. Land cover in the state is correspondingly diverse, with vast swaths of natural evergreen forests, savannah woodlands, and shrubby deserts competing for water resources with artificially-supported croplands and expansive urban sprawl.

However, some of these characteristics of California water also pose significant challenges to research. The diverse hydrological conditions translate into highly heterogeneous processes and factors that must be accounted for by models and empirical regressions; this is a particular challenge
for bottom-up, distributed approaches to modeling (§ 2.1). Intensive management and manipulation of water resources has disrupted natural processes in many watersheds, reducing the quantity and quality of hydrologic records.

Given the many competing uses of California water – from industrial production, to critical habitat for endangered species, to massive agricultural operations, to recreational use – there is a persistent and perhaps irreconcilable question of the optimization objective for water research. This research largely avoids such subjective questions, and instead focuses on interpretation of historical records as a framework that can be used to investigate particular objectives.
Figure 1: California encompasses an incredible diversity of climate and landscape conditions, as illustrated by this overview of statewide hydrology factors, clockwise from upper left: precipitation (source PRISM), PET (empirically estimated from PRISM temperature), land cover (as of 2009, source IGBP) and aridity (derived from precipitation and PET).
1.3 **THE ANNUAL WATER BALANCE**

The basic unit of observation for this research is the annual water balance of a given watershed. Watersheds are an important spatial unit for watershed management and for natural biomes, but the main advantage of watershed-scale analysis is that a watershed can generally be assumed to be a natural control volume, which means it can be used for mass balance analysis using the general form,

\[ \text{In} = \text{Out} + \text{Accumulation} \]

For a watershed the mass balance of interest is the water balance,

\[ P = R + E + \Delta S \]

where precipitation \( P \) is the input, outputs include streamflow (aka runoff) \( R \) and evapotranspiration \( E \), and the accumulation term is represented by storage change \( \Delta S \). In reality there may be other factors, such as subsurface flows in or out of the watershed, and for a particular watershed these factors may have a significant impact. But broadly speaking these are the dominant terms of the water balance.

The annual timeframe offers both conceptual and practical advantages. Annual totals of the various water balance components are important for water management and planning; for instance, total yearly runoff is an important metric for storage in surface reservoirs. The runoff for a particular watershed may be dominated by different seasons – the wet season for rain-dominated watersheds, and the dry season for snow-dominated watersheds – so the annual total provides a common reference for comparisons. Also, the storage change term \( \Delta S \) is generally viewed as less important annually than for shorter timeframes. This is conceptually more apparent in MC regions like California, where the long dry season leads to steadily diminishing streamflows that are indicative of a corresponding reduction in watershed storage. This suggests an annual cycle of storage build up during the wet season and drawdown to comparably low levels by the end of each dry season. Pragmatically, the data needed to calculate annual totals of the water balance terms is broadly available as the sum of daily or monthly estimates.

One consideration for the annual timeframe is how to measure the yearly cycle, or how to define a water year. This research uses the conventional definition of a water year as the interval October 1 through September 30. This aligns very well with the predominant seasonal cycles in California and other MC regions, and preliminary analysis of baseflow rates in California streams suggested that watershed storage levels are generally at or near a minimum toward the end of each water year. Subsequent references to annual or yearly value will refer to water year values.

This analysis treats streamflow \( R \) as the outcome variable of interest, a decision that was motivated by two considerations: first that the amount of water in streams is a broad indicator of hydrologic activity and a matter of practical importance for human and natural water uses; and secondly that streamflow is more readily measured than evapotranspiration, the other dominant component of the water cycle.
1.4 RESEARCH PHILOSOPHY

The Art of Cartography attained such Perfection that the Cartographers Guilds struck a Map of the Empire whose size was that of the Empire, and which coincided point for point with it. The following generations were not so fond of the study of Cartography as their forebears had been. In the deserts of the west, still today, there are tattered ruins of that Map; in all the land there is no other relic of the Disciplines of Geography.


An underlying theme of this research is that the description of an observed process need not be more complex than necessary to describe the observation. In other words, simple is good, and often good enough. This approach is generally referred to as “top-down”, as contrasted with the “bottom-up” approach where models are conjured from (typically many) fundamental mechanistic principles. The kernel of this research was the observation that the relationship between precipitation and runoff was remarkably straightforward for particular watersheds in the Russian River basin of California. Despite the fact that innumerable small-scale interactions between climate, landscape, and vegetation comprise the hydrological processes in these watersheds, the emergent outcome was described by a simple linear relationship. The question of how this was possible led to a deep appreciation of the merits of simplicity and interpretability.

Minimalist descriptions and models have many limitations; they are often inadequate to describe the underlying processes in terms of fundamental mechanisms, and this diminishes the potential for empirical or experimental validation of those processes. Using the example of watersheds in the Russian River basin, the true underlying processes cannot possibly be accurately characterized with the two parameters of a linear regression; there are inevitable simplifications and conceptual leaps. And yet if the outcome can be described, or better yet predicted, with only two variables then there is value in such a simplistic description.

Another motivation for simple models is that data limitations may not justify more complex representations, and the records in this research typically span just tens of years. There is a compelling argument that when data is limited then only very straightforward models are justified, specifically for rainfall-runoff models [Jakeman and Hornberger, 1993]. In other words, even if a comprehensive and adequately complex representation of processes is the goal, data constraints may not justify such complexity.

Interpretability is another fundamental goal of physical models, and there is a natural tension between complexity and interpretability. The few parameters of simplistic models necessarily combine the effects of multiple processes, whereas it is generally infeasible to isolate and characterize the many parameters of complex models. Examples of the former are the linear description of the California water balance, or the one-parameter representations of the famous Budyko curve (§ 8.1), where, depending on the structure of the model, the meaning of the parameters may be opaque. At the other end of the spectrum, the fundamental mechanisms of a bottom-up model may be perfectly interpretable in isolation, such as infiltration-excess overland flow as a function of soil properties and precipitation intensity. But the interaction of many simple mechanisms may be difficult to interpret collectively. There is not in general a definitive, objectively optimal compromise between complexity and interpretability, but models can be evaluated on their individual merits. Virtues include conceptual separation of distinct processes, such as climate and landscape processes, and consistency with prevailing understanding of hydrologic processes.
Overall this research attempted to strike an appropriate balance between simplicity and interpretability. This motivated a journey through the insights of many preceding researchers that used a broad range of tools to describe hydrological behavior at varying levels of complexity and detail. As the research was extended to include other regions of California it became clear that not all watersheds had behavior that was quite as simple as those first examples. But at each crossroads the prevailing question was whether there was a simpler way to describe the observations. To the extent that this research has resulted in any successes in regards to simplicity and interpretability, credit goes to the influence of those who came before, to whom the author is indebted for their clarity of thought and exposition.

1.5 RESEARCH SCOPE AND APPLICATIONS

As described thus far, the purpose of this research was to develop a parsimonious and interpretable model of the annual water balance for California watersheds. This scope is still quite broad, and so the purpose of this section is to further refine the scope of model development and applications for the model.

The simple relationship observed in annual precipitation-runoff estimates for watersheds in the Russian River basin prompted a number of research questions. How prevalent is this relationship across the diverse hydrologic conditions in the state? Is there a general relationship that applies throughout the state? And if so, what does this relationship say about the broad, dominant factors that determine the water balance in California? Notably, these questions are concerned with broad patterns and aggregate effects, not the nuances of any particular watershed. Indeed, a generalized model may perform poorly for any given watershed even if it is descriptive in aggregate.

With this premise, the scope of the research can be more tightly defined. Development of a general water balance model, applicable across California, was within scope; model optimization for any particular watershed or region was out of scope. Characteristics of the long-term (multi-decadal) water balance, and long-term trends, were in scope; evaluation of yearly or short-term deviations from the general behavior was out of scope. Physical interpretation of model variables and parameters was in scope; rigorous mechanistic justifications were out of scope.

It has been said that, “Science is solving puzzles; engineering is solving problems” [Hunt, James R., personal communication]. This research is largely focused on the puzzle of the simple relationship between runoff and precipitation; not solving the puzzle per se, which implies proof of the underlying processes that generate the relationship, but rather clarifying the prevalence of the pattern and the factors that may be influential. Of course, the value of any model is its usefulness for anticipating real outcomes, and there are numerous applications for the model developed in this research, as described subsequently.

1.6 CHALLENGES

There were several significant challenges specific to this research. As a data-driven study, there was a prerequisite need to develop a suitable research database for the dominant climate and landscape factors that affect the water balance (§ 3.2). There was no existing database suitable for this purpose, and each component posed distinct challenges. Watershed delineation was initially accomplished via algorithmic traversal of digital elevation maps (DEMs) using the geospatial information system software OpenGIS; these preliminary versions were largely superseded by the USGS GAGES-II watershed metadata collection [Falcone, 2011] (§ 3.2.2). Multiple data sources were evaluated to describe watershed attributes such as physical features and land cover, including DEMs for
topography, satellite data for land cover, and U.S. Department of Agriculture digital maps for soil characterization. Ultimately, the GAGES-II dataset provided comprehensive coverage of these and many more features. Streamflow data is widely accessible via the USGS, but significant curation was needed to screen for minimally-manipulated conditions and for data quality (§ 3.2.3). It was necessary to develop a new precipitation dataset, derived from two sources, that was both spatially accurate and temporally consistent for the entire period of record (§ 3.2.4). The same criteria applied to potential evapotranspiration, which was empirically approximated as a function of temperature and compared for accuracy against reference datasets (§ 3.2.5).

Given an adequate research database, water balance model development evolved from preliminary attempts with a two-segment linear model to the eventual form of a three-segment linear model. Other forms were also considered, including exponential, sigmoid, and polynomial relationships, but the interpretability of the three-segment linear model prevailed.

After the form of the model was established, the next step was to perform regressions for each watershed using the historical database. The Bayesian approach described in § 5 offered clear advantages to more common methods such as ordinary least squares, not least of which was robust treatment of observational uncertainties. The primary challenge of this approach was the definition and implementation of a probabilistic model. However, the deliberation and attention to detail that this required ultimately paid dividends in terms of comprehension and interpretation of the results.

Once the model parameter estimates were in hand, it became apparent that there was an additional challenge of interpreting the physical meaning of the parameter values across the diversity of watershed conditions in the state, especially for the purpose of evaluating geographical distributions (§ 5.3.3). This is because not all watersheds experience the same range of hydrologic conditions that trigger threshold behaviors, i.e., arid watersheds may never experience saturated wetness conditions, and very humid watersheds may never experience very dry years. Thus, while the general model structure may be adequate to describe the water balance, comparison of parameter values for different watershed conditions must be carefully considered.

1.7 RESEARCH STRUCTURE

The structure of this dissertation is as follows. Subsequent to this introduction § 2 provides a review of related research, with a focus on studies that address the hydrological processes that drive the watershed water balance at various temporal scales and a summary of the research gaps that this study strives to address. Next, § 3 describes the requirements and development of a water balance database, and empirical rainfall-runoff observations are introduced. A parsimonious model is then developed in § 4 that is consistent with prevailing water balance patterns statewide, and the parameters are contextualized using physical descriptors. In § 5 a probabilistic approach to model parameter inference is detailed, and the results of this inference are then presented and discussed for 159 California watersheds. Next, model residuals are used in § 6 to evaluate temporal trends in the water balance, controlling for precipitation and other climate and landscape factors. A machine-learning approach to estimating MCWB model parameters for ungaged watersheds is then evaluated in § 7, and in § 8 the MCWB model is contextualized further using the Budyko curve framework.
2 Prior Research

2.1 Introduction and Scope

There is a large and active body of research devoted to the water balance at various spatial and temporal scales. The applications are myriad: flooding characterization is concerned with hourly or shorter timescales, for regions ranging from hill slopes to massive basins; biome co-evolution with the water cycle may span decades or even centuries; water management for human usage is concerned with timescales from months to years, and from watershed to regional spatial scales. Research approaches and philosophies vary widely, but the underlying motivation is broadly shared: to understand the processes and principles that determine the fate of the world’s most precious resource after it falls from the sky, and the implications for natural and human use of that water. The bottom line is that interface for the water cycle is the same ground that supports and nurtures our lives, and in that sense it is difficult to conceive that we could ever know enough about how that cycle functions and its implications for the well-being of our planet.

Hydrologic research, and perhaps all research, falls into one of two general approaches: bottom-up, or top-down. The starting point for bottom-up models, also called distributed models, is the fundamental mechanisms or principles that control the system being studied; these fundamentals are used as building blocks to describe overall system outcomes. The bottom-up approach is conceptually appealing because the building blocks are typically well-established physical principles, such as conservation laws and force relationships, and because the resulting models can be predictive of otherwise unanticipated behavior of the system. However, the disadvantage of bottom-up models lies in their implementation: there is inherent uncertainty in model structure, parameters, and input variables [Blöschl et al., 2013]. This makes it difficult if not impossible to distinguish the exact source and magnitude of uncertainty in the model output. It is all but inevitable that model parameters must be calibrated to replicate observed data, and in general there will be many parameter combinations that can produce essentially similar model behavior, the concept of equifinality [Beven, 2006a]. A hydrological example is soil depth, which strongly influences the water balance by controlling storage excess runoff and vegetation root depth, among other factors. It is not generally possible to produce an accurate 3-dimensional representation of soil depth for an area larger than a small research hillslope. Furthermore, even if it was possible to characterize soil depth, soil type is another factor that exerts strong control on the water balance, and for most watershed-scale studies it would not be obvious which of those factors was responsible for impacting key aspects of the overall water balance. In general, the uncertainty associated with a bottom-up model increases with scale, due to heterogeneity of features and the complexity of interactions. Regardless of such complications, bottom-up models account for much of the most compelling, ongoing hydrologic research, as described at various points in the subsequent review. But the scope of this research, a broad survey of widely varying conditions over long timescales, is better served by the alternative approach of top-down modeling.

The starting point for top-down modeling is the overall system behavior, typically in terms of observed outcomes. The approach is then to identify the most dominant processes that influence that outcome and to iteratively introduce only as many descriptive terms as necessary to achieve the desired level of verisimilitude. An example of this approach is the famous Budyko curve, which describes the long-term water balance in terms of just one variable, aridity, and one (or more) fitted parameters. This reductionist approach can provide models that are straightforward and quite accurate, as sophisticated as they need to be for a particular use, but no more. The main disadvantage is that such models can be difficult to generalize to new, unobserved conditions, such
as locations with significantly different features or temporal changes more extreme than those observed during the period of observation. Another consideration is that top-down models generally provide less insight into the physical mechanisms that underlay emergent system behavior; interpretation of model parameters tends to be speculative rather than theoretical. Despite these limitations, the top-down method has been broadly applied to generate productive insights for hydrological study, and it is the most appropriate approach for this study.

The dominant physical and ecological controls of watershed water balances vary by timescale and prevailing climate, with more detailed process descriptions generally required for shorter timescales [Jothityangkoon et al., 2001], and for drier conditions [Atkinson et al., 2002]. Distinctive aspects of hydrology in a Mediterranean climate (MC) are emphasized as appropriate. The first part of this review is structured by decreasing timescale in terms of three coupled factors that have been shown to control the water balance across timescales: climate, soil and storage, and vegetation [Eagleson, 1978a; Milly, 1994a]. Because the purpose is to identify the dominant processes at each timescale, the review emphasizes studies that take a top-down approach to modeling, increasing complexity only as necessary to describe observed behavior, generally using lumped watershed models. Subsequently, additional important considerations are reviewed, including climate change and additional controls such as topography, followed by a brief survey of competing outlooks for the future of hydrologic research.

2.2 LONG-TERM (>DECADAL) WATER BALANCE

The long-term water balance is dominated by climate, mediated by soil water storage, and coupled with vegetation type and prevalence. Most spatial variation is explained by water and energy supply alone [Budyko, 1974]. Adding a single parameter for soil water capacity yielded an empirical model that described 96% of variation in a global study of temperate lowland watersheds [Zhang et al., 2001].

2.2.1 Climate

2.2.1.1 Aridity

Budyko [Budyko, 1974] showed that the long-term water balance at a given location is predominantly controlled by the relative availability of energy and water. This relationship can be posed in terms of the average annual evapotranspiration ratio $\bar{E}/\bar{P}$ varying as a function of the relative supply of energy and water, $\bar{PET}/\bar{P}$, where potential evapotranspiration $PET$ represents the maximum available energy for vaporization [Thornthwaite and Mather, 1955; Granger, 1989]. The framework for the Budyko curve is illustrated in Figure 2. The observed relationship (representative curve C) is constrained by bounding conditions for the water balance: in very arid, water-limited conditions $\bar{E} \approx \bar{P}$ (line A), while in very humid, energy-limited conditions $\bar{E} \approx \bar{PET}$ (line B). Empirical formulations of the “Budyko curve” by Budyko and others [Schreiber, 1904; Ol’Dekop, 1911; Turc, 1953] match global observations from large basins consistently well, with typical reported errors of 10% MAE [Budyko, 1974], 7% RMSE [Oudin et al., 2008], and coefficient of determination $\sim 0.6$ [McMahon et al., 2011], and a global bias of $\sim 45$ mm relative to a numerical climate model [Arora, 2002]. Analytical derivations have achieved comparable accuracy [Milly, 1994b; Gerrits et al., 2009]. The control of aridity on the long-term water balance has been so firmly established that the relationship has been proposed as a constraint for hydrologic study [Wagener, 2007], and one such application inverted Budyko curves to characterize watershed features [Gentine et al., 2012]. The statistical variability of the water balance in terms of sensitivity to changes in $P$ has been estimated to first-order as a function of aridity [Koster and Suarez, 1999] but this has been criticized as inadequately
simplistic for many applications [Sankarasubramanian and Vogel, 2003; McMabon et al., 2011; Wang and Alimohammadi, 2012].

2.2.1.2 Seasonality
Seasonality, the relative temporal phase of $P$ and $PET$, has a particularly important effect in MC regions where maximum $P$ occurs the winter concurrently with minimum $PET$, with the opposite phase in the summer [Jothityangkoon and Sivapalan, 2009]. This causes a hybrid of water-limited (summer) and energy-limited (winter) conditions [Latron et al., 2009; Llorens et al., 2011] that alternate water balance controls between local (vertical) and non-local (lateral, e.g. downslope subsidies) factors respectively [Llorens et al., 2011; Mahmood and Vivoni, 2011]. Evaporation $E$ is thus constrained not only by $PET$, but also by storage carryover from wet season to dry season [Baldocchi et al., 2004; Hickel and Zhang, 2006; Williams et al., 2012]; this has the effect of diminishing the importance of overall annual aridity on the annual water balance [McMabon et al., 2013].

Observations of the effect of seasonality on the long-term water balance have been mixed. The theoretical expectation of a simple soil storage model [Milly, 1994a] is that winter-dominated $P$ should cause increased $R$, and thus diminished $ET$, because $P$ in excess of soil storage capacity will quickly leave a watershed as excess runoff. A global study of flux tower field sites found that $E/P$ in MC regions was 9% lower than average [Williams et al., 2012]. Reduced $E$ was also associated with winter-dominated $P$ in study of watersheds across the United States [Wolock and McCabe, 1999] and in a derivation of the long-term water balance that explicitly accounts for canopy and surface interception dynamics [Gerrits et al., 2009]. Milly [Milly, 1994a] found that in arid regions the variation in the phase of $P$ and $PET$ was the dominant control of the water balance.

But contrary effects of seasonality have also been observed, with winter season $P$ associated with either no change in the water balance [Gentine et al., 2012] or with increased $E$ [Potter et al., 2005]. One explanation for this is that vegetation in dry or MC regions adopts a combination of intensive and extensive water use strategies [Rodriguez-Iturbe et al., 2001] that have the effect of increasing total $E$ [Schenk and Jackson, 2002], offsetting the effects of seasonality [Hickel and Zhang, 2006; Gerrits et al., 2009]. Extensive plants, such as trees, use deep roots to effectively increase active soil water capacity; intensive vegetation like grasses employs efficient water use and precise stomata control for rapid exploitation of intermittent precipitation [Rodriguez-Iturbe et al., 2001; Baldocchi et al., 2004]. Infiltration-excess runoff may be another important mechanism for the downpour storms that are often associated with summer precipitation, a mechanism that is often neglected in soil water balance models [Potter et al., 2005]. Because seasonality, soil moisture capacity, and vegetation dynamics are coupled secondary controls on the water balance, it is not straightforward to predict their individual effects across different locations [Feng et al., 2012].
Though seasonality can have an effect at timescales as brief as several days, as with the effect of \( P \) timing on grassland transpiration [Ryu et al., 2008], a number of top-down studies have successfully employed a simplified two-season model for water balance studies [Hickel & Zhang 2006, Chen et al 2013b, Wang 2012b].

### 2.2.1.3 Storminess

*Milly* [Milly, 1994a] defines storminess as “random inter-annual variability of precipitation”; this includes variations in the number, arrival interval, and intensity of precipitation events. This stochastic behavior is commonly modeled using a Poisson distribution for event occurrences and an exponential distribution that represents event depths [Rodriguez-Iturbe et al., 1999]. Conceptually, storminess affects the water balance by controlling short-term soil moisture, rapidly increasing \( R \) when moisture exceeds field capacity or total capacity thresholds [Milly, 1994a]. The observed impacts on the water balance are mixed. A study of 4 watersheds in Australia and New Zealand found storminess to be less important than seasonality for watersheds with winter-dominant (e.g. Mediterranean climate) and non-seasonal \( P \), whereas storminess was the dominant control for a watershed with summer-dominant \( P \) [Jothityangkoon and Sivapalan, 2009]. A more extensive study of 424 watersheds in the United States [Zanardo et al., 2012] found that storminess had a significant effect on the average water balance in relatively arid regions only. However, inter-annual variation of the water balance was found to be strongly controlled by storminess in some humid regions, suggesting that it plays an important but contextual role at inter-annual timescales.

### 2.2.1.4 Temperature

Near-surface air temperature is strongly correlated with \( PET \) [Granger, 1989] but it also affects the water balance directly. Snowmelt is triggered by spring warming [Molotch et al., 2009] and growing seasons are partially determined by temperature cycles [Istanbulluoglu et al., 2012]. Transpiration is inhibited as temperatures approach freezing [Kurpius et al., 2003; Thompson et al., 2011a], though a global study noted the unexpected finding that \( E \) is not generally lower in frozen environments [Williams et al., 2012].

### 2.2 Storage

#### 2.2.2.1 Soil Moisture

Soil moisture is a small fraction (~0.15%) of global freshwater storage, but it exerts a disproportional effect on the water balance by mediating atmospheric-surface fluxes, integrating landscape processes in time and space, and establishing thresholds for drainage and evaporation processes [Western et al., 2002]. Accounting for soil storage capacity significantly improves the long-term water balance estimates of Budyko curves [Zhang et al., 2001; Sankarasubramanian and Vogel, 2003], reducing errors by about one-third. Subsurface storage is particularly important to the water balance in MC regions where storage carryover from the wet season facilitates dry season vaporization [Baldocchi et al., 2004].

Soil storage influences the water balance by controlling quick runoff, deep percolation, and the rate of transpiration at various moisture thresholds [Milly, 1994a; Rodriguez-Iturbe et al., 1999]. Lumped watershed studies found that soil storage capacity is a significant secondary control of the long-term water balance, improving the RMSE of \( E \) estimates by about one-third relative to non-parametric Budyko curves using either direct estimates of soil properties [Sankarasubramanian and Vogel, 2003] or vegetation type as a proxy for soil depth [Zhang et al., 2001]. Soil depth and rockiness were found to be the primary controls on soil moisture drought during the southern California dry season [Miller...
and Poole, 1983]. A conceptually distinct approach is to use a stochastic model of $P$ to force a point-scale soil water balance and derive the average water balance by statistical integration. Eagleson [Eagleson, 1978a, 1978b] derived a long-term water balance that represented daily rates of $R$ and $E$ as threshold-controlled functions of soil moisture with constraints imposed by theoretical equilibrium relationships between soil moisture and vegetation. However, the propositions of this equilibrium, or “natural selection hypothesis”, have been criticized as ecologically unrealistic [Kerkhoff et al., 2004]. Subsequent approaches have demonstrated that non-linear, threshold-controlled daily water balances can explain the long-term water partition by extending point-scale models to the watershed scale, assuming effective lumped properties. Milly [Milly, 1994a] used step-function responses to soil moisture thresholds to emulate the Budyko curve and to show that $E$ increases with soil moisture capacity. A similar model with ramp function responses [Rodriguez-Iturbe et al., 1999] found that plant available water capacity is a prominent control on the long-term balance and soil moisture probability distributions [Porporato et al., 2004]. The specific functional shapes and threshold levels that represents landscape control of a soil water balance model were found to have a significant impact on the water balance [Koster and P. Mahanama, 2012]. These simple models are applicable primarily to areas with negligible lateral water movement. Hilly areas may require additional consideration of how downslope water subsidies and strong soil moisture gradients affect the local soil water balance [Ridolfi et al., 2003] and possibly lead to emergent hydrologic responses and vegetation patterns [Thompson et al., 2011b]. Furthermore, steeper slopes generally cause shorter water residence time and thus lower $E$ [Voepel et al., 2011].

Two early, influential frameworks for understanding the influence of soil storage on the water balance were those of Horton [Horton, 1933] and L’vovich [L’vovich, 1979], both of which emphasized two distinct modes of runoff: quick runoff $R_Q$, generated via storage excess runoff or preferential subsurface flows, and slow seepage $R_S$. Soil properties and prior wetness conditions influence the partition of $P$ into either quick runoff $R_Q$ or soil infiltration $W$, referred to as wetting by Horton; $W$ is subsequently partitioned into either $E$ or “slow” runoff $R_S$. This conceptualization essentially divides a watershed into two control volumes: surface (including preferential subsurface pathways) and subsurface. L’vovich [L’vovich, 1979] theorized that there are constraints on the partition of fluxes from each control volume. For the surface partition, $W$ is bounded by subsurface storage capacity, whereas $R_Q$ is unbounded. For the subsurface partition, $E$ is bounded by $PET$, while $R_S$ is unbounded. Recent studies have used a particular mathematical representation of these constraints [Ponce and Shetty, 1995] to explore hydrological functions within and among watersheds [Sivapalan et al., 2011b]. Following an earlier observation that the ratio $H = E/W$ was relatively consistent across multiple growing seasons in a single watershed [Horton, 1933], a broader study found that $H$, known as the Horton index, is relatively consistent compared to other climate variables, and that it varies in both space and time as a function of aridity [Troch et al., 2009a]. Furthermore, $H$ was found to be a good predictor of both vegetation greenness [Voepel et al., 2011] and inter-annual changes in vegetation cover [Brooks et al., 2011], supporting Horton’s postulation that the consistency of $H$ is indicative of optimal water use by vegetation [Horton, 1933]. The same conceptual and mathematical framework was used [Sivapalan et al., 2011a] to identify three main factors that control the long-term partitions between the surface and subsurface control volumes: maximum $E$; $P$ in excess of the initial abstraction of $E$; and maximum $W$. A related study found that the sensitivity of $R_Q$ and $R_S$ to changes in $P$ is largely determined by maximum $W$ and $E$, respectively [Harman et al., 2011]. A comparable approach applied the Budyko partitioning framework separately to surface and subsurface control volumes, yielding good agreement with observations at yearly and monthly timescales [Zhang et al., 2008]. The breadth of research and insights that grew from the
straightforward frameworks of L’vovich and Horton are exemplary of the power of top-down models to motivate new paths of inquiry.

### 2.2.2.2 Snow Storage

Seasonal snowpack is a special consideration for mountainous areas like the Sierra Nevada range in California. The mechanisms controlling storage and release of snowpack water are quite different than for soil storage, which means the dynamics are not captured by the same conceptual models [Eder et al., 2003]. In strongly seasonal settings like MC regions the general patterns of snowpack onset, peak accumulation, and melt time are largely controlled by the relative seasonality of P and air temperature [Woods, 2009], though precise estimation of snow accumulation at the watershed scale is a notoriously elusive challenge [Bales et al., 2006a]. Snowpack storage effectively delays the effect of precipitation on soil and runoff processes. This decreases winter runoff, increases spring runoff, and increases vaporization vis-à-vis winter rainfall because PET is higher during spring melt [Wolock and McCabe, 1999]. Furthermore, sublimation L may account for a significant portion of the water balance. Recent studies at high-altitude (~3000 m) study sites in the Sierra Nevada [Kattelmann and Elder, 1991; Leydecker and Melack, 1999] report values of L as a fraction of yearly P ranging from 4 – 16% for wet years and 8 – 25% for dry years, spanning a range from arguably negligible to clearly significant. One explanation for this disparity is the strong influence of local landscape and vegetation conditions on sublimation rates [Marks and Wimstral, 2009], one of many factors that complicate sublimation estimates [Bales et al., 2006a]. As already discussed, soil moisture plays a critical role in the water balance, and in alpine regions soil moisture is largely controlled by snowmelt, which is in turn controlled primarily by air temperature [Molotch et al., 2009]. Warmer spring temperatures can thus lead to earlier melt and increased soil water stress during the late summer, both within alpine watersheds [Molotch et al., 2009] and in downstream areas that rely on dry-season baseflow [Huntington and Niswonger, 2012].

### 2.2.3 Vegetation

Vegetation is important to the water balance not only because it has a strong influence on the partition of P and the formation of soil, but also because understanding the status and fate of vegetation is a critical topic in itself. The increasingly influential discipline of ecohydrology is “the science which seeks to describe the hydrologic mechanisms that underlie ecologic patterns and processes” [Rodriguez-Iturbe, 2000], or, from the plant perspective, “understanding and quantifying how the competing roles between supply and demand for water influence evaporation from vegetated landscapes” [Baldocchi and Xu, 2007]. This section of the review concentrates on the forward effects of vegetation on the water balance, but the coupling of climate, soil, and vegetation may also be an important consideration for a particular watershed.

#### 2.2.3.1 Root depth and soil

Root depth is strongly correlated with vegetation type [Canadell et al., 1996], but the correlation to climate is weaker in the west than in other regions of the United States [Stephenson, 1990]. Root depths in arid or seasonally arid regions are thought to be primarily driven by dry season soil water deficit, with secondary factors including fire, temperature, and animal grazing [Viola et al., 2008]. Physical soil depth and effective water capacity are strongly related to root depth [Federer et al., 2003; Berry et al., 2006], and this intimate relationship has been inverted to estimate soil depth based on vegetation type and growing season, suggesting that soil depths must be much deeper than survey estimates for much of California [Ichii et al., 2009]. However, it is well-known that the deep-rooted trees and shrubs of MC regions access water in fractured bedrock weathered zones and groundwater
capillary zones [David et al., 2007; Llorens et al., 2011] with measured or inferred root depths commonly in excess of 2 m [Canadell and Zedler, 1995] and over 20 m for some oaks [Lewis and Burg, 1964], a consideration that subverts the equivalence of soil moisture and plant-available water capacity. For instance, Lewis [Lewis, 1968] found that a California watershed converted from forest to grassland had negligible inter-annual change in soil moisture relative to two control watersheds, but the steady state weathered zone storage increased in the converted watershed. During the summer dry season in Spain transpiration in pines was observed to be highly dependent on water table depth [Llorens et al., 2010]. Deep roots in trees and shrubs also facilitate overnight hydraulic lift of deep moisture to near the surface, benefiting both the plants doing the lifting and nearby shallow-rooted vegetation [Llorens et al., 2011], accounting for 17-81% of dry season transpiration in cork oaks, for example [Kurz-Besson et al., 2006]. Another important role of vegetation in the soil zone is the creation of quick, preferential pathways for subsurface flows via decayed root channels [Berry et al., 2006] and bedrock fractures [Hubbard and Linde, 2011] that may be initiated or exacerbated by root intrusion [Canadell and Zedler, 1995]. Furthermore, vegetation has a homogenizing effect on soil moisture spatial distribution because uptake mediates moisture levels, reducing wetting-drying hysteresis [Ivanov et al., 2010].

2.2.3.2 Transpiration

In MC regions where maximum PET occurs during the dry season, evapotranspiration tends to be dominated by transpiration because vegetation has adapted to use water efficiently [Llorens et al., 2011] and deep roots provide access to water stores unavailable for surface evaporation [Miller et al., 2010]. Canopy interception evaporation is also important to the long-term water balance in MC regions, with estimates as a percentage of annual rainfall varying by plant type: oaks ~20%, pine forests ~25%, shrubs ~50% [Llorens and Domingo, 2007], and grasses ~25% [Gerrits and Savenije, 2011]. The magnitude of spatially averaged interception varies with vegetation heterogeneity and canopy coverage. These effects of vegetation on the water balance are manifested in paired watershed studies that show average E generally decreases with deforestation and increases with afforestation [Brown et al., 2005]. However, a global comparison of flux tower sites reached the opposite conclusion, that forest E was on average 8% lower than grasslands [Williams et al., 2012]. The reason for this discrepancy is not fully understood, but one factor may be differences between the young grasslands at deforested sites and the mature grasslands at the flux tower sites.

2.3 Annual Water Balance

2.3.1 Climate

The annual water balance is primarily driven by total annual P [Donohue et al., 2010]. A linear relationship between annual R and P is well-established in wet conditions [Keller, 1906; Budyko, 1974; Post and Jones, 2001] and for wet years in MC regions [Grunskey, 1908; Lewis, 1968; Diskin, 1970; Turner, 1991; Fischer et al., 1996; Flerchinger and Cooley, 2000; Lewis et al., 2000]. The slope of annual R versus P is commonly near 0.8 to 1.0 for wet conditions, which is consistent with observations that annual E may be relatively insensitive to variations of P in wet areas [Roberts, 1983; Oishi et al., 2010; Williams et al., 2012] and MC regions [Lewis, 1968; Baldocchi et al., 2009]. In dry conditions, P must exceed some threshold before non-negligible R is observed, resulting in a segmented linear functional form attributed to an “initial abstraction” [Ponce and Shetty, 1995] of E from water retained the unsaturated soil matrix [Budyko, 1974; Marc et al., 2001; Rodriguez-Iturbe and Porporato, 2004; Brooks et al., 2010]. One hypothesis views this threshold behavior as an emergent property of hillslope hydraulic connectivity [Tromp-van Meerveld and McDonnell, 2006].
Seasonality is particularly important to hydrology in MC regions [Potter et al., 2005], where it has been suggested that the water balance may be more sensitive to long-term changes in seasonality than changes in mean P or PET [McMahan et al., 2013], and it strongly influences the functional form of watershed partition response to inter-annual aridity [Potter and Zhang, 2009]. However, relatively little research has addressed how yearly variations in seasonality affect the annual water balance in MC regions, though some research has been suggestive of the effect. The covariance of P and PET has been shown to affect inter-annual variability of the water balance [McMahan et al., 2011]. Another recent study found that seasonality was important for modeling the annual water balance for two MC watersheds [Jothityangkoon and Sivapalan, 2009], but the statistical metrics used to present the results provided little insight about the effects for individual years. Lastly, in MC regions small changes in seasonality may strongly influence prevailing vegetation types, and thus the water balance, due to thin margins in the dry season water supply [Poole and Miller, 1981; Clary, 2008].

2.3.2 Soil and Storage

The main difference between the long-term water balance and the annual water balance is the treatment of the storage change component $\Delta S$. It is common practice to assume that $\Delta S$ in a given watershed is negligible over the long-term, but this assumption does not hold in general for the annual water balance. In many areas, including California, it is difficult to directly estimate watershed-scale $\Delta S$ due to inadequate subsurface data. In some situations, storage-discharge relationships can be used to characterize annual $\Delta S$ for watersheds with perennial outflows [Kirkham, 2009; Sayama et al., 2011]. Field studies in Mediterranean and other semi-arid climates showed that soil moisture measurements returned to comparable conditions at the end of each dry season [Miller and Poole, 1983; Joffre and Rambal, 1993; Kure and Small, 2007], evidence that the extreme wet and dry phases of MC regions may justify an assumption of negligible inter-annual $\Delta S$. It has been common to neglect $\Delta S$ for inter-annual water balance studies with a broad range of conditions [Horton, 1933; Koster and Suarez, 1999; Potter and Zhang, 2009; Troch et al., 2009a; Sivapalan et al., 2011a; Voepel et al., 2011] using the justification that the magnitude of $\Delta S$ is small relative to other terms in the water balance. However, an emerging body of evidence suggests this assumption may be applied too liberally. A study of inter-annual storage change in soil and groundwater across the state of Illinois [Wang, 2012] found that $\Delta S$ is a significant fraction of $\Delta P$ for 40% of years observed. In another study, soil and groundwater storage in a large Australian basin was observed to drop quickly and persistently in response to a rain drought [Leblanc et al., 2009]. Inter-annual storage carry-over was found to have a significant effect on annual R for 193 Australian watersheds [Xu et al., 2012]. Furthermore, extensive depletion of groundwater stores have been reported globally in the context of climate change [Taylor et al., 2012] and within California due to anthropogenic withdrawals exacerbated by drought [Chen et al., 2016]. And recent analytical studies have examined the implications of non-steady storage for Budyko curve analysis [Moussa and Lhomme, 2016; Condon and Maxwell, 2017]. It is advisable to quantify storage dynamics where possible, but because storage data is rare, especially for long-term historical analysis, acknowledging and characterizing the implications of storage assumptions may be the most pragmatic alternative.

Geospatial estimation of $E$ by remote sensing, $E_{RS}$, allows for indirect evaluation of $\Delta S$ as the residual term of the water balance. A framework for parametric analysis of inter-annual residuals relative to mean P, $E_{RS}$, and R [Roderick and Farquhar, 2011] was applied to 277 watersheds across the United States, with results indicating that relatively invariant $E_{RS}$ is explained by complementary variation in $\Delta S$ [Wang and Alimohammadi, 2012]. And $E_{RS}$ was used to develop a seasonal variation of the Budyko curve that was then used to estimate inter-annual $\Delta S$ as a function of climate forcings.
However, measurement uncertainty in the source of $E_{rs}$ used in both of these studies varies widely in space [Zhang et al., 2010] and the data have been shown to be inconsistent with the long-term water balance for watersheds in California in particular [Moran et al., 2012].

A significant consideration in MC regions is that trees and shrubs often have deep tap roots [Canadell and Zedler, 1995] that access water below the soil layer during the dry season, in the water table capillary zone or fractured bedrock [Lewis and Burgy, 1964; Jeffre and Ramhal, 1993; Baldocchi and Xu, 2007; David et al., 2007; Llorens et al., 2011]. Access to groundwater sources was shown to be necessary to explain the annual water balance for field research sites in California [Thompson et al., 2011a], suggesting that control volumes that include only soil water may miss important processes in MC regions. Similar to the approach of studies inspired by L’vovich described in § 2.2.2, the effects of distinct storages and processes can be isolated by separating the encompassing control volume into functionally distinct sub-volumes. The “representative elementary watershed” approach describes mass and momentum balances across five control volumes within a watershed: unsaturated subsurface, saturated subsurface, infiltration-excess overland flows, saturation-excess overland flows, and channel flows [Reggiani et al., 1998]. The constitutive relationships that characterize the interactions among control volumes were then derived using entropy as a constraint [Reggiani et al., 1999]. While this approach has shown promise for representing a range of hydrological conditions using strictly physical principles [Reggiani et al., 2000; Zhang and Savenije, 2005; Yokoo and Sivapalan, 2011], it is inherently limited, as all control volume approaches are, by the problem of “closure” [Beven, 2006b], whereby uncertainties in boundary measurements and scale-dependence of constitutive relationships impair precise estimation and validation of the boundary fluxes. Closure has been called the second most important problem in modern hydrology, the first being improved flux measurement techniques [Beven, 2006b]. Thus, while consideration of multiple storage control volumes may indeed improve water balance estimates, the increased modeling and estimation burden is not always justified.

