CALIFORNIA'S FIFTH
CLIMATE CHANGE
ASSESSMENT

Estimating the Impact of Drought on California's Housing Needs

An Original Research Report for:

California's Fifth Climate Change Assessment

CALIFORNIA NATURAL RESOURCES AGENCY

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About California's Fifth Climate Change Assessment

California's Climate Change Assessments are the state's scientific foundation for understanding future climate-related vulnerability across California's regions and systems. Senate Bill 1320 (Stern, 2020) requires the State to report the impacts and risks of climate change across California at least every five years, beginning with California's Fifth Climate Change Assessment (Fifth Assessment). Building on decades of climate research and previous Assessments, the Fifth Assessment presents new findings about California's climate future, with a dedicated focus on Tribal partnerships, public engagement, and communities most vulnerable to climate impacts.

The Fifth Assessment's research and tools are designed to fill knowledge gaps about California's climate future, inspire strategic climate actions, and shape planning, investments, and policies at the state, regional, and local scales. Guided by research priorities identified by state, Tribal, and local leaders, community representatives, and subject matter experts, its findings are designed to help illuminate potential climate futures, the challenges they may present, and the opportunities to build resilience through adaptation pathways.

For the full suite of Fifth Assessment research products, please visit: www.ClimateAssessment.ca.gov.

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Use of Artificial Intelligence (AI):
We acknowledge the use of AI tools in the preparation of this report. More specifically, Claude Code was used to develop initial code to process the downscaled climate data and structure output for visualization. Claude Code was also used to reformat tables and organize references and acronyms prior to manuscript completion.

Abstract

This study examines the potential for climate change-induced drought and water scarcity to constrain future housing growth in California. The study integrates downscaled climate projections with demographic and housing development scenarios to assess whether anticipated changes in water supply could limit the state's ability to meet housing needs. Using three representative counties—San Bernardino, San Luis Obispo, and San Diego—as case studies, the analysis combines climate model data, housing growth forecasts by type, and region-specific water supply and demand modeling to estimate the balance between future water reliability and the demand generated by new housing.

Results show that, under a range of plausible climate and housing growth scenarios through 2050, total water supplies generally remain sufficient to meet projected demand associated with housing growth in the target regions. This outcome is driven by trends including a shift toward multifamily housing, declining average household size, and continued improvements in water use efficiency. However, the research reveals areas of uncertainty, such as possible supply shortfalls during extreme or persistent droughts and local variation in outdoor water use behaviors. The study concludes that while current planning and conservation measures appear adequate for near-term housing needs, ongoing investments in adaptive management, including improved monitoring, integrated water-land use planning, and exploration of alternative supply strategies like on-site reuse and desalination, are necessary to safeguard both water and housing security as climate risks intensify. Recommendations highlight the need for tighter coordination between housing and water resource planning at all levels and for continued research to identify population thresholds and warning signals of impending water shortfalls.

Keywords: housing, drought, climate change, water demand, water supply

Highlights

- Climate change is projected to increase drought frequency and severity in California, raising potential risks for urban water supply and the capacity to support housing growth.
- Detailed water demand modeling for three representative counties (San Bernardino, San Luis Obispo, and San Diego) suggests that projected water supplies remain sufficient to meet future housing-related demand through 2050 under most scenarios.
- Key drivers helping to balance supply and demand include a shift toward multifamily housing, declining average household size, and continued improvements in water use efficiency.
- The findings highlight uncertainty around local supply reliability, especially during prolonged droughts, and underscore the importance of adaptive management and robust monitoring systems for future planning.
- Recommendations emphasize the need for integrated water-land use planning at the local, regional, and state level; ongoing investment in conservation and efficiency; and exploration of alternative supply strategies (such as on-site reuse and desalination) to ensure long-term resilience.
- The scenario-based approach and methods can help agencies and policymakers assess risks and inform water resource planning aligned with housing needs and climate adaptation goals.

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1: Introduction

1.1 Background

For much of modern history in the Western United States, the development of water resources has been a key driver of economic and urban growth. For water suppliers, this has meant planning and investments have long sought to optimize and enhance water supply to meet growing water demands. For land developers, this has meant water reliability has been a given. However, the socio-economic and climate dynamics of today, and even more so those of the future, are challenging these long-held assumptions, creating tensions between development needs and water security.

This challenge is particularly acute in California, where the urgent need to increase housing supply to address the state's growing affordable housing crisis conflicts directly with mounting risks of water scarcity. Climate change is intensifying both the frequency and magnitude of drought conditions across the state (Diffenbaugh et al., 2015), with recent research indicating that California faces increased vulnerability to prolonged drought and aridity in the coming decades (Cook et al., 2020; Swain et al., 2018; Williams et al., 2020). The combination of rising temperatures and increased precipitation variability is expected to exacerbate water stress in urban areas, further constraining the state's capacity to support new development (Pincetl et al., 2019; Wilson et al., 2024). In some cases, such as in Pismo Beach in 2015 (Hose, 2015), drought-related moratoriums on new development have already been considered or implemented.

California's housing affordability challenges have intensified in recent years, becoming among the most pressing socio-economic issues in the state. Decades of underproduction have left housing supply far behind demand, driving costs to historic highs and contributing to widespread housing insecurity (California Department of Housing and Community Development [HCD], 2022). According to HCD's Statewide Housing Plan, more than one-third of California households cannot afford their homes, and over half of renter households are cost-burdened, spending more than 30% of income on housing. These conditions have led to rising homelessness, increased migration of lower-income residents out of the state, and growing instability in housing markets particularly vulnerable to climate-related hazards such as wildfire and drought (HCD, 2022). In response, state policymakers have enacted a suite of measures to increase housing production, streamline development approvals, and hold local jurisdictions accountable to housing planning requirements. Central among these efforts is the Regional Housing Needs Assessment (RHNA) process, which sets housing production targets for each community in California.

Created in 1969, the RHNA program requires local governments to plan for their fair share of housing needs based on patterns of population growth and other factors. These regional housing goals are determined through a regional assessment process conducted every eight years on a rolling schedule across the state's 18 regional planning agencies or councils of governments. Over time, the program has increasingly emphasized the need for affordable housing and has incorporated more stringent requirements for local governments to meet their housing goals.

The 6th cycle RHNA process introduced significant changes aimed at promoting greater levels of housing development in infill areas, prioritizing development at locations near jobs and daily destinations, and affirmatively furthering fair housing such as promoting housing mobility and providing housing options in higher resource areas. In addition, the upcoming 7th cycle RHNA will include updates to more accurately estimate the full scope of housing needs that stem from pent-up demand for housing in the existing population. Housing planning review (Housing Element reviews) and compliance enforcement mechanisms have also been enhanced, with local governments facing increased scrutiny and accountability for committing to and taking meaningful steps to achieve these housing production goals. A notable example is rezoning to accommodate the RHNA which triggers permitting affordable multifamily development without discretionary review and often results in increasing residential densities in strategic locations. Also worth noting are the consequences of not complying with housing element law such as access to funding and the "builder's remedy," which allows developers to bypass most local zoning regulations to propose new housing developments if a municipality fails to meet its RHNA obligations.

Although coordination between those responsible for housing planning and water providers has long been required through the housing element and related processes, opportunities remain to more fully integrate water resource considerations into the RHNA process. Efforts to enhance this integration should compliment, not curtail, planning for future housing needs in response to water supply constraints. Legislation in recent decades has aimed to ensure that water reliability is considered in housing growth planning (e.g., SB 610 and SB 221 (2001)) but, improving the integration of land use, water supply, housing, equity, climate, and other considerations creates challenges and a need to improve approaches. Importantly, county general plan updates are not currently required to include a water component or climate-change projections, leaving significant gaps between local land-use planning and long-term resource planning. At the same time, statewide water-planning frameworks—such as California's Urban Water Management Plan (UWMP) requirement, initiated in 2000, and the more recent county-level SB 552 Drought Resilience Plans—provide mechanisms for assessing supply reliability under future conditions.

In parallel, current water supply planning practices often fail to fully integrate land use and development planning. While water suppliers routinely project future water demands to inform supply development and management strategies, these analyses often do not typically incorporate local land use plans or broader urban development objectives (Heberger et al., 2016; Wilson et al., 2016). Water demand projection approaches can be relatively simplistic, frequently relying on a single scenario for future growth and assuming that key variables, such as per capita water use rates, household size, and patterns of residential development, will remain unchanged over time. These methods often do not account for potential shifts in population demographics, changes in housing typology (e.g., increased prevalence of multifamily units), or the impacts of new water conservation policies and technologies, including updated building codes. Research has demonstrated that these assumptions related to housing density, typology, spatial distribution, and per capita use, have consistently resulted in inflated projections of water demand (Abraham et al., 2020). In reality, many regions in California have experienced remarkably stable urban water demand over time, even as their populations have grown, underscoring the urgent need for more nuanced and integrated planning approaches.

Finally, it is important to contextualize residential water use within California's broader resource landscape. Urban and residential demand represents a relatively small proportion of total statewide water use compared to agriculture and certain industrial sectors.

1.2 Overview

This paper addresses the need to better integrate water resource and housing planning and development in California, particularly in the context of climate change and increasing drought risk. We propose a framework for evaluating the implications of future climate scenarios on water reliability and housing growth, with the goal of informing more coordinated and resilient planning strategies.

To fill the gaps in current practice and research, this study is guided by three central questions:

1. What are the plausible future trajectories of housing growth, and how much water would be required to support them?
2. How might water reliability change under projected increases in drought and aridity?
3. To what extent could these changes constrain housing growth, and what strategies could mitigate these constraints?

We address these questions through four main analytical tasks. First, we analyze downscaled climate projections using the Cal-Adapt Analytics Engine to assess changes in drought and aridity across California for the years 2035 and 2050 under a

range of downscaled global climate model (GCM) projections. Second, we develop county-level population and housing growth forecasts, incorporating targets from the 6th cycle of the RHNA process and literature on the effects of land use planning on per capita water use. Third, we characterize the impacts of changing climate conditions on water reliability and per capita water use, employing a water balance model and both historical and projected hydrologic data. Fourth, we estimate water demand under each housing growth scenario and compare it to projected supply, quantifying potential shortages and the extent to which housing growth may be constrained by future drought.

1.3 Case Studies

The analysis focuses on three California counties—San Bernardino, San Luis Obispo (SLO), and San Diego—which exemplify the dual challenges of drought and housing affordability and offer diverse hydrologic and urban contexts for examining these dynamics. These locations were selected based on i) the availability of supply and demand data for our analysis; ii) interest in local water agencies in participating in the research; and iii) relative diversity in terms of water sources, scarcity concerns, and housing needs. Figure 1.3.1 shows a rough mapping of housing needs against potential for water scarcity based on a review of water supply portfolios, existence of drought-related housing moratoria, and state reports on housing needs.

Figure 1.3.1. Case Study Counties

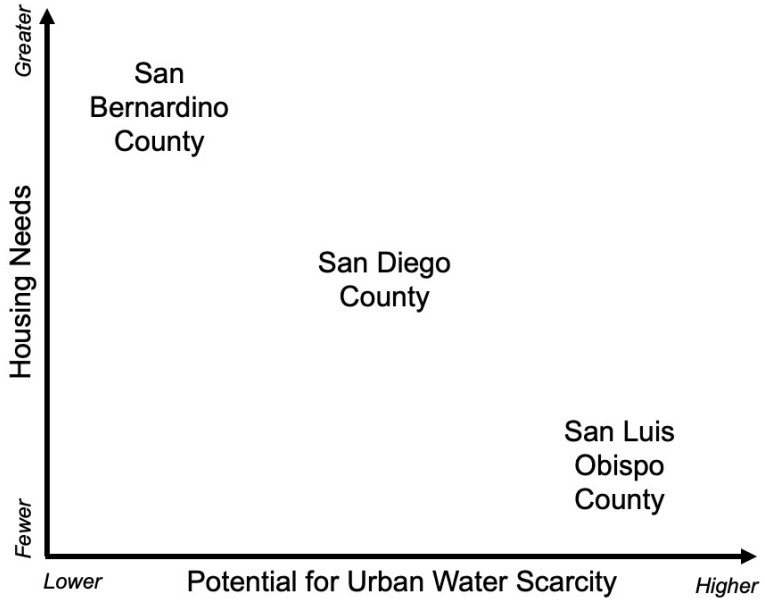


Figure 1.3.1. This figure displays the relative positioning of the three case study counties (San Bernardino, San Diego, and San Luis Obispo) according to their housing needs (vertical axis) and potential for urban water scarcity (horizontal axis). The placement is based on a review of water supply portfolios, history of drought-related housing moratoria, and state housing needs reports. Source: Authors' analysis.

Within each county, we engaged directly with regional water agencies to obtain the most recent data on both water demand and supply, including historical figures as well as agency projections. Specifically, we worked with the San Bernardino Valley Municipal Water Agency (San Bernardino Valley), the San Diego County Water Authority (SDCWA), and the San Luis Obispo County Water Resources Division. San Bernardino Valley and SDCWA serve as regional water wholesalers, managing water supplies for a network of local retail or member agencies. In contrast, the San Luis Obispo County Water Resources Division primarily supports regional water planning and coordination, rather than direct supply management. Nevertheless, all three agencies play a critical role in shaping regional water supply and demand strategies. The data we collected were primarily those used in the agencies' Urban Water Management Plans (UWMPs), supplemented by any updates or revisions made since the most recent UWMP cycle.

1.4 Limitations

While this study provides new insights into the intersection of water supply, climate change, and housing growth in California, several key limitations should be acknowledged.

1.4.1 Case Study Coverage

The analysis focused on three California counties—San Bernardino, San Diego, and San Luis Obispo—selected to represent different combinations of drought exposure, water supply characteristics, and housing affordability conditions, as well as local interest in partnering and sharing data. While these cases provide useful insight into the interaction between water resource constraints and housing growth under varied hydrologic and institutional settings, the geographic coverage of the study remains limited.

In particular, the absence of counties within the San Joaquin Valley (SJV) and the Association of Bay Area Governments (ABAG) region constrains the breadth of conclusions that can be drawn about statewide dynamics. Areas such as Santa Clara, Alameda, and Monterey counties represent substantially different conditions, including the presence of significant agricultural water demands regulated under the Sustainable Groundwater Management Act (SGMA), complex interagency water governance structures, and some of the state's highest RHNA targets. While San Luis Obispo and San Bernardino face some of these dynamics, inclusion of additional regions could have provided valuable contrasts and potential lessons regarding groundwater sustainability, integrated planning under SGMA, and institutional coordination between water and housing authorities.

Future work would benefit from expanding the set of case study regions to include both agriculturally intensive basins and major metropolitan jurisdictions. This broader

representation would help capture the full range of interactions between housing development pressures, water supply variability, and regional planning requirements and would allow for more comprehensive assessment of statewide opportunities to strengthen alignment between housing and water planning processes.

1.4.2 Water Demand Estimation

There are substantial limitations in our water demand estimates, particularly for San Luis Obispo County (SLO County). Across all case study regions, demand projections are subject to meaningful uncertainty, especially regarding outdoor water use, which can vary widely and is difficult to model accurately. In SLO County, the lack of robust historical data constrained our ability to calibrate demand models. The agency provided only aggregate urban water demand estimates from their Urban Water Management Plan (UWMP) reports, which appear to incorporate variable levels of non-residential use across the regional water districts examined. This introduces additional uncertainty into our demand estimates and limits the precision of our analysis.

Furthermore, our estimation framework does not explicitly account for potential land-use changes associated with implementation of the Sustainable Groundwater Management Act (SGMA). Groundwater Sustainability Agencies (GSAs) in affected basins may pursue land repurposing strategies to meet groundwater sustainability targets, for example, converting irrigated farmland to ecological or low-water-use areas, or in some cases facilitating transitions to new urban development. Each of these pathways could alter total water demand in ways not captured here: conversions to habitat would likely reduce demand in the near term, while urban redevelopment could increase demand depending on housing density and use patterns. The magnitude and direction of these effects remain uncertain, but monitoring SGMA-related land transitions will be important for refining future demand forecasts.

1.4.3 Water Supply Analysis

Our water supply analysis did not employ direct modeling for supply projections. This decision was driven by both the scope of our study and the lack of comparable models for all components of the water supply portfolios in each case study agency. As a result, we relied on established methods from the literature to derive relationships between climate model projections and changes in supply. This approach allowed us to represent long-term changes in climate conditions but did not enable us to isolate the effects of individual drought events or short-term supply shocks.

In addition to these methodological constraints, the highly aggregated nature of California's water supply data presents a further limitation. Water from multiple

sources, including surface water imports, local groundwater, recycled wastewater, and stormwater capture, is frequently blended within regional distribution systems before delivery to end users. As a result, available datasets often lack clear source attribution and traceability, making it difficult to disaggregate supply conditions by origin or reliability. This data aggregation complicates efforts to accurately assess the impacts of drought, climate variability, and conservation measures within individual supply components.

Moreover, the physical integrity and operational reliability of California's major conveyance systems add another layer of uncertainty. Several statewide and regional delivery infrastructures, including the State Water Project (SWP), face ongoing challenges related to subsidence, aging facilities, and deferred maintenance. Both California's SWP Adaptation Strategy and a subsidence-focused addendum to the 2023 Delivery Capability Report indicate that subsidence in the aqueduct corridor may reduce hydraulic capacity over time, potentially limiting the project's ability to meet historical delivery volumes without significant investment (California Department of Water Resources [DWR], 2025; CA DWR, 2024). These issues are not unique to the SWP; many local systems across the state face similar risks stemming from both climate impacts and infrastructure degradation. Although our study did not explicitly model these structural constraints, they represent important considerations for future assessments of water supply reliability and climate resilience.

1.4.4 Climate Model Data

The climate model data used in this study were limited to the WRF downscaled dataset, which was available for only one Shared Socio-economic Pathway (SSP) and four global climate models (GCMs). This constraint significantly reduced the range of climate uncertainty we were able to consider in our analysis and may not fully capture the breadth of possible future climate scenarios.

1.4.5 Housing Growth Data

Our population and housing need data have a few limitations worth mentioning. These data are aimed primarily at projecting patterns of population change and housing need (and associated changes such as commuting patterns) at the regional level, and they were not formulated with a specific focus on water demand. Thus, our use of the underlying small area data (at the census tract or traffic analysis zone level) to construct population and housing need patterns at water district levels may induce some further error in growth projections, though we believe most such errors would likely be random, rather than systematic in nature.

These data also differ in the selection of which future years were chosen to generate point estimates for. This means that we have a non-harmonized set of specific time periods to use in ultimately estimating water demand. In some cases (such as plotting

the paths of regional population and housing change over time,as presented below), we linearly interpolate all interstitial years, but this linearity is an assumption. Most consequentially, San Luis Obispo County data only included housing need estimates to 2045 (this was the only case where we did not have a specific 2050 estimate of housing need). In this case, we used the linear relationship between earlier years to arrive at a 2050 value. Relatedly, we also had varying access across our case study counties to past housing projection data at small area levels from which to construct historical population and housing estimates at the water district level. This affected our ability to calibrate the final residential water demand models in a harmonized way.

Additionally, unlike our other two case study counties, San Luis Obispo County housing need data also did not have small area projections of changes in average number of residents per household, instead providing only one estimate for the county.

2: Climate Change

2.1 Data and Methods

The primary goal of our climate data analysis is to quantify projected changes in key climate and hydrologic variables that influence future drought and aridity in each of our case study counties. To that end, downscaled climate projections for daily total precipitation and daily mean temperature were obtained from the Weather Research and Forecasting Model (WRF) for the period 1991–2099, covering all available Shared Socio-economic Pathways (SSPs) and global climate models (GCMs) at the time of analysis. For this study, and as part of California's Fifth Climate Change Assessment, we were directed to use the Cal-Adapt Analytics Engine as the primary source of data for climate change analyses.

2.1.1 Cal-Adapt Analytics Engine Overview

The Cal-Adapt Analytics Engine (Analytics Engine) is an open-access, web-based platform that hosts climate change projections and related datasets, much of which was generated specifically for California's Fifth Climate Change Assessment.

The climate projections available through the Analytics Engine are produced using two main downscaling methods applied to outputs from the Coupled Model Intercomparison Project Phase 6 (CMIP6) GCMs:

1. Dynamical Downscaling: Implemented by researchers at University of California, Los Angeles (UCLA) using the WRF model, this method generates physically-based, high-resolution projections for California and the Western United States.
2. Hybrid-Statistical Downscaling: Developed at Scripps Institution of Oceanography, the LOCA2-Hybrid approach uses WRF outputs to train statistical models, bias-correcting GCM outputs to better match observed station data.

These downscaled datasets differ in the number of GCMs, variables, temporal resolution, and SSPs included. For this study, we used the WRF-based dynamical downscaling, which is currently available for SSP3-7.0 and provides data at a nine-square-kilometer resolution across California. In addition to climate variables such as precipitation and temperature, the Analytics Engine provides WRF-derived hydrologic variables, including evapotranspiration, runoff, and snow water equivalent (SWE), which were important for our analysis of future drought and aridity. While the data are available at higher temporal resolutions, daily projections were sufficient for our needs. At the time of analysis, daily projections for our variables of interest were only

available from four GCMs, FGOALS-g3, EC-Earth3-Veg, CNRM-ESM2-1, and CESM2.[1] Ensemble members or measures of variance within a given GCM and SSP were not provided.

2.1.2 Data Processing and Analysis

Downloaded gridded datasets were masked to the boundaries of our three case study counties—San Diego, San Bernardino, and San Luis Obispo—as well as the local watersheds that contribute water supply to these areas: (1) Santa Ana River, (2) San Diego River, (3) Lower San Joaquin, (4) Lower Sacramento, and (5) Central Coastal. For each spatial area and GCM, we estimated average annual values for aridity, consecutive dry days, total precipitation, temperature, total runoff, evapotranspiration, and SWE for each grid cell. These calculations were performed for four time periods: 1991–2020 (climate normal), 2021–2050 (representing 2035), 2035–2064 (representing 2050), and 2070–2099 (representing end of century).

Aridity was quantified using the Aridity Index, defined as the ratio of annual precipitation to annual evapotranspiration, with climate classes as shown in Table 2.1.1.

Table 2.1.1. Aridity Index

Aridity Index Value	Climate Class
<0.03	Hyper Arid
0.03–0.2	Arid
0.2–0.5	Semi-Arid
0.5–0.65	Dry sub-humid
>0.65	Humid

2.2 Climate Projections

2.2.1 San Bernardino County

Climate projections for San Bernardino County indicate a decrease in aridity (i.e., higher aridity index values, reflecting less arid conditions), accompanied by modest increases in both mean temperature and total precipitation, with negligible changes in evapotranspiration (Table 2.2.1). The projected reduction in aridity is primarily driven by increases in precipitation across the four Weather Research and Forecasting

1 More information on data availability can be found at https://analytics.cal-adapt.org/data/catalog/

Model (WRF) models. Although these model outputs suggest a trend toward wetter conditions in San Bernardino County, the broader scientific literature does not consistently support a significant change in average annual precipitation for the region (He et al., 2018). It is also important to note that California's natural variability is also a key driver of changes in precipitation and could be as prominent, or greater, than the signal we see due to climate change alone (Swain et al., 2018). The results in Table 2.2.1 do not suggest a clear attribution to either as both the mean and the spread of the ensemble exhibit similar changes over time.

Table 2.2.1. Climate Projections for San Bernardino County

Variable	Climate Normal	2035	2050	2100
Aridity	0.04 / **0.08** / 0.14	0.04 / **0.10** / 0.16	0.05 / **0.10** / 0.17	0.04 / **0.09** / 0.17
Mean Annual Temperature	56.11 / **63.41** / 70.49	57.66 / **65.00** / 72.12	58.67 / **66.01** / 73.18	57.40 / **64.81** / 71.98
Total Annual Precipitation	5.73 / **12.09** / 22.32	7.77 / **13.26** / 25.40	8.09 / **13.43** / 26.68	7.45 / **13.43** / 26.04
Total Annual Evapotranspiration	0.00 / **0.35** / 0.78	0.00 / **0.35** / 0.77	0.00 / **0.35** / 0.77	0.00 / **0.35** / 0.76
Total Annual Runoff	0.49 / **1.11** / 2.38	0.68 / **1.20** / 3.01	0.71 / **1.25** / 3.24	0.65 / **1.22** / 3.15
Snow Water Equivalent	0.00 / **0.00** / 0.02	0.00 / **0.00** / 0.00	0.00 / **0.00** / 0.00	0.00 / **0.00** / 0.00

NOTE: In each cell, the 10th percentile is shown as the first value, the median as the bolded middle value, and the 90th percentile as the third value. These distributions are based on projections from SSP3-7.0 and four GCMs: FGOALS-g3, EC-Earth3-Veg, CNRM-ESM2-1, and CESM2.

Substantial spatial heterogeneity is evident in projected climate trends across San Bernardino County. The southwestern portion of the county, encompassing more densely populated urban centers and mountainous terrain, is characterized by lower mean temperatures and higher precipitation relative to the surrounding arid regions. This spatial pattern is illustrated in Figure 2.2.1, which presents the median projected average annual temperature for 2050.

