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# Water Resources Research

**Key Points:**

- Determined vulnerability to changes in groundwater supply for 288 rural communities in southern Central Valley, California
- Combined geographic information system-based multicriteria decision analysis with groundwater modeling and particle tracking to identify recharge locations
- Identified 2,998 agricultural land parcels for managed aquifer recharge within domestic well capture zone of 149 communities

**Supporting Information:**

- Supporting Information S1

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# Identifying Agricultural Managed Aquifer Recharge Locations to Benefit Drinking Water Supply in Rural Communities

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**Abstract** The southern Central Valley of California is one of the most productive agricultural regions in the world. Yet, decades of groundwater use beyond sustainable yield have left rural communities highly vulnerable to shortages and contamination of their drinking water supply. As state regulation begins to address these issues, a need exists to design adaptive and appropriate management systems to increase resilience of rural communities. Targeted managed aquifer recharge on agricultural land (Ag-MAR) near rural communities is one such strategy that could potentially stabilize groundwater tables and maintain or improve groundwater quality in domestic supply wells. Here we present a geographic information system-based multicriteria decision analysis that combines biophysical data (soils, land use, and surface water conveyance) with groundwater modeling and particle tracking to identify suitable agricultural land parcels for multibenefit groundwater recharge within well capture zones of 288 rural communities. Parcels are prioritized using a vulnerability index to change in groundwater supply, derived from well reliance and failures, pesticide applications, land subsidence, and socio-economic data. Our analysis identifies 2,998 suitable land parcels for Ag-MAR within the well capture zones of 149 of the 288 communities, of which 144 rely mainly on groundwater for drinking water. The majority of identified Ag-MAR parcels serve communities ranked as having extreme or very high vulnerability to changes in groundwater supply. Our research produces new understanding of factors contributing to community vulnerability and resilience to changes in drinking water supply and can be used to discuss actions to help achieve a stable and high-quality water supply.

## 1. Introduction

Groundwater access has allowed for significant social and economic development, improving food security and livelihoods worldwide (Giordano, 2009). However, growing populations and socio-economic development have required the expansion of irrigated agriculture and urbanization into areas with limited precipitation and inadequate surface water access, forcing a six-fold increase in global groundwater withdrawals over the last century (Bierkens & Wada, 2019). Over two billion people and more than 40% of the world's agricultural production systems rely on groundwater as their primary water source, and it now accounts for one-third of the global freshwater supply (Alley et al., 2002; Döll et al., 2012; Famiglietti, 2014). This development threatens groundwater resources and is apparent in high rates of aquifer depletion and degradation around the world (Gleeson et al., 2020). Decreasing reliability of surface water and depleted groundwater aquifers in groundwater-dependent regions severely impacts domestic water supplies (Hanak et al., 2019), food security (Dalin et al., 2017; Gumidyala et al., 2020), and natural ecosystems (Bierkens & Wada, 2019). This is especially the case in arid and semiarid regions where poorly monitored and often unregulated pumping has contributed to many negative impacts including lowered groundwater levels (Butler et al., 2018), loss of aquifer storage capacity (Ojha et al., 2019; Smith et al., 2017), degraded water quality (Rosenstock et al., 2014; Smith et al., 2018), seawater intrusion (Jasechko et al., 2020), land subsidence (Jeanne et al., 2019), streamflow depletion (Zimmerman et al., 2018), and degradation of groundwater-dependent ecosystems (Famiglietti, 2014; Urióstegui et al., 2017).

Managed aquifer recharge (MAR) includes a suite of methods that are increasingly used to improve the quantity and quality of groundwater (Bouwer, 2002; Brown & Signor, 1974; Dillon, 2005; Dillon et al., 2019). MAR is the intentional diversion, transport, storage, infiltration, and recharge of excess surface water into

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aquifers during a wet period for subsequent recovery during dry periods or for environmental benefit (Dillon et al., 2010). Over the last century, MAR projects have been implemented globally for different purposes ranging from flood mitigation (Pavelic et al., 2012), groundwater quality improvements (Bekele et al., 2011), protection against seawater intrusion (Russo et al., 2015), enhancement of environmental flows (Niswonger et al., 2017), to stabilization of drinking water supplies (Page et al., 2016), and other beneficial uses (Dillon et al., 2019). In rural areas, MAR has been primarily used to increase groundwater security to meet irrigation demand, reduce the lowering of groundwater tables, and improve the quality of irrigation water (Dillon et al., 2009). Varying water sources have been used for MAR, including river water (Scanlon et al., 2016), stormwater (Page et al., 2016), treated wastewater (Bugan et al., 2016), high-magnitude flows (Bachand et al., 2014; Kocis & Dahlke, 2017), and desalinated water (Kimrey, 1989). Dillon et al. (2019) provide a comprehensive summary of existing MAR methods such as river-bank filtration, infiltration basins, aquifer storage and recovery, soil aquifer treatment, and vadose zone infiltration devices (e.g., drywells, see Sasidharan et al., 2018, 2019).

In recent years, managed aquifer recharge on agricultural land (Ag-MAR) has gained popularity because it can effectively recharge aquifers using high flows from rainfall or snowmelt that could not previously be stored or used before ocean discharge (Bachand et al., 2014; Kocis & Dahlke, 2017; Kourakos et al., 2019). Ag-MAR can utilize existing irrigation infrastructure to spread low-contaminant-load water over vast agricultural areas, allowing for large amounts of recharge in short time periods (e.g., days to weeks) that would overwhelm more localized MAR systems (e.g., infiltration basins, drywells, injection wells) (Kourakos et al., 2019). Because of its larger footprint, Ag-MAR has the potential to address or reverse many of consequences of groundwater overdraft (Ghasemizade et al., 2019; Maples et al., 2019).

Identification of suitable groundwater recharge zones is often a first step in the implementation process of a MAR project (Ringleb et al., 2016), but requires the combination and prioritization of biophysical, socio-economic, and environmental criteria (Fuentes & Vervoort, 2020). Previous approaches have ranged from costly and time-consuming test drillings and stratigraphy analyses (Fetter, 1994; Todd, 1980), statistical methods (frequency ratio, logistic regression, classification trees, and others) (Guru et al., 2017), on-site field investigations (Alesheikh et al., 2008; Beganskas & Fisher, 2017), and deterministic modeling (Russo et al., 2015). However, the most common approach used in the past 2 decades is an integrated remote sensing and geographic information system (GIS)-based multicriteria decision analysis (MCDA) (e.g., Malczewski, 1999; see Sallwey et al., 2019 for a most recent review). GIS-based MCDA techniques integrate various thematic layers and/or their individual features using a set of weights, a process for which no standard exists (Giove et al., 2009).

MCDA approaches are increasingly supported or coupled with numerical modeling to provide more detailed and quantitative assessment of MAR opportunities and impacts (Sallwey et al., 2019; Zhang et al., 2019). Among the existing studies, Russo et al. (2015) used a MODFLOW-2005 model of the Pajaro Valley in California to evaluate MAR project placement and operational parameters of potential infiltration basins. They concluded that combining a GIS-based MCDA analysis with a hydrogeologic model allowed assessing the relative benefits of different MAR scenarios and helped in assuring spatial data quality in the MCDA analysis. Zhang et al. (2019) conducted a GIS-based MCDA analysis to determine suitable MAR sites along the West Coast of South Africa. They used MODFLOW and particle tracking (MODPATH) to trace the recharged water and concluded that the GIS analysis alone did not necessarily identify the most suitable sites. Likewise, Rahman et al. (2013) recommended that mathematical modeling should be combined with MCDA techniques to select optimal MAR locations even if a wide variety of thematic layers are considered in the MCDA.

The criteria most frequently considered in site suitability analyses for MAR include intrinsic factors such as hydrogeology, topography, geomorphology, soil type, land use, and climate (including precipitation and water availability), as these represent main constraints on the groundwater recharge process (Sallwey et al., 2019). However, in view of the growing global population, urban sprawl, and water scarcity that affect both irrigation water supply and drinking water supply of groundwater-dependent rural communities, there is increasing recognition that integrated water resources management must consider socio-economic and socio-ecological criteria (Bogardi et al., 2015; Zhang et al., 2019). The growing field of coupled natural human systems research in general, and socio-hydrology in particular (Sivapalan et al., 2012), explicitly

recognize the reciprocal interactions and co-evolution of coupled human-water systems. In California's Central Valley (CV), one of the most productive agricultural regions in the world, agricultural water use (Hanak & Lund, 2012) and climate-induced reduction of surface water supplies (Diffenbaugh et al., 2015) have led to severe groundwater overdraft in the past century. This has diminished access to clean, reliable drinking water in rural communities (Francis & Firestone, 2010; Pauloo et al., 2020). This unsustainable and inequitable regional change (Francis & Firestone, 2010) has disproportionately impacted disadvantaged communities (DACs), who provide most of the farm labor to the agricultural sector (Howitt et al., 2014), and perpetually decreased the economic viability and resilience of these communities to face hydro-climatic change (Huang & London, 2012; London et al., 2013; Moore et al., 2011). With the implementation of new groundwater legislation in California (Sustainable Groundwater Management Act, 2014), MAR and especially Ag-MAR could play a central role in optimizing the use of surface water to stabilize depleted groundwater aquifers while addressing critical issues of drinking water supply and quality in rural communities. Targeted Ag-MAR in the well capture zones of rural communities could provide multiple hydrological, socio-economic, and socio-ecological benefits by increasing equitable access to groundwater resources for rural or impoverished communities while supporting the needs of a groundwater-dependent agricultural economy.

The goal of this study is to delineate locations for targeted groundwater recharge on agricultural land with the potential to improve the groundwater supply in rural communities. Our study proposes a GIS-based MCDA methodology that combines biophysical and socio-economic data with groundwater modeling and particle tracking to identify and prioritize suitable Ag-MAR locations for multibenefit recharge. In contrast to previous studies which tend to first focus on-site identification and then on groundwater benefits of recharge locations, our Ag-MAR site selection is spatially constrained to benefit domestic wells located in rural communities. We developed a GIS-based MCDA methodology with the specific objectives: (i) to identify agricultural land parcels suitable for Ag-MAR, (ii) to map well capture zones in rural communities using a groundwater model and particle tracking, (iii) to estimate the vulnerability of rural communities to changes in groundwater supply, and (iv) to prioritize Ag-MAR sites of most benefit to rural communities based on community vulnerability. The methodology framework was developed for California's southern CV but could be useful to decision-makers and water resources managers in the efficient planning and management of Ag-MAR or MAR efforts worldwide.