2.3.3 Vegetation

An interesting aspect of how vegetation influences the annual water balance is the relative invariance of annual $E$ at a given location except in very dry conditions [Williams et al., 2012]. This consistency has been attributed to conservative transpiration by woody vegetation [Roberts, 1983; Baldocchi et al., 2009] and a tradeoff between increased canopy interception during wet years versus increased surface evaporation during dry years [Oishi et al., 2010]. In a California study, annual grassland $E$ was also observed to be quite consistent between years, and controlled more by the timing, or seasonality, of springtime $P$ than by total annual $P$ [Ryu et al., 2008]. This type of efficient water use by vegetation in MC regions is attributed to deep rooting, leaf area adaptation, and acute stomatal response to atmospheric conditions [Kurpius et al., 2003; Berry et al., 2006; Baldocchi and Xu, 2007; Llorens et al., 2011]. One consequence of this that the seasonal variation of LAI in MC forests is relatively small while $E$ variation is large, posing a challenge for remote-sensing methods that assume a correlation between $E$ and vegetation greenness [Garbulsky et al., 2008].

2.4 MONTHLY AND SEASONAL WATER BALANCE

At monthly to seasonal timescales, soil and storage properties and processes are increasingly important, and alpine snowpack must be accounted for explicitly. In MC regions the seasonal differences in $P$ and $PET$ cause bi-polar wet and dry conditions that necessitate distinct modeling approaches for each climate type.
2.4.1 Climate
The seasonal water balance is particularly distinct in MC regions where pronounced wet and dry seasons lead to a hybrid of water-limited (summer) and energy-limited (winter) conditions that alternate water balance controls between local (vertical) and non-local (lateral, e.g. downslope flows) respectively [Llorens et al., 2011]. For this reason, the burden in MC regions is to represent both conditions well, though in general the dry season imposes the greater challenge [Atkinson et al., 2002].

In mountainous areas, such as the Sierra Nevada, seasonal snowpack decreases winter runoff, increases spring runoff, and increases overall vaporization vis-à-vis winter rainfall because PET is higher during the spring melt [Wolock and McCabe, 1999]. The general patterns of snowpack onset, peak accumulation, and melt time are controlled by the relative seasonality of P and air temperature [Woods, 2009], though accurate, localized estimates of snowpack are notoriously challenging [Bales et al., 2006b]. Sublimation may also be a significant component of the water balance in the high Sierra Nevada, accounting for 4 – 16% of annual P during wet years and 8 – 25% in dry years [Kattelmann and Eldon, 1991; Leydecker and Melack, 1999].

2.4.2 Soil and Storage
Perhaps the most important consideration for the water balance at intra-annual timescales is increased sensitivity to soil and storage properties and processes. Soil water capacity can be as important to the seasonal water balance as P and PET, especially in dry conditions [Farmer et al., 2003], and the spatial variation of soil depths within a watershed has been found to strongly influence water balance estimates [Jothityangkoon et al., 2001]. Ideally, models would represent the actual configuration and processes of subsurface storage, but in practice limited knowledge of the subsurface necessitates inductive guesses, based largely upon runoff observations. Given this uncertainty, there is a preference for models with the simplest configuration that explains runoff behavior. In wet conditions a single soil store with a linear storage-discharge relationship may be adequate to model monthly R [Jothityangkoon et al., 2001], but drier areas may require models with a deep percolation component that can represent groundwater stores and baseflow [Atkinson et al., 2002].

2.4.3 Vegetation
Vegetation activity is largely controlled by climate seasonality, and many water balance models at monthly and shorter timescales implicitly account for reduced transpiration T in dry conditions by posing T rates as a function of soil moisture [Milly, 1994a]. While this approach neglects ecological mechanisms, the approach has been widely successful for water balance estimates. This method requires an estimate of fractional vegetation coverage so that T can be treated distinctly from direct soil evaporation, and vegetation heterogeneity may also be important [Jothityangkoon et al., 2001]. In MC regions, it should be remembered that woody vegetation with access to deep water stores subverts the equivalence of soil moisture with plant available water, though greatly diminished rates of T in the dry season [Miller et al., 2010] may mitigate the overall effect on seasonal water balance estimates.

2.5 Daily Water Balance
In general, the challenges for estimating daily water balances are an extension of those for monthly balances. Statistical metrics of the daily balance, such as the flow duration curve or soil moisture probability distributions, require less complexity than daily hydrographs that must consider surface channel timing and routing.
2.5.1 Climate
Daily water balance models are typically driven with daily $P$ and $\text{PET}$ data. Though forecasting extreme conditions like peak flows and flooding may require sub-daily granularity [Chapman, 1994], inherent uncertainties in watershed fluxes and processes generally limit the amount of complexity that is justified for daily water balance models [Jakeman and Hornberger, 1993]. The daily soil water balance models previously discussed [Rodriguez-Iturbe et al., 1999] also use daily climate data, in this case to characterize the temporal statistics of a vertical soil column. Regarding climate data availability, $P$ and $R$ are broadly reported in daily values, but accurate estimates of daily $\text{PET}$ via common formulations, such as the Penman-Monteith equation, require wind, humidity, and radiation data that are less common and may need to be approximated.

2.5.2 Soil and storage
The daily water balance is highly sensitive to soil and storage properties and processes [Jothityangkoon et al., 2001], and calibration of soil and storage parameters with observed $P$ and $R$ data is almost always necessary [Beven, 2012b]. Daily balances generally require more complex representations of subsurface storage regardless of whether the prevailing conditions are wet or dry [Atkinson et al., 2002], including deep groundwater stores that produce persistent baseflow [Jothityangkoon et al., 2001; Farmer et al., 2003]. Characterizing soil infiltration capacity may be important for areas prone to infiltration-excess runoff, such as locations with sparse vegetation and high intensity precipitation [Beven, 2012b]. Channel routing must be considered for larger watersheds where the characteristic transit time approaches or exceeds one day [Bai et al., 2009]. In arid regions, it may be impossible to accurately represent the daily water balance with any lumped watershed model due to highly heterogeneous landscape properties and complex interactions in the unsaturated zone [Atkinson et al., 2002; Bai et al., 2009]. Daily estimates in these settings may necessitate more complex, spatially explicit distributed models.

2.5.3 Vegetation
As with the monthly timescale, the influence of vegetation on the daily water balance is commonly framed in terms of a dependence of transpiration rates on soil moisture levels. While this may be sufficient for water balance estimates, the approach offers little insight about important vegetation processes that occur at a daily timescale. For instance, vegetation in MC regions relies heavily on overnight hydraulic lift of moisture from deep stores to shallow soil, benefitting the deep rooted plants that do the lifting as well as any nearby vegetation [Dawson, 1993; Miller et al., 2010]. Taking a different approach, a novel data-driven watershed model used diurnal streamflow fluctuations caused by vegetation activity to characterize the hydrological dynamics of storage-dominated flows [Kirchner, 2009]. Such pulses and undulations, from daily transpiration to annual water cycles, are the dynamics of life in a watershed.

2.6 Connectivity and Emergent Behavior
Water balance studies are rife with emergent behavior, such as threshold responses of $R$ to antecedent $P$, at nearly all temporal and spatial scales of interest [Ali et al., 2013]. It has been common to conceptually describe threshold behavior in terms of soil bucket models [Bai et al., 2009], but these are fundamentally inadequate for explaining the spatial and temporal scale dependence of emergent hydrological phenomena [Bracken and Croke, 2007; Troch et al., 2009b; Thompson et al., 2011b]. Hydrological connectivity, the ability of water to pass among parts of a landscape [Bracken and Croke, 2007], is an increasingly prevalent physical explanation. One example is the “fill and spill” hypothesis [Tromp-van Meerveld and McDonnell, 2006]. This suggests that the
threshold response of \( R \) to \( P \) events, whereby very little \( R \) is observed unless \( P \) exceeds a locally-specific threshold, can be attributed to the amount of saturation that causes heterogeneous subsurface patches to be hydraulically connected from the top to bottom of a hillslope. Below this threshold, a significant portion of water is “stranded” above small bedrock ridges upslope before seeping into the bedrock or being used by vegetation. Even without the effects of bedrock irregularities, connectivity among micro- and macro-pores within the soil matrix is a threshold process that strongly influences the spatial variability and heterogeneity of soil moisture and hysteretic wetting-drying behavior [Ivanov et al., 2010]. In a different application, connectivity between surface ponds was used to explain emergent values of the recession coefficient \( k \) \([1/T]\) in the commonly used storage-discharge relationship \( q = kS^m \), where \( q \) is channel discharge \([L/T]\), \( S \) is effective upslope storage \([L]\), and \( m \) is a nonlinearity factor [Spence, 2007]. As another example of emergent thresholds, geospatial estimates of \( E \) within a semi-arid mountain basin in California [Anderson et al., 2012] showed that \( E \) increases roughly linearly with spatially varying \( P \), except where \( P \) exceeds a threshold above which \( E \) is bounded. This suggests a spatially explicit explanation of \( E \) thresholds commonly observed in lumped watershed studies [e.g. section 2.1].

While such emergent behavior is the result of inherently complex processes in heterogeneous conditions, theoretical work has demonstrated that straightforward representations can capture key features. A simple hydrologic network model that was able to demonstrate emergent hydrologic behavior and vegetation patterns suggests a path forward for reconciling scale-dependent observations at patch, hillslope, and watershed scales [Thompson et al., 2011b]. And improved metrics of hydraulic and ecological connectivity [Larsen et al., 2012] will enhance our ability to correlate hydrological connectedness with landscape features like vegetation [Hwang et al., 2012].

### 2.7 Additional Controls

Topography is particularly important to the water balance in mountainous regions [Bales et al., 2006a] because of direct orographic effects on temperature and precipitation, hillslope influences surface and subsurface hydrology, and the effects of surface aspect and “rain shadows” on vegetation distribution. Topography exerts secondary control of the Horton index \( H = ET/W \), with mean watershed slope important for humid environments and mean elevation important as well for arid conditions [Vöpel et al., 2011]. Steeper slopes generally mean shorter water residence time and lower \( E \) [Jothityangkoon and Sivapalan, 2009; Vöpel et al., 2011] as well as increased downslope subsidies that influence emergent hydrologic responses and vegetation patterns [Thompson et al., 2011b], confounding the application of common soil water balance representations [Milly, 1994a; Rodríguez-Iturbe et al., 1999]. Steep topographic gradients in California result in sharp changes in temperature and \( P \) over short distances, resulting in heterogeneous hydrological and ecological features at relatively small scales [Bales et al., 2006a].

In general, the combined effects of climate and landscape factors must be considered to accurately describe the water balance. A study of 12 watersheds in the eastern United States [Carrillo et al., 2011; Troch et al., 2013] found that climate conditions that tend to increase average \( \overline{ET} / \overline{P} \) were associated with landscape features that generally diminished \( \overline{ET} / \overline{P} \), a result that suggests co-evolution of climate, soil, and vegetation toward some optimal configuration [Horton, 1933; Troch et al., 2009a]. An additional consideration is that the size of the study area will affect lumped water balance calculations because spatially averaged \( E \) is not generally equivalent to \( E \) calculated from spatially averaged climate observations like \( P \) and \( PET \) [Choudhury, 1999]. And inter-annual variations in cloud cover were found to be the dominant control of \( PET \) variation in California [Hidalgo et al., 2005].
2.8 Climate Change

Historically, the science and practice of hydrology relied heavily on the assumption that the past was a good predictor for future behavior. But human-induced climate change has undermined the stationarity assumption [Milly et al., 2008] and the implications may be particularly significant for MC regions where long dry seasons already stress the water supply for both ecological and managed water uses [Vicuna et al., 2007; Ruffault et al., 2013]. While temperature change predictions at regional scales are uncertain and the future of precipitation may be “speculative” [Blöschl and Montanari, 2010], impacts within the range of predicted or observed changes have been studied. Seasonal changes to temperature and $P$ in southern France in the late 20th century have increased drought, in terms of soil moisture stress, for wetter areas but for not areas that were already dry [Ruffault et al., 2013]. The snow-dominated hydrology of the Sierra Nevada is particularly sensitive to climate change [Gleick, 1987], where increased winter temperatures and decreased snow as a proportion of total $P$ have already been verified [Barnett et al., 2008; Hall, 2010]. Expected temperature increases in California [Cayan et al., 2008] will further decrease the amount of snow and advance the timing of snowmelt [Bales et al., 2006a] leading to increased flooding [Das et al., 2011] and stress on managed water supplies [Vicuna et al., 2007] and alpine vegetation [Molotch et al., 2009; Bales et al., 2011], even if total annual precipitation is unchanged [Huntington and Niswonger, 2012]. Furthermore, our ability to predict the hydrologic future is confounded by coupled climate-landscape properties, whereby the calibrated parameters of watershed models are not stationary relative to change climate [Merz et al., 2011]. And because climate is a strong determinant of vegetation distribution [Stephenson, 1990; Xu et al., 2012], changed climate will mean changed vegetation, particularly in areas like southern California where historical conditions only marginally favor one vegetation type over another [Poole and Miller, 1981]. Dry season plant water stress is closely tied to soil moisture content at the end of the wet season, so changes to the seasonal distribution of $P$ will likely alter vegetation [Viola et al., 2008] by disrupting competitive advantages of intensive versus extensive water use strategies [Rodriguez-Iturbe et al., 2001]. Changes to the timing and magnitude of fires [Monillot et al., 2002] and droughts will affect vegetation and may have unintuitive impacts on the water balance, such as diminished runoff following drought-induced die-off [Guardiola-Claramonte et al., 2011]. Climate change undoubtedly poses significant challenges to our ability to predict the water balance, but it is important to keep in mind that indirect impacts of climate change, such as human management responses, may be equally or more significant than direct effects [Beven, 2011; Jones, 2011].

2.9 Outlook

There is an emerging consensus that scientific hydrology is at a crossroads, with a need for more robust approaches for characterizing watersheds [McDonnell et al., 2007; Wagener et al., 2007] and new hydrological theories [Trock et al., 2009b; Hrachowitz et al., 2013]. A common theme is the need to understand and exploit fundamental principles that constrain hydrological behavior [Berry et al., 2006; McDonnell et al., 2007; Wagener, 2007; Sivapalan, 2009; Beven, 2012a; Hrachowitz et al., 2013]. Past applications of optimality principles include using the Budyko curve to constrain the water balance [Gentine et al., 2012] and using thermodynamic constraints to derive constitutive relationships for representative elementary watersheds [Reggiani et al., 1999]. Other thermodynamic approaches are still developmental. The principle of Maximum Entropy Production (MEP) asserts that complex non-equilibrium systems far from steady state, such as a watershed, maintain a steady state of maximum entropy production as a tradeoff between thermodynamic fluxes and the gradients that cause the fluxes [Kleidon and Schymanski, 2008]. If validated at hydrologically relevant spatial and temporal scales, MEP could offer new physical insights and a new approach to prediction. Another approach, Constructal Theory, proposes that flows of matter and energy through systems (natural
and manmade) are optimized in terms of the geometric distribution of high and low resistance regions [Bejan and Lorente, 2011]. This theory has been proposed for the study of soil configuration and evolution in terms of an optimal balance of storage (high resistance) and drainage (low resistance) [Berry et al., 2006; Troch et al., 2009b]. While these relatively young ideas are exciting, it should be remembered that even broadly adopted optimality proposals [Eagleson, 1978b] may be subject to reevaluation [Kerkhoff et al., 2004].

There are philosophical differences about how to proceed. Beven [Beven, 2008] argues that hydrological progress is hampered by observational uncertainties and an endemic failure to acknowledge the extent of that uncertainty. Sivapalan [Sivapalan, 2009] counters that such an information-centric approach to hydrology misses what can be learned by moving from a historic fixation on hydrographs toward more holistic questions about how watersheds function, using functional emergent signatures such as flow duration and regime curves at daily and monthly timescales, respectively [Hrachowitz et al., 2013]. But there is agreement that the synthesis of distinct philosophies and methodologies is the future of hydrology. Top-down hydrological studies that add complexity only as necessary to explain observations [Sivapalan et al., 2003] have been an insightful alternative to the traditional approach of bottom-up, mechanistically exhaustive models [Reed et al., 2004; Carrillo et al., 2011] that provide highly accurate hydrographs but suffer problems of equifinality [Beven, 2006a], i.e. ambiguity of whether parameters or processes are driving model results. A call to combine Newtonian (deterministic, mechanistic) and Darwinian (contextual, emergent) approaches to science to address environmental challenges [Harte, 2002] has been echoed widely in hydrology [Newman et al., 2006; McDonnell et al., 2007; Troch et al., 2009b; Kumar, 2011; Sivapalan et al., 2011b; Hrachowitz et al., 2013]. But can any hydrological representation anticipate every relevant factor, even the influence of cows and worms on the water balance of a pasture? [Blöschl and Montanari, 2010] Perhaps instead hydrologists must be mindful of another fundamental constraint: the distinction between what we want, and what we need [Jagger and Richards, 1969].

2.10 Summary
This review described prior research into the dominant controls of the water balance and considerations for modeling at various timescales, predominantly organized in terms of three critical factors: climate, storage, and vegetation. There was an emphasis on watershed-scale studies with conditions relevant to California watersheds, i.e., with a Mediterranean climate and in mountainous terrain. Of 121 total reviewed studies that included water balance observations, and not just theoretical exposition, 56 provided results from MC or semi-arid regions. Of these MC region studies, 31 explicitly considered the effects of secondary climate factors such as seasonality, primarily at intra-annual timescales. Of 7 MC studies that address the effects of seasonal factors on the annual water balance, only 4 were watershed-scale studies.

This relative lack of research devoted to the distinctive considerations of the annual water balance in MC watersheds is surprising, given the challenges of managing the water supply in these regions that are home to over 200 million people worldwide. The motivation of this study is to contribute to the understanding of the water cycle in MC regions through development of a parsimonious model, to demonstrate the use of contemporary data-driven tools to derive insights from this model, and to explore the implications of such a model in the context of a changing climate.
Figure 3: Summary of reviewed water balance studies, categorized by timescale and factors relevant to the proposed research: total studies in blue (N=121), studies that emphasize MC regions in red (N=56), and MC region studies that address seasonality in green (N=31). Of the MC studies that address seasonality at the annual timescale (N=7), only 4 were watershed-scale studies.

Not all studies summarized by this graphic are cited in this review.
3 Empirical Observations

3.1 Purpose
The objective of this research is to develop a hydrological model that can provide insights about the annual water cycle in watersheds across the state of California over a multi-decadal time period. The framework for this inquiry is the water balance,

\[ P = R + E + \Delta S \]  

(1)

where \( P \) is precipitation, \( R \) is runoff (i.e., total streamflow irrespective of path to the water channel), \( E \) is evapotranspiration, and \( \Delta S \) represents change in storage. All units are depth [L]. The importance of the \( \Delta S \) term depends strongly on the timeframe of the water balance; it is very important to California hydrology within the course of a year, arguably less so on an annual basis, and generally diminishes for longer timescales. This research focuses on the annual water balance, but the main conclusions are about multi-year trends. Thus, \( \Delta S \) is generally treated as negligible in this research, an imperfect but acceptable assumption that is addressed in more detail in § 4.3.1.

For the purpose of this research \( R \) is the outcome of interest, which is appropriate because of its importance for natural and human water systems alike. Thus, the modeling goal is to estimate annual \( R_i \),

\[ R_i \approx P_i - E_i \]

where index \( i \) refers to the total for a particular water year, September 1 through August 31. This research treats \( P_i \) as an independent variable that is taken to be a known input, which is reasonable given the broad availability of \( P \) measurements and forecasts. The challenge was then to estimate \( R_i \) as a dependent variable of \( P_i \) and other factors.

3.2 Data Sources

3.2.1 Data Requirements
In developing a data-driven model, an important consideration is the availability and coverage, both spatial and temporal, of data to drive the model. There is generally a tradeoff between data availability and reliability: data collection for a specific purpose is likely to be more reliable but less broadly available, such as a dense network of precipitation measurements in a particular watershed; whereas data collection for general usage tends to be more broadly available but less reliable, such as interpolated precipitation estimates that rely on relatively sparse direct measurements. While this tradeoff is becoming less pervasive with the advancement of technology that accomplishes high-fidelity measurements over broad regions, such data is only recently available. For the purpose of characterizing multi-decade hydrological behavior across a broad geographic region, there is a limited selection of historical data.

The data requirements for streamflow and climate data were as follows:

1. Temporal: continuous temporal coverage for multi-decadal intervals that overlap the span of reliable streamflow records, i.e., early 20th century to present; monthly or shorter temporal resolution to characterize intra-annual seasonality.
2. **Spatial**: contiguous spatial coverage of California with sufficiently fine spatial resolution to differentiate intra-watershed features, such as topographic variation, and inter-watershed variations, such as westward vs. eastward prevailing slopes for adjacent watersheds.

3. **Consistency**: given the approach of using long-term records to characterize the water balance, it was important for the data to be adequately consistent in methodology and quality throughout the period of record.

Very few types of hydrological data were available that met these criteria: precipitation $P$, streamflow $R$, and temperature $T$. Temperature is useful because it can be used to estimate potential evapotranspiration $PET$, which is second only to $P$ in importance as a climate driver. The overall approach was to treat annual $R_i$ as a function of monthly $P_m$ and $PET_m$,

$$R_i = f(P_m, PET_m)$$

### 3.2.2 Watershed Delineation & Landscape Features

It was crucial to pay special attention to watershed boundary delineation because of the potential impact on geospatial lumping and flux depth normalization. The USGS GAGES-II curated watershed metadata collection [Falcone, 2011] was the primary source for watershed boundary data. For a small number of cases where GAGES-II was absent or otherwise insufficient, the USGS StreamStats web service [U.S. Geological Survey, 2012a] was used to delineate and export watershed boundary data. The GAGES-II Hydrologic Disturbance Index was an important source of information when selecting watersheds with minimal human disruption for the study.

The GAGES-II dataset also offered a broad range of landscape features that were used as predictors of model parameters in § 7. These included topography, vegetation type, soil composition, and waterway characteristics like sinuosity. This data is a snapshot of watershed features at a particular moment in time, but given its comprehensive feature set and the lack of temporally dynamic alternatives, it was determined to be adequate for the purpose. The MODIS IGBP land cover dataset [Freidl, 2010] was also used for preliminary study of the effects of vegetation cover. While IGBP was found to offer no improvement over GAGES-II features for model development, it is one example of a data source that could be used to extend the findings of this study to ungaged watersheds where GAGES-II data is not available.

### 3.2.3 Streamflow

Streamflow data was obtained from the USGS online water data portal [U.S. Geological Survey, 2011]; daily volumetric totals were normalized by watershed area to yield runoff depth. Several criteria were applied to ensure data quality. First, water years missing more than 10 days of data were taken as invalid and dropped. Second, gages with less than 20 years of valid data were neglected. Third, all remaining records were inspected for indications of human disturbances to streamflow, such as uncannily consistent records (for instance 6 months of the same daily volume) and absence of “peaky” variations expected in natural flows following a rainstorm. An example of such behavior is shown in the daily streamflow record of Figure 4, where streamflow before the installation of an upstream dam shows the irregular variations characteristic of natural conditions, including dry season baseflow recession. After dam construction the flow is significantly manipulated, including damped peaks during the wet season for flood control and steady flow during the dry season for water supply.
Figure 4: Daily average streamflow (m$^3$) for Dry Creek at Geyserville, CA, USGS Gage 11465200. There are two years of data representing conditions before and after upstream construction of the Warm Springs Dam in 1983: pre-dam 1970 (cyan) and post-dam 2003 (red). Note vertical axis is log$_{10}$ scale.

In addition to direct data analysis, the GAGES-II hydrologic disturbance index (HYDRO_DISTURB_INDEX), which scores the relative amount of human manipulation in a watershed, was used to identify watersheds that merited closer scrutiny for disruption. Resources for this scrutiny included documentation for particular gage stations and review of water basin diversion and storage schematics [U.S. Geological Survey, 2012b].

Overall, the quality assurance process resulted in 159 California watersheds selected for study, listed in Appendix 10.1, a collection that represents a broad diversity of climate and landscape conditions across California.

While there are no viable alternatives to the USGS for extensive and comprehensive streamflow data across California, it is important to note limitations and shortcomings of the data. As with most streamflow measurements made in natural conditions, uncertainty is poorly quantified, especially for the highest flow conditions that make the biggest contributions to annual total $R$. Relative uncertainties of instantaneous $R$ measurements are estimated to range from 5% in ideal conditions to greater than 40% for flood conditions. The dominant source of uncertainty is extrapolation of rating curves; other sources include incorrect assumptions about the stage-discharge relationship, calibration measurement errors, unsteady flow, and changes to channel features such as shape, roughness, and vegetation [Sauer and Meyer, 1992; Montanari, 2011; McMillan et al., 2012]. The impacts of poorly characterized uncertainty can be mitigated with the use of structural probabilistic models [Kavetski et al., 2006; Kelly, 2007] as used in this research and described in § 5.1.1.

Another important consideration for this research is temporal consistency of data. There are many reasons why $R$ measurements may systematically deviate over time. Physical modifications of the
gage site, such as changes in location or datum, are relatively common, as is re-calibration of rating curves. Channels inevitably change, either permanently due to fluvial geomorphology, or ephemerally with seasonal changes in vegetation. Furthermore, improvements in technology and methodology provide better $R$ measurements now than a century ago, but at the cost of systematic modifications. It is possible to analytically account for such changes on a case-by-case basis, but this is beyond the scope of this research, which emphasizes broad patterns across many watersheds. It is reasonable to expect that systematic shifts in $R$ measurements are generally isolated to a subset of watersheds at any given time, mitigating the impact on aggregate or regional analysis. The potential impacts of temporal inconsistency are discussed where appropriate, particularly in the context of interpreting model results.

3.2.4 Precipitation

The precipitation data generated for this study constituted a compromise of two datasets with competing strengths. In terms of geospatial resolution, monthly accuracy, and temporal longevity, the PRISM dataset [Daly et al., 2008] was best-in-class at the time of this research. Furthermore, PRISM estimates of annual $P$ were found to compare quite favorably with the few California watersheds represented in the MOPEX dataset [Schaake et al., 2006], a widely cited reference data source for hydrologic study. Like all broad-scale precipitation datasets PRISM has questionable accuracy in outlier conditions, such as snow-dominated regions, but without any superior alternatives this was taken as an acceptable shortcoming.

However, PRISM suffered from one fatal flaw. The methodology for the publicly available PRISM dataset emphasized using the best available information for any particular estimation interval, meaning the measurements that underlie the geospatial regression varied over time in terms of quality, quantity, and location. Indeed, the PRISM documentation warned against using the publicly available data to analyze long-term patterns (a paid version of the data is intended for long-term analysis, but the cost was prohibitive).

By contrast, the VIC geospatial dataset [Maurer et al., 2002] was designed explicitly for temporal consistency, albeit with shorter temporal coverage, coarser spatial resolution, and less reliable estimates for a given year.

Exploratory analysis showed that estimates of annual $P$ in a given watershed were generally quite divergent for PRISM and VIC, with differences 1000 mm or more not unusual. However, it was also found that a linear relationship accounted for much of the difference [Figure 5]. The linear component is perhaps explained by PRISM’s improved handling of orographic and water proximity effects, which may lead to systematic differences between the datasets.

The chosen approach was to scale VIC annual estimates of $P$ using the linear relationship of a regression against PRISM data for the same watershed. This new dataset, called VIC-scaled (VICs), mitigated systematic biases on a watershed-by-watershed basis while preserving the inter-annual consistency of the underlying VIC data.
Figure 5: Comparison of annual precipitation values for PRISM (P) vs. VIC (V, black circles) and VIC-scaled (Vs, blue circles) for representative watersheds. Black markers and lines indicate the relationship between PRISM and VIC. Given the assumption that the PRISM data is more accurate than VIC on a year-to-year basis, a linear regression of PRISM vs. VIC was used to generate the VIC-scaled dataset, which by definition lies along the 1:1 relationship with PRISM. These examples demonstrate that the linear scaling was a reasonable approach to mitigating biases in the VIC precipitation data. Note that axes scales vary.

3.2.5 Temperature & Potential Evapotranspiration
As previously noted, temperature $T$ was used to estimate $PET$. The PRISM and VIC datasets both offered estimates of monthly averages of minimum, maximum, and mean daily temperature on the same geospatial grid and timeline as $P$ data. A similar linear bias was observed between the two datasets, and so the scaling method described for precipitation in § 3.2.4 was used to create a VIC-scaled dataset for $T$. 
A comparison of four commonly-used empirical estimates for \( PET \) within California [Temesgen et al., 2005] concluded that the Hargreaves relationship [Allen et al., 1998] performed most favorably across the state’s diverse conditions, and this was confirmed by independent comparison with a regionally-specific reference \( PET \) database [Hart et al., 2009]. This relationship is,

\[
PET = 0.0023 \cdot (T_{\text{mean}} + 17.8) \cdot (T_{\text{max}} - T_{\text{min}})^{0.5} \cdot R_a
\]

where: \( T_{\text{min}}, T_{\text{max}}, \) and \( T_{\text{mean}} \) are average minimum, maximum, and mean daily temperature [°C]; and \( R_a \) is extraterrestrial radiation [L], which is a function of latitude and time of year. \( PET \) was calculated for each cell of the geospatial VICs temperature grid. The resulting VICs \( PET \) dataset compared favorably with MOPEX \( PET \) values for the few California watersheds available in the latter dataset, generally differing by < 50 mm per year.

An additional reference dataset derived from California Irrigation Management Information System (CIMIS) weather station data [Hart et al., 2009] was also used to validate the Hargreaves approximation. However, because this dataset starts in 2003 it was not possible to compare against the VICs data (which ends in 2003) directly, so instead a comparison was made between PRISM \( PET \) and CIMIS \( PET \), which is reasonable because the linear scaling method aligns the average values of PRISM and VICs data. The comparison found that the PRISM-derived Hargreaves approximation for \( PET \) was with 25 mm of CIMIS \( PET \) for the cumulative October – April wet season for all 159 watersheds in the study. The difference increased during the May – September dry season, but energy-excess conditions were less important for the purpose of this study.

### 3.2.6 Overall Data Record

The overall period of record for this study was bounded by the interval of the VIC precipitation and temperature data, water years 1916 through 2003. However, availability of streamflow records was commonly the limiting factor for any particular watershed. The distribution of record lengths for the 159 watersheds in this study is summarized in Figure 6, categorized by the prevailing wetness conditions in each watershed, arid, mesic, or humid (defined subsequently in further detail).

<table>
<thead>
<tr>
<th>Type</th>
<th>Source</th>
<th>Description</th>
<th>Temporal Resolution</th>
<th>Spatial Resolution</th>
<th>Period of Record</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P, T, )</td>
<td>PRISM</td>
<td>interpolated geospatial</td>
<td>monthly</td>
<td>~4 km</td>
<td>1895 – 2017</td>
</tr>
<tr>
<td>( P, T, )</td>
<td>VIC and VIC-</td>
<td>geospatial, temporally consistent</td>
<td>monthly</td>
<td>~16 km</td>
<td>1916 – 2003</td>
</tr>
<tr>
<td>( R )</td>
<td>USGS</td>
<td>gage measurements</td>
<td>daily</td>
<td>watershed</td>
<td>varies</td>
</tr>
</tbody>
</table>

*Table 1: Summary of climate and streamflow data sources.*
3.3 DATA SYNTHESIS

Compiling, integrating, and validating data with various formats from multiple sources was a significant challenge of this research. While ultimately only a few data sources were used for the bulk of the analysis, more than a dozen data sources were processed and studied in exploratory analysis before selection of the final data and model. This necessitated development of flexible software that was easily adapted to new data sources, with particular emphasis on time series data and geospatial data. Furthermore, because the purpose of the study was to analyze many watersheds to identify emergent patterns, it would have been prohibitively inefficient to use standard Geographic Information System (GIS) software, which excels at nuanced analysis of a particular region, but less so at concurrent analysis of many regions. This presented a need to develop and implement software functions that in some ways replicated GIS functionality but in an automated pipeline that supported rapid iteration on research questions.

The author would like to note that much of the software development for this study would be far more straightforward today, even just a few years from when the effort started, due to the proliferation of open source languages such as R and Python and the active development communities that contribute tools that perform much of the same work as was developed from scratch for this purpose. Unfortunately, since much of the development for this research was done for a proprietary platform, MATLAB, there is less opportunity for this effort to benefit others with similar data processing needs. For this reason, there will be relatively little technical exposition on the software developed for this study, as it would serve little practical purpose. This is unfortunate, as the development represents significant effort and perhaps some legitimate insights. In retrospect, an open source platform would have been a better choice. One lesson is that educational institutions...
should reconsider the implicit endorsement of proprietary software tools that arises from their use in classrooms and research laboratories. Such tools are contrary to the ethos of shared knowledge, the software that results is less transferrable to the broader research community, and the skills developed are often less valuable professionally than for open source alternatives. The watershed data pre-processing code is available online [Moran, 2015b].

3.3.1 Pre-processing
In general terms, the purpose of pre-processing was to standardize data to facilitate direct comparisons across datasets and water balance calculations for a given watershed. The standardization needs were: identical temporal units (monthly) and measurement units (length); measurement values spatially averaged (lumped) across the watershed; concurrent temporal overlap for a given watershed; and consistent, high quality data.

The general pre-processing steps for hydrologic data were:

1. Import raw data from either online web services or from data downloaded in bulk.
2. Perform any necessary transformations:
   a. Standardize measurement units to length (mm) or temperature (C) as appropriate.
   b. Geospatial data: transform coordinate system to NAD83 to be consistent with watershed boundaries.
   c. Geospatial data: transform geospatial data to time series by calculating spatially weighted average of grid cells within each watershed boundary.
3. Check quality and consistency of data.
   a. Use programmatically generated exploratory analysis on each watershed to evaluate concerns such as physically impossible or unlikely outliers, indications of human intervention or disturbances in the measured values, and missing values.
   b. Neglect water years missing more than 10 days of data.
4. Aggregate sub-monthly measurements to monthly values.
5. Save standardized data in common format:
   a. Arrays with shape 366 (day of year) x N years
   b. Measurement units:
      i. $P, PET, R$ [mm]
      ii. $T$ [C]

3.3.2 Pre-processing Summary
The water balance data process flow is summarized in Figure 7. For each streamflow dataset $R$ the gage location determined the watershed boundary delineation. This boundary was used to determine which cells of a given geospatial dataset contributed to the spatial average of measurement variables $P$ and $T$, with contributions of individual cells weighted by the fraction of the cell that was within the boundary; the outcome of this spatial averaging was a monthly time series for each data type for each watershed. As described in § 3.2.4, the PRISM data was considered more accurate for a given month but temporally inconsistent, while the VIC data was designed for temporal consistency. Thus, the PRISM time series for each watershed was used to scale the VIC data and thus produce a new
dataset, VIC-scaled (VICs) which improved measurement accuracy and was appropriate for analyzing long-term patterns. The VICs $T$ time series was then used to estimate $PET$ for each watershed using an empirical relationship per §3.2.5. That was the end of the pre-processing pipeline, and subsequently monthly $P$ and $PET$ are used to derive energy-excess precipitation $P_X$, an important climate variable that is defined in § 4.2.3 but not elaborated upon here. $P_X$ and $R$ were then primary inputs to the water balance model, which will be developed in § 4.

![Water Balance data flow](image)

Figure 7: Overview of data relationships (lines) and transformations (diamond-shaped nodes) for the temporally consistent water balance dataset.

### 3.3.3 Hydrological Analysis Functions

A large number of specialized functions were developed to address specific hydrological analysis. Some examples were:

1. **BASEFLOW_FILTER**: uses a one parameter recursive filter [Voepel et al., 2011] to empirically isolate the baseflow component of daily streamflow measurements
2. **CALC_HORTON_INDEX**: calculates the yearly Horton index given $P$ and $R$
3. **wswb_annual_P_gage_find**: finds all precipitation gages located within a given watershed boundary
4. **WSWB_CALC_MEAN_RECESSION**: estimates the recession slope of the baseflow component of daily streamflow measurements
5. **WSWB_NESTED_CATCHMENT_CHECK**: identifies nested watersheds
6. **WSWB_PERENNIAL_STREAM_CHECK**: determines whether a stream is perennial by calculating the fraction of years that the stream goes dry
7. **WSWB_SEAS_CALC_WETSEAS**: calculates the first and last day of the wet season based on cumulative precipitation thresholds
3.3.4 California Watershed Database Summary

The outcome of this data processing was a first-of-its-kind database of monthly time series estimates of the critical hydrological variables $P$, $T$, $PET$, and $R$, for every USGS-gaged watershed in California, along with a broad diversity of surface feature data for each watershed. This database facilitated rapid and scalable exploratory analysis of the water balance for the broad diversity of hydrological conditions in the state, on timescales ranging from seasonal to multi-decadal. Furthermore, the data processing workflow was designed for straightforward updating as more recent data becomes available, and is easily extensible beyond California to any USGS-gaged watershed.

3.4 Water Balance Observations

3.4.1 Motivating Example in Russian River Basin

Given suitable data sources, the relationship between precipitation $P$ and runoff $R$ is introduced in Figure 8 for a watershed in the Russian River basin. The left panel A shows a time series of annual values of $P$, $R$, and their difference $P - R$, which is an approximation of evapotranspiration $E$ if storage change $\Delta S$ is assumed to be small relative to the other components. It is remarkable that even though year-to-year variation in $P$ exceeds 1 m, the difference $P - R$ is quite consistent, almost always near 500 mm. Another view of this consistency is shown in panel B, where annual $R$ is plotted against $P$ and compared with a 1:1 slope. For this particular watershed, the relationship

$$R = P - 500$$

with units of mm, is a reasonable approximation to the historical record. This relationship motivated the question of whether a similarly straightforward relationship applied to different conditions across California.

![Figure 8: Annual estimates of P, R, and P – R (as rough proxy for evaporation E) for Dry Creek at Geyserville, CA, USGS Gage 11465200, for years with undisturbed streamflow. Two views of the data, as time series (panel A) and as a predictive relationship R vs. P (panel B), illustrate the invariance of P – R year to year, even for the drought water years 1976 - 1977. This remarkable consistency was a preliminary motivation for this research.](image)
3.4.2 Runoff vs. Precipitation

The observed relationship between total annual $R$ and $P$ is illustrated in Figure 9 for representative watersheds from the three categories of prevailing wetness conditions across the state, arid, mesic, and humid. A prerequisite decision for modeling the water balance was which method to utilize, in particular whether to use an index method, which describes the water balance in terms of normalized outcomes, or a regression method. In a meta-analysis comparing methods and outcomes from the literature [McMahan et al., 2013], index and regression methods were found to offer very good prediction of mean annual $R$, performing nearly as well as spatial proximity methods and better than process-based methods and proxy data (tree-ring) methods. Index and regression methods also performed comparably well for estimation of interannual variability.

Index modeling methods are quite common in the literature. The Budyko curve is most prevalent (§ 8.1), but other influential examples include an analytic variation of the L’vovich framework [L’vovich, 1979; Ponce and Shetty, 1995] and the Horton index [Horton, 1933; Dooge, 1992]. Preliminary analysis was performed using each of these index methods, but given the clear visual alignment between $R$ and $P$, and the underlying motivation to describe the apparent simplicity of the rainfall-runoff relationship in California, a regression method was ultimately determined to be most appropriate.

The next modeling decision was the functional form of the regression relationship. Mass balance and physical constraints imposed the following requirements: $R > 0$ for all $P$; $dR/dP$ increases monotonically; for very dry conditions $dR/dP \approx 0$ and $R \approx 0$; for very wet conditions $dR/dP \approx 1$ and $R$ is unbounded. Various forms that meet these criteria were explored in preliminary analysis, including sigmoid, bounded exponential and bounded polynomial forms. However, a segmented linear form was found to be preferable for several reasons. Foremost, the form is consistent with inspection of $R$ vs. $P$ patterns in a broad variety of California watersheds. Second, for the wettest watersheds the relationship is exceedingly straightforward, a single-segment linear regression. Third, the thresholds that are implicit in a segmented linear relationship are consistent with threshold behavior that is broadly observed in hydrology. Not least, the linear form has extensive precedent in annual water balance research (§ 2.3) and given the relatively sparse data more complex models may not be justified [Jakeman and Hornberger, 1993; Dooge, 1997].
Figure 9: Representative examples of annual R vs. P for three California watersheds from each of the three categories of prevailing wetness: Arid, Mesic, and Humid. Blue line indicates best fit of a three-segment linear model described subsequently. Whisker marks at bottom of plot indicate distribution of annual P values. Note that axes scales vary.