Figure 2.2.1. Projected Mean Annual Temperature for San Bernardino County in 2050

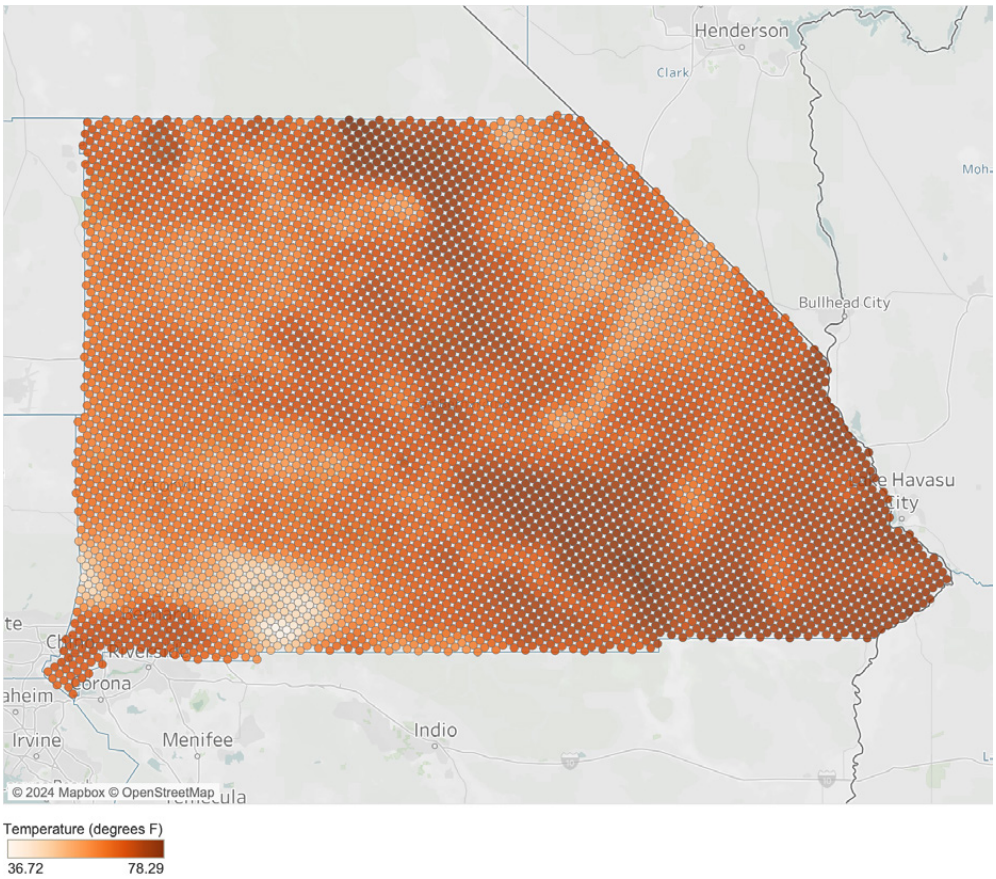


Figure 2.2.1. This map shows the projected median annual temperature for San Bernardino County in 2050, based on the median of four global climate models. Warmer colors indicate higher temperatures. Source: Cal-Adapt Analytics Engine, WRF downscaled projections.

Comparable trends are observed for the Santa Ana River Watershed. Figure 2.2.2 depicts percent changes relative to the baseline period (1991–2020) for snow water equivalent (SWE), total annual precipitation, and total annual runoff. The projections indicate a pronounced reduction in SWE concurrent with increases in both precipitation and runoff. While diminished snowpack may be offset by enhanced local water reliability from the Santa Ana River, this analysis does not account for changes in hydrologic variability or the frequency and severity of drought events. The ensemble mean reveals a consistent decline in SWE, whereas temporal changes in the ensemble spread (not pictured) indicate evolving internal variability within the model projections. Additionally, results are limited to a single Shared Socio-economic Pathway (SSP) and four GCMs, constraining the scope of future uncertainty represented.

Figure 2.2.2. Mean Projected Changes from Normal in SWE, Precipitation and Runoff for the Santa Ana River Watershed

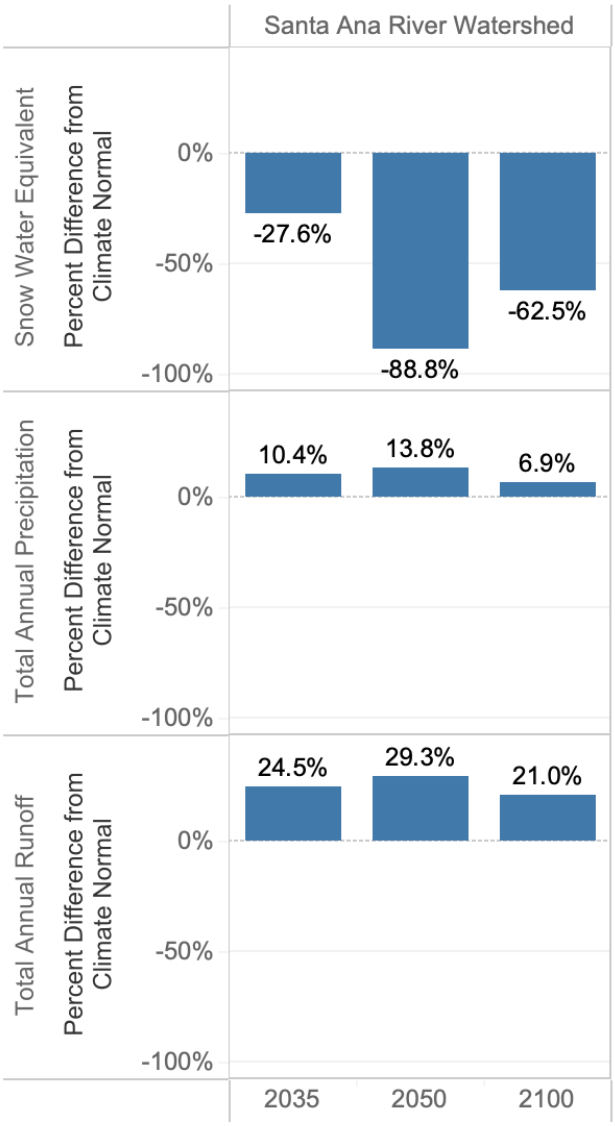


Figure 2.2.2. This figure presents the percent change from the climate normal (1991–2020) in snow water equivalent (SWE), total annual precipitation, and total annual runoff for the Santa Ana River Watershed for 2035, 2050, and 2100. Bars show ensemble means across four GCMs. Source: Cal-Adapt Analytics Engine, WRF downscaled projections.

2.2.2 San Diego County

Climate projections for San Diego County indicate minimal change in aridity, with modest increases in mean temperature and total precipitation (Table 2.2.2). Analysis of projected evapotranspiration (ET) reveals a decrease in median ET values, while

areas with historically elevated ET exhibit further increases. At finer spatial scales, substantial heterogeneity is observed: higher elevation and coastal zones remain cooler and receive greater precipitation relative to inland desert regions. These spatial patterns are expected to persist through mid-century, with no significant shifts in their distribution. Figure 2.2.3 illustrates the median projected average annual temperature for 2050.

Table 2.2.2. Climate Projections for San Diego County

Variable	Climate Normal	2035	2050	2100
Aridity	0.02 / **0.05** / 0.12	0.02 / **0.06** / 0.13	0.02 / **0.06** / 0.13	0.02 / **0.06** / 0.13
Mean Annual Temperature	55.31 / **62.85** / 69.54	56.78 / **64.17** / 71.01	57.74 / **65.01** / 72.00	56.42 / **63.63** / 70.71
Total Annual Precipitation	13.02 / **29.76** / 56.42	14.99 / **34.08** / 61.58	14.79 / **34.15** / 62.01	14.20 / **32.62** / 59.89
Total Annual Evapotranspiration	0.00 / **1.38** / 8.06	0.00 / **1.34** / 8.27	0.00 / **1.31** / 8.39	0.00 / **1.28** / 8.51
Total Annual Runoff	0.90 / **4.66** / 20.96	1.04 / **5.84** / 23.23	1.00 / **5.76** / 23.21	0.98 / **5.53** / 22.49
Snow Water Equivalent	0.00 / **0.00** / 0.03	0.00 / **0.00** / 0.01	0.00 / **0.00** / 0.01	0.00 / **0.00** / 0.01

NOTE: In each cell, the 10th percentile is shown as the first value, the median as the bolded middle value, and the 90th percentile as the third value. These distributions are based on projections from SSP3-7.0 and four GCMs: FGOALS-g3, EC-Earth3-Veg, CNRM-ESM2-1, and CESM2.

Figure 2.2.3. Projected Mean Annual Temperature for San Diego County in 2050

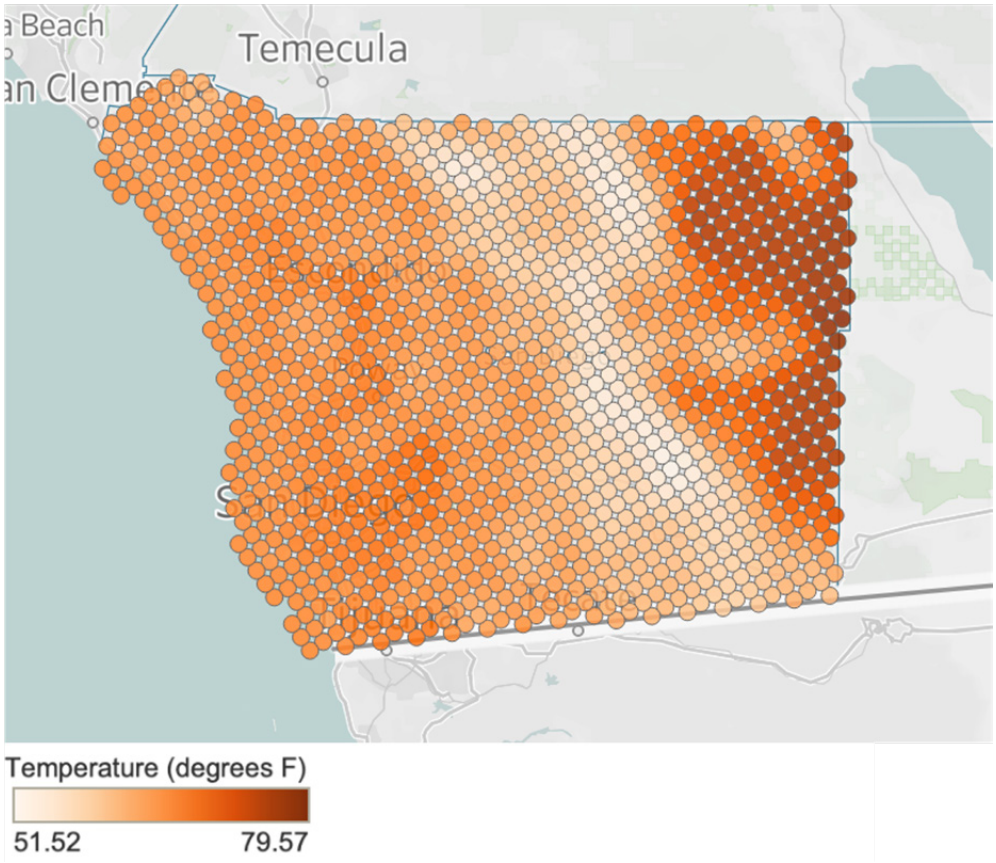


Figure 2.2.3. This map displays the projected median annual temperature for San Diego County in 2050, with grid cell values representing the median across four GCMs. Source: Cal-Adapt Analytics Engine, WRF downscaled projections.

Figure 2.2.4 displays percent changes relative to the baseline period (1991–2020) for total annual precipitation and total annual runoff in the watershed. Snow water equivalent (SWE) values are negligible in this region and are therefore excluded from the table; however, our analysis indicates a near-complete loss of SWE, with declines approaching 100% compared to climate normal values. The projections demonstrate increases in both precipitation and runoff, suggesting the potential for enhanced surface water reliability over the long term. Nevertheless, these findings should be interpreted with caution, as the current analysis does not incorporate assessments of hydrologic variability, nor does it address the frequency, duration, or severity of short- and long-term drought events. Furthermore, the reliance on a single SSP and four GCMs constrains the representation of future climate uncertainty, potentially limiting the robustness of these projections.

Figure 2.2.4. Projected Changes from Normal in Precipitation and Runoff for the San Diego River Watershed

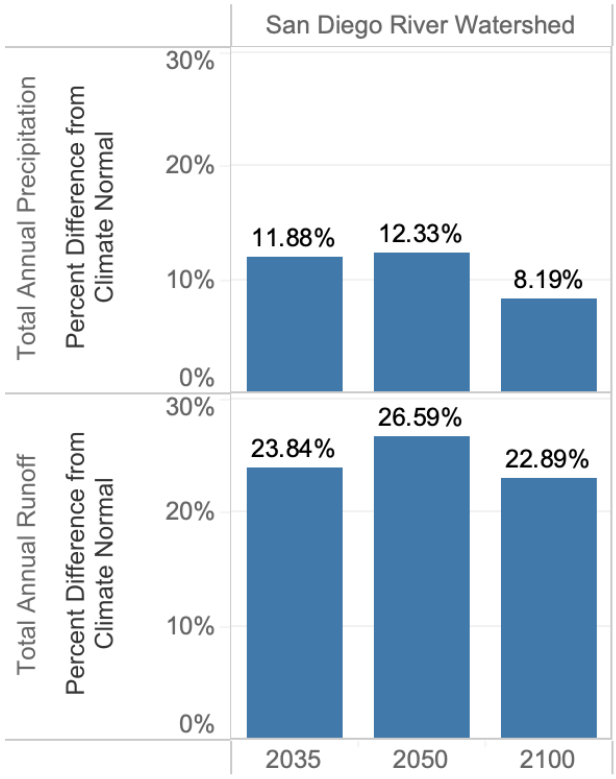


Figure 2.2.4. This figure shows the percent change from the climate normal in total annual precipitation and runoff for the San Diego River Watershed for 2035, 2050, and 2100. Bars represent ensemble means across four GCMs. Source: Cal-Adapt Analytics Engine, WRF downscaled projections.

2.2.3 San Luis Obispo County

Analysis of climate projections for San Luis Obispo County (Table 2.2.3) indicates a modest reduction in aridity (i.e., higher aridity index values, reflecting less arid conditions), accompanied by increases in both mean temperature and total precipitation. Consistent with findings for San Diego County, projected evapotranspiration (ET) exhibits a decline in countywide median values, while areas characterized by elevated ET during the climate normal period are projected to experience further increases. Spatial analysis of these variables reveals persistent geographic patterns: Figure 2.2.5 presents the median projected average annual temperature for 2050, highlighting cooler conditions at higher elevations and comparatively warmer temperatures along the coast and in the eastern, agriculturally intensive inland regions. For ET, the data indicate that the highest values are concentrated in the western portion of the county. Notably, these spatial distributions of temperature and ET are projected to remain largely unchanged from the climate

normal period through 2100, suggesting stability in the underlying geographic gradients of these climate variables.

Table 2.2.3. Climate Projections for San Luis Obispo County

Variable	Climate Normal	2035	2050	2100
Aridity	0.01 / **0.02** / 0.05	0.01 / **0.03** / 0.05	0.01 / **0.03** / 0.06	0.01 / **0.03** / 0.05
Mean Annual Temperature	56.48 / **58.63** / 60.39	57.78 / **59.96** / 61.72	58.58 / **60.84** / 62.60	57.18 / **59.57** / 61.44
Total Annual Precipitation	17.75 / **27.24** / 42.36	21.33 / **30.38** / 46.50	21.95 / **30.82** / 47.62	20.78 / **29.47** / 45.16
Total Annual Evapotranspiration	0.56 / **2.75** / 8.45	0.55 / **2.73** / 8.61	0.55 / **2.70** / 8.65	0.54 / **2.67** / 8.64
Total Annual Runoff	1.27 / **2.98** / 6.64	1.58 / **3.63** / 8.19	1.61 / **3.80** / 8.36	1.49 / **3.53** / 7.77
Snow Water Equivalent	0.00 / **0.00** / 0.00	0.00 / **0.00** / 0.00	0.00 / **0.00** / 0.00	0.00 / **0.00** / 0.00

NOTE: In each cell, the 10th percentile is shown as the top value, the median as the bolded middle value, and the 90th percentile as the bottom value. These distributions are based on projections from SSP3-7.0 and four GCMs: FGOALS-g3, EC-Earth3-Veg, CNRM-ESM2-1, and CESM2.

Figure 2.2.5. Projected Mean Annual Temperature for San Luis Obispo County in 2050

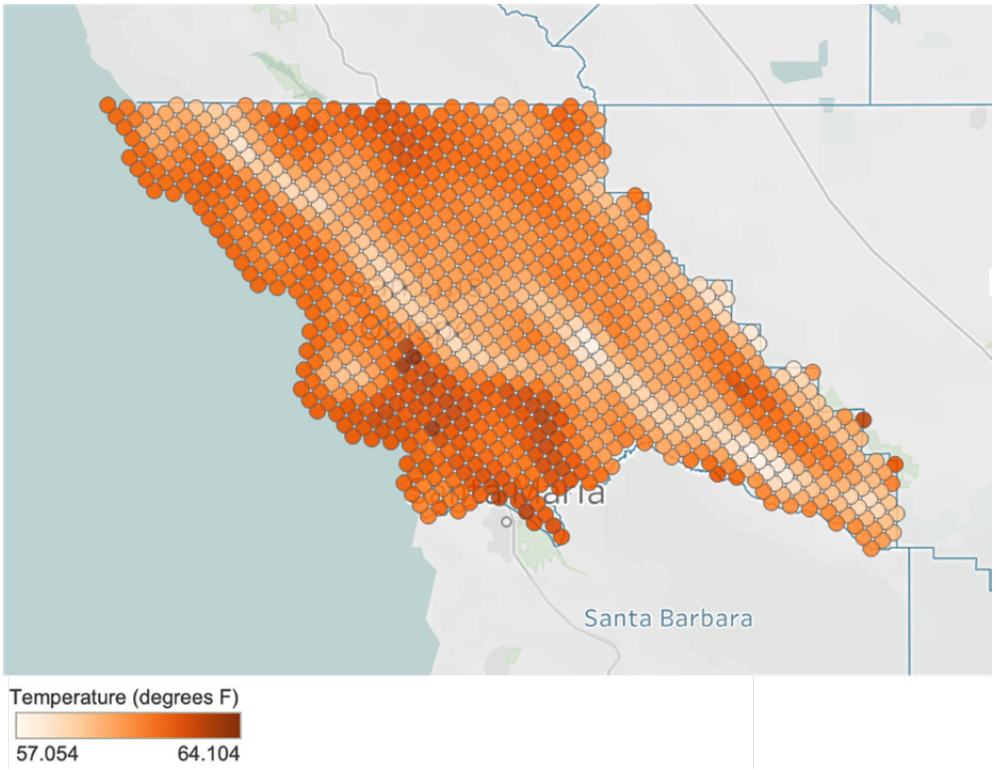


Figure 2.2.5. This map shows the projected median annual temperature for San Luis Obispo County in 2050, with grid cell values representing the median across four GCMs. Source: Cal-Adapt Analytics Engine, WRF downscaled projections.

Figure 2.2.6 illustrates percent changes relative to the baseline period (1991–2020) for total annual precipitation and total annual runoff within the watershed. Due to the negligible snow water equivalent (SWE) values observed in this region, SWE is excluded from the analysis. The projections indicate increases in both precipitation and runoff, with the most pronounced changes occurring in the northern portion of the watershed, where future scenarios suggest slightly higher magnitudes of both variables. This spatial pattern aligns with the expectation of enhanced precipitation and runoff in the northern sector under projected climate conditions.

Figure 2.2.6. Projected Changes from Normal in Precipitation and Runoff for the Central Coast Watershed

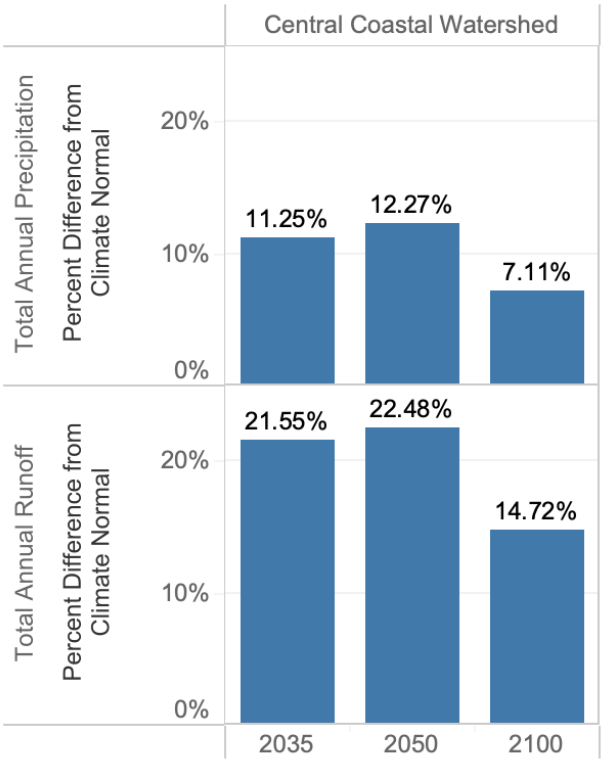


Figure 2.2.6. This figure presents the percent change from the climate normal in total annual precipitation and runoff for the Central Coast Watershed for 2035, 2050, and 2100. Bars show ensemble means across four GCMs. Source: Cal-Adapt Analytics Engine, WRF downscaled projections.

3: Housing Growth

3.1 Data and Methods

Our approach to modeling housing growth involves adapting various growth scenarios produced by the California Department of Transportation (Caltrans), multiple regional councils of government (the Southern California Associations of Governments [SCAG], the San Luis Obispo Council of Governments [SLOCOG], and the San Diego Association of Governments [SANDAG]), and the 6th cycle of the California Regional Housing Needs Assessment (RHNA) process. For each of our three case study regions, we selected from among these scenarios a set of three potential paths of housing growth: a baseline scenario, a low growth scenario, and a high growth scenario.

For San Diego and San Bernardino counties, we use the 6th cycle RHNA housing allocations to guide our high growth scenario as it represents a key planning and accountability target for housing production. While current trends indicate that achieving these allocations for San Diego and San Bernardino counties[2] may require substantial acceleration relative to recent housing production, this scenario is intended to represent the level of growth needed to meet long-term housing objectives even if full realization extends beyond the 6th-cycle timeframe. We assume housing units in this scenario are occupied at the same rate as in the baseline, based on the principle that local jurisdictions are not required to construct housing beyond demonstrated demand. Continued state policy actions, including strengthened enforcement of RHNA goals and recent CEQA reforms under AB 130 and SB 131 (2025), may further enable progress toward these targets.[3]

Figure 3.1.1 shows the proportion of current levels of housing production from annual progress report data from California Department of Housing and Community Development (HCD) compared to the level of housing production that would represent being "on track" for the 6th cycle RHNA goal (assuming linear growth over the eight-year timeline) for each case study county we focus on. In each bar area are the numbers of housing units produced as of April of 2024 and the number that should have been produced (assuming an equal share of required housing units would be built over each of the eight years). While our analysis focuses on total

2 San Luis Obispo County is roughly meeting its overall RHNA goal for total housing production to date, but these goals are much smaller than the goals for the larger counties.

3 Recently enacted state legislation, including AB 130 and SB 131 (2025), introduced reforms to the California Environmental Quality Act (CEQA) intended to expedite housing development, particularly infill projects that meet certain size, location, and density conditions (e.g., parcels up to 20 acres within incorporated or urban areas, consistent with local plans and outside designated farmland, wetland, or high-hazard zones). While the implications of these CEQA exemptions for future housing growth remain uncertain, they may affect the feasibility or timing of the modeled RHNA-based scenarios.

housing unit growth targets[4] and does not differentiate by affordability levels, it is important to note that RHNA allocations include income-based housing categories that typically correspond to denser development forms. Affordable housing, in particular, is often built at higher densities, which research and agency consultation indicate can substantially reduce per-capita water use. Staff from the California State Water Resources Control Board emphasized that denser developments generally conserve water relative to low-density housing, where most water consumption is driven by outdoor landscaping. This context underscores that incorporating affordability and density considerations in future analyses could meaningfully refine estimates of water demand associated with housing growth scenarios

Figure 3.1.1. Regional Housing Growth Compared to RHNA Goals (April 2024)

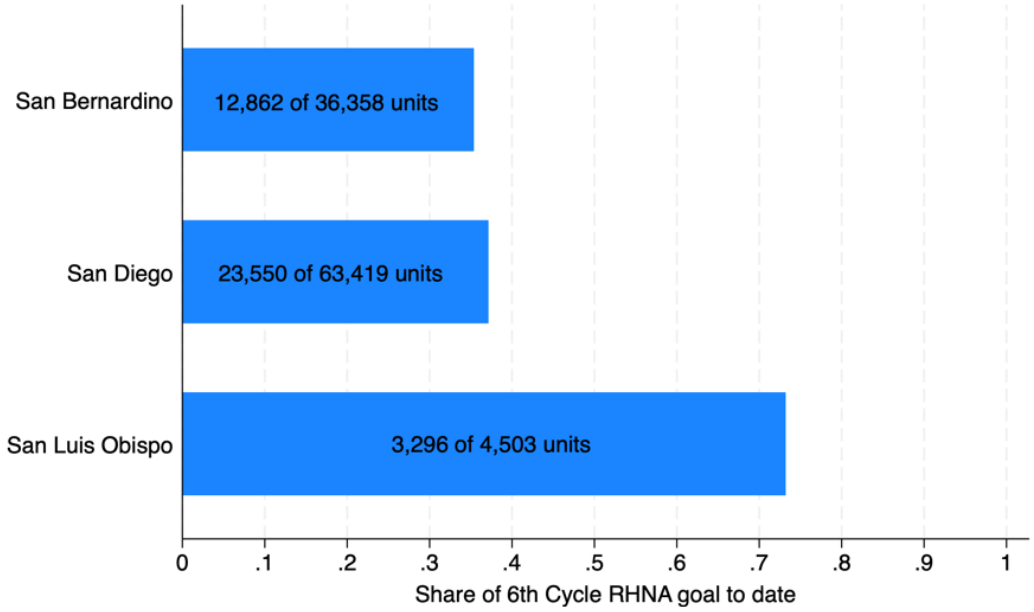


Figure 3.1.1. This bar chart compares actual housing production as of April 2024 to the levels needed to be "on track" for the 6th cycle RHNA goal in each case study county. A value of 1 would indicate that the county was on track (as of April 2024) to complete the number of housing units required. The numbers within each bar indicate units produced versus the target. Source: Author calculations from California Department of Housing and Community Development data.

