Climate-informed hydrologic modeling and policy typology to guide managed aquifer recharge

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Harvesting floodwaters to recharge depleted groundwater aquifers can simultaneously reduce flood and drought risks and enhance groundwater sustainability. However, deployment of this multibeneficial adaptation option is fundamentally constrained by how much water is available for recharge (WAFR) at present and under future climate change. Here, we develop a climate-informed and policy-relevant framework to quantify WAFR, its uncertainty, and associated policy actions. Despite robust and widespread increases in future projected WAFR in our case study of California (for 56/80% of subbasins in 2070–2099 under RCP4.5/RCP8.5), strong nonlinear interactions between diversion infrastructure and policy uncertainties constrain how much WAFR can be captured. To tap future elevated recharge potential through infrastructure expansion under deep uncertainties, we outline a novel robustness-based policy typology to identify priority areas of investment needs. Our WAFR analysis can inform effective investment decisions to adapt to future climate-fueled drought and flood risk over depleted aquifers, in California and beyond.

INTRODUCTION

Our society is facing unprecedented water security challenges from climate change. Current and future climate change is intensifying the hydrological cycle (1, 2), leading to increased variability of precipitation and runoff (3, 4). The combined effect is more frequent and severe droughts (5, 6) and floods (7, 8), as well as more frequent swings between them (9).

As natural reservoirs, groundwater aquifers store ~90% of our planet’s nonfrozen freshwater (10). This vast subsurface storage provides a crucial buffer against surface water variability (both seasonal and interannual) to ensure reliable water supplies, especially during drought periods. However, more intense and frequent droughts increase demands on regional groundwater aquifers, many of which are already in a state of chronic overdraft (11). At the same time, increases in heavy rain and earlier snowmelt exacerbate the risk of flooding (7, 12), threatening existing surface water infrastructure and further jeopardizing water supply reliability.

The dual threats of heightened drought and flood risk require transformational changes to existing water management practices to simultaneously manage droughts, floods, and depleted groundwater aquifers. In contrast to strategies that mitigate each hazard in isolation, integrated management can mitigate flood risk while conserving floodwater in wet periods to draw upon during future drought episodes. Managed aquifer recharge (MAR) is one innovative way to achieve such integrated water management (13). Its practical implementation involves improving the connections of surface-built infrastructure (e.g., reservoirs and conveyances) and underground infrastructure (e.g., groundwater aquifers and wells) to transfer floodwater across regions and store floodwater across seasons/years. Compared to conventional surface storage options, using floodwater for MAR (Flood-MAR) can be more cost-effective (14), sustainable, and adaptive to keep pace with a changing climate. In addition to augmenting groundwater supply, Flood-MAR can provide other benefits, such as flood risk reduction and ecosystem services enhancement (13, 15, 16). To date, Flood-MAR is a relatively untapped management strategy compared to traditional surface water infrastructure, even though growing evidence has demonstrated the large potential for underground water storage (17, 18).

While Flood-MAR presents a host of potential benefits, there are trade-offs between conflicting objectives (e.g., irrigation and ecological flows) that need to be balanced when planning Flood-MAR programs. Decisions about how much floodwater can or should be directed toward Flood-MAR will need to be made within a larger community dialogue about management goals. Thus, in any particular water-resources context, it is critical to understand how the water available for recharge (WAFR) is likely to vary depending on different policy and infrastructure assumptions and the extent to which these assumptions are subject to climate and other hydrologic uncertainties. Given implications for political and capital investment decisions around Flood-MAR policy and infrastructure, the analytic ability to rapidly and flexibly make such assessments is a crucial first step toward scaling up and normalizing recharge practices. However, how climate change will affect WAFR remains elusive and how much WAFR can be captured remains poorly characterized.

Here, we develop a scalable and climate-informed framework to estimate WAFR with explicit uncertainty quantification, using hybrid physical-statistical model chains (see Materials and Methods and the Supplementary Materials for details). Recognizing the large uncertainties surrounding WAFR estimates and the potential limitations of existing conveyance structures to deliver floodwater to recharge facilities, we also introduce a novel robustness-based policy typology informed by WAFR characteristics to identify the physical feasibility of expanding conveyance infrastructure. To demonstrate the value of this framework for future infrastructure prioritization, we
apply it in California, home to some of the world’s most productive agricultural regions benefiting from its complex, yet stressed, water infrastructure systems. Despite the infrastructure that transports relatively abundant surface water from Northern California to the agriculturally intensive San Joaquin Valley (SJV), many ground-water basins throughout the state are in a chronic state of overdraft. In 2014, the California legislature passed the Sustainable Groundwater Management Act (SGMA), which requires local public agencies to balance groundwater budgets by 2040 or 2042, depending on basin conditions. Passage of SGMA has prompted local groundwater sustainability agencies (GSAs) to actively explore opportunities to capture and recharge floodwater to augment water supply and thereby mitigate the groundwater pumping reductions that might otherwise be necessary to comply with SGMA.

Our study provides the first thorough analysis to quantify the potential of floodwater (defined as high-magnitude-flows) for groundwater recharge over California and its changes in response to a warming climate. We find that future maximum WAFR potential in California will increase overall, but to what extent this maximum potential can be captured is largely constrained by the physical diversion capacity, further complicated by large climate and policy uncertainties. Moreover, a warming climate will likely exacerbate existing regional differences in water availability by elevating WAFR in Northern California and decreasing it in Southern California. Elevated regional differences in WAFR are likely to place increased burdens on California’s already taxed water infrastructure systems. Our generalizable screening approach (i.e., climate-informed hydrological modeling and policy typology) can inform management options and help prioritize the development or enhancement of diversion infrastructure in the face of large uncertainties. While this paper demonstrates its application in California, this framework can be readily transferred to other jurisdictions to support the integrated management of droughts, floods, and depleted groundwater aquifers.

RESULTS

**Historical and future estimates of maximum WAFR**

Historical (1976–2005) maximum WAFR potential (WAFR\text{pot}) is unevenly distributed across California, as evidenced by both observations (Fig. 1A) and model simulations (Fig. 1B). Here, WAFR\text{pot} is defined as the annual maximum volume of water above a specific high-percentile (e.g., 90th) threshold, independent of capacity to divert it for recharge purposes. While the percentile threshold used to define WAFR\text{pot} can vary in time and space (see Discussion), all plausible thresholds show that large volumes of WAFR\text{pot} are distributed in Northern California. The semiarid southern half of California has limited WAFR\text{pot} but greater groundwater depletion and therefore potentially higher needs for harvesting high-magnitude-flows for recharge practices, compared to the WAFR-abundant Northern California.