## 2. Study Area

The southern CV of California (20,820 km$^2$, Figure 1a), located between 35° and 37°N and 118° and 121°W, supports almost half of California's $50 billion agricultural economy (CDFA, 2018). The main agricultural commodities produced in the southern CV are table grapes, milk, almonds, alfalfa, pistachio and corn (CDFA, 2018). Agriculture is the largest private employer in the region, with farm employment accounting for 25%–33% of all jobs (CDED, 2019). The area has a Mediterranean climate with most precipitation falling as rain or snow between November and April. Annual precipitation totals less than 200 mm in the valley and over 1,000 mm in the Sierra Nevada mountains (1980–2010, Kocis & Dahlke, 2017) and mean annual air temperature ranges between 17°C and 19.5°C across the valley floor. The Kings, Kern, Tule, and Kaweah rivers are major tributaries to the southern CV providing surface water to the region, most of which is stored in four major reservoirs for consumptive use during the dry summer season (Hanak & Lund, 2012). High-magnitude flow and flood flow events, defined as flows above the 90th percentile of the full record, occur, on average, 2–5 years out of 10 years in the southern CV, creating a rare but important source of water for MAR (Dahlke et al., 2018; Kocis & Dahlke, 2017). Kocis and Dahlke (2017) estimated that during years with high-magnitude flow, on average, 1.6 km$^3$ of water is available in the San Joaquin Valley including the Tulare Lake Basin between November and April.

Groundwater in the southern CV accounts for more than one-third of the water consumption, of which 68% is used for agriculture. Groundwater aquifers in the region have an average annual overdraft rate on the order of 2.2 km$^3$/year (Hanak et al., 2019) to 4.2 km$^3$ (Howitt et al., 2014). Higher rates were observed during the 2012–2016 drought and as a result of increasing groundwater use associated with the expansion of high value, perennial tree, and vine crops (Mall & Herman, 2019). One-third of the local residents in the southern CV rely on domestic wells for drinking water, which tend to be shallower and withdraw less water
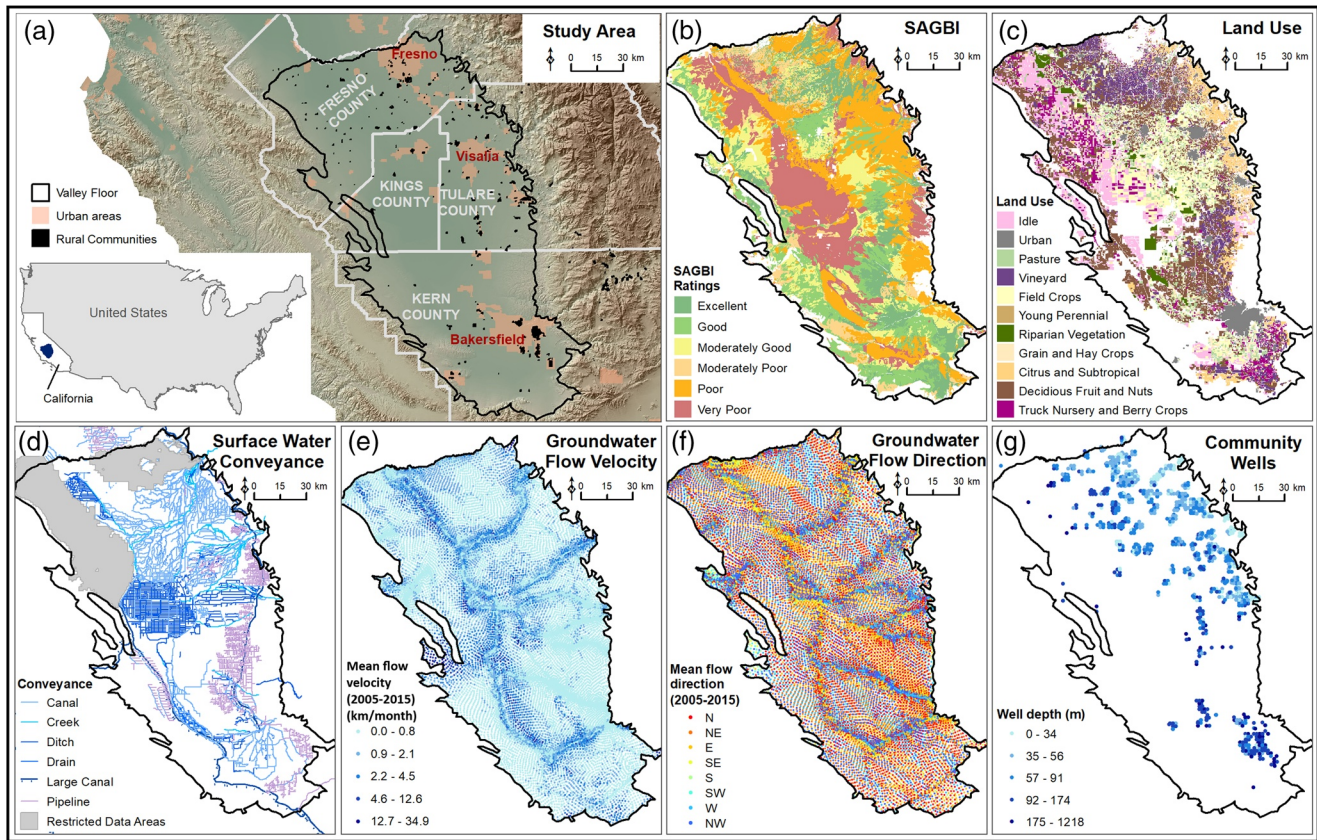
**Figure 1.** Maps show the location of the study area (a), the soil agricultural groundwater banking index (SAGBI) (b), land use, land cover (c), surface water conveyance infrastructure (d), groundwater flow velocity (e), groundwater flow direction (f), and community wells (g).

than agricultural wells (Pauloo et al., 2020). Many domestic wells are compromised due to lowering water tables (Pauloo et al., 2020; Perrone & Jasechko, 2019) and contamination with nitrate, metals, and metalloids from agricultural activities and solvents and other chemicals from industrial activities (Burow, 1999; CWC, 2011; Dubrovsky et al., 2010).

The four counties spanning the southern CV (Kings, Kern, Tulare, Fresno) have some of the lowest median household incomes in the state, $47,518–$53,869 per year (2014–2018) compared to the state's median of $75,277 (2018), and some of the highest poverty rates (18.8%–22.2%) (U.S. Census Bureau, 2019). Due to the lower income levels generally found in the southern CV, most communities meet the California Proposition 84 definition of a DAC—a community with a median household income of less than 80% of the statewide average household income (Provost & Pritchard, 2014). Approximately 353 of the 530 communities in the southern CV are considered DACs (Provost & Pritchard, 2014). In this study, we focus on 288 DACs, hereon called rural communities, located within the valley floor of the southern CV (Figure 1a).

## 3. Materials and Methods

### 3.1. Thematic Layers Used in the Study

Delineation of Ag-MAR areas that could improve drinking water supply in rural communities and estimation of community vulnerability to groundwater supply change is a multiobjective and multicriteria problem that requires an understanding of the regional social-ecological-hydrological system (Berkes et al., 2000). For this study, a total of 13 biophysical, hydrological, and socio-economic geospatial data were compiled (Table 1, Figures 1 and 2). All data used in this study are from or representative of the 2012–2016 drought period. In addition to the biophysical data frequently used in MAR site selection (e.g., soil, land use, hydrogeology) (Rahman et al., 2012; Saraf & Choudhury, 1998), this study uses surface water conveyance

**Table 1**
*Thematic Layers Used, Their Spatial, and Temporal Resolution and Sources*

| Geospatial data sets | Spatial resolution | Temporal resolution | Source; file type | Access location |
|---|---|---|---|---|
| | | Boundaries | | |
| Tulare Lake Basin boundary | Tulare Lake Basin | – | CA Department of Water Resources; shapefile | https://gis.water.ca.gov/arcgis/rest/services/Boundaries/i03_Hydrologic_Regions/MapServer |
| Central Valley floor boundary | – | – | C2Vsim-FG model, CA Department of Water Resources; shapefile | https://data.cnra.ca.gov/dataset/c2vsimfg-beta-model/resource/899d59f6-2615-47ae-86ea-aad75afb6715 |
| Rural community locations | Communities | July 24, 2014–Aug 14, 2014 | Provost & Pritchard; shapefile | Personal communication (Disadvantaged Community Water Study for the Tulare Lake Basin) |
| Public land survey system (PLSS) boundaries | PLSS sections (2.59 km$^2$) | – | CA Department of Pesticide Regulation; shapefile | https://gis.data.ca.gov/datasets/fbba842bf134497c9d611ad506ec48cc_0 |
| Public Water Supply System (PWSS) boundaries | PWSS service areas | 30 Aug 2019 | Tracking California; shapefile | https://trackingcalifornia.org/water/download |
| C2VSim-FG model finite element grid | CV floor (average element area = 1.65 km$^2$) | 2000–2015 | C2Vsim-FG model, CA Department of Water Resources; shapefile | https://data.cnra.ca.gov/dataset/c2vsimfg-beta-model/resource/899d59f6-2615-47ae-86ea-aad75afb6715 |
| | | Ag-MAR site suitability analysis | | |
| Soil suitability for recharge (SAGBI) | Sediment components | 2015 | SAGBI index (UC Davis); shapefile | https://casoilresource.lawr.ucdavis.edu/sagbi/ |
| Land use, land cover | Parcels | 2014 | Statewide Crop Mapping (CDWR); shapefile | https://gis.water.ca.gov/app/CADWRLandUseViewer/ |
| Surface water conveyance infrastructure | Recharge basins, large canals, canals, drains, creeks, ditches, pipelines, turnouts; secondary canal features | 2010–2019, varies by source and agency | Independent water management agencies, digitization from public maps; feature class; CDWR; shapefile | Personal communication and digitization (https://data.ca.gov/dataset/water-districts); https://data.ca.gov/en/dataset/canals-and-aqueducts-local2 |
| | | Well Capture Zone Determination | | |
| Domestic well construction logs | PLSS sections | 03 June 1930 – 26 Aug 2019 | Online System for Well Completion Reports (CDWR); shapefile | https://shiny.lawr.ucdavis.edu/shiny/oswcrd/ |
| Groundwater flow field | Finite element grid of C2VSim-FG (average element area = 1.65 km2) | 2000 – 2015 | IWFM (CDWR); shapefile | An output (https://data.cnra.ca.gov/dataset/c2vsimfg-beta-model/resource/f2bc889f-000a-452e-8864-71107b33f5e5) |
| | | Rural community vulnerability to change in groundwater supply | | |
| Domestic well construction logs | PLSS sections | June 03, 1930–Aug 26, 2019 | Online System for Well Completion Reports (CDWR); shapefile | https://shiny.lawr.ucdavis.edu/shiny/oswcrd/ |
| Groundwater depth surfaces | CV floor | Spring 2011, Fall 2015 | Pauloo et al. (2019) | https://doi.org/10.25338/B8Q31D |
| Reported drinking water supply shortages | 1/100th of a degree accuracy of coordinates | Feb 10, 2014–Oct 29, 2018 | Household Water Supply Shortage Reporting System (CA DWR); shapefile | Personal communication (https://mydrywatersupply.water.ca.gov/report/publicpage) |
| Pesticide applications | PLSS sections | 2015 | CA Department of Pesticide Regulation; shapefile | https://calpip.cdpr.ca.gov/format.cfm |