4 These totals are the sum of the housing goals for the four income-level targets used: very low income (up to 50% of the area median income), low income (above 50% and below 80% of the area median income), moderate income (above 80% and below 120% of the area median income), and above moderate income (greater than 120% of the area median income). Though not shown here, we note that most areas are making reasonable progress or even exceeding the goals for above moderate income housing production and are falling most profoundly short for very low and low income housing production

This evidence suggests to us that both San Diego and San Bernardino counties are unlikely to make substantial progress towards their RHNA targets over the performance period for the 6th cycle of RHNA. However, given that these estimates are a key planning benchmark for the state, we retain them as the basis of our high growth scenario. Since the RHNA goals are based on an eight-year cycle, we extend the forecasts to 2050 for each region we study by assuming housing growth up to the RHNA target at the eight-year mark, and we impute further growth beyond the final year of the RHNA (i.e., 2029) using the baseline trend from the most recent regional growth plan through 2050.

We do not use the RHNA goal in San Luis Obispo County to derive our high growth scenario as the San Luis Obispo Council of Governments (SLOCOG) projections contain a high growth scenario that is modestly higher than the RHNA target, and we believe that this is a more appropriate high growth target to use since, first, it is likely informed by better local knowledge and data than the imputation approach we use for the other counties and, second, the region's total housing growth in April of 2024 was actually fairly close to being "on track" to meeting the overall RHNA goal.

An additional note on the use of the RHNA targets in our high-growth scenario: since the RHNA targets are denominated in housing units, whereas the typical growth projections used by regional planning bodies are driven by underlying assumptions around population changes, there is a question of how to handle the relationship between housing units and population for the high-growth scenario. One way to think about a housing-driven growth measure is as if this process were driven by a central planner, and homes would be built whether there were residents to occupy them or not. In such a case, it might be reasonable to think about, for example, using a lower persons-per-dwelling measure while calculating water demand for this scenario.

However, the RHNA process is meant to induce communities to plan for growth through reforming zoning and otherwise removing barriers to housing production with the assumption that this will allow a more flexible housing supply response to meet demand. It is not the case that local jurisdictions are required to build housing that is not demanded. Therefore, we take the view that housing units produced in the high-growth scenario will be occupied at the same persons per household rate as housing in the baseline growth scenario.[5]

5 There may be merit to the idea that a relative increase in the number of housing units available to occupy could lead to some level of decompression of overcrowding. However, such adjustments to the forecast would be qualitatively small, and we believe our approach is more likely to detect any feasible bounds of potentially binding water supply scarcity in the regions we study. We do focus on estimating how this type of decompression could affect occupied housing units in the low growth scenarios as these scenarios suggest a meaningful decline in housing demand because they are primarily driven by assumptions about substantial relative increases in outmigration.

Since the RHNA targets do not prescribe the shares of housing types that must be produced, we use the forecasted trends in housing production shares by type from the regional growth plans, all of which predict a notable shift towards multifamily housing production. For example, in the San Diego County baseline scenario, roughly 87% of the growth in housing is in multifamily units, so we apply this ratio to our high growth scenario as well.

For our low-growth scenarios for San Bernardino and San Diego counties, we use housing forecasts from Caltrans that were updated last year (2023) and which are notably lower than the most recent regional forecasts produced in earlier years. We originally proposed to use a regression-based approach to project a lower bound scenario from recent historical data, but recent, substantial reductions in state population indicated that this approach might actually overshoot a more likely low growth scenario by overly depending on past trends. We do make a modest but, we believe, conceptually important adjustment to these data to incorporate the potential economic effects of lower population growth on doubled-up or tripled-up households (i.e., instances of two [or three] potential household heads occupying one dwelling unit). Namely, we anticipate an effect of "decompression" or easing from recent levels of such overcrowding, something we discuss in more detail below.

The ultimate output from these county-level forecasts are water-district level housing growth projections that we combine with data on per household residential water demand to project residential water demand at the water district level. We generate these forecasts using disaggregated growth forecasts at the census tract or traffic analysis zone (TAZ), geographic units comprising combinations of census tracts that are used by some planning organizations including SCAG. In the case of our projections using the RHNA targets, we use the existing tract or TAZ-level growth forecasts essentially as weights and allocate the higher growth levels for the RHNA targets across these geographies according to the relative level of growth projected in each small area. This proportional approach preserves any information that is embodied by the regional forecasts relating to, e.g., patterns of local demand and favorable or restrictive zoning that inform more or less likely scenarios of housing growth.

Our housing growth projections distinguish three types of housing: single family housing units, multifamily housing units, and mobile home units. This distinction, which we discuss in more detail below, is important because the majority of projected housing growth in all of the scenarios we consider is of multifamily homes, and multifamily homes tend to have meaningfully different levels of water use. Recent estimates of ratios of multifamily to single family indoor water use for three regions from the Western U.S. (San Diego, Phoenix, and Denver) range from 0.5:1 to 0.61:1 (Kiefer, 2018). We return to this topic in our chapter below on modeling residential water demand.

3.2 Housing Growth Projections

Table 3.2.1 details the source data for each of the three scenarios we ultimately used. In Sections 3.2.1–3.2.3 we then discuss the processes used for selecting growth scenarios for each county in more detail.

Table 3.2.1. Sources for Each Housing Growth Scenario

	San Bernardino County	San Diego County	San Luis Obispo County
Baseline	SCAG RTP 24	SANDAG Series 15 RGF	SLOCOG RTP 23
Low Growth	Caltrans (2023)	Caltrans (2023)	SLOCOG RTP 23
High Growth	6th Cycle RHNA/ SCAG RTP 24	6th Cycle RHNA/ SANDAG Series 15 RGF	SLOCOG RTP 23

3.2.1 San Bernardino County

Figure 3.2.1 presents the countywide projected housing growth totals for San Bernardino County across the three scenarios. The baseline growth projection for San Bernardino County comes from the Southern California Association of Governments (SCAG) 2024 Regional Transportation Plan (henceforth RTP24). This scenario predicts that the number of occupied households will grow nearly linearly from 668,024 in 2020 to 953,105 by 2050, an increase of 43%. The assumptions underlying this scenario are that headship rates, which fell during the pandemic, will trend back toward levels seen in 2005–2007, that immigration to the county will increase back toward levels from the early 2000s due to labor demand, and that the net domestic out-migration trend will continue in the short term due to high housing costs affecting most of Southern California (but that this trend will be relatively muted compared to most other areas in the SCAG region due to the relative affordability of San Bernardino County).

The RTP24 forecast also projects substantial growth in housing in San Bernardino County. A 43% increase in occupied housing units is forecast over 31 years, resulting in 953,105 housing units by 2050. This represents an average annualized growth rate of 1.4%.

Figure 3.2.1. County-level Housing Growth Projections for San Bernardino County

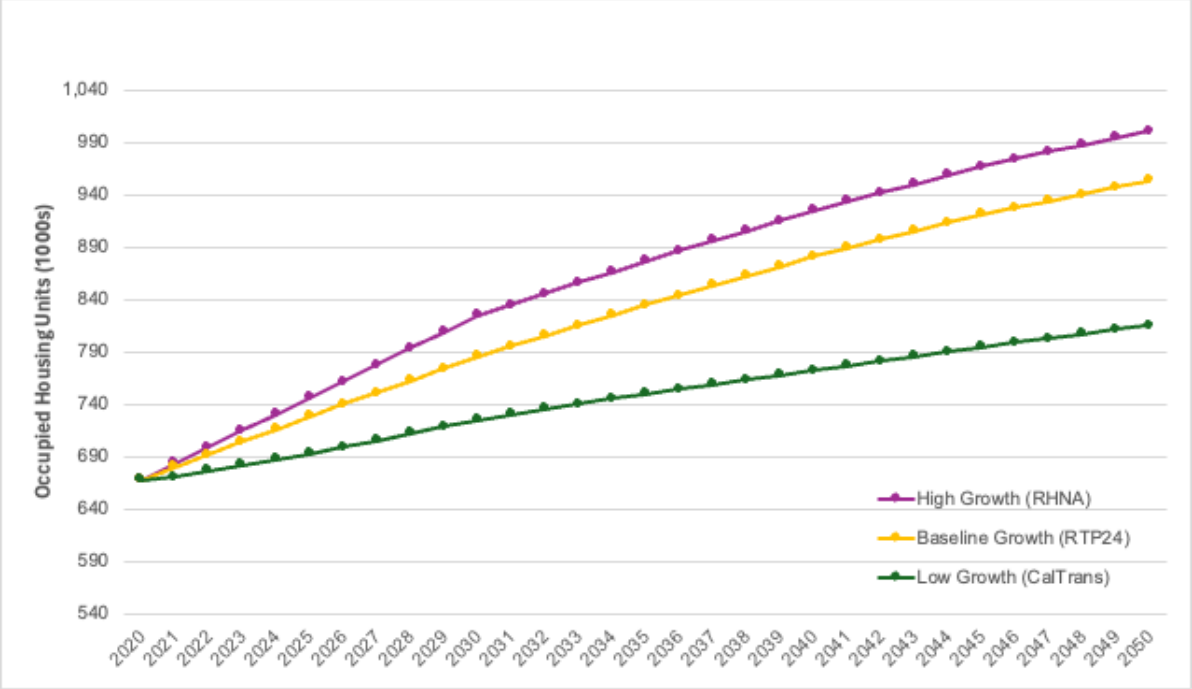


Figure 3.2.1. This line graph shows projected occupied housing units in San Bernardino County from 2020 to 2050 under high, baseline, and low growth scenarios. The high growth scenario follows RHNA targets, the baseline uses SCAG RTP24, and the low scenario uses Caltrans projections. Source: Authors' analysis of SCAG and Caltrans data.

The high growth scenario would result in a 21% growth in occupied housing units from 2020 through 2029, an annualized rate of 2.3%. As discussed, after the RHNA period, the high growth forecast uses the trend from the RTP24 forecast, resulting in a modest inflection point to a lower rate of growth past 2029. From 2029 through 2050 the annualized growth rate is 1.1%, or around half the rate of the RHNA 6th cycle period. Ultimately, the high growth scenario projects a 50% increase in occupied housing units over the 30-year horizon , from 668,024 to 1,000,760 housing units (an average growth rate of 1.7% per year over the 31-year period).

The low growth scenario uses 2023 growth projections from Caltrans. (These projections were based on 2019 baseline population projections, so we normalize them by offsetting them using base year 2024 population values from the RTP24 data). Relative to the SCAG projections, this series assumes lower rates of population growth and household formation. This low growth scenario forecasts an increase to 804,291 households by 2050, an overall growth rate of 20%, or less than half of the baseline growth rate in the RTP24 forecast.

However, we note that the methodology document from Caltrans indicates that these estimates do not account explicitly for any housing policy-related factors or any economic interactions in the housing market related to declining levels of population growth and the durability of the housing stock. The Caltrans approach uses a few past data points to estimate a regression-based trend that downweights sharp changes (in other words, their approach tends to attenuate extreme trends). If the mid or high growth housing forecasts are more likely than the low growth Caltrans forecast, then the Caltrans forecast likely underestimates the size of the overall housing stock. In such a scenario, the relatively lower population growth combined with a relatively larger housing stock would increase vacancy rates. This in turn should result in declining housing costs (both rents and prices), an environment that could be expected to relieve rates of doubled-up overcrowding. For this reason, we attempted to account for a potential reduction in the level of doubled-up overcrowding in this low growth projection.

To address this concern, we make a simple but, we believe, reasonable additional adjustment to the Caltrans projections. Our adjustment uses American Community Survey (ACS) public use microdata from 2020–2021 to estimate a county-specific rate of average overcrowding across this period. We considered these households to have a high probability of forming new households in a low-population-growth / higher housing production environment. The overcrowding rate for San Bernardino County was 7.40%.[6] We implemented this adjustment in a simple fashion that assumes that in the low scenario the current rate of doubled-up overcrowding would decline to zero by 2050.[7] This adjustment raises the total number of occupied households in 2050 by 11,009 or 1.4%. While this adjustment may be biased based on the assumptions just outlined, we believe this bias would tend towards finding a slightly higher number of occupied households, a direction that we believe is "conservative" in the sense of being more likely to reveal potential water supply constraints.

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6 The average overcrowding rate (using pairs of years for the purpose of aggregating power at the county level) grew modestly over the prior 6 years from 6.57% of households in 2016-2017 to 7.06% in 2018-2019 to this rate, but using any of these rates or the average over the entire period would not have led to qualitatively different results from using this more recent, slightly higher average.

7 While this assumption (doubled-up overcrowding going to zero) may be too strong, we believe that the magnitude of the difference between the Caltrans and other housing growth data and the lack of accounting for any economic behavioral responses in the methodology suggest to use that this approach is more realistic than no adjustment and simpler than assuming some intermediate rate of decompression. Additionally, the magnitude of this adjustment is qualitatively small overall. We implement the adjustment proportionally by taking the maximum (2050) difference between the baseline scenario and the low scenario and calculating the share of that maximum difference represented by the gap in these two forecasts at each single year between 2021 and 2050. The product of this share value, which goes from 0 in 2020 to 1 in 2050, in each year and the calculated doubled-up overcrowding rate is then multiplied by the low scenario household total for each year and the resulting number of housing units are added to the low growth annual total.

As a final note, the RTP24 projections for San Bernardino County are provided for five-year intervals from 2025 through 2050. In Figure 3.2.1, we use 2020 as our baseline year and linearly interpolate the years between these periods, but, in our final demand analysis, we calculate demand for these specific years only.

3.2.2 San Diego County

For our San Diego County baseline scenario, we use Series 15 Regional Growth Forecast (RGF) data produced by the San Diego Association of Governments (SANDAG). The Series 15 RGF was released in 2022 and assumed a COVID-related population dip and a lower level of net in-migration in the early years of the forecast that gradually returns to pre-COVID levels. The Series 15 RGF also assumes lower birthrates and lower levels of population growth. We again use the Caltrans data as our low-growth scenario. Similar to San Bernardino County, these data forecast considerably lower levels of housing growth. We apply the same adjustment described above to the Caltrans data for modeling the decompression of doubled-up overcrowding in a low growth environment. We normalize the RHNA and Caltrans data to start at the baseline 2022 housing unit levels for San Diego County in the Series 15 RGF data.

Figure 3.2.2 presents the housing growth data scenarios for San Diego County. These forecasts exhibit a key difference from San Bernardino forecasts in that the baseline and high growth scenarios are notably non-linear over the 29-year period shown. The high growth scenario has initially steep increases in occupied housing units from 1,160,472 in 2022 to 1,290,782 by 2029, the end of the 6th cycle RHNA period. This represents an increase of 11.2%, an average annualized growth rate of 1.6%. After this period of rapid housing growth, the forecasted rate from 2029 to 2040 falls to 6.8% over this 11-year period, an annualized rate of 0.6%. Housing growth slows further from 2040 to 2050 to an annualized rate of 0.18% with the total number of occupied housing units in 2050 forecasted to be 1,403,668. The inflection point that occurs in 2029 is an artifact of pivoting from the growth required to meet the RHNA target to a growth rate reflecting current forecasts for actual population and household size changes, as previously discussed. The second inflection point at 2040 is driven primarily by a combination of forecasted declines in the birth rate from the California Department of Finance (the underlying population data) and SANDAG which forecasts a flat trend in household size changes past 2036.[8]

8 To explain this more fully, SANDAG assumes that the number of occupied households grows at a faster rate as the average size of households is actively declining because older households are aging in place as their children leave to form their own, often smaller, households. Once this rate stabilizes, the overall growth rate of occupied housing units declines in magnitude.

Figure 3.2.2. County-level Housing Growth Projections for San Diego County

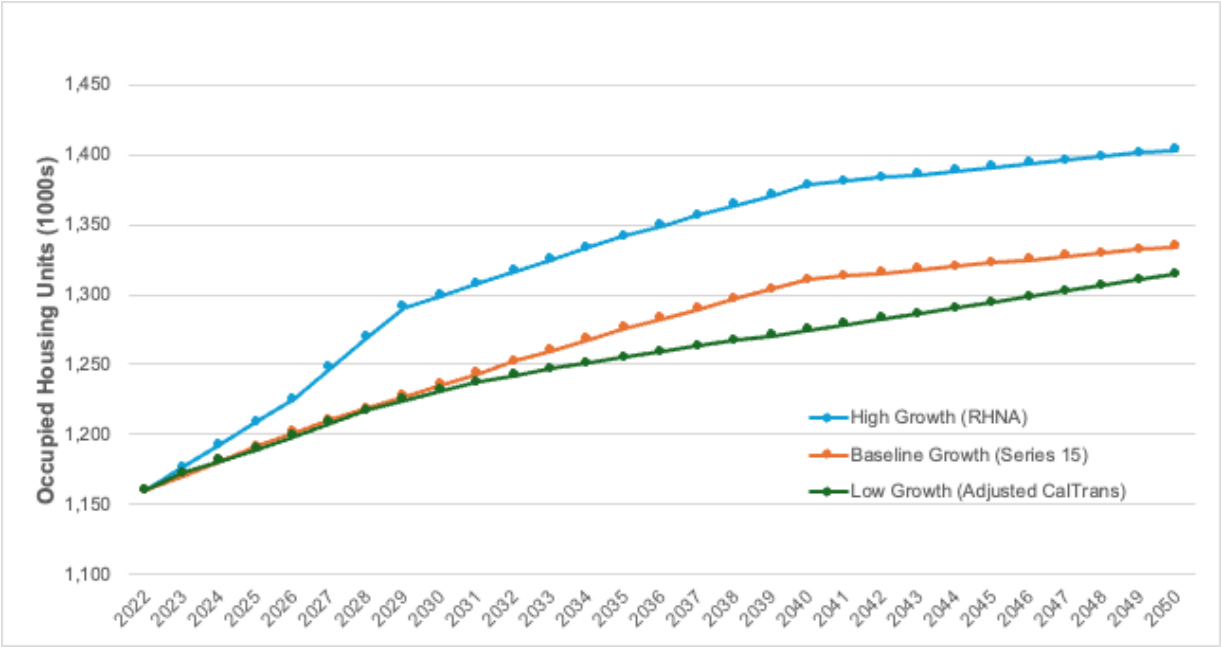


Figure 3.2.2. This line graph represents projected occupied housing units in San Diego County from 2022 to 2050 under high, baseline, and low growth scenarios. The high growth scenario follows RHNA targets, the baseline uses SANDAG Series 15 RGF, and the low scenario uses Caltrans projections. Source: Authors' analysis of SANDAG and Caltrans data.

The baseline scenario forecasts an increase to 1,334,543 households by 2050, an increase of 15% representing an average annualized growth rate of 0.54% over the full forecast period. From 2022 to 2040, the average annualized growth rate is 0.72%, but after the 2029 inflection point (visible in Figure 3.2.2), it falls to 0.18% per year through 2050.

As in the case of San Bernardino County, the low growth scenario uses Caltrans data from 2023 that is normalized to the housing totals from 2022 in the Series 15 RGF data and is then further adjusted for decompression of overcrowding. By 2050, the forecast using the adjusted Caltrans data projects growth to 1,314,343 occupied housing units by 2050. This projection forecasts 29,041 fewer units than the high scenario or a 2.2% lower level in absolute terms.

Series 15 RGP housing growth projections for San Diego County are provided for the following years: 2023, 2026, 2029, 2032, 2035, 2040, and 2050. In Figure 3.2.2, we use 2022 as our baseline year and linearly interpolate the years between these periods, but, in our final demand analysis, we calculate demand for these specific years only.

3.2.3 San Luis Obispo County

For San Luis Obispo County, we rely on data produced by the San Luis Obispo Council of Governments (SLOCOG). SLOCOG's 2023 Regional Transportation Plan (RTP) includes multiple scenarios that satisfy our high growth, low growth, and mid growth scenarios. We chose to rely on SLOCOG data entirely as the RTP 23 high growth scenario forecasts greater housing growth than the approach of using the 6th cycle RHNA target then continuing on the baseline trend as we did for the other two case study counties. This higher growth path is more likely to reveal potential constraints on growth represented by water supply limitations, which is the primary goal of the study. Second, the San Luis Obispo county region is characterized by both a high share of seasonal housing (housing that is owner occupied for only a portion of the year) and a high share of short-term rental housing that is held permanently off the long-term rental market (overall it is estimated that one of these uses may apply to up to 63% of the unoccupied housing units in the region). We felt that SLOCOG's forecasts were likely to better capture local trends in these important drivers of occupied versus unoccupied housing units than either the RHNA goal or Caltrans data, at least in part because the SLOCOG process likely better incorporates data on the regional housing production pipeline and local knowledge regarding the distribution of not permanently occupied dwelling units across the region.[9]

The SLOCOG forecast data for the high growth scenario project an increase from 103,266 occupied housing units in 2020 (we normalize all three scenarios to this baseline value) to 132,315 units in 2050, an increase of 29,049 or 28%. From 2021 through 2029, this scenario tracks the 6th cycle RHNA goals for the region almost exactly. The low growth scenario projects an increase of 8,914 occupied housing units, or 8.6%. And the mid growth scenario, SLOCOG's baseline projection, is closer to the low growth forecast than the high growth forecast, predicting an increase of 13,038 occupied housing units, or 12.6%.

The SLOCOG RTP housing growth projections are provided for only 2035 and 2045. We use 2020 as a baseline year and linearly interpolate between these points for Figure 3.2.3, but, in our final water demand projections, we calculate total water demand only for 2035, 2045, and 2050 (by linearly interpolating the 2050 value of housing growth using the trend between 2035 and 2045).

9 Furthermore, while the CalTrans data represented substantially lower estimates of the growth of occupied housing units in the cases of San Bernardino and San Diego counties, in San Luis Obispo, the CalTrans forecast was substantially higher than the baseline forecast produced by SLOCOG suggesting that these locally generated forecasts may be more appropriate.

Figure 3.2.3. County-level Housing Growth Projections for San Luis Obispo

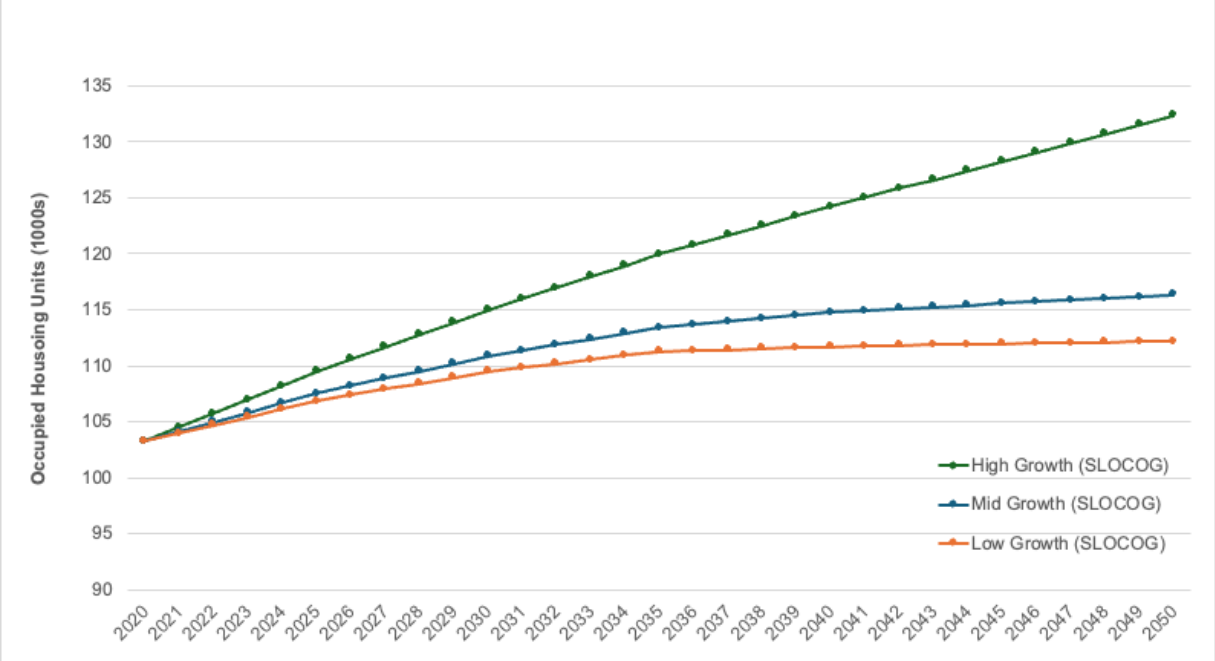


Figure 3.2.3. This line graph shows projected occupied housing units in San Luis Obispo County from 2020 to 2050 under high growth, mid, and low growth scenarios, based on SLOCOG RTP 23 projections. Source: Authors' analysis of SLOCOG data.

