Title

Examining Economic Benefits of Agricultural Land-Use Transition to Utility-Level Solar Energy Generation

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Publication Date

2024

Examining Economic Benefits of Agricultural Land-Use Transition to Utility-Level Solar Energy Generation

By

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THESIS

Submitted in partial satisfaction of the requirements for the degree of

MASTER OF SCIENCE

in

Agriculture and Resource Economics

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA

DAVIS

Approved:

Katrina Jessoe, Chair

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Committee in Charge

2024

Abstract

Agricultural water supplies are shrinking in California as an effect of a changing climate and groundwater regulations. Farmers have been adapting their practices to cope with this reality over the past many decades, but will need to do more to cut production costs as the price of water rises. One of the cost-saving techniques farmers employ when resources are scarce is to leave a portion of their land idle. Farmers could insulate from climate risk better by using their land for purposes with more predictable profits and less water needs per acre. Solar energy generation is sometimes used by farmers as a profitable alternative to traditional crop cultivation, and would create more consistent returns for the owner. This analysis identifies over 90,000 acres of active agricultural land in the San Joaquin Valley that would benefit from transitioning to solar generation. The lands identified could add 10-12 GW of solar energy generating capacity per year to the San Joaquin Valley's existing 3GW.

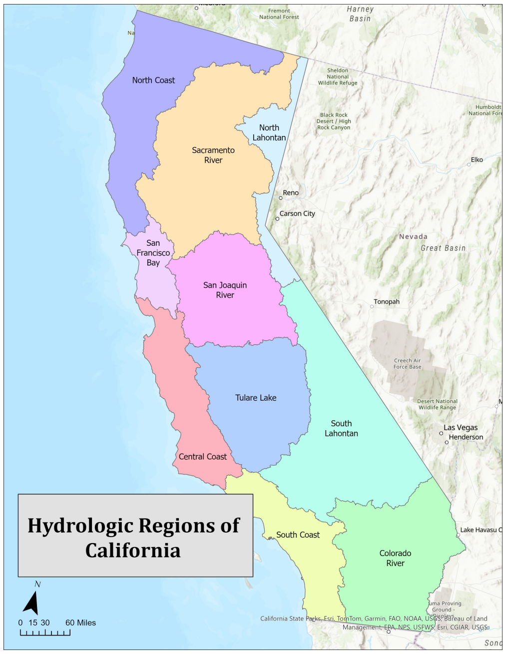
1 Introduction

As climate change advances, the future of agriculture in California becomes more uncertain. For decades, farmers have adapted their practices to adjust in response to unexpected shocks in temperature and precipitation patterns.[1] Additionally, weather conditions in the American Southwest are expected to continue to change, creating conditions that are less hospitable to farming in the coming years (Pathak et al., 2018). Groundwater is the most crucial buffer resource for irrigated crops during times of unforeseen drought, allowing farmers to have more consistent watering when crop cover decisions cannot be adjusted. Water use is dominated by agriculture in drought or drier years statewide, accounting for over 60% of total water application in a representative dry year (Mount and Hanak, 2019).

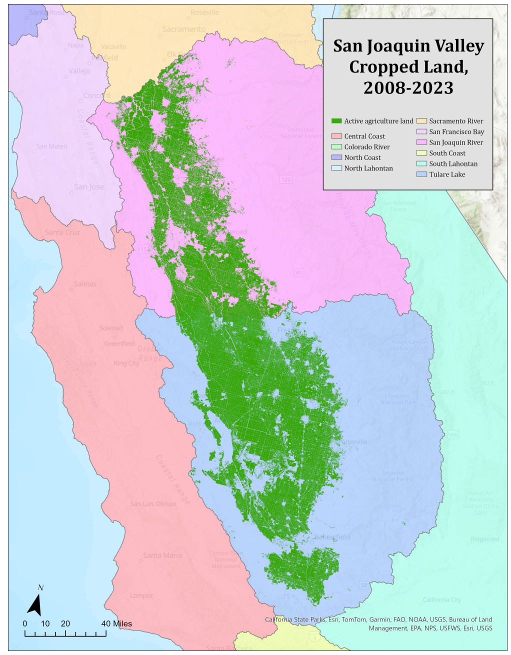
Even in years when precipitation is plentiful, water resources in the state's agrarian Central Valley are overwhelmingly diverted to agricultural uses. The percentage of land experiencing severe drought conditions has increased significantly in California since the turn of the century, and will likely not improve in the coming decades (NIDIS, 2024). Farmers in California increasingly rely on groundwater for their operational needs, while water table water levels throughout the state continue to trend downward (CNRA, 2022). Depleting water supplies mean higher pumping costs for farmers; as a result of the 2012-2016 drought, farmers experienced an estimated \$600 million increase in pumping costs per year (Lund et al., 2018). High water costs often prompt farmers to fallow parts of their usable cropland for one or more growing seasons, wasting valuable land and leading to loss of profits and reduced agricultural production (Wilson, 2022).

The Sustainable Groundwater Management Act (SGMA), passed by the California state government in 2014, adds additional pressure to the agriculture sector to reduce water consumption by implementing sustainable water use requirements for regions that derive their

[1] Reints et al. (2020) find that California avocado farmers frequently adopt and invest in water efficiency technologies due to water quality problems brought on by water scarcity. The degree to which farmers invest in such technologies depends on various economic and demographic variables, such as farm location, access to information, and age of the farmer.



(a) Source: Author's own analysis using ArcGIS Pro. Data from CA Dept. of Water Resources (DWR, 2022).



(b) Source: Author's own analysis using ArcGIS Pro. Data from CA Dept. of Water Resources & NASS (DWR, 2022; USDA-NASS, 2016, 2024).

Figure 1: Maps showing the hydrologic regions of California (left), and the cropped land in the regions that make up the San Joaquin Valley (right).

water from overdrafted basins. The San Joaquin Valley (SJV), the lower two-thirds of the Central Valley, is one of these affected regions. The San Joaquin Valley is defined by the two hydrologic regions it is comprised of: San Joaquin River and Tulare Lake, shown in figure 1a above. Figure 1b shows land parcels that have been active (non-fallow) for at least one growing year 2008-2023. Most of the irrigated land acreage is concentrated in the western side of the valley, where surface water runoff from the surrounding mountain ranges feeds crops.

SGMA classifies 13 of the 19 total groundwater basins that supply the SJV as high-priority, and therefore subject to more stringent regulations regarding groundwater usage (DWR, 2019). Moreover, over half of the entire state's basins classified as the most severely depleted are in the SJV. Due to these new regulations, it is projected at least 500,000 acres of existing irrigated land fed by the affected basins will have to be removed from irrigation by 2040 to meet sustainable water extraction requirements (Ayres et al., 2022). The necessary reduction in irrigated farmland acreage could be as much as 1 million acres, meaning around

10-20% of the 5 million acres of existing farmland in the SJV may be unable to be irrigated after 2040 as a result of groundwater regulations alone.

Farmers operating agricultural land that may eventually be removed from irrigation, or that has become prohibitively expensive to water, could transition to solar energy production as a profitable alternative to crop cultivation. In many ways, agricultural land is ideal for large-scale solar production. Farmland has often been made relatively flat, receives direct sunlight for multiple hours a day, and provides large swatches of land to build necessary infrastructure. Agricultural land makes utility solar production feasible and more likely to be profitable due to the abundance of sunlight and relatively low cost of land.

From a social planner's perspective, crop-to-energy land transition would be especially ideal for a variety of reasons. Firstly, farmers could turn their idle (or under-productive) land into financially productive land, thereby increasing their overall welfare. This would, in turn, decrease irrigated land acreage and avoid other negative environmental externalities that result from agricultural cultivation, like pesticide runoff and fertilizer leaching. Taking irrigated farmland out of crop production would simultaneously help California achieve it's groundwater management an environmental protection goals.

Finally, providing new sources of renewable, zero carbon energy is exceptionally beneficial to California's clean energy goals. Two recent laws passed in California have encouraged planning and investment in solar energy statewide. Senate Bill 100 (SB 100), passed in 2018, requires that 100% of electricity sales are renewable or zero-carbon by 2045. As an effect of this bill alone, the California Energy Commission estimates that the state will need to triple its electricity power capacity in the renewable sector to achieve this goal. In 2022, the California Air Resources Board (CARB) passed a plan mandating that all new cars sold in California be electric starting in 2035. The combination of these two laws creates a desperate need for increased electricity production capacity fueled by renewable energy. As more of the California economy 'electrifies', the need for clean energy sources will only increase. The timelines of SGMA, SB 100 and the CARB mandate align well with one another to form an ideal environment for farmers to transition from traditional crop production to energy production. Policymakers could leverage these alignments to incentivize solar energy infrastructure investment and lessen farmer losses from water scarcity.

The aim of this paper is to identify agricultural land parcels in the San Joaquin Valley that would provide both private and social benefit from switching to solar energy generation. This paper analyzes crop choice from both a private farmer's and a social planner's perspective and will rank land parcels based on the estimated total benefits generated by permanently transitioning agricultural land to energy production. I will analyze usable farmland in the San Joaquin Valley that has been fallow for at least one recent growing season and use computed water application and revenues per acre for different crops to find relative sensitivities to water price shocks induced by continued water scarcity and regulation. A wide range of crops are grown in the region, and crop choice drives most of the variation in revenue and water cost per acre. I will compare traditional crop revenues with projected solar energy revenues to determine if a land use transition would be privately profitable. Current water application to the land parcel and total acreage will determine the water savings and added solar generation capacity (i.e. social benefits from solar transition).

2 Background

2.1 Water scarcity & agriculture

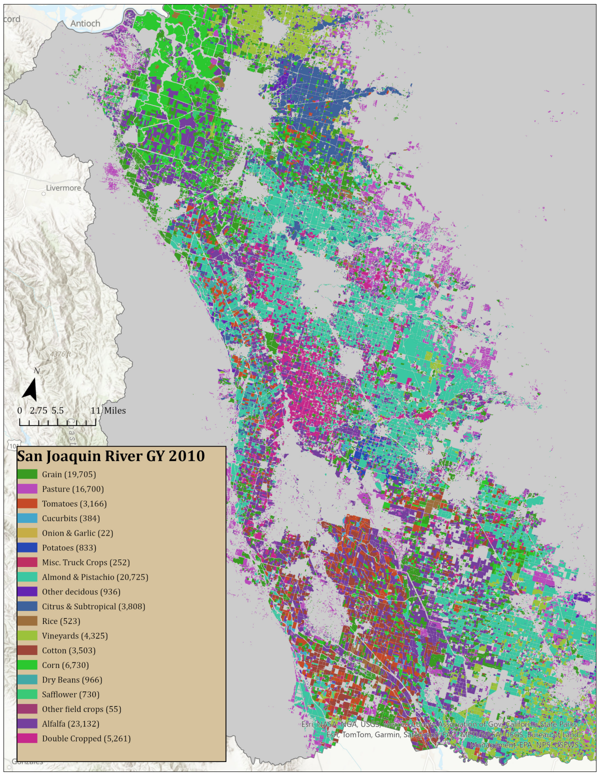
Growers in California have experienced increasingly varied precipitation and, consequently, surface water availability since the 1980s (OEHHA, 2023). 75% of California's rain and snow occurs in the top third of the state, far from where the bulk of the agricultural activity occurs (DWR, 2024). In response to this reality, multiple water projects were created by the state to move water from where water is relatively plentiful (and population is relatively sparse) in the north to the parched southern population hubs and central agricultural regions. Moving this water expends energy, and those requesting water delivery bear the cost. The price of water varies heavily by region due to variation of relative water availability, and is a large part of farmers' variable costs of producing an acre of crop. The amount of precipitation is hugely important in farmer cropping decisions, and land allocation choices vary based on the relative wetness or dryness of the growing year.