The chosen model was a linear regression with 2 or 3 segments. Analysis of many watersheds in diverse conditions revealed that the 2 segment relationships are special cases of the more general 3-segment version, which is illustrated in Figure 10. These three segments are associated with the amount of precipitation in a given water year. Dry water years are those when $R$ approaches zero; wet or saturated water years signify conditions where a marginal increase in $P$ results in an approximately 1:1 increase in $R$; and intermediate or mid-range water years are characterized by a lower proportion of $R$ per marginal increase in $P$. These labels are annotated along the horizontal axis of Figure 10.

The terminology used to describe the prevailing wetness conditions in a given watershed is heuristic but grounded these distinct and measureable types of water year. Humid watersheds are those where $dR/dP_X$ is consistent and near unity, and $R$ rarely if ever stops altogether; these are primarily found in the wet northwest of California and in alpine regions of the Sierra Nevada range. Arid watersheds are signified by a prevalence of dry years with negligible runoff and few if any wet years when $dR/dP_X$ approaches unity; these are found in hot and dry regions of the state, such as the southernmost quarter. Mesic watersheds experience a broad range of wetness conditions, with two distinct segments with different values of $dR/dP_X$, and are commonly found in the central region of the state.
3.4.3 Runoff vs. Energy-Excess Precipitation $P_X$

The structure of the water balance relationship can be simplified further by noting that the dry segment of Figure 10 represents conditions where the relationship between $E$ and $P$ is 1:1, and thus $R \approx 0$. In this first segment, any $P$ that falls within the watershed is evaporated before the water traverses to a surface outlet channel. This component of $E$ as is defined to be direct evapotranspiration, $E_d$. The complementary component of $P$, the fraction that is not evaporated, is defined as energy-excess precipitation $P_X$,

$$P_X = P - E_d$$

(2)

This metric has been used for water balance research under other names, such as water surplus [Thornthwaite, 1948] and residual rainfall [Zhang et al., 2004; Hickel and Zhang, 2006]. The concept of $P_X$ is central to this research and will be described in mathematical detail in § 4.2.3, but for the purpose of this section it is asserted that annual $P_X$ can be estimated as a deterministic function of monthly precipitation $P_m$ and monthly potential evapotranspiration $PET_m$. It was observed that the relationship of $R$ to $P_X$ is even more straightforward than the $R$ vs. $P$ relationship, as illustrated in Figure 11, which shows $R$ vs. $P_X$ for the same watersheds as Figure 9. Note that $R$ vs. $P_X$ is always represented by a 2 segment linear relationship.
Figure 11: Representative examples of annual R vs. energy-excess precipitation $P_X$ for the same California watersheds as the R vs. $P$ examples in Figure 9. Black lines indicate the best regression fit; grey lines indicate other plausible fits from probabilistic regression; whisker marks along bottom indicate distribution of $P$ values. Note that axes scales vary.

Another view of this relationship is shown in Figure 12, which shows yearly R vs. $P_X$ plotted simultaneously for 159 California watersheds. Colors indicate mean $P$ for a given watershed, in 3 quantiles. The sloped dashed line indicates the relationship $R = P_X - 200$, which was determined by inspection. The general agreement with this approximation suggests that the statewide water balance can be broadly described as a function of $P_X$. 
As illustrated in Figure 13, the form of the relationship of $R$ to $P_X$ can be expressed as

$$R = \alpha_{\text{mid}} P_x + \left( \alpha_{\text{wet}} - \alpha_{\text{mid}} \right) (P_x - c) H_c$$

(3)

Where $\alpha_{\text{mid}}$ and $\alpha_{\text{wet}}$ represent the slope $dR/dP_X$ for mid-range and wet water years, respectively, $c$ is the threshold value of $P_X$ that signifies the transition between mid-range and wet conditions, and $H_c$ is the Heaviside function relative to $c$.

$$H_c = \begin{cases} 
0 & \text{for } P_X \leq c \\
1 & \text{for } P_X > c 
\end{cases}$$

Note that the slope $\alpha_{\text{mid}}$ may be zero, such as for arid watersheds like the one in Figure 11.
Figure 13: Diagram of the prevailing observed relationship of R (blue) and E (green) to $P_X$. Dry years are not represented in this illustration as, by definition, such years typically result in negligible R. Note that E is treated as the complement of R, which applies only with the assumption that inter-annual storage change is negligible. Bars along the top of the figure indicate representative ranges of $P_X$ for the three wetness categories, Arid, Mesic, and Humid.

The same three categories of prevailing wetness conditions for a given watershed, arid, mesic, and humid, were attributed based on properties of $dR/dP_X$ using heuristic guidelines. Arid watersheds were defined as those for which the slope of the mid-range segment is approximately zero, which implies that some fraction of $P_X$ is entirely evaporated before measurable R is observed. Mesic watersheds were classified as those with two distinct, measurable non-zero values of $dR/dP_X$ in the mid-range and wet segments. Watersheds with only one measurable value of $dR/dP_X$ with a value near unity were classified as humid.

3.5 **Discussion of Empirical Water Balance Observations**

This section started by describing the requirements for and development of a database for the study of the annual water balance in California watersheds. The USGS GAGES-II metadata collection was a critical resource for definition and characterization of watersheds. Runoff records were easily accessed, but the data required careful curating for completeness and to ensure representation of predominantly natural conditions; the outcome was 159 California watersheds that were suitable for this research. There were no suitable existing sources for climate data, precipitation and potential evapotranspiration, and thus a new geospatial dataset was created that combined the temporal consistency of one data source and the improved yearly accuracy of another data source.

These various data sources were synthesized in an automated data pipeline, the outcome of which was a database of monthly values of R, P, and PET for each of the 159 watersheds of the study, in addition to the rich set of GAGES-II watershed attributes. The period of record for the water balance for each watershed was determined by availability of each data type; all records were
bounded by the interval of the geospatial climate data, 1916 – 2003, but most watersheds were limited by the period of $R$ records. The distribution of values is summarized in Figure 6.

The preliminary motivation for this research was the remarkable simplicity and consistency of the relationship between annual $R$ and $P$ for watersheds in the Russian River basin. Examination of diverse conditions across the state showed that a three-segment linear relationship between runoff and precipitation was broadly applicable. This relationship was further simplified to a two-segment linear relationship by introducing the concept of energy-excess precipitation $P_X$. The prevalence of this bi-linear relationship between $R$ and $P_X$ motivated the development of a water balance model that will be described in the next section.
4 WATER BALANCE MECHANISMS AND MODEL

The objective of this section is to introduce the conceptual and mathematical basis of an annual water balance model that describes the pervasive 2-segment linear relationship between $R$ and energy-excess precipitation $P_X$. First, a conceptual model will be presented to provide an intuitive foundation for the subsequent analysis. Then the climate factors affecting the water balance are described, particularly intra-annual seasonality and its relationship to $P_X$ and evapotranspiration components. Landscape controls will then be discussed, including the capacity of the subsurface to retain storage and a threshold transition in this retention capacity. Finally, these elements will be unified to develop a model of the Mediterranean Climate Water Balance (MCWB) using parameters with clear physical interpretations.

4.1 CONCEPTUAL WATERSHED MODEL

A conceptual model is first introduced to serve as a reference point for subsequent model development. Several key elements of the model will be discussed in detail subsequently, but their intuitive meaning can be discerned with the aid of Figure 14.

Suppose that all water enters the watershed as precipitation $P$. Some fraction of yearly $P$ is evaporated either before the water infiltrates the soil or relatively quickly after infiltration – this is the component defined as direct evapotranspiration $E_d$ in § 3.4.3. The remainder of $P$ is defined as energy-excess precipitation $P_X$, which is assumed to infiltrate the soil during the wet season (or, in the case of alpine watersheds, to be captured in snowpack). As will become clear via subsequent definitions, one of two outcomes can then occur for any amount of $P_X$; either it can depart the watershed as $R$, or it can be carried over from the wet season to the dry season as storage $S$ and subsequently evaporated; recent research indicates that the stores for transpiration and runoff are often isolated [Brooks et al., 2010; Evaristo et al., 2015], but this distinction is beyond the scope of this research. The latter component is defined here as storage evapotranspiration $E_S$. This supposes no inter-annual change in $S$, which is a strong assumption but one with minimal implications for the purpose of this model.

It is important to note that Figure 14 does not represent a bucket model in the sense that $P_X \neq S$. Rather, there is assumed to be continuous seepage of $R$ from the soil column at some rate $\frac{dR}{dP_X}$, signified as $\alpha_{\text{mid}}$ or $\alpha_{\text{wet}}$, where the subscripts indicate whether the annual precipitation conditions are mid-range or wet. It is beyond the scope of this research to estimate intra-annual runoff or storage, so no attempt was made to quantify or characterize the dynamic relationship between $R$, $S$, and $E$. However, it is instructive to consider a bounding case where all $R$ occurs during the wet season, an approximation that is not entirely unreasonable for many humid watersheds where the amount of streamflow during the wettest months greatly exceeds that of the drier months. In this case, $S$ represents the entirety of storage carried over into the dry season, or inter-seasonal storage, and all $S$ is subsequently evaporated as $E_S$.

In some watersheds, there is a prominent change in $\alpha$ when $S$ exceeds a threshold value $S^*$, signifying a transition from mid-range ($\alpha_{\text{mid}}$) to wet ($\alpha_{\text{wet}}$) conditions. There are multiple conceptual mechanisms that can explain this change in the runoff rate. Per § 2.2.3, evapotranspiration rates are generally lower for deeper roots than shallow roots, so deep infiltration may be more likely to runoff than evaporate. Per § 2.6, various landscape and storage factors may play a role: soil saturation thresholds are known to trigger preferential flow from the soil matrix; infiltration excess overland flow may contribute to annual $R$ in watersheds with certain conditions; deep infiltration may access a
water table, porous rocky substrate, or other fast-flow channels; and bedrock contours or depressions may facilitate fast-flow thresholds. Mechanisms differ significantly for alpine watersheds dominated by snow, as described in § 2.2.2.2, but interestingly the overall structure of the empirical water balance relationship is similar.

![Conceptual illustration of the MCWB](image)

**Figure 14:** Conceptual illustration of the MCWB. Precipitation \( P \) is assumed to be the sole input source of water. Some fraction of \( P \) is vaporized relatively quickly (same month) as direct evapotranspiration \( E_d \); this includes components such as surface evaporation, intercept evaporation, and shallow soil transpiration. The remaining monthly balance is energy-excess precipitation \( P_X \), which is either retained as storage \( S \) until energy is available for evapotranspiration component \( E_s \), or it departs the watershed as streamflow \( R \). Water balance observations indicate two distinct rates of \( dR/dP \): a lower rate during years with mid-range wetness, and a high rate during very wet years, annotated as \( \alpha_{\text{mid}} \) and \( \alpha_{\text{wet}} \) respectively. Note that the subsurface vertical axis indicates \( P_X \) increasing downward, and as \( P_X \) increases past the threshold \( S \) the runoff rate changes; this is not intended to imply that \( \alpha_{\text{mid}} \) and \( \alpha_{\text{wet}} \) emanate from different physical stores.

### 4.2 Climate Factors

#### 4.2.1 Two-Season Water Year Simplification

One signature characteristic of a Mediterranean climate like California’s is the strong seasonality of \( P \) and \( PET \) which are almost exactly out of phase with each other, as illustrated in Figure 15.
A commonly applied simplification of this pattern is to specify just two intervals, a wet season and a dry season [Hickel and Zhang, 2006; Feng et al., 2012; Chen et al., 2013; Vico et al., 2015]. The wet season comprises months when monthly precipitation $P_m$ exceeds monthly $PET_m$, and the dry season is defined as all months when the opposite is true.

\[
P_m > PET_m \rightarrow \text{wet season month}
\]

\[
P_m \leq PET_m \rightarrow \text{dry season month}
\]

Following this convention, for the climate data shown in Figure 15 the wet season would be November through March, and the dry season would be April through October, timeframes that are typical for California watersheds. Wet season precipitation $P_{wet}$ and potential evapotranspiration $PET_{wet}$ can then be defined as:

\[
P_{wet} = \sum_{m \in \text{wet}} P_m
\]

\[
PET_{wet} = \sum_{m \in \text{wet}} PET_m
\]

Dry season values $P_{dry}$ and $PET_{dry}$ are defined similarly. This two-season model is illustrated in Figure 16.
Figure 16: Simplified representation of Mediterranean climate as two intervals, wet and dry. Energy-excess precipitation $P_X$ is defined as the difference of wet season precipitation $P_{\text{wet}}$ and wet season potential evapotranspiration $PET_{\text{wet}}$. Note that months do not necessarily correspond to the beginning and end of the water year, nor is it necessary that months are contiguous for either season.

Of course, wet and dry seasons are not necessarily contiguous as in the idealized representation of Figure 15. For instance a wet November may be followed by a very dry December when $P_m < PET_m$, and then by a wet January. However, there is no impact on the calculation of $P_{\text{wet}}$ and $PET_{\text{wet}}$ which are defined strictly in terms of the monthly values of $P_m$ and $PET_m$, with no requirement for seasonal continuity.

4.2.2 Seasonality Metrics: $\omega_P$ and $\omega_{PET}$
A particularly useful and straightforward representation of annual seasonality is the proportion of $P$ and $PET$ that occur during the wet season, defined as

$$\omega_P = \frac{P_{\text{wet}}}{P}$$

$$\omega_{PET} = \frac{PET_{\text{wet}}}{PET}$$

In highly seasonal Mediterranean climates, typical values are $\omega_P \approx 0.2$ and $\omega_{PET} \approx 0.8$. A value of 0.5 represents no distinction between wet and dry seasons, i.e., no seasonality, while a value of 1 or 0 would indicate perfect seasonal separation. Note that these ratios are dynamic year to year, but the magnitude of variation is typically small relative to overall variation in $P$ and $PET$. Note that while there are other useful representations of seasonality, e.g., by [Feng et al., 2012], this form captures the essential variation and simplifies subsequent interpretation and derivations.

4.2.3 Energy-Excess Precipitation $P_X$ in terms of Seasonality
Given the definitions of $P_{\text{wet}}$ and $PET_{\text{wet}}$, the difference in these values represents precipitation that cannot be evaporated during the wet season due to energy limitations. This difference is an equivalent definition of energy-excess precipitation $P_X$.\[47\]
Using Eqs. (4) and (5), $P_X$ can be restated in terms of the seasonality parameters,

$$P_X = \omega_p \cdot P - \omega_{PET} \cdot PET$$

(7)

4.2.4 $P_X$ as a Function of $P$

Total annual precipitation $P$ is the sum of wet and dry season precipitation $P_{wet}$ and $P_{dry}$

$$P = P_{wet} + P_{dry}$$

Considering the consistent seasonality in Mediterranean climates, it is reasonable to estimate that on average there is a proportional relationship between seasonal precipitation and total annual precipitation

$$P_{wet} \approx \frac{P_{wet}}{P} \cdot P = \bar{\omega}_p \cdot P$$

$$PET_{wet} \approx \frac{PET_{wet}}{PET} \cdot PET \approx PET_{wet}$$

where overbars indicate long-term averages. The last step of approximating $PET_{wet}$ derives from the inter-annual consistency of $PET$ for most regions of California, and thus $PET \approx PET$.

Substituting these approximations into Eq. (6) yields,

$$P_X = \bar{\omega}_p \cdot P - \bar{PET}_{wet}$$

(8)

This linear relationship between $P_X$ and $P$ is indeed observed for the majority of watersheds across California, with one example provided in Figure 17. The main exceptions are arid watersheds, for which $P_X$ is commonly near zero even when $P$ is significant; this truncation has the effect of clustering values of $P_X$ along the $P$ axis in a non-linear fashion. However, because arid watersheds are characterized by negligible runoff for small values of $P_X$, there net impact on the overall model is minimal.
4.2.5 Evapotranspiration Components: Direct $E_d$ and Storage $E_s$

Direct evapotranspiration $E_d$ was implicitly defined in Eq (2) as

$$ E_d = P - P_x $$

It is worth revisiting $E_d$ because of its conceptual importance. Perhaps the most important assumption of this research is that monthly precipitation $P_m$ is consistently evaporated in the same month that it falls, up to the energy limit of total potential evapotranspiration for that month, $PET_m$. Annual $E_d$ represents the sum of such same-month evapotranspiration. Given the definition of $P_{dry}$ and $PET_{wet}$, it follows that,

$$ E_d = P_{dry} + PET_{wet} $$

and thus,

$$ E_d = (1 - \omega_P) \cdot P + \omega_{PET} \cdot PET $$

It should be clear that $P_x$ and $E_d$ are dynamic variables that vary year to year; they should not be mistaken for persistent parameters. However, because in general $P_{dry} \ll P$ and $PET_{wet} \ll PET$ in
MC regions, the variation in $E_d$ tends to be small relative to the overall variation of the water balance.

Per Eq. (9) and § 4.2.1, $E_d$ represents the sum of energy-limited $E$ during the wet season ($PET_{\text{wet}}$) and water-limited $E$ during the dry season ($PET_{\text{dry}}$). Thus, any additional contribution to annual $E$ must come from water stored in the wet season and carried over into the dry season when additional energy is available for evaporation. This component is defined to be storage evapotranspiration $E_s$, such that,

$$E = E_d + E_s$$

(10)

### 4.3 Landscape Factors

#### 4.3.1 Inter-annual Storage Change $\Delta S$

Due to inadequate historical measurements it was not feasible to estimate inter-annual storage dynamics for the watersheds in this study. For the few relevant basins where adequate groundwater level data was available, such as the Navarro River and Napa River, preliminary analysis indicated that the groundwater stores were generally at comparable levels at the beginning of each water year. Additional preliminary analysis of streamflow levels and recession rates for two-dozen perennial waterways likewise indicated that inter-annual differences in water supplies were very small relative to total annual $P$. And temporal examination of streamflow levels indicated negligible impact of using a static definition of the water year, starting on October 1, as opposed to a dynamic definition based on yearly hydrological conditions.

These preliminary explorations were suggestive, though not conclusive, that inter-annual storage change $\Delta S$ may be small relative to the magnitude of $P$, $R$, and $E$ fluxes for many California watersheds. Given that it was neither possible to account for $\Delta S$ via measurement nor to unequivocally assert that it is negligible for all watersheds in the study, it is important to clarify the impact that $\Delta S$ may have on subsequent results and interpretation. As reviewed in § 2.3.2, this is consistent with a growing body of research that questions whether the assumption of negligible $\Delta S$ was too broadly applied in decades of hydrological research.

Recalling the basic water balance,

$$P = R + E + \Delta S$$

Taking $R$ as an observed outcome, if $\Delta S$ is incorrectly assumed to be negligible it may affect understanding of $P$ or $E$ or both. Since this research treats $E$ as an implied flux, the more relevant consideration is how $\Delta S$ influences interpretation of $P$. If $\Delta S$ is negligible then $P$ represents the net amount of water that contributes to hydrological functions in a given year; this is the implication of the water balance represented in Figure 10. If $\Delta S$ is not negligible, then $P$ may represent more or less than the net water usage for a given year, and thus the predictor axis of Figure 10 would be more appropriately represented by a measure of effective precipitation $P_{\text{eff}}$, that accounts for annual storage carry-over or deficit [Wang, 2012]. There are two major implications of this. At worst, it could be that the overall structure of the $R$ vs. $P_{\text{eff}}$ relationship would be different than the segmented linear structure used here to describe the water balance, which would undermine the validity and utility of this approach. But given the prevalence of the observed patterns across many

50
watersheds with presumably diverse storage behavior, this possibility appears unlikely. However, it is probably the case that instances of non-negligible $\Delta S$ influence dispersion of the observed $R$ vs. $P$ (or $P_X$) relationship. Consider a trivial model $P_{\text{eff}} = P + \Delta S_{t-1}$, where the subscript $t-1$ indicates storage change in the prior year relative to some baseline. If excess storage is carried over from the prior year, then $\Delta S_{t-1} > 0$ and this extra water might be assumed to contribute to increased $R$ in the next water year, relative to the amount of $P$ that year; with this simplistic view, the opposite would hold for a carry-over deficit $\Delta S_{t-1} < 0$. Either type of carry-over would result in broader dispersal of $R$ observations relative to the true underlying relationship with $P$, and in this scenario $\Delta S$ could be considered a noise term. By contrast, if $\Delta S$ were consistently positive or negative, i.e., persistent drawdown or recharge of watershed storage, this would have the effect of systematically translating the $R$ vs. $P$ relationship in the negative or positive direction of the $P$ axis, respectively.

For this research, the implications of non-negligible $\Delta S$ vary by application. For MCWB parameter estimation using historical records in gaged watersheds (§ 5), increased noise and systematic shifts in the water balance both have the effect of increasing parameter uncertainty. For evaluating changes in the water balance (§ 6), $\Delta S$ is one factor that may contribute to systematic shifts or trends. And for comparison of the MCWB model with the Budyko curve (§ 8) recent research has shown that $\Delta S$ may be a significant factor in the shape of the partition relationship [Wang, 2012; Moussa and Lhomme, 2016; Condon and Maxwell, 2017]. These contextual considerations for $\Delta S$ are discussed in subsequent sections as applicable.

A possible enhancement of the MCWB model could include antecedent-year $P$ as an additional predictor, with the expectation that this might provide an indication of annual carry-over storage [Xu et al., 2012].

### 4.3.2 Runoff Release Rates $\alpha_{\text{mid}}$ and $\alpha_{\text{wet}}$

By inspection of the water balance diagram in Figure 18, it can be seen that $\alpha_{\text{mid}}$ and $\alpha_{\text{wet}}$ represent the rate $dR/dP_X$ for mid-range and wet conditions,

$$
\frac{dR}{dP_X} = \begin{cases} 
\alpha_{\text{mid}} & \text{for} \quad P_X \leq c \\
\alpha_{\text{wet}} & \text{for} \quad P_X > c
\end{cases}
$$

It is useful to note that runoff rate $\alpha$ encompasses all possible mechanisms for generating streamflow, including soil seepage, groundwater seepage, and overland flows. Furthermore, there are no assumptions about the timing of runoff, e.g., whether it occurs during the wet or dry season. All that can be confidently asserted is that $\alpha$ represents some sense of the ease with which energy-excess precipitation passes through a watershed and into a surface flow channel, or conversely a watershed’s lack of ability to retain that water.
Figure 18: Diagram of the two-segment linear relationship of $R$ (blue) and $E$ (green) to $P_X$, with additional annotation for direct evapotranspiration $E_d$, storage evapotranspiration $E_s$, and storage retention threshold $S^*$. 

It is more straightforward to interpret the complementary slope $1 - \alpha$ due to the constraints implied by the definition $P_X = P - E_d$. Because $E_d$ includes all $E$ that occurs during the wet season (limited by $PET_{wet}$) as well as all dry season $P$, it follows that the remaining component of $E$ must have originated in storage carried over from the dry season to the wet season, $E_s$, as illustrated in Figure 18. Since this component was necessarily in storage for some amount of time, the rate $dE_s/dP$ can be thought to quantify a watershed's ability to retain water in storage rather than allow it to exit as streamflow. Thus, $1 - \alpha_{mid}$ and $1 - \alpha_{wet}$ are defined as the storage retention rates for mid-range and wet conditions, respectively.

While it is beyond the scope of this work to specify the particular mechanisms in a given watershed that drive runoff rates and storage retention, it is instructive to describe a plausible example. Consider a California watershed with moderate wetness and non-alpine conditions such as the Navarro River near Navarro, CA, as shown in Figure 19. For the wettest years, one imagines that fast-flow runoff mechanisms, such as preferential seepage paths or storage-excess overland flow, will be triggered for some portion of the year, perhaps after the largest rainstorms. Thus $\alpha_{wet}$ may approach unity, and conversely storage retention would be low. Years with mid-range precipitation might mean the thresholds for fast-flow are rarely or never met in the course of the year. Thus $R$ would be a smaller fraction of precipitation-excess, and instead the water would remain in storage and be more susceptible to evapotranspiration mechanisms.
Note that because total annual $E$ is the sum of direct evapotranspiration $E_d$ and storage $E_s$, the annual water balance dictates that,

$$R + E_d + E_s = P$$

It then follows from Eq. (2) that,

$$R + E_s = P_x$$

And thus by mass balance continuity,

$$\frac{dR}{dP_x} + \frac{dE_s}{dP_x} = 1$$

(12)

This relies on the assumption that $\Delta S$ can be neglected on an annual or longer timescales, which means that Eq. (12) only applies for annual timescales, and thus the relationship between $R$ and $E$ that is shown in Figure 18 should not be expected to hold for shorter timescales. Specifically, it would be incorrect to assume that this framework can describe the progression of the water balance as $P_x$ accumulates during a given year, i.e., it cannot predict the intermediate state of the water balance at a particular moment of a water year.
The runoff release rates $\alpha_{\text{mid}}$ and $\alpha_{\text{wet}}$ and their complementary storage retention rates $1-\alpha_{\text{mid}}$ and $1-\alpha_{\text{wet}}$ are likely to be controlled by the landscape and subsurface features of a watershed described in §2.4.3. Per that review, factors that affect runoff rates include vegetation abundance and type, overland flow mechanisms, soil matrix properties, water table connectivity, and surface channel access. The rate values are considered to be characteristics of a given watershed, not a particular water year, and so values are estimated via multi-year regressions of $R(P_X)$ for each watershed.

4.3.3 Storage Retention Threshold $S^*$

Referring to Figure 18, the threshold parameter $\epsilon$ indicates the transition between mid-range and wet conditions as signified by the change in runoff rate from $\alpha_{\text{mid}}$ to $\alpha_{\text{wet}}$. By inspection of the geometry in that figure, this threshold can be equivalently specified as

$$c = \frac{S^*}{1-\alpha_{\text{mid}}}$$

(13)

where $S^*$ represents the maximum amount of storage evapotranspiration $E_s$ that occurs in mid-range precipitation conditions before the transition to a decreased $E_s$ rate in wet conditions,

$$S^* = (1-\alpha_{\text{mid}}) \cdot c$$

(14)

Because $E_s$ is drawn from storage it is reasonable to think of $S^*$ in terms of a storage capacity threshold for a watershed, but this interpretation requires a strong caveat. It does not represent the static storage capacity of a watershed in the sense of a bucket model; instead $S^*$ is a type of dynamic storage capacity that may, for instance, encompass various wetting and drawdown cycles in the course of a water year. But given the connection to $E_s$ and the storage retention rates $1-\alpha_{\text{mid}}$ and $1-\alpha_{\text{wet}}$, $S^*$ is referred to here as the storage retention threshold.

The advantage of defining the runoff rate threshold in terms of a storage parameter is the straightforward conceptual interpretation: storage controls the runoff rate. When the amount of inter-seasonal storage exceeds some threshold $S^*$, $dR/dP_X$ increases significantly. While the particular mechanisms in a given watershed are beyond the scope of this research, there are multiple categories of storage-centric concepts that may explain why $E_s$ decreases for wet conditions, as reviewed in §2. Evapotranspiration rates are generally higher for shallow roots than for deeper roots, which implies a drop in $E$ rates for deep infiltration in wetter years. Soil saturation thresholds are known to trigger preferential flow from the soil matrix, causing water to depart the watershed before it can evaporate. Likewise, deep infiltration may create connectivity with a water table, porous rocky substrate, or other fast-flow channels, or bedrock contours may facilitate fast-flow thresholds.

4.4 Considerations for Alpine (Snow-Dominated) Watersheds

The conceptual mechanisms and arguments in this research are oriented towards watersheds where the subsurface soil matrix is the predominant mode of storage, as illustrated in Figure 14. However, snowpack is a significant storage medium for many important hydrologic regions in California, and the mechanisms and timing of the water balance are quite different for such snow-dominated, alpine watersheds. Interestingly, the empirical relationship between $R$ and $P_X$ was found to be widely applicable to both alpine and rain-dominated watersheds.
For this research, alpine watersheds were defined as those where snow accounted for greater than 30% of annual precipitation, on average. An estimate of the average amount of precipitation that is snowfall was provided for each watershed by the GAGES-II dataset, and 39 of 159 total watersheds were classified as alpine.

Why not treat non-alpine and alpine watersheds separately? A large amount of exploratory analysis for this research followed the path of distinguishing between these types. This approach did indeed provide some improvement in the performance of water balance regressions and parameter predictions. However, the improvements were ultimately not sufficient to justify the loss of generality and scope that is the purpose of this research. So rather than segmenting analysis by precipitation type, the chosen approach was to note conceptual, mechanistic, and analytic distinctions as appropriate.

4.4.1 Alpine Climate Drivers

The simplification of treating intra-annual annual hydrology as only two seasons, wet and dry, is a key characteristic of the MCWB model, per § 4.2.1. This framework holds just as well for alpine watersheds as for non-alpine because the seasonality of $P$ and $PET$ is an important consideration in either case. Furthermore, the MCWB model is not explicitly concerned with the intra-annual timing of the water balance, e.g., whether R occurs predominantly in the wet or dry season, so the approach has the effect of aggregating seasonal effects that might otherwise impact a water balance model.

One might reasonably question whether energy-excess precipitation $P_X$, the dominant climate driver for the MCWB model, is a meaningful climate factor for alpine watersheds. Recall that,

\[
P_X = P - E_d
\]
\[
E_d = P_{dry} + PET_{wet}
\]

By definition $P_{dry}$ occurs in warmer months when $PET$ exceeds $P$, so the evaporation mechanisms are similar to non-alpine watersheds. $PET_{wet}$ is typically small for cold alpine watersheds, diminishing the importance of whether evaporation or sublimation is the mechanism for vaporization in a snowy watershed.

4.4.2 Alpine Landscape Controls

A key concept of the MCWB model is that $P_X$ is partitioned into either runoff or inter-seasonal storage that is carried-over from the wet season until the dry season. This partition also holds for alpine watersheds, where the storage medium is snowpack.

The main conceptual hurdle to applying the MCWB to alpine watersheds is the storage retention threshold $S^*$, which signifies a transition from mid-range to wet conditions. Because storage is essentially unbounded for alpine watersheds, the mechanisms that may explain this transition for non-alpine watersheds do not have direct analogies for snow-dominated conditions.

Snowpack is essentially unbounded, which poses a conceptual contradiction with the MCWB parameter $S^*$, the storage retention threshold transition from mid-range to wet conditions. However alpine watersheds are invariably also humid watersheds with few years when precipitation is less than the wet domain of Figure 18. Thus, in practice the runoff rate was always observed to be $\alpha_{wet}$ for alpine watersheds, with no transition threshold $S^*$. While this does not reconcile any conceptual
discordance, in practice the MCWB regression was sufficient to capture the annual water balance behavior of alpine watersheds in California.

4.5 THE MEDITERRANEAN CLIMATE WATER BALANCE MODEL

4.5.1 Process Recap

The preceding sections can be summarized with reference to the diagram in Figure 20. Precipitation $P$ may occur in either the wet or dry season; the proportion of wet season $P$ to total $P$ for a given year is described by the seasonality variable $\omega_p$. All dry season precipitation $P_{dry}$ is evaporated during the dry season, and wet season precipitation $P_{wet}$ is evaporated during the wet season up to the energy limit $PET_{wet} = \omega_{PET} \cdot PET$; those components comprise direct evapotranspiration $E_d$. What then remains is energy-excess precipitation, $P_X = P - E_d$.

Landscape controls then determine further partitioning of $P_X$ into either runoff $R$ or storage evapotranspiration $E_S$. Recalling that all wet-season $PET$ was accounted for during the evaporation of $P_{wet}$ into $E_d$, the supply for $E_S$ must come from inter-seasonal storage that held water within the watershed until additional energy was available in the dry season. The fraction of $P_X$ that contributes to $R$ as opposed to inter-seasonal storage is determined by the runoff release rates $\alpha_{mid}$ and $\alpha_{wet}$, and the storage retention threshold $S^*$, each of which have physically intuitive interpretations as landscape controls.

The diagram of Figure 20 is inspired by the water balance framework described by L’vovich, which describes the landscape partition of $P$ into a fast runoff component and an infiltration component; infiltration subsequently becomes either evapotranspiration or slow-release runoff. The MCWB framework additionally specifies the seasonality of $P$, and distinguishes between energy-limited...
evapotranspiration $E_d$ and the supply-limited component $E_s$. However, the MCWB approach is specific to the annual water balance whereas the L’vovich approach is generalizable to arbitrary timeframes, and thus the resemblance is largely superficial.

### 4.5.2 MCWB Equation

The parameters of the MCWB model can thus be restated from Eq. (3),

$$ R = \alpha_{mid} P_x + \left( \alpha_{wet} - \alpha_{mid} \right) (P_x - c) H_c $$

in terms of measurable, physical parameters.

$$ R = \alpha_{mid} \left( \omega_p \cdot P - \omega_{PET} \cdot PET \right) + \left( \alpha_{wet} - \alpha_{mid} \right) \left( \omega_p \cdot P - \omega_{PET} \cdot PET - \frac{S^*}{1 - \alpha_{mid}} \right) H_{c'} $$  \hspace{1cm} (15)

Where variables and parameters are summarized in Table 2.

Note the change to the Heaviside function; the subscript $c'$ signifies the transformation from $P_x$ to $P$, to maintain consistency with the representation of $R$ as a function of $P$,

$$ H_{c'} = \begin{cases} 0 & \text{for } P \leq c' \\ 1 & \text{for } P > c' \end{cases} $$

and,

$$ c' = \frac{\omega_{PET} \cdot PET}{\omega_p} + \frac{S^*}{\omega_p \left( 1 - \alpha_{mid} \right)} $$

Eq. (15) can be simplified somewhat as:

$$ R = \left( \omega_p \cdot P - \omega_{PET} \cdot PET \right) \left( \alpha_{mid} + \left( \alpha_{wet} - \alpha_{mid} \right) H_{c'} \right) - \frac{\alpha_{wet} - \alpha_{mid} \cdot S^* \cdot H_{c'}}{1 - \alpha_{mid}} $$  \hspace{1cm} (16)
<table>
<thead>
<tr>
<th>Variable, Parameter</th>
<th>Description</th>
<th>Estimation Method</th>
<th>Key Relationships</th>
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<tr>
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<tr>
<td>P</td>
<td>Annual precipitation [L]</td>
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</tr>
<tr>
<td>$P_X$</td>
<td>Excess precipitation [L]; annual precipitation in excess of</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>$P_X = \omega_P \cdot P - \omega_{PET} \cdot PET$</td>
</tr>
<tr>
<td>PET</td>
<td>Potential evapotranspiration [L]</td>
<td>Annual empirical geospatial estimate as function of temperature $T$ and month of year</td>
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<td>$E = P - R - \Delta \dot{S}$</td>
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<td>Direct evapotranspiration [L], occurs same month as any $P$ for that month, up to energy-limit of monthly $PET_m$</td>
<td>Residual of $P_X$ estimate</td>
<td>$E_d = P - P_X$</td>
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<tr>
<td>$E_S$</td>
<td>Storage evapotranspiration [L], drawn from storage carried over from wet season to dry season</td>
<td>Residual of $E$ and $E_d$ estimates</td>
<td>$E_S = E - E_d$</td>
</tr>
<tr>
<td>$\omega_P$</td>
<td>$P$ seasonality proportion; fraction of annual $P$ that occurs during the wet season of a given year</td>
<td>Annual estimation from monthly $P_m$ given definition of wet season</td>
<td>$\omega_P = \frac{P_{wet}}{P}$</td>
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<tr>
<td>$\omega_{PET}$</td>
<td>$PET$ seasonality proportion; fraction of annual $PET$ that occurs during the wet season of a given year</td>
<td>Annual estimation from monthly $PET_m$ given definition of wet season</td>
<td>$\omega_{PET} = \frac{PET_{wet}}{PET}$</td>
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<tr>
<td>$\alpha_{mid}$</td>
<td>Runoff rate $\Delta R / \Delta P_X$ for mid-range wetness</td>
<td>Multi-year regression of $R(P_X)$ relationship</td>
<td></td>
</tr>
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<td>Runoff rate $\Delta R / \Delta P_X$ for very wet conditions</td>
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<td>$S^*$</td>
<td>Storage retention threshold [L]; wet-season storage capacity associated with transition to wet runoff conditions</td>
<td>Multi-year regression of $R(P_X)$ relationship for $P_X$ threshold $\epsilon$</td>
<td>$S^* = c \cdot (1 - \alpha_{mid})$</td>
</tr>
</tbody>
</table>

Table 2: Summary of key variables and parameters for the MCWB.
4.6 DISCUSSION AND SUMMARY

This section first introduced a conceptual watershed model that is consistent with the bi-linear behavior observed in § 3.4.3. The salient features of the conceptual model are two modes for evapotranspiration and two for runoff, as well as a threshold that describes the transition between modes. The evapotranspiration modes are direct evapotranspiration \(E_d\), which represents complete vaporization of any monthly \(P_m\) up to the energy limit of \(PET_m\) for that month, and storage evapotranspiration \(E_s\), which represents water evaporated from storage carried over from wet months \((P_m > PET_m)\) into dry months \((PET_m \geq P_m)\). The runoff modes include two rates of \(dR/dP_X\), one for water years with mid-range wetness, \(\alpha_{\text{mid}}\), and a higher runoff rate \(\alpha_{\text{wet}}\) for very wet years. The transition between mid-range and wet conditions is conceptually represented as the storage retention threshold \(S^*\), which is a dynamic value, not necessarily the physical storage capacity of a watershed.

Next the impact of climate on the model was described, beginning with introduction of a simplified two-season representation of \(P\) and \(PET\) that captures the influence of the highly seasonal Mediterranean climate. This allowed for definition of the seasonality metrics \(\omega_P\) and \(\omega_{PET}\), the fraction of \(P\) and \(PET\) respectively that occur during the wet season. Next, energy-excess precipitation \(P_X\) was framed in terms of these seasonality metrics and then approximated as a linear function of \(P\), with a slope of the average fraction of wet season precipitation \(\bar{\omega}_P\) and an intercept of average total wet season potential evapotranspiration \(PET_{\text{wet}}\). Direct evapotranspiration \(E_d\) was then described in terms of seasonal \(P\) and \(PET\) and storage evapotranspiration \(E_s\) was defined as the residual of total \(E\) and \(E_d\).

Landscape effects on the water balance model were addressed next, starting with a justification for neglecting inter-annual storage change \(\Delta S\), which is general an important consideration but was expected to have relatively little impact on the definition and applications of this model. The runoff release rates \(\alpha_{\text{mid}}\) and \(\alpha_{\text{wet}}\) are assumed to be largely controlled by landscape features, such as overland flow mechanisms or preferential seepage paths. Mass balance continuity was invoked to show that the complement of the runoff rates, \(dE_s/dP_X\) can be considered as a storage retention rate, and also to note the caveat that this model is strictly applicable to total annual values, not intra-annual timeframes when \(\Delta S\) is less likely to be negligible. The storage retention threshold \(S^*\) was then shown to be a particularly interpretable parameterization of the transition between mid-range and wet conditions, representing the ability of the landscape to retain water into the energy-abundant dry season.

Snow-dominated alpine conditions were then considered, in particular the mechanisms that are contrary to assumptions of rain-dominated conditions, such as seasonality effects and storage. It was shown that while these differences are conceptually important, in practice the water balance observations for alpine watersheds are broadly consistent with the model as developed. This is because alpine conditions tend to be limited to the wet regime, meaning there is no observed transition controlled by the threshold \(S^*\).