**Table 1**
*Continued*

| Geospatial data sets | Spatial resolution | Temporal resolution | Source; file type | Access location |
|---|---|---|---|---|
| Land subsidence | Raster, 90 × 90m pixel size | May 07, 2015–Sept 10, 2016 | Tom Farr (NASA's Jet Propulsion Laboratory); raster | https://data.cnra.ca.gov/dataset/nasa-jpl-insar-subsidence |
| Socio-economic information (poverty status, linguistic isolation, educational attainment) | Block groups | 2015 (average of 2011–2015) | American Community Survey (U.S. Census Bureau); shapefile | https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-data.2015.html |

infrastructure and groundwater flow fields (C2VSim, Brush et al., 2013) to identify agricultural land parcels suitable for multibenefit Ag-MAR and well source areas (CDWR, 2020b). To estimate the vulnerability of rural communities to change in groundwater supply, pesticide applications, land subsidence, and U.S. Census data are combined. Figure 3 displays the GIS-based MCDA framework. All thematic layers were processed and integrated using the ArcGIS 10.6.1 Desktop software from https://www.esri.com/.

### 3.1.1. Suitability of Agricultural Land Parcels for Ag-MAR

Agricultural land parcels suitable for Ag-MAR were identified based on soil characteristics, land use, and vicinity to existing surface water conveyance infrastructure.

#### 3.1.1.1. Soil Suitability for Recharge

The Soil Agricultural Groundwater Banking Index (SAGBI) was used to identify land parcels suitable for Ag-MAR based on soil suitability (Figure 1b). SAGBI considers five factors (deep percolation, root zone residence time, topography, chemical limitations, and soil surface condition) to accommodate groundwater recharge while maintaining soil health, crop growth, recharge efficiency, or groundwater quality (O'Geen et al., 2015). SAGBI ranks soils on a six-class scale ranging from Excellent to Very Poor. For this study, only agricultural areas with soil ranked as Excellent, Good, or Moderately Good were selected as suitable Ag-MAR locations based on recommendations provided by Dahlke et al. (2018).

#### 3.1.1.2. Land Use and Land Cover

Land in the southern CV is mainly used for agriculture (50%), with only minimal urban settlements (5%) and riparian land cover (1%) remaining (Figure 1c). The major crops grown in the southern CV are deciduous fruit and nut tree crops (18%), field crops (9%), and vineyards (7%) (Figure 1c). Because prolonged flooding can cause waterlogging and anoxic conditions in the root zone, which can promote plant diseases and other pests (Drew & Lynch, 1980), implementing Ag-MAR on agricultural land planted with perennial crops can increase the risk of yield loss. However, little research exists on crop tolerance to prolonged flooding conditions created by Ag-MAR. Preliminary research shows that vineyards and alfalfa show no significant yield penalties after controlled flooding from the end of winter to early spring when the fields overlay highly permeable soils (Bachand et al., 2014; Dahlke et al., 2018; Dokoozlian et al., 1987). Thus, land parcels planted with vineyards, pasture (5%), idle lands (10%), grain and hay crops (2%), and field crops, which likely are fallowed in the wet season, were deemed suitable for Ag-MAR.

#### 3.1.1.3. Surface Water Conveyance Infrastructure

Geospatial data of existing surface water conveyance infrastructure were provided by nine water management agencies (Arvin Edison Water Storage District, Buena Vista Water Storage District, Fresno Irrigation District, Kern County Water Agency, Kern Delta Water District, Madera Irrigation District, North Kern Water Storage District, Tulare Irrigation District, Westlands Water District). For the remaining surface water districts, conveyance infrastructure was digitized from publicly available maps (e.g., groundwater management plans, integrated regional water management plans; Table S2) and aerial images. In areas where surface water conveyance infrastructure was visible in air photographs, features (e.g., open canals, ditches) were digitized at a scale of 1:10,000. GIS data of larger conveyance infrastructure (e.g., California Aqueduct, Friant-Kern Canal) were obtained from the California Open Data Portal (CDWR, 2020a, 2020b, 2020c).
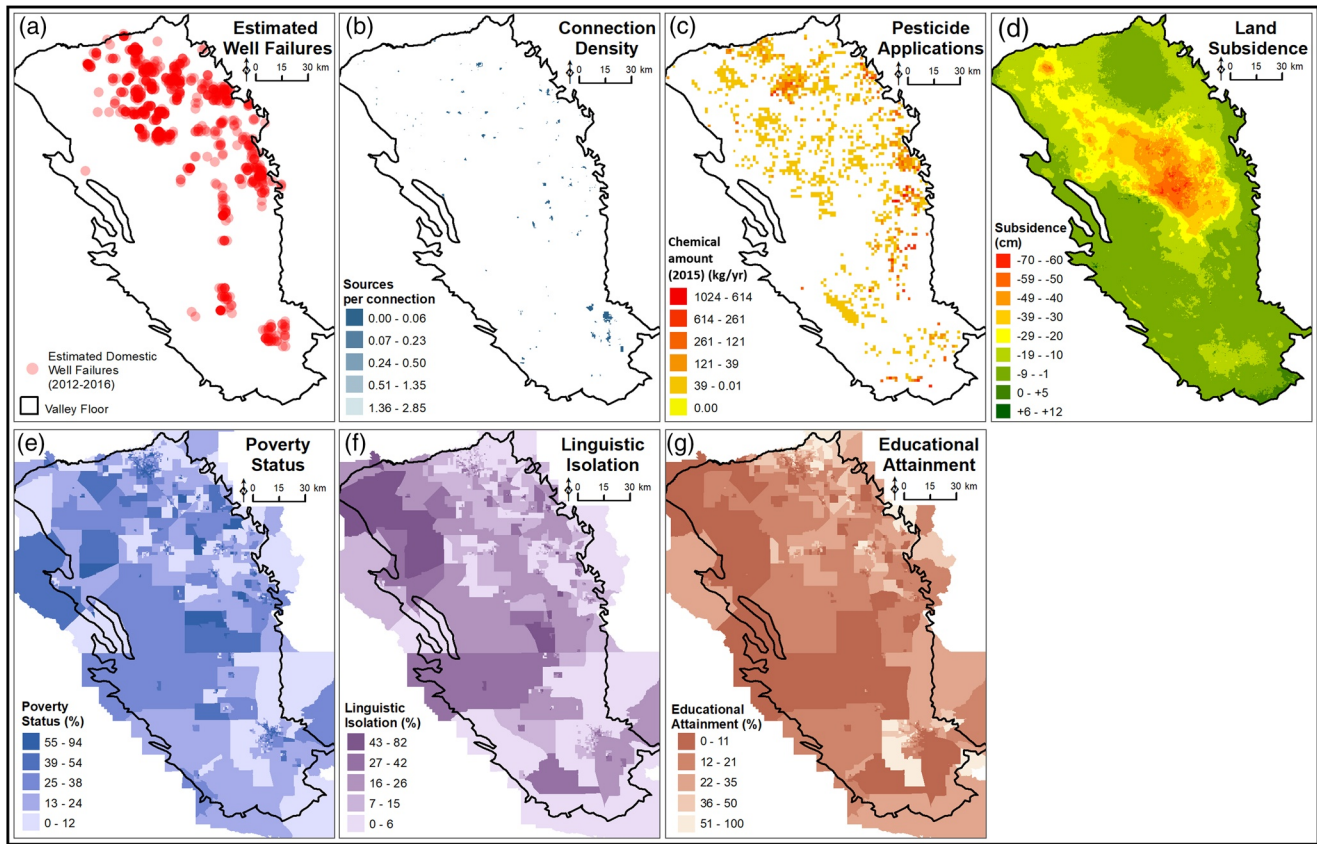
**Figure 2.** Maps show the estimated well failures for 2012-2016 (a), connection density to public water supply systems (b), pesticide application amounts (c), land subsidence (d), US Census block group poverty status (e), linguistic isolation (f), and educational attainment (g).

All surface water conveyance data were classified into the following conveyance types based on district information: recharge basins, large canals, canals, drains, creeks, ditches, pipelines (underground pipes), and turnouts. Surface water conveyance types were classified based on their accessibility for easier or less costly construction of surface water diversion points (e.g., new turnouts, pump stations, gates) or exten-
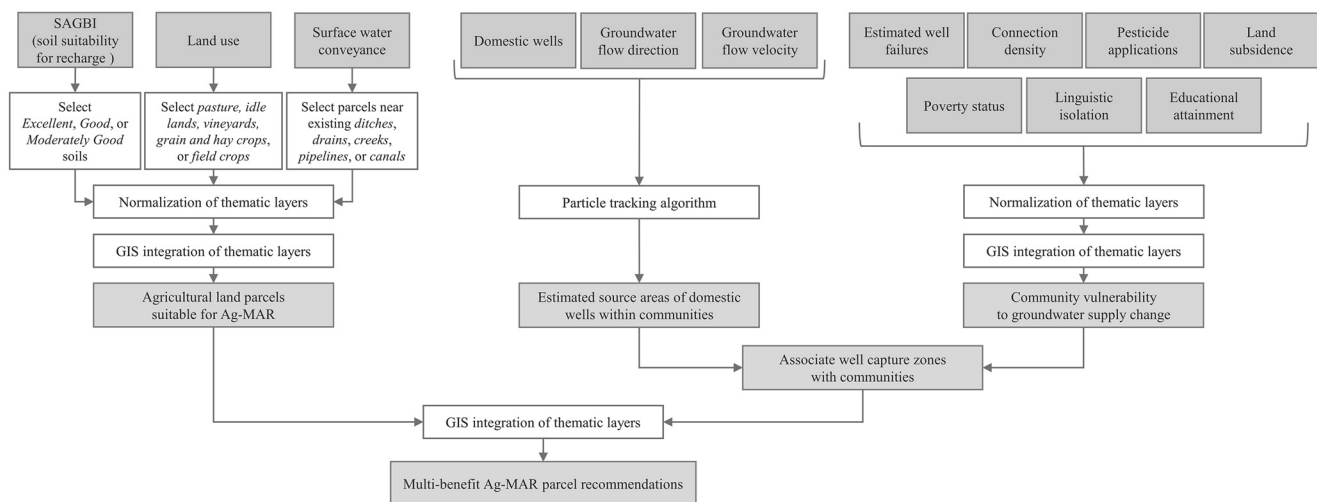


**Figure 3.** GIS-based MCDA methodology for the delineation of multibenefit Ag-MAR locations. GIS, geographic information system; MCDA, multicriteria decision analysis.

sions of existing infrastructure. The resulting classification used in the analysis was ditches, drains, creeks, pipelines, and canals, each comprising 22%, 1%, 10%, 25%, and 38% of the drainage network, respectively (Figure 1d). Unique buffers were placed around each conveyance type based on typical distances measured between diversion points (e.g., field turnouts) and conveyance sources (e.g., canals, ditches, pipelines, etc.). Distances were estimated from public surface water district maps and aerial images. Land parcels were prioritized based on which buffer they intersected.