In figures 2 and 3, crop cover and fallow land in the SJV for growing years 2010 & 2014 are shown by hydrologic region. 2010 represents a year with relatively typical precipitation, and 2014 was a drought year in the midst of historic drought conditions lasting from 2012-2016 (OEHHA, 2023). In each figure, I display the crop cover choices and fallow land from two years relatively close to one another, but with very different surface water availability. Panels (b) and (d) show fallow land in each of the hydrologic regions that make up the San Joaquin Valley. Comparing these figures, there is a pronounced increase in fallow land from the 'wet' year (above) to the 'dry' year (below).

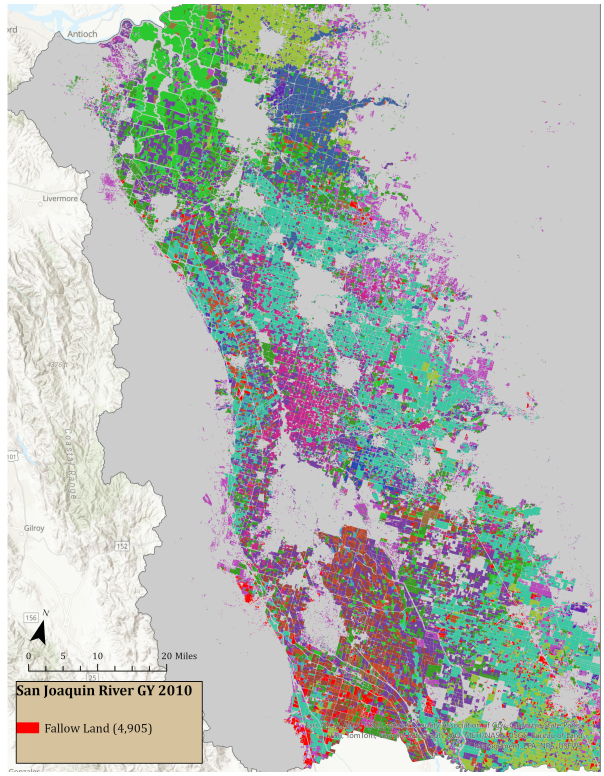
Differences in crop mix for farmers are to be tied to the precipitation conditions they grew under. Comparing panels (a) and (c) of figure 2, the marked decrease in double cropping activity in the central portion of the San Joaquin River in 2014 is apparent. In the same panels in figure 3, deciduous tree fruits and nuts are nearly wiped out by the dry conditions, and the acreage of cotton planted decreases as well. Surface water availability plays a massive role in farmers' land use and crop mix decisions.

Relevant literature in the agricultural economics field study farmers' adaptation decisions when facing water scarcity. Hagerty (2022) finds that in the short-term, California farmers operating irrigated land choose to fallow some or all of their usable land when confronted with water scarcity. This finding is supported visually by the increase in the fallow land acreage from 2010 to 2014, as shown in figures 2 and 3. Water is more costly in years with decreased precipitation for two reasons: less surface water is available and groundwater levels are lower, which means that water is more expensive to pump. Hagerty estimates that a 10% decrease in annual surface water level predicts a 3.6% decrease in farm revenues for the growing season due to inability to grow high-value annual crops that are generally more water intensive than the more stable perennial crops.

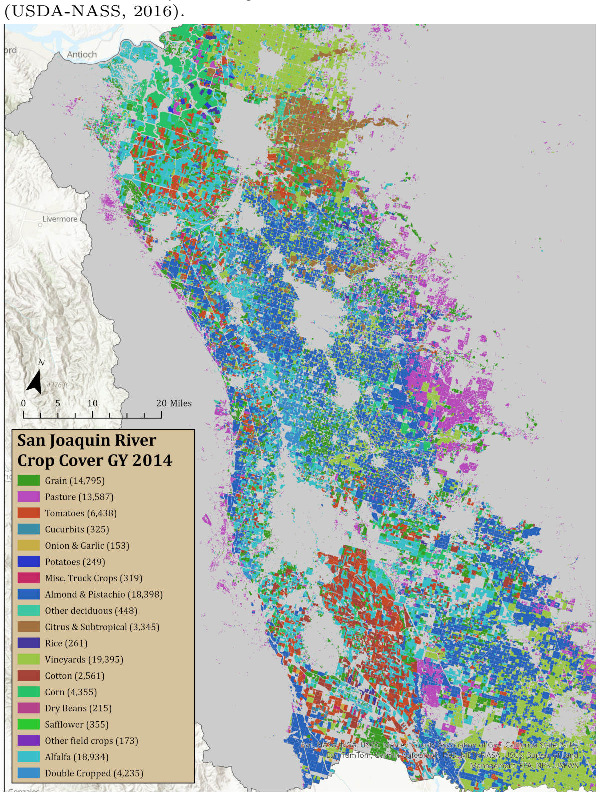
Further, when facing long-term water scarcity, Hagerty finds that California-based farmers adapt by permanently removing fallow land from cultivation. This retired agricultural



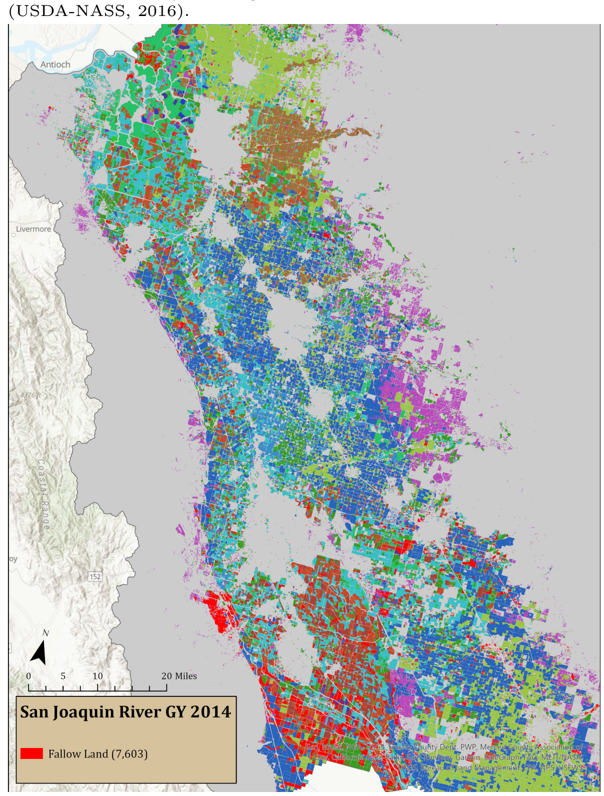
(a) Crop cover of San Joaquin River, growing year 2010. Map Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2016).



(b) Fallow land in San Joaquin River, growing year 2010. Map Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2016).

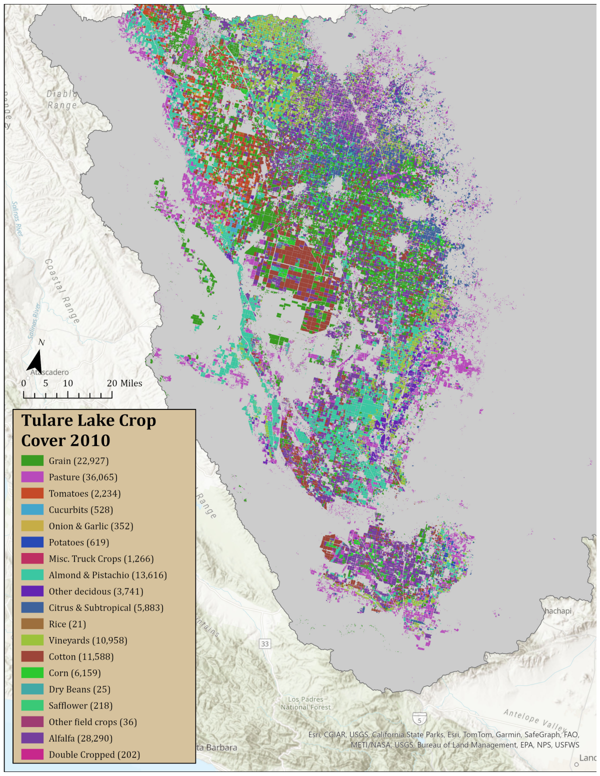


(c) Crop cover of San Joaquin River, growing year 2014. Map Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2016).

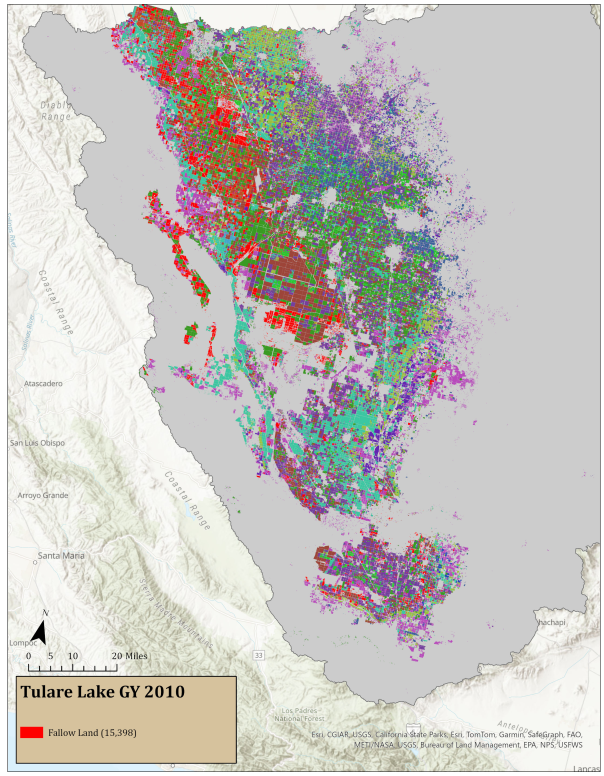


(d) Fallow land in San Joaquin River, growing year 2014. Map Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2016).

