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Research Paper

Economic and policy drivers of agricultural water desalination in California's central valley

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ABSTRACT

Water desalination is a proposed solution for mitigating the effects of drought, soil salinization, and the ecological impacts of agricultural drainage. In this study, we assess the public and private costs and benefits of distributed desalination in the Central Valley (CV) of California. We employ environmental and economic modeling to estimate the value of reducing the salinity of irrigation water; the value of augmenting water supply under present and future climate scenarios; and the human health, environmental, and climate change damages associated with generating power to desalinate water. We find that water desalination is only likely to be profitable in 4% of the CV during periods of severe drought, and that current costs would need to decrease by 70–90% for adoption to occur on the median acre. Fossil-fuel powered desalination technologies also generate air emissions that impose significant public costs in the form of human health and climate change damages, although these damages vary greatly depending on technology. The ecosystem service benefits of reduced agricultural drainage would need to be valued between \$800 and \$1200 per acre-foot, or nearly the full capital and operational costs of water desalination, for the net benefits of water desalination to be positive from a societal perspective.

1. Introduction

The twin stressors of water scarcity and soil salinization diminish agricultural yields and grower profitability in arid regions (Welle and Mauter, 2017). Climate models project expansion of arid regions and increased probability of drought in both the western United States and the majority of agricultural regions worldwide (Cook et al., 2015; Huang et al., 2016; Wang, 2005). In these water stressed regions, growers often augment water supply with alternative sources including brackish groundwater and agricultural drainage water. The application of these lower quality water sources can lead to the accumulation of salts and, in areas with insufficiently permeable soil, to the development of shallow saline water tables (Ghassemi et al., 1995). Recent studies estimate the cost of soil salinization in California at \$1.7 to \$7 billion dollars per year (Howitt et al., 2009; Welle and Mauter, 2017). As a result, improving the sustainability of food production systems in arid, drought prone, and salinizing regions is a high environmental and policy priority (Sabo et al., 2010).

Traditional responses to the diminished yields associated with soil salinization increase agricultural land area, intensify agricultural water consumption, and impose downstream environmental impacts. Local land fallowing reduces agricultural production and drives land-use change, which is often associated with increased greenhouse gas emissions (Tilman et al., 2011). The second response, salinity leaching from salt-impaired fields via the excess application of irrigation water, consumes scarce water resources, raises elevated groundwater tables, and often leads to the discharge of saline tile drainage to sensitive environmental ecosystems (Wichelns and Oster, 2006). While alternative drainage management schemes include re-application of tile drainage to salinity tolerant crops or storage in evaporation ponds, most tile drainage is discharged to the environment (Schwabe et al., 2006; Wichelns and Oster, 2006). Specific contaminants found in this agricultural drainage, notably selenium and boron, impair reproduction, inhibit growth, suppress the immune system, and cause mutagenesis in fish and birds (Chang and Brawer Silva, 2014; Ohlendorf, 1989). Thus, conventional salinity management practices force trade-offs in agricultural productivity and environmental sustainability (Schoups et al., 2005).

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Nomenclature

List of Symbols

R	Revenues
S^S	Soil salinity
b	Crop salt tolerance slope parameter
p	Prices
Y_M	Theoretical maximum yield
L	Leaching fraction
S_W	Water salinity
W^T	Water treated
Π	Profits
W	Applied water
υ	Prices
Y	Production
δ	Exponential response function intercept
γ	Exponential response function elasticity
X	Resources use
ω	Resource cost
τ	Factor productivity
β	Resource coefficient
ρ	CES elasticity parameter

Subscripts

g	Region
i	SWAP crop group
j	Resource
ws	Water source (project water, surface diversion or groundwater)
land	Land resource

Water treatment technologies offer a potential remedy to this impasse by allowing farmers to treat existing irrigation waters or access new impaired water sources, including saline groundwater or agricultural tile drainage. Drainage water leached from agricultural soils and discharged through tile drains can be deionized and beneficially reused as a source of irrigation water, while the residual brine concentrate may be disposed of through subsurface injection or crystallized and disposed of as solid waste. Desalination of tile drain discharge would simultaneously minimize ecosystem damages, limit soil salinization, reduce agricultural water intensity (acre-feet/acre-year), and offer a new source of irrigation supply.

Technologies potentially applicable to agricultural water desalination are distinct from conventional seawater desalination technologies for municipal water treatment in requiring higher water recovery, tolerance of highly variable feed streams, and cost-effectiveness at small to medium scales. The cost-effectiveness of these technologies will also be facilitated by limited requirements for pre-treatment, low operator oversight, and resiliency to intermittent or variable water quality. Several technologies for distributed agricultural water desalination have been piloted or installed commercially, including thermal desalination (e.g. multi-effect distillation), membrane-based desalination (e.g. reverse osmosis), and electrochemical desalination (e.g. electrodialysis)(Brame et al., 2011; McCool et al., 2010; Stuber, 2016). In each case, the technology is capable of reducing the total dissolved solids concentration of the product water to effectively zero.

Growing demand for drought mitigation and agricultural drainage treatment has motivated a number of studies assessing the technical feasibility and cost of specific agricultural water desalination technologies (Karagiannis and Soldatos, 2008; McCool et al., 2010; McCool et al., 2013; Rahardianto et al., 2008; Stuber, 2016; Yermiyahu et al., 2007). These studies have generated estimates of water treatment cost, but we are unaware of complementary work assessing the private benefits of technology adoption or the broader consequences of technology adoption for integrated food, energy, and water systems. There remains significant uncertainty about the implications of widespread water desalination for agricultural management practices such as soil leaching, the energy consumption of water desalination technologies and any associated air emission impacts, or the ecosystem services benefits of reduced discharge salinity. Explicitly quantifying these benefits and costs is critical for assessing the likelihood of technology diffusion and the role for policy interventions that maximize public benefits.

The present work quantifies the marginal public and private costs and benefits of agricultural water desalination under a range of future precipitation and climate scenarios in the Central Valley (CV) of California. We present the first assessments of the marginal private benefits of water desalination, realized as improved agricultural yields, using high-resolution multi-modal soil salinity and crop data. We then assess private adoption at the field-level by comparing private benefits to current desalination costs. Next, we contribute the first assessment of potential marginal public costs associated with adoption of agricultural water desalination. Public costs in the form of human health and climate damages are estimated for three different desalination technologies that use renewable, grid, and fossil energy sources. Finally, we back out the effective value of human health and environmental benefits in watersheds impaired by agricultural drainage that would be required for the technology to have net positive effects from a societal perspective.

2. Methods and data sources

We quantify the public and private costs and benefits associated with desalination systems in the CV, a region of high agricultural value, severe water scarcity, and impaired air and water quality. The most agriculturally productive region in the US, the CV includes about 9 million acres of cropped land producing the majority of California growers' $46 billion USD of revenue in 2013 (USDA, 2015). Water availability for irrigation is often scarce due to the aridity of the region, persistent drought conditions exacerbated by a warming climate (Cook et al., 2015), unsustainable groundwater withdraws (DWR, 2015; Medellin-Azuara et al., 2015), and suboptimal market mechanisms for water transfers (Draper et al., 2003). In addition to water scarcity, soil salinization has required widespread installation of tile drains that enable salinity leaching. Discharging this tile drainage into surrounding ecosystems has impaired surface water throughout the CV (Quinn et al., 2010).

A complete system analysis that incorporates the regulatory, legal, economic, and technical factors that impact water use and allocation is beyond the scope of the present work. Instead, this analysis is framed in marginal terms, and therefore limits the decision space by assuming that present-day regulatory environment, legal conditions, and management practices remain constant. Additionally, on the technological modeling side, we limit the analysis to that of a theoretical desalination system capable of reducing water salinity to 0 ppm TDS with 100% recovery for a cost of $1 per m^3 of feed, a middle value in the literature range of $0.78–$1.33 per m^3 of feed. This cost includes the financial costs of brine disposal, but assumes no environmental externalities associated with brine management. While no desalination system is capable of providing this exact service, it reduces the need to model all possible desalination system design choices. As a result of these assumptions, the analysis provides an upper bound estimate on the marginal benefits of actual desalination systems.