Increases in future projected WAFR\text{pot} reveal great opportunities for state-wide recharge practices (Fig. 1, C and D), but climate change is likely to exacerbate the uneven north-south distribution of WAFR\text{pot}, especially under a high-emission trajectory (RCP8.5, Fig. 1D). We find that there are widespread (over 56 and 80% of subbasins) and robust (\(P < 0.05\)) increases in WAFR\text{pot} in the far-future period (2070–2099) under the RCP4.5 and RCP8.5 scenarios. The largest robust increases are concentrated over WAFR-abundant Northern California, including the Sacramento River and North Coast hydrologic regions. These findings are in line with previous research (19, 20), which also found substantial and widespread increases in high-magnitude-flow events, especially for basins in the northern and central Sierra Nevada. In contrast, there is almost no increase (and in some cases, even a decrease) in the WAFR-limited dry Southern California (Fig. 1, C and D). This implies that existing disparities in WAFR\text{pot} will likely deepen under climate change, with an emerging pattern of “wet-gets-wetter, dry-gets-drier” in high-magnitude-flow availability (fig. S2). This will pose additional challenges to California’s existing diversion infrastructure and ecosystems if more interbasin north-to-south water transfers are required for Flood-MAR implementation, especially during wet seasons when reservoirs and aqueducts are already at full capacity and therefore may not be able to move future intensified high-magnitude-flows further south. Moreover, future WAFR\text{pot} will be concentrated over a narrower wet season compared to historical periods, as shown by the projected increase in WAFR\text{pot} sharpness (a measure of WAFR seasonality, see fig. S3 and its definition in Materials and Methods), due to increased seasonality of extreme rainfall (9, 21).

Making the most of high-magnitude-flows for recharge could bring a large portion of depleted groundwater aquifers into balance over the SJV, California’s largest agricultural region. On the basis of the median (outlier-robust) response of multimodel ensembles and streamflow observations, our long-term (1976–2005) regional estimates of the water-year (October to September) WAFR\text{pot} are 1.62 and 1.80 km\(^3\)/year, respectively, and are similar to other existing estimates (see detailed comparison in Materials and Methods). If completely captured and recharged with no losses, this could make up 73 and 81% of the historical groundwater depletion [2.22 km\(^3\)/ year over 1988–2017, (22)]. Compared to historical estimates, there is a tendency toward higher median estimates of WAFR\text{pot} in future projections, but these are associated with large interannual variability (Fig. 1E). Therefore, capturing and stabilizing these high-magnitude-flows will likely require concerted management actions, including reservoir reoperations and expansion of existing conveyance infrastructure. We find that increases in future projected WAFR\text{pot} relative to historical estimates are statistically significant (\(P < 0.05\)) for both near-future and far-future periods (see box plots in Fig. 1E). Such increases are more pronounced in the 2070–2099 period (median increase is 0.68/1.38 km\(^3\)/year for RCP4.5/8.5) but are associated with larger model uncertainty with a stronger dependence on the emission trajectory, compared to the near-future horizon (median increase is 0.48/0.58 km\(^3\)/year for RCP4.5/8.5).

**Impacts of diversion capacity and high-magnitude-flow threshold on captured WAFR**

The overall projected increase in WAFR\text{pot} (Fig. 1) highlights the maximum recharge potential from high-magnitude-flows. The extent to which these maximum volumes can be captured (WAFR\text{cap}) at a particular site is limited by several factors, including the diversion capacity of physical infrastructure, legal constraints, and land and recharge basin availability—collectively referred to here as “diversion capacity” for convenience (Fig. 2). Given the nature of the hydrograph, the volumetric constraints of WAFR\text{cap} respond nonlinearly to diversion capacity, as reflected by the captured WAFR share (defined as the ratio of WAFR\text{cap} to WAFR\text{pot}). For example, with a referenced diversion capacity of 150 m\(^3\)/s (equivalent to the design capacity of the Friant-Kern Canal, an aqueduct that delivers water within the southern SJV) (22), the median WAFR share across all...
135 subbasins is 70/58%, and more than 35/44% of California’s subbasins have WAFR share less than 50% during 2070–2099 under RCP4.5/RCP8.5 (Fig. 2, A and B). The share of captured WAFR is likely to further decrease in the future and is associated with increased WAFR seasonality, mainly over the Northern half of California, implying a heightened winter flooding risk (Fig. 2, A and B). Decreasing diversion capacity to 50 m$^3$/s results in a 37 and 45% reduction in the median WAFR share and the percentage of subbasins with WAFR share less than 50% increases to 56 and 66% under RCP4.5 and RCP8.5, respectively (Fig. 2, C and D). This implies that in a warming climate, especially in a high-warming scenario (RCP8.5), an increased fraction of subbasins could miss opportunities to fully tap the elevated potential of WAFR, if existing diversion capacity is not added. However, diversion capacity expansion needs to be carefully assessed, as the marginal gain in captured WAFR decreases rapidly per unit expansion in diversion capacity and is associated with large uncertainties resulting from climate models and scenarios (Fig. 2, C and D).

The choice of high-magnitude-flow threshold, combined with the diversion capacity, further shapes how much WAFR can be captured. Here, we explore the sensitivity of WAFR$^{pot}$ to joint changes of these two factors over the SJV (Fig. 2, E and F). We find that diversion capacity plays a key role in balancing the nonlinear trade-offs in terms of how to allocate high-magnitude-flows to achieve recharge benefits versus other benefits (e.g., ecosystem services). This is reflected in the concave-upward WAFR$^{pot}$ contours, which show that if the allocation of high-magnitude-flows for nonrecharge purposes increases (by setting a high threshold to define WAFR), then diversion capacity will need to be expanded to achieve the same potential recharge volume. There even exists a distinct knee in the curve, beyond which the marginal value of expanding diversion capacity is close to zero. For example, under the target of capturing...
Fig. 2. Multiscale assessment of how captured WAFR (WAFR\textsuperscript{cap}) is constrained by diversion capacity and high-magnitude-flow threshold in the far future (2070–2099). (A and B) Maps showing the state-wide estimates of annual WAFR\textsuperscript{cap} volume (waterdrop size) and the share of captured WAFR\textsuperscript{cap} (colorbar) at subbasin level under RCP4.5 (A) and RCP8.5 (B) scenarios with a referenced diversion capacity of 150 m\textsuperscript{3}/s (design capacity of Friant-Kern Canal) and a constant 90% high-magnitude-flow threshold. (C and D) Median (thick lines) and model spread of WAFR\textsuperscript{cap} climatology in SJV conditional on different diversion capacities under RCP4.5 (C, blue color) and RCP8.5 (D, orange color) scenarios compared to historical (gray color) conditions. Thin lines represent each individual model. High-magnitude-flow threshold is defined at the 90% level. (E and F) Bivariate heatmaps showing how WAFR\textsuperscript{cap} volume and WAFR share in SJV covary with different combinations of high-magnitude-flow threshold (x axis) and diversion capacity (y axis). Contour lines with gray and red colors represent a constant volume (\(\approx 0.5\) km\textsuperscript{3}) of captured WAFR\textsuperscript{cap} estimated from streamflow gauges and global climate models (GCMs), respectively. The thick lines show multimodel ensemble median and thin lines represent each individual model. Red dashed lines show current estimates of groundwater depletion over the San Joaquin River Basin and Tulare River Basin. Blue contours represent WAFR share. Horizontal dashed lines are referenced diversion capacity, equal to the design capacity of Friant-Kern Canal. Note: Here we use a state-wide constant diversion capacity in (A) and (B) mainly for purposes of illustrating the problem. USGS, United States Geological Survey.
0.5 km$^3$ of high-magnitude-flows, when the threshold passes 98%, diversion capacity needs to increase substantially. This is likely due to the increased frequency and intensity of extreme rainfall (23, 24), which translates to more flashy streamflow conditions, as evidenced by the widened space between the 25 and 50% contours of WAFR share under the RCP8.5 scenario (Fig. 2F) compared to the RCP4.5 scenario (Fig. 2E).