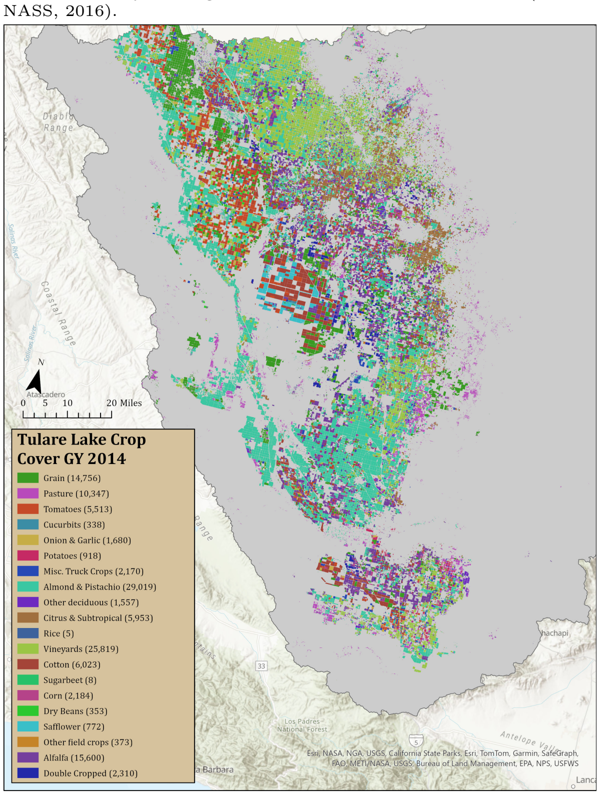
Figure 2: San Joaquin River crop coverage and fallow land for a representative wet (upper) and dry (lower) year. The count of farm plots of each type are shown in parentheses. Plots are not necessarily equal in area.



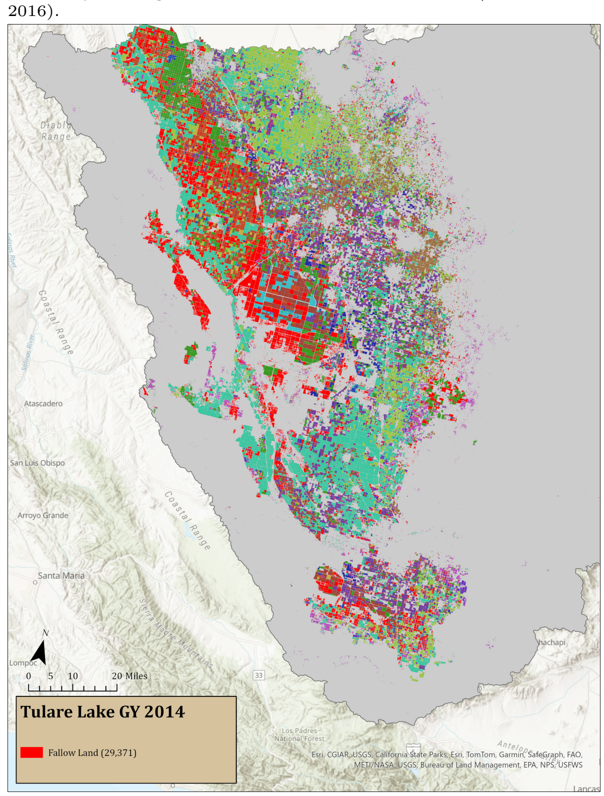
(a) Crop cover of Tulare Lake, growing year 2010. Map Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2016).



(b) Fallow land in Tulare Lake, growing year 2010. Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2016).



(c) Crop cover of Tulare Lake, growing year 2014. Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2016).



(d) Fallow land in Tulare Lake, growing year 2014. Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2016).

Figure 3: Tulare Lake crop coverage and fallow land for a representative wet (upper) and dry (lower) year. The count of farm plots of each type are shown in parentheses. Plots are not necessarily equal in area.

land becomes grassland, which can be used to graze cattle, or is left untouched. This kind of unirrigated rangeland has a mean revenue of $11, where the mean revenue of the least water intensive crop category (grains) is $622 with mean water needs of 1.31 acre-feet per acre (Hagerty, 2022). Although grain has the smallest mean water needs per acre, the volume of water needed to cultivate any crops successfully is a massive cost to farmers. Delivery of water alone averages around $250 per acre-foot in the San Joaquin Valley, and water right permits can cost over $30,000 to obtain (David Sunding, 2023; CSWRCB, 2024). Farmers who have no choice but to stop irrigating some or all of their land are suffering huge losses as compared to those that are able to shift land toward less water intensive crops. These losses are even greater when compared to the average revenue per acre of utility-scale solar production. Annually, renting land to solar energy generators could earn between $1,000 - $1,500 per acre of farmland (Ayres et al., 2022). This value is larger than returns from cultivating most annual crops (about $250 - $400/acre/year), and some perennial orchard crops (up to a few thousand dollars/acre/year).

In addition to crop choice, political factors like access to water rights impact a farmer's decision to fallow a piece of land. Smith (2023) finds that growers with lower priority water access are more likely to fallow their land, whereas farmers with better access tend to make water conservation choices that are less costly. Growers who have higher priority water rights are more likely to make smaller adjustments to planting decisions when water supply is constrained, like planting earlier or planting varietals that develop quickly. This means there are also distributional impacts of water scarcity, and farmers who may be historically excluded or limited in their water access will be hurt more by the continued scarcity in the coming decades.

Taken together, the agricultural water scarcity literature suggests that agricultural land in the San Joaquin Valley that is currently oscillating between active and fallow will be taken offline in years to come, with potentially devastating consequences for farmers' economic well-being. If farmers were able to shield themselves from climate-related income risk with solar energy generation, they may be more able to tolerate increasing water costs caused by

SGMA-induced scarcity and increased drought frequency.

2.2 Solar Energy

Although rooftop solar PV panels are easily installable in neighborhoods across California and the American Southwest, there are unique challenges and benefits associated with scaling up solar energy generation to the farm level. Electricity transmission lines are a major limiting factor in building out utility-scale solar energy, and current infrastructure is concentrated in residential distributed generation areas and areas with existing large-scale solar generation (Ayres et al., 2022). However, to its benefit, utility-scale farming may not be plagued by the solar rebound effect that is present for residential solar generation.

The household solar rebound effect (SRE) is the ratio of the increase in total electricity consumption to the amount of energy generated from a household's solar panel system (Beppler et al., 2023). Various studies investigate the percent solar rebound effect in the US and abroad, with estimates ranging from 12% to as much as 50% for an individual household's rebound effect (Frondel et al., 2023; Beppler et al., 2023; Qiu et al., 2019). The increase in electricity usage driven by adoption of residential solar PV diminishes the positive externalities that solar adoption provides. Oliver (2023) argues that SRE is avoided when bringing utility-scale solar generating sites because the very drivers that cause the phenomenon on an individual household level do not exist. Utility-scale solar decouples households' electricity consumption decisions from the generation itself, which avoids the need for additional policies to induce adoption. This makes utility-scale solar relatively more energy efficient than distributed generation or rooftop solar tends to be due to the solar rebound effect.

Utility-scale solar generation is commonly defined as solar projects with more than 5MW of generation capacity (Berkeley Lab, 2023). For utility-scale solar energy generation, there are two dominant technologies farmers could choose to use on their farms: primary photovoltaic (PV) or concentrated solar power (CSP) (SEIA, 2024b). CSP uses mirrors to amplify solar radiation, making it a more efficient, but more expensive, system. Typical fixed solar PV panels are less energy efficient, but a much more accessible and widely adopted technology. There is substantially more information on energy generation using fixed solar PV, both in economic literature and in practical experience from users of the technology. In this analysis, I will assume all farmers who switch to solar energy generation will use a fixed PV system, and all costs associated with installing the system are equal across farmers.

I will assume additionally that all adopting farmers have the same electricity generating capacity per acre of land, and thus equal revenues from using an acre of land for solar. This requires that all PV systems installed by farmers have the same energy conversion efficiency. In reality, solar panel systems can have a variety of (costly) features that increase sunlight exposure, like rotating in accordance with the optimal sun angle (NREL, 2020). I will assume all farmers choosing to produce solar energy will use ground-mounted PV panels with equal energy conversion rates and equal installation costs.

Equal electricity generating capacity across farmers also requires that all farm plots receive equal amounts of usable solar radiation per acre. Figure 5 shows statistics for two different measures of solar radiation: direct normal irradiance (DNI) and global horizontal irradiance (GHI). Both are used in determining solar PV generating capacity, though GHI is most commonly used to calculate fixed solar panel generating potential (Sengupta et al., 2018). Average daily GHI in the U.S. is shown in the map in figure 4. Visually, it is clear that the majority of solar resources are concentrated in the Southwest.

Analyzing average daily DNI and GHI values, I find that the SJV has substantially more energy-generating potential than the rest of the Americas and California, with less variation. What little variation there is has a relatively small impact on energy generating ability, and thus revenues per year. Using the resource ranking system from NREL (2023), all land in the SJV falls into the top four of the ten categorizations of solar potential based on GHI values. Thus, the San Joaquin Valley has ample solar resources to support utility-level generation.

Currently in the valley, some land is already used for utility-scale solar generation. The PPIC estimates that the existing 3GW of capacity in the SJV takes up 15,000 - 25,000 acres of land, with projects averaging a density between 5-8MW per acre (Ayres et al., 2022). By comparison, there were over 170,000 fallow acres of land in the same area in 2023 alone

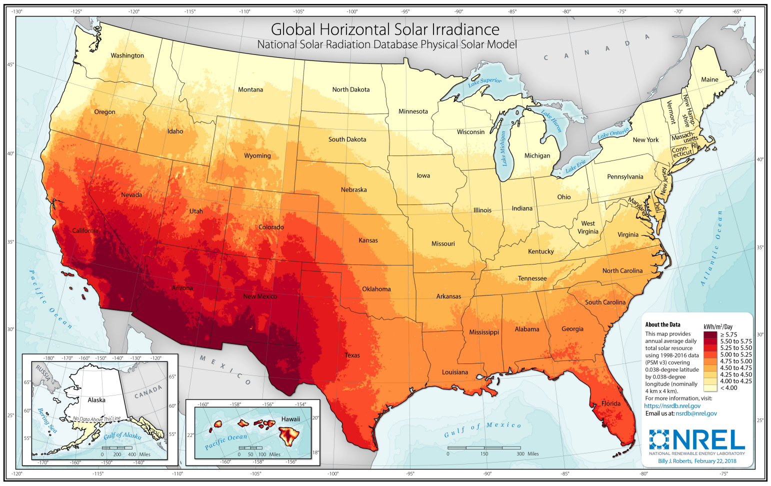


Figure 4: Annual average daily GHI using 1998-2016 data. Map from Sengupta et al. (2018).

	DNI				GHI			
	Mean	SD	Max	Min	Mean	SD	Max	Min
Americas	4.74	1.239	10.34	0.912	4.554	1.114	7.534	1.56
California	7.028	0.719	8.784	3.912	5.381	0.4178	6.168	3.816
SJV	7.041	0.43	8.784	6.216	5.415	0.18	6.048	5.064

Figure 5: Mean daily DNI & GHI using annual data from Sengupta et al. (2018). Summary statistics collected via author's analysis of geospatial data from Sengupta in ArcGIS Pro.