2.1. Private costs

While the costs of large-scale seawater desalination have decreased to nearly \$0.5/m^3 (Reddy and Ghaffour, 2007) distributed, inland, brackish water desalination systems do not benefit from the same economies of scale or ease of concentrate disposal. Instead, inland desalination systems must combine technologies for desalination with those for brine management, which typically range from \$0.40 – \$1.80 per m^3 of concentrate (Johnson et al., 1997; McCool et al., 2013; Mickley, 2006). Finally, minimizing these brine volumes requires high water recovery, which can lead to membrane scaling and increased maintenance costs. As a result, the total system lifecycle costs of inland brackish water desalination are often significantly higher than seawater desalination systems.

This analysis utilizes existing estimates of the lifecycle costs of distributed inland brackish water desalination costs sourced from the peer-reviewed literature. These estimates include the costs associated with pretreatment, desalination processes, and concentrate management, as well as amortized fixed costs. Recent estimates of lifecycle water desalination costs in the CV by McCool et al. (2013) and Stuber (2016) are consistent with an earlier review of small scale desalination system costs ranging between \$0.78–\$1.33 per m^3 of feed (Karagiannis and Soldatos, 2008). When calculating the benefit gap, we simplify our calculations by selecting a mid-range value of \$1/m^3 of feed. The lifecycle system costs may reduce as desalination technologies mature (Reddy and Ghaffour, 2007).

2.2. Private benefits

The private benefits of increased agricultural revenue from reduced soil salinity and additional water supply are developed by extending two existing modeling approaches described elsewhere (Medellín-Azuara et al., 2011; Welle and Mauter, 2017). Both estimates are developed as marginal quantities with units of [\$/acre-ft] or [\$/m^3], which represent the marginal revenues of improved quantity (an additional unit of water) or quality (a completely desalinated unit of water). Due to the marginal nature of the calculations, these benefits do not account for any potential benefits associated with switching from lower value to higher value crops, a theme more fully addressed in the discussion section.

Additionally, the two models for water quality and water quantity are performed at different levels of spatial aggregation. Modeling improved water quality is highly dependent on local estimations of crop types and soil salinity, and so this model is resolved at a 30-m pixel (referred to in this paper as field-scale) resolution. Modeling the value of improved water supply is performed over hydrologic regions (referred to as regional-scale) with an average size of 2040 km^2. This approach allows estimation of a use value of water absent detailed water pricing data.

2.2.1. Improved water quality

Reducing the total dissolved solids (TDS) concentration of irrigation water reduces the soil salinity, increases agricultural yields, and confers higher revenues to the producer. Revenues are assessed marginally, according to Eq. (1).

$$\frac{dR}{dW^T} = \frac{dR}{dS^S} \cdot \frac{dS^S}{dS^W} \cdot \frac{dS^W}{dW^T} \tag{1}$$

The value $\frac{dR}{dW^T}$ is the increased revenue R per unit of water treated W^T on the margin, which is further decomposed into three components – (1) the change in revenue per change in soil salinity $\frac{dR}{dS^S}$, (2) the change in soil salinity per change in salinity of applied water $\frac{dS^S}{dS^W}$, and (3) the change $\frac{dS^W}{dW^T}$ in salinity of applied water per change in quantity of water treated

These three components are represented in Eqs. (2)–(4) respectively.

$$\frac{dR}{dS^S} = \begin{cases} 0; S^S \le t_1 \; or \; S^S \ge t_2 \\ b \cdot p \cdot Y_M; S^S > t_1 \; and \; S^S < t_2 \end{cases} \tag{2}$$

$$\frac{dS^S}{dS^W} = \frac{1}{L} + \frac{0.2}{L} \cdot ln\left(L + (1-L)\right) e^{-5} \tag{3}$$

$$\frac{dS^W}{dW^T} = -\frac{S_0^W}{W} \tag{4}$$

Eq. (2) is developed through differentiating the yield reduction model presented in Maas and Hoffman (Maas and Hoffman, 1977). The parameter b, which is negative for all crops in the study, is the crop-specific sensitivity parameter, which determines how quickly yield decreases as salinity increases. The two parameters p and Y_M are crop-specific county level values of price and theoretical maximum yield (for non salt-affected crops). The expression $\frac{dR}{dS^S}$ is zero when salinity is less than the salinity threshold (t_1) at which relative yield is 100% or above the threshold (t_2), where the yield is 0%.

The equilibrium relationship between soil salinity and the salinity of applied water is provided in Eq. (3). The model, originally presented in Hoffman and Van Genuchten (1983), is calculated as a single function of the leaching fraction, L. The leaching fraction is the fraction of total water that percolates through the soil column, and determines how quickly soil salinity changes as the salinity of the applied water shifts.

Finally, we employ a simple dilution model in Eq. (4) to calculate the salinity of the applied water when mixed with desalinated water, which throughout this analysis is modelled as water with no dissolved solids. The two parameters S_0^W and W represent the salinity of the applied water and the total water applied, respectively. In the absence of high-resolution data on the salinity or relative volumes of surface water, groundwater, and precipitation applied to crops during the growing season, the present analysis assumes that the salinity of the irrigation water before being mixed with desalinated water is constant at an average value of 490 ppm TDS (approximated in dS/m by assuming $TDS = 640 \cdot EC$). Appendix C provides further detail on the estimation of the salinity of the applied water as well as sensitivity to final results of changing assumptions on which this estimation is based. Eq. (4) thus represents the change in water salinity from 490 ppm that results when a marginal amount of 0 ppm TDS desalinated water is introduced.

Each of these equations is resolved at a 30 m pixel resolution across the CV. Crop type is detected according to a satellite-based crop classifier, and all other parameters are measured locally at the county level (Welle and Mauter, 2017).

2.2.2. Augmented water supply

We employ the Statewide Agricultural Production (SWAP) model to estimate the economic value of water to agricultural producers under historical and future warm and dry climate scenarios (Medellín-Azuara et al., 2011). SWAP uses the deductive Positive Mathematical Programming (PMP) technique to estimate the economic value of irrigation water over hydrologic regions assuming that growers seek to maximize net returns to land and management in irrigating crops (Howitt, 1995). PMP consists of a four step procedure described in detail in Howitt et al. (2012). The basic methodology can be outlined as follows: (1) a linear program with Leontief technology is solved to obtain marginal values on a calibration constraint; (2) a PMP exponential cost function is parameterized; (3) a constant elasticity of substitution (CES) production function is calibrated which makes use of the Lagrange multiplier on the calibration constraint in the first step; and (4) a non-linear program that includes the CES production function and the PMP cost function is solved. The model specified by this four step procedure calibrates exactly to the base dataset. SWAP uses four production inputs (land, water, labor, and supplies) and a 20-crop group set compatible with the California Department of Water Resources classification. The fully calibrated program is provided by the set of Eqs. (5) through (7):

$$max\,\Pi = \sum_{g}\sum_{i}(\upsilon_{gi}Y_{gi}) - \delta_{gi}e^{\gamma_{gi}X_{gi,land}} - \sum_{j\neq land}\omega_{gij}X_{gij} \tag{5}$$

where,

$$Y_{gi} = \tau_{gi}\left(\sum_{j}\beta_{gij}X_{gij}^{\rho}\right)^{\upsilon/\rho} \tag{6}$$

$$\sum_{i}X_{gi,land} \leq \sum_{ws}W_{g,ws} \tag{7}$$

and g is the set of regions, i is the set of crops, and j is the set of production factors. The decision variable is X_{gij}, which is the amount of resources j allocated for production of crop i in region g. The parameters υ_{gi} and Y_{gi} are prices and yields in region g and crop i. Land cost is represented by an exponential area response function with intercept and elasticity parameters δ_{gi} and γ_{gi}. Resource costs are represented as ω_{gij}.