3.2.4. Creating Water District-Level Projections of Housing Growth by Housing Type

To make best use of downscaled climate projections and distinctions in changing shares of housing types over time that are critical to credibly modeling water demand, we produce projections of housing growth by housing type at the water district-level. We accomplish this by mapping either of the two small-area geographies (census tracts or TAZs) into water agency service areas using shapefiles obtained from each water authority. These projections of housing growth by housing type by water district are then used in our modeling of water demand over time.

4: Water Demand

4.1 Background

To assess the current state of science and practice for water demand forecasting, we conducted a targeted literature review focusing on shortcomings and best practices relevant to California and the broader American Southwest. The primary aim was to inform regional water demand estimation, as well as the incorporation of climate change impacts into our demand model. Our review identified three principal findings: (1) water demand is frequently overestimated, (2) demand is influenced by price and customer demographics, and (3) demand is sensitive to climate. Each of these findings carries important implications for demand forecasting efforts.

First, the literature consistently demonstrates that water demand is often overestimated due to persistent underestimation of declines in per capita water use and inflated population forecasts (Abraham et al., 2020). Studies show that, despite population growth, total water use has declined across California, a trend that traditional forecasting models have failed to capture accurately (Cooley, 2020; Frost et al., 2016; Mini et al., 2015; Lee et al., 2021). Additionally, land use, particularly as defined by zoning regulations, plays a significant role in shaping both long-term demand and supply management strategies (Wilson et al., 2020). Best practices emerging from this body of work emphasize the need to incorporate near-term conservation trends, to anticipate policy changes, and refine forecasts by analyzing land use and housing dynamics, and to avoid overestimates of growth.

Second, water demand is strongly influenced by both price and customer demographics. Research in Los Angeles found that water price significantly affects demand across most user categories, with the notable exception of single-family households (Ashoori et al., 2016). System-wide conservation efforts also impact demand, though their effects vary by user type. Household income is another key driver, with higher-income households typically exhibiting greater per capita water use, partly due to their housing stock (Havranek et al., 2018). The literature suggests that demand forecasts should incorporate price elasticity and demographic factors, such as housing type and land use, to better characterize long-term demand.

Finally, water demand is highly sensitive to climate, particularly in regions like Southern California where outdoor irrigation constitutes a substantial portion of residential use (LADWP, 2015; Ashoori et al., 2016). Studies have quantified the sensitivity of demand to temperature and precipitation, highlighting the need to adjust historical assumptions as climate change alters seasonal patterns (Christian-Smith et al., 2012; Gonzales and Ajami, 2017; Miro et al., 2018; Polebitski et al., 2010;

Roy et al., 2010). Incorporating climate projections and demand sensitivities into forecasting models is recommended to improve the accuracy and plausibility of long-term water demand estimates.

4.2 Demand Modeling Approach

Our model of water demand combines data on changes in the number of occupied housing units and projected changes in residents per housing unit with data on estimated water demand by water district. Estimates of water demand are further adjusted by estimated changes over time in the use of both indoor and outdoor water saving technologies and by an estimated elasticity of demand to temperature change.

There are two adjustable parameters in this model: indoor and outdoor demand in gallons per capital per day (GPCD). We initiate the model for each water district with baseline values for these two parameters then calibrate the model by adjusting them proportionally to get a credible match with observed past residential demand totals. The extent of available data for both the initial indoor and outdoor demand estimates and historical total residential demand varies across the three counties, an issue we discuss in more detail below.

We begin by outlining our demand model in broad terms, then we turn to discussing the model's assumptions and how we calibrate it to provide the water agency-level demand estimates we employ in our analysis.

4.2.1. Data

We relied on a comprehensive set of data sources to construct nuanced, region-specific urban water demand forecasts that account for demographic, technological, and climatic drivers. First, we developed housing growth projections by housing type and water district, drawing on forecast data from the San Diego Association of Governments (SANDAG), Caltrans, and county- and municipal-level Regional Housing Needs Assessment (RHNA) targets. These projections, described in detail in Chapter 3, provided the foundation for estimating future residential water demand by accounting for anticipated changes in the built environment across the study area.

To estimate average indoor and outdoor water demand, as well as total residential or urban water demand by water district, we utilized several region-specific datasets. For San Bernardino County, we relied on "average baseline 10-15" data points from the 2020 Urban Water Management Plan (UWMP) provided by the California Department of Water Resources (2020), which reflect estimated baseline urban water demand over a period spanning from the mid-1990s to 2010. We supplemented these with total demand data, combining "Single Family" and "Multifamily" categories,

from both the 2015 and 2020 UWMPs.[10] In San Diego County, we used indoor and outdoor water demand data for each member agency from 2014 through Spring 2023, provided directly by the San Diego County Water Authority (SDCWA). Indoor demand estimates were derived by SDCWA, while outdoor demand was calculated as the average of monthly use estimates from 2017 onward, thereby excluding years affected by the most recent drought. We also incorporated historical total residential demand data from SDCWA for 2015–2018 and 2022. For San Luis Obispo County, we applied the same baseline and total residential demand measures as used for San Bernardino County, drawing from the 2015 and 2020 UWMPs.

Our model incorporates published estimates of the ratio of multifamily to single-family water use. For indoor use, we referenced "Water Use in the Multifamily Sector" (Kiefer, 2018), and for outdoor use, we used findings from "Building Type, Housing Density, and Water Use: Denver Water Data and Agency-Based Simulations" (Sampson, Quay, and Horrie, 2022).[11] Projections of average residents per dwelling were sourced from SANDAG and Southern California Association of Governments (SCAG) regional growth forecasts, ensuring demographic trends were accurately reflected in our demand estimates.

To account for the impact of water-saving technologies, we drew on data from East Bay Municipal District (2002), Emrath (2017), Koeller (2017), and Cooley et al. (2022). Climate-related variables were also integrated into our forecasts: we used county-level predicted temperature changes from our analysis of downscaled climate projections, as described in Chapter 2, and incorporated estimates of the temperature elasticity of water demand (Bowman et al., 2018; Samimimotlagh and Wang, 2024; Kenney et al., 2008; Lott et al., 2014).

4.2.2. Demand Model

Figure 4.2.2 presents a visual diagram representing the approach to estimating annual water demand for each water district. The figure shows four pathways representing indoor use among existing housing units, indoor use among new housing units, outdoor use among existing housing units, and outdoor use among new housing units, respectively. For existing housing units in water district k in year t, we assume that average indoor water demand in GPCD is the product of the number of housing units for each housing type j (either single family, multifamily, or mobile homes), multiplied by the average indoor demand per capita, multiplied by the

10 In certain small water districts residential demand is reported as one category, typically when there are a very small number of multifamily units in an area.

11 San Bernardino Valley, which is the agency of focus of our analysis in Chapter 6, only provides water to the following subset of water utilities: City of Colton, East Valley Water District, Fontana Water Company, City of Loma Linda, Marigold Mutual Water Company, Muscoy Mutual Water Company, City of Redlands, City of Rialto, City of San Bernardino Municipal Water Department, Terrace Water Company, West Valley Water District, Western Heights Water Company, Yucaipa

predicted average number of persons per household in each year, multiplied by a water saving technology scalar that adjusts water use downward. These intermediate values for each housing type are then multiplied by a scalar that attributes differing levels of water use to single-family and multifamily housing types. These scalars for indoor and outdoor use for each water district are derived by solving for following system of equations:

$$\text{demand} = \theta_{\text{sf}} x_{\text{sf}} + (1 - \theta_{\text{sf}}) x_{\text{mf}} \quad (1)$$

$$x_{\text{mf}} = x_{\text{sf}} * \rho \quad (2)$$

Equation 1 decomposes average demand in GPCD into average demand for single-family homes (x_sf) and average demand for multifamily homes (x_{mf}). These typology-specific demands are weighted by the share of each housing type (θ_sf, for the share of single-family housing units) in the area in the baseline year for each county. Equation 2 uses a constant, ρ, for the relative share of indoor or outdoor water use to reduce the problem to solving for a single demand value. The value of ρ for indoor water demand is 0.533:1 and for outdoor demand the value is 0.272:1.

Figure 4.2.2 Diagram of Water District-Level Demand Modeling Process

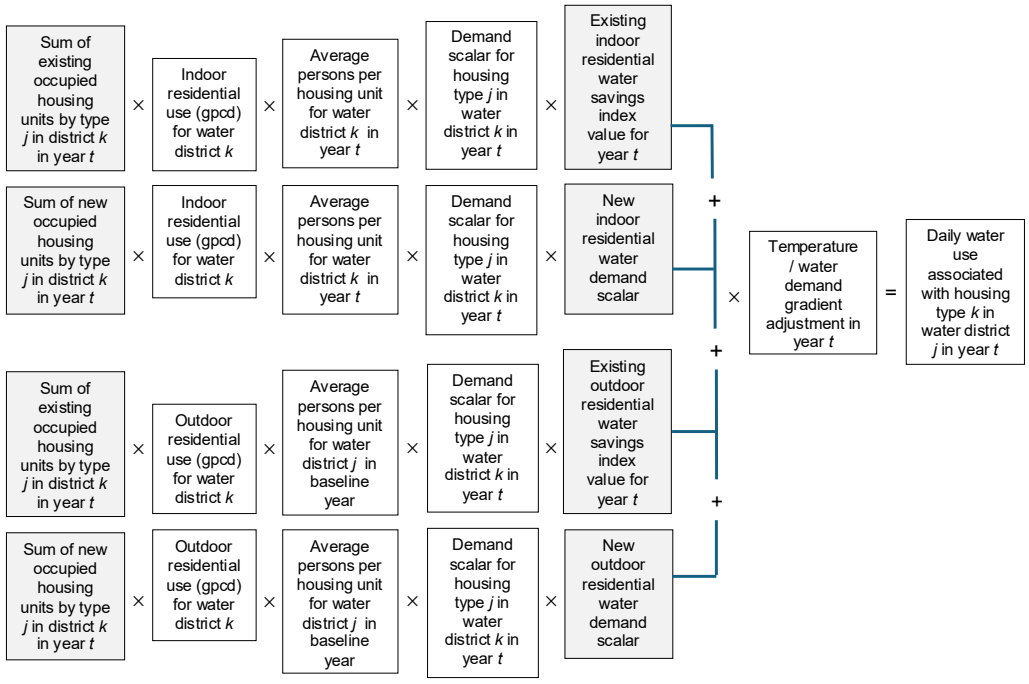


Figure 4.2.2. This diagram illustrates the modeling process for estimating annual water demand at the water district level. It shows the calculation pathways for indoor and outdoor use among existing and new housing units, incorporating factors such as average persons per household, water-saving technology adoption, and temperature adjustments. Source: Authors' model schematic.

Finally, the demand estimate for each path in the figure (indoor or outdoor, existing or new) is then adjusted by a scalar reflecting adoption of water saving technologies. Our adjustment for indoor water use is based on calculations of differences in water use for the primary fixtures or appliances in a home for three scenarios: non-efficient, current California standards, and frontier technology. Table 4.2.2 shows these calculations and the relative declines in indoor water demand we calculate from them.

Table 4.2.2. Estimated Effects of Water Saving Technology on Indoor Water Demand

End Use	Non-efficient (GPCD)	CA Standards (GPCD)	Frontier Tech (GPCD)
Toilet	17.5	6.4	4.0
Clothes Washer	11.1	5.7	4.1
Showerhead	20.0	14.4	8.0
Faucet	14.0	10.0	10.0
Dishwasher	0.9	0.4	0.2
Other (incl. leaks)	4.5	4.0	3.5
Total	68.0	40.86	29.76
Change: non-efficient → CA standards	–	−39.9%	–
Change: non-efficient → frontier tech	–	–	−56.2%
Change: CA standards → frontier tech	–	–	−56.2%

Note: California (CA). SOURCES: Author calculations using data from East Bay Municipal District (2002), Koeller (2017), Emrath (2017), and Cooley et al. (2022).

Among existing housing units, we assume that, in our baseline year (2020), 16.9% of homes in each area are non-efficient, 73.1% meet current California standards, and 10% of homes have frontier water-saving technology. We assume a rate of change from non-efficient to California standards and from California standards to frontier technology of 4% each year (so that in around 18 years, the share of non-efficient homes is reduced by about half and the share of frontier technology homes doubles). With these assumptions, we generate an index that sums these changes in demand (the flow from inefficient to California standards to frontier technology) over the existing housing stock. From 2020 to 2050, this index predicts a roughly 11% decline in overall indoor water use among existing homes.

For new housing units, we apply the scalar representing the change from existing California standards to frontier technology (a level of demand that is 27.2% lower than the average historical GPCD for each district). This value is then held constant from 2020 to 2050 for this stock.

We calculate reductions in outdoor use similarly. We use an estimated decline in water use resulting from going from non-efficient outdoor planting and irrigation practices to current California standards (drought tolerant plantings and efficient irrigation) derived from data in Cooley et al. (2022) of 31.25%. We then create an index to apply to existing housing units based on assuming that 10.5% of homes are at California standards in 2020 and that the rate of adoption is 2.5% per year. For new housing units, we apply this difference directly and then hold it constant.[12]

After these adjustments, the resulting daily water use values for single family, multifamily, and mobile homes are summed and multiplied by 365, and this total is converted to acre feet to express total water demand for water district k in forecast year t. Finally, this value is adjusted globally to reflect the temperature elasticity of water demand (how much demand rises with temperature). We assume that water use rises by 2.25% for each degree of rise in average temperature. This represents the average of a range of findings from the four recent studies referenced above.

4.3 Historical Demand Analysis

Our model is calibrated using historical demand data. As mentioned above, in San Diego County, we received a wealth of historical data including water district-level total residential demand for 2015 or 2016 through 2022 and indoor and outdoor

12 We also note one additional aspect of our approach. Outdoor calculations are made by water agencies in GPCD terms and the number of persons per household is falling in all of our data estimates. Since we do not believe that households reduce irrigation as families become smaller, we hold constant household size at the baseline year value for calculating outdoor water use so that outdoor use does not decline from this gradual demographic change.

demand in terms of monthly averages of gallons per capita per day (GPCD) from 2014 through spring of 2023. For San Bernardino and San Luis Obispo counties, we use historical demand data from 2015 and 2020 taken from Tables 4.1 (total urban or residential demand) and 5.1 (total residential demand, typically by single-family or multifamily housing types, in GPCD terms) of Urban Water Management Plant (UWMP) data.[13]

We "initiate" the model by inputting the average historical residential indoor and outdoor water demands at baseline into the model. For San Diego County, where we were provided with historical data for these use types, we have distinct values for each. For other counties, we use a heuristic assumption that, on average, 70% of the residential demand is indoor and 30% is outdoor. This is a very close approximation of the average indoor share among the higher-quality data from San Diego County (69.2%). In practice, this assumption is also quantitatively unimportant primarily since the adoption of water saving technology factors we implement track quite closely, and the declines in household size we discuss above that only affect indoor use are relatively small. Moving this share to a 50/50 split, for example, has almost no measurable effect on our overall estimates.

After inputting these initial values, we assess how well they predict past historical total residential demand and calibrate the model by scaling the average residential demand estimates up or down proportionally to achieve a match with the most recent data point (this is 2020 for San Bernardino and San Luis Obispo counties and 2022 for San Diego County). Tables 4.3.1 through 4.3.3 show, for our three case study counties, the initial values for each district's average indoor and outdoor demand, the final calibrated values, and the scaling factor that was used for this calibration.

For both San Diego and San Luis Obispo counties, the magnitude of adjustment required to calibrate these models was relatively small (a scaling factor of 1.19 for San Diego and 1.22 for San Luis Obispo) despite the level of detail in the data available to us being quite different for these two regions. In contrast, the scaling factor required to calibrate the model for San Bernardino County was much larger (1.79).[14] The notes for these tables discuss a small amount of imputation that was done for certain water districts that we did not have valid demand estimates for, but overall, we believe this procedure is highly unlikely to affect our results in any qualitatively important way.

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13 For SLO County, we obtained demand data for Atascadero Mutual Water Company, Cambria Community Services District, City of Arroyo Grande, City of Grover Beach, Morro Bay, Nipomo Community Services District, Paso Robles, Pismo Beach, San Luis Obispo and Templeton Community Services District and restrict our analysis to these locations.

14 Due to the much larger average level of adjustment required to calibrate our San Bernardino demand model for the 22 districts we had valid initial estimates and final demand totals for, we adjusted the initial estimates for the seven districts we did not have valid data points for upward by the average scaling factor for the other districts with the expectation that leaving these initial imputed estimates unadjusted would have likely led to an under-underestimate of demand.

As a general note on assessing the reasonableness of our calibration approach, we focused on the most recent year available (2020 or 2022) as the single target calibration point. But, we also used data further in the past, specifically during the 2012–2016 drought (California Natural Resources Agency, 2021) and the initial years after it ended to provide further support for the likely validity of our model fit. Specifically, while we calibrate the model to the baseline year, we find that historical water demand for 2015 (for San Bernardino) and 2016 (for San Diego) is, on average, around 8% below the model's predicted demand (the median difference was also 8%). This is consistent with research suggesting that California water agencies generally met reduction targets ranging from 4 to 36% during these years (Nemati, Tran, and Schwab, 2023).

Table 4.3.1. Initial and Calibrated Demand Values for San Bernardino County[15]

Water District:	Big Bear City C.S.D.	Big Bear Lake City	*California Institution For Men*
Multifamily Share (2020)	8.02%	13.70%	22.54%
Indoor Initial GPCD	32	34	49
Indoor Calibrated GPCD	57	141	88
Outdoor Initial GPCD	14	14	21
Outdoor Calibrated GPCD	24	60	38
Calibration scalar	1.77	4.16	1.79

Table 4.3.1. Initial and Calibrated Demand Values for San Bernardino County (Continued)

Water District:	Chino City	Chino Hills City	Colton, City of
Multifamily Share (2020)	24.68%	15.79%	33.30%
Indoor Initial GPCD	48	48	72
Indoor Calibrated GPCD	61	72	64
Outdoor Initial GPCD	20	21	23
Outdoor Calibrated GPCD	26	31	27
Calibration scalar	1.28	1.51	1.19

15 San Bernardino Valley, which is the agency of focus of our analysis in Chapter 6, only provides water to the following subset of water utilities: City of Colton, East Valley Water District, Fontana Water Company, City of Loma Linda, Marigold Mutual Water Company, Muscoy Mutual Water Company, City of Redlands, City of Rialto, City of San Bernardino Municipal Water Department, Terrace Water Company, West Valley Water District, Western Heights Water Company, Yucaipa

Table 4.3.1. Initial and Calibrated Demand Values for San Bernardino County (Continued)

Water District:	Crestline Village C.W.D.	*Crestline/Lake Arrowhead W.A.*	Cucamonga Valley W.D.
Multifamily Share (2020)	6.79%	6.93%	29.66%
Indoor Initial GPCD	30	69	97
Indoor Calibrated GPCD	48	123	86
Outdoor Initial GPCD	13	29	42
Outdoor Calibrated GPCD	21	53	37
Calibration scalar	1.63	1.79	0.89

Table 4.3.1. Initial and Calibrated Demand Values for San Bernardino County (Continued)

Water District:	East Valley W.D.	Fontana Water Company	Lake Arrowhead C.S.D.
Multifamily Share (2020)	31.62%	20.37%	5.80%
Indoor Initial GPCD	43	39	67
Indoor Calibrated GPCD	67	65	135
Outdoor Initial GPCD	18	17	29
Outdoor Calibrated GPCD	29	28	58
Calibration scalar	1.55	1.64	2.00

Table 4.3.1. Initial and Calibrated Demand Values for San Bernardino County (Continued)

Water District:	Loma Linda, City of	*Marigold Mutual W.C.*	Monte Vista W.D.
Multifamily Share (2020)	47.04%	50.27%	34.68%
Indoor Initial GPCD	63	39	41
Indoor Calibrated GPCD	82	70	56
Outdoor Initial GPCD	27	17	18
Outdoor Calibrated GPCD	35	30	24
Calibration scalar	1.29	1.79	1.34

Table 4.3.1. Initial and Calibrated Demand Values for San Bernardino County (Continued)

Water District:	*Muscoy M.W.C.*	Ontario City	Redlands, City of
Multifamily Share (2020)	3.00%	35.30%	28.07%
Indoor Initial GPCD	69	51	89
Indoor Calibrated GPCD	123	71	122
Outdoor Initial GPCD	29	22	38
Outdoor Calibrated GPCD	53	30	52
Calibration scalar	1.79	1.38	1.38

Table 4.3.1. Initial and Calibrated Demand Values for San Bernardino County (Continued)

Water District:	Rialto, City of	Riverside Highland W.C.	Running Springs W.D.
Multifamily Share (2020)	28.41%	37.85%	22.93%
Indoor Initial GPCD	39	59	40
Indoor Calibrated GPCD	72	137	133
Outdoor Initial GPCD	17	25	17
Outdoor Calibrated GPCD	31	59	57
Calibration scalar	1.88	2.33	3.35

Table 4.3.1. Initial and Calibrated Demand Values for San Bernardino County (Continued)

Water District:	*San Antonio W.C.*	*San Bernardino, City of*	South Mesa W.C.
Multifamily Share (2020)	0.27%	29.59%	24.20%
Indoor Initial GPCD	69	50	70
Indoor Calibrated GPCD	123	76	144
Outdoor Initial GPCD	29	21	30
Outdoor Calibrated GPCD	53	32	62
Calibration scalar	1.79	1.52	2.05

Table 4.3.1. Initial and Calibrated Demand Values for San Bernardino County (Continued)

Water District:	*Terrace W.C.*	Upland City	West Valley W.D.
Multifamily Share (2020)	20.64%	35.68%	12.51%
Indoor Initial GPCD	49	68	51
Indoor Calibrated GPCD	88	98	96
Outdoor Initial GPCD	21	29	22
Outdoor Calibrated GPCD	38	42	41
Calibration scalar	1.79	1.43	1.88

Table 4.3.1. Initial and Calibrated Demand Values for San Bernardino County (Continued)

Water District:	*Western Heights W.C.*	Yucaipa Valley W.D.
Multifamily Share (2020)	31.62%	29.59%
Indoor Initial GPCD	49	70
Indoor Calibrated GPCD	88	134
Outdoor Initial GPCD	21	30
Outdoor Calibrated GPCD	38	57
Calibration scalar	1.79	1.90

NOTE: Average calibrated level relative to initial demand level: 178.9%. Seven water districts in italics did not have distinct initial water demand estimates. For these districts, we used imputed initial values drawn from the provided set of values in a manner correlated to their baseline shares of multifamily housing, which are included. We imputed the median for California Institute for Men, Terrace, and Western Heights; the 25th percentile for Marigold; and the 75th percentile for Crestline-Lake Arrowhead, Muscoy, and San Antonio. Due to the magnitude of the average adjustment required for calibration among districts we had initial estimates for, we applied a global adjustment to these districts with missing data equal to the average adjustment across all the other water districts in San Bernardino County (1.789). Note that not all water providers in this table are retail agencies for San Bernardino Valley; only a subset of these are included in our analysis in Chapter 6. SOURCE: Author calculations from California Department of Water Resources (2015) and 2020 UWMP data.