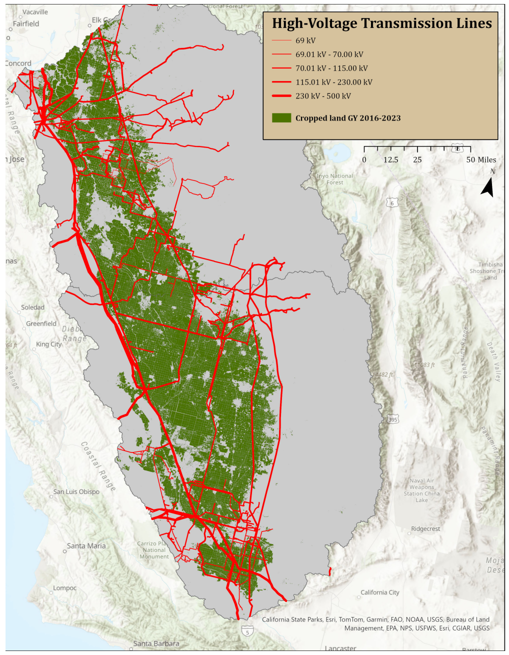


Figure 6: Electricity transmission lines varying in width by kV with agricultural land used 2016-2023 below. Transmission line data from CEC (2017).

(USDA-NASS, 2024). Because of the existence of these solar projects, there is already some infrastructure to support the distribution of the energy currently generated in SJV.

In order to feed utility-scale amounts of electricity into the California energy system, solar farms must be connected to high-voltage transmission lines, which are defined as those able to handle 69 kV or more (SEIA, 2024a). Figure 6 shows the various existing transmission lines over the active agricultural land in the SJV. Although Ayres et al. (2022) estimate that more high-voltage transmission lines will need to be built to handle incoming solar projects, the existing infrastructure can be built upon, and is near much of the active agricultural land.

Land that is both suitable for solar and agriculturally under-productive is plentiful in the San Joaquin Valley. As a result, some land is already being used for energy generation, and energy transmission lines have been installed across the valley to distribute the harvested solar. Above, figure 6 shows transmission lines that are able to carry utility-generated electricity.

3 The farmer's problem

I will first take the perspective of a hypothetical farmer owning agricultural land that has been fallow for one or more recent growing seasons. This portion of land is single-cropped, meaning that only one crop is grown on it per year. The boundaries of this land parcel begin and end where the single crop is planted, and any adjacent land with a different crop planted will be considered a separate parcel. A single farmer may own and operate more than one parcel of land, each with a unique crop on it.[2] In this case, a farmer solves separate optimization problems for each single-cropped parcel they operate.

As profit-maximizing actors, farmers are fallowing their least profitable land, whether that be due to low intrinsic crop value or high water costs. When operators choose to fallow portions of their land, I assume that farmers will fallow portions that are least profitable first, followed by more profitable acreage as more acreage must be taken out of production.

In this model, a farmer pre-determines what crop type c to plant on acreage A. Crop c generates $P_c * A$ dollars when sold on the market, where P_c is the market price for the typical yield of acre of crop c, and the farmer chooses the number of acres A to devote to crop c. Water costs are the sole component of the farmer's cost function, and are exogeneously given for each crop type c. The total costs for a farmer are determined by the mean volume of water applied to an acre of crop c (W_c), times the number of planted acres A of crop c, times the current price of water per unit of volume P_W. A farmer's maximization problem for a single field of traditional crops can be represented as:

$$\max_{A} \pi = (P_c * A) - ((W_c * A) * P_W) \tag{1}$$

where A is the number of acres a farmer chooses to grow a particular crop on. W_i and P_i are exogenous, and the only agency a farmer has is over acreage. [3] A is the choice variable for the

[2]This follows the structure of the USDA Crop Sequence Boundaries dataset used in the analysis to come. Further discussion of the CSB dataset in the data section.

[3]W_i is determined by the average water application per acre (measured in acre-feet) for crop category i, as derived in Hagerty (2022). Further discussion of this choice follows in the data section.

farmer, representing the inflexibility in land allocation after initial planting has happened. The farmer can only set A up to the full acreage of the plot, and cannot have acreage lower than 0.

Taking the first-order condition of equation 1 with respect to A and rearranging, the equation becomes:

$$P_c = P_W * W_c \tag{2}$$

This result tells us that a farmer will choose crop c such that the market price of an acre of the crop to be planted is equal to the cost of watering an acre of that crop in order to profit maximize. In other words, a farmer will choose the acreage of crop c such that the marginal cost of producing an acre of crop c is the price of one acre-foot of water, times the water required (in acre-feet) to grow one acre of crop c.

If a farmer is growing nothing on some or all of a plot, it can be assumed that this choice was made because the farmer believed planting more acres would lead to profits less than or equal to zero. Thus, the only acreage that will be considered in the analysis to follow will be cropland that has been fallow for at least one year out of the last 15 growing seasons. This will isolate land that is sometimes unprofitable to the farmer, and thus more likely to benefit from the comparatively steady stream of profits solar would provide.

In this model, the farmer is not involved in the choice of whether to transition to solar or not. Instead, they only have agency over their crop choice, and will respond to the planner's choice between traditional crop cultivation or solar generation. The farmer's profit when producing solar is simply $P_S * A$, the dollar value generated from producing solar energy for one growing year on one acre of agricultural land, times the number of acres in the pertinent land parcel.

4 The planner's problem

The social planner's objective is to maximize benefits for land that is sometimes idle with acreage A. The farmer has already determined what crop c goes on a given parcel of land when it is active, and the planner cannot adjust that choice. I assume here that the farmer has more information about the type of land they own, and thus, what crop should be planted on a given land parcel.[4] The planner chooses how many acres that, at maximum , the farmer may plant of crop c (i.e. farmer does not fallow land). The traditional crop grown on a plot will be determined by what the operating farmer planted in its most recent active growing season. The problem can be represented as:

$$\max_{A} -(P_T * A) + (W_T * P_W * A) + (P_S * A) \tag{3}$$

where A is the number of acres on a given plot of single-cropped land, P_T is the market price of the traditional crop that is typically grown on a plot , W_T is the volume of water (in acre-feet) necessary to produce one acre of crop T, P_W is the price of one acre-foot of water, and P_S is the dollar value of solar energy that is produced on one acre of land over the course of a year. The planner dictates how many acres of land are in a given land parcel, which is the maximum amount of land (A) a farmer can use for planting crop (c). A farmer can then choose to plant or fallow acres. The sum of acres planted and acres fallow will be equal to A for each single-cropped land parcel.

Using equation 3, the planner will determine whether solar panels or crops are more appropriate for a given parcel. If the value is positive, it indicates that solar energy production is more socially beneficial than the current crop planted. The middle term of equation

[4] This assumption is founded in the fact that 95% of California farms are family-owned, and the average age of a farmer has been over 50 since the 1980s (CDFA, 2017). These two statistics imply that there is generational transfer of agricultural knowledge, and a building of skills and information as a farmer becomes more experienced. This observation is evidenced further by the importance of learning by doing and learning from community members in agricultural skill formation literature (Yang and Shumway, 2020; Foster and Rosenzweig, 1995; Sumane et al., 2018). Additionally, this view is used as motivation for a widely-used agricultural production modeling technique, positive mathematical programming (PMP), formalized by Howitt (1995). The calibration method used in PMP takes observed farmer behavior on economic variables like land allocation, water application, and crop mix as solutions to the first-order condition of the farmer's objective function in a base year.

3, the water applied to the acreage when planted with crop c, is added as a social benefit (water conserved). The first and last terms represent the producer (private) benefits under traditional crops and solar, respectively. The negative sign before the first term represents the opportunity cost to the producer of transitioning their land to solar production.

Taking the first-order condition of the above equation with respect to acreage yields:

$$P_T = W_T * P_W + P_S$$

This result tells us the planner will choose to forego the traditional crop and instead choose solar for a plot of land if the revenues generated from selling an acre of crop T are less than the water cost per acre, plus the opportunity cost of producing solar energy on an acre of land. In this analysis, the choice between solar generation and crop cultivation is strict; land cannot be used for dual purposes.[5]

The planner's goal is to identify what land parcels would jointly maximize farmer and social surplus if used for solar energy generation instead of traditional crop cultivation. Marginal social benefit per acre of land transitioned to solar generation is equal to the value of the water applied to an acre of traditional crop on that land.

5 Data & methods

Using the Crop Sequence Boundaries (CSB) dataset from USDA, I isolate farm plots that have been idle at least one year in growing years 2016-2023. The CSB produces estimates of field boundaries, crop acreage, and crop rotations using satellite data in combination with other publicly available data. The boundaries are drawn without regard to property ownership or rights. This data is non-confidential, and not tied to or based off of specific producer information. The CSB provides the crop reported by the Cropland Data Layer

[5]In practice, installing solar panels on farmland may not prevent agricultural activity from occurring. Some farmers have successfully implemented 'agrivoltaic' systems where shade-tolerant crops and solar panels coexist in the same fields (Friedlander, 2023; NREL, 2020).

(CDL) for each area defined over an 8 year period. The field boundaries defined in this analysis are based off of cropping decisions for growing years 2016-2023 (USDA-NASS, 2024).

I use the crop sequence boundary layer instead of yearly CDLs because the CSB aggregates land to field level, which reduces noise and any error that is inherent in the data used to construct the CDLs (Hagerty, 2022). The CSB also allows me to follow the cropping decisions for a single plot of land over multiple growing seasons. This allows me to have certainty when identifying the last crop grown on a plot of fallow land. Maps showing the crops last grown on fallow land are shown in figure 7.

I use data from the California Department of Water Resources to construct the bounds of the analysis (DWR, 2022). The San Joaquin Valley is composed of the San Joaquin River and Tulare Lake hydrologic regions. I combine these two areas into a layer to use as the boundary for the SJV in the rest of the analysis.

Hagerty (2022) constructs mean water requirement per acre and mean revenues per acre for 19 different crop categories using data from California 2007-2018. These data are shown in Appendix 1. I assign CDL crop code values found in the CSB data to these categories. I take the constructed mean revenue and mean water needs to use in equation (1), the farmer's optimization problem. I leave A as a parameter and derive with respect to A. I solve equation (3) for MC_W to derive a "choke price" of water per acre at which point a farmer would no longer want to plant their crop and instead will fallow their land. Crops are ordered from lowest value of MC_W to highest. A low calculated value of MC_W implies that the farmer cannot afford higher costs of water, and will likely make adaptations to reduce water costs. The land growing crops that have a low tolerance for rising water costs will be the first candidates for solar transition.

The other ordering condition will be proximity to existing transmission lines. Transmission lines are hugely important in determining initial costs of bringing a solar farm online, and thus, planned solar projects in SJV are concentrated around existing infrastructure (Ayres et al., 2022). Land parcels within 100 meters of high-voltage transmission lines will be preferred to those farther away.