The holistic process was recapped conceptually by the diagram of Figure 20, which shows the various steps that partition \(P\) into \(R\) and \(E\), grouped by climate and landscape factors. Then finally the annual partition of \(R\) was expressed as a bi-linear function of \(P\) and \(PET\), parameterized by the seasonality controls \(\omega_P\) and \(\omega_{PET}\), and the landscape factors \(\alpha_{\text{mid}}, \alpha_{\text{wet}},\) and \(S^*\), as shown in the MCWB model of Eq. (16).
The MCWB model has a number of desirable characteristics. It is parsimonious in the sense that it is only as complex as necessary to describe the bi-linear behavior observed in the annual water balance in California watersheds. Climate and landscape effects are largely separated. The data required for the climate variables, monthly estimates of $P$ and $PET$, are broadly available, and the significant impact of seasonality is explicit. The landscape variables are physically interpretable and may be inferred from either regression of the historical water balance in a watershed (§ 5) or as a function of watershed attributes (§ 7). And the model explicitly accounts for threshold behavior that is a broadly recognized characteristic of watershed hydrology.

Subsequent sections will demonstrate the value of the MCWB model for various uses: characterizing the water balance across California; predicting $R$ given $P$, $PET$, and their seasonality coefficients; evaluating temporal changes in the water balance, and the sensitivity of the water balance to changes in the climate and landscape factors of the MCWB model; a step toward predicting $R$ for ungaged basins; and interpretation of the broadly-used Budyko curve.
5 MCWB Regression and Validation

Given the MCWB model developed in § 4 and the hydrological database described in § 3.3.4, the next objective was to estimate watershed-specific parameters for the MCWB for each of the 159 California watersheds in this study. Based on preliminary exploratory analysis, the expectation was that these inferred parameter values would provide insight about the factors that influence the water balance of a given watershed or a broader region, and also provide a baseline for trend analysis.

Regression was performed on observations of $R$ and estimates of $P_x$ for each watershed in the study, providing estimates of water balance parameter values and uncertainties for each watershed. This section describes the methodology, presents results in detail for three representative watersheds, and summarizes results for all watersheds.

5.1 Methodology: Bayesian Inference of Parameters

5.1.1 Bayesian Modeling Overview

This research used a Bayesian approach to parameter inference for several reasons. Foremost, the uncertainties in estimates of $R$ and $P$ at the watershed scale are typically quite significant but poorly characterized. Because there is uncertainty in both the predictor ($P$) and response ($R$) variables, ordinary least squares regression of the linear segments would introduce systematic biases in the inferred parameter values. Bayesian linear regression reduces these biases [Kelly, 2007], and furthermore the approach provides a robust and explicit method for uncertainty propagation and characterization [Kavetski et al., 2006]. Additionally, a hierarchical Bayesian model offers a flexible framework for sensitivity analysis, model structure comparison, and it facilitates incorporation of additional information, in the form of prior distributions, to constrain model outcomes.

Bayesian inference is accomplished via a structural probabilistic model, where the approach is to represent the model components in terms of statistical distributions, and to consider the random outcomes of each distribution as the inputs to dependent components of the model. The overall outcome of the model is also a distribution of values, and these modeled outcomes are compared with observed outcomes (i.e., input data) to calculate the likelihood of a given set of parameters over many model realizations.

The first and most important step is to specify the model components and relationships, where each component is represented as either a statistical distribution or a deterministic process. An example of the former is representation of total annual $P$ for a given watershed using a probabilistic distribution, and an example of the latter is the deterministic MCWB model that describes the functional relationship between the input variables. Data inputs to the model, e.g. values of $P_x$ and $R$, are modeled as distributions of noisy observations, and the parameters of the noise terms may be described by their own distributions of values.

Given a model that represents the process of interest, in this case the annual water balance, the inference objective is to estimate model parameters that are consistent with the structure of the model and the input data, i.e., observations of $P_x$ and $R$. While in principle it may sometimes be possible to derive these estimates analytically by calculating the marginal probability integral for the parameters of interest, in practice it is often more feasible to use a computational approximation. The standard approach is use Markov Chain Monte Carlo (MCMC) sampling to probe the parameter space and converge on optimal parameter values. MCMC sampling is a family of methods for
stochastic exploration of parameter values that are computationally efficient and result in outcome
distributions that are representative of the underlying, sought distributions [Gelman et al., 2013].

MCMC sampling of a probabilistic model is conceptually straightforward. Beginning with a random
set of parameter values for the specified model, the output of the model is compared with the
observed data to calculate the likelihood of that particular realization. The parameter values are then
varied semi-randomly in a way that is expected to improve the likelihood of the observed data, and
the likelihood is calculated. This process is repeated many times, ideally until the likelihood estimates
converge around the optimal set of parameter values that are consistent with the model structure
and the observed data.

The implementation of MCMC sampling methods and software can be very complex, with
consideration for computational efficiency and stability, fast convergence, and comprehensive
sampling of the parameter space. However, the proliferation of software tools has made MCMC
methods quite accessible and straightforward for data-driven researchers, and the ease with which
these sophisticated methods can be implemented was a strong incentive for the chosen
methodology.

The result of MCMC sampling is a set of values for each parameter of the probabilistic model, each
value the outcome from one model iteration. For instance, a MCMC sampling process with 1,000
iterations will produce 1,000 values for each probabilistic parameter of the model. The distribution
of values for a particular parameter is called the posterior distribution, and MCMC sampling ensures
that this distribution is representative of the posterior probability of the underlying Bayesian
relationship. This posterior distribution is a marginal distribution that implicitly accounts for all
stochastic attributes of the specified model, including observational uncertainties and also
information from the prior distributions specified for all parameters. The spread in a posterior
distribution can be quantified in terms of the credible interval, which as a more intuitive
interpretation than the frequentist confidence interval, best explained by example: if the credible
interval represents 90% of the area of the posterior distribution, then this is interpreted as a 90%
probability that the true value of the parameter lies within this interval.

5.1.2 Bayesian Model for the MCWB
5.1.2.1 Observed Data: \( P_X \) and \( R \)

The model input data consists of \( R \) and \( P_X \) observations for a given watershed, both of which are
assumed to have observation uncertainties that follow a normal distribution with heteroscedastic
standard deviations. Following the Bayesian reasoning about measurement uncertainty [Kelly, 2007],
a given observation \( P_{Xi} \) is assumed to differ from the true, unknown energy-excess precipitation
amount \( \varphi_i \) by measurement error \( \varepsilon_{Pi} \). Likewise, observation \( R_i \) differs from the true streamflow
depth \( \nu_i \) by error \( \varepsilon_{Ri} \),

\[
P_{Xi} = \varphi_i + \varepsilon_{Pi} \\
R_i = \nu_i + \varepsilon_{Ri}
\]

where \( i \) is the observation index, i.e. a particular year. In probabilistic terms, the observations are
assumed to be drawn from a normal distribution, denoted as \( \mathcal{N}(\cdot) \), that is centered about the true,
unknown value, with standard deviations \( \sigma_{PXi} \) and \( \sigma_{Ri} \).
The next sections describe the distribution models for uncertainty parameters $\sigma_{P_x}$ and $\sigma_R$, the estimated true predictor variable $\varphi$, and the estimated true outcome variable $\nu$.

### 5.1.2.1.1 Uncertainty Parameters $\sigma_{P_x}$ and $\sigma_R$

As previously noted, measurement uncertainties are poorly characterized even for the best available sources for $P$, $PET$, and $R$ data, but assumptions can be made about the general characteristics of uncertainty. Since annual values are calculated as the sum of monthly ($P_x$) or daily ($R$) observations with uncertainties that are typically proportional to the absolute observed value, multiplicative uncertainty is a reasonable structure for $\sigma_{P_x}$ and $\sigma_R$.

$$
P_{X,j} \sim N(\varphi_i, \sigma_{P_x,j})
$$

$$
R_i \sim N(\nu_i, \sigma_{R_i})
$$

(18)

where $\sigma_{P_x,o}$ and $\sigma_{R,o}$ are specified lower bounds, and the coefficients $a_{P_x}$ and $a_R$ are characteristic of a given watershed and data source [McMillan et al., 2011]. The lower bounds $\sigma_{P_x,o}$ and $\sigma_{R,o}$ were imposed to reflect the reality that there is always observational uncertainty, and to mitigate computational issues that can arise if a standard deviation is randomly assigned a value very close to zero. Values of $\sigma_{P_x,o} = 10$ mm and $\sigma_{R,o} = 25$ mm were chosen as plausible lower bounds on the observation uncertainty for annual estimates.

Note that the multiplicative uncertainty is a function of the true, unknown values of precipitation and streamflow, $\varphi_i$ and $\nu_i$, not the observed values $P_{X,i}$ and $R_i$. The coefficients are not known a priori, but they can be treated as a stochastic parameter. To establish generality across watersheds with a wide variety of features that may influence measurement uncertainty, a uniform prior distribution is assumed, meaning any value between the specified upper and lower bounds is equally likely.

$$
a_{P_x} \sim U(a_{P_x,\min}, a_{P_x,\max})
$$

$$
a_{R} \sim U(a_{R,\min}, a_{R,\max})
$$

(20)

The $\max$ and $\min$ bounds were chosen based on a multiple considerations: typical uncertainties for daily gage observations, model sensitivity analysis, mass balance constraints for annual fluxes, and uncertainty estimates in prior studies.

$$
\begin{bmatrix}
a_{P_x,\min} & a_{P_x,\max} \\
-0.10 & 0.10
\end{bmatrix}
$$

$$
\begin{bmatrix}
a_{R,\min} & a_{R,\max} \\
-0.10 & 0.10
\end{bmatrix}
$$

(21)

This represents a maximum standard deviation of approximately 10% of the absolute amount of precipitation or runoff. Inspection of the inferred distributions (i.e., posterior distributions) of $a_P$
and $a_R$ indicated that the optimal estimate typically fell between these bounds. For ~10% of watersheds these bounds led to unfavorable model outcomes, i.e., the estimated values were essentially the same as the upper bound, suggesting that the bound was artificially constraining estimation of the true value of $a_P$ or $a_R$. In these cases, the upper bound was manually adjusted to achieve satisfactory model convergence.

5.1.2.1.2 Estimated True Predictor $\phi$

Recall that observations of energy-excess precipitation $P_X$ can be calculated as,

$$P_X = P_{\text{wet}} - PET_{\text{wet}}$$

The true, unknown value of annual excess precipitation, $\phi_i$, is assumed to be drawn at random from some source distribution $p(\phi | \psi)$, where $\phi$ is a vector of $\phi_i$ realizations and $\psi$ is a vector of parameters that describe the source distribution. Precipitation accounts for the vast majority of the variation in annual excess precipitation, as shown in the representative example of Figure 17, where by contrast the effect of $PET$ is relatively consistent and proportional year-to-year. Thus, $\psi$ is dominated by the factors that determine annual precipitation at a given location. Quite simply this means the weather, which is influenced by climate dynamics, proximity to water bodies, and orography, among many other variables. This combination of stochastic and deterministic factors drives the likelihood of a given amount of precipitation in any year.

This study assumes that the source distribution of true, unknown $\phi_i$ in a given watershed is the same as the observed historical distribution of $P_X$ values at that location. One advantage of this approach is that the long-term historical $P_X$ record is the best available estimate of future $P_X$ under stationary conditions. While it is shown in § 6.1.5 that $P_X$ is not generally stationary, the rate of change is typically small relative to the magnitude of $P_X$. One disadvantage of this approach is the conceptual discordance of sampling true precipitation values from a source distribution constructed from noisy observations, though observational noise is small relative to the magnitude of variation in $P$ and can be expected to largely cancel out within the distribution.

The long-term records of $P_Xs$, derived from $P$ and $PET$ estimates, were found to be well-approximated by a mixture of two normal distributions that captures the skew and bi-modality observed in the historical data,

$$\phi_i \sim \sum_{k=1}^{2} \pi_k N(\mu_{\phi k}, \sigma_{\phi})$$

where $\pi_k$ is the mixture proportion, $\mu_{\phi k}$ is the mean value for normal distribution $k$, and $\sigma_{\phi}$ is the standard deviation common to both normal distributions. It was found that restricting both normals to have the same standard deviation $\sigma_{\phi}$ yielded more consistent fitting than allowing the value to vary across the mixture, a purely computational constraint. The parameter vector for the predictor distribution was thus defined as $\psi = [\pi_k \mu_{\phi k}, \sigma_{\phi}]$, and parameter values for each watershed were inferred using historical $P_X$ records, as demonstrated for a representative watershed in Figure 21.
Figure 21: Historical distribution of annual $P_X$ for the Russian River watershed at Ukiah. The histogram (solid black) and density (dashed black) lines indicate the empirical distribution of observed $P_X$. The estimate for the precipitation source distribution $\varphi$ is the sum (blue) of two normal distributions (red and green) with differing means and weights (sum = 1) but identical variance. This mixed normal distribution provides a good approximation to the empirical density and is representative of results across California. For this example $\mu_1 = 463$ mm, $\mu_2 = 811$ mm, $\pi_1 = 0.71$, $\pi_2 = 0.29$, and $\sigma_\varphi = 147$ mm.

5.1.2.1.3 Predictor Data Recap

The predictor data model is summarized as follows,

$$\varphi_i \sim \sum_{k=1}^2 \pi_k N(\mu_{\varphi k}, \sigma_\varphi)$$

(22)

$$P_{X,i} \sim N(\varphi_i, \sigma_{P_X,i})$$

(23)

$$\sigma_{P_X,i} = \sigma_{P_X,o} + a_{P_X} \varphi_i$$

(24)

$$a_{P_X} \sim U(0,a_{P_X,max})$$

(25)

For year $i$ the true total energy-excess precipitation $\varphi_i$ is assumed to be drawn at random from a source distribution that is approximated by a mixed normal fit to the long-term $P_X$ record, specified by mixing proportions $\pi_k$, distribution means $\mu_{\varphi k}$, and standard deviation $\sigma_\varphi$. The observation $P_{X,i}$ is taken to be a noisy realization of $\varphi_i$ with standard deviation $\sigma_{P_X,i}$. The observational uncertainty $\sigma_{P_X,i}$ is assumed to have a linear structure, with some minimum value $\sigma_{P_X,o}$ and slope $a_{P_X}$ that is unknown but assumed to be uniformly likely between zero and $a_{P_X,max}$.
An implication of this model structure is that estimates of $\phi_i$ tend toward the most likely values (i.e., the peaks) of the mixed normal historical distribution via Eq. (22), and simultaneously implicitly tend toward observed values of $P_X$ per Eq. (23). The “strength” of this tendency is determined by the standard deviations $\sigma_{\phi}$ for the historical distribution and $\sigma_{P_X}$ for the observations, with observations dominating the annual estimates and the historical likelihood exerting a smaller but non-trivial effect.

5.1.2.2 Estimated True Runoff $\nu$

The objective of the MCWB model is to estimate $R$ as a function of $P_X$, so the true, unknown runoff $\nu$ is necessarily assumed to be a function of true energy-excess precipitation $\phi$, specified by a parameter vector $\theta$. This functional relationship is subject to an additional error term $\epsilon$ that represents the intrinsic or structural uncertainty of the model, i.e. random variations in the runoff response that are not accounted for by $P_X$ even if predictors and response are perfectly characterized.

$$\nu_i = f(\phi_i, \theta) + \epsilon_i$$  \hspace{3cm} (26)

where as before $i$ is the index for given water year. The model parameters, form, and intrinsic uncertainty are described next.

5.1.2.2.1 MCWB Model Parameters $\theta$

The main objective of the Bayesian model is to estimate values for the hydrological parameters $\theta$ that are specific to each watershed in the study. As described in detail in § 4.5.2 and summarized in Figure 18, the MCWB parameters are,

$$\theta = \left[ \alpha_{\text{mid}}, \alpha_{\text{wet}}, c \right]$$  \hspace{3cm} (27)

where $\alpha_{\text{mid}}$ and $\alpha_{\text{wet}}$ are the slopes $dR/dP_X$ for mid-range and wet conditions respectively, and $\epsilon$ is the threshold value of $P_X$ that signifies the transitions between mid-range and wet conditions (recall from Table 2 that the storage retention threshold $S^*$ is easily derived from $\epsilon$). As with all outputs from a Bayesian model, estimates of the elements in $\theta$ are not single-valued but rather a distribution of values that are consistent with the specified model and observed data. In terms of prior expectations for the parameters, uniform distributions were chosen to maintain generalizability,

$$\alpha_{\text{mid}} \sim U\left(0, \alpha_{\text{mid max}}\right)$$
$$\alpha_{\text{wet}} \sim U\left(\alpha_{\text{mid max}}, \alpha_{\text{wet max}}\right)$$
$$c \sim U\left(0, c_{\text{max}}\right)$$

The bounds for the uniform distributions were chosen as follows. In principle, $\alpha_{\text{wet max}}$ would be constrained $\leq 1$ to honor mass conservation, but in practice a value of $\alpha_{\text{wet max}} = 1.2$ was used to accommodate the prevalence of uncertainties in the input variables, such as systematic underestimates of $P$ or overestimates of $R$ that caused $dR/dP$ to sometimes exceed unity. The maximum value of $\epsilon$ was simply chosen to be $\epsilon_{\text{max}} = \max(P_X)$, which constrains the transition between mid-range and wet conditions to fall within the bounds of observed $P_X$. 

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Selecting a value for $\alpha_{\text{mid, max}}$ required more careful consideration. Given an upper bound $\alpha_{\text{wet, max}}$, the value for $\alpha_{\text{mid, max}}$ essentially constrains the range of values of $dR/dP$ that would be considered wet runoff conditions. Considering the conceptual framework that suggests wet conditions are at or near saturation, such that any increase in $P_X$ results in a nearly equivalent amount of $R$, it would be desirable to define a narrow range for wet $dR/dP \sim 1$, and several iterations of parameter selection did indeed use values of 0.8 or more for $\alpha_{\text{mid, max}}$. However, as is often the case in data-driven modeling, the results were not as tidy as expectations. Specifically, there were a non-trivial number of watersheds (~30) where there was a distinct change in the runoff rate, but the steepest segment of the slope was in the range of 0.7. Following extensive experimentation with a range of values for this critical hyperparameter, a value of $\alpha_{\text{mid, max}} = 0.6$ was found to provide the most satisfactory results in terms of good convergence around estimates of $\theta$ and very few watersheds (<10) where the posterior distributions appeared to be artificially influenced by this choice.

5.1.2.2.2 Response Model $f(\phi, \theta)$

The general form of the response of true runoff $\nu_i$ to true energy-excess precipitation $\phi_i$ for a given water year $i$ was defined in Eq. (26). Uncertainty in $\phi_i$ propagates to uncertainty in $\theta$, as does every uncertainty in the model; the output estimates, or posterior distributions, of $\theta$ are marginal distributions that account for all specified model uncertainties. This explicit propagation of uncertainties, and a flexible framework for quantifying information about these uncertainties, are advantages of the Bayesian approach.

Note that Eq. (26) can be extended to allow for time dependent variations in the MCWB model parameters, $\theta(t)$. Examples of such variations include changes to climate forcing factors, land cover conversion, natural vegetation changes, or streamflow manipulation. Such influences could also affect the intrinsic model uncertainty, such that, in general,

$$\nu_i = f(\phi_i, \theta(t)) + \epsilon_i(t)$$

This more general model was explored for applications such as automatically detecting changes to MCWB parameters, including both step changes and continuous changes. Ultimately, it was determined that the available data record was insufficient to support robust conclusions about such changes, and so those results are not presented here.

5.1.2.2.3 Intrinsic Model Uncertainty $\sigma_i$

Because runoff must be positive or zero (except in the case of nested watersheds with a net decrease in runoff) the assumed form for a probabilistic representation of $\nu$ was a truncated normal distribution,

$$\nu_i \sim N(f(\phi_i, \theta), \sigma_i) \ T[0, \infty]$$

where $T[.]$ indicates the truncation bounds and $\sigma_i$ is the standard deviation of the intrinsic uncertainty $\epsilon_i$. Note that $\sigma_i$ is not generally known and therefore it must be inferred as a probabilistic estimate, however it can be constrained based on knowledge of the modeled relationship. Specifically, a lower bound $\sigma_{\theta} = 25$ mm was specified to reflect the reality that $R$ is never perfectly predicted by $P_X$ and to prevent over-fitting of the model. Following recommended practice for
estimating a homoscedastic standard deviation [Gelman, 2006], the prior of $\sigma_I$ is a Cauchy distribution with a broad scaling parameter,

$$\sigma_I \sim C(\sigma_{Io}, \zeta_I)$$

(29)

where the scale hyperparameter $\zeta_I = 100$ mm was specified to be large enough that the prior distribution is only weakly informative, i.e. $\sigma_I$ is only weakly constrained for values above $\sigma_{Io}$.

It is worth noting that two types of errors contribute to uncertainty in the response axis: runoff observation uncertainty $\sigma_R$ and intrinsic model uncertainty $\sigma_I$. In principle these can be inferred individually because the structure differs; $\sigma_R$ is heteroscedastic, increasing linearly with $\nu$, whereas $\sigma_I$ is homoscedastic and independent of $\nu$. However, the lower bound for observational uncertainty $\sigma_{Ro}$ is structurally similar to $\sigma_I$ because it is also a homoscedastic component. Furthermore, as $\alpha_R$ approaches zero the observational and intrinsic uncertainties become structurally indistinguishable. This does not inhibit the ability to infer the MCWB parameters $\theta$, which are the primary interest, but it introduces some ambiguity about uncertainty characterization, as illustrated in Figure 22.

![Figure 22: Illustration of the general relationship between the standard deviation of response variables and the value of the predictor variable $\phi$. Total response uncertainty $\sigma_v$ is a function of runoff observation uncertainty $\sigma_R$ and intrinsic model uncertainty $\sigma_I$. The observation uncertainty slope $\alpha_R$ can be independently estimated, but the minimum observation uncertainty $\sigma_{Ro}$ is ambiguous with $\sigma_I$.](image)

5.1.2.3 Model Summary

Given the preceding description of the model predictors, outcomes, and uncertainty terms, the model can be summarized holistically using Figure 23 as a guide, with numbered items corresponding to labels in that figure.

1. The modeling objective was to estimate MCWB parameters $\theta = \left[ \alpha_{mid}, \alpha_{wet}, c \right]$, which were assigned uniform prior distributions with heuristically-derived bounds.
2. The true predictor values $\phi$ (i.e., true, unobserved values of $P_X$) were assumed to be realizations of a mixed normal distribution, per Eq. (22).
3. The prior distributions of the mixed normal parameters were assumed to be uniform, reflecting the lack of prior expectations about the source distribution of $P_X$. 
4. The true response values $\nu$ (i.e., true, unobserved values of $R$) were estimated using a deterministic function of $\phi$ and $\theta$, generically referred to as $\nu = f(\phi, \theta)$. This relationship was assumed to have intrinsic model noise $\sigma_I$ that was inferred by the model using a Cauchy prior distribution.

5. The specific form of $\nu = f(\phi, \theta)$ was the MCWB model, Eq. (16).

6. Observations of $P_X$ and $R$ were incorporated into the model via normal distributions that assumed the observations were realizations of a noisy measurement centered on the true, unknown value of $\phi$ or $\nu$ respectively.

7. The observation uncertainties $\sigma_{P_X}$ and $\sigma_R$ $P_X$ and $R$ were assumed to be heteroscedastic and multiplicative functions of the true predictor and response values, where the multiplier coefficients $a_{P_X}$ and $a_R$ were inferred by the model.

The uncertainty parameters that were inferred by the model were collectively assigned to the vector $\Omega = [\sigma_I, a_{P_X}, a_R]$. The model’s functional relationships are summarized in Table 3, and parameter descriptions and values are summarized in Table 4.

---

**Figure 23:** MCWB Bayesian inference model, segmented (from bottom to top) by input $P_X$ and $R$ data with observation uncertainties, intrinsic model uncertainty, model and hyperparameters, and input data from observed precipitation distributions. Detailed description provided in § 5.1.2.3.
<table>
<thead>
<tr>
<th>Functional Relationship</th>
<th>Form</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Energy-Excess Precipitation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>True, unknown precipitation excess</td>
<td>$\varphi_i \sim \sum_{k=1}^{2} \pi_k N(\mu_{\varphi_k}, \sigma_{\varphi_k})$</td>
<td>Mixed normal, $\pi_k$, $\mu_{\varphi_k}$, and $\sigma_{\varphi_k}$ empirically estimated from long-term $P_X$ record</td>
</tr>
<tr>
<td>$P_X$ observation noise</td>
<td>$a_{P_x} \sim U(0, a_{P_{x,\text{max}}})$</td>
<td>Heteroscedastic, multiplicative uncertainty with specified min value $a_{P_{x,\text{min}}}$ and slope $a_{P_x}$ with a uniform prior</td>
</tr>
<tr>
<td>Observed P</td>
<td>$P_{X,i} \sim N(\varphi_i, \sigma_{P_{X,i}})$</td>
<td>Normal centered on $\varphi_i$ with noise std. dev. $\sigma_{P_{X,i}}$</td>
</tr>
<tr>
<td><strong>Runoff</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>True, unknown runoff</td>
<td>$\nu \sim N(f(\varphi, \theta), \sigma_i) \cdot T[0, \infty]$</td>
<td>Truncated normal centered on modeled runoff value with intrinsic uncertainty $\sigma_i$</td>
</tr>
<tr>
<td>Modeled R</td>
<td>$\theta = \begin{bmatrix} \alpha_{\text{mid}}, \alpha_{\text{wet}}, c \end{bmatrix}$</td>
<td>$\alpha_{\text{mid}} = \text{mid-wetness } dR/dP$ $\alpha_{\text{mid}} = \text{wet conditions } dR/dP$ $c = \text{wetness threshold}$</td>
</tr>
<tr>
<td></td>
<td>$f(\varphi, \theta) = \text{MCWB Model}$</td>
<td>Model uncertainty given perfect observations; Cauchy prior distribution</td>
</tr>
<tr>
<td>Intrinsic model uncertainty</td>
<td>$\sigma_i \sim C(\sigma_{I_0}, \zeta_i)$</td>
<td>Model uncertainty given perfect observations; Cauchy prior distribution</td>
</tr>
<tr>
<td>R observation noise</td>
<td>$a_R \sim U(0, a_{R_{\text{max}}})$</td>
<td>Multiplicative uncertainty with specified min value $a_{R_{\text{min}}}$ and slope $a_R$ with uniform prior</td>
</tr>
<tr>
<td>Observed R</td>
<td>$R_i \sim N(\nu_i, \sigma_{R_{ij}})$</td>
<td>Normal centered on $\nu_i$ with noise std. dev. $\sigma_{R_{ij}}$</td>
</tr>
</tbody>
</table>

*Table 3: Summary of MCWB Bayesian model functional relationships.*
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \pi_k )</td>
<td>mixed normal proportions for ( \varphi )</td>
<td>inferred from historical ( P_X ), uniform prior</td>
</tr>
<tr>
<td>( \mu_{\varphi_k} )</td>
<td>mixed normal means for ( \varphi )</td>
<td>inferred from historical ( P_X ), uniform prior</td>
</tr>
<tr>
<td>( \sigma_{\varphi} )</td>
<td>mixed normal std. dev. for ( \varphi )</td>
<td>inferred from historical ( P_X ), uniform prior</td>
</tr>
<tr>
<td>( \psi )</td>
<td>vector of excess precip source distribution parameters ( [\pi, \mu_{\varphi}, \sigma_{\varphi}] )</td>
<td>inferred from historical ( P_X )</td>
</tr>
<tr>
<td>( a_{P_X} )</td>
<td>( P_X ) observation noise multiplicative coefficient</td>
<td>inferred by model</td>
</tr>
<tr>
<td>( a_{P_X,\text{max}} )</td>
<td>max value for ( P_X ) observation noise multiplicative coefficient</td>
<td>= 0.15, i.e. 15% uncertainty</td>
</tr>
<tr>
<td>( \sigma_{P_X,o} )</td>
<td>minimum std. dev. of ( P_X ) observations</td>
<td>= 10 mm</td>
</tr>
<tr>
<td>( \sigma_I )</td>
<td>intrinsic uncertainty of ( R ) as function of ( P_X )</td>
<td>inferred by model</td>
</tr>
<tr>
<td>( \sigma_{I_0} )</td>
<td>lower bound for intrinsic uncertainty</td>
<td>= 25 mm</td>
</tr>
<tr>
<td>( \zeta_I )</td>
<td>scale value for ( \sigma_I ) Cauchy distribution</td>
<td>= 100 mm</td>
</tr>
<tr>
<td>( \sigma_{R_o} )</td>
<td>minimum std. dev. of ( R ) observations</td>
<td>= 0 mm</td>
</tr>
<tr>
<td>( a_R )</td>
<td>( R ) observation noise multiplicative coefficient</td>
<td>inferred by model</td>
</tr>
<tr>
<td>( a_{R_{\text{max}}} )</td>
<td>upper bound on ( a_R )</td>
<td>= 0.1, i.e. 10% uncertainty</td>
</tr>
<tr>
<td>( \alpha_{\text{mid}} )</td>
<td>( \frac{d R}{d P_X} ) for mid-level wetness conditions</td>
<td>inferred by model</td>
</tr>
<tr>
<td>( \alpha_{\text{wet}} )</td>
<td>( \frac{d R}{d P_X} ) for wet conditions with</td>
<td>inferred by model</td>
</tr>
<tr>
<td>( c )</td>
<td>threshold value of ( P_X ) for transition from mid-level to wet conditions</td>
<td>inferred by model</td>
</tr>
<tr>
<td>( \theta )</td>
<td>vector of model parameters ( [\alpha_{\text{mid}}, \alpha_{\text{wet}}, c] )</td>
<td>inferred by model</td>
</tr>
<tr>
<td>( \Omega )</td>
<td>vector of model uncertainties ( [\sigma_{\varphi}, a_{P_X}, a_R] )</td>
<td>inferred by model</td>
</tr>
<tr>
<td>( \alpha_{\text{mid,max}} )</td>
<td>max value for ( \frac{d R}{d P_X} ) for mid-level wetness conditions</td>
<td>= 0.6</td>
</tr>
<tr>
<td>( \alpha_{\text{wet,max}} )</td>
<td>max value for ( \frac{d R}{d P_X} ) for wet conditions</td>
<td>= 1.2</td>
</tr>
<tr>
<td>( c_{\text{max}} )</td>
<td>max value for wetness threshold ( c )</td>
<td>= ( \max(P_X) ) for given watershed</td>
</tr>
</tbody>
</table>

*Table 4: Summary of MCWB model parameters and assigned values.*
5.1.3 Model Inference
Given the probabilistic model of § 5.1.2, the inference challenge is to estimate the joint vector of unknowns \( \nu, \phi, \theta, \Omega \), where as before \( \nu \) and \( \phi \) are the true, unknown values of streamflow and excess precipitation, \( \Omega \) is the vector of MCWB model parameters to be estimated, and \( \theta \) is the vector of model uncertainties, per Table 4. The solution will maximize the posterior probability of the model conditioned on the observations \( P_X \) and \( R \) and the parameters of the \( P_X \) source distribution \( \psi \). In probabilistic notation,

\[
p(v, \phi, \theta, \Omega | P, R, \psi) \propto p(P, R | v, \phi, \theta, \Omega, \psi) p(v, \phi, \theta, \Omega)
\]

where \( p(v, \phi, \theta, \Omega | P, R, \psi) \) is the desired posterior probability, the data likelihood is \( p(P, R | v, \phi, \theta, \Omega, \psi) \), and the prior probability is \( p(v, \phi, \theta, \Omega) \).

An analytical solution to the posterior \( p(v, \phi, \theta, \Omega | P, R, \psi) \), if it is possible, would require full specification of the marginal data likelihood averaged over \( \phi \) and \( v \) [Gelman et al., 2013],

\[
p(P, R | \theta, \Omega, \psi) = \int \int p(P, R, v | \theta, \Omega, \psi) d\phi dv
\]

Assuming independent priors for \( \theta \) and \( \psi \), the posterior becomes,

\[
p(\theta, \Omega | P, R) \propto p(\theta) p(\Omega) \int \int p(P, R | \phi, v, \Omega) p(v | \phi, \theta, \Omega) p(\phi | \psi) d\phi dv
\]

The power of the MCMC sampling approach is that it eliminates the need to evaluate these integrals by iteratively proposing and evaluating model parameter values in search of an overall solution that is statistically comparable to the analytical solution.

5.1.4 Inference Software: Stan Probabilistic Programming Language
Bayesian modeling and MCMC sampling was accomplished with the Stan Probabilistic Programming Language [Carpenter et al., 2016] and the R statistical computing language [R Development Core Team, 2008]. Stan uses the No-U-Turn sampler [Hoffman and Gelman, 2014], a variation on the Hamiltonian Monte Carlo sampler which offers straightforward implementation and faster convergence for high-dimensional models relative to alternatives such as Gibbs and Metropolis-Hastings MCMC samplers.

The Bayesian inference programming code for this research is available online [Moran, 2015a]. The Bayesian model consists of roughly 100 lines of C++ code, with an additional 2,000 lines of R code to support an automated data processing pipeline.

5.2 Inferred Parameters: Representative Watersheds
5.2.1 Model Outcomes: Representative Watersheds
To develop an intuition for the outcomes of the probabilistic model described in § 5.1, outputs for three representative watersheds are first discussed. Referring to the same set of watersheds as...
previously discussed in Figure 11, one from each of the wetness regimes *Arid*, *Mesic*, and *Humid*, the posterior distributions of inferred model parameters $\Omega = [\alpha_{\text{mid}}, \alpha_{\text{wet}}, c]$ are shown in Figure 24, recalling that parameter $c$ was inferred rather than the physically interpretable $S^*$ for computational considerations. These density plots were produced from the individual parameter outcomes of 10,000 iterations of MCMC sampling for each watershed. Recall that the posterior distribution represents the marginal probability of the true parameter value given the input observations and the model structure, including uncertainties in all other parameters and hyperparameters. Unless otherwise specified the best estimate of a parameter is taken to be the median of the posterior distribution.

Starting with the arid watershed, note that the range of values for $\alpha_{\text{mid}}$ is very small, reflecting high confidence that $\alpha_{\text{mid}} \approx 0$. The posterior distribution for $\alpha_{\text{mid}}$ peaks near 0.9 mm/mm that tapers steadily toward zero in the vicinity of 0.7 and 1.1 mm/mm. This type of unimodal distribution is desirable for parameter estimation because it implies that there is a single most likely value with well-characterized uncertainty in the estimate, and that the overall model structure is stable with respect to the input observations. The estimate for $c$ is likewise well-behaved, with a mode near 170 mm and a roughly normal distribution.

The watershed with mesic wetness yielded a posterior distribution of $\alpha_{\text{mid}}$ that is tightly centered near 0.5 mm/mm. The estimate for $\alpha_{\text{wet}}$ is less definitive, with values essentially equally likely between

---

*Figure 24: Posterior distributions of Bayesian model parameter estimates for representative California watersheds from each of the three wetness categories: Tahquitz Creek (arid), Kaweah River (Mesic), and the Russian River at Ukiah (wet), the same examples as Figure 11 and Table 5. Note that axes scales vary by parameter and wetness type.*
0.95 and 1.25 mm/mm. Noting the observations in Figure 11, this uncertainty appears to stem from the relatively few data for wet conditions. In this situation the median value of the distribution is not particularly informative as a best estimate, as the true value is just as likely to lie anywhere within 0.3 mm/mm near the median, but it is as reasonable a choice as any value in that range. The distribution of estimates for \( c \) is notable because most of the area of the distribution is centered near 750 mm, but there is a long tail of zero likelihood that the value is much larger. Referring again to Figure 11, this represents realizations of the probabilistic model where the two largest values of \( R \) are treated as outliers, such that the best fit of the model is simply an indefinite extension of mid-range wetness slope, as represented by the faint blue lines that continue along the path of the \( \alpha_{\text{mid}} \) line.

The posterior of \( \alpha_{\text{mid}} \) for the humid watershed is highly skewed, with the mode, the most likely value, near 0.45 mm/mm and a wide tail toward 0. This suggests that the mode might sometimes be preferable to the median as a best estimate, but the median is more robust to anomalous posterior distributions such as multi-modality (not shown here). Furthermore, in this particular case, Figure 11 shows that the skew in this estimate of \( \alpha_{\text{mid}} \) is driven by just a single data point; without that observation the posterior would be essentially flat between the bounds of the uniform prior distribution of \( \alpha_{\text{mid}} \) between 0 and 0.6 mm/mm. This lack of data in mid-range conditions is broadly the case for humid watersheds, and thus model estimates of \( \alpha_{\text{mid}} \) are generally not very informative for this watershed type. In contrast, estimates for \( \alpha_{\text{wet}} \) are centered fairly tightly around 0.93 mm/mm, indicating confident convergence near this value. The posterior for \( c \) is somewhat broad in the region of 150 to 250 mm, and this breadth is again symptomatic of the lack of mid-range wetness data that would improve characterization of the transition to wet conditions.

Parameter estimates for these representative watersheds are summarized in Table 5, with the median of the posterior distribution used as the best estimate and 80% credible intervals specified in square brackets.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Arid</th>
<th>Mesic</th>
<th>Humid</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_{\text{mid}} ) [mm/mm]</td>
<td>0.005 [0.0011, 0.009]</td>
<td>0.50 [0.47, 0.53]</td>
<td>0.34 [0.09, 0.48]</td>
</tr>
<tr>
<td>( \alpha_{\text{wet}} ) [mm/mm]</td>
<td>0.91 [0.81, 1.0]</td>
<td>1.1 [0.91, 1.30]</td>
<td>0.93 [0.88, 0.99]</td>
</tr>
<tr>
<td>( c ) [mm]</td>
<td>185 [163, 211]</td>
<td>750 [639, 902]</td>
<td>216 [147, 299]</td>
</tr>
</tbody>
</table>

*Table 5: Estimated parameter values of R vs. P relationship for representative watersheds of each wetness type: Tahquitz Creek (arid), Kaweah River (Mesic), and the Russian River at Ukiah (wet). The median of the posterior distribution is cited as the best estimate, with 80% credible intervals in square brackets.*
5.3 **Inferred Parameters: Statewide Results**

The primary objective of this study was to broadly characterize the annual water balance across many watersheds in California, and so these broader patterns will receive the most attention and explication. This section presents various views of the results of MCWB model parameter estimates for the 159 watersheds in the study. Interactive versions of all maps as well as analysis outcomes for each watershed are available online [Moran, 2014].

5.3.1 **Watershed Wetness Categories**

Once parameters were inferred for each of the 159 watersheds in this study, each watershed was categorized by the prevailing wetness of the watershed as *Arid*, *Mesic*, or *Humid*. This was accomplished by visual inspection of $R$ vs. $P_X$ plots, such as those in Figure 11, using the heuristics described in § 3.4.3. An additional category of “no fit” was assigned to watersheds for which the regression shape does not conform to the expectations that a) $a_{mid} < a_{wet}$, and b) that $R$ and $P_X$ converge at the origin, both of which are implications of mass conservation; such cases were rare (7 watersheds). The geographic distribution of watershed types is shown in Figure 25, with pronounced regionalization and clustering that generally corresponds to the prevailing climate and landscape features in each area: humid watersheds are found primarily in the far north and high Sierras, arid watersheds in the southern inlands, and mesic conditions in the central foothills and higher elevations in the south.

Overall there is a strong correspondence between the average aridity of a watershed, as shown in Figure 26, and the watershed wetness category. This relationship is explored in more detail in § 7.2.2.1.
Figure 25: Geographic distribution of wetness categories for the 159 study watersheds, color-coded by wetness category: arid (blue), mesic (red), humid (green), and “no fit” (grey).
5.3.2 MCWB Model Parameter Estimates
Best estimates of the three primary MCWB model parameters for all 159 study watersheds are summarized in the boxplots of Figure 27. Note the wetness threshold parameter is represented as $S^*$ rather than $c$. This is because the storage retention threshold $S^*$ has a more physically intuitive interpretation than the energy-excess precipitation threshold $c$, and the transformation between the two is trivial (Table 2).
5.3.2.1 Storage Retention Threshold $S^*$

Recall that $S^*$ represents the wet-season storage capacity associated with a transition to wet runoff conditions. The distribution of $S^*$ values for arid and mesic watersheds is centered fairly narrowly near 250 mm, as shown in Figure 27. Note that $S^*$ is not interpreted as the physical storage capacity of a watershed; it captures only the evaporation component of inter-seasonal storage, and thus it is not possible to make direct comparisons with physical sub-surface storage in a watershed. However, $S^*$ has some association with physical storage, and it is noteworthy that a value of 250 mm is consistent with rule-of-thumb estimates of soil water storage, for example soil with a depth of 1 m and porosity of 0.25 would have effective storage capacity of 250 mm.
Estimates of $S^*$ for humid watersheds have limited utility because, as illustrated in Figure 11, conditions are almost always wet for such watersheds. Thus, estimates of the transition from mid-range to wet conditions are essentially driven by parameter constraints imposed by the probabilistic model, rather than by the underlying data.