We find that about a quarter of projected WAFR$^\text{pot}$ over SJV can be captured in the far future with a diversion capacity equal to the design capacity of the Friant-Kern Canal (=150 m$^3$/s). Albeit a small WAFR share, the absolute volume of captured high-magnitude-flows is probably enough to replenish groundwater aquifers over the San Joaquin River Basin with its historical annual groundwater deficit of 0.2 km$^3$ (WAFR$^\text{cap}$ contours are above groundwater overdraft contours, see Fig. 2, E and F). However, even with its original capacity, the captured high-magnitude-flows are still not enough to offset the groundwater overdraft for Tulare River hydrologic region (long-term annual groundwater deficit is 1.96 km$^3$). Purely relying on WAFR$^\text{cap}$ to bring Tulare’s groundwater into balance will require a total diversion capacity larger than 800 m$^3$/s, even under a higher WAFR potential future (i.e., RCP8.5) with a low-threshold setting (Fig. 2F).

This reinforces the need for pairing physical infrastructure with nonphysical measures (e.g., reservoir reoperation) to jointly manage the increased WAFR potential.

**WAFR-informed policy typology to guide future infrastructure investment**

To determine policy implications for infrastructure investment, we further partition uncertainties in WAFR$^\text{cap}$ to different sources. We find that dominant uncertainties are from climate models (fig. S5A), followed by greenhouse gas emission scenarios (fig. S5B). Together, model and scenario uncertainties account for more than half of the total variation in WAFR$^\text{cap}$ over the majority of subbasins. In addition, large disparities in WAFR projections could also come from internal variability and its irreducible uncertainty, which is another type of climate uncertainty that could be similar or even larger than intermodel variability (25) and deserves further exploration. These findings highlight the need to take climate uncertainties into account in risk management practices and adaptation strategies (26). Although climate uncertainties are dominant, there are also considerable uncertainties from nonclimatic factors, including the choice of high-magnitude-flow thresholds (fig. S5C) and the constraints of diversion capacity (fig. S5D). This highlights the important role of infrastructure provision as a key adaptation strategy to buffer future uncertain climate locally and the potential to partially bridge the north-south geographic mismatch of WAFR, evidenced by California’s historical development of state-wide water transfer projects. The importance of expanding diversion capacity to capture high-magnitude-flows is further supported by a recent recharge survey in California (22). It shows that local stakeholders (e.g., GSAs) are highly concerned about infrastructure capacity issues (e.g., system conveyance and district basin capacity), but funding these gray infrastructure might be difficult due to the potential large environmental impacts.

To inform adaptation strategies on the appropriate levels of infrastructure investment, we outline a screening-level policy typology informed by key WAFR-related metrics (Fig. 3 and Table 1; see Materials and Methods and figs. S6 to S7 for details). We first consider the initial potential of robust expansion of diversion capacity ($C_R$) regardless of how uncertainties in WAFR$^\text{cap}$ will evolve in future. Here, $C_R$ is the minimum diversion capacity one region may consider expanding to, while remaining confident that the gains of expanding diversion capacity (i.e., marginal increase in WAFR$^\text{cap}$, δWAFR$^\text{cap}$) will exceed a threshold level of benefit [a generalized conception of diversion capacity marginal cost (MC), horizontal dashed lines in Fig. 3A]. $C_R$ is a conservative measure of WAFR potential and therefore can be used for the immediate recommendation; in other words, how much infrastructure investment can be considered regardless of the realization of future uncertainties. Our framework also explicitly incorporates uncertainty quantification beyond $C_R$, acknowledging the important role of WAFR$^\text{cap}$ uncertainties in investment strategies. We partition total uncertainties into two general categories, climate and policy (i.e., nonclimatic factors such as the choice of high-magnitude-flow threshold) uncertainties, which are proxies for the broader concepts of whether the uncertainty is

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**Fig. 3. WAFR informed policy framework to guide future infrastructure investment.** (A) Schematic illustration of the conceptual framework for developing policy typologies informed by three WAFR-derived metrics $C_L$, $C_E$, and $C_C$ (see Materials and Methods for details). $C_L$ represents the robust potential of expanding diversion infrastructure before running into the uncertainty band. $C_L$ shows how different high-magnitude-flow threshold policies could influence the marginal increase in captured WAFR (δWAFR$^\text{cap}$, y axis). Here, $C_L$ is used as a proxy measure of policy uncertainty which is reducible in near term. $C_E$ is similar to $C_L$, but it shows how different climate models and different emission scenarios could influence WAFR$^\text{cap}$, considering the choice of high-magnitude-flow thresholds. $C_C$ shows how different climate models and different emission scenarios could influence WAFR$^\text{cap}$, considering the choice of high-magnitude-flow thresholds. Detailed description of types 1 to 5 can be found in Table 1. (B) Priority of future (2070–2099) investments in diversion infrastructure based on the policy typology in (A) and Table 1. Example subbasins are highlighted.
resolvable in the near term (e.g., policy questions that are yet to be settled) or not [as is the case for climate, (27)]. We further estimate the expected average increase in robust expansion (Cp) if policy uncertainty is reduced (still conditional on climate uncertainty), as well as the range of further expansion (Cp) subject to learning about currently irreducible long-term climate uncertainties. To provide an initial guide to high-level prioritization, we then cluster all subbasins in California into five typologies mapped to different investment priorities informed by these three key metrics (Fig. 3A).