Eq. (6) represents the CES production function which models Y_{gi} using parameters β, τ, υ, ρ. Eq. (7) is the resource constraint that defines the boundary for applied water W in region g according to a particular water source ws (local diversions, state or federal water projects, and groundwater).

We conducted three SWAP model runs to obtain shadow values of water from the water resource constraint (Eq. (7)). We employed base observed water availability for the pre-drought year of 2010, the drought year of 2014, and a climate scenario for 2050 with a warm-dry form of climate change following Medellín-Azuara et al. (2011).

2.3. Public costs

Assuming responsible brine management, the human health and environmental externalities of agricultural water desalination will be dominated by the air emissions associated with powering desalination technologies. To quantify these damages, we estimated energy consumption and associated criteria pollutant and greenhouse gas emissions of three desalination technologies: (1) solar powered, grid supplemented, multi-effect distillation (MED) (Solar Thermal or ST); (2) natural gas powered, grid supplemented MED (Gas Thermal or GT); and (3) grid powered reverse osmosis (RO). We estimated the energy consumption of MED desalination at 125 MJ/m^3 supplemented with 1.5 kWh/m^3 of grid energy, and the energy consumption of membrane pretreatment and RO of 5 kWh/m^3. These energy estimates are sourced from the literature for small-scale systems with high (>90%) recovery and are constructed to include pretreatment, treatment, and brine disposal (Karagiannis and Soldatos, 2008; McCool et al., 2013; Stuber, 2016). Using these technologies, we then estimate the emissions associated with grid electricity using CA state-level average emissions factors for CO_2, NO_x and SO_2 in 2012 derived from the EPA's Emissions & Generation Resource Integrated Database (eGRID) (EPA, 2016b). eGRID does not monitor $PM_{2.5}$, so we instead used CA state-level average emissions factors in 2011 from the EPA's National Emissions Inventory (EPA, 2011). We estimate emissions from the combustion of primary fuel in small scale natural gas boilers using US EPA AP-42 Compilation of Air Pollution Emission Factors (EPA, 1998). Further detail is available in Appendix B.

We estimate the damages for NO_x, SO_2 and $PM_{2.5}$ associated with air emissions from primary fuel and electricity consumption using the Air Pollution Emissions Experiments and Policy Version 2 (AP2) model for each county in California (Muller, 2011; Muller and Mendelsohn, 2007). Damages from emissions sourced from primary fuel are placed in the county which they occur, while damages associated with emissions sourced from grid locations are localized by assigning generation to each plant in proportion to their estimated relative contribution to the California grid (see Appendix B). Damages to human health are typically high in those locations with large populations and poor existing ambient air quality. For CO_2 emissions, we assumed a social cost of carbon of $41.10 per metric ton in 2014 USD based on estimates from the US Environmental Protection Agency (IWG, 2013). This estimate is similar to the $49.70 per metric ton in 2014 USD estimated by the Organization for Economic Cooperation and Development (Smith and Braathen, 2015).

2.4. Public Benefits

Agricultural drainage water desalination and concentrate disposal would reduce the amount of selenium, boron, nitrate, TDS and other contaminants in environmental systems. The diversity of methods for valuing ecosystem services, however, makes estimating the public benefits highly uncertain (Young and Loomis, 2014). Instead, we select environmentally sensitive areas (ESAs) in the CV that are highly impaired by agricultural drainage and estimate ecosystem valuation that would be required for drainage water desalination to confer positive net benefits at a societal level. This required valuation is termed the "benefit gap."

To estimate the benefit gap, we subtract private and public costs from private benefits of water desalination within the ESAs. ESAs are selected using EPA's Healthy Watershed program (EPA, 2016a) by first selecting those HUC12 watersheds that contain both agriculture and artificial drainage areas, and sub-selecting the watersheds with rank normalized median summer conductivity greater than 0.8 (Appendix B Figure B.1). The at-risk zone is determined to include 88 watersheds, or 21% of the cropped area in the study. Private costs are likely to vary depending on local electricity prices, brine disposal options, and regulations. In this analysis, we adopt a uniform midpoint estimate of 1 \$/m^3 for all systems. Private benefits and public costs are determined at the field level or county level as described above.

3. Results

We estimate the private and public costs and benefits of agricultural water desalination to assess independent technology adoption as well as the potential role for policy intervention. Desalination adoption is determined by the net private benefits of the technology for the grower, estimated as the additional revenues associated with lower irrigation water salinity and augmented water supply, minus the additional costs associated with system fixed and variable costs. In addition to the benefits and costs of desalination for agricultural producers, the adoption of widespread desalination confers benefits and imposes costs to the public at large. The balance of these public costs and benefits determine the socially optimal level of technology adoption and the policy interventions that may be warranted to encourage or discourage desalination. We explore the role for policy by quantifying the human health impacts of reduced air quality associated with higher energy use and exploring the requisite breakeven benefits of reduced drainage on downstream ecosystems.

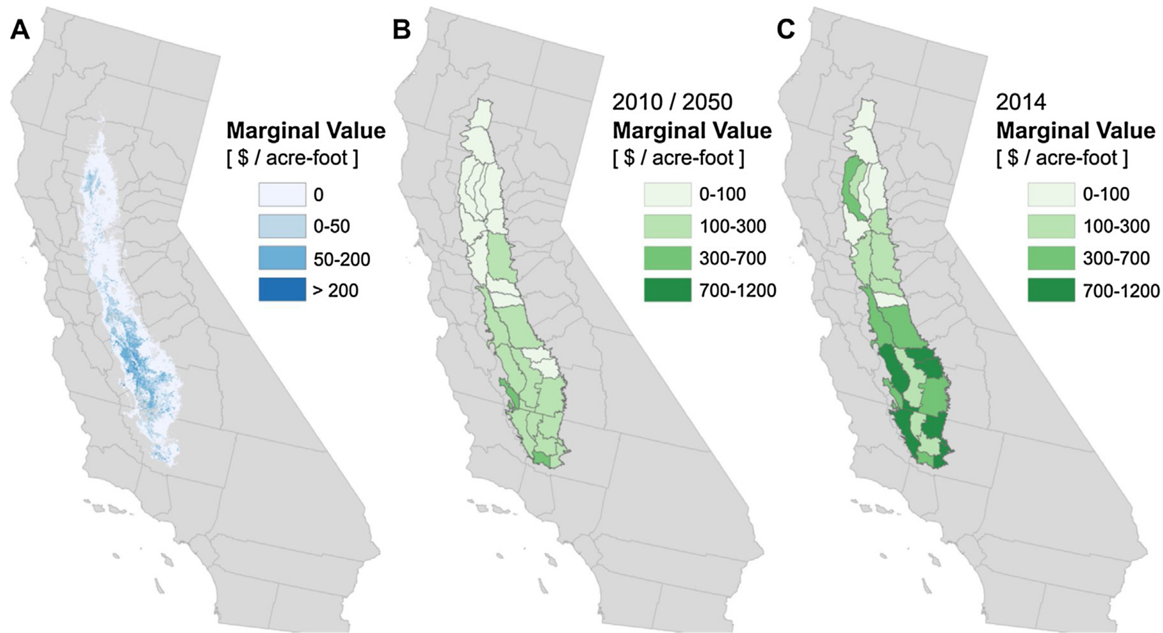

Fig. 1. Marginal value of improved water quality and additional water supply. A) Marginal value of removing dissolved solids from a cubic meter of irrigation water, while holding the volume of irrigation water constant. B) Marginal value of an additional acre-ft of irrigation water at salinities equivalent to current irrigation water (490 ppm TDS) (Welle and Mauter, 2017) under pre-drought (2010) and future climate (2050) scenarios. C) Marginal value of an additional cubic meter of irrigation water under drought scenarios represented by water availability in 2014. One acre-ft is equivalent to 1233 m^3.