5.3.2.2 Mid-range Runoff Rate $\alpha_{\text{mid}}$

The best estimates for $\alpha_{\text{mid}}$ vary significantly by wetness regime. Per Figure 27, all arid watersheds have values near zero by definition; this was the heuristic for classifying arid watersheds. For humid watersheds there is a concentration of values near 0.3 mm/mm, and this is also not surprising since such watersheds generally have few if any years with mid-range conditions, and thus the median of the posterior distribution of $\alpha_{\text{mid}}$ estimates simply reflects equally likely values between the bounds of 0 and 0.6 mm/mm that were specified in § 5.1.2.2.1. By contrast, the estimates for mesic watersheds are driven by observations, and there is a broad spread of values, with some central tendency between 0.15 and 0.35 mm/mm.

5.3.2.3 Wet Conditions Runoff Rate $\alpha_{\text{wet}}$

The parameter $\alpha_{\text{wet}}$ represents the runoff rate for wet years in a given watershed. A value near unity means that any marginal increase in wet-season precipitation contributes directly to runoff, which implies saturated conditions. As shown in Figure 27, slope values for mesic and humid watersheds are typically between 0.8 and 1.1 mm/mm, with a narrower spread for humid watersheds. In principle it should be true that $\alpha_{\text{wet}} \leq 1$ for consistency with mass conservation of the water balance of Eq. (1), unless storage change is non-negligible or there are other factors contributing to the water balance such as subsurface flow. While those possibilities cannot be ruled out, perhaps a more likely explanation for observations of $\alpha_{\text{wet}} > 1$ is systematic overestimation of R or underestimation of P for those watersheds. For arid watersheds $\alpha_{\text{wet}}$ does not necessarily represent saturated conditions, but simply the slope of the first segment of non-negligible runoff, which may be more appropriately categorized as mesic wetness conditions. This ambiguity is addressed in the context of standardized water balance features in the next section.

5.3.3 Standardized Water Balance Features

To more robustly compare water balance parameter estimates for all 159 watersheds of this study it is necessary to resolve ambiguities in the interpretation of the parameters across the watershed wetness categories. Figure 28 introduces four water balance features, runoff threshold TR, wet conditions threshold TW, initial slope SI, and terminal slope ST, and the corresponding MCWB model parameter values for each wetness type. These standardized features are used only in this section for the purpose of discussing statewide patterns. The features are briefly introduced here then elaborated upon individually in the subsequent sections.
The runoff threshold TR is the typical value of $P_X$ for which $R$ is non-negligible. For arid watersheds this corresponds to MCWB parameter $c$, for mesic watersheds the value is always 0, and for humid watersheds the value is the $g$ intercept of Figure 13. The wet conditions threshold TW is the value of $P_X$ at which there is a transition from mid-range to wet conditions as the runoff slope increases from $\alpha_{\text{mid}}$ to $\alpha_{\text{wet}}$. For arid and mesic watersheds this value is $c$, whereas humid watersheds do not generally exhibit such a transition because conditions are always wet. The “initial runoff slope” SI refers to the runoff rate $dR/dP_X$ for the first linear segment where $P_X > 0$; this value is $\alpha_{\text{mid}}$ for arid and mesic watersheds and undefined for humid watersheds. The “terminal runoff slope” ST is the largest observed runoff rate, which is always $\alpha_{\text{wet}}$ for all wetness categories. These definitions are summarized in Table 6. The “no fit” category is included in Figure 28 for completeness, but this pathological type is not generally addressed in discussions.
<table>
<thead>
<tr>
<th>Parameter term</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Runoff threshold <strong>TR</strong></td>
<td>Value of $P_X$ for which $R &gt; 0$</td>
</tr>
<tr>
<td>Wet conditions threshold <strong>TW</strong></td>
<td>Value of $P_X$ where runoff slope increases from $\alpha_{\text{mid}}$ to $\alpha_{\text{wet}}$</td>
</tr>
<tr>
<td>Initial runoff slope <strong>SI</strong></td>
<td>Initial slope $dR/dP_X$ for $P_X &gt; TR$</td>
</tr>
<tr>
<td>Terminal runoff slope <strong>ST</strong></td>
<td>Slope of $dR/dP_X$ for $P_X &gt; TW$</td>
</tr>
</tbody>
</table>

Table 6: Definition of water balance features defined for comparison across wetness types.

5.3.3.1 Runoff Threshold **TR**

The runoff threshold **TR** is the typical value of $P_X$ for which non-negligible $R$ is observed in a given watershed. Recall that $P_X$ represents the portion of $P$ that is not evaporated during the wet season and thus it either departs the watershed as $R$ or is carried over into the dry season as storage. High values of **TR** indicated that some amount of $P_X$ is entirely retained as storage and then completely evaporated during the dry season. Low values of **TR** indicate that some fraction of $P_X$ is always conveyed into $R$, either in the wet season or dry season.

![Figure 29: Boxplot of estimated values for the runoff threshold TR, by watershed type. Observations are indicated by blue x, central bars indicate the median, boxes indicate 50th percentile, stems indicate 90th percentile, and outliers are represented as black dots. Watersheds counts: arid N=23, mesic N=86, humid N=50.](image)

The distributions of **TR** values are depicted by watershed category in Figure 29. For many watersheds the value of **TR** is near 0, which is expected because mesic watersheds are defined to have $TR \approx 0$. Occurrences of **TR** $>> 0$ are generally limited to arid watersheds (see Figure 11), where it is plausible that long intervals between precipitation events and rapid evapotranspiration cause $E$ to dominate except for relatively wet years. Humid watersheds are characterized by prevailing wet
conditions, with little or no data in the mid-range wetness regime. Thus, the values of $TR$ for humid watersheds are not true estimates but rather inferred upper bounds calculated via the $g$ parameter along the $P_X$ axis of Figure 18; that is, the best that can be said is $TR \leq g$ for humid watersheds.

The geographic distribution of $TR$ values is shown in Figure 30. There is regionalization of similar values, though for this feature the perspective is not particularly informative because the values closely track the watershed wetness type, and as noted the values for humid watersheds are not credible.

Figure 30: Geographic distribution of estimates for runoff threshold $TR$ for the 159 study watersheds, color-coded by value in mm. There is some regional clustering of values, but for the TR feature this is not particularly informative because the values are tightly correlated with the watershed wetness type. Estimates are not credible for humid watersheds in the far north and high Sierras due to sparsity of data years when conditions are dry enough to observe the runoff threshold.
5.3.3.2 Wet Conditions Threshold \( TW \)

The Wet Conditions Threshold \( TW \) is the value of \( P_X \) at which the runoff slope \( dR/dP_X \) increases from \( \alpha_{\text{mid}} \) to \( \alpha_{\text{wet}} \). High values of \( TW \) imply that \( P_X \) must be substantial to trigger saturated runoff conditions such that \( dR/dP_X \approx 1 \), whereas small values of \( TW \) indicate that saturation is associated with even small amounts of \( P_X \). To understand the mechanisms that may explain this, it is useful to consider extreme hydrological scenarios. A watershed with no ability to retain water, such as a sloped parking lot, would have a very small value of \( TW \); a watershed with perfect storage, like a pond with no outlet and no seepage, would have an infinitely large value of \( TW \).

![Boxplot of estimated values for the wet conditions threshold TW, by watershed wetness type. Observations are indicated by blue x, central bars indicate the median, boxes indicate 50th percentile, stems indicate 90th percentile, and outliers are represented as black dots. Watersheds counts: arid N=23, mesic N=86, humid N=50.](image)

However, it is not straightforward to validate this intuition with the data. As shown in Figure 31, values of \( TW \) vary by nearly 1 m across the 159 watersheds of the study, with little central tendency around average values. There are relatively few arid watersheds that experience the wet conditions required to estimate \( TW \). Mesic watersheds exhibit a broad range of \( TW \) values, but also encompass a broad range of surface conditions. Per the rubric in Figure 28, the estimate of \( TW \) for humid watersheds is not credible due to few if any years for which there are mid-level wetness conditions to signify the transition to wet conditions.

The geographic representation in Figure 32 shows relatively little spatial clustering or regionalization compared with the other parameters.
Figure 32: Geographic distribution of estimates for the wet conditions threshold TW for the 159 study watersheds, color-coded by value in mm. There is some clustering of values in proximate watersheds, but little obvious regionalization. The consistently low values in the high Sierras are suggestive of the different hydrologic mechanisms of alpine conditions, but this interpretation is tentative because there are few data years with which to estimate the transition from mid-level to wet conditions.
5.3.3.3 Initial Runoff Slope $SI$

The Initial Slope $SI$ is the value of $dR/dP_X$ for the first interval of $P_X > 0$. Per the rubric of Figure 28, this is $a_{mid}$ except for watershed humid watersheds for which it cannot be reliably estimated due to few if any years of data in the mid-range interval. Small values of $SI$ indicate that some initial amount of $P_X$ is entirely converted to $E$; process explanations for this include high rates of evapotranspiration or sporadic precipitation that does not significantly accumulate within a watershed. A more prosaic explanation could be underestimates of $P_X$ for a given watershed, resulting in a bias in the opposite direction as the one presumed to account for the “no-fit” watersheds per Figure 28. A large value of $SI$ suggests that a significant fraction of any $P_X$ is converted to streamflow, which may be explained by a landscape incapable of retaining water long enough for it to evaporate, such as shallow soil and sparse vegetation, or by particularly wet watersheds where annual $P$ far exceeds the amount of storage that can be retained from the wet season into the dry season.

![Boxplot of estimated values for the initial slope $SI$, categorized by watershed wetness type. Humid watersheds not shown because $SI$ estimates are not credible for these watersheds. Observations are indicated by blue x, central bars indicate the median, boxes indicate 50th percentile, stems indicate 90th percentile, and outliers are represented as black dots. Watershed counts: arid $N=23$, mesic $N=86$.](image)

As shown in Figure 33, the values of $SI$ are generally near zero for arid watersheds and distributed between 0.1 and 0.65 with no clear central tendency for mesic watersheds. The geographic representation of $SI$ values in Figure 34 largely reflects the wetness type of each watershed, with some clustering of comparable values for mesic watersheds in the north of the state.
Figure 34: Geographic distribution of estimates for initial slope SI for arid and mesic watersheds (N=109), color-coded by values (mm/mm). Values near zero are exclusively arid watersheds. There is some clustering of comparable values for mesic watersheds in the north of the state.
5.3.3.4 Terminal Runoff Slope $ST$

The Terminal Slope $ST$ is the largest observed value of $dR/dP_X$ for a watershed. For humid watersheds $ST$ is the only observed slope; for mesic watersheds $ST$ is the slope of the wet segment; and for arid watersheds $ST$ is the initial non-zero slope, i.e. for $P_X > TR$. In principle the largest value of $ST$ that respects mass conservation (and the assumption of negligible inter-annual storage) should be unity, though as previously discussed it is not uncommon to observe larger slopes, probably due to biases in the measurement of $P_X$ or $R$. [Notably, this suggests a derivative research question that is not addressed here: can the water balance be used to diagnose flaws in climate or streamflow data?] Values of $ST \sim 1$ suggest totally saturated conditions where all additional $P_X$ is partitioned into $R$, such as for very wet watersheds where annual $P$ far exceeds storage capacity.

![Boxplot of estimated values for Terminal Slope $ST$, by watershed type.](image)

Figure 35: Boxplot of estimated values for Terminal Slope $ST$, by watershed type. Note that the humid watershed type includes values for “no-fit” watershed types with small values for $ST$. Observations are indicated by blue $\times$, central bars indicate the median, boxes indicate 50th percentile, stems indicate 90th percentile, and outliers are represented as black dots. Watershed counts: arid $N=23$, mesic $N=86$, humid $N=50$.

As shown in Figure 35, values of $ST$ are generally greater than 0.8, especially in wetter climates. The geographic distribution of $ST$ values is shown in Figure 36. The estimates demonstrate clustering and regionalization of comparable values.

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5.4 **MCBW Model Predictive Performance**

One application of the MCBW model is to predict annual $R$ given estimates of seasonal $P$ and $PET$ in a watershed where the model parameters have been estimated via regression or some other method. To robustly characterize the usefulness of the model for this purpose it is necessary to measure the model’s performance against new observations. The established approach for quantifying predictive uncertainty is to train the model on a subset of the total available data and then validate model performance using the withheld data. As a supplemental comparison, the $r^2$ statistic was calculated and compared with results from the literature.
5.4.1 Validation Method

The following steps were used to quantify the predictive uncertainty of the MCWB model for each watershed in the study:

1. Split the N total available observations into TRAIN and TEST subsets:
   a. Randomly select M = 30 years of TRAIN data
   b. Use the remaining V = N − M years as TEST data; require V ≥ 10
2. Estimate MCWB model parameters using TRAIN data
3. Calculate residuals between observed and modeled R using TEST data
4. Estimate predictive uncertainty as the root mean squared error (RMSE) of the residuals

The number of years of TRAIN data, M = 30, was heuristically chosen as a compromise between including more watersheds in the evaluation, since larger M excludes watersheds with insufficient data years, and improving regression results, since larger M improves parameter estimates. The lower limit of 10 years of TEST data thus required at least 40 years of water balance records. This resulted in 67 California watersheds for validation, with good representation of each watershed type: 15 arid, 28 mesic, and 24 humid watersheds. RMSE is a standard metric for uncertainty evaluation and it is reasonable for this use case because the Bayesian regression effectively optimizes for a normal distribution of residuals. It is also informative to normalize the uncertainty metric to compare performance across diverse conditions. The coefficient of variation of RMSE, CV(RMSE), is RMSE normalized by average R,

\[
CV(RMSE) = \frac{RMSE}{R}
\]

5.4.2 Validation Results

The results for absolute RMSE are shown in Figure 37, where the RMSE of the TEST data is presented opposite a baseline comparison of the RMSE for all observations relative to the models trained using all data, i.e. the parameter outcomes presented previously in this section. The baseline may be considered the overly-optimistic, lower-bound for MCWB uncertainty, which is not suitable for evaluating predictive ability but is useful for reference. The cross-validation RMSE is inflated relative to this baseline, as expected, but the increase is relatively small and indicates that the MCWB can be useful for predicting R given at least 30 years of training data and monthly estimates of P and PET for the year that R is to be predicted.
The normalized errors, CV(RMSE), are shown in Figure 38, with TEST data results shown opposite a baseline comparison of RMSE of regression on the full dataset; the latter is known to be a biased underestimate of error, but is useful for comparison with the more reliable TEST results. This perspective indicates that the relative performance of the MCWB model is weakest for arid watersheds where the predictive uncertainty is roughly equivalent to typical observed values of $R$. One reason for this is that the average value of $R$ for arid watersheds is about 50 mm/year, which is quite small compared to the dominant climate forcings: average $P$ is larger by a factor of 5, and average $PET$ is larger by a factor of 50. Predicting $R$ as a relatively small outcome of much larger inputs, with their correspondingly large measurement uncertainties, is a challenge not just for the MCWB model, but for other approaches as well [Flint et al., 2013]. Yearly values of $R$ are larger for mesic and humid watersheds, averaging roughly 300 mm and 700 mm, respectively, and the relative uncertainties are correspondingly smaller.
5.4.3 R-squared for Predicted vs. Observed Values of R

The $r^2$ statistic was calculated for predicted vs. observed values of $R$ for each watershed to further assess model performance and to facilitate comparison with previously reported results from the literature. This was done only for the case of using all available data to train a regression model, and thus the resulting estimates of $r^2$ are overly optimistic in terms of predictions for unobserved conditions. Unfortunately, the separate TRAIN and TEST datasets used for RMSE calculations were corrupted prior to this analysis, and the research timeline did not afford reconstructing this data. However, the reported results are still useful in comparison with training data statistics for previous work.

Comparing observed values of $R$ with values predicted by a regression of all available data (i.e., a training dataset), the average $r^2$ was 0.88 for all study watersheds ($N=159$); 0.82 for arid conditions ($N=23$); 0.89 for mesic conditions ($N=86$); and 0.89 for humid conditions ($N=50$). This compares favorably with average $r^2$ values reported using the Basin Characterization Model (BCM) [Thorne et al., 2012; Flint et al., 2013] for calibration watersheds that likewise exploited all available data for regressions: 0.84 for all calibration watersheds ($N=68$); 0.63 for watersheds in the southwest quadrant of the state that are roughly comparable to the arid watersheds of this study ($N=6$); 0.86 for watersheds in the central western region comparable to the mesic watersheds of this study ($N=32$); and 0.85 for watersheds in the northwestern and Sierra Nevada regions of the state, comparable to the humid watersheds of this study ($N=30$). As one would expect, the $r^2$ values for validation watersheds were generally lower, with an average value of 0.77 ($N=70$).

These results indicated that the MCWB model performs comparably to the BCM, in terms of $r^2$, for gaged watersheds across diverse conditions in California, and providing significantly better $r^2$ for arid conditions and very similar performance for mesic and humid conditions. The mechanistic approach of the BCM has been demonstrated to be effective for a broad range of conditions with relatively
modest data needs for a bottom-up approach. But it is interesting to note that, at least in the case of
the watersheds studied here, the outcome of this flexible mechanistic approach has the net effect of
approximating a straightforward linear model. This does not diminish the value of the BCM, but as
with any mechanistic model that is subject to equifinality of outcomes, the comparison is a reminder
that interpreting the impact of any particular model parameter or input must be carefully weighed
against alternative interpretations that are consistent with the model structure.

5.5 DISCUSSION

The probabilistic model developed in § 5.1 and summarized in Figure 23, Table 3, and Table 4 was
implemented using the Stan probabilistic programming language with historical water balance
observations as inputs. The resulting outputs were posterior distributions of likely values for the
model parameters $\Omega = [\alpha_{\text{mid}}, \alpha_{\text{wet}}, c]$ for each of the 159 watersheds in this study. These posterior
distributions represent the marginal probability of a particular parameter value given the model
structure and input observations, and MCMC sampling ensures that they are consistent with the true
underlying distributions. Examples of these posteriors were reviewed for representative Arid, Mesic,
and humid watersheds, with discussion of the factors that impact the size of the credible interval for
a given parameter estimate, such as the number of observations in a given segment of the bi-linear
model.

Statewide results for all watersheds were then presented, beginning with the geographic distribution
of watersheds characterized as arid, mesic, and humid, which showed noteworthy spatial clustering
and strong correspondence with prevailing regional aridity. The best estimates of each MCWB
model parameter were the shown, categorized by watershed wetness type. Values of the storage
retention threshold $S^*$ were generally in the vicinity of 250 mm, which is consistent with typical
physical storage capacities but not directly equivalent. The mid-range runoff rate $\alpha_{\text{mid}}$ varied widely
for mesic watersheds, from 0.1 to 0.6 mm/mm; arid watersheds have values near zero by definition,
and humid watersheds generally lack data in this segment. The wet conditions runoff rate $\alpha_{\text{wet}}$ was
often near 1 mm/mm for mesic and humid watersheds, implying saturated conditions, whereas rates
for arid watersheds were generally smaller, suggesting that $\alpha_{\text{wet}}$ actually represents mesic wetness
conditions for these watersheds that rarely experience truly wet conditions.

Given this sort of ambiguity in interpreting the physical meaning of the MCWB model parameters
across the various watershed wetness types, a set of standardized terms were introduced to facilitate
statewide comparisons. The runoff threshold $TR$ was shown to be an indicator of the amount of
inter-seasonal storage that is wholly evaporated by a watershed before any significant runoff occurs;
values were generally higher for arid watersheds. The wet conditions threshold $TW$ is an indication
of how much energy-excess precipitation is needed for a watershed to become saturated, such that
the runoff rate approaches unity. This was most meaningful for mesic watersheds, which
demonstrated a broad range of values for $TW$. The initial runoff slope $SI$ suggests a watershed’s
tendency to retain excess precipitation, with small values indicating that most $P_X$ is retained in the
watershed and eventually evaporated, and large values showing a tendency for $P_X$ to depart as
runoff. Mesic watersheds showed broad variation in SI with some regional clustering, whereas arid
watersheds had a value of 0 by definition and estimates for humid watersheds were indeterminate.
The terminal runoff slope $ST$ is the largest observed runoff rate for a given watershed. For mesic
and humid watersheds the value was typically near 1 mm/mm, indicating saturated conditions,
whereas for arid watersheds the value was typically between to 0.5 and 0.8 mm/mm.
Then, the utility of the MCWB model for predicting annual $R$ was quantified using training and validation subsets of the total available data record. The uncertainty of modeled $R$ was shown to be generally near 50 mm for arid watersheds, 100 mm for mesic watersheds, and 125 mm for humid watersheds. Normalizing for average runoff in each watershed, the coefficient of variation for RMSE indicated the largest relative uncertainty for arid watersheds, followed by mesic then humid, a result that is not surprising considering that measurement uncertainties for the dominant climate drivers, $P$ and $PET$, are likely to be large relative to $R$ for arid watersheds with average runoff of only 50 mm per year. A comparison of $r^2$ statistics showed that the MCWB model performs somewhat better than the mechanistic BCM model for this metric, comparing historical regressions for gaged watersheds.
6 Evaluating Changes to the Water Balance

There are many reasons why the water balance may be altered for a given watershed or region, and these can be broadly categorized as changes to forcing factors, i.e., climate and weather conditions, and changes in partition controls, i.e., landscape characteristics. The hydrological impacts of climate and landscape may be coupled, as with vegetation adaptation induced by climate changes, or isolated, as with anthropogenic landscape conversion. The climate in California has changed significantly over the last century and the changes are expected to be even more pronounced in coming decades, per § 2.8. Over the same timeframe, human development and manipulation of the region’s landscape continued as it has for over two hundred years [Pincetl, 2003] and other rapid transformation events such as wildfires have increased due to anthropogenic factors [Westerling et al., 2006]. It is important to understand what impact these changes have had, and will have, on hydrology in California.

There is an immense amount of literature devoted to the hydrological effects of climate and landscape changes, using both empirical and mechanistic approaches. The purpose of this section is to contribute to this body of knowledge by quantifying and characterizing observed changes in the water balance across a broad range of conditions in California in the context of the climate and landscape factors of the MCWB model. Specifically, three research questions were addressed:

- Did the amount of water in California streams and rivers change during the 20th century, relative to the controlling climate and landscape factors?
- If changes in runoff were observed, what factors accounted for the change?
- What does the MCWB model reveal about how changes to climate and landscape factors can affect the overall water balance?

6.1 Observed Changes to the Water Balance

The general approach to characterizing historical changes in California streamflow was to evaluate temporal trends while controlling for various climate and landscape factors. It is, for example, trivially obvious that in most circumstances a decrease in the overall water supply, $P$, will lead to a decrease in $R$. The general method was thus to consider the time rate of change of the residuals $\delta_R$ of observed runoff $R_{\text{obs}}$ relative to modeled runoff $R_{\text{modeled}}$:

$$\delta_R = R_{\text{obs}} - R_{\text{modeled}}$$

where $R_{\text{modeled}}$ implicitly accounts for $P$ and other water balance controls. The rate of change was then estimated via a linear regression of $\delta_R$ as a function of time. More sophisticated approaches for measuring temporal changes were also explored, including polynomial regressions and change point detection, but given relatively limited data (typically ~30 years of records) such methods were not robustly conclusive.

It is important to note that residual analysis does not require assumptions about the stationarity of the modeled processes and controls. On the contrary, it is a useful approach for detecting non-stationarity. First recall that the MCWB model regression ignores time. Given that the water balance regression employs all available observations, the fitted parameters of the regression will represent the average behavior over the observation interval. When the residuals of this fit are then ordered by time, heteroscedastic variations imply the presence of non-stationary effects relative to the average
modeled behavior; detection of such effects, specifically long-term trends, is the purpose of this section.

The next sections will first review the requirements and considerations for water balance data suitable to temporal trend analysis. Then, overall trends in annual $R$ will be evaluated while controlling for annual $P$. Next, changes in $R$ that are primarily attributable to landscape controls will be quantified by controlling for $P_X$. The difference of these first two residuals will then be used to evaluate trends in $R$ that are associated with changes in the seasonality of $P$ and $PET$, and finally historical changes in $P_X$ relative to $P$ will be calculated.

### 6.1.1 Data Considerations

Given the objective of estimating observed changes in $R$ relative to other factors, it was essential to use temporally consistent data to generate residual estimates. As described in § 3.2, watersheds with predominantly natural flow conditions were selected for study. However, other factors such as changes to measurement methodology may also inflict temporal changes on $R_{obs}$. For this reason it should be assumed that changes in the water balance observed for any particular watershed may require closer contextual assessment; this research instead emphasizes regional and geographically clustered trends.

The method for obtaining temporally consistent geospatial estimates of $P$ and $PET$ was described in § 3.2.5. The key point was the synthesis of a geospatial data source that was designed for time consistency (VIC) with a data source that emphasizes year-to-year accuracy and geographic granularity (PRISM). This hybrid dataset (VICs) preserves inter-annual consistency while reducing observed biases in the VIC dataset. The tradeoff of diminished accuracy for a given year was acceptable for the research purpose. It is acknowledged that estimating $PET$ as an empirical function of temperature $T$ introduces further uncertainty, but there was no feasible alternative source of $PET$ data for the scope and timeframe of the study.

### 6.1.2 Overall Change in Streamflow: $R$ as a Function of $P$

Perhaps the most obvious question to ask about climate change impact on $R$ is whether it has changed relative to $P$. That is, for a given amount of total annual $P$, was there more or less water discharged from a particular watershed throughout the period of record? This question was addressed by temporal analysis of the residual $\delta R$ from a variation of the MCWB that describes $R$ as a function of $P$:

$$ 
R(P) = 0 + (1 - \beta_{mid})(P - a)H_a + (\beta_{mid} - \beta_{wet})(P - b)H_b 
$$

where the parameters are illustrated in Figure 10 and the labels indicate the wetness segment. It should be noted that the parameter definitions of this section follow the general description in § 0, not the simplified variations used for the Budyko analysis in § 1.

The parameters $\beta_{mid}$, $\beta_{wet}$, $a$, and $b$ were inferred for each watershed using a variation on the statistical model that was developed in § 5.1.2, the code for which is available online [Moran, 2015a]. The difference of observed $R$ and the fitted model of Eq. (30) provided the desired residual $\delta_{R,P}$.
where the subscript “$R,P$” refers to $R$ relative to modeled $P$, and the rate $d\delta_{R,P}/dt$ represents the temporal change in $R$ relative to $P$.

Examples of $\delta_{R,P}$ over time are shown for three representative watersheds in Figure 39, with regression lines and parameter estimates. The strongest temporal trend is observed in the top panel, Redwood Creek at Orick, CA, a large (718 km$^2$), humid watershed along the far north coast. There is significant scatter in the residual, roughly ± 250 mm, but there is a notable negative trend that is dominated by the years 1995 and later. The linear fit suggests that, for a given amount of annual $P$, average runoff decreased by ~5 mm per year during the second half of the 20$^{th}$ century.

The middle panel shows the South Fork of the Eel River near Branscomb, CA, a smaller (118 km$^2$) but also humid watershed slightly inland from the coast. There is a negative trend of around 5 mm per year, but the data is less conclusive. Notably, the interval is much shorter, ending in 1970, and the trend is less statistically significant (p-value 0.3).

The bottom panel, Red Bank Creek near Red Bluff, CA, is a mid-sized (232 km$^2$) watershed with mesic wetness that is at comparable latitude as the other two, but on the drier, eastern slope of an inland range. The runoff trend shows an increase of 2 mm per year, though the p-value of 0.3 indicates low statistical significance for the regression.

Recalling the previous caveat about interpreting the results for any particular watershed, the broader patterns of changes to $R$ across the state are of greater interest. Figure 40 visualizes aggregate estimates of the slope $d\delta_{R,P}/dt$, categorized by watershed type, Arid, Mesic, and Humid. The left panel shows boxplots with slope values for all 159 watersheds in the study, regardless of the statistical significance, in terms of p-value, of a given regression. The median is slightly negative for each watershed category, indicating a general pattern of somewhat reduced runoff across the state during the observation period that included most of the 20$^{th}$ century. The right panel shows only watersheds with p-value < 0.1 for the slope regression, an arbitrary but useful threshold that is inclusive enough to examine broad trends but exclusive of the most dubious regressions. These results are more strongly biased toward negative trends for all categories, with a median decreases of ~2 mm for mesic watersheds, < 1 mm for arid watersheds, and ~3 mm for humid watersheds.

Given that greater slopes necessarily lead to smaller p-values, it is not surprising that the more significant regressions suggest more dramatic changes, but the insight is that when change is observed, it is more likely that $R$ is decreasing than increasing.
Another view of this change is provided in Figure 41, which illustrates estimated linear $d\delta_{R,P}/dt$ for each watershed in the study, categorized by watershed type. There were several notable observations. First, this view reinforces the previous conclusion that significant changes in R are more likely to have been negative than positive. Second, while many of the available records are unfortunately not much longer than two decades, it is not just the shorter records that demonstrate significant changes. Not surprisingly the longer records tend to have less extreme slopes because they experience a broader variety of conditions, but they are still consistent with the overall decrease. Furthermore, records that begin in the middle of the 20th century are more likely to demonstrate significant negative change than positive change.
Figure 40: Boxplots of the best estimates for linear temporal change in runoff residual $\delta_{R,P}$, controlling for $P$, for all watersheds in study (left) and for watersheds where slope p-value is < 0.1 (right), categorized by wetness type. Horizontal bars indicate median, boxes indicate 50th percentiles, whiskers indicate 90th percentiles, dots indicate outliers. Counts for all watersheds: arid N=23, mesic N=86, humid N=50. Counts for p-value < 0.1 : arid N=8, mesic N=21, humid N=17.

The conclusion of these observations is that the amount of water in California streams decreased for most gaged watersheds in the 20th century, relative to a given amount of precipitation. This is, to the best of the author’s knowledge, the first time that this result has been reported. The question of what accounts for this change, landscape controls or climate drivers, is the topic of the next two sections.
Figure 41: Estimates of linear change in runoff over time, controlling for P, for Arid, Mesic, and humid watersheds. Regressions with p-value < 0.1 are indicated in dark blue, less significant fits in light blue. All lines originate at dR = 0 on the y-axis; start and stop along x-axis indicate first and last year of water balance data used for the regression; thus, the slope is identical to linear regression value.
6.1.3 Influence of Landscape Controls on $R$

The MCWB model of $R$ as a function of $P_X$, referred to here as $R(P_X)$ and defined per Eq. (16), explicitly accounts for annual variation in several important climate drivers: $P$, PET, and their seasonality coefficients $\omega_P$ and $\omega_{PET}$. Thus, temporal changes in the residual of $R$ observations relative to modeled $R$,

$$\delta_{R,X} = R_{obs} - R(P_X)$$

must be attributable to other factors, such as landscape controls or aspects of climate not captured by $P_X$. Examples of other climate controls include the sub-seasonal timing and intensity of $P$ and PET, and while such factors may indeed be important to the hydrology of a particular watershed, they are assumed to be generally less significant than the many ways in which landscape can control the water balance. The landscape control parameters of the MCWB model, runoff rates $\alpha_{mid}$ and $\alpha_{wet}$ and the storage retention threshold $S^*$, are implicitly assumed to be static attributes of a watershed that are derived via regressions using long-term observations. This assumption is at odds with the declaration that “stationarity is dead” [Milly et al., 2008] for hydrology in the era of climate change. However, for the purpose of evaluating changes to the water balance, the implicit assumption of stationary landscape features provides an opportunity to evaluate temporal changes in landscape controls. Specifically, because $\delta_{R,X}$ is controlled for dominant climate factors, any temporal changes in this residual should be predominantly attributable to temporal changes in the MCWB landscape parameters. The linear regression $d\delta_{R,X}/dt$ was thus used to estimate the temporal change in runoff that is associated with changes to landscape features.

Specific examples of $d\delta_{R,X}/dt$ are provided in Figure 42 for the same watersheds as the $\delta_{R,P}$ examples in Figure 39. The direction of change for $\delta_{R,X}$ is the same as for $\delta_{R,P}$ for these three examples. The distribution of aggregate estimates $d\delta_{R,X}/dt$ in Figure 43 is consistent with the prevailing direction of change for $\delta_{R,P}$ for arid and mesic watersheds in Figure 40. However, note that the aggregate trend for humid watersheds is positive for $\delta_{R,X}$, whereas $\delta_{R,P}$ trends are predominantly negative. This pattern is also clear in the visualization of temporal $\delta_{R,X}$ trends in Figure 44, where many of the humid watersheds with the longest records have positive trends of $\delta_{R,X}$. This contrasts with $\delta_{R,P}$ depicted in Figure 41, where humid watersheds have generally negative trends, indicating a decreased in $R$, a disparity that will be discussed subsequently in more detail.
Given the premise that \( \frac{d\delta_{R,X}}{dt} \) captures changes to landscape controls of the water balance, the preceding analysis suggests that during the 20th century, landscape controls contributed to a decrease in California streamflow for arid and mesic watersheds, but an increase for humid watersheds.
Figure 43: Boxplots of best estimates for the linear temporal change in runoff residual $\delta_r$, controlling for $P_{so}$, for all watersheds in study (left) and for watersheds where slope p-value is $< 0.1$ (right), by watershed wetness type. Horizontal bars indicate median, boxes indicate 50th percentiles, whiskers indicate 90th percentiles, dots indicate outliers. Counts for all watersheds: arid $N=23$, mesic $N=86$, humid $N=50$. Counts for p-value $< 0.1$: arid $N=8$, mesic $N=21$, humid $N=17$. 
6.1.4 Influence of Seasonality on R

Analysis of observed changes to the water balance has been guided thus far by two premises: first, that the overall change in streamflow, controlling for $P_X$, can be approximated by the linear residual trend $d\delta_{R,P}/dt$; and secondly, that since $P_X$ controls for dominant climate effects, the linear trend $d\delta_{R,X}/dt$ is a reasonable surrogate for the impact of landscape controls on streamflow trends. The
next objective is to use both of these premises to estimate the effect of seasonality on water balance
trends.

To recap, $\delta_{R,P}$ captures all factors other than $P$ that influence $R$, and $\delta_{R,X}$ is assumed to capture all
factors other than $P_X$, which explicitly accounts for total annual $P$ and $PET$, and their seasonality ratios $\omega_P$ and $\omega_{PET}$. It follows that the difference between these residuals ought to describe
something about the contribution of $PET$, $\omega_P$ and $\omega_{PET}$ to any trends in $R$. That is,

$$\delta_{R,S} = \delta_{R,P} - \delta_{R,X}$$

where subscript $R,S$ refers to the residual of $R$ that is attributable to climate controls $PET$, $\omega_P$ and $\omega_{PET}$. An argument can be made that the seasonality terms $\omega_P$ and $\omega_{PET}$ will dominate $\delta_{R,S}$ in a
Mediterranean climate because total annual $PET$ is less important to the water balance than the
relative timing of $P$ and $PET$, per the sensitivity analysis of § 6.2.3. This is because a large majority
of total annual $PET$ occurs during the dry season when water is in short supply, resulting in “excess”
$PET$ that has relatively little impact on the overall water balance. By contrast, the seasonality terms
capture the critical factor of whether $P$ occurs during a time of year when it is susceptible to direct
evaporation $E_d$, which has a strong impact on the overall annual partition. Thus, $\delta_{R,S}$ was taken to
represent the residual of $R$ that is attributable primarily to the seasonality terms $\omega_P$ and $\omega_{PET}$.

While there are likely to be feedback processes between landscape and seasonality effects, the
residual components of Eq. (31) were assumed to be independent as a simplifying assumption. This
is justified by two considerations. First, much of the vegetation in the Mediterranean climate of
California is characterized by resilience to inter-annual weather variations, per § 2.2.3, and so it is
plausible to speculate that timescales for persistent changes to California landscape hydrology is
perhaps of the same order as changes to the water balance. Second, given that the objective of this
study is to characterize broad trends across diverse landscape and climate conditions, it is reasonable
to postulate that the direction and magnitude of climate-landscape interactions will vary
considerably, such that on aggregate the effects may be mitigated relative to the impact for any
particular watershed.

Given the assumption of independence between landscape and climate controls, the temporal rates
of change of the residuals can be expressed as,

$$\frac{\delta_{R,S}}{dt} = \frac{\delta_{R,P}}{dt} - \frac{\delta_{R,X}}{dt}$$

That is, the temporal trend of the impact of seasonality on $R$, $d\delta_{R,S}/dt$, can be approximated as the
difference of the two residual trends that were previously estimated. The results of this calculation
are shown in Figure 45 as boxplot summaries of slope values, shown on the same scale as slope
values for overall and landscape effects.
Several interesting conclusions are suggested by the seasonality effect boxplots in the right panel of Figure 45. First, the median values are negative for all watershed types, indicating that seasonality controls had the effect of decreasing $R$ for the majority of the watersheds in the study. The decrease in $R$ is most pronounced for humid watersheds, and least so for arid watersheds. However, the magnitude of the effect is small ($< 1 \text{ mm/year}$) for the preponderance of watersheds.

For arid and mesic watersheds the effect of seasonality is primarily in the same, negative direction as landscape effects. For humid watersheds the predominant climate effects trend is negative, in the opposite direction as landscape, and the overall change in $R$ is slightly negative. This suggests that in some humid watersheds the landscape effects may offset seasonality effects, i.e., seasonality controls that decrease $R$ (increase $E$) may be counteracted by landscape controls that increase $R$ (reduce $E$). Conceptually, this could happen if seasonality conditions that led to decreased $R$, such as a larger proportion of annual $PET$ during the wet season, also caused diminished vegetation activity, and thus lower evapotranspiration rates. But validation of such a hypothesis would require mechanistic detail, and associated data, that is beyond the scope of this research.
The overall conclusion of this section is that the seasonality factors of the MCWB appear to have contributed to a decline in streamflow for the majority of California watersheds during the 20th century.

6.1.5 Observed Changes in \( PX \)

The previous sections examined how \( R \) changed in the 20th century, controlling for \( P \) and \( PX \). A related question is whether and how much the climate forcings themselves have changed. Energy-energy-excess precipitation \( PX \) captures the net effect of several key climate drivers, and temporal changes to this variable can offer additional insight about the relationship between climate and streamflow.

Change in \( PX \) was estimated relative to \( P \) using a linear regression of the residual of modeled \( PX \) over time. Recall that the relationship of \( PX \) to \( P \) is approximated by,

\[
P_X = \bar{\omega}_P \cdot P - \bar{\omega}_{PET} \cdot \bar{PET} + \delta_{px}
\]

which is a variation on Eq. (8), where overbars indicate long-term averages and \( \delta_{px} \) is introduced as the residual difference of observed and modeled \( PX \). Note the effect on \( PX \) for various parameters: it changes in the same direction as \( \omega_P \), the fraction of \( P \) that falls during the wet season; it moves in the opposite direction as \( \omega_{PET} \), the fraction of PET that occurs during the wet season; and it changes in the opposite direction as total PET.

The metric of interest is \( \frac{d\delta_{px}}{dt} \), the temporal, linear change in \( PX \), controlling \( P \). An important consideration in evaluating change in \( PX \) is that the calculation requires only \( P \) and PET data, so the period of record is the same for all watersheds, 1916 to 2003. This regression interval is typically longer than that for the water balance, which is often limited by availability of \( R \) records. Thus, the outcomes are less sensitive to short-term, transient fluctuations in the underlying relationship, and estimates of temporal changes in \( PX \) are likely to be more reliable than estimated changes to \( R \).