4.3.2. Initial and Calibrated Demand Values for San Diego County

Water District:	Carlsbad M.W.D.	*Del Mar, City of*	Escondido, City of
Multifamily Share (2018)	27.06%	27.71%	49.56%
Indoor Initial GPCD	68	66	51
Indoor Calibrated GPCD	69	74	110
Outdoor Initial GPCD	26	55	11
Outdoor Calibrated GPCD	27	62	24
Calibration scalar	1.02	1.12	2.16

4.3.2. Initial and Calibrated Demand Values for San Diego County (Continued)

Water District:	*National City, City of*	Oceanside, City of	San Diego, City of
Multifamily Share (2018)	47.10%	30.42%	41.80%
Indoor Initial GPCD	51	54	44
Indoor Calibrated GPCD	51	51	51
Outdoor Initial GPCD	11	19	12
Outdoor Calibrated GPCD	11	18	14
Calibration scalar	1.00	0.95	1.16

4.3.2. Initial and Calibrated Demand Values for San Diego County (Continued)

Water District:	*Fallbrook Public Utility*	Helix W.D.	Lakeside W.D.
Multifamily Share (2018)	34.02%	39.37%	28.72%
Indoor Initial GPCD	55	55	53
Indoor Calibrated GPCD	55	56	56
Outdoor Initial GPCD	23	21	26
Outdoor Calibrated GPCD	23	21	28
Calibration scalar	1.00	1.01	1.06

4.3.2. Initial and Calibrated Demand Values for San Diego County (Continued)

Water District:	Olivenhaim M.W.D.	Otay W.D.	Padre Dam M.W.D.
Multifamily Share (2018)	22.02%	26.30%	18.89%
Indoor Initial GPCD	62	56	54
Indoor Calibrated GPCD	70	57	56
Outdoor Initial GPCD	56	23	18
Outdoor Calibrated GPCD	63	23	19
Calibration scalar	1.13	1.02	1.03

4.3.2. Initial and Calibrated Demand Values for San Diego County (Continued)

Water District:	*Camp Pendleton*	Poway, City of	*Rainbow M.W.D.*
Multifamily Share (2018)	0.00%	15.18%	10.98%
Indoor Initial GPCD	66	54	66
Indoor Calibrated GPCD	66	57	66
Outdoor Initial GPCD	90	62	55
Outdoor Calibrated GPCD	90	66	55
Calibration scalar	1.00	1.06	1.00

4.3.2. Initial and Calibrated Demand Values for San Diego County (Continued)

Water District:	Ramona M.W.D.	Rincon Del Diablo M.W.D.	San Dieguito W.D.
Multifamily Share (2018)	14.60%	14.56%	23.12%
Indoor Initial GPCD	54	59	66
Indoor Calibrated GPCD	63	31	75
Outdoor Initial GPCD	40	46	34
Outdoor Calibrated GPCD	46	24	38
Calibration scalar	1.16	0.53	1.13

4.3.2. Initial and Calibrated Demand Values for San Diego County (Continued)

Water District:	Santa Fe I.D.	South Bay I.D.	Vallecitos C.W.D.
Multifamily Share (2018)	28.50%	30.40%	29.31%
Indoor Initial GPCD	141	47	52
Indoor Calibrated GPCD	179	71	62
Outdoor Initial GPCD	177	8	22
Outdoor Calibrated GPCD	225	12	26
Calibration scalar	1.27	1.50	1.19

4.3.2. Initial and Calibrated Demand Values for San Diego County (Continued)

Water District:	Valley Center M.W.D.	Vista I.D.	*Yuima M.W.D.*
Multifamily Share (2018)	0.80%	35.03%	8.28%
Indoor Initial GPCD	61	56	66
Indoor Calibrated GPCD	135	64	66
Outdoor Initial GPCD	1	18	55
Outdoor Calibrated GPCD	2	21	55
Calibration scalar	2.21	1.14	1.00

NOTE: Average calibrated level relative to initial demand level: 118.7%. Six water districts in italics did not have distinct initial water demand estimates. For these districts, we used imputed initial values drawn from the provided set of values in a manner correlated to their baseline shares of multifamily housing, which are included. We imputed the median for Fallbrook; the 25th percentile for National City; and the 75th percentile for Del Mar, Camp Pendleton, Rainbow, and Yuima. For Del Mar, we had a valid total demand number of calibrated average demand, but for the other districts we did not and, hence, we left these unadjusted at the initial imputed value. SOURCE: Author calculations from SDWA data.

Table 4.3.3. Initial and Calibrated Demand Values for San Luis Obispo County

Water District:	Atascadero Mutual W.C.	Cambria C.S.D.	Arroyo Grande U.D.
Multifamily Share (2018)	23.53%	5.25%	22.82%
Indoor Initial GPCD	52	30	50
Indoor Calibrated GPCD	80	31	57
Outdoor Initial GPCD	22	13	22
Outdoor Calibrated GPCD	34	13	24
Calibration scalar	1.53	1.06	1.12

Table 4.3.3. Initial and Calibrated Demand Values for San Luis Obispo County (Continued)

Water District:	Grover Beach P.W.D.	Morro Bay P.W.D.	Nipomo C.S.D.
Multifamily Share (2018)	30.37%	25.96%	22.65%
Indoor Initial GPCD	37	34	61
Indoor Calibrated GPCD	45	33	104
Outdoor Initial GPCD	16	14	26
Outdoor Calibrated GPCD	19	14	44
Calibration scalar	1.22	0.97	1.69

Table 4.3.3. Initial and Calibrated Demand Values for San Luis Obispo County (Continued)

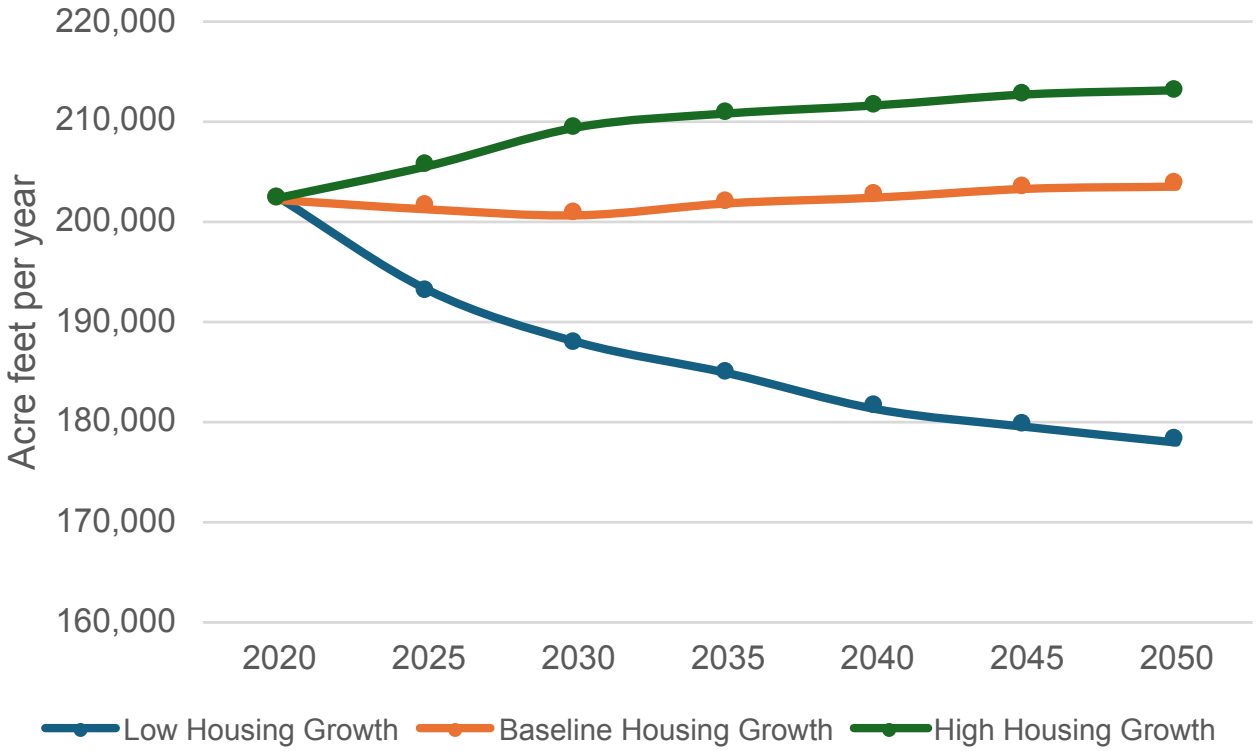
Water District:	Paso Robles W.D.	Pismo Beach W.D.	San Luis Obispo W.D.	Templeton C.S.D.
Multifamily Share (2018)	27.71%	23.78%	47.01%	28.27%
Indoor Initial GPCD	64	63	32	63
Indoor Calibrated GPCD	70	59	37	91
Outdoor Initial GPCD	27	27	14	27
Outdoor Calibrated GPCD	30	25	16	39
Calibration scalar	1.10	0.95	1.13	1.45

NOTE: Average calibrated level relative to initial demand level: 122.2%. These are a subset of all water providers in San Luis Obispo County. We include water supply estimates for each of these water providers in our analysis in Chapter 6. SOURCE: Author calculations from California Department of Water Resources (2015) and 2020 UWMP data.

4.4 Projected Demands

Our final estimates for projected demand at the county level without the final adjustment for temperature-related demand changes are shown in Figures 4.4.1 through 4.4.3. Results for San Bernardino County (Figure 4.4.1) show that the low housing growth scenario results in a predicted decline in residential water demand relative to 2020 of 8.5% by 2035 and 12% by 2050. The baseline housing growth scenario is virtually unchanged (a decline of 0.2% by 2035 and an increase of 0.7% by 2050). The high housing growth scenario model predicts an increase of 4.2% by 2035 and a total increase of 5.4% by 2050.

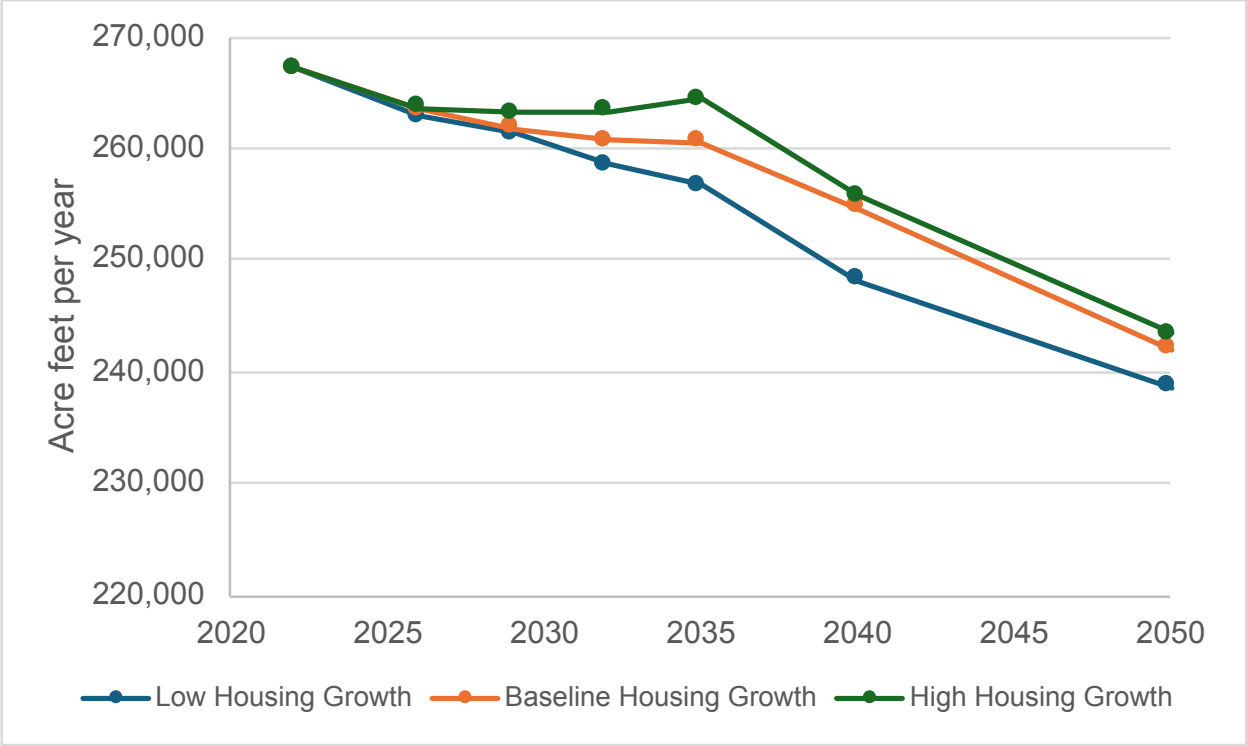
Figure 4.4.1. Estimated Residential Water Demand for San Bernardino County



This line graph shows projected total residential water demand (acre-feet per year) for San Bernardino County from 2020 to 2050 under low, baseline, and high housing growth scenarios. Temperature-related demand adjustments are not included. Source: Authors' model results.

For San Diego County (Figure 4.4.2), all scenarios lead to predicted declines in residential water use relative to 2022. In 2035, our model predicts a decline of 3.9% for the low housing growth scenario, a decline of 2.5% in the baseline housing growth scenario, and a decline of just 1% for the high housing growth scenario. By 2050, these predicted declines are much larger: 10.6% in the low growth scenario, 9.4% in the baseline growth scenario, and 8.9% in the high growth scenario.

Figure 4.4.2. Estimated Residential Water Demand for San Diego County



This line graph represents projected total residential water demand (acre-feet per year) for San Diego County from 2020 to 2050 under low, baseline, and high housing growth scenarios. Temperature-related demand adjustments are not included. Source: Authors' model results.

These declines are driven by a combination of factors including 1) an average decline in persons per household of 7%, 2) the bulk of housing growth occurring in new multifamily units (roughly 80% of overall growth) that we assume will use substantially less water than existing units even as existing units are slowly being retrofitted with water saving technology, and 3) relatively modest predicted housing growth overall for the region (the high growth scenario for San Diego is only an approximately 20% increase from 2022).

Broadly speaking, these predicted trends of declining water use are in alignment with historical trends from San Diego County. For example, between 1990 and 2020 per capita water use declined by roughly 50% (San Diego County Water Authority [SDCWA], 2025). To provide external validation for the results of our demand model, we made a simple comparison of our predicted residential demand with an estimate of total residential demand derived from SDCWA's 2020 Urban Water Management report (SDCWA, 2021). We made a simple calculation based on the multiplying SDCWA's predicted total demand by their reported share of residential water demand from among all uses (66.24%) and derived a ratio of our predicted use to these estimated demand levels.[16] Table 4.4.1 shows the comparisons of these two sources of estimated demand.

The ratios of our model's estimated residential demand to the derived SDCWA estimates suggest our estimates are conservative (more likely to be overestimates than underestimates) for all years except 2050, where they are slightly smaller. However, it is important to note that we are using a constant value to convert these SDCWA total demand estimates to residential estimates. Thus, if residential water use is falling over time at a faster rate than other water uses, this approach will tend to increasingly overestimate residential use since the scalar is not falling over time. For example, if the scalar values fell from 0.6624 to 0.64 (a 3.4% decline in this value), predicted demand would match exactly. Thus, we feel that our predicted residential demand is, on balance, in agreement with SDCWA's own projections, and, if they are biased at all, they are likely biased slightly upwards in magnitude.

Table 4.4.1. Comparisons of Estimated Residential Demand for San Diego County (RAND Model Compared to SDCWA 2020 Water Management Plan Data)

Demand model year	SDWA management plan year	Derived SDWA residential demand	Low growth ratio	Baseline growth ratio	High growth ratio
2022	2020	229,476	1.16	1.16	1.16
2025	2025	254,823	1.03	1.03	1.03
2029	2030	253,217	1.03	1.03	1.04
2035	2035	226,756	1.13	1.15	1.17
2040	2040	239,434	1.04	1.06	1.07
2050	2045	250,318	0.95	0.97	0.97

NOTE: Ratios shown are the ratio of demand estimates (RAND estimate/SDCWA estimate). We multiply SDCWA total demand estimates by 0.6624 to derive estimated residential demand. SOURCE: Author calculations and SDCWA 2020 Water Management Plan data.

16 This scalar is the product of the estimated share of total demand that is municipal and industrial ("M&I") in the region (92%) and the estimated share of M&I water that is for residential use (72%).

Figure 4.4.3 presents total residential demand estimates for San Luis Obispo County. In the baseline growth scenario, our model predicts that total residential demand by 2035 will be 5.1% higher than in 2020. By 2050, residential demand will be more moderate despite continuing housing growth and will end up at a level that is 2.6% higher than in 2020. The low housing growth scenario projections indicate that by 2035 total residential demand will be virtually unchanged from 2020 levels (+0.4%) but that by 2050 it will fall by 6.8%. The high growth scenario projections indicate an increase relative to 2020 of 6.4% by 2035 and a very modest further increase between 2035 and 2050 for a total change from 2020 levels of 7.1% by 2050.

Figure 4.4.3. Estimated Residential Water Demand for San Luis Obispo County



This line graph represents projected total residential water demand (acre-feet per year) for San Luis Obispo County from 2020 to 2050 under low, baseline, and high housing growth scenarios. Totals do not include adjustments for temperature-related changes in demand. Source: Authors' model results.

5: Water Supply

5.1 Data

For the water supply analysis in this study, we collaborated directly with three regional water agencies—San Diego County Water Authority, San Bernardino Valley Municipal Water District, and San Luis Obispo County—to obtain empirical water supply data for each of our case study counties. These agencies, which serve as either water wholesalers or regional management entities, provided the most current data available on their respective water supply portfolios. The primary sources of these data were the agencies' Urban Water Management Plans (UWMPs), with most information drawn from the 2020 planning cycle.

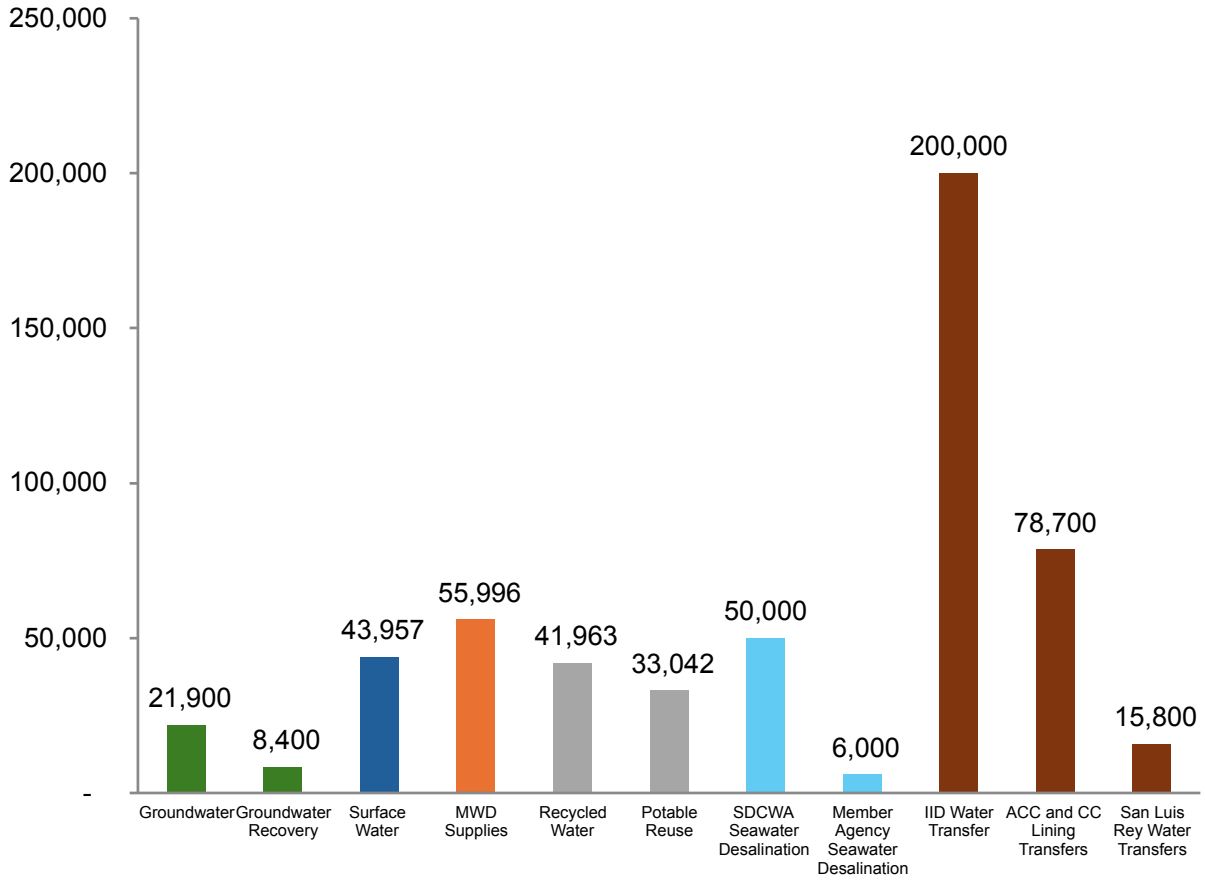
The data received included both historical estimates and future projections of water supply, as reported in each agency's UWMP. These supply portfolios encompass the major sources and components of water supply relevant to each region, such as imported water, local surface and groundwater, recycled water, and other supplemental sources. The data reflect the agencies' official planning assumptions and are used for regional water management and regulatory compliance.

It is important to note that, due to limitations in available modeling tools and resources, there was no single, comprehensive suite of models covering all aspects or major components of water supply that could be shared and utilized within the scope of this project. Consequently, our analysis is based on the empirical data provided by the agencies or selected modeling outputs, as detailed in the sections that follow.

5.1.1 San Diego County Water Authority

The San Diego County Water Authority (SDCWA) has the most diverse portfolio of the three agencies, as shown in Figure 5.1.1 below. They have a high dependence on contracted imported water, from Metropolitan Water District (MWD) or various imported water transfers. They also produce supply from desalination and recycled sources. Local surface water and groundwater do contribute meaningfully to their portfolio.

Figure 5.1.1. SDCWA Water Supply Portfolio (2020)

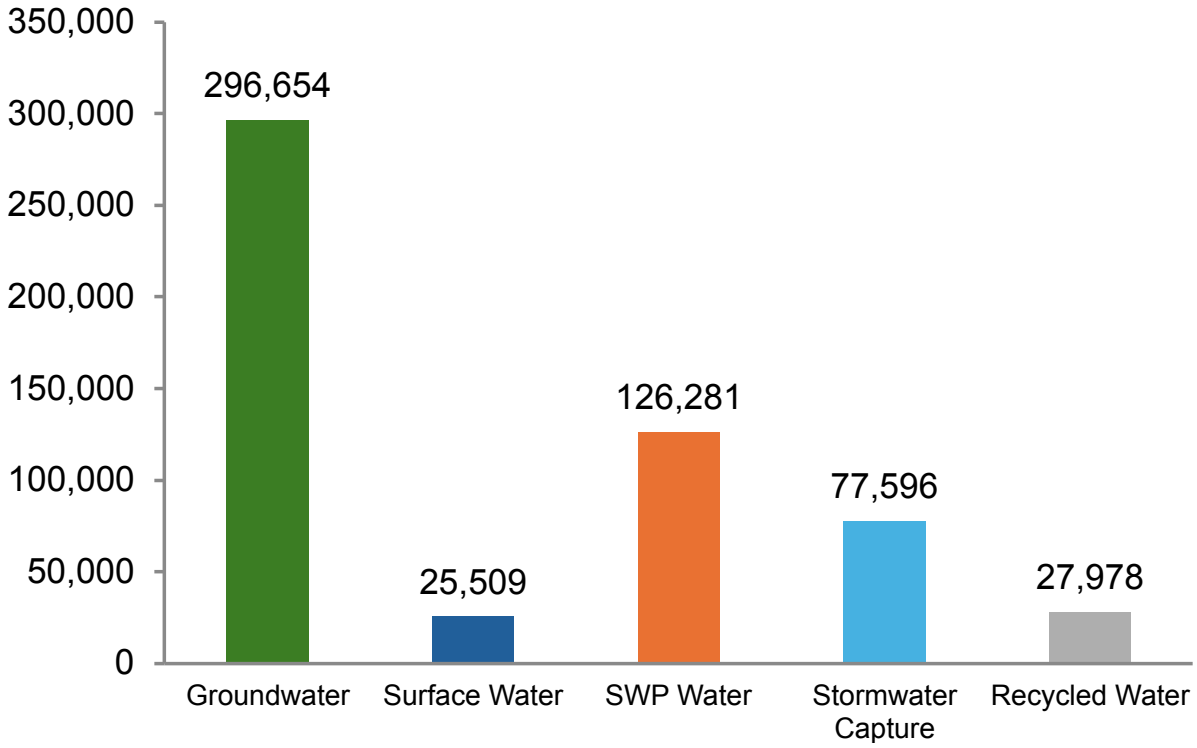


This bar chart shows the composition of the SDCWA's water supply portfolio in 2020, including groundwater, surface water, imported water, recycled water, desalination, and transfers. Source: SDCWA 2020 Urban Water Management Plan.

5.1.2 San Bernardino Valley Municipal Water District

San Bernardino Valley is the largest water supplier in San Bernardino County and manages a large portion of groundwater in its water supply portfolio (see Figure 5.1.2). Imported water from the State Water Project (SWP) makes up the second largest component of supply, followed by stormwater capture. San Bernardino Valley supplies water to a portion of San Bernardino County, including the following agencies from our demand analysis in Chapter 4: City of Colton, East Valley Water District, Fontana Water Company, City of Loma Linda, Marigold Mutual Water Company, Muscoy Mutual Water Company, City of Redlands, City of Rialto, City of San Bernardino Municipal Water Department, Terrace Water Company, West Valley Water District, Western Heights Water Company, Yucaipa Valley Water District, Riverside Highland Water Company, South Mesa Water Company, Big Bear City CSD, and City of Big Bear Lake Department of Water.