3.1. Private benefits of improved water quality

We estimate the marginal value of reducing the salinity of CV irrigation water to zero while holding the volume of water applied constant. The average marginal value of improved quality is \$0.01 per m^3 (5th percentile \$0.00; 50th percentile \$0.00; 95th percentile \$0.08) and is highest in areas with high crop value, high salinity levels, low crop water needs, and high crop salt sensitivity (Fig. 1A). Areas with a higher marginal value of desalinated water are clustered in the southern and western CV, where salinity values are highest. Almonds, pistachios, alfalfa and grapes report the highest crop revenue gains from decreasing the salinity of applied irrigation water, and these crops accounted for 2.2 million planted acres (or approximately 45% of planted acreage in the CV) in 2014.

3.2. Private benefits of improved water supply

Desalination technology also offers the possibility of increasing water supply by treating impaired water sources such as brackish groundwater or agricultural drainage water. This additional water has an economic value to agricultural producers that increases with increasing water scarcity. We model the additional value of water by using the shadow price as determined by training the SWAP model to 2010 (pre-drought), 2014 (drought), and 2050 (climate change) scenarios for each of the 27 SWAP regions in the CV. The average regional difference in value between the pre-drought and drought years is \$250 per acre-ft, but varies between \$0 and \$880 per acre-ft depending on SWAP region. The 2050 warm-dry climate change scenario, by contrast, increases the average regional difference by only \$4.20 per acre-ft, or 3.1%. The increase in value between non-drought and drought years is concentrated in the southern CV where water scarcity is highest (Fig. 1B and C).

Fig. 2A plots the marginal values in Fig. 1 as a cumulative density function (CDF). The marginal values of augmented water supply for 2010 and 2014 are summed with estimates for the value of water quality to calculate a single combined value of water quality and quantity. This value can be interpreted as the farmer's willingness to pay for desalinated water from untapped sources. The average value is \$0.12 per m^3 (5th percentile \$0.02; 50th percentile \$0.09; 95th percentile \$0.26) in 2010 and \$0.30 (5th percentile \$0.02; 50th percentile \$0.26; 95th percentile \$0.75) in 2014. Under drought conditions, just 4% of land area receives a value of desalinated water within the \$0.78-\$1.33 per m^3 range of inland desalination costs reported in the literature. Absent drought, however, very little land is likely to receive net private benefits from installing desalination technologies.

3.3. Public air emissions costs

Desalination processes consume primary fuel or electricity and may increase emissions of criteria air pollutants and greenhouse gasses. We find that air emission damages to human health and the environment associated with desalinating agricultural water vary considerably depending on technology and power source. Solar thermal (ST) desalination systems consume only a small amount of electricity for pumping and therefore generate the fewest air emission damages per volume of desalinated water at \$0.05 per m^3, or 58.40 per acre-ft. Electricity driven reverse osmosis (RO) desalination technologies impose significantly larger damages of \$0.16 per m^3, or \$196 per acre-ft. The damages from electricity-driven desalination technologies are estimated using generation-normalized average emissions factors for the CA electricity grid and, thus, the spatial distribution and proportion of damages from each pollutant are constant. The estimated damages from criteria air pollutant and CO_2 emissions are approximately equal, though the exact proportion depends on the specific technology (Fig. 2B).

Gas thermal (GT) systems impose significantly larger human health and environmental damages of \$0.36 per m^3, or \$449 per acre-ft. The estimated air emission damages vary based on the county in which desalination activity occurs, and range between \$404 and \$550 per acre-ft. Nearly two-thirds of these damages are attributed to CO_2 emissions, a value that is substantially higher than that of ST or RO (Appendix A Table A.1).

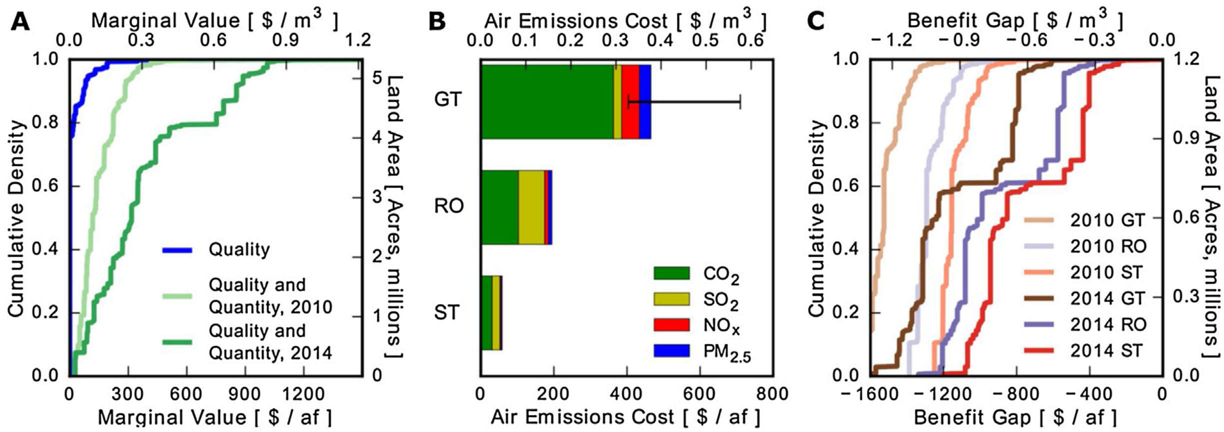

Fig. 2. Private and public benefits and costs by crop and land area. A) CDF of private benefits for improved water quality and summed benefits of improved water quality and augmented supply in 2010 and 2014. B) Estimated air emission damages per unit of desalinated water for the gas powered thermal (GT), grid-powered reverse osmosis (RO), and solar-powered thermal systems (ST). C) CDF of private benefits minus social costs (the benefit gap) for GT, RO, and ST systems for 2010 and 2014 values of augmented supply. This benefit gap represents the minimum ecosystem valuation required for desalination technologies to have net societal benefits.

Lastly, while it is theoretically possible to treat brine with low energy use in evaporation ponds, in some areas this may not be feasible or permitted. We perform an auxiliary supplementary analysis in Appendix D that estimates the air emission damages from employing a brine crystallizer. We find that the addition of a crystallizer widens the benefit gap by $0.10 to $0.30, a second-order effect.

3.4. *Public benefits of agricultural drainage treatment*

Capturing and desalinating agricultural tile drainage will reduce the ecosystem damages associated with current leaching practices. To circumvent the uncertainty associated with estimating marginal ecosystem services conferred by reduced agricultural water treatment, we instead assess the minimum value of ecosystem services necessary for policy interventions incentivizing technology adoption to be worthwhile from a public perspective.

The required value of ecosystem services depends on both the desalination process and the water availability in a given year. In both drought (2014) and non-drought (2010) years, the ST system had the highest combined net social benefits, followed by grid-powered reverse osmosis, and finally natural gas powered thermal systems. In non-drought years, the benefit gap for solar thermal is −$0.94 per m^3 or −$1160 per acre-ft for the median acre, indicating that nearly the entire private system cost would need to be supplied by the public. During drought years this benefit gap for the median acre drops to −$0.69 per m^3 or −$850 per acre-ft, and for the top 25th percentile the benefit gap drops to just −$0.35 per m^3 or −$436 per acre-ft. Very few acres report net positive benefits, suggesting that policy interventions would be necessary to close the benefit gap and incentivize technology adoption.