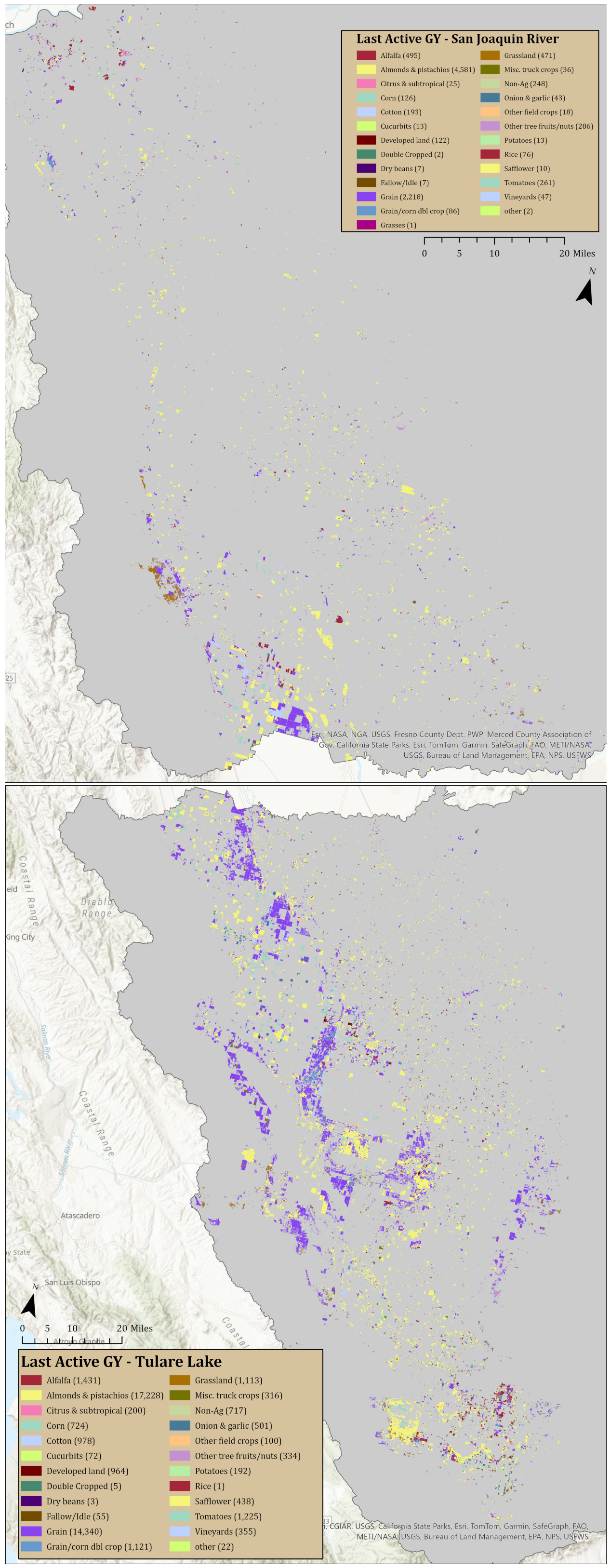


Figure 7: Crop choice in the last active growing season for land that has been fallow in SJV for one or more growing seasons 2016-2023

Crop	MC_W (2009$)
Grassland (non-irrigated)	0
Grasses (irrigated)	16.49
Safflower	227.64
Alfalfa	262.17
Corn	332.57
Other field crops	388.01
Grains	474.81
Cotton	479.56
Rice	551.56
Dry beans	573.11
Sugar beets	604.14
Almonds, pistachios	1,054.15
Other tree fruits/nuts	1,193.80
Tomatoes	1,610.42
Citrus, other subtropical	1,744.91
Onions, garlic	1,961.39
Grapes	1,993.56
Cucumbers, melons, squashes	2,424.90
Potatoes	4,549.42
Other truck crops	9,344.33

Table 1: Threshold per-acre cost of water for crop categories in 2009 U.S. dollars.

6 Results

The calculated MC_W values for crop categories are shown in the table below, listed from lowest value to highest value. These values represent the highest possible water cost per acre that a farmer growing a given crop would be willing to tolerate. These values are an upper bound estimates because the only costs considered in a farmer's production function in this analysis are water costs. These values are calculated using Hagerty (2022) derived mean revenues and water needs per acre.[6] In the map below, these values are represented with graduated colors representing the threshold water cost per acre values for the last crop grown in a non-fallow year on a land parcel.

Farmers owning unirrigated grassland are unwilling to pay for water because they don't use it on this kind of land. Should these lands be transitioned to solar energy generation,

[6]The crop categories correspond to California Department of Water Resources data on mean water application. See full text of Hagerty for details on aggregation techniques for individual crops.

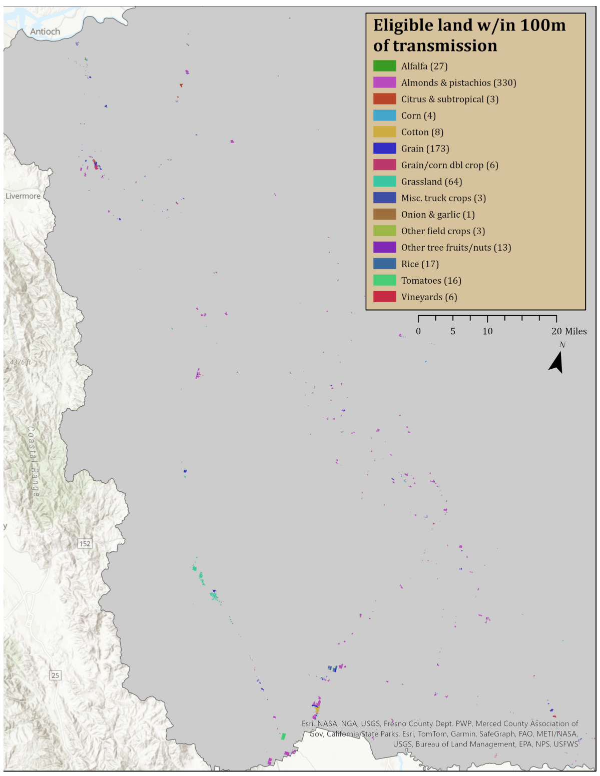
they would not provide any social benefit in the form of water savings, but would provide private benefit to the farmer by substantially increasing their revenues per acre.

Other crops that have lower tolerances for water price shocks are safflower and alfalfa. Safflower is not very water intensive, but does not provide much value per acre. Alfalfa, on the other hand, provides four times the revenue per acre of safflower , but has over twice the water needs per acre. Referring back to figures 2 and 3, safflower is preferred in drier years, and alfalfa grown on plots in wet years are commonly fallowed or swapped for vineyards, which have slightly lower water intensity. These kinds of farmers are the ideal targets for policy intervention to induce solar adoption.

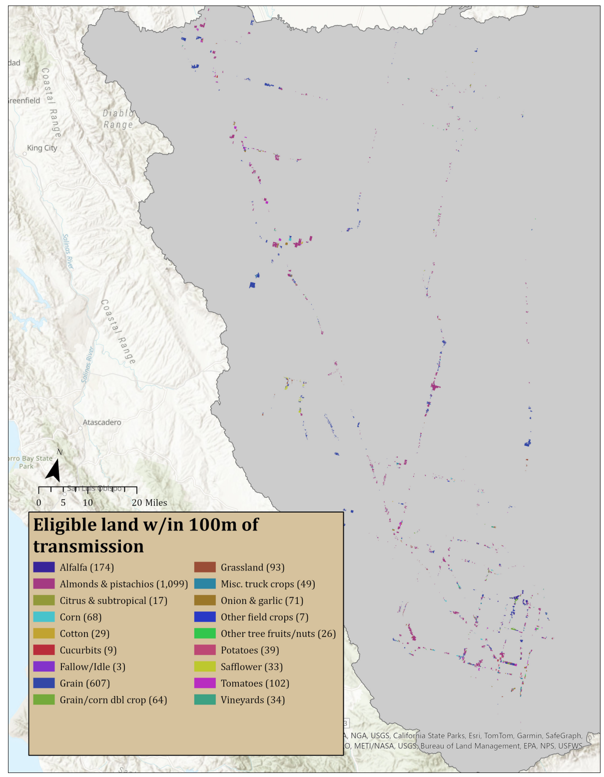
On the other end of the spectrum, truck crops like carrots and berries have extremely high tolerance for increasing water costs, as they are hugely valuable per acre, and aren't hugely water intensive. These farmers will not likely be enticed into using their acreage for solar energy, and thus, the lands housing these crops should not be targeted by policy for land transition.

Given the importance and expense of high-voltage transmission lines, I isolate plots of land that are within 100 meters of pre-existing high-voltage transmission infrastructure. These land parcels have been fallow in one or more growing season 2016-2023, and are symbolized based on the crop coverage in its last active season in figure 8. The number of single-cropped land parcels are displayed in parentheses. Such lands previously grew almonds and pistachios, grains, and tomatoes most commonly, followed by previously non-irrigated grassland. In total, there are over 30,000 acres of land identified in the SJV that have been fallow at least once out of the last eight growing seasons and are within 100m of existing high-transmission transmission lines.

If the search criteria is expanded to include any farm plots within 400m (roughly 0.25 miles) of existing high-voltage transmission lines, an additional 60,000 acres qualify for solar transition. The maps of agricultural lands eligible for solar transition in the San Joaquin Valley are displayed in figure 9.

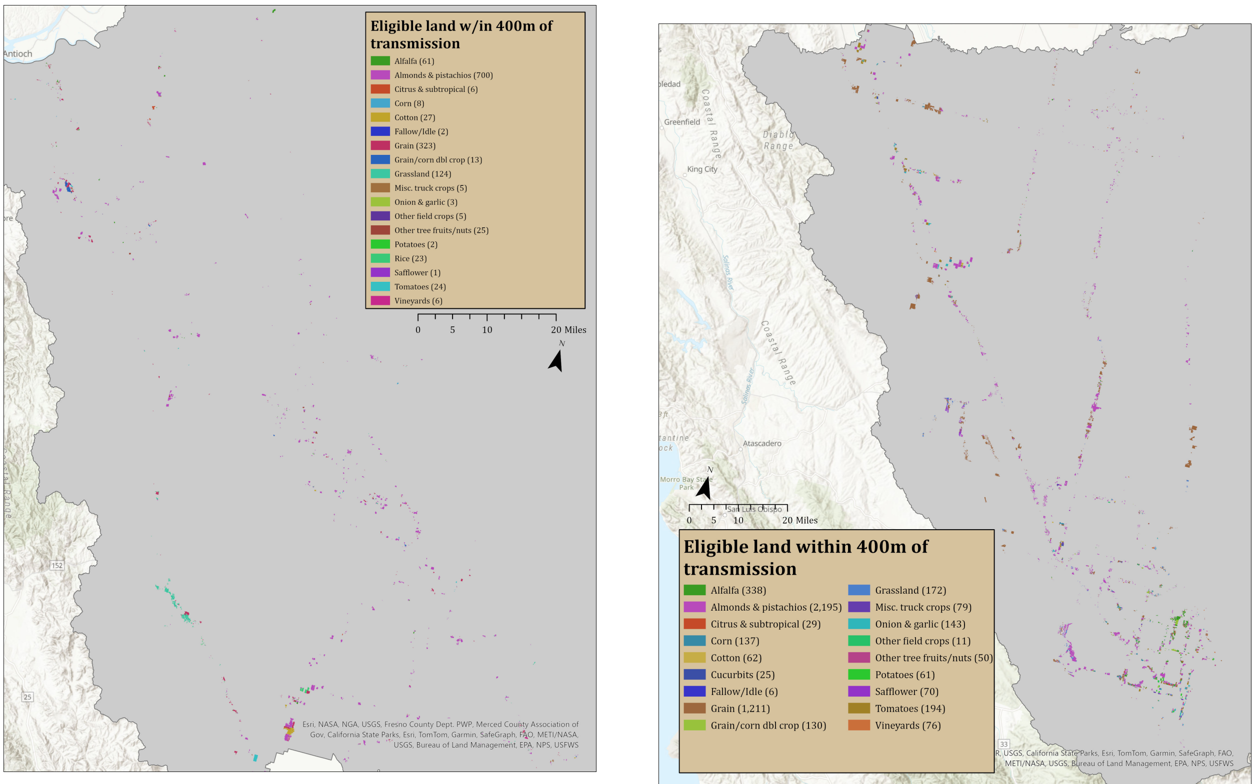


(a) Land parcels in San Joaquin River colored by crop grown in last active year. Count of parcels is displayed in parentheses by each crop category. *Total acreage displayed = 10,457* Map Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2024).(USDA-NASS, 2016).