Figure 5.1.2. San Bernardino Valley Water Supply Portfolio (2020)



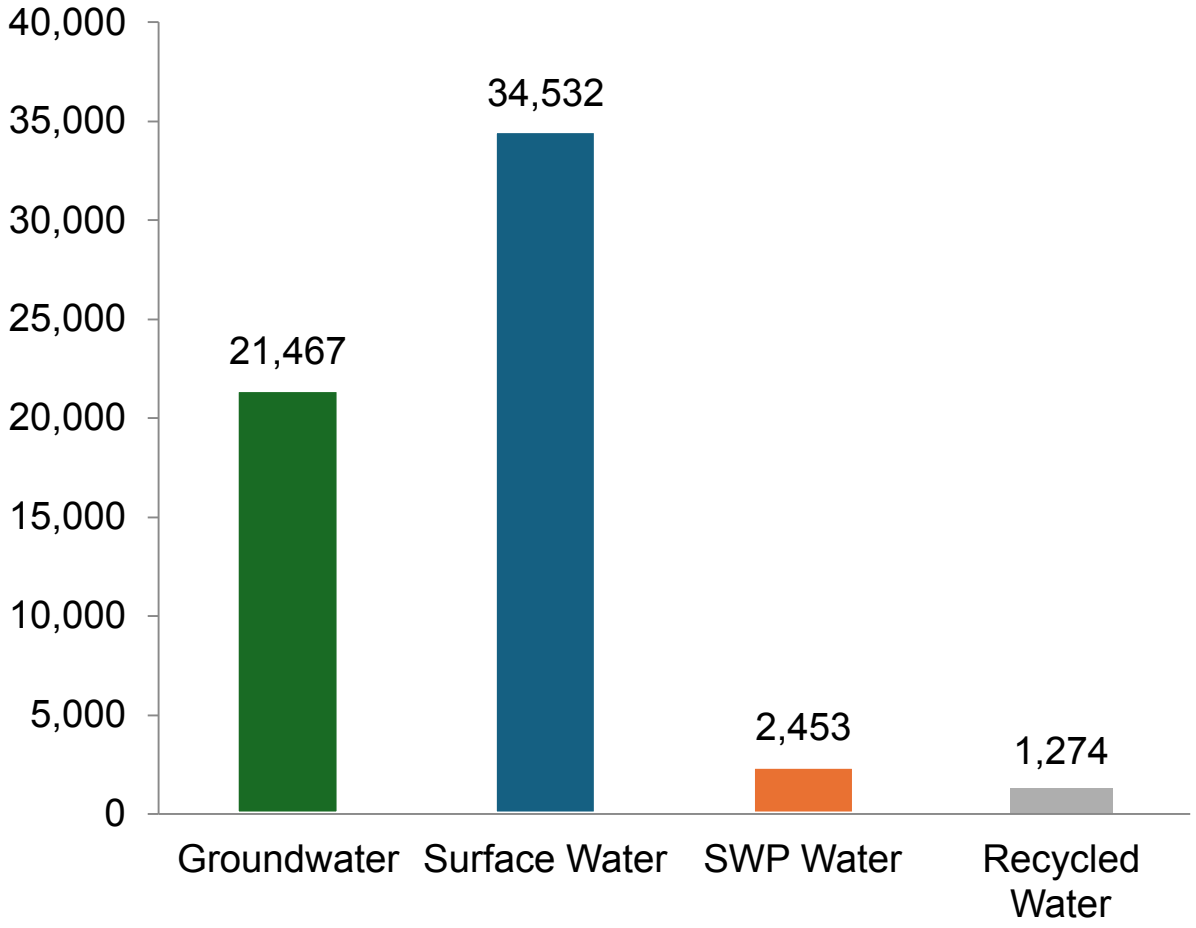
This bar chart displays the San Bernardino Valley Municipal Water District's water supply portfolio in 2020, including groundwater, surface water, State Water Project imports, stormwater capture, and recycled water. Source: San Bernardino Valley Municipal Water District 2020 Urban Water Management Plan.

5.1.3 San Luis Obispo County

San Luis Obispo (SLO) County contains a number of local water providers that each have a different balance of SWP water, local surface water, and groundwater. For this analysis, the following local water providers were included: Atascadero Mutual Water Company, Cambria Community Services District, City of Arroyo Grande, City of Grover Beach, Morro Bay, Nipomo Community Services District, Paso Robles, Pismo Beach, San Luis Obispo, and Templeton Community Services District. The data provided by SLO County was the same as reported to the State's Electronic Annual Report database in 2020.[17]

17 Data is provisional and has not been verified for accuracy. The County of San Luis Obispo does not warrant the accuracy of the data and is not responsible for damages resulting from its use.

Figure 5.1.3. SLO County Water Supply Portfolio (2020)



This bar chart presents the water supply portfolio for selected providers in San Luis Obispo County in 2020, including groundwater, surface water, State Water Project water, and recycled water. Source: San Luis Obispo County, Electronic Annual Report database (2020).

5.2 Methods

To assess and project future water supplies, researchers have utilized a number of approaches, ranging from high resolution modeling to larger scale water balance approaches. Water balance methods generally involve comprehensively tracking water inputs, outputs, and storage changes within a defined system (e.g., Xu and Singh, 1998; Mohajerani et al., 2021). These approaches integrate precipitation, surface water, groundwater, water demand, or other human systems data to develop models that predict future water supplies under various climate scenarios (e.g., Kundu et al., 2017). Research has also demonstrated how water balance modeling can unveil critical climate change vulnerabilities in regional water systems, particularly in areas experiencing rapid environmental transformation and increasing water stress (e.g., Schmied et al., 2016).

Beyond water balance models, researchers have employed a range of methodological approaches to investigate the impacts of climate change on water supply. For example, researchers have used systems models to analyze the interconnectedness of water resources with other sectors, demonstrating how climate-induced shifts in precipitation and temperature can cascade through agricultural, energy, and urban systems (Persad et al., 2020).

Other methods have included paleoclimatic reconstructions, which provide historical context for understanding the nature of projected future droughts (Cook et al., 2015), and complex hydrological models, which integrate surface water and groundwater dynamics to assess resource reliability under changing climatic conditions (Ojha et al., 2013). Advanced computational methods, such as machine learning algorithms (e.g., Miro et al., 2021), have also been utilized for downscaling global climate models or predicting localized water supply changes, enabling more targeted water resource management strategies in regions facing significant climatic uncertainties.

In this analysis, we utilize a partial water balance approach to examining water supplies. A full water balance would typically require comprehensive tracking of all hydrological inputs such as precipitation, surface water inflows, groundwater recharge, and water transfers, as well as outputs including agricultural and urban consumption, environmental releases, evaporation, and system losses. By contrast, our approach concentrates specifically on the supply-side elements that directly impact water resource reliability and management strategies, deliberately omitting some of the more complex or less immediately relevant hydrological interactions. This approach allows us to provide a targeted analysis of future water while acknowledging that a truly comprehensive water balance would require more extensive data collection and more complex modeling of the entire hydrological system.

We combine this partial water balance approach with climate projections by accounting for these projections via a climate change factor. Change factors are common to water resources studies and climate impact work more broadly. Researchers have increasingly utilized the change factor approach to assess potential climate change impacts on water systems and resources, providing a methodological framework for understanding future hydrological transformations. The change factor method applies climate model-projected changes to historical observation data, enabling researchers to generate scenario-based projections of water resource reliability, precipitation changes, or other climate variables (Miro et al., 2021; DeGaetano and Castellano, 2017). It compares baseline climatic conditions with future model projections, allowing researchers to quantify potential shifts in precipitation patterns, evapotranspiration rates, and streamflow characteristics.

Below, we describe how change factors were estimated, how we conceptualized the climate sensitivity of the main components of supply for each agency, and how the change factor was applied to model future water supply.

5.2.1 Change Factors

As described in Chapter 2, downscaled climate projections were obtained from the Weather Research and Forecasting Model (WRF) from 1991–2099 for all available Shared Socio-economic Pathway (SSPs) and global climate models (GCMs).[18] As downscaled WRF projections are currently available only for SSP3-7.0,[19] to estimate change factors, we first calculated 30-year temporal averages for each grid cell for a climate normal (1991–2020) and two future time periods 2035 (2021–2050) and 2050 (2036–2065). Percent changes between the climate normal and each future time period were calculated for each grid cell, then were spatially averaged to the bounds of the regional watersheds of relevance to each agency. The percent changes for the aridity index,[20] total annual precipitation, and total annual runoff are shown below in Table 5.2.1. Note that aridity here is the ratio of precipitation to evapotranspiration and percent increases suggest less aridity over time.

Table 5.2.1. Watershed Change Factors for Aridity, Precipitation and Runoff

Watershed:	Central Coastal	Central Coastal	Central Coastal	Central Coastal
Climate Model	WRF-UCLA-CESM2	WRF-UCLA-CNRM-ESM2-1	WRF-UCLA-EC-Earth3-Veg	WRF-UCLA-FGOALS-g3
Aridity 2035	13.38%	0.45%	0.61%	19.50%
Aridity 2050	21.37%	1.95%	0.69%	11.47%
Total Annual Precipitation 2035	20.49%	2.50%	1.88%	20.55%
Total Annual Precipitation 2050	28.57%	4.00%	3.23%	16.41%
Total Annual Runoff 2035	27.75%	7.15%	7.25%	43.18%
Total Annual Runoff 2050	48.90%	8.58%	7.79%	32.57%

18 These included: CESM2, CNRM-ESM2-1, EC-Earth3-Veg, FGOALS-g3

19 If additional SSPs become available, these will be incorporated into our analysis.

20 An aridity index value of less than 0.03 corresponds to a hyper-arid climate, values between 0.03 and 0.2 indicate an arid climate, those ranging from 0.2 to 0.5 signify a semi-arid climate, values between 0.5 and 0.65 represent a dry sub-humid climate, and any value greater than 0.65 denotes a humid climate.

Table 5.2.1. Watershed Change Factors for Aridity, Precipitation and Runoff (Continued)

Watershed:	Santa Ana River	Santa Ana River	Santa Ana River	Santa Ana River
Climate Model	WRF-UCLA-CESM2	WRF-UCLA-CNRM-ESM2-1	WRF-UCLA-EC-Earth3-Veg	WRF-UCLA-FGOALS-g3
Aridity 2035	32.60%	-2.41%	2.84%	28.30%
Aridity 2050	35.56%	4.09%	6.17%	28.34%
Total Annual Precipitation 2035	34.30%	-4.31%	3.05%	27.01%
Total Annual Precipitation 2050	36.78%	0.30%	2.55%	29.43%
Total Annual Runoff 2035	72.00%	-10.53%	1.73%	72.30%
Total Annual Runoff 2050	64.74%	-2.65%	3.29%	79.65%

Table 5.2.1. Watershed Change Factors for Aridity, Precipitation and Runoff (Continued)

Watershed:	San Diego River	San Diego River	San Diego River	San Diego River
Climate Model	WRF-UCLA-CESM2	WRF-UCLA-CNRM-ESM2-1	WRF-UCLA-EC-Earth3-Veg	WRF-UCLA-FGOALS-g3
Aridity 2035	32.86%	0.18%	10.11%	21.50%
Aridity 2050	32.09%	2.70%	11.04%	25.37%
Total Annual Precipitation 2035	28.83%	-7.03%	6.78%	23.76%
Total Annual Precipitation 2050	26.90%	-6.18%	3.45%	24.73%
Total Annual Runoff 2035	61.85%	-9.59%	16.70%	49.19%
Total Annual Runoff 2050	53.84%	-8.42%	11.66%	60.02%

NOTE: Changes shown are from SSP3-7.0. WRF modeling was only available for SSP3-7.0 for these variables.

Each GCM–WRF configuration represents one downscaled simulation per SSP; multiple ensemble members for individual GCMs were not available. Accordingly, the inter-model differences in projected runoff and precipitation partly capture both structural model differences and natural variability inherent to the climate system. California's regional hydrology is particularly sensitive to that variability, which can result in large model-to-model contrasts even under similar forcing conditions. Future work could incorporate multiple ensemble members per GCM to better quantify internal variance and distinguish forced trends from natural fluctuations.

5.2.2 Groundwater

To project changes in future groundwater reliability, we focused on the direct impacts of climate change—those from changes in natural recharge—but not from responses to climate change, such as increases or decreases in pumping, artificial or managed recharge, or other management factors affecting groundwater supplies.[21] There is a growing body of research examining how climate change may alter groundwater recharge dynamics. Berghuijs et al. (2024) demonstrate that even modest increases in aridity can lead to substantial reductions in groundwater recharge. Studies in the western United States and California highlight that climate change is projected to reduce natural groundwater recharge in California in critical groundwater basins, particularly in the Central Valley, due to increasingly variable precipitation patterns and heightened evapotranspiration rates (Alam et al., 2019; Meixner et al., 2016).

To quantify these dynamics, we specifically utilized empirical modeling done by Berghuijs et al. (2024) which quantified the relationship between groundwater recharge, precipitation, and aridity, as shown in Equation 3, below.

$$R = P\alpha \left(1 - \frac{\ln\left(\phi^{\beta}+1\right)}{1+\ln\left(\phi^{\beta}+1\right)}\right) \qquad (3)$$

R is recharge, P is precipitation, and ϕ is aridity (potential evapotranspiration divided by precipitation). α and β are empirical parameters from Berghuijs et al. (2024), where α = 0.72 and β = 15.11. The equation is derived from a global analysis that found aridity is a robust predictor of the proportion of precipitation that becomes recharge. By establishing this relationship, the researchers developed a framework that allows for predicting how changes in precipitation and aridity will influence groundwater recharge rates. Here, we apply their analysis directly to sustainable yield values, relying on the fundamental assumption that sustainable yield is constrained by the local recharge.

21 Such efforts include Flood Managed Aquifer Recharge (Flood-MAR), which have the potential to capture and infiltrate large flood events for groundwater replenishment.

To apply this equation, we develop a recharge change factor by applying estimates of future changes in aridity and precipitation (ϕ and P, respectively), in Equation 1. This yields a percent change in recharge which is then multiplied by estimates of current groundwater yield (either safe yield, sustainable yield, or annual use). We use changes in aridity and precipitation at the watershed scale, based on the assumption that groundwater basins receive the majority of their recharge from surface water or from the direct infiltration throughout the watershed in these regions. These results are shown below in Figure 5.2.1.

Figure 5.2.1. Percent Change in Groundwater Recharge by Watershed

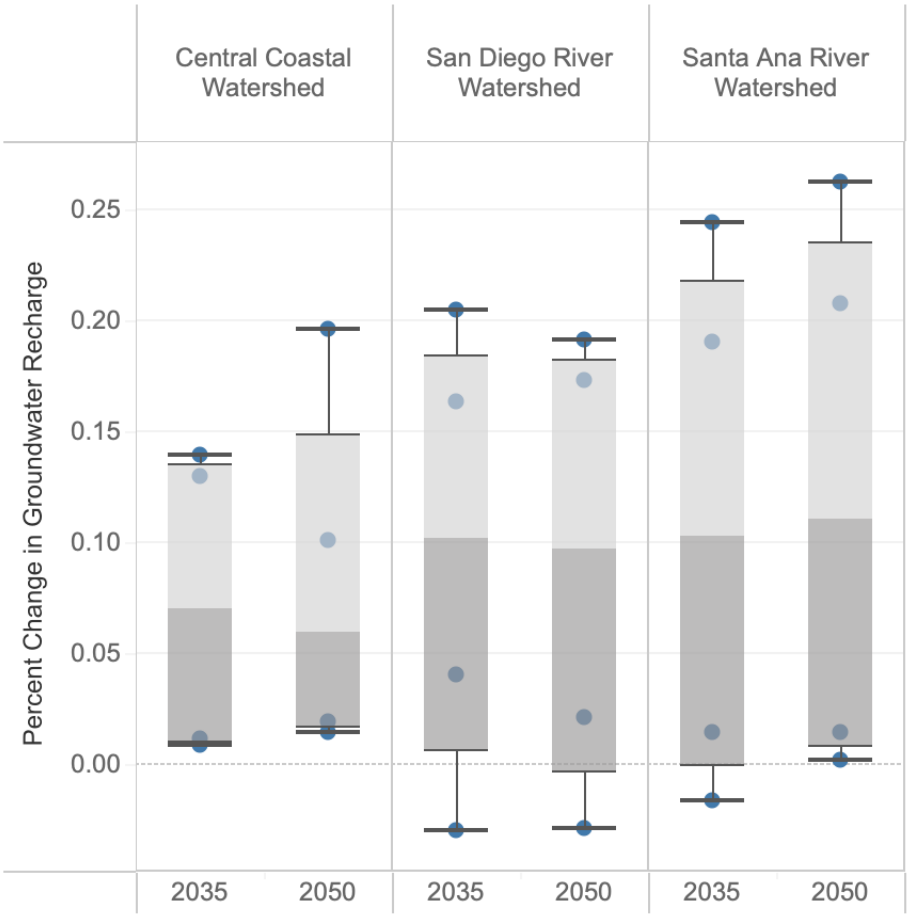


Figure 5.2.1. This figure shows projected percent changes in groundwater recharge for the Central Coastal, San Diego River, and Santa Ana River watersheds for 2035 and 2050. Points represent model means and bars indicate the range across four GCMs. Source: Authors' calculations using Berghuijs et al. (2024) method and Cal-Adapt data.

5.2.3 Surface Water

Estimates of future changes in surface water runoff are directly modeled from WRF, as shown above in Table 5.2.1. Here we use the watershed average change factors as a proxy for changes in local surface water and scale surface water values by these percentages.

Figure 5.2.2. Percent Change in Surface Water Runoff by Watershed

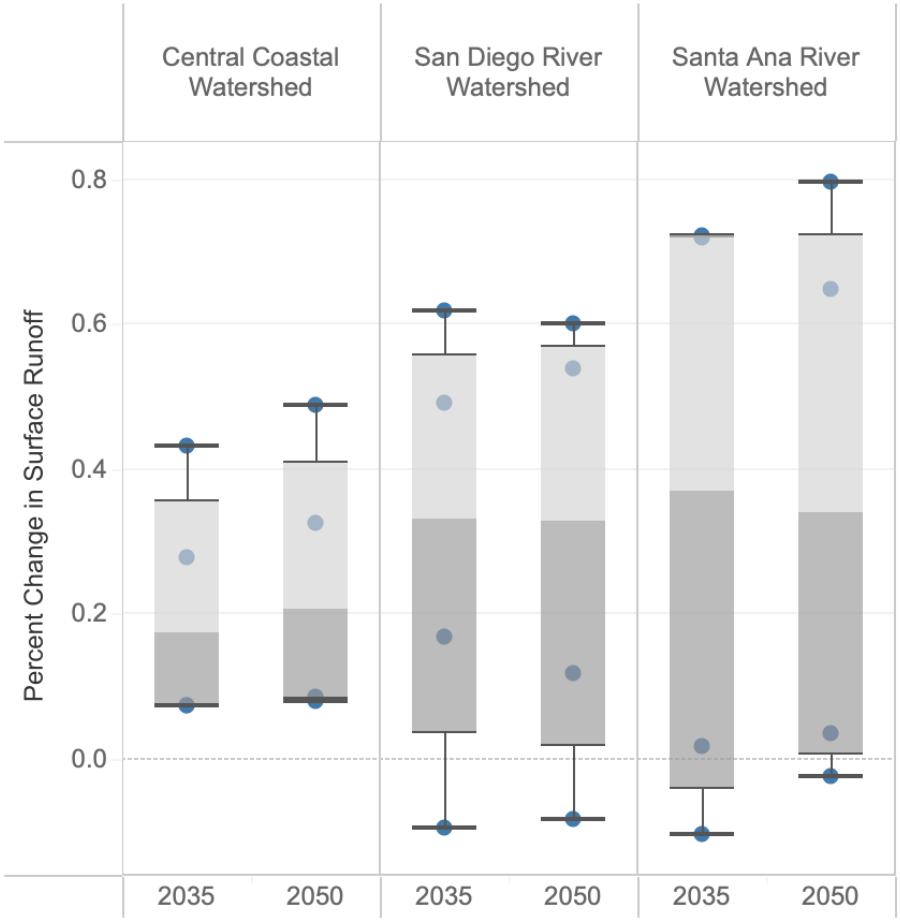


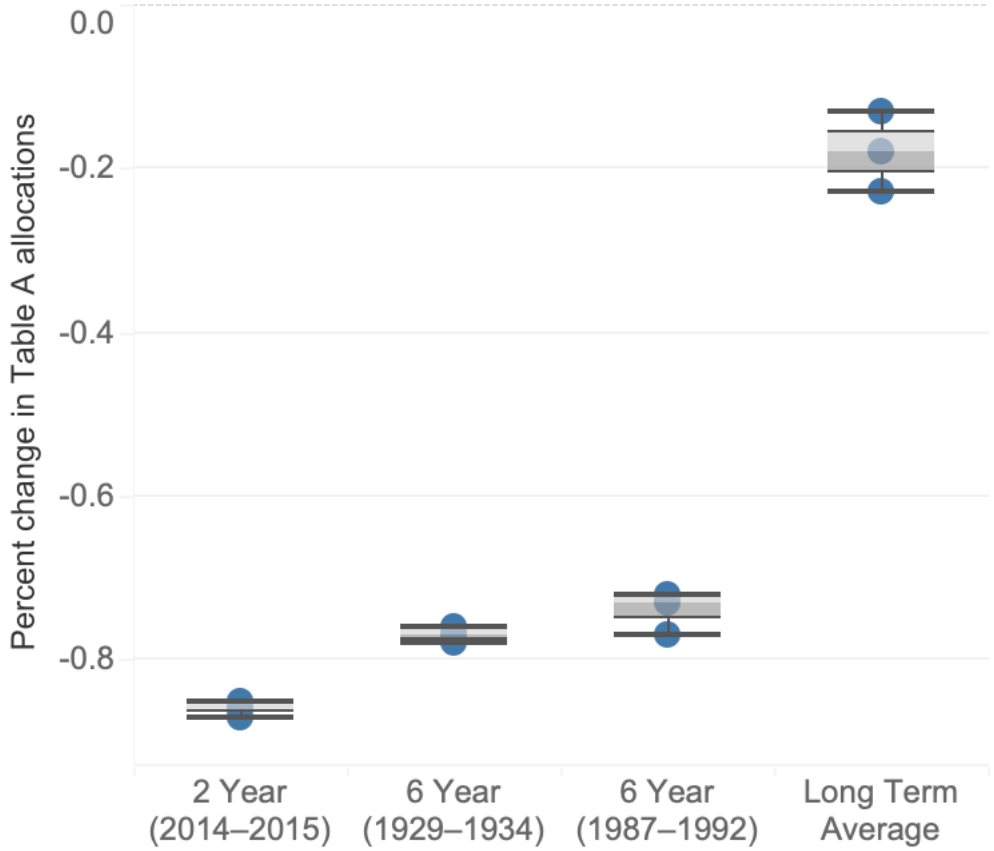
Figure 5.2.2. This figure presents projected percent changes in surface water runoff for the Central Coastal, San Diego River, and Santa Ana River watersheds for 2035 and 2050. Points show model means and bars indicate the range across four GCMs. Source: Cal-Adapt Analytics Engine, WRF downscaled projections.

5.2.4 Imported Water

California's Department of Water Resources (DWR) Delivery Capability Report (DCR) provides long-term projections of State Water Project Table A water deliveries under different hydrology scenarios (DWR, 2024). These projections account for climate change impacts, environmental regulations, infrastructure constraints, and

hydrological variability. These percent changes in Table A allocations can be used to scale normal year State Water Project (SWP) deliveries for each agency. These changes are shown for a subset of hydrologic scenarios in Figure 5.2.3. The DCR includes three climate scenarios, represented as the three dots in the box and whisker plots, as well as multiple hydrologic conditions, including long term average conditions (right most box and whisker) and various drought conditions (three of which are shown in the three left most box and whiskers). Across the climate and hydrologic uncertainty shown in Figure 5.2.3, the change factors range from a 13% decrease from historical conditions to an 87% decrease (see the 2-year 2014-2015 drought column below).

Figure 5.2.3. Percent Change in SWP Table A Allocations



This figure displays projected percent changes in State Water Project Table A allocations under different hydrologic scenarios (2-year, 6-year, and long-term average) for three climate scenarios, as reported in the DWR Delivery Capability Report (2024). Source: California Department of Water Resources (2024).

SDCWA also receives imported water from the Colorado River Basin under transfer agreements (see transfers in Figure 5.1.1). As these imports represent fixed contractual quantities within current planning frameworks, our analysis does not incorporate climate-change adjustments to these amounts.

5.2.5 Other Water Supplies

Across the three case studies, there are a range of other supplies, including recycled water, desalinated supplies and other contracted water sources. For those, we rely on agency projections of future production from their Urban Water Management Plans.