4. Discussion

Desalination technologies confer benefits and costs to agricultural producers as well as society at large. In this study we quantify those benefits and costs to assess desalination adoption and the potential role of policy in stimulating societally optimal outcomes. This analysis suggests that water desalination by private growers is unlikely to be widely adopted in the CV, as the costs of small-scale desalination units under current policy and regulatory frameworks exceed the benefits that growers are likely to realize from improved water quality or augmented water supply.

Desalination technologies also generate benefits and impose costs to outside parties beyond agricultural producers. Water treatment technologies can be energy intensive and may lead to human health and climate impacts. If growers installed desalination capacity to treat a quarter of the agricultural water applied to most economically beneficial 10% of the CV, annual air emission damages would range between $97 and $726 million. Desalination technology and system location explain this variation in the magnitude of public costs, with solar powered MED reported damages nearly an order of magnitude smaller than on-site natural gas combustion driven MED systems. These damages are significant with respect to the private costs to growers, varying between 4.7% and 36% of the system's estimated private cost.

Given the human health and climate damages associated with air emissions from water desalination, considerable ecosystem service benefits from reduced agricultural loading to the environment would be necessary to justify policy incentives for technology adoption. During non-drought periods, we find the net public benefits associated with implementing desalination technologies will only be positive if ecosystem service benefits are on the order of the cost of the technology itself. This implies that the private benefits are essentially entirely offset by public air emission damages. For technology implementation to occur, this benefit gap could be closed by policy in the form of either a subsidy or a tax.

The conclusions of this study are qualified by several assumptions delineated in the methods section. First, the benefits of desalinated water to the growers are quantified using economic modeling in marginal terms, meaning that non-marginal effects (such as crop switching) are not included. The marginal assumption is likely to be more important for land currently cultivating low revenue crops (e.g. corn, wheat, rice, alfalfa, cotton), which may increase revenue by switching to high-revenue crops. The decision to switch from low value to high value crops is complex – for instance, while we observe that 42% of the land area in our study correspond to low value crops, 52% of these low-value crops already have salinity below the threshold where yields of salt-sensitive almonds would be completely unimpaired. While salinity is no doubt important for crop selection, a wide variety of other variables including market factors, capital and operational expenses, risks exposure associated with perennial crops, water availability (both groundwater and surface water), soil fertility, applicability of irrigation technologies, and availability of drainage dictate what growers will ultimately cultivate. While not accounting for crop switching may cause us to underestimate the value of desalinated water in some areas, resolving salinity does not imply that salt-sensitive high value crops will yield significantly higher revenue.

Second, we assume that growers are rational agents with good information on water resources. In reality, many perennial crop farmers were surprised by the drought and paid significantly more than the average costs for water modelled in this study.

Third, agricultural water is assumed to have a fixed concentration of dissolved solids of 490 ppm, estimated in previous work. (Welle and Mauter, 2017) We make this assumption in the absence of spatially resolved data on the salinity of the applied irrigation water, which is dependent upon the site-specific mix of groundwater, surface water, rainwater, and tile drainage water that a grower chooses to apply. A grower using higher salinity sources may realize significantly greater value from implementing desalination technologies than reported in this study. On the other hand, growers applying less saline sources would realize even less value.

Fourth, each desalination system is assumed to have amortized costs of \$1 per m^3, regardless of desalination technology, energy inputs, or system recovery. In reality, there may be a tradeoff between public and private costs of different technologies, a tradeoff that could be explored with further research into theoretical energy requirements and more precise cost estimation. Finally, the present analysis does not value the human health, environmental, or climate damages associated with brine disposal technologies or the environmental externalities associated with manufacturing the capital equipment for water desalination.

Despite the absence of strong economic or policy drivers for agricultural water desalination, there are several technological, economic, regulatory, and climate factors likely to evolve over the next two decades that may increase the net benefits of agricultural water desalination for growers in the CV. The costs of water desalination could decrease as a result of research, development, deployment, and standardization of distributed brackish water desalination technologies. In addition, CV growers are transitioning toward high value, perennial tree crops with higher capital costs and longer payback periods on the order of 30 years (Lobell and Field, 2011). These crops reduce the elasticity of water demand during drought years, and may increase grower willingness to pay under future drought conditions. Recent regulatory action limiting groundwater withdraws, which currently provide ∼40% of the California water supply in a non-drought year and much more in a drought year (DWR, 2014), may further increase the price of water in the CV above the SWAP predictions and thereby encourage on-farm water reuse efforts. At the same time, restricting state-issued discharge permits and the provision of in-basin drainage management may limit the discharge of agricultural drainage to vulnerable ecosystems. Finally, recent climate models predict that the western United States will become drier and more drought prone. Despite these expected changes in water availability, we find that desalination is still not likely to offer significant net benefits to growers in an average, non-drought year circa 2050. Since system capital costs are amortized over decades, economic assessments based upon conditions from short drought periods may be overly optimistic.

Policy makers will need to consider a range of environmental, economic, and sociological factors when evaluating policy interventions affecting agricultural desalination in the CV. Examples include alterative water sourcing costs; the value of the agricultural sector outputs; technology impacts to marginalized groups; expected changes in ecological impacts; and the hydrological implications of pumping saline groundwater (Haddad, 2013). Policy interventions could take the form of a subsidy or a tax, with taxes either incentivizing adoption or forcing farm closure.

In conclusion, we find that the primary private benefits of agricultural water desalination are derived from increased water availability under drought scenarios. A small percentage of planted acreage in the CV may independently adopt desalination technologies if extreme drought conditions were forecast to persist over two decades, but the median acre is unlikely to experience adoption under the modelled drought or climate scenarios without significant policy intervention. Under current and foreseeable technological and economic conditions the major role for desalination technology, if there is one, is confined to ecosystem protection.

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Appendix A. : Air Emission Damage Analysis

In order to quantify public costs we value the damages associated with additional energy use, arriving at a value with units [\$/m^3] or [\$/acre-ft]. We quantify the damages for three hypothetical systems – (1) solar powered, grid supplemented thermal desalination (ST); (2) gas powered, grid supplemented thermal desalination (GT); and (3) grid powered reverse osmosis (RO). The two thermal systems are assumed to use 125 MJ/m^3 for driving the desalination process and 1.5 kwh/m^3 of auxiliary grid electricity. The reverse osmosis system is assumed to be powered by 5 kwh/m^3 of grid electricity. In this study we focus on four key air pollutants: SO_2, NO_x, PM 2.5 (criteria air pollutants) and CO_2.

The first step of the valuation methodology is to quantify the emissions associated with unit energy use. For grid electricity, we consider in state generation as well as imports from other regions. California generates roughly 66% of its energy use in-state, while 13% come from the northwest region (Alberta, British Columbia, Idaho, Montana, Oregon, South Dakota, Washington, and Wyoming) and 21% comes from the southwest region (Arizona, Baja California, Colorado, New Mexico, Nevada, Texas, and Utah)(CEC, 2016). We assume each plant contributes to emissions in proportion to its share of annual generation by using a series of weights (Eqs. (A.1) and (A.2)). Generation from out of country sources (Alberta and British Columbia) are omitted due to their relatively small contribution and limits in data availability.

$$EF_{i,p}^{Cal} = p_i \cdot EF_{i,p} \tag{A.1}$$

$$p_i = f_r \cdot \frac{G_i}{G_r} \tag{A.2}$$

In Eq. (A.1), $EF_{i,p}^{Cal}$ is the California specific emission factor which indicates the additional quantity of pollutant (subscript p) is emitted at a particular plant (subscript i) given an additional unit of energy used in California. This is calculated by multiplying the plant specific emission $p_i$factor $EF_{i,p}$ by the share of California's consumption produced at plant i,

The share of generation (p_i) is calculated in Eq. (A.2), where G_i is the generation that occurs at plant i, G_r is the generation that occurs in region r, and f_r is the fraction of generation in region r that is exported to California. We use plant data for all plants in states within the northwest, southwest, and Californian regions.