We find that most of subbasins (67 of 135) in California have limited near-term opportunities to invest in diversion infrastructure, due to the low potential of initial robust expansion (Cp) (Fig. 3B). These subbasins land on the low-priority space within the typology (type 5). They are mostly located in the Southeast part of California, where WAFR is limited by the dry climate (e.g., Mojave subbasin, fig. S7A). Note that there could be some watersheds within this type where near-term resolution of policy uncertainty could still yield some expansion potential, but this can be assessed in a more focused regional planning effort. We envisage that nonphysical interventions (e.g., demand management and market-based policy instruments such as water trading and banking) and alternative water sources beyond surface floodwater (e.g., treated wastewater in urban areas, reclaimed water produced from oil extraction, and desalinated brackish groundwater) could be considered over these areas to facilitate groundwater recharge.

High investment priorities for capacity expansion are identified for nine subbasins in California. These regions have high CR and the likely ranges of further expansion beyond CR due to uncertain policy (Cp) and climate (Cp) are both low (belong to type 1, see example in fig. S7B). Capacity expansion is therefore worth including in the management portfolio with an initial investment and is better paired with long-term contingent plans. Traditional cost-benefit analysis combined with multiobjective, multitarget sequential optimization techniques could be implemented to determine the size, sequence, and location of these proposed diversion infrastructure but needs to factor in the nonmonetary costs of infrastructure (e.g., environmental impacts).

Climate uncertainties play a dominant role in infrastructure investment for subbasins assigned the medium high priority (type 2). Over these regions (such as Upper Merced, fig. S7C), capacity expansion beyond the initial range (Cp) is primarily sensitive to projected climate conditions but negligibly sensitive to policies (e.g., high-magnitude-flow-threshold). As large climate uncertainties are both epistemic and aleatory (27), they are usually not easily reducible in the near term. For subbasins with medium investment priority (type 3), capacity expansion decisions are primarily sensitive to uncertain policies, not to future projected climate conditions (e.g., Big-Navarro-Garcia; fig. S7D). As policy uncertainties are potentially reducible in the near term, the value of resolving those uncertainties can be high, suggesting that decision-makers could at least “wait-and-see,” or better yet, work to accelerate resolution of those uncertainties via information gathering efforts or engagement on the relevant policy fronts. More than one-third (53/135) of subbasins in California have medium-low priority (type 4, such as Upper King, fig. S7E) for infrastructure provision due to both high policy and climate uncertainties. Investment decisions need to be carefully assessed at the beginning of the decision-making process before construction actions take place and need to be regularly adjusted at a later stage.

### DISCUSSION

MAR has been proposed to tackle groundwater overdraft in California and elsewhere in the world, but only a handful of studies (22–28–30) have focused on WAFR, a key constraint on the implementation and scale-up of MAR practices. Moreover, existing WAFR studies only focus on historical periods and therefore are not adequate to facilitate long-term, forward-looking climate adaptation strategies. To fill this research gap, we develop and implement a scalable and policy-relevant modeling workflow to quantify the changing characteristics of WAFR under climate change.

Our future projections of WAFR provide clear evidence that increases in high-magnitude-flows are highly likely under climate change in California (Fig. 1), as supported by previous studies reporting substantial and robust increases in projected extreme precipitation (23, 31) and streamflow (16, 19, 20). Earlier snowmelt and larger increases in rain–on–snow events also contribute to more extreme streamflow (32), implying higher WAFR under climate change. However, increases in high-magnitude-flows under climate change are anticipated to be more concentrated in a narrower window of the wet season (fig. S3). This could be due to increased seasonality of extreme precipitation (9, 21) and increased rain–on–snow events in a warming climate (32), leading to more rainfall–driven and rain–on–snow–driven floods in the winter season (32).

| Table 1. WAFR informed policy typology for infrastructure provision. |
|---------------------------------------------------------------|
| **Typology type (number of subbasins)** | 1 (n = 9) | 2 (n = 2) | 3 (n = 4) | 4 (n = 53) | 5 (n = 67) |
| Investment priority | High | Medium high | Medium | Medium low | Low |
| Robust expansion (Cp) | High | High | High | High | Low |
| Policy uncertainty (Cp) | Low | Low | High | High | Low–High |
| Climate uncertainty (Cp) | Low | High | Low | High | Low–High |
| Policy actions | Recommend first or immediate actions, but paired with contingent plans | Incremental implementation with adaptive plans and modular designs | Understand and resolve near-term policy uncertainty first | Need transformational changes in management practices | Consider alternative ways beyond physical infrastructure investment |
| Example basins (see Fig. 3B and fig. S7) | Lake Tahoe | Upper Merced | Big-Navarro-Garcia | Upper King | Mojave |
The changing timing and magnitude of these floodwaters may place additional burdens on California’s existing and aging water infrastructure, requiring long-term reoperation and adaptation of these systems. These trends are likely to be exacerbated by the spatial disparities observed in future WAFR projections (Fig. 1, C and D), indicating that a warming climate will produce additional north-south disparities in high-magnitude-flow availability. The geographic mismatch between high-magnitude-flow availability and groundwater overdraft reveals a profound challenge for recharge practices, in terms of how to move high-magnitude-flows from where they are available (Northern California) to where they are most needed (southern half of California). This spatial mismatch will also increase the challenges of simultaneously alleviating flood and drought risks within regions. Northern California is likely to face an increased risk of flooding, which can cause larger damages, compounded by the accelerated deterioration of existing infrastructure; while there will be less WAFR over the southern half of California. Challenges are particularly acute over the agriculturally intensive SJV, which has more than half (11 of 21) of the state’s critically overdrafted groundwater basins and will require the largest reductions of groundwater pumping to meet the sustainability requirements under SGMA. Previous studies estimate that without additional surface water supplies, SJV farmers may permanently retire on the order of 90,000 hectares and temporarily fallow even greater amounts (33), with some estimates suggesting fallowing of up to one-fifth of the total farmland in the Valley, resulting in an estimated 42,000 direct job losses and $7.2 billion annual farm revenue loss (34). Such potential consequences due to SGMA requirements reinforce the need to explore opportunities to harvest floodwater as an alternative to augment water supply to lessen the simultaneous impact of climate change and SGMA.