Examples of \( \delta_{px} \) time series are provided in Figure 46, for the same representative watersheds used to illustrate changes to \( R \). Notably, the linear slopes \( \frac{d\delta_{px}}{dt} \) are less prominent than those observed for \( \delta_{R,P} \) (changes in \( R \) relative to \( P \)) in Figure 39 or \( \delta_{R,X} \) (changes to \( R \) relative to \( PX \)) in Figure 42. The map in Figure 47 shows watersheds that experienced the most significant changes in \( PX \) (p-value < 0.05), which represent a relatively small subset (\( N=31 \)) of all watersheds in the study, with regional clustering in the high Sierras and inland of the Santa Barbara coast.
Figure 46: Change in the residual of $P_X$ over time for the same watershed examples as used for runoff residual analysis.
Estimates of $d\delta_{px}/dt$ for 159 California watersheds are summarized by watershed type in Figure 48. The magnitude of the change rate is rather small, generally $< 0.5$ mm/year, but over the 87 year period of record this translates into tens of millimeters of net change. The direction of change is perhaps more interesting. Given that $P_X$ represents the amount of annual $P$ that is available to become $R$ or inter-seasonal storage (i.e., not directly evaporated as $E_d$), the naïve expectation might be that a decrease in $P_X$ should be associated with decreased $R$. In fact, the observed relationship between $P_X$ and $R$ is more nuanced, as are the underlying mechanisms, which vary by watershed type.
Figure 48: Temporal change in \( P_X \), controlling for \( P \), by watershed wetness type. Watershed counts: arid \( N=23 \), mesic \( N=86 \), humid \( N=50 \). Boxes indicate 50th percentile, stems indicate 90th percentile, central bars indicate median, and outliers are represented as black dots.

A large majority of humid watersheds saw \( P_X \) decrease in the 20th century by a small amount, typically < 0.5 mm/year. The direction of change is conceptually consistent with commensurate climate-driven decreases in \( R \) indicated in Figure 45, since humid watersheds are characterized by saturated conditions with values of \( \frac{dP_X}{dR} \approx 1 \).

For arid and mesic wetness watersheds, a slight increase in \( P_X \) was most common, which contrasts with the general reductions in \( R \) for these types of watersheds as shown in Figure 45. On closer consideration, this is not necessarily surprising. Recall from Figure 20 that \( P_X \) is subsequently partitioned into either \( R \) or inter-seasonal storage, and that this storage is carried over from the wet season to the dry season and then evaporated as storage evapotranspiration \( E_v \). Also recall that arid and mesic watershed types do not typically experience saturated conditions, which suggests that an increase in \( P_X \) may be captured as inter-seasonal storage, and subsequently evaporated, as opposed to contributing to \( R \). This conceptual explanation suggests that there is no contradiction in observing increased \( P_X \) along with decreased \( R \), but unfortunately the precise mechanisms of the interplay between the water balance components are beyond the scope of this study.

6.1.6 Discussion of Observed Changes in the California Water Balance
This section evaluated observed historical changes to the annual water balance in California in the context of changes to annual \( R \). Specifically, the residual \( \delta_R \) was calculated as the difference between observed and modeled \( R \) for two variations on MCWB model, as a function of \( P \) and then as a
function of \( P_X \) resulting in \( \delta_{R,P} \) and \( \delta_{R,Px} \), respectively. Change in the water balance was quantified as the linear trend in \( \delta_R \) over the period of record for a given watershed.

The trend in \( \delta_{R,P} \) was assumed to represent the overall change the water balance relative to \( P \). Results were discussed for three watersheds that had trends of -5, -6, and +2 mm of \( R \) per year, though only one was significant at the p-value < 0.05 level. Of greater interest were the aggregate results statewide, which indicated that negative trends in \( R \) relative to \( P \) were slight but prevalent. Evaluation of only watersheds where trends were significant at p-value < 0.1 showed that, for locations where there was a clear trend, \( R \) was more likely to be decreasing than increasing. Overall, the amount of water in California streams decreased during the 20th century for most watersheds in this study.

Next, an argument was made that temporal changes in the residual \( \delta_{R,X} \) are driven by underlying changes to the structure of the MCWB model of \( R \) as a function of \( P_X \). The relevant parameters, runoff rates \( \alpha_{mid} \) and \( \alpha_{wet} \) and the storage retention threshold \( S \), are interpretable as landscape control factors, and thus changes in \( \delta_{R,X} \) were assumed to be predominantly attributable to changes in those landscape factors. On aggregate, trends of \( \delta_{R,X} \) were shown to be slightly negative for arid and mesic watersheds, and somewhat positive for humid watersheds. The implication was that during the 20th century landscape controls contributed to a decrease in California streamflow for arid and mesic watersheds, but an increase for humid watersheds.

The effect of seasonality was approximated by the difference of the total residual \( \delta_{R,P} \) and the landscape residual \( \delta_{R,X} \), applying the argument that the former encompasses all effects except \( P \) and the latter accounts for the effects of \( P \), \( PET \), and their seasonality coefficients \( \omega_p \) and \( \omega_{PET} \). Thus, their difference \( \delta_{R,S} \) accounts for variations in \( PET \) and seasonality, and seasonality has a much stronger effect than total annual \( PET \). Independence of \( \delta_{R,P} \) and \( \delta_{R,P} \) was invoked as a simplifying assumption, which allowed the rates of change of these residuals to be treated as additive per Eq. (32). The linear slope \( d\delta_{R,S}/dt \) was modestly negative for the majority of watersheds in the study, with the strongest effect for humid watersheds. Interestingly, this is opposite the direction of the landscape effect for humid watersheds, which suggests that landscape effects may counteract the impact of seasonality. Overall, seasonality factors of the MCWB appear to have contributed to a decline in streamflow for the majority of California watersheds during the 20th century.

Finally, temporal trends in \( P_X \) were evaluated using the residual \( \delta_{P} \), the difference between observed \( P_X \) and estimates modeled as a function of \( P \). The trend in \( P_X \) predominantly decreased for humid watersheds, with a magnitude < 0.5 mm/year for most watersheds. This direction of change is consistent with the observed decreasing trend in overall \( R \) and the seasonality-driven change in \( R \) for humid watersheds. The trend for arid and mesic watersheds was slightly positive, which is opposite the observed direction of the \( R \) trend for these watersheds, which suggests a more complex relationship between \( P_X \) and \( R \) for drier prevailing conditions.

Note that relatively modest trends in \( R \) and \( P_X \) can translate into a significant total magnitude of change over the multi-decadal timespans of this study. For instance, a rate of change of 0.5 mm/year translates into an absolute change of almost 44 mm across the maximum period of record of 87 years in this study. For a mid-sized watershed with area 200 km², this represents a volumetric change of \( 8.8 \times 10^6 m^3 \), which is about half of the annual water consumption of the city of Berkeley, California, population 120,000.
6.2 Sensitivity Analysis of MCWB Drivers and Controls

Sensitivity analysis of MCWB model parameters can be used to quantify the relative influence its various climate and landscape factors on the overall water balance. This is useful to anticipate how future changes to those factors might affect the amount of water in California streams and rivers.

6.2.1 Partition Expression

A common and powerful metric for examining change in the water balance is the normalized annual fraction of evapotranspiration \( E \) relative to annual \( P \), the evaporation ratio \( \Phi \),

\[
\Phi = \frac{E}{P}
\]

Note that \( \Phi \) ranges between 0 and 1 and it is also the response variable for the Budyko curve studied in more detail in § 8.

\[
\begin{align*}
E &= E_d + S' + (P - b) \cdot \beta_{wet} \\
\text{(33)}
\end{align*}
\]

By inspection of the 3-segment linear representation of the annual water balance that was introduced in § 3.4.2 and illustrated in Figure 49, the relationship of annual \( E \) to annual \( P \) is,

\[
E = E_d + S' + (P - b) \cdot \beta_{wet}
\]

where a simplifying assumption has been applied to focus on wet conditions, i.e., \( P \geq b \), in order to streamline analysis by neglecting threshold discontinuities and to treat the water balance as continuous and differentiable. Substituting terms from Table 2 and rearranging to isolate particular contributions, the relationship can be expressed in terms of climate and landscape factors as,
\[ E = \{ \text{PET} \cdot \omega_{\text{PET}} + P \left( 1 - \omega_p \right) \} + \left\{ S' \right\} + \left\{ \left( P \cdot \omega_p - \text{PET} \cdot \omega_{\text{PET}} - S' / \beta_{\text{mid}} \right) \beta_{\text{wet}} \right\} \]

dry mid wet

where the labels dry, mid, and wet are included to clarify which segment of the relationship is described by the various components. Normalizing this relationship by \( P \) provides the normalized evapotranspiration partition,

\[
\Phi = \frac{\text{PET} \cdot \omega_{\text{PET}} + P \left( 1 - \omega_p \right) + S'}{P} + \left( P \cdot \omega_p - \text{PET} \cdot \omega_{\text{PET}} - S' / \beta_{\text{mid}} \right) \beta_{\text{wet}}
\]

where aridity \( \phi = \frac{\text{PET}}{P} \) has been substituted as appropriate. The relationship was somewhat simplified by grouping terms,

\[
\Phi = 1 + \phi \cdot \omega_{\text{PET}} \cdot \left( 1 - \beta_{\text{wet}} \right) - \omega_p \cdot \left( 1 - \beta_{\text{wet}} \right) + \frac{S'}{P} \left( 1 - \frac{\beta_{\text{wet}}}{\beta_{\text{mid}}} \right)
\]

which is the form used for sensitivity analysis.

6.2.2 Evaporation Partition Differentials

To assess the relative impact of various factors of the MCWB model on the partition \( \Phi \), the partial derivative of Eq. (34) was calculated for each term, first for the climate factors \( \omega_{\text{PET}}, \omega_p \), and total \( \text{PET} \), and then for each landscape factors \( \beta_{\text{mid}}, \beta_{\text{wet}}, \) and \( S' \).

6.2.2.1 \( \omega_{\text{PET}}, \text{PET} \) Seasonality

\[
\frac{d\Phi}{d\omega_{\text{PET}}} = \phi \left( 1 - \beta_{\text{wet}} \right)
\]

The effect on \( \Phi \) for a change in \( \omega_{\text{PET}} \) is proportional to the aridity of the watershed and the complement of the wet season storage retention rate, \( 1 - \beta_{\text{wet}} \), which represents the runoff rate for wet conditions. Typically \( 1 - \beta_{\text{wet}} \sim 1 \), so aridity would be expected to be the dominant factor. This means impact of \( \omega_{\text{PET}} \) is strong for very arid watersheds and weaker for wet watersheds, which is intuitive since increased wet-season \( \text{PET} \) would directly increase wet season \( E_d \) and thus overall annual \( E \).

6.2.2.2 \( \omega_p, \text{P} \) Seasonality

\[
\frac{d\Phi}{d\omega_p} = -\left( 1 - \beta_{\text{wet}} \right)
\]

The effect of \( \omega_p \) on \( \Phi \) is in the opposite direction as the wet conditions runoff rate \( 1 - \beta_{\text{wet}} \). This is because an increase in \( \omega_p \), i.e. a greater fraction of \( P \) during the wet season, results in greater runoff
during the wet season, as well as lower $E_d$ during the dry season, reducing overall $E$. As $\beta_{\text{wet}}$ approaches 0 and the wet runoff rate $dR/dP$ approaches 1, any marginal increase in $P_X$ is converted directly to $R$ and thus $E$ decreases by the same amount.

### 6.2.2.3 Annual PET

$$\frac{d\Phi}{d\text{PET}} = \frac{\omega_{\text{PET}}}{P}(1 - \beta_{\text{wet}})$$  \hspace{1cm} (37)

The effect of a change in PET is proportional to $\omega_{\text{PET}}$ because only the wet season portion of PET has a direct effect on $E$, via increased direct evapotranspiration $E_d$. By contrast, dry season evapotranspiration is water-limited by definition, so a change in dry season PET has no effect on total $E$. The fact that $\omega_{\text{PET}}$ is typically small in a Mediterranean climate diminishes the influence of total annual PET on the water balance. Furthermore, any increase in wet season $E_d$ will come at the expense of runoff, and thus be proportional to the runoff rate $1 - \beta_{\text{wet}}$.

### 6.2.2.4 $\beta_{\text{mid}}$, storage retention coefficient for mid-wet conditions

$$\frac{d\Phi}{d\beta_{\text{mid}}} = \frac{1}{P} \frac{S^* \beta_{\text{wet}}}{\beta_{\text{mid}} \beta_{\text{mid}}}$$  \hspace{1cm} (38)

The storage retention ratio for mid-range wetness conditions, $\beta_{\text{mid}}$, influences $\Phi$ via three terms other than $P$. First note that when $\beta_{\text{wet}} = 0$, i.e., when all marginal $P$ is converted directly to $R$ in wet conditions, $\beta_{\text{mid}}$ does not affect $\Phi$, which is as expected because wet conditions are assumed for this analysis. Next, note from the geometry of Figure 49 that the ratio $S^*/\beta_{\text{mid}}$ represents the span of the mid-range wetness interval $b - E_d$; this interval will be referred to as $\Delta P_{\text{mid}}$. The product $\Delta P_{\text{mid}} \cdot \beta_{\text{wet}}/\beta_{\text{mid}}$ thus represents the tradeoff between the wet slope and the mid-range slope as $\Delta P_{\text{mid}}$ varies. The bottom line is that the effect on $\Phi$ increases with $S^*$ and $\beta_{\text{wet}}$, and decreases with $\beta_{\text{mid}}$.

### 6.2.2.5 $\beta_{\text{wet}}$, storage retention coefficient for wet conditions

$$\frac{d\Phi}{d\beta_{\text{wet}}} = \omega_P - \phi \cdot \omega_{\text{PET}} - \frac{1}{P} \frac{S^*}{\beta_{\text{mid}}}$$  \hspace{1cm} (39)

The effect of $\beta_{\text{wet}}$ on $\Phi$ is influenced by a number of MCWB factors. It is in the opposite direction as $\phi \cdot \omega_{\text{PET}}$, which is equivalent to $\text{PET}_{\text{wet}}/P$ and might be thought of as wet season aridity. This is reminiscent of the fraction of wet season precipitation, $\omega_P$, which can also be expressed as $P_{\text{wet}}/P$. As already noted, $S^*/\beta_{\text{mid}}$ represents the extent of the mid-range wetness interval $\Delta P_{\text{mid}}$. The overall effect on $\Phi$ is that $\omega_P$ has an additive influence whereas $\text{PET}_{\text{wet}}/P$ and $\Delta P_{\text{mid}}$ are subtractive.

### 6.2.2.6 $S^*$, storage retention threshold

$$\frac{d\Phi}{dS^*} = \frac{1}{P} \left( 1 - \frac{\beta_{\text{wet}}}{\beta_{\text{mid}}} \right)$$  \hspace{1cm} (40)
Because $\beta_{\text{mid}} > \beta_{\text{wet}}$ is defined to be true for the MCWB framework, increasing the storage retention threshold $S^*$ has the effect of increasing the fraction of precipitation that is captured in the mid-range interval and then retained in storage until the dry season when it can be evaporated. This effect is partially offset by the proportion $\beta_{\text{wet}}/\beta_{\text{mid}}$, which represents the tradeoff between higher evaporation rates in the mid-range segment vs. the wet segment.

### 6.2.3 Sensitivity Analysis

To build an intuition for the relative impact of the parameters on $\Phi$ it is useful to quantify the effect of changing the value of each parameter, starting with a baseline of typical values observed in California watersheds. The values listed in Table 7 of the MCWB model yield the following for rates of change for each partial derivative,

\[
\frac{d\Phi}{d\omega_{\text{PET}}} = \frac{1500}{1000} (1-0.1) = 1.35 \text{ mm/mm}
\]

\[
\frac{d\Phi}{d\omega_{p}} = -(1-0.1) = -0.9 \text{ mm/mm}
\]

\[
\frac{d\Phi}{d\text{PET}} = \frac{0.1}{1000} (1-0.1) = 0.00009 \text{ mm}^{-1}
\]

\[
\frac{d\Phi}{d\beta_{\text{mid}}} = \frac{250}{1000} \frac{0.1}{0.5^2} = 0.1 \text{ mm/mm}
\]

\[
\frac{d\Phi}{d\beta_{\text{wet}}} = -\frac{0.9}{1000} \frac{1500}{1000} \frac{0.1}{0.5} - \frac{250}{1000} \frac{1}{0.5} = 0.25 \text{ mm/mm}
\]

\[
\frac{d\Phi}{dS^*} = \frac{1}{1000} \left( \frac{0.1}{0.5} - 1 \right) = -0.0008 \text{ mm}^{-1}
\]

These rates cannot be directly compared because the units vary, but their relative importance to the water balance can be evaluated by comparing the impact that plausible changes to each term would have on the partition $E/P$. For ratios and rates a change of 0.1 mm/mm is assumed, whereas for depth values a 20% change is considered. The computed partial derivatives were then multiplied by the corresponding representative change to yield an estimate of the overall impact on $E/P$.

As summarized in Table 7, the there is a large variation in the effect of individual parameters on the water balance. The largest impact is observed for the seasonality terms $\omega_{\text{PET}}$ and $\omega_p$; the effect on $E/P$ is approximately proportional to the change in either parameter. Changes to the storage retention threshold $S^*$ have about half of the impact as the seasonality terms. And the effect of changes to the storage retention coefficients $\beta_{\text{mid}}$ and $\beta_{\text{wet}}$ and total annual $\text{PET}$ is roughly an order of magnitude smaller than seasonality changes.
**Table 7: Sensitivity analysis of the effect on the water balance partition \( E/P \) for changes to each of the climate and landscape factors of the MCWB model, assuming typical values.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Units</th>
<th>Typical Parameter Value</th>
<th>Slope of partial derivative for typical values</th>
<th>Representative deviation from typical value</th>
<th>Effect on ( E/P ) (mm/mm, magnitude)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \omega_{PET} )</td>
<td>PET(_{wet}/PET )</td>
<td>mm/mm</td>
<td>0.1</td>
<td>1.35 mm/mm</td>
<td>( \pm 0.1 )</td>
<td>0.135</td>
</tr>
<tr>
<td>( \omega_P )</td>
<td>( P_{wet}/P )</td>
<td>mm/mm</td>
<td>0.9</td>
<td>-0.9 mm/mm</td>
<td>( \pm 0.1 )</td>
<td>0.09</td>
</tr>
<tr>
<td>PET</td>
<td>total annual PET</td>
<td>mm</td>
<td>1500</td>
<td>0.00009 mm(^{-1} )</td>
<td>( \pm 300 )</td>
<td>0.027</td>
</tr>
<tr>
<td>( \beta_{mid} )</td>
<td>storage retention fraction, midrange</td>
<td>mm/mm</td>
<td>0.5</td>
<td>0.1 mm/mm</td>
<td>( \pm 0.1 )</td>
<td>0.01</td>
</tr>
<tr>
<td>( \beta_{wet} )</td>
<td>storage retention fraction, wet</td>
<td>mm/mm</td>
<td>0.1</td>
<td>0.25 mm/mm</td>
<td>( \pm 0.1 )</td>
<td>0.025</td>
</tr>
<tr>
<td>( S^* )</td>
<td>storage retention threshold</td>
<td>mm</td>
<td>250</td>
<td>-0.0008 mm(^{-1} )</td>
<td>( \pm 50 )</td>
<td>0.04</td>
</tr>
</tbody>
</table>

6.2.4 Discussion of Sensitivity Analysis

Sensitivity analysis of the MCWB model parameters is useful because it quantifies how changes to individual landscape and climate factors can affect the overall water balance. The objective variable for this analysis was the annual partition \( \Phi = \frac{E}{P} \), and thus the three-segment variation of the MCWB model as a function of \( P \), Eq. (34), was used to evaluate the effects of the climate factors \( \omega_{PET}, \omega_p, \) and total \( PET \), and the landscape factors \( \beta_{mid}, \beta_{wet}, \) and \( S^* \). The analysis assumed wet conditions to make the partition continuous and differentiable by eliminating discontinuities at segment thresholds.

Partial derivatives were then derived for each factor in turn. The impact of the \( PET \) seasonality coefficient \( \omega_{PET} \) was shown to be determined primarily by the aridity of a watershed. The effect of the \( P \) seasonality coefficient on \( \Phi \) is controlled only by the complement of the wet conditions \( S^* \), which typically has a value near 1. The partial derivative of \( PET \) is primarily determined by \( \omega_{PET} \), which is intuitive since this controls the amount of \( PET \) during the wet season when \( E \) is limited only by energy. The partition impact of the mid-range storage retention rate \( \beta_{mid} \) increases with \( S^* \) and \( \beta_{wet} \), and decreases with \( \beta_{mid} \). The impact of \( \beta_{wet} \) on \( \Phi \) is controlled by the additive influence of \( \omega_{p} \) and the subtractive influence of wet season \( PET \) and the ratio \( S^*/\beta_{mid} \). And the storage retention threshold \( S^* \) is determined by the ratio \( \beta_{wet}/\beta_{mid} \), which represents a tradeoff between higher evaporation rates in the mid-range segment versus the wet segment.

To facilitate sensitivity calculations, typical values of the MCWB model parameters and climate drivers were assumed, as shown in Table 7. Given these values, deviations were assumed to quantify the impact on \( \Phi \): variations of 0.1 mm/mm for ratios and slopes, and a 20% change for absolute values. The impact of the seasonality terms \( \omega_{PET} \) and \( \omega_p \) was found to be roughly an order of magnitude larger than \( PET \) or the landscape properties \( \beta_{mid}, \beta_{wet} \), while \( S^* \) had an intermediate effect.
6.3 SUMMARY

The results and findings of this chapter are summarized in the context of the motivating research questions:

**Did the amount of water in California streams and rivers change during the 20th century, relative to the controlling climate and landscape factors?**

Yes, the analysis of § 6.1 demonstrated that most of the watersheds in this study showed a slight negative trend in \( R \) during the period of record for each watershed. For the 53 watersheds with more significant trends (p-value < 0.1) the decrease in \( R \) was more pronounced for mesic and humid watersheds. And while the magnitude of the trends was generally small, on the order of 1 mm/year, this can translate into a significant volumetric change in the water supply for even modestly sized watersheds.

**If changes in runoff were observed, what factors accounted for the change?**

By controlling for different climate drivers in § 6.1.3 and § 6.1.4 it was possible to partially isolate the impact of landscape factors and seasonality respectively, as summarized in Figure 45. For most arid and mesic watersheds the effects of both landscape and seasonality were to depress \( R \), whereas for humid watersheds seasonality acted to decrease \( R \) while the landscape controls tended to increase \( R \) for most watersheds. Furthermore, energy-excess precipitation \( P_x \) was shown to be broadly decreasing for humid watersheds, which is consistent with a corresponding decrease in \( R \).

**What does the MCWB model reveal about how changes to climate and landscape factors can affect the overall water balance?**

Sensitivity analysis was conducted for climate and landscape factors of the three-segment MCWB model of \( R \) as a function of \( P \). The seasonality terms \( \omega_{PET} \) and \( \omega_p \) were found to be the dominant controls of the annual evaporative partition \( \Phi \), with \( S^* \) about half as important, and \( PET \) and the landscape properties \( \beta_{mid}, \beta_{wet} \) roughly an order of magnitude less important than seasonality. These findings indicate that future changes to the water balance can be anticipated given suitably accurate climate forecasts of \( P, PET \), and their seasonality.

There are several possible paths to build upon these findings. Climate forecast data could be used to predict future changes to the water balance. In terms of historical analysis, the metric for this analysis was normalized runoff depth, which was useful for comparison across many watersheds, but extending the analysis to include volumetric streamflow could address additional interesting research questions such as whether the overall amount of water in California streams changed in the 20th century. Another extension would be to compare the three runoff trend components – total, landscape, and seasonality – on a per-watershed basis to understand the extent to which landscape and seasonality controls are working with or against each other, a question that was not possible to address with the aggregate approach of this research.

Overall, the straightforward structure and interpretable parameter of the MCWB model was shown to be a useful tool for identifying historical trends in the water balance and for anticipating future changes.
7 Estimating MCWB Parameters for Ungaged Watersheds

It was demonstrated in § 5 that the MCWB model of \( R \) as a function of \( P \) provides a good estimate of observed annual \( R \) for watersheds where historical water balance data is available. A potentially valuable extension of the MCWB model is to estimate annual \( R \) in ungaged watersheds. To do so requires estimation of model parameters using a method other than regression with historical records, and two approaches are assessed in this section: to assume similar parameter values as for nearby gaged watersheds, and to estimate parameter values as a function of various landscape and climate features of a given watershed.

7.1 Proximate Watersheds

As demonstrated by the results of § 5.3, estimates of MCWB model parameters were often geographically clustered, which suggests that spatial proximity may be a useful predictor for parameter values. Put simply, the question is whether model parameters estimated in one watershed can also be used for nearby watersheds, and if so then how is “nearby” defined?

7.1.1 Spatial Autocorrelation

Spatial autocorrelation (SA) quantifies the degree to which the distance is predictive of the similarity of a particular feature that both items share. In this case, SA quantifies whether nearby watersheds are more similar, in terms of MCWB parameter values, than watersheds that are far from each other. A standard metric for evaluating SA is Moran’s I test [Moran, 1950], which is a multivariate extension of the Pearson correlation coefficient, but with important differences in interpretation: a value of +1 indicates perfect spatial clustering of similar values, a value of -1 indicates uniform spatial dispersion of values, and a value of 0 indicates no autocorrelation, i.e., random spatial distribution of values. SA is often dependent on the scale of evaluation, so a common approach is to evaluate Moran’s I test across a range of characteristic distances.

The results of Moran’s I test for SA among the 159 watersheds of this study are presented in the correlogram of Figure 50 for the three primary MCWB model parameters: \( \alpha_{\text{mid}} \), \( \alpha_{\text{wet}} \), and \( S^* \). Pairwise distances between watersheds were calculated relative to their geographic centroids. There is a clear and significant (p-value < 0.05) proximity correlation for the mid-range wetness runoff rate \( \alpha_{\text{mid}} \) and a significant but less prominent relationship for the wet runoff rate \( \alpha_{\text{wet}} \). For the storage retention threshold \( S^* \) there is a subtle indication of SA only for very close watersheds. For all watersheds SA is at a maximum for the closest distance, 25 km, tapering towards zero and non-significant p-values for distances greater than 75 km, with the exception of \( S^* \) which is significant only at the 25 km range.
The implication of this SA analysis is that the runoff rates tend to be more similar for nearby watersheds than for distant watersheds, but this is not necessarily true for the threshold $S^*$. For all parameters there is a distance threshold above which the estimates from nearby watersheds are no better than random; the average value of a given parameter is arguably as good a choice as any. This suggests a spatial rubric for estimating MCWB parameters in ungaged watersheds: if the nearest gaged watershed is within 175 km use the values of $\alpha_{\text{mid}}$ and $\alpha_{\text{wet}}$ from that watershed, otherwise use the statewide averages of those parameters; if the nearest gaged watershed is within 25 km use the value of $S^*$ from that watershed, otherwise use the statewide average for that parameter. These rules are summarized in Eq. (41),

$$
\begin{align*}
\alpha_{\text{mid}}, \alpha_{\text{wet}} &= \begin{cases} 
\text{nearest gaged} & \text{if } d_{\text{nearest}} \leq 175 \text{ km} \\
\text{statewide average} & \text{if } d_{\text{nearest}} > 175 \text{ km}
\end{cases} \\
S^* &= \begin{cases} 
\text{nearest gaged} & \text{if } d_{\text{nearest}} \leq 25 \text{ km} \\
\text{statewide average} & \text{if } d_{\text{nearest}} > 25 \text{ km}
\end{cases} 
\end{align*}
$$

Additional approaches to strictly spatial analysis were considered but rejected with the reasoning that many of the landscape and climate factors that are known to affect the water balance are not necessarily associated with distance. For example, watersheds that are adjacent but on opposite faces of a mountain range are likely to have very different hydrological characteristics, whereas two barren
watersheds in distant corners of California’s arid regions may have very comparable hydrology. Using such features to predict MCWB parameter values is the topic of the next section.

7.2 Machine Learning Estimates of MCWB Parameters

7.2.1 Methodology

7.2.1.1 Overview

A general approach for estimating MCWB model parameters $\theta_j$ for a watershed $j$, 

$$\theta_j = [\alpha_{\text{mid},j}, \alpha_{\text{wet},j}, S_j^*]$$

is to identify relationships between $\theta_j$ and watershed characteristics $\Omega_j$, and then estimate $\theta_j$ as a function of $\Omega_j$, 

$$\theta_j \approx f(\Omega_j)$$

where $\Omega_j$ consists of some combination of features expected to impact the water balance, i.e., climate factors $\omega_{\text{climate}}$ and landscape factors $\omega_{\text{landscape}}$, such that $\Omega_j = [\omega_{\text{climate}}, \omega_{\text{landscape}}]$. In general $\Omega_j$ will vary spatially and temporally, but for the lumped analysis of this study the features are averaged in space and time for the watershed. Example climate features include aridity, fraction of precipitation as snow, and 10th percentile of annual precipitation; example landscape features include elevation, soil properties, vegetation type, and stream sinuosity. A full list of watershed features that were considered is provided in the Appendix § 10.2.

In principle it could be that the same set of features is useful to estimate all three parameters of $\theta_j$, but in practice it was found that the importance of features varied by parameter type. This is not surprising, since § 4 described the different mechanisms underlying each MCWB model parameter. Thus, a more accurate representation of the relationship is, 

$$\theta_{k,j} \approx f(\Omega_{k,j}) + \epsilon_{k,j}$$  \hspace{1cm} (42)

where $k$ is the MCWB parameter type (e.g., $\alpha_{\text{mid}}$), and $\epsilon_{k,j}$ is the estimation error for parameter $k$ in watershed $j$. Features were selected and their relationship to $\theta_{k,j}$ was generalized by minimizing $\epsilon_k$ across various watersheds $j$.

To recap, regressions were performed for each MCWB parameter as a function of watershed landscape and climate features, across many watersheds, to determine the underlying relationship between $\theta_{k,j}$ and $\Omega_{k,j}$. The resulting models, Eq. (42), provide a method for estimating the annual water balance in ungaged watersheds by first estimating each unknown MCWB parameter $\theta_{k,j}$ using known features $\Omega_{k,j}$.

7.2.1.2 Outcome Variable Selection

The outcome variables were the MCWB model parameters for each the 159 California watersheds as estimated in § 5. Parameters $\alpha_{\text{mid}}$ and $\alpha_{\text{wet}}$ were evaluated directly, but regressions for parameter $S^*$
required more careful consideration because preliminary results indicated poor performance for modeling $S^*$ as a function of watershed features. As illustrated in the MCWB diagram of Figure 18, an equivalent inference problem is to estimate the $P_X$ threshold for wet conditions $c$, or the intercept of the wet segment $g$. This is because $S^*$ can be calculated from either of these values in combination with the slope estimates. Recall that humid watersheds typically provide little information about the transition from mid-range to wet conditions, and so for these watersheds MCWB estimates of $c$ have little or no data to support the estimate. By comparison, $g$ is robustly estimated for every watershed type because the wet segment of the MCWB is almost always calculated from 10 or more data points that provide a reasonable estimate of the x-axis intercept at $g$. Thus, $g$ was chosen as a proxy for $S^*$, and this improved regression results relative to direct evaluation.

7.2.1.3 Predictor Feature Selection

To ensure a generalizable process that can be extended to ungaged regions, it was important to choose watershed features $\Omega_j$ that would be straightforward to estimate for an arbitrary location. Thus, the analysis was limited to two sources of data: those provided in the GAGES-II watershed database, and climate parameters derived from the geospatial data sources described in § 3.2. The GAGES-II data cover thousands of U.S. watersheds, and furthermore the features in the dataset can generally be derived from broadly available source data, such as landscape cover, soil features, and topography databases; a subset of 86 relevant watershed features are enumerated in Appendix § 10.2.2. A feature pre-selection step consisted of manual filtering of uninformative or irrelevant features, including exclusion of:

- Data that is specific to the streamflow gage location rather than watershed-wide features, such as average temperature.
- Irrelevant metrics such as dam obstructions; watersheds with dams were excluded from this study.
- Streamflow values, which were excluded to maintain the generalizability of results to watersheds with no gage records.

After this pre-selection, 149 potential features remained. Two additional pre-processing steps were performed to further mitigate uninformative or redundant features:

- Removal of features with zero or near-zero variance, i.e., values that are identical or nearly identical for all watersheds.
- Removal of highly correlated and linearly redundant features, which add little or no predictive power to the model outcomes and may be problematic for certain regression algorithms.

The outcome of this feature selection process was a set of 81 landscape and climate metrics that were used as regression predictors for each of the 159 watersheds in the study. An additional 5 features were derived from the climate and water balance data used for the MCWB model, including precipitation quantiles, aridity, and watershed type ($\text{Arid, Mesic, Humid}$). These are enumerated and described in Appendix § 10.2.1, for a total of 86 predictors. This is a large number of predictors given the count of watersheds in the study, but since one objective of this section was to identify relevant features, and since the selected classification and regression algorithms provide either feature selection or feature importance metrics, the breadth of features was appropriate. Preliminary analysis suggested that allowing for feature interactions (e.g., polynomial models) did not appreciably
improve model performance, and so the features were considered independent for all regression algorithms.

### 7.2.1.4 Regression and Classification Algorithms

Regression and classification algorithms were selected based on effectiveness and interpretability. For regression of MCWB parameters $a_{\text{min}}$, $a_{\text{cen}}$, and $g$, effectiveness was measured in terms of minimizing root mean squared error (RMS). Regression algorithms that were considered included generalized linear models (including variants of L1 and L2 regularization), tree-based algorithms (including decision trees, random forest, and gradient boost models), support vector machines, Gaussian process models, and neural networks. Based on exploratory analysis of dozens of algorithms, the following three regression algorithms were selected:

- **GLM Net**: Generalized Linear Model with Regularized Elastic-Net [Friedman et al., 2010]
  - Selected for its relative simplicity and interpretability, this was used as a baseline model for comparison with other methods. This linear model uses the elastic-net penalty to seek an optimal combination of the parameter selection benefits of L1 (LASSO) penalization and the stability of L2 (ridge) regularization.

- **EV Tree**: Decision Trees with Evolutionary Learning Algorithm [Grubinger et al., 2014]
  - Selected for interpretability of outcomes and good performance. The benefit EVTree relative to other single-tree approaches is improved global optimization provided by an evolutionary algorithm that iteratively modifies “generations” of the tree to achieve an optimal structure. This method can produce favorable results, but, like all single-tree decision models, the regressions tend to be unstable, i.e., small variations in inputs, such as different splits of TEST/TRAIN data, may yield very different model outcomes.

- **Random Forest**: Random Forest Regression [Liaw and Wiener, 2002]
  - Selected for its consistently high performance across all MCWB parameters, the main drawback of this approach is poor interpretability of the algorithm. “Forest” refers to the ensemble of decision trees used by the algorithm, and “Random” refers to random variations in both the tree structures and the subsets of predictor data used to fit the model. Random forest models are widely used because they offer good predictive performance for a wide variety of problems with minimal parameter intervention.

Classification algorithms were used to evaluate the use of predictor features to determine watershed wetness type, *Arid*, *Mesic*, or *Humid*; accuracy was the evaluation metric. The approaches that were considered included logistic regression, tree-based models, discriminant analysis, and bagging models. Classifier versions of EVTree and Random Forest were selected for interpretability and effectiveness, respectively; one additional approach was also used,

- **FDA**: Flexible Discriminant Analysis [Hastie et al., 1994]
  - Discriminant analysis seeks combinations of discriminants that separate two or more outcome classes. Linear discriminant analysis uses linear regression for this separation, and flexible discriminant analysis uses non-parametric regression to achieve more flexible classifiers that are effective for a broad variety of classification problems.
7.2.1.5 Implementation

The general workflow for performing regressions and evaluating outcomes was as follows:

1. Choose which outcome is to be evaluated, i.e., $a_{\text{mid}}$, $a_{\text{wet}}$, $g$, or watershed wetness type.
2. Specify algorithm and its associated parameter vector $\Pi$ that must be optimized to achieve best performance.
   - Example: GLMNet model with parameter vector $\Pi = [\text{normalization penalty}, L1/L2 \text{ mix parameter}]$.
3. Split data into TRAIN and TEST datasets
   - TEST: 25% of the data ($N=39$ watersheds) was withheld from the parameter optimization and model training process for the purpose of evaluating model performance. TEST data were randomly selected with the constraint that the distribution of outcome values should be representative of the distribution for the entire dataset.
   - TRAIN: the remaining 75% of the data ($N=120$ watersheds) was used to optimize and train the machine learning model.
4. Select optimal $\Pi$ via iterative training and evaluation of the algorithm using TRAIN data
   - Starting with some initial values for the vector $\Pi$, iterate a grid search over a specified range of values, specific to each parameter, using a specified increment.
   - FOR given values of $\Pi$:
     - FOR 10 validation iterations:
       - Randomly split TRAIN data into FIT and VALIDATION samples, using 0.8/0.2 split, i.e. 96 FIT watersheds and 24 VALIDATION watersheds.
       - Perform regression using FIT data.
       - Predict outcomes for VALIDATION data, and calculate error relative to observations.
     - Calculate average performance across sampling iterations.
   - Choose optimal $\Pi$ that provides best average model performance.
5. Use optimal $\Pi$ to train machine learning model
   - Final training uses all TRAIN data.
   - Use trained model to predict outcomes for TEST data.
   - Test errors are best estimate of generalized model performance.

The model optimization and evaluation workflow was implemented using the Caret package for R [Kuhn, 2008].

7.2.1.5.1 Assumptions

There were two significant simplifications applied to the watershed predictor features: spatial averaging, and temporal snapshots and averaging. There is an implicit assumption that these simplifications are appropriate for the intended modeling application, and this merits discussion. Regarding spatial averaging, the approach is justified because it is consistent with the one-dimensional representation of the MCWB model.
Temporal snapshots and averaging are more conceptually problematic. As acknowledged in § 6.1.3, in some sense this research tries to have it both ways with regards to stationarity. On one hand, the MCWB model regressions based on the long-term average water balance were shown in § 5 to provide insights about hydrology mechanisms and regional commonalities. On the other hand, the analysis of § 6 identified significant changes to the water balance during the period of record in the 20th century. The intent has been to demonstrate that both of these perspectives have merit to the extent that the analysis results are useful, and the same criteria is applied again here. It is a limitation of the methodology that temporal averages or, in many cases, discrete temporal snapshots, of the conditions in a watershed are used to predict MCWB parameters that encompass decades of hydrological activity. However, despite this limitation, the relationship was found to be remarkably robust. An extension of this research would be to examine the relationship between temporal changes in watershed features and MCWB parameters.

7.2.2 Results

7.2.2.1 MCWB Watershed Type

Classification of $\zeta$ was quite effective, as quantified by accuracy for overall results and balanced accuracy for each of the individual categories of $\zeta$ as summarized in Table 8. Note that balanced accuracy [Brodersen et al., 2010] is less biased than accuracy for this application because the outcomes are imbalanced, i.e., the type counts for the TEST data sample were $N_{\text{arid}} = 5$, $N_{\text{mesic}} = 12$, and $N_{\text{humid}} = 21$. By either metric the accuracy is ~0.9 for the model with the best performance, FDA, implying that $\zeta$ can be correctly inferred for 90% of watersheds given the appropriate predictor features. The sample size is admittedly small, but the reported results were representative of multiple permutations of TRAIN and TEST data samples.

As is commonly the case, feature selection and importance varied by algorithm. The FDA algorithm required only 5 features to achieve a high level of accuracy, per Figure 51: aridity, number of wet days per month (WDMIN_BASIN), amount of shrub vegetation (SHRUBNLCD06), PET, and number of road-stream intersections (RD_STR_INTERS) which is a measure of human development.