### 3.1.2. Domestic Well Capture Zones

Groundwater well capture zones are defined as the areal extent and volumetric portion of a groundwater system that contribute discharge to a particular well (Barlow et al., 2018). Captures zones were derived for all domestic wells in rural communities using the California Department of Water Resources' (CDWR) On-line System for Well Completion Reports (OSWCR) and the California Central Valley Groundwater-Surface Water Simulation Model (C2VSim) (Brush et al., 2013; Kourakos et al., 2019).

#### 3.1.2.1. Groundwater Flow Velocity and Direction

C2VSim was used to extract a generalized groundwater flow field for the study area. C2VSim is an integrated surface water-groundwater model based on the finite element code of the Integrated Water Flow Model capable of accounting for reservoir deliveries, streamflow, stream diversions, canal distribution systems, irrigation, runoff, crop water uses, vadose zone processes, and groundwater-surface water-irrigated landscape interactions typical of irrigated agricultural basins (Brush et al., 2013; Kourakos et al., 2019). The model domain covers the entire CV alluvial aquifer. More information on the model development, calibration and validation, and application for Ag-MAR can be found in Brush et al. (2013), Brush and Dogrul (2013), and Kourakos et al. (2019). The fine grid model version (average finite element size of 2.6 km$^2$) was used to extract a quasisteady-state representation of the regional groundwater flow field (Figures 1e and 1f), taken as the mean of the monthly flow fields from October 2005 to September 2015, to best inform recharge efforts.

#### 3.1.2.2. Domestic Well Information

In the State of California, construction of a new well must be reported to OSWCR. Well locations in OSWCR are reported at a 2.6 km$^2$ resolution by stating the centroid coordinates of the 2.6 km$^2$ Public Land Survey System (PLSS) section a well is located within (CDWR, 2018). For this study, well logs of 27,482 domestic wells located within the study area were downloaded from OSWCR. Wells located within a 1.61 km radius of any of the 288 rural communities were extracted, reducing the number of domestic wells to 7,673 (Figure 1g). Well logs were screened for completeness of the following well construction information: well depth, depth to the top of the well screen, and depth to the bottom of the well screen (Figure S1). For wells with incomplete records, well status modeling was used to impute missing information, specifically the depth to the top of the well screen and the submergence depth of the well pump (Section 3.1.3.1).

### 3.1.3. Community Vulnerability to Change in Groundwater Supply

Investigation and mapping of factors that increase vulnerability to or probability of natural and socio-economic hazards can provide a useful way to prioritize where efforts should be focused (Starrs et al., 2018). To determine community vulnerability to change in groundwater supply, data describing domestic well failures, domestic well reliance, pesticide applications, land subsidence, and socio-economic factors were used.

#### 3.1.3.1. Domestic Well Failures

A thematic layer describing "domestic well failures" (Figure 2a) was generated using domestic well construction logs, groundwater table information, and self-reported drinking water supply shortages (CDWR, 2020b). The California Household Water Supply Shortage Reporting System contains information on self-reported household drinking water supply shortages due to well failure, well underperformance, or loss of surface water supply. During the 2012–2016 drought, 867 wells were reported dry within our 288 rural communities. However, this is assumed to be an underestimation of the actual water supply shortages experienced during the 2012–2016 drought, since reporting is optional and many rural communities likely lack access to these tools.

A linear model was developed to impute missing data in well logs describing the depth to the top of the well screen, $z_t$. Following a similar approach to that developed by Pauloo et al. (2020), the logarithm of $z_t$ was related to the logarithm of the depth to the bottom of the well screen ($z_b$):

$$\log\left(z_t\right) = \beta_0 + \beta_1 \times \log\left(z_b\right) + \epsilon \tag{1}$$

where $z_t$ is the depth to the top of the well screen, $z_b$ is the depth to the bottom of the well screen, and $\varepsilon$ is the residual error term. The recorded value of $z_b$ was used where available (60% of all wells) and was otherwise taken as 6 m above the total completed well depth (Figure S2). Gailey et al. (2019) recommends a value of 6 m to be used as the regional minimum separation difference between $z_b$ and total completed well depth to ensure the expected accumulation of sediment does not impair well function.

Submergence of the well screen and pump intake are desired to ensure proper well function (Gailey et al., 2019). The initial installation of the pump intake is usually above $z_t$ to minimize costs of screen installation and to maximize the capacity for useable water production (Figure S2). It was assumed that the cost of rehabilitating wells to alleviate well production losses caused by falling groundwater levels would be prohibitive for rural communities. Thus, the analysis assumed that pump intakes would remain at some depth above $z_t$ and wells would become inactive if the groundwater level dropped below the pump intake (Figure S2). Since the OSWCR contains no information on the pump intake depth, a submergence value, $h_s$, was calibrated using the reported well failures as a validation data set. Submergence in this study is defined as the depth of the top of the well screen below the groundwater table.

Depth to the groundwater table and estimated $z_t$ values were used to quantify changes in well status between Spring of 2011 (highest groundwater table before the 2012–2016 drought) and Fall of 2015 (lowest groundwater table during the 2012–2016 drought). Groundwater depths at each well location were extracted from interpolated seasonal groundwater levels spanning the entire shallow to semi-confined CV aquifer system (Pauloo et al., 2020). To calibrate the required submergence value, $h_s$, $z_t$ values were compared to predrought (Spring 2011) and postdrought (Fall 2015) groundwater levels to identify wells that became inactive as a result of groundwater level declines. Using the reported well failures in rural communities ($n = 867$) as validation data, the required pump submergence value was calibrated to be $h_s = 10$ m for which the model estimated 923 well failures during the drought period, most of which were concentrated in the northeastern region (Figure 2a).

### 3.1.3.2. Water Supply Connection Density

Many rural communities in the southern CV are not connected to municipal water supply systems and generally rely on a single water source, typically a groundwater well, which puts them at risk of water supply failures (Provost & Pritchard Consulting Group, 2014). Water supply connection density is a metric that describes the pressure exerted on community drinking water supply sources, given as the ratio of active public water supply sources (e.g., number of public wells) to water supply connections (e.g., number of households) in each community (Figure 2b). Lower values indicate a higher per capita reliance on active public water supply sources, indicating the community has lower water supply security. Communities that rely on a single public water supply source are especially vulnerable to shortages and contamination, as the failure of a single source compromises the community's entire water supply. In the study area, 91 rural communities only have a single public water supply source of which more than 75% rely on groundwater. Communities solely reliant on unregulated domestic wells (118 out of the 288 rural communities) do not have any access to public water supply sources and as such, are the most vulnerable to shortages and contamination. The communities reliant on single or unregulated sources are concentrated in the northeastern and eastern regions of the southern CV.

### 3.1.3.3. Pesticide Applications

The California Department of Pesticide Regulation recognizes the following seven active ingredients contained in pesticides as a public health risk having the potential to pollute groundwater: atrazine, simazine, bromacil, diuron (except <7% diuron applied to foliage), prometon, bentazon, and norflurazon (California

Code of Regulations, 2014). Records of total annual application amounts of these active ingredients were obtained from the California Pesticide Information Portal for the year 2015. Values range between 0 and 1,024 kg within the study area (Figure 2c), with higher loads concentrated in northeastern and eastern regions (CDPR, 2015).

#### 3.1.3.4. Land Subsidence

Prolonged and unsustainable groundwater pumping causes severe settling or sinking of the land surface due to subsurface compaction of earth materials, known as land subsidence (Figure 2d). Land subsidence rates estimated with InSAR technology between May 2015 and September 2016 was used in this analysis. The data reveal two major subsidence bowls in the northwestern and eastern regions of the southern CV and the development of a new hot spot between them (Jeanne et al., 2019). Land subsidence is of particular concern because it directly affects major surface water conveyance systems and threatens the integrity of shallow, domestic wells.

#### 3.1.3.5. Socio-Economic Parameters

Socio-economic parameters of poverty status, linguistic isolation, and educational attainment were selected as unique and complementary factors contributing to community vulnerability to change in groundwater supply (Faust et al., 2017; London et al., 2018; Marsh et al., 2010; Provost & Pritchard, 2014). Socio-economic data were obtained by block group from the U.S. Census Bureau's American Community Survey's (ACS) 5-year estimates for 2011–2015 and processed using the R library *tidycensus* (Walker et al., 2018). For each of the three parameters described below, demographic percentages were calculated for all block groups in the region. If multiple block groups intersected a community, an area-weighted average was calculated and the value was applied to each respective community.

Poverty status is defined as the percentage of the population for whom the ratio of income to national poverty level in the previous 12 months was below one (Figure 2e). Poverty status is believed to contribute to community vulnerability as poorer households have less financial capacity to preemptively address or remediate water supply shortages (London et al., 2018). Linguistic isolation is defined as the percentage of households that are limited English-speaking households (i.e., households where the primary language is "Spanish," "Other Indo-European languages," "Asian and Pacific Island languages," or "Other languages") (Figure 2f). Households that have limited English-speaking capacity are to a lesser extent able to engage with administrative authorities to voice concerns or resolve problems, and thus have increased community vulnerability (London et al., 2018). Educational attainment is defined as the percentage of population over 25 years of age, who have completed some education above the high school level (i.e., completion of some college or obtained an Associate's, Bachelor's, Master's, Professional school, or Doctorate degree) (Figure 2g). Educational attainment can influence risk perception, skills and knowledge, and access to information and resources, hence less educated populations may be less empowered to prepare and recover from resource shortages (London et al., 2018; Muttarak & Lutz, 2014).