Besides assessing the long-term response of WAFR to changes in the climate system, our study conducts the first uncertainty attribution analysis for floodwater-related recharge potential by partitioning WAFR uncertainties to different sources. Such uncertainty analysis could aid regional water managers and local GSAs to understand the dominant sources of uncertainty and thus develop targeted programs or analyses to minimize them. A specific focus is the inadequacy of diversion infrastructure to capture floodwater on-site and conveyance infrastructure to deliver captured floodwater to recharge facilities, which is also an important concern of local GSAs (22). Given aging infrastructure in California, conveyance infrastructure may need to be rebuilt or expanded to accommodate increased WAFR potential to scale up recharge practices. Intertwined with diversion capacity, policies that set high-magnitude-flow thresholds add another layer of uncertainty and complexity. These thresholds could be time- and context-dependent and involve complex floodwater allocation trade-offs between recharge and nonrecharge (e.g., ecological flow) purposes. Moreover, the range of high-magnitude-flow thresholds reflects the degree of flexibility of allocating floodwater among different purposes. With a high and strict threshold, and assuming not much infrastructure expansion, there is only a limited amount of floodwater that can be captured. This will require more substantial and immediate reduction of groundwater pumping to meet SGMA requirements and such actions could be very costly (34). To balance the trade-offs among multiple conflicting goals, diversion capacity may need to be expanded at an appropriate level.

To facilitate infrastructure planning to realize the potential benefits of expanding diversion and conveyance infrastructure, we develop a policy typology to identify priorities for future investment needs. Our typology framework explicitly incorporates and classifies uncertainties with a focus on their nature (i.e., whether reducible or deep) and source (i.e., whether climate induced or policy driven). At the subbasin scale, local managers can use this analytical framework (Fig. S6) to quantify the range of potential capacity expansion through estimates of $C_p$, $C_b$, and $C_C$, which are key metrics to develop tailored investment policies to adapt to future changing WAFR. Application of this conceptual typology (Fig. 3A) to a regional scale (Fig. 3B) allows regional planners to have a full picture of where to invest in floodwater capture infrastructure and with what degree of priority, although they will likely benefit from local parameterization of marginal capture and benefit parameters.

Policy actions and investment priorities are well defined for subbasins landing on the two ends of the typology spectrum (types 1 and 5). However, it is challenging to develop specific policies for subbasins falling between these two end members (types 2 to 4) because of large climate and/or policy uncertainties or both. Therefore, more effort and resources will need to be devoted to developing tailored solutions. Additional monitoring and exploratory modeling efforts could be useful to better quantify uncertainty and the value of its possible reduction (35), which could be achieved through improved physical understanding of climate processes, using weighted model ensembles or removing poorly performed models, and assimilating new information (e.g., local observations and empirical knowledge) in existing modeling platforms. We suggest that instead of building rigid infrastructure through immediate actions, subbasins in typology classes 2 to 4 should design agile, flexible, and adaptable infrastructure guided by planning approaches for deep uncertainty, including Robust Decision-Making (36, 37), Decision Scaling (38, 39), or hybrid frameworks combining adaptive management and optimization, such as Dynamic Adaptive Policy Pathways (40, 41) or Engineering Options Analysis (42). In particular, subbasins suffering from deep climate uncertainties (types 2 and 4) could consider building out a certain amount of capacity at the beginning, and building more as climate behavior is realized. For large-scale infrastructure, it is safe to consider modular capacity expansion. For small and localized projects, they can be paired with green infrastructure and other types of recharge approaches, such as designing multiple recharge basins in a series with different recharge priority and frequency to facilitate flexible and adaptive capacity to manage WAFR increases. As for subbasins only sensitive to near-term reducible uncertainties (type 3), efforts and resources should be expended to proactively resolve these uncertainties first. Dynamic planning approaches with a focus on stochastic learning [e.g., (43)] to assimilate new knowledge are good options to reduce such policy-related uncertainties. Besides modeling efforts, state and local agencies can set practical guidelines and prepare manuals to clarify the definition of WAFR (e.g., the choice of high-magnitude-flow thresholds) as a means to reduce uncertainties.

The spatial snapshot of typology (Fig. 3B) provides indicative results with coverage across the state but should not be overstretched to imply highly local-level (GSA) priorities. Rather, it is most helpful taken as an illustration of classification and prioritization that can be reexamined at a regional planning level with locally relevant parameters. In applying such a prioritization for policy purposes, several dependencies should be noted. First, our clustering algorithm to classify subbasins into different typologies is presented under the assumption that each subbasin has the same threshold level...
of benefit. While locally varying and adjustable thresholds would be more realistic to be included within the algorithm, their estimation was beyond the scope of this study. Nevertheless, results are similar as we vary the threshold (fig. S8). Moreover, the relative importance of climate and policy uncertainty for decision-making is scale dependent. At the regional scale, it may be reasonable to assign equal weights to climate and policy uncertainty for typology clustering. With improved knowledge of local infrastructure conditions, weights of policy and climate uncertainties may need to be adjusted on the basis of their relative importance. For a certain subbasin, this could potentially change the priority class from one type to another. In other words, the current static typology map (as shown Fig. 3B) serves as a long-term outlook and additional dynamics could be included. Nevertheless, the recommended policy actions (Table 1) for a particular typology will stay the same. Regional managers may need to periodically revisit the priority class.

It should also be noted that our current priority assessment is only based on the physical availability of floodwater, while socio-technological, financial, and environmental feasibility, in reality, may play equally or more important roles in the investment decisions. In particular, the current policy typology does not take into account variations in the local governance context (44). California has decentralized and fragmented groundwater governance, whose jurisdictional boundaries (e.g., GSA) in many cases do not overlap with the geographical boundaries of our policy typology (i.e., hydrologic unit at the sub-basin level). Recent studies find that 80% of the land area subject to management requirements under SGMA are managed by multiple management entities (45), with as many as 24 management entities within a single groundwater basin (46). In addition to the standard contestation of objectives and priorities among different agencies and stakeholders, such degree of fragmentation may create specific challenges for decisions on cross-basin infrastructure investments, which require high levels of coordination and collaboration. Policymakers should not use the proposed typology as a prescriptive plan for practical guidance, but rather as a tool to catalyze or stimulate endeavors across various stakeholders toward sustainable and adaptive investment. Given the above governance issues, it may also be worth extending the typology to account for variations in governance context.