While annual generation and emission factors for NO_x, SO_2, and CO_2 are all available through CEMS, PM 2.5 is not included in this program. Data is instead incorporated from US EPA National Emissions Inventory (NEI)(EPA, 2012). NEI reports gross emissions in tons at three year intervals. We acquire separate data for biomass, coal, natural gas, and oil at the state level for 2011. The gross emissions are divided by the total generation of each plant type in each state to estimate the emission rate. Once the emission rate for each

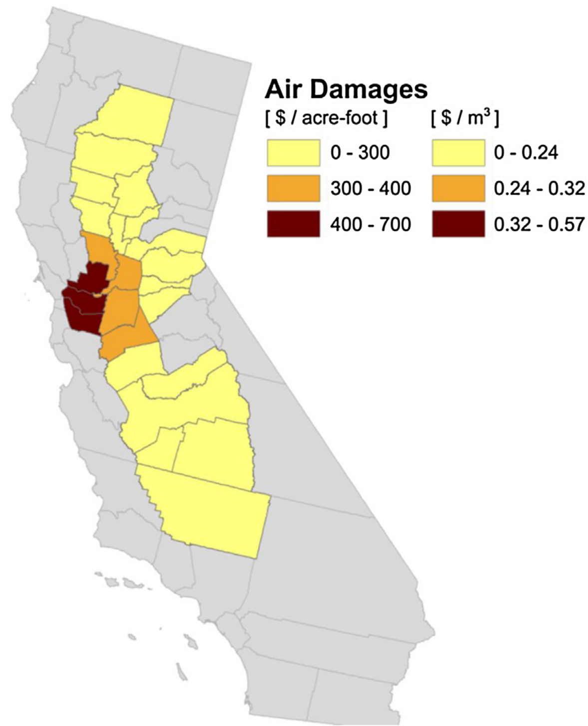

Fig. A.1. Air damages from a gas-powered, thermal desalination unit varies depending on location. Damages from solar-powered, thermal desalination and grid-powered reverse osmosis (not shown) do not vary spatially.

plant is determined, the weighting structure specified in Eqs. (A.1) and (A.2) are applied.

In addition to grid emission, emissions from local natural gas generation for the GT system must be calculated. We estimate these emissions by using the US EPA AP-42 Compilation of Air Pollution Emission Factors, which reports that 120,000 lb/million standard cubic feet (mscf) of CO_2, 7.6 lb/mscf PM, 0.6 lb/mscf SO_2, 100 lb/mscf NO_x are emitted by small boilers in the generation process (EPA, 1998).

The second step in valuation is converting emissions to damages. For CO_2, a social cost of carbon of $36/metric ton (2007 dollars) is applied. For the three criteria air pollutants, damages depend on the location in which the pollutants are emitted. The emission rates are aggregated from the plant to the county level, and damages rates from the Air Pollution Emission Experiments and Policy (APEEP) model are applied (Muller and Mendelsohn, 2007). APEEP quantifies human health impacts from air pollutants based on where the pollutants are emitted – areas with high population density report more aggregate damages than sparsely populated zones.

Grid emissions therefore have constant damages, since the emissions profile is identical regardless of the location of the desalination unit. For the GT system, however, the location of the desalination system is important. The closer the emissions are to population centers, the greater the estimate damages. Table A.1 shows the magnitude of damages per unit of water treated for each system, with a range reported for the GT system depending on which county the unit is located. Fig. A.1 shows the spatial variation of damages of the GT system for counties with agricultural production included in this analysis.

Appendix B. : Defining Environmentally Sensitive Areas

Treating agricultural drainage at the farm level provides a mechanism for preventing harmful pollutants from arriving at environmentally sensitive areas (ESAs). This public benefit, while difficult to quantify, may be an important driver of adoption for desalination technologies. In the main text we analyze how large this public benefit would need to be in order to reap a net positive societal benefit.

ESAs are chosen using data from EPA's Healthy Watersheds Program (EPA, 2016a). This mission of this program is to generate a series of aggregated indices that indicate watershed health, and to publish these indices in GIS format. ESAs are chosen by first selecting HUC12 watersheds that contain agriculture and artificial drainage areas, and from those selecting the watersheds with rank normalized median summer conductivity greater than 0.8. This method selects 88 watersheds which define our selected at-risk zone, together accounting for 21% of the cropped area in the study. Fig. B.1 shows the selected areas for the analysis.

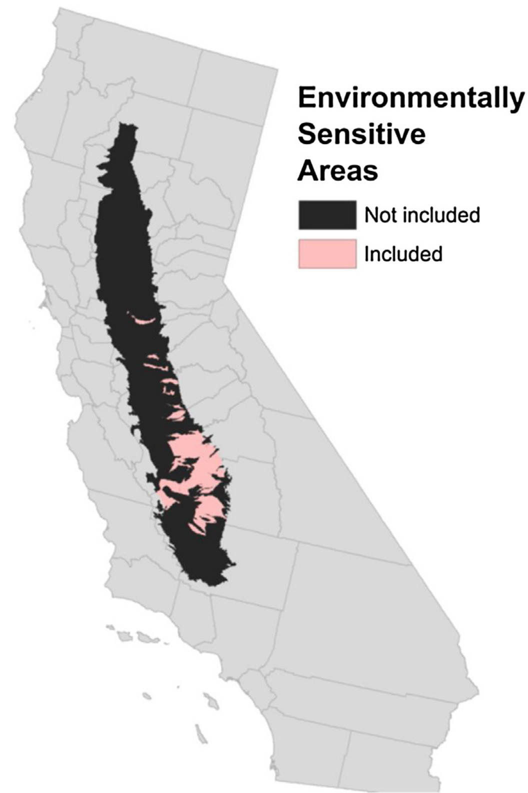

Fig. B.1. Subset of environmentally sensitive area included in the analysis.

Appendix C. : Irrigation Salinity Data

One of the key data limitations in our study is the lack of high-resolution data on the salinity of the applied water. This parameter will differ from field to field, pursuant to the grower's usage of groundwater and surface water as well as the quality of the available local sources. Additionally, the quality of each of these sources is likely to vary on annual time scales. As such, no data exists at sufficient resolution to quantify this parameter, and it must be estimated. The main analysis uses a single point estimate of water salinity of 490 mg/L. In this Appendix we both detail the calculation that lead to this point estimate as well as discuss other possible approaches for estimating salinity of the applied irrigation water. We then use each of these estimates to analyze the sensitivity of our results to modeling choices surrounding this parameter.

Table A.1
Estimated public damages of desalination in $/acre-ft.

[$/acre-ft]	Thermal (solar)	Reverse Osmosis	Thermal (natural gas)
CO_2 Damages	$31.00	$103.00	$363.00
SO_2 Damages (county range)	$21.60	$71.90	$22.70 ($21.90 – $24.40)
NO_x Damages	$3.15	$10.50	$39.90
PM 2.5 Damages (county range)	$2.75	$9.10	$23.40 ($6.20 – $62.20)
Total Damages (county range)	$58.40	$196.00	$449.00 ($404 – $550)

Modeling Water Salinity

The first approach for estimating the salinity of the applied water uses high-resolution data on soil salinity and converts this to implied irrigation water salinity using the same model presented in the main manuscript (Hoffman and Van Genuchten, 1983). The conversion from soil salinity to water salinity can be accomplished through Eq. (C.1).

$$S^W = \frac{S^S}{\frac{1}{L} + \frac{0.2}{L} \cdot ln(L + (1 - L))e^{-5}} \tag{C.1}$$

In Eq. (C.1), S^W is the salinity of the applied water, S^S is the soil salinity, and L is the crop-specific leaching fraction.