### 3.2. GIS-Based Multicriteria Decision Analysis

A GIS-based MCDA was used to combine the biophysical, hydrological, and social-ecological data listed in Table 1 to delineate and prioritize locations for multibenefit Ag-MAR. An equal weighting scheme for thematic layers and proposed rankings of categorical features was adopted in this study following recommendations of Visser (2017) and based on the variability present in existing recharge mapping studies (Chowdhury et al., 2010; Russo et al., 2015) (Table 2).

### 3.2.1. Assessment of Land Parcels Suitable for Ag-MAR

Thematic layers "soil suitability for groundwater recharge," "land use and land cover," and "surface water conveyance infrastructure" were combined to assess the suitability of land parcels for Ag-MAR (Figure 3). Boolean criteria were used to restrict focus to soil types that allow percolation of surface water into groundwater aquifers, land use, and land cover types that show tolerance to prolonged flooding conditions, and land parcels that are near existing surface water conveyance infrastructure. The weights listed in Table 2

**Table 2**
*Weights of the Thematic Layers and Their Features for Suitability Index Determination*

| Thematic layer | Feature class | | Boolean criteria | Feature weight |
|---|---|---|---|---|
| Soil suitability for groundwater recharge | Excellent | | 1 | 5 |
| | Good | | 1 | 3 |
| | Moderately good | | 1 | 1 |
| | Moderately poor | | 0 | – |
| | Poor | | 0 | – |
| | Very poor | | 0 | – |
| Land use, land cover | Pasture | | 1 | 5 |
| | Idle | | 1 | 4 |
| | Vineyards | | 1 | 3 |
| | Grain and hay crops | | 1 | 2 |
| | Field crops | | 1 | 1 |
| | Citrus and subtropical | | 0 | – |
| | Deciduous fruits and nuts | | 0 | – |
| | Riparian vegetation | | 0 | – |
| | Truck nursery and berry crops | | 0 | – |
| | Urban | | 0 | – |
| | Young perennial | | 0 | –- |
| Distance to surface water conveyance infrastructure | Ditches | =<40 m | 1 | 5 |
| | | >40 m | 0 | – |
| | Drains | =<40 m | 1 | 4 |
| | | >40 m | 0 | – |
| | Creeks | =<55 m | 1 | 3 |
| | | >55 m | 0 | – |
| | Pipelines | =<10 m | 1 | 2 |
| | | >10 m | 0 | – |
| | Canals | =<20 m | 1 | 1 |
| | | >20 m | 0 | – |
| | Large Canals | | 0 | – |

were assigned to the remaining features of all themes before the Suitability for Ag-MAR Index (SAI) was computed for individual land parcels as follows:

$$\text{SAI} = \frac{\sum\limits_{i=1}^{n} w_i \times x_i}{n} \tag{2}$$

where $w_i$ is the Boolean criteria and $x_i$ is the feature weight of the soil suitability, land use, and surface water conveyance themes. The continuous range of suitability values for land parcels in the study area were classified using the Jenks natural breaks method (de Smith et al., 2007).

### 3.2.2. Identification of Domestic Well Capture Zones

The capture and source area of a groundwater well is dependent on the depth of the well, length of the screened section, and the groundwater flow field. A particle tracking algorithm using the Runge-Kutta-Fehlberg numerical method was implemented to identify the capture areas for all domestic wells within rural communities. The Runge-Kutta-Fehlberg uses a self-adaptive step procedure, where the step size is reduced

as the curvature of the particle trajectory is increased (Kourakos et al., 2019; Mathews & Fink, 2004). Using the quasisteady-state groundwater flow field extracted from CDWR's C2VSim model, the particle tracking algorithm calculates the velocity and trajectory of a particle by interpolating the velocities between the nearest points of simulated groundwater heads in the model, then transporting the particles backward in time to determine their exit points using discrete steps of a predefined time length. Well construction information from the OSWCR database and well status modeling (Section 3.1.3.1), including the well location, depth of well screen, and screen length, are used for each domestic well within a rural community. More information on the parameters used in the particle tracking can be found in the Supplemental Materials.

### 3.2.3. Estimation of Community Vulnerability to Change in Groundwater Supply

Community vulnerability to change in groundwater supply was estimated by integrating biophysical parameters of "domestic well failures," "water supply connection density," "pesticide applications," and "land subsidence," and socio-economic parameters of "poverty status," "linguistic isolation," and "educational attainment" (Figure 3, Figures S3 and S4). Each theme was separately normalized to preserve their respective distributions but allow for integration of all themes. Outliers (i.e., values greater than the upper limit [UL = Q3 + 1.5 × IQR] or less than the lower limit [LL = Q1−1.5 × IQR] where Q1 and Q3 are the first and third quartiles of data and IQR is the interquartile range [IQR = Q3−Q1]) were omitted during normalization. Thematic layers were normalized according to the following equation:

$$
\begin{cases}
Z_i = \dfrac{\left(x_i - x_{\min}\right)}{\left(x_{\max} - x_{\min}\right)} \\
Z_i = 1 - \dfrac{\left(x_i - x_{\min}\right)}{\left(x_{\max} - x_{\min}\right)}
\end{cases}
\tag{3a,b}
$$

where $x_i$ is the value of a particular theme for the $i$th community and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the theme among all communities, respectively. Equation 3a was applied for themes with a positive correlation to community vulnerability, while Equation 3b was applied for themes with a negative correlation to community vulnerability (Table S1). $Z = 0$ and $Z = 1$ represent the lowest and highest contributions of each theme to community vulnerability, respectively, and outliers were assigned a 0 or 1 value depending on the correlation of the theme with community vulnerability (Table S1) (Ahmadalipour & Moradkhani, 2018).

Normalized thematic layers were integrated to compute the Community Vulnerability Index (CVI) for each rural community as follows:

$$
\text{CVI} = \frac{\sum\limits_{i=1}^{n} x_i}{n}
\tag{4}
$$

where $x_i$ represents the normalized values of domestic well failures, water supply connection density, pesticide applications, land subsidence, poverty status, linguistic isolation, and educational attainment themes. All layers were equally weighed in the analysis. The continuous range of vulnerability index values for communities in the study area were classified using the Jenks natural breaks method into five classes. The CVI provides a relative measure of the biophysical factors that constrain the quantity and quality of drinking water supply and socio-economic factors that limit the ability of communities to secure sufficient and suitable water access.

### 3.2.4. Final Ag-MAR Location Recommendations for MultiBenefit Recharge

Final Ag-MAR parcels that could potentially improve the groundwater supply in rural communities were identified and prioritized by overlaying the map of suitable parcels for Ag-MAR with the well capture zones and the community vulnerability (Figure 3). Suitable parcels for Ag-MAR were retained if they were located
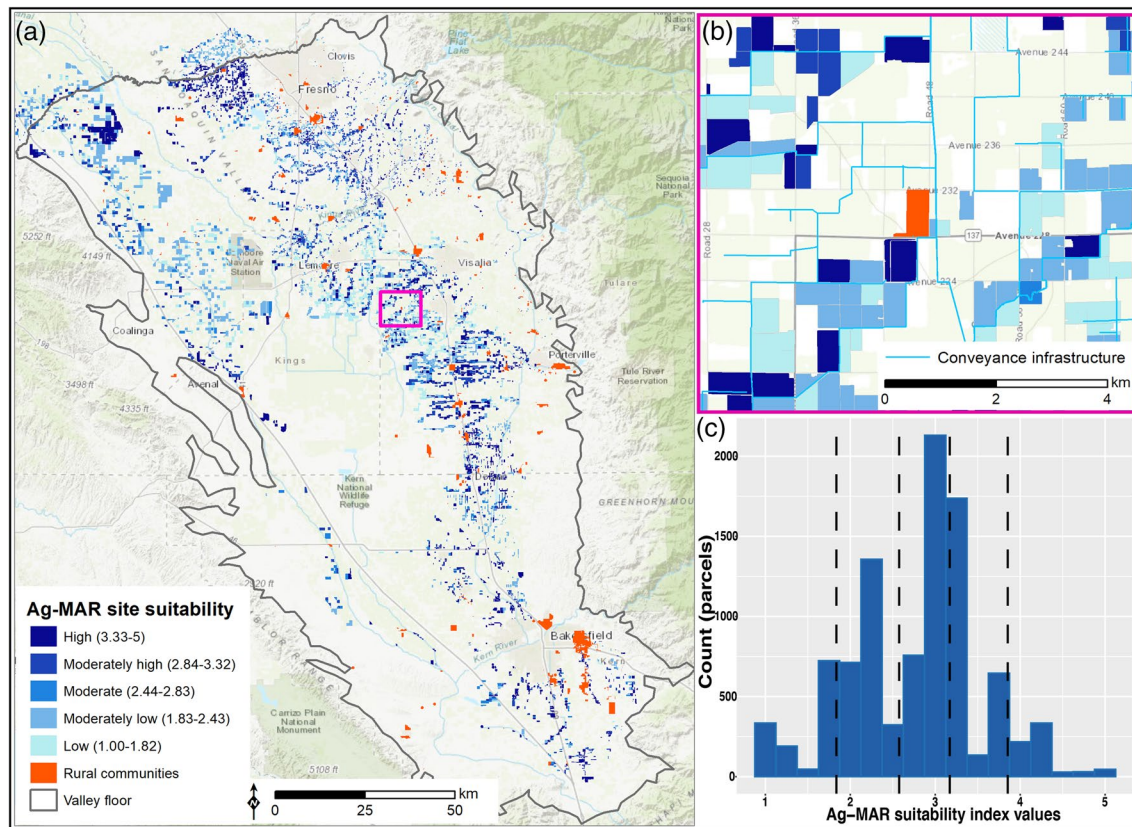
**Figure 4.** Agricultural land parcels suitable for Ag-MAR. Inset (b) shows a close-up around the Okieville community, west of Tulare, CA. Inset (c) shows a histogram of the Ag-MAR suitability index values; class breaks are indicated by dashed lines.

within the well capture zones of any of the 288 rural communities. Next, all retained parcels were assigned the community vulnerability index of their associated community as a means for prioritization of Ag-MAR implementation.

## 4. Results

### 4.1. Land Parcels Suitable for Ag-MAR

Agricultural land parcels suitable for Ag-MAR were identified by overlaying SAGBI classes Excellent (2,684 km$^2$), Good (3,206 km$^2$), and Moderately good (2,820 km$^2$) (Figure 1b) with land use classes field crops (1,917 km$^2$), grain and hay crops (506 km$^2$), idle land (1,954 km$^2$), pasture (944 km$^2$), and vineyards (1,465 km$^2$) (Figure 1c), that were located within a specified distance of existing surface water conveyance systems. Table 2 summarizes the distance thresholds for each surface water conveyance type. The overlay produced a total of 9,758 parcels covering a total area of 1,679 km$^2$ (8% of study area). The resulting parcels were classified into five suitability classes using the Jenks natural breaks method. The parcels shown in Figure 4a are classified as "Low" (290 km$^2$, index values 1.0–1.8), "Moderately Low" (185 km$^2$, 1.9–2.4), "Moderate" (551 km$^2$, 2.5–2.8), "Moderately High" (449 km$^2$, 2.9–3.3), and "High" (205 km$^2$, 3.4–5.0) suitability for Ag-MAR.