There is increasing recognition that climate change will place additional burdens on water systems around the globe. Heightened drought and flood risk are likely to tax aging infrastructure and require policy-makers and water managers to think creatively about mitigating these risks while protecting the environment and minimizing costs. Recharging floodwater to overdrafted groundwater aquifers presents a significant opportunity to mitigate these risks. However, doing this requires water managers to develop a proactive vision of managing the drought-flood nexus simultaneously. Although there is an increasing trend (5%/year) of MAR implementation at the global scale, this is recharging only ~1% of global groundwater extraction (13), far from being adequate to bring depleted groundwater aquifers into sustainable use. The untapped MAR potential demonstrated for our California case study could be a proof of concept that helps translate MAR from local aspiration to global practice, supported by the growing evidence of increased likelihood of heightened peak flows elsewhere in the world (4, 7, 47). However, the potential to generalize the framework to other areas needs to consider regional differences in hydroclimatic conditions (e.g., precipitation and streamflow generation mechanisms), water management policies (e.g., environmental flow requirements versus recharge needs), as well as data availability and quality for reliable WAFR estimates. Beyond California, other stressed aquifers, such as the U.S. High Plains and the North China Plains aquifers, also benefit from high-resolution climate projections and long-term historical observations and therefore could rapidly deploy this framework to develop similar policy typologies. However, this could be challenging over aquifers with limited data, such as in Africa, where additional downsampling and bias correction of climate projections may be needed as well. Such uncertainties associated with downsampling may be dominant over smaller geographies (e.g., local subwatershed level) compared to climate and policy uncertainties and therefore may need to be incorporated into current typology. With increased dimensions of uncertainty, and to better account for their relative importance, machine learning-based algorithms could be used to aid a more automatic typology classification.

In addition to challenges on the large-scale uncertainties of WAFR, there are other recharge-related concerns that will need to be considered. While our study focuses primarily on active recharge, recharge happening naturally also contributes to groundwater recovery. This includes mountain system recharge, diffuse recharge, focused recharge, and recharge from irrigation (48). In California, there is high confidence that projected mountain system recharge will decline in a warming climate due to the loss of the winter snowpack (49) and shifts from snow to rain (32), which increases the likelihood of surface runoff rather than percolation. Diffuse and focused recharge may decrease in Southern California due to combined effects of decreasing precipitation and increasing temperature, but their changing directions are not clear in Northern California, given that extreme precipitation will largely increase in future climates (9, 21, 23, 31). It is also challenging to quantify projected changes in irrigation recharge (48). On one hand, warmer temperatures will lead to increased irrigation water demand, which can potentially increase irrigation return flow and therefore percolation (50). Alternatively, they may result in similar or declining recharge rates as evapotranspiration rates increase. On the other hand, adaptation strategies such as increased irrigation efficiency and changing crop practices could potentially reduce irrigation. Robustly quantifying these natural recharge fluxes in addition to our projected estimates of managed recharge water availability is therefore necessary to provide a more comprehensive picture of the magnitude and timing of the total recharge potential. This requires more detailed physically based hydrological modeling to better understand how projected changes in precipitation and temperature may propagate through the above recharge mechanisms and how they interact with various types of human interventions. Other nonclimatic factors also need to be factored in before undertaking local or regional-scale recharge efforts, including land use planning and zoning requirements, land acquisition and permitting, evaporation loss from open surfaces, crop recharge suitability [for on-farm recharge, (51)], and potential impacts to water quality (52). Moreover, the ability to recover the charged water for use in later periods requires better regulatory policies on water rights and permits. More holistic assessment considering hydrologic, hydrogeologic, regulatory, social, and institutional constraints is needed. Future work also needs to explore how to incorporate WAFR information to facilitate a more integrated strategy of pairing Flood-MAR with other diversified portfolios (e.g., demand side management and reservoir reoperation) across different scales. Nevertheless, our climate-informed WAFR database and the stylized
typology are key first steps toward facilitating the transition of our water management to a more resilient and adaptive future under a changing climate.

**MATERIALS AND METHODS**

**Overall framework for WAFR estimates**

We develop a hybrid physical-statistical model workflow to quantify WAFR under a warming climate (see fig. S1). The hybrid approach enables us to use a large number of scenarios to directly and systematically assess multiscale WAFR characteristics and associated uncertainties without the computational burden of using physics-based water system models. Avoiding such computational burden allows us to develop a screening-level tool that is readily scalable and can provide insights into regions that would benefit from existing hydrological data. Our workflow starts with a large-scale hydrodynamic model to route gridded runoff to generate state-wide estimates of unimpaired streamflow (UIF) in California at the subbasin level. We then implement a quantile mapping–based statistical algorithm to translate UIF to impaired flow (IF) to account for human activities over affected subbasins. WAFR characteristics are then assessed by using a threshold-based approach on the basis of high-magnitude-flow quantiles. Detailed procedures of these steps are provided below.

**High-resolution simulation of runoff and unimpaired flow**

**Runoff**

Historical (1950–2005) and projected (2006–2100) runoff is obtained from the Cal-Adapt database. Daily gridded runoff is simulated from Variable Infiltration Capacity (VIC) land surface model (53) at high-spatial resolution (1/16°, ~6 km), driven by bias-corrected and downscaled daily climate forcings from nine global climate models (GCMs; see model details in table S1) under two Representative Concentration Pathway (RCP) greenhouse gas scenarios (i.e., RCP4.5, medium emissions; RCP8.5, high emissions). These nine climate models are selected on the basis of the suggestion from California’s Climate Action Team Research Working Group according to their performance in simulating California's historical climate conditions (54).

**Unimpaired flow (UIF)**

We use a large-scale physics-based hydrodynamic model called CaMa-Flood [Catchment-based Macro-scale Floodplain, (55)] to convert daily gridded runoff to daily UIF from 1950 to 2100 at the 1/16° resolution. Compared to the default routing scheme used in VIC, CaMa-Flood can better capture the magnitude and variability in flood peaks due to its explicit representation of flood stage, more realistic representation of hydrodynamic processes (e.g., bifurcation channels and backwater effects), as well as improved river network discretization derived from high-resolution hydrography data, yet still remain computationally efficient (55).

**Subbasin classification**

Our state-wide WAFR analysis is performed at the HUC8 (8-digit Hydrologic Unit Code) level with a total number of 135 subbasins. The outlet of each subbasin is identified by intersecting the reach-level river flowlines (56) with HUC8 boundaries. As the point location of the outlet may not be located exactly in the river network (1/16°) of CaMa-Flood, we correct the outlet location (latitude and longitude) by searching the surrounding four pixels to find the closest drainage area compared to that from (56). Within each HUC8, we further search whether there exists a downstream gauge with long-term (at least 30 years) daily streamflow records covering the period 1976–2005 and is also close enough to the outlet. Of the 2380 gauges in California, 44 gauges meet these criteria (fig. S9). Subbasins with/without qualified gauges are treated as gauged/ungauged subbasins. Over gauged subbasins, to use streamflow observations to translate UIF to IF (see the next section), we do not use the simulated UIF at the outlet. Instead, we extract simulated UIF from the pixel where the streamflow gauge is located and then scale UIF based on the differences in drainage area between gauge and HUC8. It should be noted that some of the HUC8 in California are not natural basins and there are cases where multiple rivers in the upstream HUC8 flow into the same downstream HUC8. For these cases, we consider the upstream-downstream typology of river network to differenced out the upstream WAFR volume to avoid the double counting in the downstream WAFR estimates.