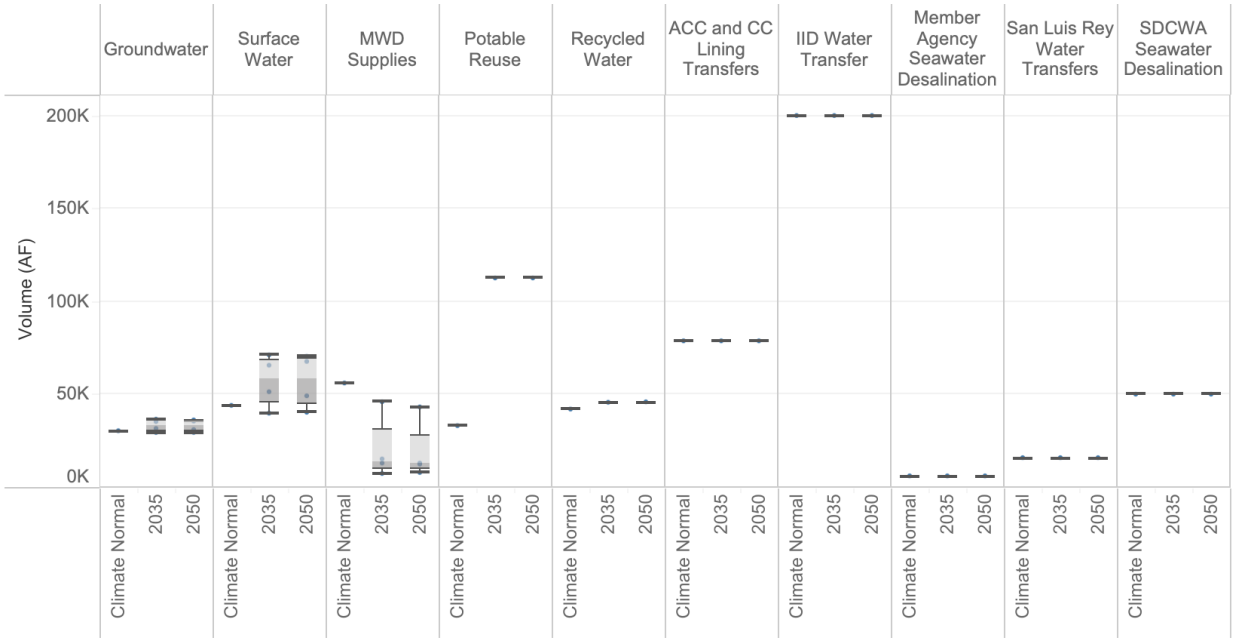
5.3 Projected Supplies by County

By applying these change factors and utilizing agency estimates for all other supplies (contracts, recycled water, etc.), we estimated future water supply portfolios, with a range of possible values for groundwater, State Water Project (SWP), and surface water reliability. The following figures present these results for each agency. It is important to note that imported water estimates for Metropolitan Water District (MWD) or SWP values are solely based on scaling historical deliveries by change factors in the Delivery Capability Report (DCR).

By applying climate change adjustment factors and utilizing agency-supplied estimates for other supply categories (such as contractual entitlements and recycled water), we projected the future water supply portfolios for the three case study agencies. Our analysis provides a range of possible outcomes for groundwater, SWP, and surface water supplies under future climate scenarios, with Figures 5.3.1, 5.3.2, and 5.3.3 highlighting both the projected values for 2035 and 2050, as well as the historical climate normal baseline (1991–2020) for comparison.

For San Diego County Water Authority (SDCWA), future projections for 2035 and 2050 demonstrate considerable ranges. Given wet precipitation projections for the four models and one Shared Socio-economic Pathway (SSP) available for this analysis, climate change factors increase estimated surface water and groundwater reliability in most futures, with DCR decreases in Table A allocations resulting in lower projections for imported sources.

Figure 5.3.1. SDCWA Water Supply Projections



This figure shows projected volumes of water supply components for the San Diego County Water Authority for the climate normal, 2035, and 2050. Components include groundwater, surface water, imported water, recycled water, desalination, and transfers. Source: Authors' analysis using agency data and climate change factors.

For the San Bernardino Valley Municipal Water District (SBVMWD), our analysis reveals similar findings to SDCWA: there is a slight projected increase in groundwater reliability across most models, as well as a decrease in SWP water. Uncertainty is highest for groundwater and SWP water.

Figure 5.3.2. San Bernardino Valley Water Supply Projections

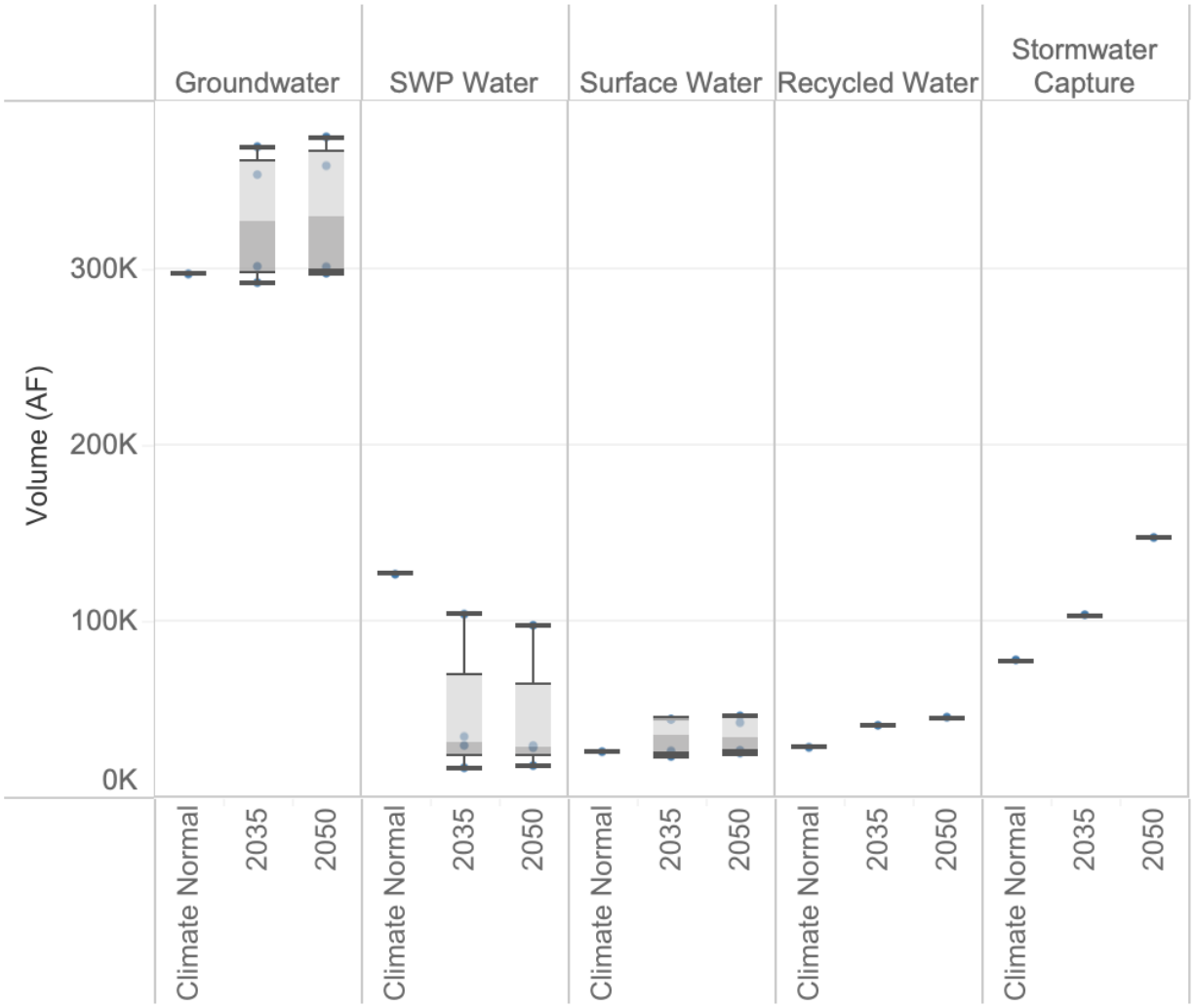
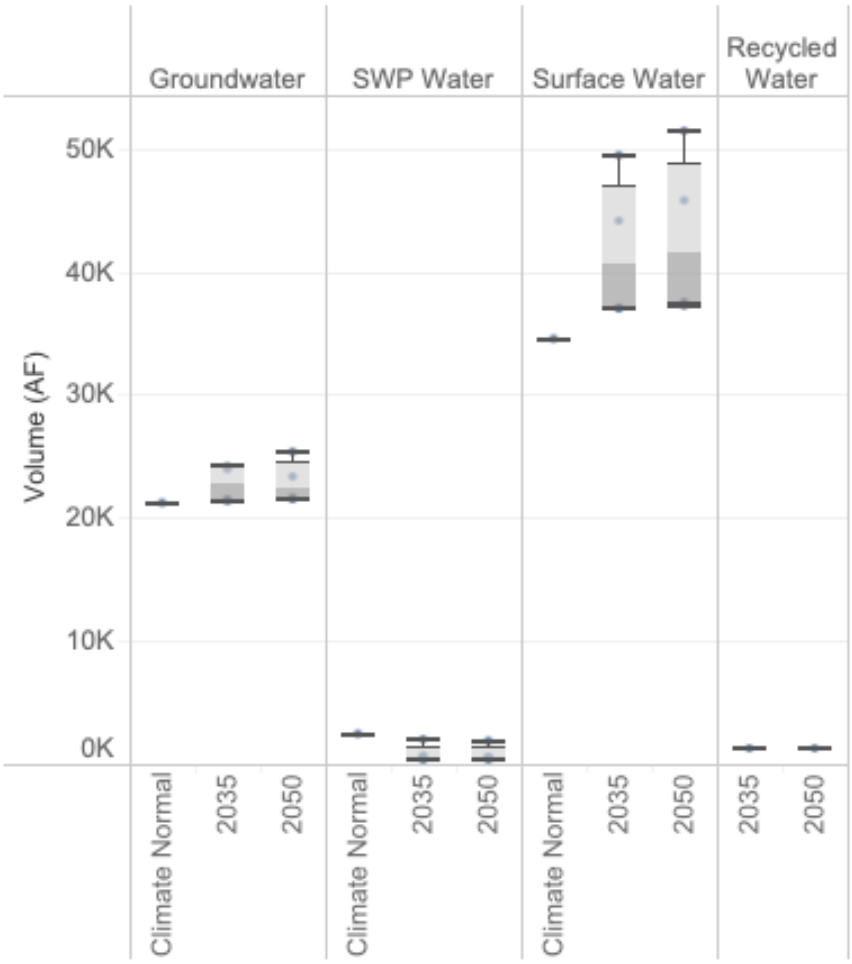


Figure 5.3.2. This figure presents projected volumes of water supply components for the San Bernardino Valley Municipal Water District for the climate normal, 2035, and 2050. Components include groundwater, SWP water, surface water, recycled water, and stormwater capture. Source: Authors' analysis using agency data and climate change factors.

In San Luis Obispo County, uncertainty is greatest in projected surface water, but, due to projected increases in total annual precipitation among the four models and one SSP, this analysis shows a potential for increased surface water reliability.

Figure 5.3.3. SLO County Water Supply Projections



This figure shows projected volumes of water supply components for selected providers in San Luis Obispo County for the climate normal, 2035, and 2050. Components include groundwater, SWP water, surface water, and recycled water. Projections are estimated for Atascadero Mutual Water Company, Cambria Community Services District, City of Arroyo Grande, City of Grover Beach, Morro Bay, Nipomo Community Services District, Paso Robles, Pismo Beach, San Luis Obispo, and Templeton Community Services District. Source: Authors' analysis using agency data and climate change factors.

6: Climate Impacts on Housing Growth

6.1 Overview

To estimate if future water supply reliability could constrain housing growth and the ability of each county to meet its housing needs, we bring together the two main components of our analysis—1) our projections of water demand under various future housing growth and climate conditions and 2) our projections of water supply under future climate conditions. Our goal is to identify potential water supply shortages and their implications for housing development.

To calculate gaps between water supply and demand, researchers typically employ scenario-based modeling that integrates projections of water reliability under climate change with estimates of future demand based on demographic and land use trends. Supply projections often rely on hydrological models that simulate streamflow, groundwater recharge, and reservoir storage under varying climate scenarios (e.g., Groves et al., 2008). Demand projections, on the other hand, are derived from population growth forecasts, per capita water use estimates, and housing development targets, often adjusted for anticipated conservation measures (Heberger et al., 2016). The gap between supply and demand is calculated by subtracting projected demand from available supply for each scenario, with unmet demand representing the magnitude of water shortages (Miro et al., 2018). Advanced approaches may account for uncertainties in both supply (e.g., variability in precipitation patterns) and demand (e.g., changes in water use behavior, population growth), to estimate a range of plausible outcomes (Miro et al., 2021).

In this work, we use multiple projections of both supply and demand to estimate the range of plausible gaps, if any, that San Bernardino, San Luis Obispo (SLO) County, and the San Diego County Water Authority (SDCWA) may see in their service areas. We specifically explore three future housing growth scenarios: a baseline, low growth, and high growth future. These are coupled with four climate model projections for changes in temperature to produce 12 demand projections for 2035 and 2050. The temperature changes for San Bernardino County from each of the four climate models downscaled as a part of the climate assessment process are shown below in Figure 6.1.1.

Figure 6.1.1. Projected Temperature Changes by County

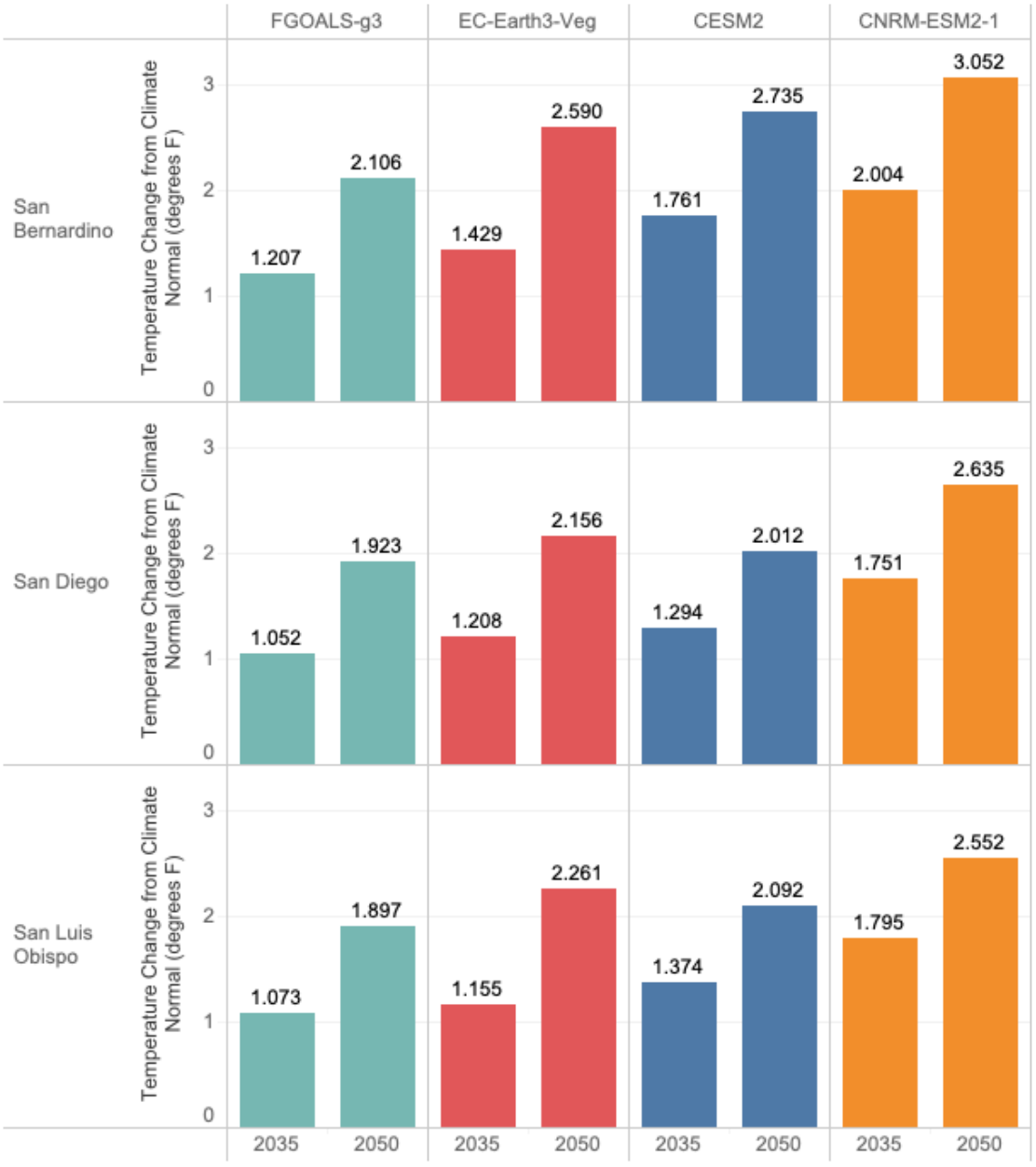


Figure 6.1.1. This bar chart shows projected changes in mean annual temperature (degrees F) from the climate normal for San Bernardino, San Diego, and San Luis Obispo counties for 2035 and 2050, as simulated by four GCMs. Source: Cal-Adapt Analytics Engine, WRF downscaled projections.

Combined with the housing growth scenarios, the aggregate demand projections are shown below in Figure 6.1.2 for the warmest model CNRM-ESM2-1.

Figure 6.1.2. Projected Demands for CNRM-ESM2-1

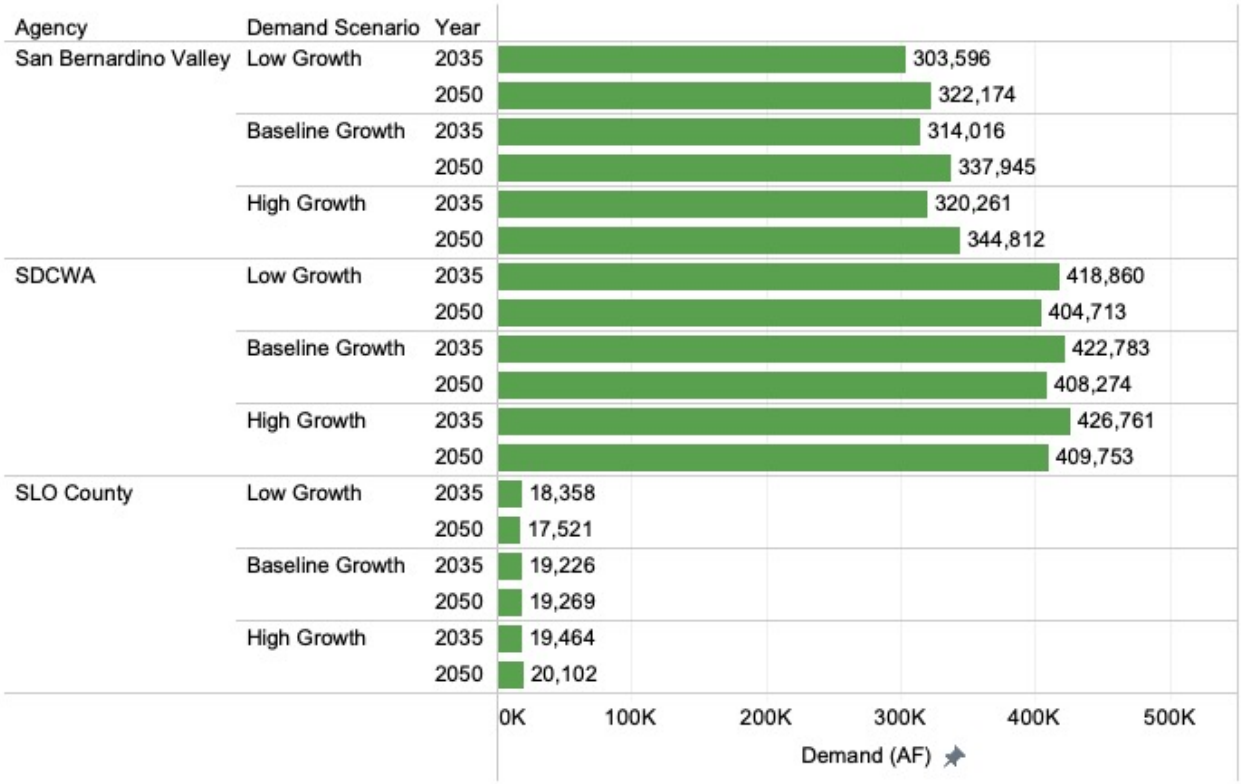


Figure 6.1.2. This bar chart presents projected aggregate water demand (acre-feet, AF) for each agency and housing growth scenario for 2035 and 2050, using the CNRM-ESM2-1 climate model. Source: Authors' model results.

The full table of aggregate demands for all 12 scenarios is shown below in Table 6.1.1. As shown in Figure 6.1.2 and Table 6.1.1, the differences in demand across housing growth scenarios are relatively minor, ranging from about 9% below baseline to about 2% above baseline. Demand projections exhibit relatively minor variation across housing growth scenarios due to three key factors that significantly dampen the spread in demand estimates.

Table 6.1.1. Projected Demands for All Scenarios (acre-feet, AF)

Agency	GCM Number	Demand Scenario	2035	2050
San Bernardino Valley	FGOALS-g3	High Growth	318,033	342,163
San Bernardino Valley	FGOALS-g3	Baseline Growth	311,896	335,434
San Bernardino Valley	FGOALS-g3	Low Growth	301,654	319,977
San Bernardino Valley	EC-Earth3-Veg	High Growth	318,653	343,517
San Bernardino Valley	EC-Earth3-Veg	Baseline Growth	312,486	336,718
San Bernardino Valley	EC-Earth3-Veg	Low Growth	302,194	321,100
San Bernardino Valley	CESM2	High Growth	319,583	343,925
San Bernardino Valley	CESM2	Baseline Growth	313,371	337,105
San Bernardino Valley	CESM2	Low Growth	303,005	321,439
San Bernardino Valley	CNRM-ESM2-1	High Growth	320,261	344,812
San Bernardino Valley	CNRM-ESM2-1	Baseline Growth	314,016	337,945
San Bernardino Valley	CNRM-ESM2-1	Low Growth	303,596	322,174
SDCWA	FGOALS-g3	High Growth	422,605	405,852
SDCWA	FGOALS-g3	Baseline Growth	418,687	404,396
SDCWA	FGOALS-g3	Low Growth	414,824	400,889
SDCWA	EC-Earth3-Veg	High Growth	423,535	407,130
SDCWA	EC-Earth3-Veg	Baseline Growth	419,604	405,667
SDCWA	EC-Earth3-Veg	Low Growth	415,727	402,142
SDCWA	CESM2	High Growth	424,045	406,341
SDCWA	CESM2	Baseline Growth	420,107	404,882
SDCWA	CESM2	Low Growth	416,223	401,368

Agency	GCM Number	Demand Scenario	2035	2050
SDCWA	CNRM-ESM2-1	High Growth	426,761	409,753
SDCWA	CNRM-ESM2-1	Baseline Growth	422,783	408,274
SDCWA	CNRM-ESM2-1	Low Growth	418,860	404,713
SLO County	FGOALS-g3	High Growth	19,160	19,705
SLO County	FGOALS-g3	Baseline Growth	18,926	18,887
SLO County	FGOALS-g3	Low Growth	18,071	17,173
SLO County	EC-Earth3-Veg	High Growth	19,194	19,843
SLO County	EC-Earth3-Veg	Baseline Growth	18,960	19,020
SLO County	EC-Earth3-Veg	Low Growth	18,104	17,295
SLO County	CESM2	High Growth	19,287	19,846
SLO County	CESM2	Baseline Growth	19,051	19,023
SLO County	CESM2	Low Growth	18,191	17,296
SLO County	CNRM-ESM2-1	High Growth	19,464	20,102
SLO County	CNRM-ESM2-1	Baseline Growth	19,226	19,269
SLO County	CNRM-ESM2-1	Low Growth	18,358	17,521

NOTES: San Bernardino Valley estimates demand as 388,533 AF (2035), 410,712 AF (2050).

The most impactful factor is the shift in housing stock composition toward multifamily housing. Across all scenarios, nearly all projected housing growth is in multi-family housing, with some scenarios even showing modest declines in single-family housing. This substitution has a meaningful impact on water demand because per capita water use in multi-family housing is significantly lower than in single family. Based on estimates from the literature, indoor water use per capita in multifamily housing is modeled at 53% of single-family indoor use, while outdoor water use per capita in multi-family is modeled at just 27% of single family housing outdoor use. For example, if the indoor use for a single-family home is 50 gallons per capita per day (GPCD) and outdoor use is 30 GPCD (totaling 80 GPCD), switching to multifamily

would reduce indoor use to 25 GPCD and outdoor use to 8 GPCD, yielding a total of 33 GPCD. This reduction means that one single-family home could be replaced by approximately 2.5 multifamily homes with no net increase in water demand. Consequently, the shift to multifamily significantly compresses the differences in demand across high and low housing growth scenarios.

The second factor contributing to smaller demand variation is the modest decline in persons per household (PPH) across all scenarios. Even as the number of housing units increases, the average water use per unit is declining globally due to smaller household sizes. This trend further reduces the differences in demand between high and low housing growth scenarios, as the reduction in PPH offsets the impact of housing unit expansion.

Finally, the assumed adoption of water-saving technologies across all scenarios further reduces overall water use, shrinking the absolute magnitude of demand gaps by 2050. These technologies, modeled to reduce both indoor and outdoor water use, ensure that all housing units, regardless of growth scenario, consume less water than they would under current conditions. As a result, the differences between high and low growth scenarios are compressed even further, as the baseline water use for all units is lower.