(b) Land parcels in Tulare Lake colored by crop grown in last active year. Count of parcels is displayed in parenthesis. *Total acreage displayed = 20,001* Map Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2024).

Figure 8: Using land that has been fallow for one or more growing years 2016-2023, I show the plots of land that are within 100 meters of existing high-voltage transmission lines. The plots of land are colored by the crop grown in its last active growing season.



(a) Land parcels in San Joaquin River colored by crop grown in last active year. Count of parcels is displayed in parentheses. *Total acreage displayed = 17,877* Map Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2024).(USDA-NASS, 2016).

(b) Land parcels in Tulare Lake colored by crop grown in last active year. Count of parcels is displayed in parenthesis. *Total acreage displayed = 73.500* Map Source: Author's own analysis using ArcGIS Pro. Data from USDA CSB (USDA-NASS, 2024).

Figure 9: Using land that has been fallow for one or more growing years 2016-2023, I show the plots of land that are within 400m of existing high-voltage transmission lines. The plots of land are colored by the crop grown in its last active growing season.

7 Conclusion

This analysis identifies over 90,000 acres of agricultural land that would benefit from solar transition. If all of the acreage identified were to produce solar energy instead of traditional crops, very little other agricultural land would need to be removed from irrigation to help the San Joaquin Valley achieve its groundwater conservation goals as set forth by SGMA. The land identified can provide 3-4x as much energy generating capacity as already exists in the San Joaquin Valley, given average generating capacity per acre in the area (Ayres et al., 2022).

The calculated threshold cost of water shows relative sensitivity to water pricing increases, as it is based on a ratio of water usage and crop value. The ordering of these values tells us which farmers are more likely to benefit privately from a solar land transition. As scarcity increases due to increased pressure from policymakers on cutting back agricultural water use, local governments may find it beneficial to target lowest-cost land transitions first, before taking more profitable agricultural land out of production.

Using the calculated values of MC_W, policymakers can better anticipate which farmers are more sensitive to water price shocks. These farmers growing crops that are especially sensitive may be targeted by policy interventions that incentivize investment in solar farming. Further, using existing transmission line infrastructure allows for lower input costs to bring solar farms online. Combining these two data can be a powerful way to guide land transition in the San Joaquin Valley.

Future research can relax the assumption of equal water access across farmers, and allow for more nuanced production and cost functions for growers. These additions will better reflect the reality that farmers face with water, land, and other input costs. This ordering system provides a loose guide for which farmers may react to increased water prices induced by scarcity and regulation, and adding more flexibility will improve the ability to apply results to policy. This analysis aligns well with economic literature utilizing positive mathematical programming. These economic tools used in more comprehensive agricultural production models including Howitt (1995), Mérel and Howitt (2014), and Howitt et al. (2012).

The results of the analysis above give geo-spcific predictions of where solar is likely to be adopted on agricultural land due to intrinsic land and crop values. Other planning, like transmission line building, could benefit from the guide that this paper provides to solar land-use transition.

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Appendices

A Data used

Panel B. Crop characteristics by category

Crop category	Share	Mean water needs per acre (acre-feet)	Mean revenue per acre (2009$)
Perennial, long-term crops			
Almonds, pistachios	13.5%	4.82	5,081
Grapes	6.0%	3.88	7,735
Citrus, other subtropical fruit	2.4%	3.83	6,683
Other tree fruits, nuts	3.8%	4.03	4,811
Annual & short-term crops			
Alfalfa	7.7%	4.97	1,303
Grains	7.0%	1.31	622
Rice	5.9%	2.89	1,594
Corn	4.3%	2.61	868
Cotton	3.7%	3.62	1,736
Tomatoes	2.5%	2.59	4,171
Safflower	0.6%	1.99	453
Onions, garlic	0.5%	3.03	5,943
Melons, squash, cucumbers	0.3%	2.41	5,844
Sugar beets	0.2%	3.62	2,187
Dry beans	0.2%	2.12	1,215
Potatoes	0.2%	1.72	7,825
Pasture, grass	0.1%	7.58	125
Other vegetables, berries	1.0%	1.94	18,128
Other field crops	0.7%	2.67	1,036
Not crops			
Grassland (unirrigated rangeland)	15.9%	0.00	11
Fallow	10.3%	0.00	0
Natural vegetation	13.2%	0.00	0

Figure 10: Data table from Hagerty (2022). These data are used in calculating threshold MC_W values. Mean water needs are calculated using estimates from the California Department of Water Resources (DWR) model Cal-SIMETAW, which is an agricultural water balance model developed by the DWR for the California Water Plan Update 2018. Mean revenues are calculated using County Agricultural Commissions' Reports.

B Selected full-sized figures

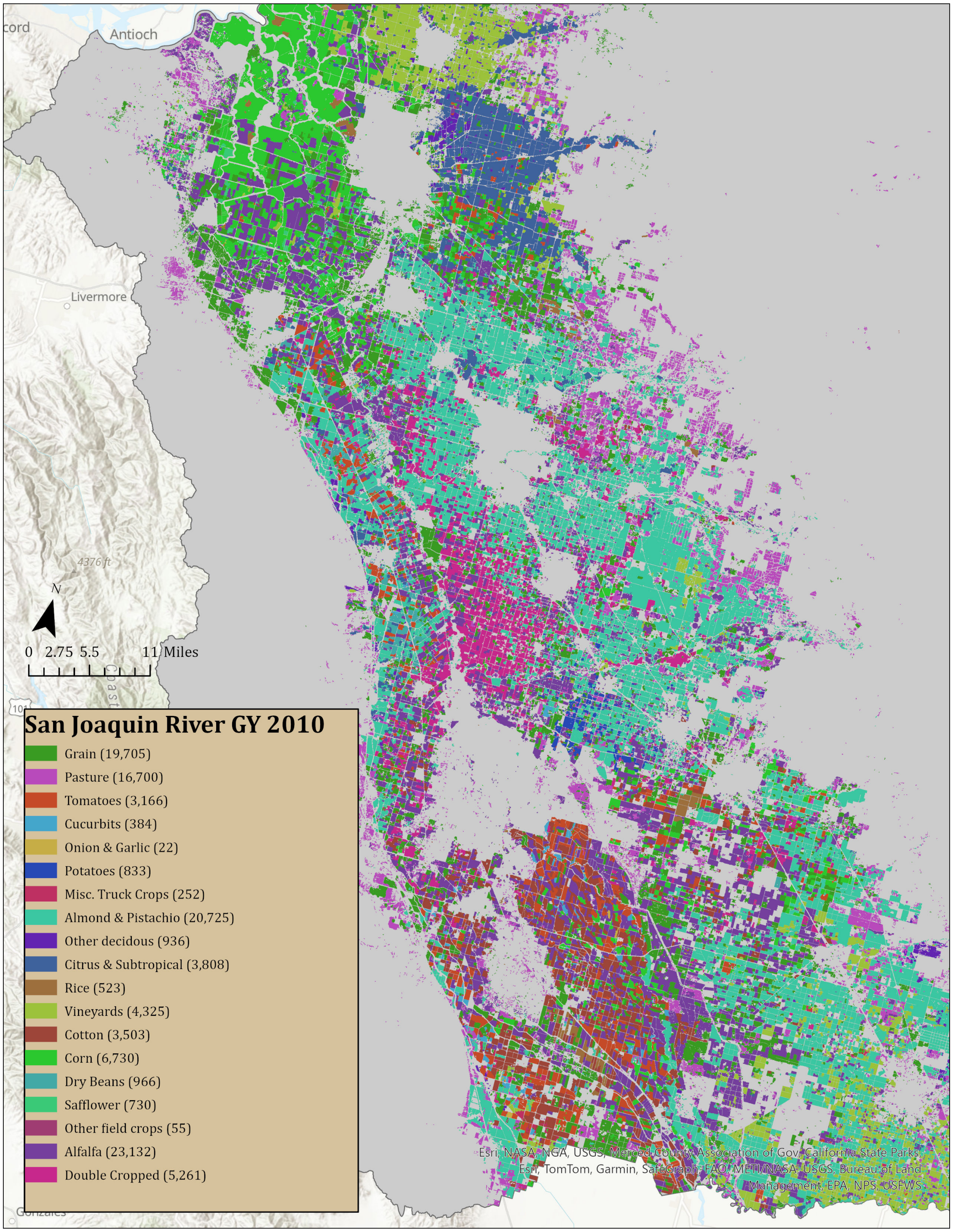


Figure 2a: Crop cover of San Joaquin River HR, growing year 2010. Count of land parcels in parentheses by crop type.