The implied irrigation water salinity can be seen in Fig. C.1A. When soils report salinity values of 0.0 mg/L total dissolved solids (TDS), the model implies that the grower is applying water with 0.0 mg/L TDS. This is likely an underestimate, as all irrigation water contains some quantity of dissolved solids. It can also be seen in Fig. C.1A that certain areas purport to use water salinity values of >4000 ppm. These are likely overestimates which result from violations of a fundamental assumptions built into the model, namely that the soil be well-drained. Much of the saline areas of California, however, are plagued by shallow groundwater tables (see Fig. C.1B).

Averaged Modeling Results

Since the first approach likely overestimates the salinity of applied water in areas with high salinity and underestimates in areas with low salinity, an approach that avoids these shortcomings would be to use the average of the estimated modeling results outlined in the previous section. Applying this technique causes there to be a loss of spatial heterogeneity in the modeling of this parameter, but avoids error being introduced by outliers.

This can be accomplished in two ways. The first is averaging the modeling results across all pixels, which yields an estimate of TDS of 585 mg/L. Since the model is known to be inaccurate in areas with shallow groundwater tables, however, a second approach would be to take a spatial average of all areas outside of the shallow groundwater zone (Fig. C.1B). This second average yields an estimate for TDS of 490 mg/L, and is the baseline approach taken in the main analysis.

Surface Water and Groundwater Estimates

An alternative to deriving water salinity estimates from modeling results is to use information about the salinity of available surface and groundwater. While 38% of the California's net human water use is groundwater, this number varies drastically by year and location (DWR, 2014). As such, we perform a bounding analysis, calculating reasonable point estimates by assuming that farms use either only surface water or only groundwater.

The quality of surface water imports is carefully monitored and managed through the use of electrical conductivity sensors in the major import canals. The California Aqueduct and Delta-Mendota canal, which supply irrigation water to much of the San Joaquin and Tulare Lake Basins, typically report salinity values between 300 and 350 mg/L (Medellín-Azuara et al., 2008). While these values represent a large portion of the surface water imports in the south, other irrigation sources may have higher levels of salinity (USGS, 2016b). We apply the upper side of this range (350 ppm) to represent a farmer consuming surface water.

The quality of groundwater is much more variable. The Groundwater Ambient Monitoring and Assessment (GAMA) program assesses water quality across the state and produces publications as to the state of groundwater quality (USGS, 2016a). In reviewing the results from three such studies in the Sacramento, Tulare, and San Joaquin Basins it was found that groundwater quality could vary between 123 and 2670 μS/cm (78 and 1708 mg/L), though the averages for all the wells in each study were in the range of 400–500 mg/L (Bennett et al., 2017; Bennett et al., 2009; Burton and Belitz, 2008). Since our earlier approaches already contain estimates in the range of the averages, and in the interest of conducting as broad of a sensitivity analysis as possible, we use the upper and lower range for groundwater conductivity (78 mg/L and 1708 mg/L, respectively) as two additional approaches. It should be noted, however, that these are aggressive ranges. The upper range (1708 mg/L) in particular, assumes that the entire state applies irrigation levels well in excess of the 1000 mg/L upper secondary maximum contaminant level (SMCL-CA) set by the state of California (Burton and Belitz, 2008).

Sensitivity of Results to Modeling Choices

The salinity of the applied irrigation water enters the analysis when modeling the private benefits of improved water quality, Eq. (4) in the main manuscript. Since the salinity of applied water term enters linearly, for each approach we can calculate the change in the value of improved water quality relative to the baseline scenario by applying a simple ratio between the salinity of the new approach and the salinity of the baseline.

Improved water quality, however, does not make up the entirety of the private benefits. The second component is the value of augmented supply, which is not affected by the quality of existing irrigation water.

In Table C.1, we report the percentage change from the baseline scenario for improved water quality, total private benefits (assuming 2010 pre-drought values of water), as well as the share of cropped area with private benefit above the estimated cost of desalination, $1/m^3. The more moderate assumptions of 350 and 585 mg/L show modest adjustments to total private benefits, but do not affect the result that no land is available that exceeds the current costs of desalination. While the more aggressive assumptions of 17 mg/L and 1708 mg/L change the computed private benefits more drastically, they still do not meaningfully adjust the amount of land in which total benefits exceeding system cost.

The percentage change from baseline cannot be computed for the modelled water salinity results, as it will be different depending where in the distribution it is being assessed. Fig. C.2 shows the

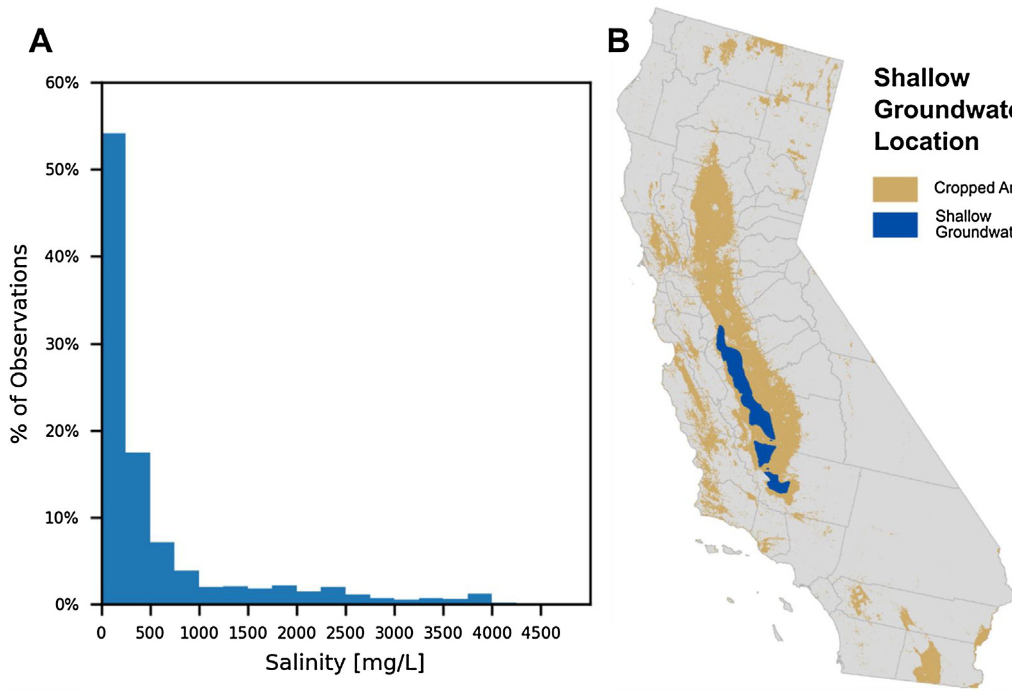

Fig. C.1. Modelled salinity results (A) and locations affected by shallow groundwater table (B). The y-axis in A shows the percentage of total observations in each bin. For example, 54% of observations have salinity between 0 and 250 mg/L. Data for B from https://water.ca.gov/drainage.

Table C.1
Sensitivity to Assumed Water Salinity Values. The total private benefits includes improved water quality as well as the value of augmented supply for 2010 (pre-drought conditions).