![Graph: WS-type: Variable Importance, FDA](image)

Figure 51: Variable importance for FDA classification of watershed wetness category $\zeta$. 

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The decision tree for EV Tree classification of \( \zeta \) is shown in Figure 52. Node [1] splits results by the amount of roads per square mile, another measure of human development. Watersheds with fewer roads are then split in node [2] according to whether the first frost of the year occurs before or after October 30. Watersheds where frost generally happens before this data are classified as humid in node [3]. If frost occurs later, then the next consideration is aridity: watersheds with average aridity values less than 1.599 are classified as mesic watersheds in node [5], while higher aridity is associated with arid watersheds in node [6]. Returning to node [1], watersheds with a higher density of roads are bifurcated in node [7] according to the average amount of precipitation in August. If August \( P \) is essentially zero, then it is likely to be a mesic watershed per node [8], but if there is generally some \( P \) that month then the watershed is classified as humid.

![Figure 52: EV Tree model structure for classification of watershed type \( \zeta \). Outcomes shown for training data: a = Arid, d = Humid, m = Mesic.](image)

An overall view of classification performance for watershed type \( \zeta \) is shown in the confusion matrix of Table 8. Perfect classification would result in values only along the diagonal, i.e., the modeled and observed outcomes would all be the same. As it is, the arid and humid watersheds are sometimes confused for each other, and likewise for mesic and humid watersheds. However, arid and mesic watersheds were never mistaken for each other for this particular TEST data sample.
Table 8: Watershed type $\zeta$ classification results for test data. The confusion matrix summarizes Predicted categories (rows) vs. Actual categories, with counts listed sequentially for the three classification algorithms: EV Tree (EV), Random Forest (RF), and Flexible Discriminant Analysis (FDA).

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Arid</th>
<th>Mesic</th>
<th>Humid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arid</td>
<td>3, 4, 4</td>
<td>0, 0, 0</td>
<td>5, 1, 0</td>
</tr>
<tr>
<td>Mesic</td>
<td>0, 0, 0</td>
<td>10, 11, 11</td>
<td>0, 3, 3</td>
</tr>
<tr>
<td>Humid</td>
<td>2, 1, 1</td>
<td>2, 1, 1</td>
<td>16, 17, 18</td>
</tr>
</tbody>
</table>

A special consideration for MCWB parameter estimation was whether to treat the watershed wetness type $\zeta$ as a predictor or an outcome. Recall from § 3.4.3 that wetness types were initially assigned via visual inspection of the shape of the MCWB regression for a given watershed. Given the very good classification performance and the significant predictive power of $\zeta$ for other MCWB parameters, the chosen approach was to assume that $\zeta$ can be classified as a preliminary step and to subsequently treat it as a predictor for regression of MCWB parameters.

7.2.2.2 MCWB Parameter $\alpha_{mid}$

The distribution of values estimated for $\alpha_{mid}$ is shown in the histogram of Figure 53. The most noteworthy features are spikes the number of watersheds with values near 0.3 and 0. The values near 0 are all arid watersheds, where $\alpha_{mid} \sim 0$ by definition. Most of the values near 0.3 are humid watersheds; 42 out of 50 humid watersheds have $0.29 < \alpha_{mid} < 0.36$. This is not surprising, due to two aspects of the MCWB regression. Referring to Figure 11, first recall that humid watersheds have few if any data points in the mid-range wetness segment characterized by slope $\alpha_{mid}$. Second, recall from § 5.1 that a constraint values of $\alpha_{mid}$ were constrained as $0 < \alpha_{mid} < 0.6$ for the MCWB regression (with 4 exceptions), and thus the estimate $\alpha_{mid} \sim 0.3$ is simply the average of random, uninformed guesses for the mid-level wetness segment of humid watersheds.

Figure 53: Distribution of regression estimates for MCWB parameter $\alpha_{mid}$ for 159 California watersheds.

These two artifacts of the MCWB model structure simplify the regression burden for $\alpha_{mid}$ and the explicit connection to watershed type $\zeta$ helps explain why that feature is so important to the
regression. Nonetheless, these considerations do not diminish the utility of predicting \( \alpha_{\text{mid}} \) from watershed features.

The performance of the three regression models, GLM Net, EV Tree, and Random Forest, is summarized in Table 9 in terms of RMSE and \( R^2 \) of modeled vs. observed values of \( \alpha_{\text{mid}} \) for the TEST dataset that was withheld from model regressions. RMSE is rather small for all models, and \( R^2 \) values suggest that the models explain roughly 60 – 70% of the variation observed in values of \( \alpha_{\text{mid}} \).

<table>
<thead>
<tr>
<th>( \alpha_{\text{mid}} ) TEST data</th>
<th>GLM Net</th>
<th>EV Tree</th>
<th>Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE [\text{~}]</td>
<td>0.1</td>
<td>0.1</td>
<td>0.09</td>
</tr>
<tr>
<td>( R^2 ) [\text{~}]</td>
<td>0.61</td>
<td>0.56</td>
<td>0.68</td>
</tr>
</tbody>
</table>

Table 9: Summary of performance of each regression algorithm for MCWB parameter \( \alpha_{\text{mid}} \) evaluated with test data.

The regression outcomes are visualized in Figure 54, which shows modeled and observed values of \( \alpha_{\text{mid}} \) for each algorithm, for both the TRAIN and TEST datasets. As expected, performance was generally much better for the TRAIN data, especially for the Random Forest model. Notably, this algorithm used all 86 watershed features \( \Omega \); given that there were 120 values for \( \alpha_{\text{mid}} \) in the TRAIN data, there were few remaining degrees of freedom in the outcomes. This suggests a risk of over-fitting, and indeed this is observed in the difference in Random Forest performance for the TRAIN and TEST samples.

By contrast, automated feature selection by the GLM Net and EV Tree models resulted in training with a subset of predictors: 30 predictors were selected by the GLM Net, including the top 10 enumerated in Figure 55; and only 3 predictors were selected by EV Tree, as shown in Figure 56. The use of fewer predictors reduces the potential for over-fitting, and this is observed in the closer alignment of TRAIN and TEST performance for these two models in Figure 54.
Figure 54: Comparison of predicted vs. observed values for MCWB parameter $\alpha_{\text{mid}}$ for training data (left column) and test data (right column), for three regression algorithms: Random Forest (top row), EVT Tree (middle row), and GLMNet (bottom row).
Solid line indicates ideal 1:1 relationship. Note that scales differ across plots.
Is there agreement among the algorithms about which features are important to determine $\alpha_{\text{mid}}$? The 10 most important predictors for GLM Net and Random Forest are shown in Figure 55 and all EV Tree predictors are shown in Figure 56. As expected, watershed type is the most important factor for all models. Interestingly, no other factors are shared across the top 10 for all models. The average percentage of precipitation that falls as snow (SNOW_PCT_PRECIP) is common to both Random Forest and EV Tree. Several factors are shared between GLM Net and Random Forest: aridity, average value for the range of available water capacity for the soil layer or horizon (AWCAVE), historical mean May precipitation (MAY_PPT7100_CM).

The EV Tree model is again useful for developing an intuition about how the predictor factors interact. Note that for regression trees the median value of a leaf node is taken as the modeled value. Node [1] splits the watersheds by wetness type $\zeta$, with all arid watersheds assigned a value $\alpha_{\text{mid}} \sim 0$ in leaf node [2]. The remaining mesic and humid watersheds are next split by the fraction of precipitation that falls as snow in node [3]. Snow fractions $> 10\%$ are bucketed into leaf node [7], with a median value $\alpha_{\text{mid}} \sim 0.37$. Watersheds with little snow are then separated by longitude in node [4]. A longitude of $122.4^\circ$ is roughly aligned with San Francisco, which means that westward of this value encompasses the northwest coastal range of California, with $\alpha_{\text{mid}} \sim 0.34$ in leaf node [5]. East of this longitude values of $\alpha_{\text{mid}} \sim 0.18$ are seen in leaf note [6].
7.2.2.3 MCWB Parameter $\alpha_{\text{wet}}$

The distribution of estimated values for $\alpha_{\text{wet}}$ is shown in Figure 57. Recall that the MCWB model regression constraint was $0.6 < \alpha_{\text{wet}} < 1.2$ for most watersheds, with a small number of exceptions for watersheds where this constraint did not yield satisfactory convergence of the MCMC regression. The distribution of values is roughly normal, with a mean value of 0.89 and standard deviation of 0.18 mm/mm. As previously noted, values of $\alpha_{\text{wet}} > 1$ are physically questionable because they imply that $R$ increases faster than $P$, a discrepancy that was assumed to be an artifact of systematic underestimates of $P$ or overestimates of $R$.

Performance of the three regression algorithms for predictions of $\alpha_{\text{wet}}$ is summarized in Table 10 in terms of RMSE and $R^2$. The estimation uncertainty is rather large relative to the magnitude of the parameter values. As a reference, consider that the lowest RMSE of 0.16 is comparable to the standard deviation of the source distribution.

Modeled vs. observed outcomes are shown in Figure 58 for the Random Forest model, which demonstrated the best performance. The TEST data shows a general monotonic agreement that is consistent with the $R^2$ value of 0.47, which suggests that the model accounts for about 50% of the variation in $\alpha_{\text{wet}}$. Notably, the performance metrics are significantly better for the TRAIN data, an indication of over-fitting, i.e., high variance. This suggests that more data (estimates of $\alpha_{\text{wet}}$ for more watersheds) would improve the model.
The most important predictors for the Random Forest model were a mix of climate and landscape factors: watershed type $\zeta$, the date of the first frost in the watershed (FST32F_BASIN), average precipitation in November (NOV_PPT7100_CM), soil silt content (SILTAVE), and latitude (LATN).

<table>
<thead>
<tr>
<th>$\alpha_{wet}$ TEST data</th>
<th>GLM Net</th>
<th>EV Tree</th>
<th>Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE [mm/mm]</td>
<td>0.18</td>
<td>0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>R^2</td>
<td>0.39</td>
<td>0.36</td>
<td>0.47</td>
</tr>
</tbody>
</table>

Table 10: Summary of performance for each regression algorithm for MCWB parameter $\alpha_{wet}$ evaluated with test data.

Interestingly, the EV Tree decision tree achieved the same RMSE as the Random Forest, but with the use of only one feature, watershed type $\zeta$. Figure 59 shows arid watersheds generally had values of $\alpha_{wet}$ between 0.6 - 0.8, whereas mesic and humid watershed had values between 0.8 – 1.0.

Figure 57: Distribution of regression estimates for MCWB parameter $\alpha_{wet}$ for 159 California watersheds.
Figure 58: Predicted (modeled) vs. observed values of $\alpha_{\text{wet}}$ for the Random Forest model, showing outcomes for training data (left) and test data (right). Solid line indicates ideal 1:1 relationship. Note that the vertical scales differ.

Figure 59: Visualization of the EV Tree regression of MCWB parameter $\alpha_{\text{wet}}$ outcomes for training data.
7.2.2.4 MCWB Parameter $g$-intercept

A histogram of estimated values for the intercept $g$ for the 159 watersheds in the study is shown in Figure 60. The distribution is skewed toward the origin, with a mean of 225 mm and median of 210 mm, and values are constrained to $g \geq 0$.

Regression performance is summarized in Table 11, and the Random Forest model again provided the best overall performance. The RMSE of 124 mm is fairly high relative to the distribution of estimated values for $g$, comparable to the 50th percentile around the median. However, note in Figure 61 that two outliers contribute disproportionally to RMSE; without these two values the RMSE is roughly 80 mm and $R^2 > 0.5$.

<table>
<thead>
<tr>
<th>g-intercept TEST data</th>
<th>GLM Net</th>
<th>EV Tree</th>
<th>Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE [mm]</td>
<td>163</td>
<td>124</td>
<td>124</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0</td>
<td>0.26</td>
<td>0.44</td>
</tr>
</tbody>
</table>

*Table 11: Summary of performance for each regression algorithm for MCWB parameter $g$, evaluated for withheld test data.*

The importance of watershed features for predicting $g$-intercept is interesting in the context of interpretation of its physical meaning. Note that via the geometry of Figure 13, $S^*$ is a proportional to $g$, scaled by MCWB model slope values,

\[
S^* = \frac{1 - \alpha_{mid}}{1 - \alpha_{mid} + \alpha_{wet}} \cdot g
\]
Recall that $S^*$ was interested as the storage retention threshold, the amount of dynamic storage that triggers a transition to wet runoff conditions. In the special case when $\alpha_{\text{wet}} = 1$, $S^*$ can be considered the overall storage capacity; all energy-excess precipitation $P_N$ above this threshold becomes streamflow. This implies that $g$, like $S^*$, should be controlled by landscape features, and in particular features related to water storage and retention.

As shown in Figure 62, soil clay content (CLAYAVE) is the second most important predictor for the Random Forest model, and it is the only predictive factor identified by the EV Tree model, per Figure 63. The importance of this feature support the storage capacity interpretation of $S^*$. 

![Figure 61: Predicted (modeled) vs. observed values of $g$-intercept using the Random Forest model, evaluated on training data (left) and test data (right). Solid line indicates ideal 1:1 relationship. Note that the vertical scales differ.](image)
7.2.2.5 Results Summary

The overall results for prediction of the three MCWB model parameters $\alpha_{mid}$, $\alpha_{wet}$, and $g$ are presented in Table 12. The Random Forest model provided the best predictive performance, though as noted there was a tendency to over fit to the training data. The EV Tree algorithm was generally comparable to Random Forest for estimation error RMSE, but it consistently lagged Random Forest in terms of $R^2$. The GLM Net algorithm was chosen for conceptual simplicity rather than expected
performance, and indeed it lagged the non-linear algorithms, implying that non-linearity is an important aspect of the relationship between watershed features and the MCWB parameter values.

\[
\begin{array}{|c|c|c|}
\hline
\text{Parameter} & \text{GLM} & \text{EV} & \text{RF} \\
\hline
\alpha_{\text{mid}} [-] & 0.10, 0.10, 0.09 & 0.61, 0.56, 0.68 & \\
\alpha_{\text{wet}} [-] & 0.18, 0.16, 0.16 & 0.39, 0.36, 0.47 & \\
g_{\text{intercept}} [\text{mm}] & 163, 124, 124 & 0.0, 0.26, 0.44 & \\
\hline
\end{array}
\]

Table 12: Summary of MCWB parameter modeling performance in terms of RMSE and \( R^2 \), as scored on withheld test data. Listed sequentially for GLM, EV, and RF models. Best outcomes in bold.

The significant predictors for each MCWB parameter are summarized in Table 13. These can be compared with predictors of the annual water balance found to be important in the annual water balance literature in a far-reaching survey [McMahon et al., 2013], and grouped by climate processes and landscape processes. Watershed wetness type \( \zeta \) was defined in terms of climate features, i.e., the prevailing wetness of a watershed. Notably, the dominant predictors were found to include aridity, average minimum wet days per month (a measure of storminess), and total annual PET. These predictors are in agreement with the widely reported importance of aridity and storminess. Another commonly cited climate factor, seasonality, is explicitly accounted for in the MCWB model, and so it is not surprising that does not surface in this regression, though the relatively small importance of total annual PET (roughly half the importance of minimum wet days) for predicting \( \zeta \) is an indirect indication of the importance of seasonality. There are also two landscape predictors of \( \zeta \), percent of shrub vegetation and number of road-stream intersections. The former might be considered a proxy for climate conditions, as shrubs are prevalent in arid regions of the state, and the latter may represent anthropogenic disturbances that influence the water balance.

The MCWB model parameters \( \alpha_{\text{mid}}, \alpha_{\text{wet}}, \) and \( \delta \) were described as representing landscape features in § 4.3. In this context, it is notable that Table 13 indicates a number of climate processes that are predictive of these parameters. This is not necessarily unexpected since, as noted previously, the value of these parameters in a given watershed is strongly influenced by the wetness type \( \zeta \), and so the climate factors that determine \( \zeta \) are also implicit predictors of the landscape parameters. Thus, this comparison will focus on landscape controls, and since other literature does not distinguish these particular landscape parameters, the MCWB landscape predictors will be grouped. Collectively, the MCWB predictors include several soil characteristics: silt or clay content, soil water capacity, and permeability. These are consistent with previous findings that soil type and texture significantly influence the water balance, and capacity and permeability are among the properties that control runoff mechanisms, such as whether infiltration-excess or storage-excess overland flows are prevalent in a watershed. Two important MCWB predictors signify whether a watershed predominantly stores water in the subsurface or as snow, the percentage of P that falls as snow and the average first day of frost, and these storage modes have radically different mechanisms and resultant flow patterns. Snow may also be considered a proxy for elevation, one of many topographic features shown to influence the water balance. Given that topography has been shown to be particularly important in strongly seasonal climates, it is notable that explicit metrics such as slope and aspect are missing from the MCWB predictors. Furthermore, there are no landscape predictors that explicitly describe vegetation processes. One reason may be that the MCWB model explicitly accounts for interception via the direct evapotranspiration component. Additionally, it may be that vegetation was too heterogeneous within watersheds to provide a strong predictive signal. Given prior research, the expectation was that vegetation type should have a significant effect on
evaporation dynamics, and thus the overall water balance, but this did not emerge from the MCWB parameter predictions.

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Predictors (model)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wetness Type $\zeta$</td>
<td>aridity, average minimum wet days per month, percent shrub vegetation, PET, road-stream intersections (FDA)</td>
</tr>
<tr>
<td>$\alpha_{\text{mid}}$</td>
<td>percentage of precipitation as snow (RF, EV)</td>
</tr>
<tr>
<td></td>
<td>aridity, average range of available water capacity for the soil layer or horizon, May precipitation (RF, GLM)</td>
</tr>
<tr>
<td>$\alpha_{\text{wet}}$</td>
<td>watershed wetness type (RF, EV)</td>
</tr>
<tr>
<td></td>
<td>first frost date, November precipitation, soil silt content, latitude (RF)</td>
</tr>
<tr>
<td>$g$-intercept (or $S^*$)</td>
<td>soil clay content (EV, RF)</td>
</tr>
<tr>
<td></td>
<td>aridity, PET, percent of precipitation as snow, average minimum number of wet days, May precipitation, soil permeability (RF)</td>
</tr>
</tbody>
</table>

Table 13: Significant predictors for each MCWB model parameter, reported for the predictive algorithms with the best performance for each outcome.

7.3 DISCUSSION AND SUMMARY

The purpose of this chapter was to take a step towards using the MCWB model to predict $R$ for ungaged basins by addressing the prerequisite question of how to estimate model parameters without historical observations of the water balance.

Geographical clustering of MCWB model parameter estimates, shown in § 5.3, suggested spatial proximity as a useful predictor. Moran’s I test for spatial autocorrelation (SA) was applied to each parameter, $\alpha_{\text{mid}}$, $\alpha_{\text{wet}}$, and $S^*$, as a function of pairwise distance between each of the 159 watersheds in this study. The outcome showed statistically significant (p-value < 0.05) proximity relationships for all parameters, with the largest effect for $\alpha_{\text{mid}}$ and the smallest for $S^*$. The results suggested a spatial rubric for estimating MCWB parameters in ungaged watersheds: if the nearest gaged watershed is within 175 km use the values of $\alpha_{\text{mid}}$ and $\alpha_{\text{wet}}$ from that watershed, otherwise use the statewide averages of those parameters; if the nearest gaged watershed is within 25 km use the value of $S^*$ from that watershed, otherwise use the statewide average for that parameter.

The second approach was to predict MCWB model parameters as a function of various watershed attributes. A feature selection process resulted in 86 landscape and climate predictor features, 81 from the GAGES-II watershed database and 5 derived climate features. Selection of regression and classification algorithms was based on effectiveness and interpretability. The three selected regression algorithms were the Generalized Linear Model with Regularized Elastic-Net (GLM Net), Decision Trees with Evolutionary Learning Algorithm (EV Tree), and Random Forest regression. For classification, Flexible Discriminant Analysis (FDA) was selected in addition to EV Tree and Random Forest classification. Algorithms were tuned using 10-fold cross validation and performance was evaluated on test data that was withheld from the tuning and training process.

The watershed wetness type $\zeta$ was determined using the classification algorithms. The best performance was achieved by FDA, with an accuracy of ~90%. The FDA algorithm achieved this
accuracy after programmatically down-selecting to just 5 predictive features: aridity, minimum wet days per month, fraction of shrub vegetation, PET, and number of road-stream intersections. Based on the good classification performance and the usefulness of wetness type as a predictor of other model parameters, subsequently ζ was assumed to be classified as a preliminary step and was then treated as a predictor for estimation of MCWB parameters.

For regression of parameter αmid the best performance was achieved by the Random Forest algorithm, with RMSE = 0.09 and R² = 0.68, suggesting that almost 70% of the variation in αmid is explained by the watershed predictor attributes. There is evidence of over-fitting in comparison of observed and predicted outcomes for Random Forest; the EV Tree and GLM Net achieved comparable RMSE and R² near 0.6 with considerably lower variance. While Random Forest and GLM Net both employed many predictor features, EV Tree required only three: watershed type ζ, fraction of frozen precipitation, and longitude.

For predicting αwet as a function of watershed features, Random Forest was again the most effective algorithm with RMSE = 0.16 and R² = 0.47. The most important features were watershed type ζ, average day of first watershed frost, average November precipitation, soil content, and latitude. Interestingly, the EV Tree model achieved the same RMSE with just one predictor, watershed type ζ.

Finally, the most effective estimates of the g-intercept (from which S* can be derived) were yet again delivered by Random Forest, with RMSE = 124 mm and R² = 0.44. Performance was influenced by the presence of two physically questionable outliers. The g-intercept is the only parameter for which ζ was not a significant predictor; rather, aridity, soil clay content, and total annual PET were the dominant factors for Random Forest, and only soil clay content mattered to the EV Tree regression. Given the relationship of g to S*, the importance of the soil content for this regression supports the interpretation of S* as representing a dynamic storage capacity.

Random Forest offered the best performance for all three MCWB model parameters, and in general the superior performance of the non-linear algorithms suggests a non-linear relationship between watershed attributes and water balance outcomes.

Overall, the results of this chapter suggest that it is indeed possible to estimate MCWB model parameters for ungaged watersheds. The spatial proximity rubric offers one straightforward approach that should be expected to perform better than the trivial baseline of using statewide average values of the parameters. Using machine learning, the uncertainty in slope estimates was 0.1 to 0.16, and the g-intercept uncertainty was roughly 100 mm, which are respectable given the comparable values of estimation uncertainty for gaged watersheds described in § 5.2.

The next step for this research would be to evaluate the performance of the MCWB model to estimate R in ungaged basins using inferred parameters values. One approach would be to use watersheds with runoff records that were too brief to be included in this research, and to compare the performance of the proximity and machine learning approaches.
8 CONTEXTUALIZING THE BUDYKO CURVE IN A MEDITERRANEAN CLIMATE

The Budyko curve (BC) is perhaps the most broadly applied empirical framework for characterizing the water balance in a basin or watershed. The key insight of the BC is that aridity $\phi$ is a dominant control of the evaporative partition $\gamma$, where,

$$\phi = \frac{PET}{P}$$
$$\gamma = \frac{E}{P}$$

The relationship is strongest for the long-term (multi-decade) water balance in large (>1000 km$^2$) basins, but the curve has also been applied to shorter timescales and smaller regions. However, the BC has been less useful for Mediterranean climates where total annual $PET$ is less important to the water balance than the seasonal interaction of $PET$ and $P$ [Jothityangkoon and Sivapalan, 2009].

This section examines the relationship between the MCWB model and the BC for the purpose of gaining insight about the landscape and climate processes that determine the shape of the BC in a Mediterranean climate. The theme of much Budyko curve research is to explain the deviation of the observed water balance from idealized constraints imposed by the availability of energy and water. Milly [Milly, 1990] described this difference in terms of the “inefficiency” of watershed in converting water to vapor. The contribution of this section is to explicitly identify and parameterize the various climate and landscape controls that contribute to this inefficiency, particularly for MC regions.

8.1 THE BUDYKO CURVE

8.1.1 Overview

Budyko [Budyko, 1974] showed that the long-term water balance is predominantly controlled by the prevailing relative availability of energy and water in a given watershed. This relationship can be posed in terms of the relationship between the average evaporative partition $\bar{\gamma}$ and average aridity $\bar{\phi}$, as illustrated in Figure 64. Various empirical and analytical formulations of this relationship [Budyko, 1974; Milly, 1994a; Gerrits et al., 2009] aim to describe the observed functional shape (curve C) that is constrained by bounding conditions for the water balance: in very arid, water-limited conditions $E \approx P$ (line $A$), whereas in very humid, energy-limited conditions $E \approx PET$ (line $B$). The ubiquity and utility of these analytical curves has been so convincingly established [Arora, 2002] that the relationship has been proposed as a fundamental constraint for hydrological studies [Wagener, 2007].

The difference between the energy bounds $A$ and $B$ and the curve $C$ can be thought of as inefficiency of the watershed in converting $P$ to $E$. If inter-annual storage is assumed to be negligible, as is commonly the case for Budyko studies, this inefficiency is manifested as runoff $R$. So, in a sense, the utility of the Budyko curve is to answer the question of why $R$ is observed to be larger than $P - PET$.

Two important secondary climate factors that influence the water balance are seasonality, the relative phase of $P$ and $PET$, and storminess, the frequency and intensity of $P$ events. Seasonality is particularly important in MC regions where $P$ and $PET$ are directly out-of-phase [Potter et al., 2005]. Based on climate considerations alone, $E$ should be diminished in MC regions [Milly, 1994a], but the
actual effect may be offset by vegetation strategies that increase water use efficiency in dry areas [Hickel and Zhang, 2006]. The effect of storminess on the mean water balance is generally less than that of seasonality; storminess is relatively stronger in arid regions, but it has also been shown to exert some control of inter-annual variability in humid conditions [Zanardo et al., 2012].

![Water balance partition diagram](image)

**Figure 64:** Water balance partition diagram showing the evapotranspiration ratio as function of aridity, with aridity increasing to the right. C shows the Budyko [1974] curve, with water-limited asymptote A and energy-limited asymptote B. Adapted from Milly [1994].

The Budyko relationship for 219 California watersheds is shown in Figure 65, where each point represents the long-term average relationship between aridity and the evaporative partition. The evaporative partition was approximated as $\gamma = (P - R)/P$, and average aridity $\bar{\phi} = PET/P$, using data sources described in § 3.2. The set of watersheds includes the 159 that are the focus of most of the study, as well as 60 watersheds with data records that were too short for inclusion in the broader analysis. This representation is in many ways typical of Budyko curve studies, except that the vertical spread is more pronounced, which is characteristic of the Mediterranean climate.

### 8.1.2 Budyko Curve Parameterizations

Before describing various representations of the Budyko curve, it is important to note that most applications have focused on the long-term average water balance of a watershed. Thus, most of these parameterizations were derived for the purpose of describing how the long-term water balance varies across watersheds with differing mean aridity, not the inter-annual annual water balance of a particular watershed. Nonetheless, variations of the Budyko curve have also been successfully employed to describe the inter-annual variation within a watershed [Koster and Suarez, 1999; Potter and Zhang, 2009], which is consistent with the derivation and usage of the MCWB model.
There have been many proposed forms for the Budyko curve as a function of aridity $\phi$. Budyko’s own representation of this curve [Budyko, 1974],

$$E = \left\{ P \left[ 1 - \exp(-\phi) \right] \cdot PET \cdot \tanh\left( \frac{1}{\phi} \right) \right\}^{1/2}$$

(43)

was empirically derived via a global study of large basins. Notably, this version has no free parameters, only the climate variables $E$, $P$, and $PET$, but the most commonly applied parameterizations of the Budyko curve utilize one or more parameters to account for observed deviations from a single curve. One commonly applied form is Fu’s one-parameter equation [Fu, 1981],

$$\frac{E}{P} = 1 + \phi - \frac{1}{1 + \phi^w}$$

(44)

where $w$ is a fitted parameter. A closely related variation is that of Choudhury [Choudhury, 1999],

$$\frac{E}{P} = \frac{\phi}{(1 + \phi^n)^{1/n}}$$

(45)

where the fitted parameter is now $n$. Both $w$ and $n$ have been explored as generally related to “evapotranspiration efficiency” [Zhang et al., 2008], i.e., a combination of landscape and climate controls. However, a priori estimation of $w$ and $n$ has been somewhat elusive, with limited success relating one or the other to vegetation [Donohue et al., 2010; Li et al., 2013] or various ecohydrological
variables such as soil water holding capacity, \( P \) storm depth, and effective rooting depth [Donohue et al., 2012].

The parameterization that is most closely related to this research is that of [Chen et al., 2013], which modifies the Ture-Pike parameterization [Pike, 1964],

\[
\frac{E}{P} = (1 + \phi^{-w})^{-1/w}
\]

(46)

to model evaporation in terms of wet and dry season components,

\[
\begin{align*}
\frac{E_{\text{wet}}}{P_{\text{wet}} - \Delta S_{\text{wet}}} &= 1 + \left( \frac{\text{PET}_{\text{wet}}}{P_{\text{wet}} - \Delta S_{\text{wet}} - \phi_{\text{wet}}} \right)^{-w_{\text{wet}}} - 1/w_{\text{wet}} \\
\frac{E_{\text{dry}}}{P_{\text{dry}} - \Delta S_{\text{dry}}} &= 1 + \left( \frac{\text{PET}_{\text{dry}}}{P_{\text{dry}} - \Delta S_{\text{dry}} - \phi_{\text{dry}}} \right)^{-w_{\text{dry}}} - 1/w_{\text{dry}}
\end{align*}
\]

(47)

where the subscripts indicate totals for the wet and dry season. However, beyond the commonality of explicitly considering seasonality, the form and purpose of the relationship are quite different from the MCWB model. The form is continuous (within a season) and relies on the fitting parameters \( w_w \) and \( w_d \) which do not have an intuitive physical interpretation. The purpose of this derivation was to estimate intra-annual storage change, using the relationships to estimate seasonal \( E \) and then back out the commensurate change in seasonal storage.

The subsequent section will adapt the MCWB model to describe the form of the Budyko curve with a three segment linear model. This serves two purposes. First, the approach facilitates description of the Budyko curve in terms of the physically interpretable parameters of the MCWB model. Specifically, the MCWB model explicitly accounts for threshold behavior that is widely observed and acknowledged in hydrologic research. In contrast, all representations of the Budyko curve that are familiar to the author assume a continuous relationship between \( E/P \) and aridity, neglecting threshold effects. While this reduces the number of parameters needed to describe the partition, this comes at the expense of model interpretability and diminished applicability for highly seasonal conditions like MC regions.

### 8.2 MCWB Simplifying Assumptions

Recall from § 3.4.2 that observations of total annual \( R \) for a watershed can be described as a function of \( P \) using a three-segment linear model (Figure 66). This was a precursor to the two-segment MCWB model of \( R \) as a function of energy-excess precipitation \( P_X \). The three-segment relationship of \( R \) to \( P \) is referred to as MCWBp. The model has two thresholds, labeled \( a \) and \( b \), that specify transitions from dry to mid-range and mid-range to wet conditions respectively within a watershed. For the purpose of comparison with the Budyko curve, we consider annual evapotranspiration \( E \) rather than \( R \), invoking the relationship \( E = R - P \), where inter-annual storage \( \Delta S \) is assumed to be negligible.
Additional simplifying assumptions are used to streamline the analysis. First, it is assumed that \( \frac{dE}{dP} = 0 \) for wet conditions when \( P > b \), which is equivalent to \( \frac{dR}{dP} = 1 \) which was observed to be approximately true for many watersheds (§ 5.3). Second, total PET is assumed to be constant year-to-year for a given watershed, an approximation that is justified by the observation that inter-annual variation in PET is generally much less than variation in the other components of the water balance. This simplification implies that aridity \( \frac{PET}{P} \) varies as a function of \( P \) alone.

The threshold \( a \) between dry and mid-range wetness is subsequently labeled as initial evapotranspiration \( E_0 \) (Figure 67) so named because it is the average amount of \( P \) that is evaporated before any \( R \) occurs for a given year. For mesic and humid watershed types, \( E_0 \) is equivalent to long-term average direct evapotranspiration, \( E_d \). For arid watersheds, it is common that the \( P \) threshold for non-negligible \( R \) may be in excess of \( E_d \) (Figure 11), but because the objective is to characterize the general relationship between the MCWB\(_p\) and Budyko curves, these special cases will be neglected and the analysis assumes that \( E_0 \approx E_d \).

There is a visual symmetry between the Budyko curve and the MCWB\(_p\) structure, as illustrated in Figure 67, but in fact the axes are quite different. The MCWB\(_p\) axes portray \( E \) vs. \( P \), with wetter conditions increasing to the right with \( P \). Contrast this with the Budyko axes, \( E/P \) vs. \( PET/P \), where the wettest conditions approach the origin to the left.
Figure 67: Comparison of the 3-segment MCWB\(_P\) model (top) with the Budyko relationship (bottom). Variables: precipitation \(P\), evapotranspiration \(E\) approximated as \(P-R\), and potential evapotranspiration \(PET\). Parameters: initial evapotranspiration \(E_0\), evapotranspiration limit \(E_{lim}\), wet conditions threshold \(b\), storage retention threshold \(S^*\).
8.3 Transformation of MCWBₚ to Budyko

The transformation from the MCWBₚ axes to the Budyko axes was straightforward. For each wetness segment of the MCWBₚ, dry, mid-range, and wet, the MCWBₚ relationship is simply normalized by P.

For example, the transformation for the mid-range section begins as

\[ E = E₀ + \beta(P - E₀) \]

Dividing by P and rearranging variables,

\[ \frac{E}{P} = \frac{E₀}{P} + \beta \left(\frac{P - E₀}{P}\right) \]

\[ = \frac{E₀}{P} + \beta \left(1 - \frac{E₀}{P}\right) \]

\[ = \beta + \frac{E₀}{PET} \left(1 - \frac{E₀}{PET}\right) \phi \]

where the last step follows from the definition of aridity, such that \(1/P = \phi/PET\). The outcome of a similar transformation for each segment is summarized in Table 14.

<table>
<thead>
<tr>
<th>Conditions</th>
<th>MCWBₚ</th>
<th>Budyko</th>
<th>Transition Thresholds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry</td>
<td>(E = P)</td>
<td>(\frac{E}{P} = 1)</td>
<td>(\phi_{dry} = \frac{PET}{E₀})</td>
</tr>
<tr>
<td>Mid-range</td>
<td>(E = E₀ + \beta(P - E₀))</td>
<td>(\frac{E}{P} = \beta + \frac{E₀}{PET} \left(1 - \frac{E₀}{PET}\right) \phi)</td>
<td></td>
</tr>
<tr>
<td>Wet</td>
<td>(E = E_{lim})</td>
<td>(\frac{E}{P} = \left(\frac{E_{lim}}{PET}\right) \phi)</td>
<td>(\phi_{wet} = \frac{PET}{b} = \frac{PET}{S + E₀ \cdot \beta})</td>
</tr>
</tbody>
</table>

Table 14: Summary of transformations of MCWBₚ axes to Budyko curve axes for the three distinct precipitation regimes.

8.4 Observations and Implications of the Budyko Transformations

8.4.1 Dry Conditions

For the driest conditions in a given watershed, all P is evaporated before any streamflow is generated. This well-known behavior in water-limited conditions is represented by the \(E/P\) asymptote of the Budyko curve and the 1:1 slope between \(E\) and \(P\) for the MCWBₚ in the “dry” segment of both axes.
The implication for the Budyko curve is that a transition to these driest conditions occurs at
\[ \phi_{\text{dry}} = \frac{\text{PET}}{E_0} \]. Recalling that \( E_0 \approx E_d \), and that \( E_d = P - \overline{P_X} \), it follows from the definition of \( P_X \) in Eq. (7) that,
\[ E_0 \approx E_d = \left(1 - \overline{\omega}_p\right) \cdot P + \overline{\omega}_{\text{PET}} \cdot \text{PET} \]  
(48)

where overbars indicate long-term averages and the assumption \( \text{PET} \approx \overline{\text{PET}} \) was applied. It follows that the aridity threshold for dry conditions, \( \phi_{\text{dry}} \), can be expressed in terms of MCWBp climate factors as,
\[ \phi_{\text{dry}} \approx \frac{\text{PET}}{E_d} = \frac{\text{PET}}{\left(1 - \overline{\omega}_p\right) \cdot P + \overline{\omega}_{\text{PET}} \cdot \text{PET}} \]  
(49)

In words, this states that runoff is negligible until \( P \) exceeds the average direct evapotranspiration \( \overline{E_d} \). The effects of the various climate factors on \( \phi_{\text{dry}} \) are summarized in Table 15. Notably, increased seasonality of \( P \) and \( \text{PET} \) are both associated with an increase in \( \phi_{\text{dry}} \), as is an increase in total annual \( \text{PET} \) independent of seasonality. An increase in average \( P \) independent of seasonality is associated with decreased \( \phi_{\text{dry}} \).

<table>
<thead>
<tr>
<th>Factor</th>
<th>Description</th>
<th>Effect on ( \phi_{\text{dry}} ): factor increase causes…</th>
</tr>
</thead>
<tbody>
<tr>
<td>( 1 - \overline{\omega}_p )</td>
<td>average fraction of ( P ) that falls in dry season (~); as this increases, ( P ) seasonality decreases</td>
<td>decrease</td>
</tr>
<tr>
<td>( \overline{\omega}_{\text{PET}} )</td>
<td>average fraction of ( \text{PET} ) that occurs in wet season (~); as this increases, ( \text{PET} ) seasonality decreases</td>
<td>decrease</td>
</tr>
<tr>
<td>( \overline{P} )</td>
<td>average annual ( P ) ([\text{L}])</td>
<td>decrease</td>
</tr>
<tr>
<td>( \text{PET} )</td>
<td>annual ( \text{PET} ) ([\text{L}])</td>
<td>increase</td>
</tr>
</tbody>
</table>

*Table 15: Effects of MCWB climate factors on the Budyko curve dry condition threshold \( \phi_{\text{dry}} \).*

The value of \( \phi_{\text{dry}} \) is unity, i.e., the ideal Budyko asymptote transition, only for extreme seasonality conditions, such as if all months are wet months, \( P_m \geq \text{PET}_m \), and thus \( \overline{\omega}_p = \overline{\omega}_{\text{PET}} = 1 \), or the unlikely edge case when \( P_m = \text{PET}_m \) for all months and thus \( \overline{\omega}_p = \overline{\omega}_{\text{PET}} = 0 \). In practice, generally \( \phi_{\text{dry}} > 3 \) for MC regions that are characterized by \( \overline{\omega}_{\text{PET}} < 0.3 \) and \( \overline{\omega}_p \sim 1 \).

### 8.4.2 Wet Conditions

In the wettest conditions when water is plentiful, the upper bound on \( E \) is available energy \( \text{PET} \). The Budyko energy asymptote, line \( B \) in Figure 64, suggests that for such conditions the relationship of \( E/P \) to aridity \( \phi \) should be 1:1 since then \( E = \text{PET} \). The MCWBp representation offers an explanation for why this ideal relationship is typically not observed.

The MCWBp transformation in Table 14 shows that for wet conditions,
\[
\Phi = \left( \frac{E_{\text{lim}}}{\text{PET}} \right) \cdot \phi
\]  

(50)

where \( E_{\text{lim}} \) represents some observed upper limit on annual evapotranspiration, and the simplifying assumption \( dE/dP = 0 \) for \( P > b \) has been applied. By inspection of Figure 67,

\[
E_{\text{lim}} = E_0 + S^* \approx E_0 + S^*
\]

recalling that \( S^* \) was previously defined as the storage retention threshold, a landscape control parameter related to the inter-seasonal storage capacity of a watershed (Table 2). Substituting the relationship for \( E_0 \) from Eq. (48),

\[
E_{\text{lim}} \approx 1 - \omega_P \cdot \bar{P} + \omega_{\text{PET}} \cdot \text{PET} + S^*
\]

(51)

It follows from Eq. (50) that,

\[
\frac{d\Phi}{d\phi} \approx \left( 1 - \omega_p \right) \cdot \bar{P} + \omega_{\text{PET}} \cdot \text{PET} + S^*
\]

\[
\approx \frac{1 - \bar{\phi} + \omega_{\text{PET}} + S^*}{\bar{\phi} + \omega_{\text{PET}} + S^*}
\]

(52)

where average aridity \( \bar{\phi} = \text{PET}/\bar{P} \), recalling that \( \text{PET} \) is assumed to be essentially constant year-to-year.