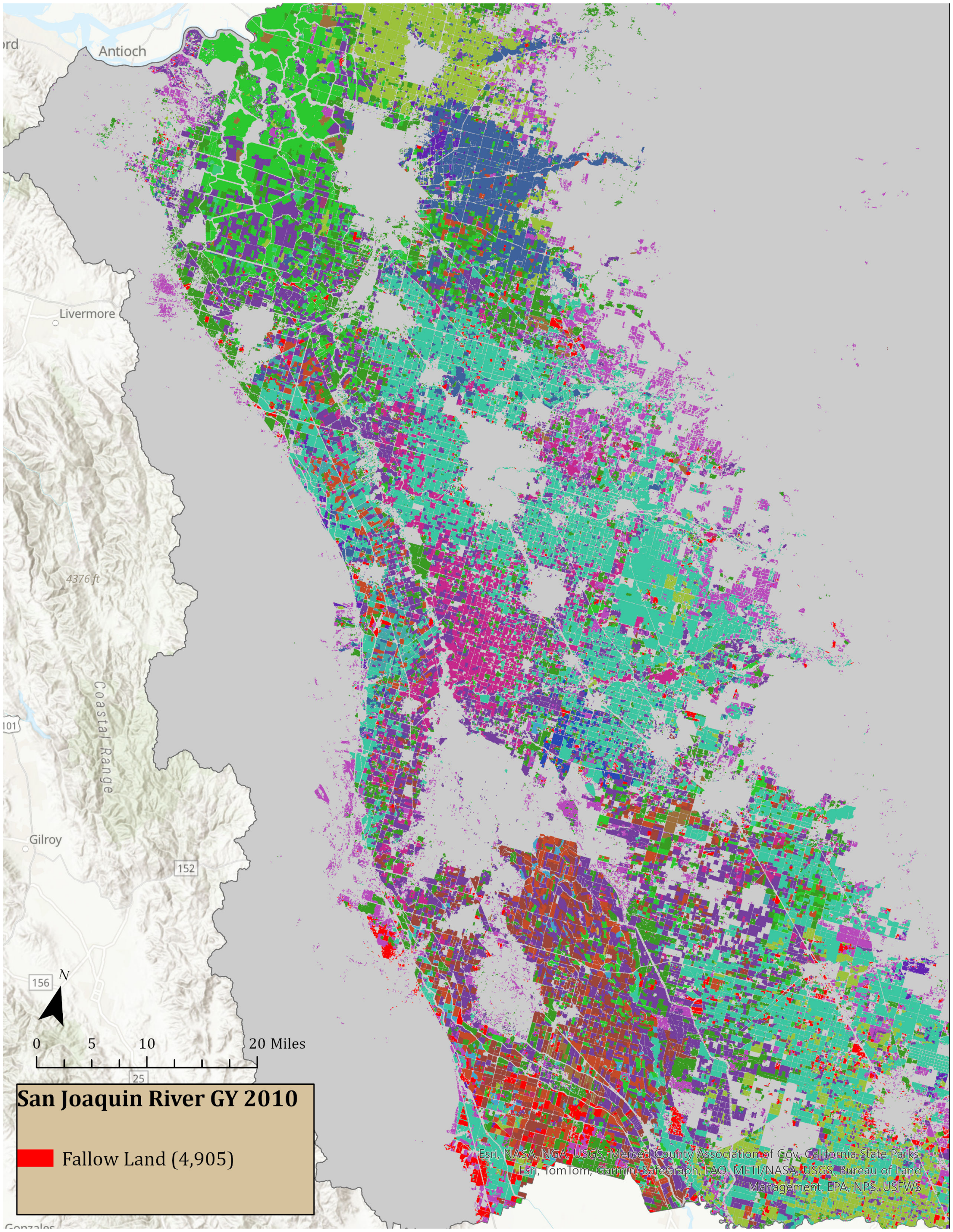


Figure 2b: Fallow land in San Joaquin River HR, growing year 2010. Count of land parcels in parentheses.

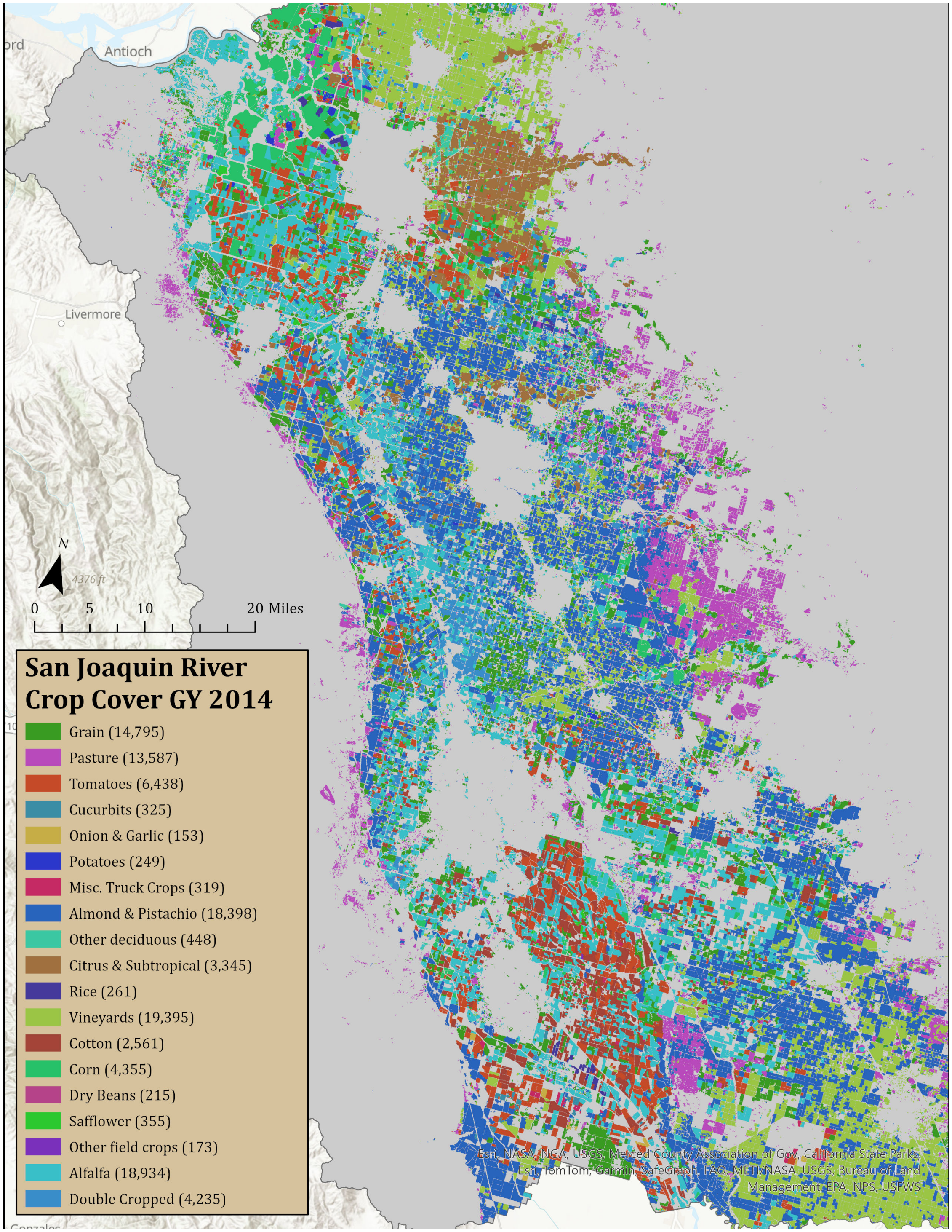


Figure 2c: Crop cover of San Joaquin River HR, growing year 2014. Count of land parcels in parentheses by crop type.

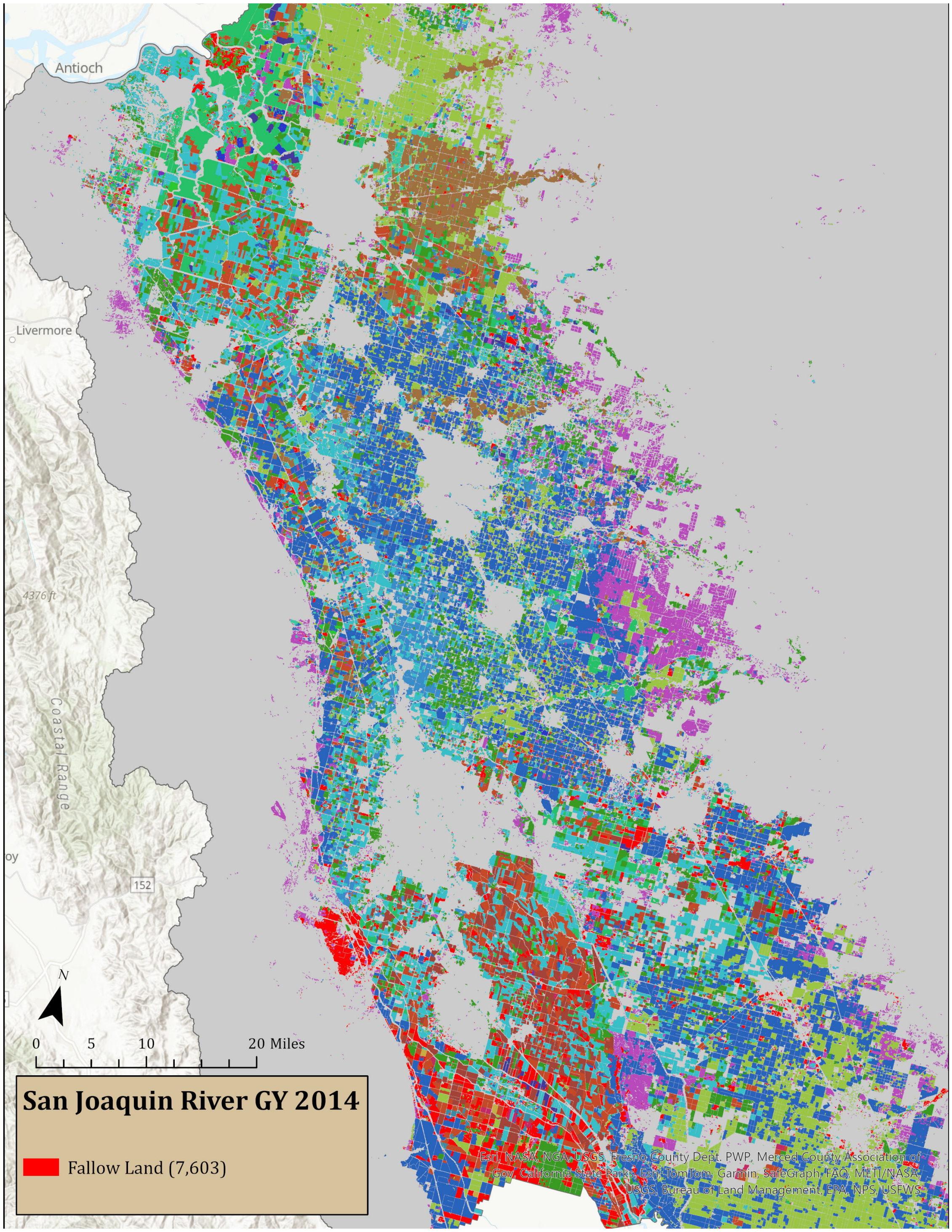


Figure 2d: Fallow land in San Joaquin River HR, growing year 2014. Count of land parcels in parentheses.