**Translating UIF to IF**

As the land surface model (VIC) and routing model (CaMa-Flood) do not adequately consider human activities (e.g., reservoir operation and irrigation), it is necessary to further translate UIF to IF to get realistic WAFR estimates. There are two main goals of translating UIF to IF, particularly as they apply to future projections for this analysis. First, because we are interested in WAFR from high-magnitude-flow events, it is important to preserve streamflow variability at a daily time scale. Second, it is important to capture the monthly-to-decadal response to climate change. The first is important for considering the implications of diversion capacity, while the second is critical for seasonal and long-term adaptation planning. To address these challenges, we use an improved quantile mapping–based algorithm called PresRat (57) to statistically add impairment to UIF over gauged subbasins (see fig. S1A for illustration). This algorithm is implemented over three consecutive 30-year periods (i.e., 2010–2039, 2040–2069, and 2070–2099). Choice of this 30-year segment is based on the following two considerations. On the one hand, a 30-year period is short enough to assume that the statistical characteristics of streamflow will not experience marked changes, and therefore, a stationarity assumption is reasonable. On the other hand, 30 years is also long enough that we can assure a reasonable estimate of streamflow climatology while also considering climate variability. To avoid discontinuities of bias corrections at the edges of the time windows, we implement this algorithm iteratively on a single day-of-year basis using data points pooled from a surrounding 31-day moving window (i.e., monthly, see section S1 for robustness checks on the choice of the moving window). The adjusted IF is further scaled by a correction factor \( K = \langle R^{\text{GCM}} \rangle / \langle R^{\text{IF}} \rangle \) to preserve the original model-predicted mean changes in streamflow, where \( R \) indicates the change (expressed as a ratio) in mean streamflow averaged over all days in the moving window. We find that PresRat can reasonably reproduce the magnitude and variability of observed daily IF over the historical period (1976–2005) [see the significant increase in the Kling-Gupta efficiency (58) after impairment adjustment for an example river basin, fig. S10].

**WAFR definition and characteristics**

We recognize that there are multiple sources of water (e.g., surface water, recycled, and conserved water) that physically could be available for groundwater recharge. Here, we want to emphasize that our study only focuses on surface water, especially those high-magnitude-flows. We use a threshold-based approach to estimate high-magnitude-flows...
(see fig. S1B) (22, 28, 30). Here, the high-magnitude-flow threshold is selected as the pth (p = 90, …, 99) percentile daily 1F/UIF over the historical period (1976–2005) for gauged/ungauged HUC8. We assume that high-magnitude-flows above this threshold will not compete with water rights and environmental flow requirements, a reasonable simplification of practices and is also widely implemented in environmental flow communities [e.g., (59)]. Without conveyance or policy constraints, the total volume (red area above the red dashed line in fig. S1B) of these high-magnitude-flows represents the maximum potential of WAFR (WAFR\textsuperscript{pot}). We also estimate how much WAFR volume can be captured on-site (defined as captured WAFR, WAFR\textsuperscript{cap}) and catchment area between green dashed and red dashed lines in fig. S1B) conditional on the diversion capacity, C (green dashed line). We measure the share of captured WAFR through the ratio of WAFR\textsuperscript{cap} to WAFR\textsuperscript{pot}. To quantify WAFR seasonality, we calculate a metric called wet-season WAFR sharpness, similar to a precipitation-based index used in previous studies [e.g., (21)]. The WAFR sharpness is defined as the winter (December–January–February) WAFR minus the WAFR averaged in fall (October–November) and spring (March–April) seasons. Changes of this WAFR sharpness in future projections relative to the historical period can be used to quantify the relative shift in WAFR seasonality.

Validation of model derived WAFR\textsuperscript{pot} (with p = 90) against gauge-based estimates can be found in Fig. 1A. We find that 87 and 64% of gauged HUC8 have biases within ±15 and ±10%, respectively, demonstrating that our hybrid workflow can well reproduce the climatology of observed WAFR\textsuperscript{pot} in the historical period. However, the performance over ungauged HUC8 is hard to assess directly due to lack of streamflow observations. Alternatively, we examine the relationship between percentage errors in WAFR\textsuperscript{pot} and the degree of regulation [DOR, a proxy of impairment obtained from (60)] over gauged HUC8 (fig. S11). We find that percentage errors tend to be smaller over gauged HUC8 with smaller DOR (DOR <15). We therefore expect that percentage errors over ungauged HUC8 will also be small given that the majority of them (66%) have relatively low DOR. Besides the state-wide validation, we also compare our WAFR estimates against other existing studies at the regional scale focusing on the entire SJV. Our multimodel ensemble median estimate of the long-term (1976–2005) annual WAFR\textsuperscript{pot} volume in the SJV is 1.62 km\textsuperscript{3}/year, which is slightly higher than the estimate based on (28) (1.60 km\textsuperscript{3}/year over 1989–2014), (22) (1.48 km\textsuperscript{3}/year over 1986–2015), and (29) (1.51 km\textsuperscript{3}/year over 1935–2015, unadjusted maximum value).

Climate-informed WAFR typology to guide infrastructure investment

Robustness-based estimation of diversion capacity expansion under uncertainty

We use marginal analysis to determine the appropriate level of infrastructure investment (measured by diversion capacity, C) by weighing marginal benefit (MB) against MC of expanding conveyance. Monetary values (e.g., net present values) of MB and MC would be ideal to perform such analyses. However, given the difficulty and large uncertainties of quantifying economic values of WAFR, here, we assume that MB can be approximated by the physical gains in WAFR\textsuperscript{cap} (y axis in Fig. 3A), defined as the marginal increase in captured WAFR [δWAFR\textsuperscript{cap} (km\textsuperscript{3} m\textsuperscript{-2} s\textsuperscript{-1})] per unit (m\textsuperscript{3}/s) expansion of C. Because of the difficulty in reliably estimating infrastructure costs, we define a threshold level of benefit (denoted as α, horizontal dashed lines in fig. 3A) as a generalized conception of MC related to C. The optimal diversion capacity C* is reached when δWAFR\textsuperscript{cap} is equal to α. Given that there could be considerable uncertainties associated with C* due to the ubiquitous system uncertainties from climate and high-magnitude-flow threshold, we derive the following three metrics to explicitly factor in these uncertainties: (i) C\textsubscript{R}, the initial robust potential of expanding diversion infrastructure, i.e., the diversion capacity above which MBs are expected to achieve MCs regardless of how uncertainties are ultimately manifested; (ii) C\textsubscript{P}, expected increase in C beyond C\textsubscript{R} due to policy uncertainty (i.e., the average amount of diversion capacity that would be added after resolving policy uncertainties); (iii) C\textsubscript{C}, expected increase in C beyond C\textsubscript{R} + C\textsubscript{P} due to climate uncertainty. Estimation of C\textsubscript{R}, C\textsubscript{P}, and C\textsubscript{C} involves the following three steps (see fig. S6 for illustration):