Northern and eastern regions of the southern CV are more suitable for Ag-MAR, especially because of the prominence of suitable soils, vineyards and field crops, and the greater density of surface water conveyance infrastructure from the Friant-Kern Canal and major Sierra Nevada tributaries. Note that the agricultural land suitability map contains almost no parcels in the Tulare Lake area, a 1,780 km$^2$ freshwater dry lake formerly located at the center of the study area that dried out by 1899. The fine sediment forming the lake bed make this region largely unsuitable for recharge. Figure 4b focuses in on suitable parcels for Ag-MAR
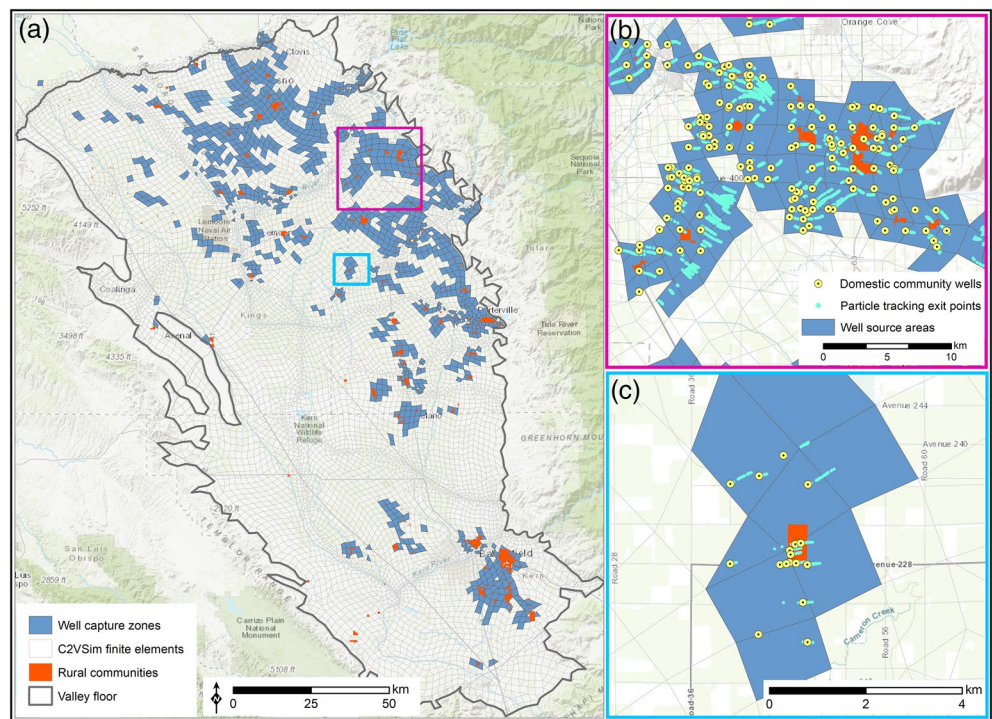
**Figure 5.** Domestic community well capture zones (a). Insets (b) and (c) show a close-up around the Orosi and Cutler communities east of Dinuba, CA, and the Okieville community, west of Tulare, CA, respectively.

around the Okieville community, located west of Tulare, CA. The community has several agricultural land parcels in near proximity with "Moderate," "Moderately High," and "High" suitability, displaying the potential opportunity and feasibility of implementing Ag-MAR to improve community groundwater supply. Land parcels located at greater distance to the east and northwest of the community are less suitable for Ag-MAR because of the presence of a restrictive clay layer in the soil profile, land use types (grain and hay crops, field crops) less tolerant to flooding, or poor connection to surface water conveyance infrastructure.

### 4.2. Domestic Well Capture Zones

The well status model was used to impute missing well data and provide a more spatially complete estimate of the domestic well failures that occurred during the 2012–2016 drought. Of the 27,482 domestic wells in the study area, 2,907 wells were excluded from the model development because the top of the well screen was shallower than the predrought groundwater levels in spring of 2011. The remaining 24,575 wells were used to estimate the depth to the top of the well screen, $z_t$, using Equation 1. Of the 7,673 domestic wells located within the rural communities, 291 wells were missing $z_b$ and the total completed well depth information, thus $z_t$ could not be estimated. However, $z_t$ was estimated for 279 of the 282 wells only missing $z_t$ data. For these 7,673 wells, well capture zones were estimated using groundwater modeling and particle tracking.

Most of the capture zones (1,333 finite elements) delineated for the domestic wells within rural communities are concentrated in the northeastern and eastern regions of the study area, where the majority of the communities and domestic wells are located (Figure 5). Figures 5b and 5c focus in on the Orosi and Cutler communities east of Dinuba, CA, and the Okieville community, west of Tulare, CA. Both maps show a diverse pattern for the particle exit points of each well (Figure 5b) highlighting major differences in the groundwater flow velocity, well depths, and lengths of the well screen across the domestic wells in the study area. Well capture zones extend generally between 1 and 6 km upgradient of wells (Figure 5b). Some neighboring wells show clear differences in groundwater flow direction and upgradient capture area, which are likely due to differences in well depth and well screen length (Barlow et al., 2018).
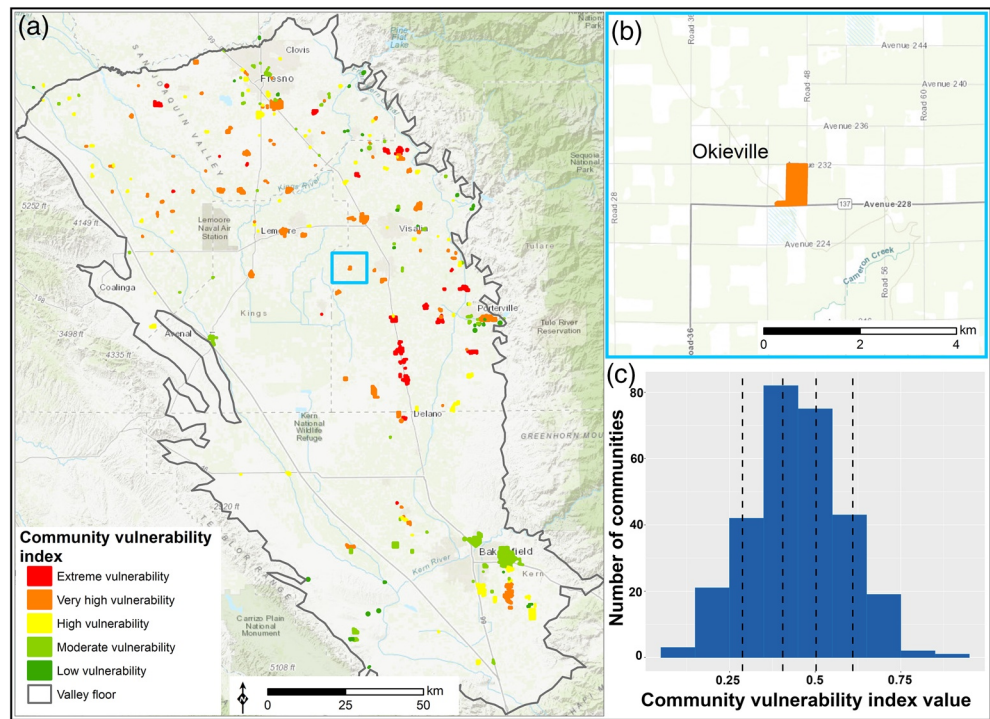
**Figure 6.** Community vulnerability index (a). Inset (b) shows a close-up around the Okieville community, west of Tulare, CA. Inset (c) shows a histogram of the Ag-MAR suitability index values; class breaks are indicated by dashed lines.

### 4.3. Community Vulnerability to Change in Groundwater Supply

Community vulnerability index values were classified into five classes representing "Extreme Vulnerability," "Very High Vulnerability," "High Vulnerability," "Moderate Vulnerability," and "Low Vulnerability" (Figure 6, Table S1).

Communities classified as extremely vulnerable are concentrated in the eastern part of the study area (e.g., Tulare County) while highly and very highly vulnerable communities are mainly seen in the northern and northeastern part of the southern CV (Figure 6a). There are clear differences in the mean theme scores between the most and least vulnerable communities (Table 3). For example, in the 30 communities classified

**Table 3**
*Summary of Theme Statistics for Each Community Vulnerability Class*

| Vulnerability group | N | Population | Community size | Well failure | Connection density | Applied pesticide amount | Land subsidence | Poverty | Linguistic isolation | Educational attainment |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Ha | % | Sources per household | kg in 2015 | cm | % | % | % |
| Extreme vulnerability | 30 | 1,133 | 92.8 | 27.8 | 0.0049 | 53.76 | −22.09 | 44.6 | 30.7 | 8.1 |
| Very high vulnerability | 72 | 8,556 | 80.3 | 15.8 | 0.0127 | 28.41 | −16.94 | 36.5 | 24.8 | 10.7 |
| High vulnerability | 72 | 372 | 32.1 | 10.4 | 0.0457 | 8.63 | −11.30 | 30.1 | 25.3 | 12.2 |
| Moderate vulnerability | 78 | 1,157 | 70.0 | 8.5 | 0.0229 | 2.47 | −10.23 | 25.5 | 13.8 | 15.3 |
| Low vulnerability | 36 | 174 | 15.6 | 2.5 | 0.2430 | 0.00 | −7.90 | 18.4 | 8.0 | 23.7 |
| Population mean | 288[a] | 218,940[a] | 16,901 | 12.1 | 0.0517 | 15.53 | −13.12 | 30.5 | 20.5 | 13.7 |