Together, these three factors—housing stock substitution toward multifamily housing, declining PPH, and water-saving technology adoption—create conditions under which demand projections are relatively stable across housing growth scenarios, despite variations in the scale of development. This stability highlights the importance of considering structural and behavioral shifts in housing and water use patterns when modeling future demand.

Our aggregate water supply projections for each water agency across the four climate models show substantially more variation in volumes, as shown in Figure 6.1.3. This is not surprising given that water supplies regularly change due to seasonal as well as long-term changes in climate. Figure 6.1.3 also shows that our estimates are higher than those estimated by each agency as part of their 2020 Urban Water Management Plans. While we need to examine this further, water supply projections could be higher than agency estimates due to inherent characteristics of the climate models used in the analysis. The four models available at the time of analysis tend to project slightly wetter futures, with increases in annual runoff over time. Another possible cause is that we relied on annual total runoff values, which may obscure seasonal fluctuations in local surface water and fail to capture the impacts of extended dry periods or shifts in precipitation timing, critical considerations for water management. Additionally, the models themselves may represent a wetter future than the agencies are currently planning for, potentially underestimating the severity and frequency of drought conditions.

Figure 6.1.3. Water Supply Projections by Climate Model

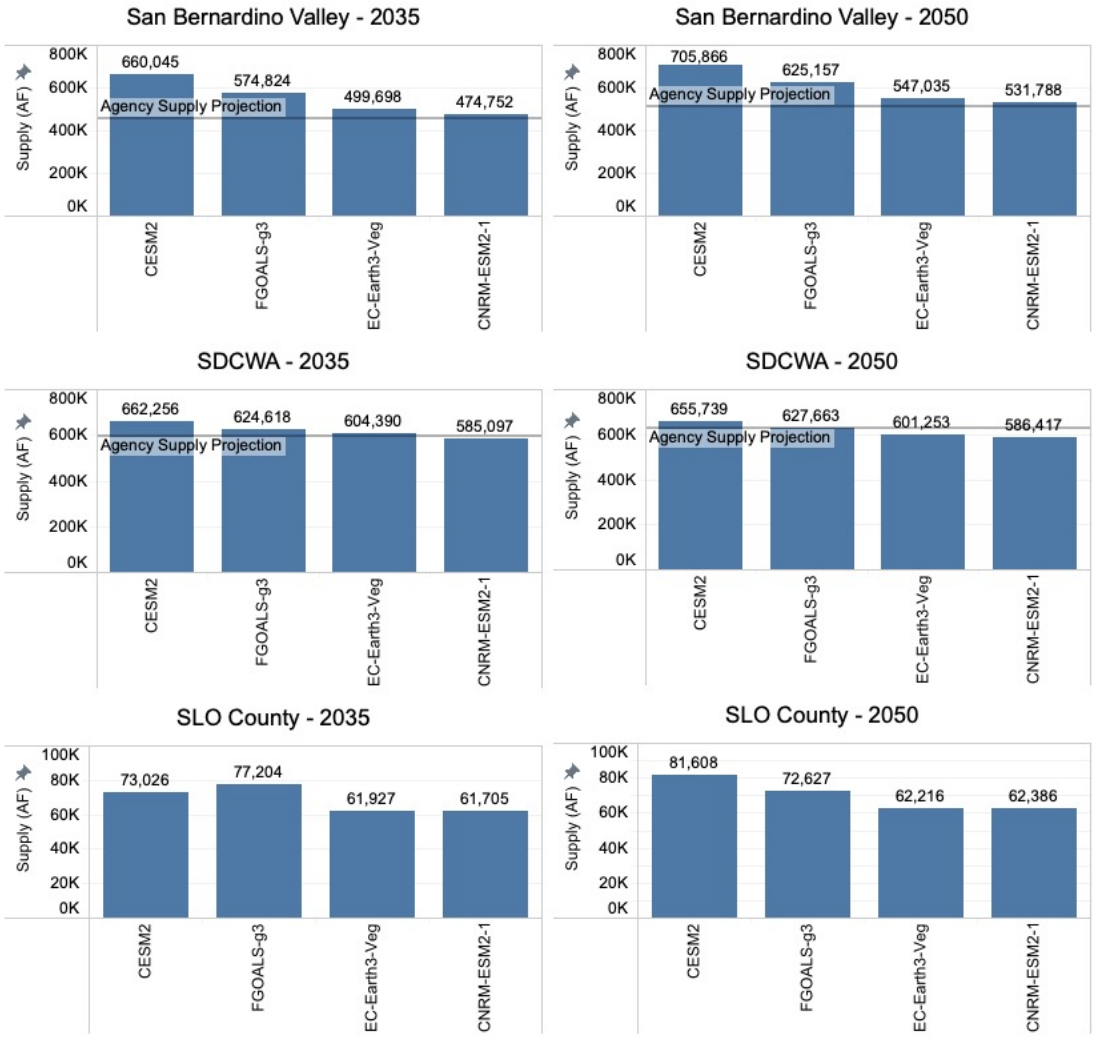


Figure 6.1.3. This figure shows projected aggregate water supply volumes for each agency for 2035 and 2050, as simulated by four GCMs. Bars represent supply under different climate models, with agency supply projections for comparison. Source: Authors' analysis using agency data and climate change factors.

Finally, Figure 6.1.4 shows agency aggregate demands and supplies for 2035 and 2050 for the high growth housing scenario and the hottest and driest model—CNRM-ESM2-1. This represents the worst-case scenario for water agencies. Under these conditions, all three locations appear to have sufficient water to meet demands, even under high growth scenarios where counties aim to meet housing needs. Based on this analysis, in the long-term, it does not appear that changes in temperature and precipitation, as well as other hydrologic variables impacting water supplies, will be

a major constraint on housing growth. However, the picture for individual local water providers may look quite different, which is not considered in this analysis. Table 6.1.2 provides data on the percent of surplus water, estimated as supply minus demand divided by total supply, for the high growth scenario and CNRM-ESM2-1.

Figure 6.1.4. Supply and Demand Projections by Agency

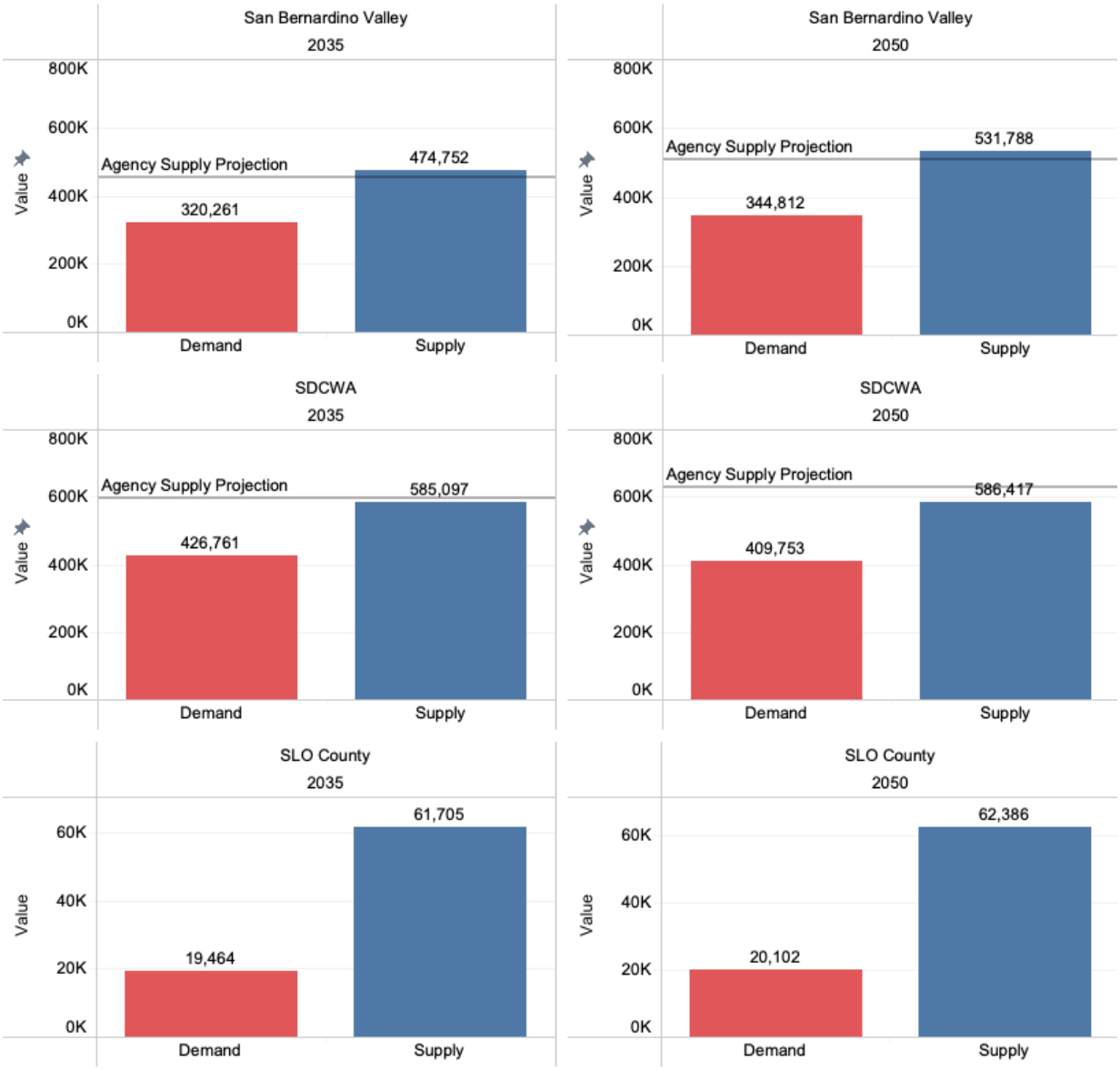


Figure 6.1.4. This figure compares projected aggregate water supply and demand for San Bernardino Valley, San Diego County Water Authority (SDCWA), and San Luis Obispo (SLO) County for 2035 and 2050 under the high growth scenario and the hottest, driest climate model (CNRM-ESM2-1). 2050 Agency Supply Projections are based on 2045 estimates in each agency's 2020 Urban Water Management Plan. Agency projections for SLO County were not available. Source: Authors' model results.

Table 6.1.2. Percent Surplus Water by Agency

	2035	2050
San Bernardino Valley	32.54%	35.16%
SDCWA	27.06%	30.13%
SLO County	68.46%	67.78%

NOTES: Estimates are from the high growth housing scenario combined with CNRM-ESM2-1.

7: Adaptation Strategies

Our analysis finds that across San Bernardino, San Diego, and San Luis Obispo counties, projected water supply is sufficient to meet future demand, even under higher housing growth scenarios and warmer climate conditions. The lack of significant gaps between supply and demand in our results, however, is contingent on the continuation of long-term declines in per capita water use observed in recent decades. If these trends do not persist, or if water use rates stabilize or rise due to changes in policy, consumer behavior, or economic conditions, the risk of future supply shortfalls may increase. At the same time, the four models included in our analysis indicate a wetter future on average than baseline conditions. What we did not assess was the intra-annual variability of this precipitation and its effects on water supply, or models that project drier conditions in the future. Given these dynamics, a central focus for county and regional adaptation planning should be on 1) sustaining reductions in water use through demand management strategies integrated into housing policy, water agency programs, and infrastructure; 2) monitoring and managing changing precipitation conditions to capture precipitation when it does fall and to identify when climate trajectories shift to a drier future.

7.1 Demand Management Strategies

7.1.1 Housing Policy and Land Use Codes

Housing and land use policies provide foundational opportunities to influence water use at the community scale. Local governments can use zoning, building codes, and permitting requirements to mandate or strongly encourage water-efficient development. Examples from Santa Monica, which has implemented "net-zero water" building ordinances, demonstrate the potential impact of rigorous water-neutral requirements for new housing (City of Santa Monica, 2017). Santa Monica's approach includes mandates for onsite recycling of greywater, minimized outdoor irrigation, and integration of water reuse systems into new construction.

Other jurisdictions, such as San Francisco, have adopted similar requirements for onsite non-potable water systems in large new developments, further reducing potable water demand (San Francisco Public Utilities Commission, n.d.). In Los Angeles, the city's Green Building Code requires new residential and commercial buildings to meet strict water efficiency standards, including landscape water use limits and mandatory use of weather-based irrigation controllers (LADWP, 2016).

Policies can also incentivize higher-density, multifamily housing, which generally results in lower per capita water use compared to single-family homes due to reduced outdoor irrigation and shared infrastructure. For example, the City of San

Diego's Climate Action Plan encourages infill development and transit-oriented housing, which has been shown to reduce both water and energy use per capita (City of San Diego, 2022).

Current incentives in denser urban areas, such as tiered water rates and development impact fees, help mitigate the growth rate of water demand. However, in areas more prone to greenfield development or urban sprawl (e.g., San Bernardino County), policy adaptation over time may need to tilt incentives more strongly toward multifamily or smaller/denser single-family home developments. This could include density bonuses, expedited permitting for water-efficient projects, or requiring water budgets for new subdivisions.

Importantly, however, policies aimed at increasing water efficiency that result in higher production costs for housing may also have a direct, negative effect on housing production (Ward and Schlake, 2025). Thus, local and state regulations aimed at increasing water efficiency should be considered in terms of both effects on water use and effects on housing production if increasing the supply of housing is an important goal. To balance these objectives, policymakers could prioritize integrated approaches that simultaneously advance housing affordability and water efficiency, for example, by offering incentives or streamlined permitting for developments that incorporate high-efficiency fixtures and recycled-water systems. Such measures would align water-conservation goals with housing production targets.

7.1.2 Behavioral Demand Management Programs

Water agencies also play a crucial role in maintaining and reducing per capita demand through demand management strategies, such as water pricing, water use monitoring, and voluntary conservation. These programs involve both behavioral interventions and technical support targeted at residential, commercial, and institutional customers.

Behavioral management approaches include wide-reaching public education campaigns on conservation, drought alerts, and direct communication strategies that nudge users toward lower water consumption. The Metropolitan Water District of Southern California (MWD) runs large-scale public campaigns during droughts, such as "Being Waterwise," and provides rebates for water-saving actions (MWD, n.d.). Las Vegas Valley Water District has implemented tiered pricing and "water waste" enforcement, resulting in significant per capita use reductions (Las Vegas Valley Water District, n.d.).

Agencies are also increasingly using digital tools, real-time usage feedback, and personalized notifications to encourage conservation, especially among high-use customers and during periods of water stress. Irvine Ranch Water District's WaterInsight Program provides personalized water use tracking, leak detection, and

incentives to users (Irvine Ranch Water District, n.d.). Expanding and refining these interventions, coupled with strategic investment in utility data systems and analytics, can help agencies sustain or deepen per capita water use reductions even as housing grows.

7.1.3 Structural Interventions

Structural interventions, ranging from drought-tolerant landscaping requirements to the installation of high-efficiency fixtures and appliances, have already been widely used across Southern California. Many local agencies already offer rebates and credits to encourage adoption of low-flow showerheads, toilets, and washing machines. These measures are often required of new developments but can also be incorporated into retrofit programs for existing buildings. Some of the greatest water savings can result from widespread conversion of outdoor landscaping to drought-tolerant or California-native species, along with advanced irrigation controls and smart meter deployment.

Los Angeles Department of Water and Power (LADWP), for example, offers rebates for turf removal and installation of California-friendly landscaping, as well as incentives for high-efficiency toilets and washing machines and free showerheads and aerators (LADWP, n.d.). Santa Clara Valley Water District (Valley Water) has a "Landscape Rebate Program" with incentives for converting lawns to drought-tolerant gardens and installing smart irrigation controllers (Valley Water, n.d.).

The overlap between housing policy and structural interventions is pronounced: codes may require efficient fixtures and appliances, but voluntary programs and financial incentives can accelerate uptake in existing housing stock. Additionally, for larger housing projects, the integration of greywater reuse and rainwater capture systems, as seen in some new developments in California, can further reduce potable water demand.

It is also important to recognize the limits of efficiency measures. As fixtures, appliances, and landscapes approach their practical minimum water use, the marginal gains from additional efficiency measures diminish. Beyond that point, sustaining per-capita reductions will rely more on behavioral change, technological innovation, and structural adaptation, such as water reuse and supply diversification, rather than continual tightening of indoor or landscape standards.

7.2 Water Supply Adaptation

7.2.1 Local Water Supply Resilience

While our findings do not show substantial gaps between supply and demand, the climate projections are only a subset of plausible futures and may overestimate future available supplies. Given this, it is important for water suppliers to maintain and

strengthen their current resilience strategies, particularly those related to harnessing local water supplies. Given the importance of local surface water and groundwater to each county's water supply portfolios, increased efforts to capture water during atmospheric river events can augment critical surface and groundwater supplies. Further, since we did not assess the intra-annual variability of precipitation, increases in local surface water and groundwater values shown in Chapter 5 may only be realized if agencies are able to utilize the precipitation from atmospheric rivers.

This underscores the need for proactive investment in stormwater capture infrastructure, managed aquifer recharge, and flexible operational practices that can take advantage of episodic, high-intensity precipitation events. Without such adaptive measures, much of the potential benefit from increased precipitation could be lost to runoff, flooding, or missed recharge opportunities, especially as climate change is expected to increase the frequency and intensity of both wet and dry extremes. By prioritizing the development of local capture and storage capacity, and by integrating real-time monitoring and adaptive management into their operations, water agencies can better ensure that the episodic nature of future precipitation translates into reliable, long-term water supply benefits. This approach not only enhances drought resilience but also positions agencies to respond more effectively to a wide range of future climate scenarios, including those that may be drier or more variable than the models considered in this analysis.

Efforts already exist throughout California. The Los Angeles Department of Water and Power (LADWP) has already invested in stormwater capture, such as the Tujunga Spreading Grounds Enhancement Project, which can recharge groundwater basins with millions of gallons of stormwater during major rain events (LADWP, 2022). San Bernardino Valley already operates major spreading grounds for both stormwater and imported water. In addition, the Seven Oaks Dam along the Santa Ana River has begun implementing Forecast-Informed Reservoir Operations (FIRO), an approach that integrates weather and climate forecasts into reservoir management to improve both flood protection and water supply reliability during atmospheric river events (Center for Western Weather and Water Extremes, 2025). Los Angeles County is also advancing its Water Plan, which includes a target to develop approximately 580 thousand acre-feet per year of sustainable local water supplies through stormwater capture, recycled water, and groundwater recharge initiatives (LA County Water Plan, 2023). Several coastal agencies, including in San Diego County, have expanded local desalination capacity as part of their drought-resilience portfolios. Finally, emerging strategies such as Flood Managed Aquifer Recharge (Flood-MAR) offer opportunities to route high flows from major storm or flood events to recharge groundwater basins.

7.2.2 Triggers and Tracking for Adaptation

Adaptive management is a well-established practice in California's water sector, enabling agencies to systematically respond to evolving climate and hydrologic conditions. Because this analysis considers only a limited range of climate scenarios, there is a need for more robust monitoring of long-term precipitation patterns and aridity indices. Enhanced tracking will improve early detection of shifts toward drier conditions, which could reduce the margin between supply and demand. Water agencies can operationalize adaptive management by employing a comprehensive set of quantitative indicators, such as annual and seasonal precipitation totals, drought indices, reservoir storage levels, and imported water allocations, to identify when supply trajectories deviate from the scenarios considered here or in broader planning efforts. These metrics can serve as actionable triggers for implementing contingency measures and guiding infrastructure or policy adjustments in anticipation of emerging water supply risks. Planning efforts with the Metropolitan Water District of Southern California (MWD) and San Bernardino Valley have already identified these kinds of triggers (Groves et al., 2014; Miro et al., 2021), which could be adapted to track when risk of supply shortages may begin to threaten development.

7.2.3 Building Adaptation into Infrastructure Investments

Traditional infrastructure design typically optimizes for a single, anticipated future scenario, which can limit adaptability under changing climate and hydrologic conditions. In contrast, infrastructure can be engineered with built-in flexibility and design margins to accommodate a range of plausible futures. For example, adjustable infrastructure such as inflatable dams on the Santa Ana River enables real-time management of flows and storage, allowing operators to respond dynamically to variable hydrology (OCWD, 2025). Flexible infrastructure design extends asset longevity and operational relevance by enabling agencies to adjust system capacity and function as conditions change. This approach can reduce lifecycle costs and enhance system performance by minimizing the risk of over- or under-building relative to actual future needs. Such adaptive solutions can be helpful for managing uncertainty in future supply and demand, allowing agencies to scale water delivery in response to increased demand or to curtail supply plans if future conditions warrant a more conservative approach. Flexible design can also reduce the risk of over- or under-investment for agencies.

7.3 Integrated Policy and Planning

Achieving long-term resilience will require not only technical and behavioral changes but also integrated policy frameworks that align housing, water supply, and equity objectives. California's recent legislation underscores the importance of such coordination. Government Code Section 65589.7 establishes that local jurisdictions must consult with water suppliers during Housing Element and

Regional Housing Needs Allocation (RHNA) updates, ensuring that projected residential growth is consistent with available water resources and planned infrastructure. Likewise, Government Code Section 66300, the Housing Crisis Act of 2019, limits moratoria or zoning actions that unduly constrain housing production, particularly for multifamily developments that serve lower-income households. These statutes reinforce that housing and water planning are interconnected priorities, and that equitable access to both safe housing and reliable water must be jointly advanced.

State policy is increasingly guided by a commitment to integrate adaptation and equity into program development and funding criteria. This means that local climate resilience efforts should account not only for water conservation and supply security but also for affordability and fair-housing outcomes. Coordinated planning offers an opportunity to achieve multiple benefits: higher-density and infill housing can reduce per-capita water use while expanding affordable housing near transit; streamlining water-efficient building approvals can support both environmental and social goals; and shared data between planning and water agencies can yield more consistent regional forecasts of growth and demand.

Developing integrated plans that explicitly connect housing production, water management, and climate adaptation ensures that communities can respond effectively to future uncertainties. Incorporating these policy linkages into local planning processes, through RHNA coordination, equitable funding criteria, and transparent interagency collaboration, positions jurisdictions to meet housing needs while sustaining water reliability under changing climate conditions.

8: Conclusions and Future Directions

This study investigates the extent to which climate change-driven changes in water supply may constrain water demand and, by extension, impact future housing growth in California. By integrating downscaled climate projections, demographic and housing growth scenarios, and estimates of both future water supply and demand, our research provides a comprehensive assessment of whether aggressive efforts to meet regional housing needs can be sustained in the face of mounting drought risk and water scarcity. We focused on three California counties—San Bernardino, San Luis Obispo, and San Diego—representing diverse hydrologic, urban, and policy contexts. Our analysis incorporated multiple housing growth scenarios (baseline, low, and high) and four distinct climate model projections, generating a range of supply and demand estimates for the target years 2035 and 2050.

The principal finding is that, in all case study regions, even under the hottest and driest projected futures, aggregate water supplies appear sufficient to meet projected demand associated with high housing growth through 2050. This outcome is driven in large part by three factors: 1) increasing substitution of single-family homes with multifamily units (which have lower average per capita water use), 2) steady declines in persons per household, and 3) the ongoing adoption of water-conserving technologies and policies. These structural and behavioral shifts act to moderate demand growth, even as population and housing numbers increase. Nevertheless, our work identifies key uncertainties, especially surrounding the reliability of supply during extended droughts and the accuracy of outdoor water use projections, that merit caution and suggest that seemingly ample supplies may not uniformly buffer all localities or sub-sectors against future shortages.

The study's methods and findings have significant implications for a range of audiences. Local and state-level water agencies can use our scenario-based framework to assess the risks and tradeoffs associated with housing growth, informing more integrated water and land use planning. For policymakers, the results validate the importance of aligning housing ambitions with water demand management, supporting policies such as water-neutral development requirements, incentive programs for retrofits, and expanded conservation initiatives. Researchers can extend this work by refining models of housing-water interactions, better incorporating factors like behavioral change, technology adoption, and equity impacts, as well as exploring a broader range of climate scenarios. Our results reinforce the necessity of ongoing monitoring and flexible policy responses: real-time data systems and adaptive management can act as early warning mechanisms, facilitating timely course corrections in the face of emerging shortages.

Looking forward, several critical areas for future research remain. One is determining the point at which housing growth becomes unsustainable given plausible lows for water supply, particularly under chronic or multi-decadal drought. Second, more work is needed to identify the indicators that would signal when water demand is on track to consistently outstrip supply, such as rapid declines in reservoir storage, sharp increases in groundwater overdraft, or failures to meet conservation targets. Ultimately, the challenge is not only technical but governance-related: California's ability to navigate these water-related housing risks will depend on continued investments in integrated planning, regional coordination, and proactive adaptation strategies.

Overall, this research demonstrates that while California's urban future need not be limited solely by water supply under most scenarios, maintaining that equilibrium will require continued vigilance, innovation, and policy commitment. The findings reinforce the need for coordinated water and housing policy, as well as investments in flexible infrastructure and adaptive management, to ensure that housing needs can be met as the climate continues to change.

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