- Step 1 (fig. S6A): Select a high-magnitude-flow threshold i (e.g., i = 99%). Use a power-law function to fit the nonlinear relationship between δWAFR\textsuperscript{cap} and C under all plausible future climate scenarios (j = 1 to 18, combinations of 9 GCMs and 2 RCPs). Apply quantile regression to get outlier-robust estimates of C* at the lower and upper 25th percentile (C\textsubscript{25th}, C\textsubscript{75th}). Here, we assume that C\textsubscript{25th}/C\textsubscript{75th} are the minimum/maximum diversion capacities that planners would consider without/with the influence of climate uncertainties; ΔC\textsuperscript{ï} = C\textsubscript{75th} − C\textsubscript{25th} represents the uncertainty bound of diversion capacity expansion due to the presence of climate uncertainties.

- Step 2 (fig. S6, A to C): Repeat step 1 to calculate C\textsubscript{25th} and ΔC\textsuperscript{ï} for all high-magnitude-flow thresholds (i = 90, …, 99%).

- Step 3 (fig. S6D): Calculate C\textsubscript{R}, C\textsubscript{P}, and C\textsubscript{C}. Here, C\textsubscript{R} can be calculated as the minimum value of {C\textsubscript{25th}, i = 90, …, 99 %} as this is the robust level of diversion capacity expansion regardless of any uncertainties from climate and high-magnitude-flow threshold. C\textsubscript{P} is the expected increase in additional diversion capacity beyond C\textsubscript{R} if there is no uncertainty surrounding high-magnitude-flow threshold. In other words, C\textsubscript{P} reflects the additional capacity one would be willing to invest if uncertain high-magnitude-flow thresholds turn out to be “true.” Therefore, we calculate C\textsubscript{P} as the averaged value of {C\textsubscript{25th}, i = 90, …, 99 %}. Further expansion of diversion capacity subject to long-term climate uncertainties (C\textsubscript{C}) beyond C\textsubscript{R} + C\textsubscript{P} can be calculated in a similar way as C\textsubscript{P}, based on the averaged value of {ΔC\textsuperscript{ï}, i = 90, …, 99 %}.

Clustering algorithms to develop WAFR typology

Our WAFR typology (Fig. 3A) is a high-level categorization of investment priorities and is classified on the basis of C\textsubscript{R}, C\textsubscript{P}, and C\textsubscript{C}. A key parameter to estimate these three metrics is the threshold level of benefit, α. Here, we apply a uniform value of α for all subbasins, assuming that MC of expanding conveyance is similar across regions. This assumption may be reasonable for regional planning purposes and could be further developed in subsequent local-level analyses. As it is infeasible to estimate the baseline α for all HUC8 without context-specific information, the 25th percentile of the maximum δWAFR\textsuperscript{cap} across all subbasins is used as a conservative estimate (see section S1 and fig. S8 for a sensitivity analysis on α). After α is defined, C\textsubscript{R}, C\textsubscript{P}, and C\textsubscript{C} could be sensitive to the choice of α and are also region dependent (e.g., large versus small and dry versus wet). To reduce such impacts, as well as to enable comparison across regions, we standardize C\textsubscript{R}, C\textsubscript{P}, and C\textsubscript{C} using outlier-robust transformations by removing the median and scaling the data based on the interquartile...
range (i.e., the difference between 75th and 25th percentiles). Centering and scaling are performed independently for $C_{p1}$, $C_{p2}$, $C_{s}$. Such standardization allows us to further classify these three features of each HUC8 into "high" and "low" categories relative to the median of each feature. Typology class and associated investment priority are then determined on the basis of the combination of these three metrics (see Table 1, Fig. 3A, and examples in fig. S7).

SUPPLEMENTARY MATERIALS
Supplementary material for this article is available at http://advances.sciencemag.org/cgi/content/full/7/17/eabe6025/DC1

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**Acknowledgments:** We would like to thank C. Hammond Wagner at Stanford University for ongoing helpful discussions. This work also benefited from the input of A. Escriva-Bou, A. Ayres, and J. Jezdimirovic (Public Policy Institute of California); G. Persad and J. P. Ortiz Partida (Union of Concerned Scientists); P. Lin (Princeton University); and S. Alam (University of California, Los Angeles). **Funding:** This work was supported by the S.D. Bechtel Jr. Foundation (X.H. and T.M.) and the Ishiyama Foundation (X.H. and B.P.B.). X.H. would like to acknowledge additional financial support from Singapore Ministry of Education (MOE) Academic Research Fund Tier-1 project (R-302-000-265-133). K.J.M. is supported by the University of Miami Rosenstiel School of Marine and Atmospheric Science. **Author contributions:** X.H., T.M., and B.P.B. conceived the research. X.H. and B.P.B. developed the policy typology. X.H. performed the analysis, prepared the figures, and drafted the manuscript. B.P.B., T.M., K.J.M., Z.W., and D.L.F. commented and revised the manuscript. **Competing interests:** The authors declare that they have no competing interests. **Data and materials availability:** Historical and future runoff data can be downloaded from the Cal-Adapt database (https://cal-adapt.org/data/download/). Local gauges can be obtained from the Gage Gap tool developed by The Nature Conservancy (https://gagegap.codeformature.org/). Hydrography datasets (e.g., stream order, stream lines, and drainage area) are available at http://hydrology.princeton.edu/data/panm/ MERIT_Basins. Degree of dam regulation datasets are available at https://zenodo.org/record/3552776#.Xrs2oxNKhQb. WAFR data are available upon request to X.H. (hexg@nus.edu.sg; hexg@stanford.edu). CaMa-Flood codes can be obtained from https://hydro.iis.u-tokyo.ac.jp/~yamada/caama-flood/. Python and R scripts used to produce results in this paper are available upon request to X.H. (hexg@nus.edu.sg; hexg@stanford.edu).

Submitted 1 September 2020
Accepted 4 March 2021
Published 21 April 2021
10.1126/sciadvab6025

**Citation:** X. He, B. P. Bryant, T. Moran, K. J. Mach, Z. Wei, D. L. Freyberg, Climate-informed hydrologic modeling and policy typology to guide managed aquifer recharge. *Sci. Adv.* **7**, eabe6025 (2021).
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Sci Adv 7 (17), eabe6025.
DOI: 10.1126/sciadv.abe6025