*Note.* The table shows totals for the number of communities (N) and population in each community vulnerability class and mean values for the remaining themes.
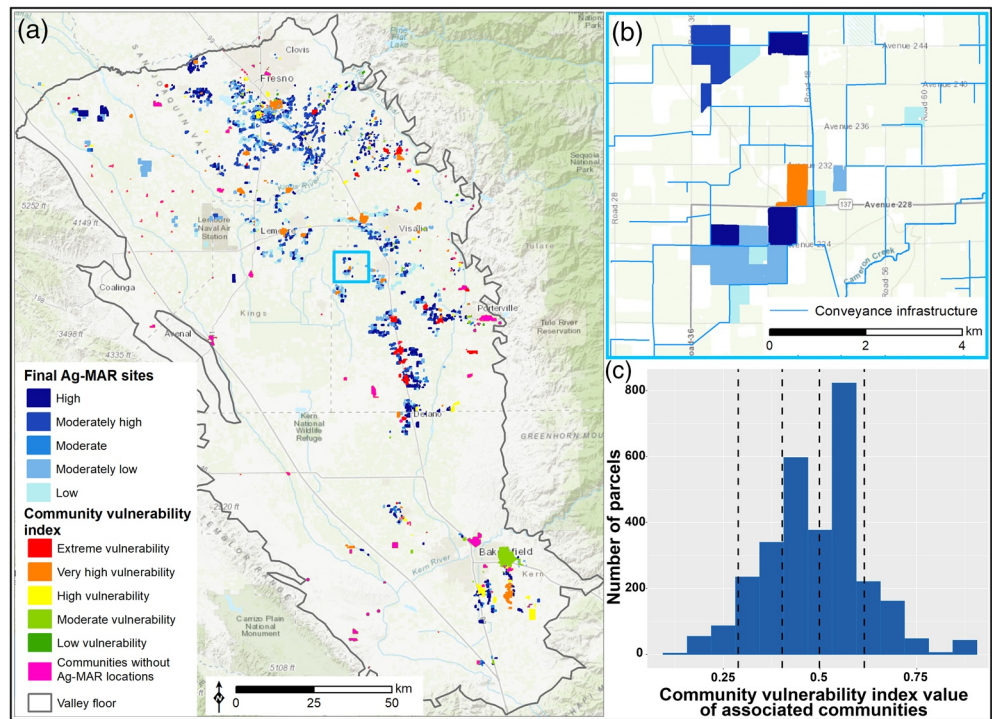[a]Totals and not mean values.

**Figure 7.** Final location recommendations for multibenefit, targeted Ag-MAR in the capture zones of rural community wells (a). Communities in (a) are ranked by their vulnerability to change in groundwater supply. Inset (b) shows a close-up around the Okieville community, west of Tulare, CA. Inset (c) shows a histogram of the community vulnerability index values associated with the final Ag-MAR parcel recommendations; class breaks are indicated by dashed lines.

as extremely vulnerable, on average, 44.6% of the population live below the poverty line, 30.7% of the households are limited English-speaking, and only 8.1% of the population above 25 years have completed some education above a high school degree. Extremely vulnerable communities are also characterized by higher well failure rates, greater land subsidence, and higher pesticide applications on fields surrounding these communities (Table 3). In these communities, on average, over 99 households rely on a single water supply source (e.g., groundwater well).

Less vulnerable communities ($N = 36$) are mainly concentrated in the southern part of the study area near larger urban centers (e.g., Bakersfield, CA) (Figure 6a). These communities had, on average, much lower well failure rates during the 2012–2016 drought, less land subsidence, and no reported applications of the seven active ingredients contained in pesticides known to pollute groundwater. These communities also have a much lower percentage of the population living below the poverty line (18.4%), a lower percentage of households that are limited English-speaking (8%), and a higher percentage of the population above 25 years that have completed some education above a high school degree (23.7%) (Table 3). In addition, the number of households that rely on a single water supply source is only 22 on average, and more communities have access to surface water as drinking water supply source.

### 4.4. Final Ag-MAR Sites of Most Benefit to Domestic Wells in Rural Communities

Final Ag-MAR parcels that could help stabilize or improve the groundwater supply in rural communities are depicted in Figure 7a and are available as an online decision support tool at https://agra.ucdavis.edu. Of the 9,758 agricultural land parcels (1,679 km², 8% of study area) identified as suitable for Ag-MAR (Section 4.1), 2,998 parcels (372 km², 1.79% of study area) were located within the capture zones of domestic wells within rural communities. The final parcels were assigned the community vulnerability index value of the associated rural communities (i.e., "Extreme Vulnerability," "Very High Vulnerability," "High Vulnerability," "Moderate Vulnerability," "Low Vulnerability") (Figure 7a).

**Table 4**
*Summary of Soil Suitability and Land-Use Distribution Across the Final Parcels Recommended for Targeted Ag-MAR in the Well Capture Zones of Rural Communities in the Southern CV*

| Vulnerability group | Area (km²) | N | SAGBI rating | | | | | | Land use | | | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| | | | Excellent (km²) | N | Good (km²) | N | Moderately good (km²) | N | Idle (km²) | N | Pasture (km²) | N | Vineyards (km²) | N | Grain and hay (km²) | N | Field crops (km²) | N |
| Extreme vulnerability | 68.8 | 417 | 36.2 | 298 | 13.1 | 62 | 19.5 | 57 | 4.1 | 34 | 2.1 | 35 | 44.3 | 242 | 0.4 | 4 | 17.8 | 102 |
| Very high vulnerability | 154.2 | 1,097 | 70.6 | 706 | 20.1 | 98 | 64.8 | 293 | 28.6 | 136 | 21.6 | 114 | 56.9 | 598 | 3.2 | 23 | 43.9 | 226 |
| High vulnerability | 91.8 | 847 | 48.8 | 607 | 25.5 | 151 | 17.5 | 89 | 22.8 | 185 | 11.5 | 90 | 30.9 | 401 | 7.0 | 36 | 19.6 | 135 |
| Moderate vulnerability | 45.3 | 487 | 25.9 | 330 | 13.1 | 82 | 6.3 | 75 | 4.7 | 63 | 7.4 | 44 | 18.7 | 280 | 3.0 | 19 | 11.5 | 81 |
| Low vulnerability | 11.3 | 150 | 6.7 | 115 | 3.3 | 20 | 1.4 | 15 | 2.6 | 53 | 2.0 | 27 | 3.1 | 44 | 0.5 | 7 | 3.1 | 19 |
| Total | 371.5 | 2,998 | 155.8 | 2056 | 75.1 | 413 | 109.4 | 529 | 62.9 | 471 | 44.7 | 310 | 153.9 | 1,565 | 14.1 | 89 | 96.0 | 563 |

*Notes.* Parcels are grouped by the community vulnerability index of the associated community. *N* indicated the number of parcels.

About half of the final Ag-MAR parcels are associated with extremely and very highly vulnerable communities; most are located within Tulare County (Figure 7a). A total of 1,334 parcels are associated with communities with high and moderate vulnerability, while 150 Ag-MAR parcel are associated with low vulnerability communities. Among the Ag-MAR parcels associated with extremely, very highly, and highly vulnerable communities, about 68% of the parcels have excellent soil suitability and are planted with vineyards (Table 4). Likewise, Ag-MAR parcels associated with moderate and low vulnerability communities have predominantly excellent soil suitability (70%) and the majority of the parcels are either vineyards, planted with field crops, or idle (Table 4). There are fewer Ag-MAR parcels surrounding rural communities in the southern part of the study area where large urban centers provide less opportunity to implement Ag-MAR as a mitigation strategy.

Figure 7a also indicates that there are some communities, particularly in the western and southwestern part of the study area, where no suitable Ag-MAR parcels could be found within the well capture zones. In fact, suitable Ag-MAR parcels could only be identified for about half (149) of the 288 communities, leaving 139 communities without nearby Ag-MAR sites. For these communities, Ag-MAR potential was mainly diminished by soil suitability (Figure 1b) and lack of surface water conveyance infrastructure (Figure 1d). Of the 149 communities for which suitable Ag-MAR parcels could be identified, 88 communities had at least 10 associated Ag-MAR parcels, and 60 communities had at least 20 associated parcels. There were 61 communities with less than 10 associated parcels, 14 of which had only one associated parcel.

## 5. Discussion

### 5.1. Implications for Ag-MAR in California's Central Valley

Although a wide variety of decision support tools are available for general surface and groundwater management (California Statewide Groundwater Elevation Monitoring Program, California Water Data Library [CDWR, 2020a], Streamflow Availability Rating for Recharge [Dahlke & Kocis, 2018]) and drinking water quality in California (e.g., OEEHA Human Right to Water Data Tool [Faust et al., 2017], Community Water Center Drinking Water Tool [CWC, 2019]); none of these tools provide information on mitigation or remediation options for chronic groundwater overdraft or contamination. This study is the first effort to systematically explore the potential for targeted Ag-MAR to directly improve the drinking water supply from groundwater in rural communities. In past decades, MAR has been used to achieve varying objectives (Dillon et al., 2019; Perrone & Rohde, 2016), however, implementation of MAR is often limited by challenges of recharge water availability (both amount and timing), locating suitable groundwater recharge zones, regulatory constraints, and funding obstacles (Bouwer, 2000; Hanak et al., 2018; Niswonger et al., 2017). Ag-MAR overcomes many of these challenges due to low capital cost and permitting requirements (Kocis & Dahlke, 2017; Perrone & Rohde, 2016; Tran et al., 2020), and with appropriate planning can be used to provide multiple benefits to a region including stabilized domestic and agricultural water supply, flood control, and climate change mitigation (Niswonger et al., 2017). However, Ag-MAR implementation in the southern CV might be constrained by the existing surface water conveyance capacity, which Hanak et al. (2018) deemed inadequate for capturing and moving high flows to suitable recharge locations. Conveyance capacity data were not available for this analysis, but according to Hanak et al. (2018) represents one of the major limitations for MAR implementation.

In this study, almost 3,000 land parcels suitable for Ag-MAR ranging in size from 0.2 to 260 ha have been located within the well capture zones of rural communities. Of the 288 rural communities included in this analysis, 253 communities rely on groundwater as their main source of drinking water. However, suitable Ag-MAR parcels could only be identified within the capture zones of 149 of the 288 communities, 144 of which are

reliant on groundwater for their drinking water supply. Most of the communities for which no nearby Ag-MAR parcels could be identified are located near large urban areas (Figure 7) or near the CV rim, where topography and a lack of conveyance infrastructure prohibit Ag-MAR. A complex political and socio-economic environment around water governance in the region has historically prevented more inclusive water management (Pannu et al., 2018) but for these communities, other types of MAR (e.g., injection wells), well head treatment, or incorporation into nearby public water supply systems might be the only options to improve the quantity and quality of drinking water supplies. For reference, 118 of the 288 communities studied have no access to public water supply sources but 56% of these communities (66 of 118) are within the boundaries of existing public water supply systems.