This states that the slope \( d\Phi/d\phi \) is controlled by climate factors \( \bar{P}, \omega_p, \bar{\text{PET}}, \omega_{\text{PET}} \) and the landscape parameter \( S^* \). Note that this slope is constrained to be \( \leq 1 \) by the definitions for \( \omega_p \), \( \omega_{\text{PET}} \), and \( S^* \). The impact of these factors on \( d\Phi/d\phi \) is summarized in Table 16. Note that the slope decreases with increased seasonality of \( P \) and \( \text{PET} \), with increased aridity, with increased annual \( \text{PET} \), and with lower \( S^* \).
<table>
<thead>
<tr>
<th>Factor</th>
<th>Description</th>
<th>Effect on $d\Phi/d\phi$ : factor increase causes…</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1 - \bar{\omega}_p$</td>
<td>average fraction of P in dry season [$\sim$]; as this increases, P seasonality decreases</td>
<td>increase</td>
</tr>
<tr>
<td>$\bar{\phi}$</td>
<td>average aridity [$\sim$]</td>
<td>decrease</td>
</tr>
<tr>
<td>$\bar{\omega}_{PET}$</td>
<td>average fraction of PET in wet season [$\sim$]; as this increases, PET seasonality decreases</td>
<td>increase</td>
</tr>
<tr>
<td>$S^*$</td>
<td>storage retention threshold [L]; landscape factor</td>
<td>increase</td>
</tr>
<tr>
<td>$PET$</td>
<td>annual PET [L], independent of seasonality</td>
<td>decrease</td>
</tr>
</tbody>
</table>

Table 16: Effects of MCWB climate factors on the Budyko curve wet conditions slope $d\Phi/d\phi$.

Per Eq. (50), the Budyko asymptote $d\Phi/d\phi = 1$ is observed only in the special circumstances when $E_{\lim} = PET$. One scenario where this could occur, per Eq. (51), is if all P fell during the wet season ($\bar{\omega}_p = 1$) and the amount of inter-seasonal storage that did not depart as streamflow was exactly equal to dry season PET, i.e., $S^* = (1 - \bar{\omega}_{PET}) \cdot PET$. In reality, typical observed values for climate and landscape factors in California’s Mediterranean climate correspond to $E/P$ slopes near 0.5 for wet conditions.

The transition to this wet segment occurs at some threshold value of aridity, $\phi_{wet}$, which per Table 14 is,

$$\phi_{wet} = \frac{PET}{b} = \frac{PET}{\bar{E}_d + S^* \beta}$$  \hspace{1cm} (53)

Where $\beta = dE/dP$ for mid-range wetness conditions, per Figure 67. Note that $\phi_{wet} \geq 1$. The directional relationship of the MCWBp factors with $\phi_{wet}$ is summarized in Table 17. Increased seasonality of P and PET, via $\bar{E}_d$, corresponds to an increase in $\phi_{wet}$, as does larger total PET and a greater rate $dE/dP$, which is taken as a landscape control. An increase in $S^*$ is associated with decreased $\phi_{wet}$. Notably, $\phi_{wet}$ is a function of both landscape and climate factors, whereas $\phi_{dry}$ is a function of climate factors only.
Table 17: Effects of MCWB climate factors on the Budyko curve wet condition threshold \( \phi_{wet} \).

<table>
<thead>
<tr>
<th>Factor</th>
<th>Description</th>
<th>Effect on ( \phi_{wet} ): factor increase causes…</th>
</tr>
</thead>
<tbody>
<tr>
<td>( PET )</td>
<td>annual PET ([L]), independent of seasonality</td>
<td>increase</td>
</tr>
<tr>
<td>( S^* )</td>
<td>storage retention threshold ([L]); landscape factor</td>
<td>decrease</td>
</tr>
<tr>
<td>( \bar{E}_d = (1 - \bar{\omega}<em>p) \cdot P + \bar{\omega}</em>{PET} \cdot PET )</td>
<td>average direct evapotranspiration ([L]); increases as seasonality of ( P ) and ( PET ) decreases</td>
<td>decrease</td>
</tr>
<tr>
<td>( \beta = dE/dP )</td>
<td>evaporation slope for mid-range wetness conditions ([-]); landscape factor</td>
<td>increase</td>
</tr>
</tbody>
</table>

The relationship between \( \phi_{wet} \) and \( \phi_{dry} \) can also be explored in terms of bounding values. As \( \beta \) approaches 1, \( \phi_{wet} \) approaches \( \phi_{dry} \) except for the factor \( S^* \), per Eqs. (49) and (53). As \( S^* \) increases, the threshold \( \phi_{wet} \) decreases. This makes sense if we recall that wet conditions are signified by an upper bound on \( E \), and that some fraction of \( S^* \) is converted to storage evapotranspiration \( E_S \). Thus, total \( E \) increases directly with \( S^* \). As \( \beta \) approaches 0 it is clear that \( \phi_{wet} \) also approaches 0, since the upper bound on \( E \) is never reached regardless of how much \( P \) falls, though the increase in \( E \) may be very slight.

### 8.4.3 Mid-range Conditions

In between extreme wet and dry conditions is the mid-range wetness interval of the MCWBp. Conceptually, this segment represents storage evapotranspiration, \( E_S \), the component of \( E \) that is stored during the wet season, when \( P \) is abundant but \( PET \) is limited, and then evaporated during the dry season when \( PET \) is abundant and \( P \) is limited. This is represented in the Budyko curve as some central segment of line C in Figure 64, which is apparent via inspection of Figure 67. The transformation from the MCWBp to Budyko axes yields,

\[
\Phi = \beta + \frac{E_0}{PET} (1 - \beta) \phi
\]

per Table 14. The slope of this segment is then,

\[
\frac{d\Phi}{d\phi} = \frac{E_0}{PET} (1 - \beta)
\]

and recalling again that \( E_0 \approx \bar{E}_d \),

\[
\frac{d\Phi}{d\phi} = \frac{\bar{E}_d}{PET} (1 - \beta)
\]

This linear function can be understood in terms of the directional effects of the individual factors, summarized in Table 18. The slope \( d\Phi/d\phi \) decreases as the seasonality of \( P \) and \( PET \) increases, via
An increase in annual PET also decreases $d\Phi/d\phi$, whereas an increase in the MCWB runoff slope $dR/dP$, a landscape factor, causes $d\Phi/d\phi$ to increase.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Description</th>
<th>Effect on $d\Phi/d\phi$: factor increase causes…</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{E}_d = \left(1 - \bar{\omega}<em>p\right)\bar{P} + \bar{\omega}</em>{PET} \cdot PET$</td>
<td>average direct evapotranspiration [L]; increases as seasonality of P and PET decreases</td>
<td>increase</td>
</tr>
<tr>
<td>PET</td>
<td>annual PET [L], independent of seasonality</td>
<td>decrease</td>
</tr>
<tr>
<td>$1 - \beta = dR/dP$</td>
<td>runoff slope for mid-range wetness conditions [~]; landscape factor</td>
<td>increase</td>
</tr>
</tbody>
</table>

*Table 18: Effects of MCWB climate factors on the Budyko curve mid-range conditions slope $d\Phi/d\phi$.*

As $1 - \beta$ approaches 1, no water is stored into the dry season, and thus maximum evapotranspiration $E_{im}$ approaches average direct evapotranspiration $\bar{E}_d$. Conceptually this may happen in conditions with negligible storage, or where there is little seasonality, meaning $P$ falls when PET is high. This implies an abrupt transition between dry and wet conditions, and indeed if $\beta=0$ then the mid-range relationship is identical to the wet relationship for $E/P$, as shown in Table 14. At the other extreme, as $\beta$ approaches 1 this suggests that the landscape that is effective at capturing and holding water until the dry season and then converting this storage to evaporation. As $\beta \to 1$ the mid-range Budyko relationship approaches the dry conditions equation. Recall that in an MC region where $P$ and PET are out of phase there is relatively little energy for evaporation during the wet season, and likewise little dry season precipitation, and thus $E_d << PET$. Note that small $E_d$ does not necessarily imply that total $E$ is small because in some conditions storage evapotranspiration $E_s$ may be the dominant component of $E$. Examples of this are very wet watersheds which may have significant capacity for storing water from the wet season until the dry season. In contrast, $E_d /PET$ approaches 1 as $E_d$ approaches PET, which is the edge case when all months are wet months, i.e. $P_m \geq PET_m$ for all months $m$. Note that this also implies that watershed storage is perpetually full, and thus that $dR/dP = 1$ and $dE/dP = 0$, and per Eq. (54) it follows that $\bar{\beta} = 0$, meaning there is no mid-range interval but just an abrupt transition from dry to wet.

### 8.4.4 Overall Representation

While the main insights of the MCWB$_p$ representation of the Budyko curve are gleaned from examining the individual segments, the segments can be combined into a tri-linear model. The general form of this equation is,

$$
\Phi = a_1 \cdot \phi + (a_2 - a_1)(\phi - A) \cdot H_A + (a_3 - (a_2 - a_1))(\phi - B) \cdot H_B
$$

where $a_1$, $a_2$, and $a_3$ represent the segment slopes, with $a_1$ beginning at the origin; A and B refer to the values of $\phi$ where transition occur between segments 1-2 and 2-3 respectively; and the Heaviside function $H_X$ is applied at the transition knots between segments, i.e., $x=A$ and $x=B$. This relationship can be simplified by isolating terms and noting that $a_3 = 0$, yielding,
\[
\Phi = \left[ a_1 \left( 1 - H_A + H_B \right) + a_2 \left( H_A - H_B \right) \right] \phi + \left( a_1 - a_2 \right) \left( A \cdot H_A - B \cdot H_B \right)
\]

Per Figure 67 and Table 14, the parameter values are:

\[
a_1 = \frac{E_d}{\text{PET}} = \frac{E_d + S^*}{\text{PET}}
\]

\[
a_2 = \frac{E_d}{\text{PET}} \cdot (1 - \beta)
\]

\[
A = \frac{\text{PET}}{b} = \frac{\text{PET}}{S^* + E_d \beta} \cdot \beta
\]

\[
B = \frac{\text{PET}}{E_d}
\]

Substituting these terms in the general form yields,

\[
\Phi = \left[ \frac{E_d + S^*}{\text{PET}} \cdot (1 - H_A + H_B) + \frac{E_d}{\text{PET}} \cdot (1 - \beta) \cdot (H_A - H_B) \right] \phi
\]

\[
+ \left[ \frac{E_d + S^* - E_d}{\text{PET}} \cdot (1 - \beta) \right] \left( \frac{\text{PET}}{S^* + E_d \beta} \cdot \beta \cdot H_A - \frac{\text{PET}}{E_d} \cdot H_B \right)
\]

where the Heaviside functions have retained the nomenclature \( A \) and \( B \) for brevity. This can be simplified somewhat by canceling terms,

\[
\Phi = \left[ \frac{E_d + S^*}{\text{PET}} \cdot (1 - H_A + H_B) + \frac{E_d}{\text{PET}} \cdot (1 - \beta) \cdot (H_A - H_B) \right] \phi
\]

\[
+ \left( S^* - E_d \beta \right) \left( \frac{\beta}{S^* + E_d \beta} \cdot H_A - \frac{1}{E_d} \cdot H_B \right)
\]

This form is admittedly not as concise as the one-parameter Budyko curve representations of § 8.1.2, but it is arguably more interpretable given the physically meaningful parameters and explicit treatment of hydrologic thresholds.

### 8.4.5 Comparison with Prior Work

Referring to the Budyko axes diagram of Figure 67, the “curve” (i.e., tri-linear segments) diverges from the ideal water- and energy-limited asymptotes as the thresholds \( \phi_{\text{dry}} \) and \( \phi_{\text{wet}} \) increase and as the wet conditions slope \( d\Phi / d\phi \) decreases, noting that the mid-range conditions slope can be inferred from the other three parameters. This means that the MCWB\(_P\) climate factors that drive divergence of the Budyko curve from the ideal are the seasonality of \( P \) and \( \text{PET} \) as well as average aridity. The landscape factors that cause divergence are decreased \( S^* \) and decreased \( dR/dP \) in the mid-range wetness segment of the MCWB\(_P\).
The impact of P and PET seasonality has been extensively documented (§ 2.2.1.2, § 2.3.1). An increase in the average aridity of a given watershed has the effect of shifting the Budyko curve thresholds away from the origin, which, per inspection of Figure 67, would be expected to increase the gap between the curve and the asymptotes. Other climate controls not accounted for by the MCWBp include storminess [Zanardo et al., 2012] and whether P is frozen or liquid [Berghuijs et al., 2014].

Landscape factors that have been reported to affect the Budyko curve include vegetation type [Zhang et al., 2001; Donohue et al., 2012; Williams et al., 2012; Li et al., 2013], vegetation interception [Gerrits et al., 2009], soil properties [Porporato et al., 2004], soil moisture capacity [Potter et al., 2005], the influence of varying water stores [Milly and Dunne, 2002; Condon and Maxwell, 2017], and spatial heterogeneity and lateral redistribution [Ronbolahnejad Freund and Kirchner, 2017]. The MCWBp landscape parameters $S^*$ and $dR/dP_{mid}$ do not directly correspond with these features, but § 7 provided context for the physical features that are predictive of these parameters: $S^*$ is associated with soil clay content and soil permeability, and $dR/dP_{mid}$ is predicted in part by soil water capacity. These soil properties are consistent with a subset of the reported landscape factors, and one explanation for why the other factors are not represented in the MCWBp is that this study was concerned with emergent high-level properties, whereas the studies that identified other factors were narrowly focused on specific processes.

### 8.5 DISCUSSION

The objective of this chapter was to use the MCWB model as a framework to understand the climate and landscape processes that determine the shape of the Budyko curve in a Mediterranean climate. A brief review of BC research noted that while the most common application is characterization of the long-term water balance across a collection of watersheds, the BC has also been successfully employed to describe the inter-annual partition within a particular watershed, which is consistent with development and applications of the MCWB model. Previous representations of the curve have employed one or more parameters that were empirically adjusted to fit observations, but a priori prediction of these parameter values as a function of climate and watershed features has met limited success.

A preliminary requirement was to transform the MCWB model to the same axes as the BC, the evaporative partition $\gamma = E/P$ versus aridity $\phi = PET/P$. The three-segment variation of the MCWB model, describing the water balance as a function of $P$, was used and labeled as MCWBp. Several simplifying assumptions were applied to streamline analysis: for wet conditions it was assumed that $dE/dP = 0$; total annual PET was treated as constant year-to-year; and inter-annual storage $\Delta S$ was assumed to be negligible. The transformation of the MCWBp was a straightforward matter of normalizing each wetness segment by $P$, with the results summarized in Figure 67 and Table 14.

For the driest conditions all $E$ is constrained by water availability, such that all $P$ is evaporated and $E/P = 1$. A more interesting value is the aridity threshold $\phi_{dry}$, which marks the transition from dry to mid-range wetness conditions where some $R$ occurs. The relationship $\phi_{dry} \approx PET/E_d$ states that $R$ is negligible until $P$ exceeds the average direct evapotranspiration $E_d$ for a given watershed. The ideal BC transition, $\phi_{dry} = 1$, is only observed for conditions where monthly $P$ is equal or greater than monthly $PET$ for all months. In MC regions observed values of $\phi_{dry} > 3$ are typical.
In very wet, saturated conditions $E$ is constrained by available energy $PET$. The ideal BC slope is 1:1 for such conditions, but the MCWB parameterization explains why this is not typically observed. As described by Eq. (52) the BC slope in wet conditions varies as a function of aridity, dry season $P$, wet season $PET$, and the ratio of the storage retention threshold and total $PET$, $S^*/PET$. The ideal slope of 1 is only observed for special cases, such as if all $P$ fell during the wet season, all dry season $PET$ was exactly equal to $S^*$. Typical observed values of these climate and landscape features result in a wet conditions slope of roughly 0.5 in in California. The transition threshold from wet to mid-range conditions, $\phi_{wet}$, is a function of climate and landscape factors, while $\phi_{dry}$ was shown to be a function of climate only.

In the context of the MCWB, evaporation for mid-range wetness conditions comes entirely from storage evapotranspiration $E_s$, which is drawn from water stored in the wet season and evaporated in the dry season. As shown in Eq. (54), the evaporative partition in this segment is a linear function of aridity, with intercept $\beta$ and slope $(E_d/PET) \cdot (1 - \beta)$. The term $\beta$ represents the fraction of energy-excess precipitation $P_x$ that is captured in wet season storage, carried-over into the dry season, and then evaporated. If $\beta$ approaches zero this implies that the storage retention threshold $S^*$ approaches zero, i.e., watershed storage is negligible, then the mid-range slope approaches the wet slope and there is no mid-range segment. Likewise, as $\beta$ approaches 1 the mid-range slope approaches the dry slope. At either extreme, there are just two wetness regimes, similarly to the ideal BC asymptote. The other relevant component is the ratio of direct evapotranspiration to total annual $PET$, which is small for MC regions where $E_d \ll PET$. Typical slopes in MC regions are near 0.2 mm/mm.

The individual segments were then combined to a single relationship using Heaviside functions to the segment transitions. The overall relationship of the evaporative partition $\Phi$ to aridity $\phi$ is shown in Eq. (55) employing four parameters: direct evapotranspiration $E_d$, the storage retention threshold $S^*$, total annual $PET$ (assumed to be constant), and the storage retention slope $\beta$. This form of the Budyko relationship is arguably more interpretable than forms with fewer parameters whose physical meaning is more opaque.

This representation suggests possible paths for future inquiry. The predictive performance of the MCWB formulation could be compared against previous representations of the Budyko curve. And a comparison of the MCWB formulation with previous representations of the BC may clarify the meaning of the fitting parameters employed for those representations.

The analysis in this chapter demonstrated the use of the MCWB to describe the climate and landscape factors that determine the shape of the Budyko relationship. Budyko’s curve was traded for a three-segment linear relationship with transitions that respect oft-cited threshold behavior observed in hydrology. Furthermore, the transformation of the MCWB to the Budyko axes illustrates the standing of the MCWB framework in the lineage of a large body of work devoted to top-down, parsimonious approaches to describing the annual water balance.
References


Hall, A. (2010), Simulating and understanding variability in runoff from the Sierra Nevada, Technical Completion Reports, Technical Completion Report, UC Berkeley, University of California Water Resources Center.


Horton, R. E. (1933), The role of infiltration in the hydrologic cycle, Trans Am Geophys Union, 14, 446–460.


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Thornthwaite, C. W., and J. R. Mather (1955), The water balance, Drexel Institute of Technology Centerton, NJ, USA.


## APPENDIX A: CALIFORNIA WATERSHEDS INCLUDED IN ANNUAL WATER BALANCE ANALYSIS

<table>
<thead>
<tr>
<th>USGS-ID</th>
<th>Site Name</th>
<th>area (km²)</th>
<th>start wy</th>
<th>end wy</th>
<th>count wys</th>
<th>alpine</th>
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<td>51</td>
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<td>11426150</td>
<td>ONION C NR SODA SPRINGS CA</td>
<td>9</td>
<td>1961</td>
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<td>11433260</td>
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<td>11436000</td>
<td>SILVER LK OUTLET NR KIRKWOOD CA</td>
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<td>11449500</td>
<td>KELSEY C NR KELSEYVILLE CA</td>
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<td>1948</td>
<td>2003</td>
<td>55</td>
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<td>11451100</td>
<td>NF CACHE C A HOUGH SPRING NR CLEARLAKE OAKS CA</td>
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<td>11451500</td>
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<td>11451720</td>
<td>BEAR C NR RUMSEY CA</td>
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<td>11452000</td>
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<td>11453500</td>
<td>PUTAH C NR GUENOC CA</td>
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<td>11454000</td>
<td>PUTAH C NR WINTERS CA</td>
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<td>SONOMA C A AGUA CALIENTE CA</td>
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<td>11465200</td>
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<td>11468000</td>
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<td>11475800</td>
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<td>11480390</td>
<td>MAD R AB RUTH RES NR FOREST GLEN CA</td>
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<td>11481200</td>
<td>LITTLE R NR TRINIDAD CA</td>
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<td>REDWOOD C NR BLUE LAKE CA</td>
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<td>REDWOOD C A ORICK CA</td>
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<td>11489500</td>
<td>ANTELOPE C NR TENNANT CA</td>
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<td>1954</td>
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<td>SALMON R A SOMES BAR CA</td>
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<td>11525600</td>
<td>GRASS VALLEY C A FAWN LODGE NR LEWISTON CA</td>
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<td>SF TRINITY R BL HYAMPOM CA</td>
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10.2  APPENDIX B: WATERSHED FEATURES USED FOR MCWB MODEL PARAMETER ESTIMATION

10.2.1 Derived Climate and Landscape Features

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Source</th>
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<tr>
<td>P.10</td>
<td>10th percentile of annual $P$</td>
<td>VICs precipitation records</td>
</tr>
<tr>
<td>P.50</td>
<td>Median annual $P$</td>
<td>VICs precipitation records</td>
</tr>
<tr>
<td>P.90</td>
<td>90th percentile of annual $P$</td>
<td>VICs precipitation records</td>
</tr>
<tr>
<td>Aridity</td>
<td>Average long-term annual $P$/PET</td>
<td>VICs precipitation records and PET estimate</td>
</tr>
<tr>
<td>Watershed</td>
<td>Wetness category [Arid, Mesic, Humid]</td>
<td>Inspection of MCWB regression shape</td>
</tr>
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</table>

10.2.2 GAGES-II Dataset Features

GAGES-II features selected for water balance analysis.

<table>
<thead>
<tr>
<th>VARIABLE_TYPE</th>
<th>VARIABLE_NAME</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>BasinID</td>
<td>DRAIN_SQKM</td>
<td>Watershed drainage area, sq km, as delineated in our basin boundary</td>
</tr>
<tr>
<td>Bas_Morph</td>
<td>LAT_CENT</td>
<td>Latitude of centroid location of basin, decimal degrees</td>
</tr>
<tr>
<td>Climate</td>
<td>T_MAXSTD_BASIN</td>
<td>Standard deviation of maximum monthly air temperature (degrees C) from 800m PRISM, derived from 30 years of record (1971-2000).</td>
</tr>
<tr>
<td>Climate</td>
<td>T_MINSTD_BASIN</td>
<td>Standard deviation of minimum monthly air temperature (degrees C) from 800m PRISM, derived from 30 years of record (1971-2000).</td>
</tr>
<tr>
<td>Climate</td>
<td>RH_BASIN</td>
<td>Watershed average relative humidity (percent), from 2km PRISM, derived from 30 years of record (1961-1990).</td>
</tr>
<tr>
<td>Climate</td>
<td>FST32F_BASIN</td>
<td>Watershed average of mean day of the year of first freeze, derived from 30 years of record (1961-1990), 2km PRISM. For example, value of 300 is the 300th day of the year (Oct 27th).</td>
</tr>
<tr>
<td>Climate</td>
<td>FST32F_SITE</td>
<td>Site average of mean day of the year of first freeze, derived from 30 years of record (1961-1990), 2km PRISM. For example, value of 300 is the 300th day of the year (Oct 27th).</td>
</tr>
<tr>
<td>Climate</td>
<td>WDMAX_BASIN</td>
<td>Watershed average of monthly maximum number of days (days) of measurable precipitation, derived from 30 years of record (1961-1990), 2km PRISM.</td>
</tr>
<tr>
<td>Climate</td>
<td>WDMIN_BASIN</td>
<td>Watershed average of monthly minimum number of days (days) of measurable precipitation, derived from 30 years of record (1961-1990), 2km PRISM.</td>
</tr>
<tr>
<td>Climate</td>
<td>PET</td>
<td>Mean-annual potential evapotranspiration (PET), estimated using the Hamon (1961) equation.</td>
</tr>
<tr>
<td>Climate</td>
<td>SNOW_PCT_PRECIP</td>
<td>Snow percent of total precipitation estimate, mean for period 1901-2000. From McCabe and Wolock (submitted, 2008), 1km grid.</td>
</tr>
<tr>
<td>Climate</td>
<td>PRECIP_SEAS_IND</td>
<td>Precipitation seasonality index (Markham, 1970; Dingman, 2002). Index of how much annual precipitation falls seasonally (high values) or spread out over the year (low values). Based on monthly precip values from 30 year (1971-2000) PRISM. Range is 0 (precip spread out exactly evenly in each month) to 1 (all precip falls in a single month).</td>
</tr>
<tr>
<td>Climate</td>
<td>FEB_PPT7100_CM</td>
<td>Mean February precip (cm) for the watershed, from 800m PRISM data. 30 years period of record 1971-2000.</td>
</tr>
<tr>
<td>Climate</td>
<td>MAY_PPT7100_CM</td>
<td>Mean May precip (cm) for the watershed, from 800m PRISM data. 30 years period of record 1971-2000.</td>
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<tr>
<td>Climate</td>
<td>JUN_PPT7100_CM</td>
<td>Mean June precip (cm) for the watershed, from 800m PRISM data. 30 years period of record 1971-2000.</td>
</tr>
<tr>
<td>Climate</td>
<td>JUL_PPT7100_CM</td>
<td>Mean July precip (cm) for the watershed, from 800m PRISM data. 30 years period of record 1971-2000.</td>
</tr>
<tr>
<td>Climate</td>
<td>AUG_PPT7100_CM</td>
<td>Mean August precip (cm) for the watershed, from 800m PRISM data. 30 years period of record 1971-2000.</td>
</tr>
<tr>
<td>Climate</td>
<td>SEP_PPT7100_CM</td>
<td>Mean September precip (cm) for the watershed, from 800m PRISM data. 30 years period of record 1971-2000.</td>
</tr>
<tr>
<td>Climate</td>
<td>NOV_PPT7100_CM</td>
<td>Mean November precip (cm) for the watershed, from 800m PRISM data. 30 years period of record 1971-2000.</td>
</tr>
<tr>
<td>Hydro</td>
<td>STREAMS_KM_SQ_KM</td>
<td>Stream density, km of streams per watershed sq km, from NHD 100k streams</td>
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<tr>
<td>Hydro</td>
<td>STRAHLER_MAX</td>
<td>Maximum Strahler stream order in watershed, from NHDPlus.</td>
</tr>
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<td>VARIABLE_TYPE</td>
<td>VARIABLE_NAME</td>
<td>DESCRIPTION</td>
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<tr>
<td>Hydro</td>
<td>MAINSTEM_SINUOSITY</td>
<td>Sinuosity of mainstem stream line, from our delineation of mainstem stream lines (see Falcone and others, 2010b). Defined as curvilinear length of the mainstem stream line divided by the straight-line distance between the end points of the line.</td>
</tr>
<tr>
<td>Hydro</td>
<td>ARTIFPATH_PCT</td>
<td>Percent of stream kilometers coded as &quot;Artificial Path&quot; in NHDPlus. Note this does not necessarily mean the stream is modified, only that it is wide enough to be represented as a polygon rather than a line. In some cases this is indicative of damming.</td>
</tr>
<tr>
<td>Hydro</td>
<td>ARTIFPATH_MAINSTEM_PCT</td>
<td>Percent of mainstem stream(s) coded as &quot;Artificial Path&quot; in NHDPlus, from our delineation of mainstem streamlines. Note this does not necessarily mean the stream is modified, only that it is wide enough to be represented as a polygon rather than a line. In some cases this is indicative of damming.</td>
</tr>
<tr>
<td>Hydro</td>
<td>HIRES_LENTIC_PCT</td>
<td>Percent of watershed surface area covered by &quot;Lakes/Ponds&quot; + &quot;Reservoirs&quot; in NHD Hi-Resolution (1:24k) data</td>
</tr>
<tr>
<td>Hydro</td>
<td>BFI_AVE</td>
<td>Base Flow Index (BFI), The BFI is a ratio of base flow to total streamflow, expressed as a percentage and ranging from 0 to 100. Base flow is the sustained, slowly varying component of streamflow, usually attributed to ground-water discharge to a stream.</td>
</tr>
<tr>
<td>Hydro</td>
<td>PERDUN</td>
<td>Dunne overland flow, also know as saturation overland flow, is generated in a basin when the water table &quot;outcrops&quot; on the land surface (due to the infiltration and redistribution of soil moisture within the basin), thereby producing temporary saturated areas. These saturated areas generate Dunne overland flow through exfiltration of shallow ground water and by routing precipitation directly to the stream network.</td>
</tr>
<tr>
<td>Hydro</td>
<td>PERHOR</td>
<td>Horton overland flow, also known as infiltration-excess overland flow, is generated in a basin when infiltration rates are exceeded by precipitation rates.</td>
</tr>
<tr>
<td>Hydro</td>
<td>TOPWET</td>
<td>Topographic wetness index, ln(a/S); where &quot;ln&quot; is the natural log, &quot;a&quot; is the upslope area per unit contour length and &quot;S&quot; is the slope at that point. See <a href="http://ks.water.usgs.gov/Kansas/pubs/reports/wrir.99-4242.html">http://ks.water.usgs.gov/Kansas/pubs/reports/wrir.99-4242.html</a> and Wolock and McCabe, 1995 for more detail</td>
</tr>
<tr>
<td>Hydro</td>
<td>CONTACT</td>
<td>Subsurface flow contact time index. The subsurface contact time index estimates the number of days that infiltrated water resides in the saturated subsurface zone of the basin before discharging into the stream.</td>
</tr>
<tr>
<td>Hydro</td>
<td>PCT_1ST_ORDER</td>
<td>Percent of stream lengths in the watershed which are first-order streams (Strahler order); from NHDPlus</td>
</tr>
<tr>
<td>Hydro</td>
<td>PCT_2ND_ORDER</td>
<td>Percent of stream lengths in the watershed which are second-order streams (Strahler order); from NHDPlus</td>
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<tr>
<td>Hydro</td>
<td>PCT_3RD_ORDER</td>
<td>Percent of stream lengths in the watershed which are third-order streams (Strahler order); from NHDPlus</td>
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<tr>
<td>Hydro</td>
<td>PCT_4TH_ORDER</td>
<td>Percent of stream lengths in the watershed which are fourth-order streams (Strahler order); from NHDPlus</td>
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<tr>
<td>Hydro</td>
<td>PCT_5TH_ORDER</td>
<td>Percent of stream lengths in the watershed which are fifth-order streams (Strahler order); from NHDPlus</td>
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<tr>
<td>Hydro</td>
<td>PCT_6TH_ORDER_OR_MORE</td>
<td>Percent of stream lengths in the watershed which are sixth or greater-order streams (Strahler order); from NHDPlus</td>
</tr>
<tr>
<td>Hydro</td>
<td>PCT_NO_ORDER</td>
<td>Percent of stream lengths in the watershed which do not have any streamorder in NHDPlus; these are typically canals, pipelines, and ditches.</td>
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<tr>
<td>LC06_Basin</td>
<td>DEVNLCD06</td>
<td>Watershed percent &quot;developed&quot; (urban), 2006 era (2001 for AK-HI-PR). Sum of classes 21, 22, 23, and 24</td>
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<tr>
<td>LC06_Basin</td>
<td>FORESTNLCD06</td>
<td>Watershed percent &quot;forest&quot;, 2006 era (2001 for AK-HI-PR). Sum of classes 41, 42, and 43</td>
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<tr>
<td>LC06_Basin</td>
<td>PLANTNLCD06</td>
<td>Watershed percent &quot;planted/cultivated&quot; (agriculture), 2006 era (2001 for AK-HI-PR). Sum of classes 81 and 82</td>
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<tr>
<td>LC06_Basin</td>
<td>DEVLOWNLCD06</td>
<td>Watershed percent Developed, Low Intensity (class 22)</td>
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<td>DEVMEDNLCD06</td>
<td>Watershed percent Developed, Medium Intensity (class 23)</td>
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<td>LC06_Basin</td>
<td>DEVIHNLCD06</td>
<td>Watershed percent Developed, High Intensity (class 24)</td>
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<tr>
<td>LC06_Basin</td>
<td>BARRENNLCD06</td>
<td>Watershed percent Natural Barren (class 31)</td>
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<tr>
<td>LC06_Basin</td>
<td>DECIDNLCD06</td>
<td>Watershed percent Deciduous Forest (class 41)</td>
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<tr>
<td>LC06_Basin</td>
<td>EVERGRNLCD06</td>
<td>Watershed percent Evergreen Forest (class 42)</td>
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<tr>
<td>LC06_Basin</td>
<td>SHRUBLCD06</td>
<td>Watershed percent Shrubland (class 52)</td>
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<tr>
<td>LC06_Basin</td>
<td>GRASSLCD06</td>
<td>Watershed percent Herbaceous (grassland) (class 71)</td>
</tr>
<tr>
<td>LC06_Basin</td>
<td>PASTURENLCD06</td>
<td>Watershed percent Pasture/Hay (class 81)</td>
</tr>
<tr>
<td>LC06_Basin</td>
<td>WOODYWETNLCD06</td>
<td>Watershed percent Woody Wetlands (class 90)</td>
</tr>
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<td>LC06_Basin</td>
<td>EMERGWETNLCD06</td>
<td>Watershed percent Emergent Herbaceous Wetlands (class 95)</td>
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<td>Pop_Infrastr</td>
<td>PDEN_DAY_LANDSCAN_2007</td>
<td>Population density in the watershed during the day, persons per sq km, from 90-m 2007 Landscan</td>
</tr>
<tr>
<td>Pop_Infrastr</td>
<td>PDEN NIGHT_LANDSCAN_2007</td>
<td>Population density in the watershed at night (residential population), persons per sq km, from 90-m 2007 Landscan</td>
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<tr>
<td>Pop_Infrastr</td>
<td>ROADS_KM_SQ_KM</td>
<td>Road density, km of roads per watershed sq km, from Census 2000 TIGER roads</td>
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<td>DESCRIPTION</td>
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<tr>
<td>Pop_Infrastr</td>
<td>RD_STR_INTERS</td>
<td>Number of road/stream intersections, per km of total basin stream length (2000 TIGER roads and NHD 100k streams)</td>
</tr>
<tr>
<td>Pop_Infrastr</td>
<td>IMPNLCD06</td>
<td>Watershed percent impervious surfaces from 30-m resolution NLCD06 data</td>
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<tr>
<td>Pop_Infrastr</td>
<td>NLCD01_06_DEV</td>
<td>Watershed percent which changed to &quot;Developed&quot; (urban) land (NLCD classes 21-24) between NLCD 2001 and 2006</td>
</tr>
<tr>
<td>Soils</td>
<td>HGA</td>
<td>Percentage of soils in hydrologic group A. Hydrologic group A soils have high infiltration rates. Soils are deep and well drained and, typically, have high sand and gravel content.</td>
</tr>
<tr>
<td>Soils</td>
<td>HGB</td>
<td>Percentage of soils in hydrologic group B. Hydrologic group B soils have moderate infiltration rates. Soils are moderately deep, moderately well drained, and moderately coarse in texture.</td>
</tr>
<tr>
<td>Soils</td>
<td>HGC</td>
<td>Percentage of soils in hydrologic group C. Hydrologic group C soils have slow soil infiltration rates. The soil profiles include layers impeding downward movement of water and, typically, have moderately fine or fine texture.</td>
</tr>
<tr>
<td>Soils</td>
<td>HGD</td>
<td>Percentage of soils in hydrologic group D. Hydrologic group D soils have very slow infiltration rates. Soils are clayey, have a high water table, or have a shallow impervious layer.</td>
</tr>
<tr>
<td>Soils</td>
<td>AWCAVE</td>
<td>Average value for the range of available water capacity for the soil layer or horizon (inches of water per inches of soil depth)</td>
</tr>
<tr>
<td>Soils</td>
<td>PERMAVE</td>
<td>Average permeability (inches/hour)</td>
</tr>
<tr>
<td>Soils</td>
<td>BDAVE</td>
<td>Average value of bulk density (grams per cubic centimeter)</td>
</tr>
<tr>
<td>Soils</td>
<td>OMAVE</td>
<td>Average value of organic matter content (percent by weight)</td>
</tr>
<tr>
<td>Soils</td>
<td>WTDEPAVE</td>
<td>Average value of depth to seasonally high water table (feet)</td>
</tr>
<tr>
<td>Soils</td>
<td>ROCKDEPAVE</td>
<td>Average value of total soil thickness examined (inches)</td>
</tr>
<tr>
<td>Soils</td>
<td>NO4AVE</td>
<td>Average value of percent by weight of soil material less than 3 inches in size and passing a No. 4 sieve (5 mm)</td>
</tr>
<tr>
<td>Soils</td>
<td>NO200AVE</td>
<td>Average value of percent by weight of soil material less than 3 inches in size and passing a No. 200 sieve (.074 mm)</td>
</tr>
<tr>
<td>Soils</td>
<td>CLAYAVE</td>
<td>Average value of clay content (percentage)</td>
</tr>
<tr>
<td>Soils</td>
<td>SILTAVE</td>
<td>Average value of silt content (percentage)</td>
</tr>
<tr>
<td>Soils</td>
<td>KFACT_UP</td>
<td>Average K-factor value for the uppermost soil horizon in each soil component. K-factor is an erodibility factor which quantifies the susceptibility of soil particles to detachment and movement by water. The K-factor is used in the Universal Soil Loss Equation (USLE) to estimate soil loss by water. Higher values of K-factor indicate greater potential for erosion</td>
</tr>
<tr>
<td>Soils</td>
<td>RFACT</td>
<td>Rainfall and Runoff factor (&quot;R factor&quot; of Universal Soil Loss Equation); average annual value for period 1971-2000</td>
</tr>
<tr>
<td>Topo</td>
<td>ELEV_MAX_M_BASIN</td>
<td>Maximum watershed elevation (meters) from 100m National Elevation Dataset</td>
</tr>
<tr>
<td>Topo</td>
<td>ELEV_MIN_M_BASIN</td>
<td>Minimum watershed elevation (meters) from 100m National Elevation Dataset (may include sinks)</td>
</tr>
<tr>
<td>Topo</td>
<td>ELEV_MEDIAN_M_BASIN</td>
<td>Median watershed elevation (meters) from 100m National Elevation Dataset</td>
</tr>
<tr>
<td>Topo</td>
<td>ELEV_STD_M_BASIN</td>
<td>Standard deviation of elevation (meters) across the watershed from 100m National Elevation Dataset</td>
</tr>
<tr>
<td>Topo</td>
<td>RRMEDIAN</td>
<td>Dimensionless elevation - relief ratio, calculated as (ELEV_MEDIAN - ELEV_MIN)/(ELEV_MAX - ELEV_MIN)</td>
</tr>
<tr>
<td>Topo</td>
<td>SLOPE_PCT</td>
<td>Mean watershed slope, percent. Derived from 100m resolution National Elevation Dataset, so slope values may differ from those calculated from data of other resolutions.</td>
</tr>
<tr>
<td>Topo</td>
<td>ASPECT_DEGREES</td>
<td>Mean watershed aspect, degrees (degrees of the compass, 0-360). Derived from 100m resolution National Elevation Data. 0 and 360 point to north. Because of the national Albers projection actual aspect may vary.</td>
</tr>
<tr>
<td>Topo</td>
<td>ASPECT_NORTHNESS</td>
<td>Aspect &quot;northness&quot;. Ranges from -1 to 1. Value of 1 means watershed is facing/draining due north, value of -1 means watershed is facing/draining due south.</td>
</tr>
<tr>
<td>Topo</td>
<td>ASPECT_EASTNESS</td>
<td>Aspect &quot;eastness&quot;. Ranges from -1 to 1. Value of 1 means watershed is facing/draining due east, value of -1 means watershed is facing/draining due west.</td>
</tr>
</tbody>
</table>