	Percentage Change, Improved Water Quality	Percentage Change, Total Private Benefits	Percentage Cropped Area with Private Benefit >$1/m^3$
Baseline (490 mg/L)	–	–	0%
Modeled Salinity	see Fig. C.2A	see Fig. C.2B	0%
Average with Shallow Groundwater (585 mg/L)	19.3%	6.7%	0%
Surface Water (350 mg/L)	28.6%	−9.8%	0%
Groundwater, Low Estimate (17 mg/L)	−96.5%	−29%	0%
Groundwater, High Estimate (1708 mg/L)	249%	86%	1.1%

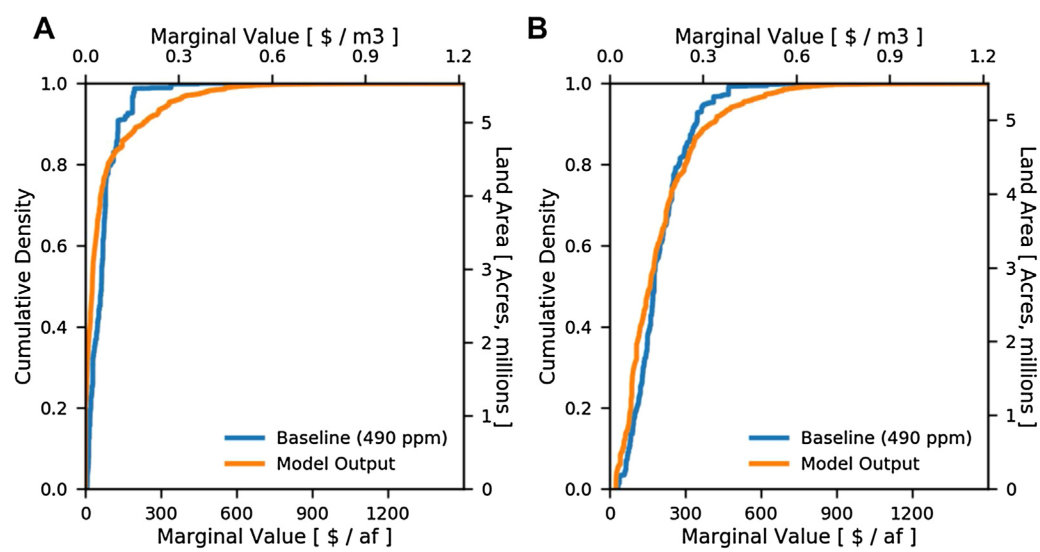

Fig. C.2. Cumulative Density Function of Improved Water Supply (A) and Total Private Benefits (B) for baseline (490 ppm) and spatially modelled output.

respective cumulative density functions with the modelled data. Since the baseline results use an average of the modelled results, the higher values are larger for the modelled results and the lower values are smaller. Despite being the higher values being larger than the baseline, 0% of the benefits exceed $1/m^3$, the estimated cost of desalination. We thus find, across a broad range of mod-

Table C.2
Typical Constituents in Tile Drainage, Groundwater and Surface Water Sources.

	pH	Boron mg/L	Chloride mg/L	Nitrate mg/L	Sodium mg/L	Alkalinity mg/L	TDS mg/L	EC μS/cm	SAR mg/L
Tile Drainage	6.2–8.4	10.87	1,040.60	116.76	1,597.7	283.1	6517	7,790.20	16.06
Groundwater	6.3–9.8	0.35	92.04	4.90	76.52	162.64	495.27	–	–
Surface Water	6.9–8.2	–	–	2.70	–	–	–	399.43	–

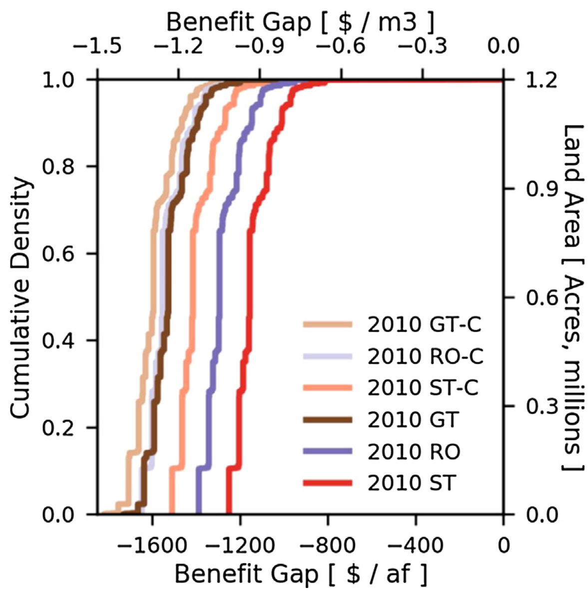

Fig. D.1. Modified benefit gap for the GT, RO, and ST systems. GT-C, RO—C, and ST-C indicate systems with crystallizer while GT, RO, and ST indicate systems without.

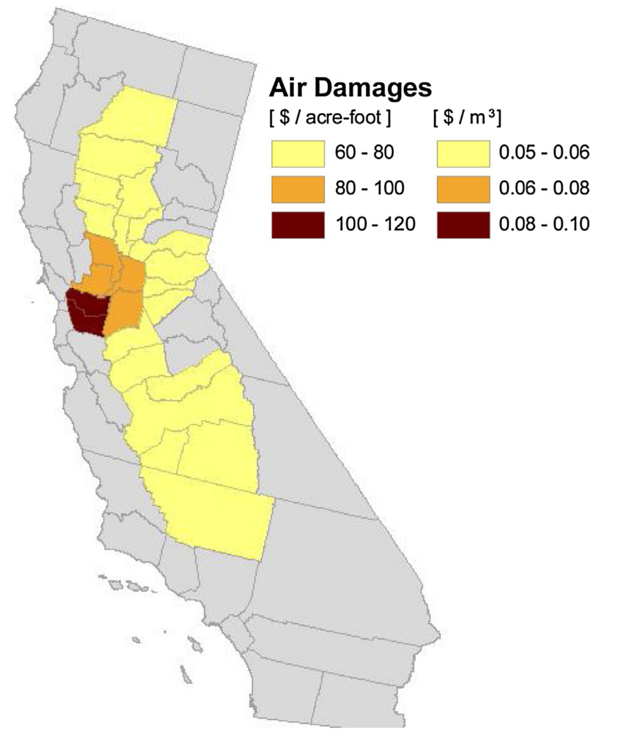

Fig. D.2. Geographic air emissions damages associated with the crystallizer for the GT-C system.

eling assumptions, that our major conclusions are unaffected for reasonable values of the salinity of applied irrigation water.

Lastly, for reference, we include the typical concentrations of various constituents for Boron, Chloride, Nitrate, Sodium, Alkalinity, Total Dissolved Solids, Electrical Conductivity, Sodium Absorption Ratio and pH in tile drainage, groundwater, and surface water. For tile drainage, we average the constituent concentrations from wells sampled in the San Joaquin Valley Drainage Monitoring Program during 2011–2012 (Laird et al., 2015). For groundwater, we average the constituents from the GAMA program for all reports within the study area (Bennett et al., 2006; Bennett et al., 2009; Dawson et al., 2008; Landon and Belitz, 2008; Shelton et al., 2008; Burton et al., 2008; Schmitt et al., 2008). Surface water data were taken from a current assessment of constituent levels from USGS WaterQualityWatch (USGS, 2016b) (Table C.2).

Appendix D. : Modeling the Air Emissions Damages Associated with Brine Disposal

In the main analysis the costs of brine disposal are assumed to be incorporated in the private costs. However, there are likely public costs from the air emissions damages of brine disposal if evaporation ponds are not used. In this Appendix D we model the air emissions damages of brine management by adding a brine crystallizer to the trains of the GT, RO, and ST systems. We then reanalyze the benefit gap with these losses included.

Fig. D.1 plots CDF of private benefits minus social cost (the benefit gap) for GT, RO and ST systems for 2010 values of augmented supplies for GT, RO, and ST systems, and demonstrates the change in the CDF in these systems when a brine crystallizer is employed for brine management. When employing a brine crystallizer, we conservatively estimate that retentate volume is 10% of feed volume and brine crystallization energy consumption of the vapor compression crystallizer is 66 kW h/m3 feed volume (Mickey, 2008). Including brine crystallization costs widens the benefit gap by \$0.10-\$0.30 per m^3.

Fig. D.2 demonstrates the air damages associated solely with the crystallizer use for brine management depending on location for gas-powered thermal brine crystallization. Damages for solar thermal or grid powered brine crystallizers are not mapped as they do not vary spatially. Air damages from brine crystallizer addition are overshadowed by air damages from the gas-powered thermal desalination unit for which it treats retentate (Fig. A.1).

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