### 5.2. Transferability of GIS-Based MCDA Approach

MAR site selection studies using GIS-based MCDA approaches have been developed in many regions across the world (Africa: Saidi et al., 2017; Americas: Russo et al., 2015; Asia: Chowdhury et al., 2010; Fuentes & Vervoort, 2020; Rahman et al., 2013; Singh et al., 2017; Europe: Escalante et al., 2014; Kazakis, 2018). The majority of these studies use slope, land use, geology and soil type as the main criteria for identifying MAR sites (Russo et al., 2015; Sallwey et al., 2019). Similarly, our study uses soil characteristics and land use as the main criteria to determine Ag-MAR site suitability, but differs from earlier studies in that we refine suitable sites by linking the GIS analysis with deterministic groundwater modeling and particle tracking to only select sites with potential to benefit the drinking water supply in rural communities. The integration of groundwater modeling and particle tracking also ensured the inclusion of climate and hydrogeological data (e.g., transmissivity, vertical, and horizontal hydraulic conductivity) in the analysis. However, the groundwater modeling also introduced uncertainty in the estimated well capture zones, due to the spatio-temporal resolution of the model (i.e., mean finite element area is 1.65 $km^2$; monthly time step) and because a quasi-steady-state groundwater flow field was used for the particle tracking. The generalized groundwater flow field likely does not capture local spatio-temporal dynamics in the flow field caused by seasonal pumping, which can change or reverse some of the flow directions depicted in Figure 5. These seasonal dynamics should be considered in the final selection of Ag-MAR locations using field-level studies. In addition, in groundwater-dependent regions where an integrated surface water-groundwater model is not available, well capture zones may need to be derived from field observations.

The Ag-MAR locations identified in this study relied on the integration of regionally specific data for the southern CV, but the methodology can be applied to other groundwater-dependent regions. To implement the Ag-MAR site suitability analysis, regional soil or geomorphology data can be used instead of SAGBI, and land use and surface water hydrology can be inferred from air photographs and satellite images. Similarly, data descriptive of the socio-economic status of rural communities in groundwater-dependent regions (e.g., drinking water shortages, reliance on water systems) or adverse environmental effects of human activities and groundwater overdraft on rural populations (e.g., pesticide or other contaminant loading) can be substituted with locally available demographic data (e.g., Twitter data: Vyas & Kumaranayake, 2006) or remote sensing data (e.g., Doell et al., 2014), respectively. In regions where little geologic or physiographic data exists, growing availability of high-resolution remote sensing data of land surface and subsurface characteristics may be useful (Jha et al., 2007; Sallwey et al., 2019).

Many previous MAR site suitability studies were conducted to inform sustainable groundwater management (Agarwal et al., 2013), to serve as guidelines and decision support for farmers and policy makers (Owusu et al., 2017), or to raise general interest for MAR development (De Winnaar et al., 2007; Raviraj et al., 2017; Saidi et al., 2017; Selvam et al., 2016). However, as showcased in this study, GIS-based MCDA can also be used to identify priority areas for intervention or disaster management if site suitability analysis is combined with vulnerability analysis (Starrs et al., 2018). This combination can be particularly useful in water resources management because the outputs can provide easily interpretable visual information, help refine the spatial focus of the problem, support priority development, and allow for assessment of different management scenarios before field-level investigations begin.

### 5.3. Study and Data Limitations

To date, few MAR site suitability studies have conducted a sensitivity analysis or validation of recommended sites (Chowdhury et al., 2009; Ghayoumian et al., 2007; Owusu et al., 2017). Previous MAR suitability assessment studies have used indirect methods (e.g., comparison of maps to actual MAR sites, water budget analysis) to validate MAR locations (Saidi et al., 2017), while few have used numerical models and in situ observations (Fuentes & Vervoort, 2020; Mahmoud, 2014; Russo et al., 2015). With this study, we propose to guide selection of suitable (Ag-)MAR sites by ensuring quantifiable benefits to groundwater levels, storage, water quality, and land subsidence. Although water management agencies maintain multiple MAR basins in the southern CV, most of these facilities have not been implemented to benefit the domestic water supply to rural communities. Only one MAR facility within the study area is being used for this specific objective. The Tulare Irrigation District has a 42 ha MAR basin located south of the Okieville community (12 km west of Tulare, CA) that has been operational since the 1940 (Figure 7b). The recharge basin overlays the capture zone of the community's southern groundwater wells. Its location was accurately identified by this study as suitable Ag-MAR location (Figure 4b). Data from Okieville domestic wells (Figure S5, Table S3; Paul Boyer, Selfhelp Enterprises personal communication) show groundwater quality improvements from MAR, including lower nitrate, uranium and arsenic concentrations, which are well below the groundwater concentrations of nearby communities (e.g., Waukena, Lone Oak Tract, Soults Tract; Figures S5 and S6). These indicate that our methodology has positively identified locations where recharge can improve the drinking water supply of rural communities in a region of our study area.

Although many studies have used GIS-based MCDA for MAR suitability studies, there is no consensus on appropriate criteria, weights, and methods as these are generally dependent on the study objective, data availability, and local experience (Sallwey et al., 2019). The assignment of (Malczewski, 1999) weights to each thematic layer or feature is one of the most subjective factors of MCDA and thus, one of the main sources of uncertainty (Malczewski, 1999). To address this issue, AHP is increasingly used to convert subjective assessments of relative importance into a set of weights (Cinelli et al., 2014; Malczewski & Rinner, 2015), though sometimes the relative importance of themes may not be discernable (Chowdhury et al., 2010). In this study, local experts in hydrology and human ecology similarly recommended the use of equal weights for thematic layers in both the site suitability and community vulnerability analyses. However, future iterations of these analyses will require the active involvement of local stakeholders (e.g., community members, farmers, water managers, and policy makers), a process that may benefit greatly from the integration of AHP into the GIS-based MCDA (Chowdhury et al., 2010).

One main difficulty when estimating suitable recharge areas is the spatial and temporal variability of the physical system. We acknowledge that our analysis mainly uses land surface characteristics (e.g., soil characteristics, land use, surface water conveyance) to determine suitable Ag-MAR sites, while subsurface characteristics (e.g., hydrogeology, vertical, and horizontal hydraulic conductivity) were not directly included. Other factors not accounted for in our analysis include water availability, water quality, unsaturated zone transport, and willingness of landowners to flood agricultural land. Although robust quality control measures were taken, the accuracy of our results relies on the integrity of input data. Issues of accuracy and completeness of proprietary, hand-digitized, or self-reported data are inevitable, hence field-level studies of local surface and subsurface characteristics should be completed as part of project scoping and pilot testing. They are also essential to assess soil surface conditions, the presence of potential unprotected wellheads, capacity of connected surface water conveyance systems, feasible Ag-MAR water application amounts (and beneficial or adverse groundwater mounding effects on nearby wells and agricultural production; Ghasemizade et al., 2019), and cropping and agro-chemical application history to determine potential legacy contaminant loading in the unsaturated zone that could be mobilized by recharge (Van Meter et al., 2016; Waterhouse et al., 2020). Although nitrate loading to groundwater has been assessed at larger scales in California's CV (e.g., Harter & Lund, 2012; Ransom et al., 2017), parcel-level data on fertilizer application rates and nitrogen removal by crops is not publicly available, preventing the assessment of legacy nitrate loading in the unsaturated zone. Future improvements of this methodology should include the addition of contaminant transport modeling or site-specific simulation of drinking water contaminants to address this gap.

Climate projections and impacts on surface water availability for recharge require further investigation (Brooks, 2017; Escriva-Bou et al., 2016). As shown by Bachand et al. (2014), despite its semiarid climate, the

southern CV faces frequent flood risks. Along the Kings River, flows have exceeded the flood stage almost once every 7 years in the last 4 decades, creating total losses exceeding $1.2 billion (2012 dollars). Kocis & Dahlke (2017) showed that excess surface water from high flows occur on average every 4.7 (ranging from 2 to 7) out of 10 years with total amounts reaching up to 1.6 km$^3$ between November and April in years when high flows are available. Water scarcity is expected to increase (Brooks, 2017; Escriva-Bou et al., 2016) as the southern CV experiences more frequent and longer droughts and more frequent extreme events during wet years (Berg & Hall, 2015). Integrated water management solutions like Ag-MAR are urgently needed to stabilize groundwater supplies in the region.

## 6. Conclusion

In this study, we present a GIS-based MCDA coupled with groundwater modeling and particle tracking to identify suitable locations for Ag-MAR that may directly improve drinking water supply for rural communities in the southern CV of California. Biophysical and socio-economic data and modeling were integrated to develop a holistic approach to increasing groundwater supply security in rural communities. Our analysis identified 373 km$^2$ (1.79% of total area of 20,819 km$^2$) of suitable agricultural land for Ag-MAR upgradient of the 288 rural communities studied in the southern CV. Most of the land identified as suitable for Ag-MAR is planted with vineyards (table grapes), which have been shown to tolerate prolonged flooding in the winter, and field crops, which are often fallowed during winter. The most vulnerable communities to groundwater shortages are clustered in the eastern part of the study area where rates of well failure, pesticide applications, and land subsidence are the most extreme. These communities tend to have more socio-economically disadvantaged populations, suggesting that mitigation efforts and policy measures to improve the sustainability of water resources must be multifaceted and inclusive.

Ag-MAR parcel recommendations from this analysis are publicly available as webtool at https://agra.ucdavis.edu. However, before implementation of Ag-MAR projects, there is a need for complementary field-level studies that include soil analyses to better quantify legacy contaminants and their potential effects on groundwater quality, geologic analyses to accurately determine recharge potential, and stakeholder focus groups to gauge support for these mitigation efforts. Ongoing efforts to assess the suitability of Ag-MAR in the southern CV include assessments of targeted MAR on the water supply of rural communities and crop tolerance to prolonged flooding. Data from these efforts will help to inform future research aiming to increase the resilience of rural communities to change in groundwater supply.

Due to uncertainties associated with climate-induced and policy-induced changes to the agricultural and hydrological system in the southern CV, the GIS-based MCDA methodology presented here provides a useful tool for preliminary planning of targeted Ag-MAR. The methodology can be generalized to other regions in the world facing similar water scarcity challenges, or adapted to identify suitable areas where other forms of recharge (e.g., MAR spreading, injection wells) may benefit other underrepresented or threatened communities (e.g., native tribes, migratory birds) or ecosystems. This study can help guide discussions of fundamental changes in land use and water resources management to achieve sustainable supply and quality of water resources, and can be further adapted to understand the implications of other resource scarcities.

## Data Availability Statement

The model code for the C2VSim model used in this study can be downloaded from the CDWR at https://data.cnra.ca.gov/dataset/c2vsimfg-beta-model. The particle tracking code to be used with the C2VSim groundwater flow field can be downloaded at https://gwt.ucdavis.edu/news/iwfm-track-tutorial. All input data presented in this paper are available from the CUAHSI Hydroshare data repository at https://doi.org/10.4211/hs.8f203765ba964f148eeab0d95ccb7159. Results from our analysis are available as public decision support tool at https://agra.ucdavis.edu.

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