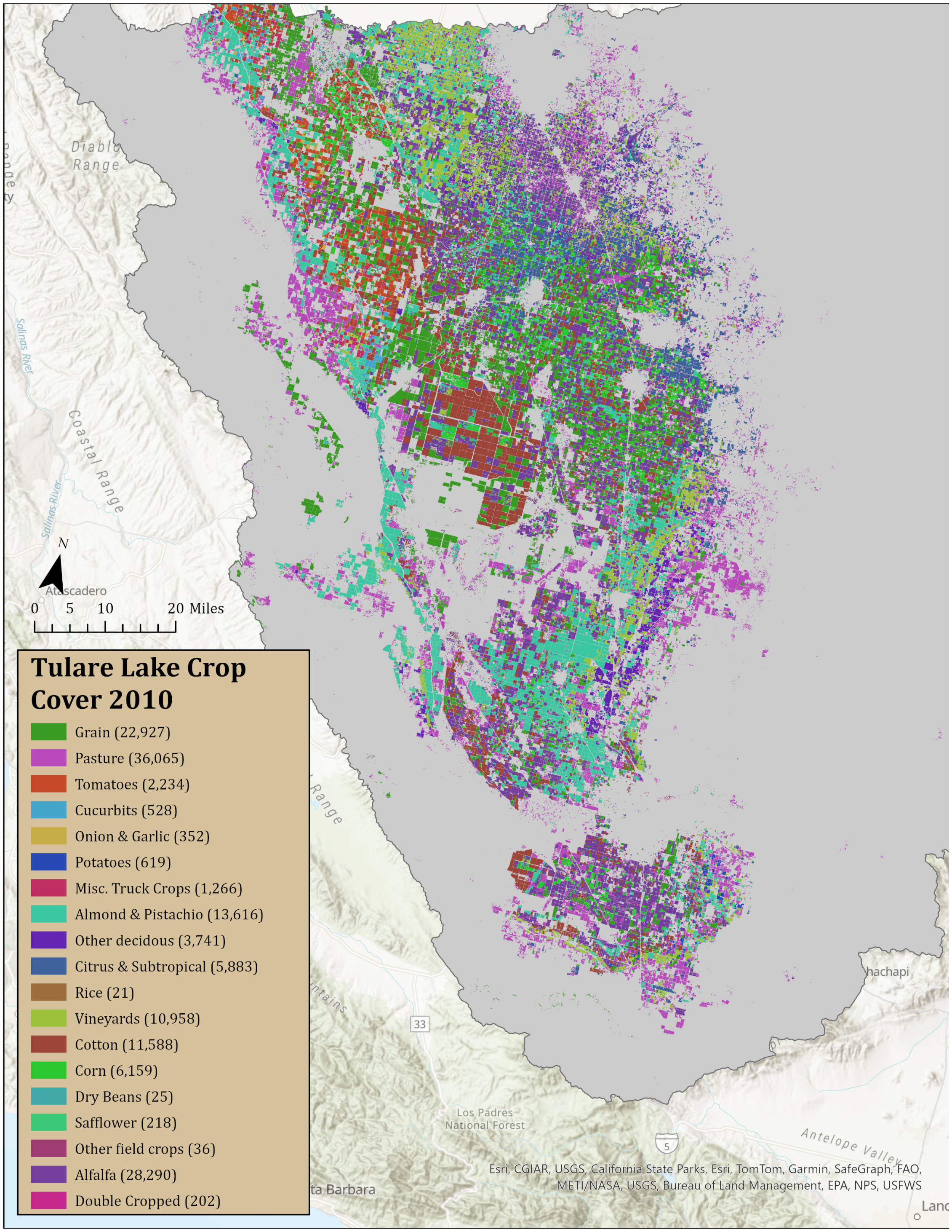
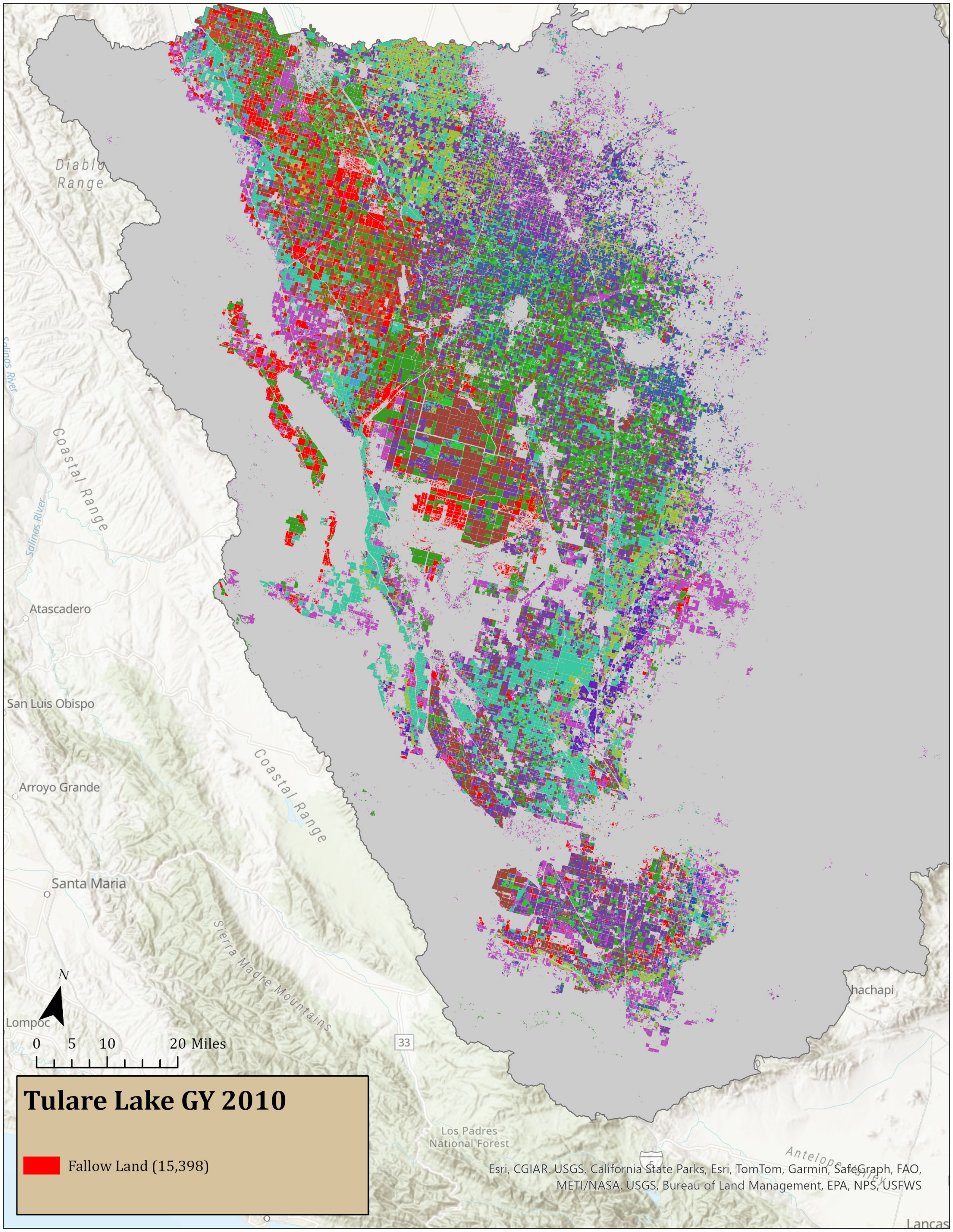


Figure 3a: Crop cover of Tulare Lake HR, growing year 2010. Count of land parcels in parentheses by crop type.



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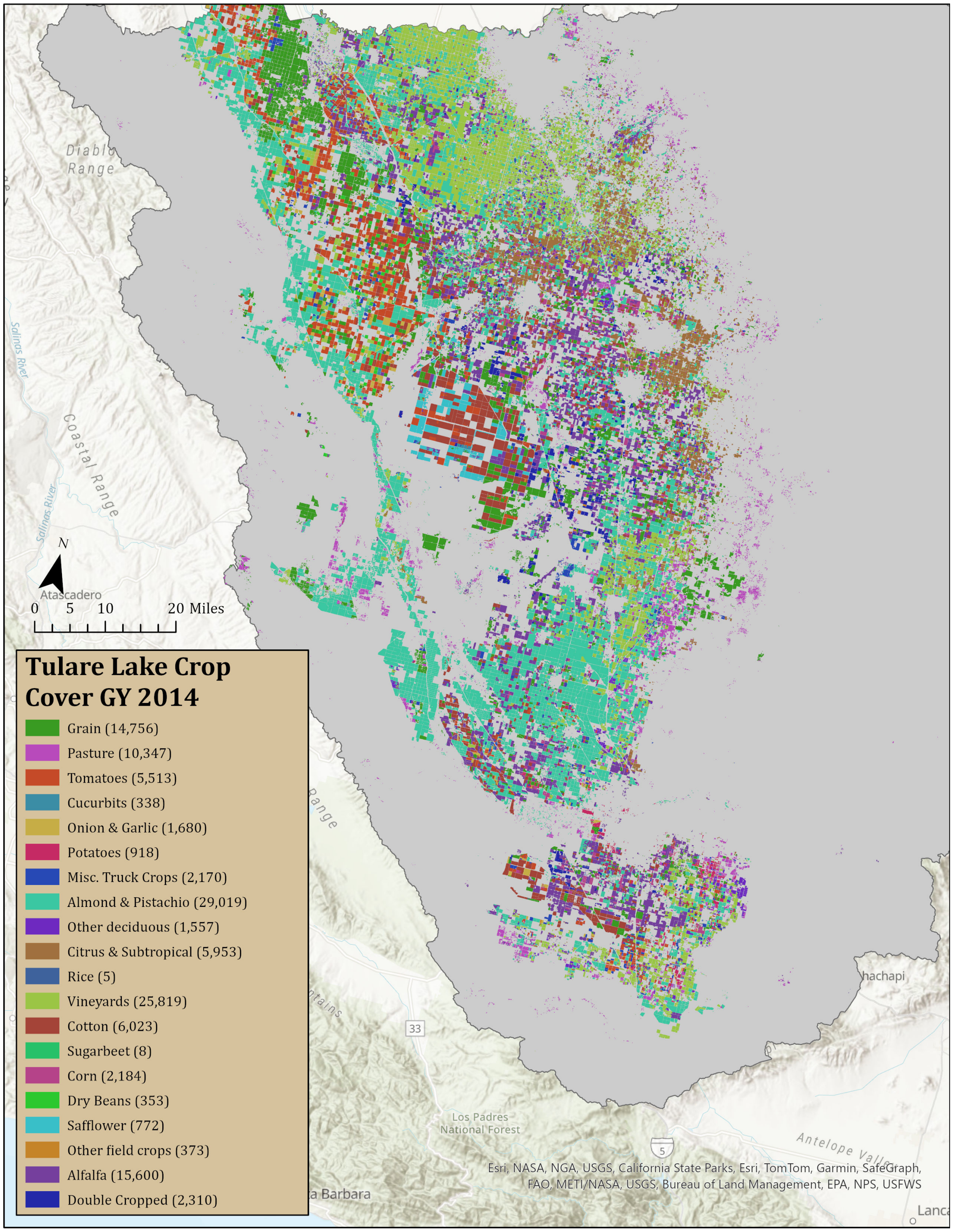

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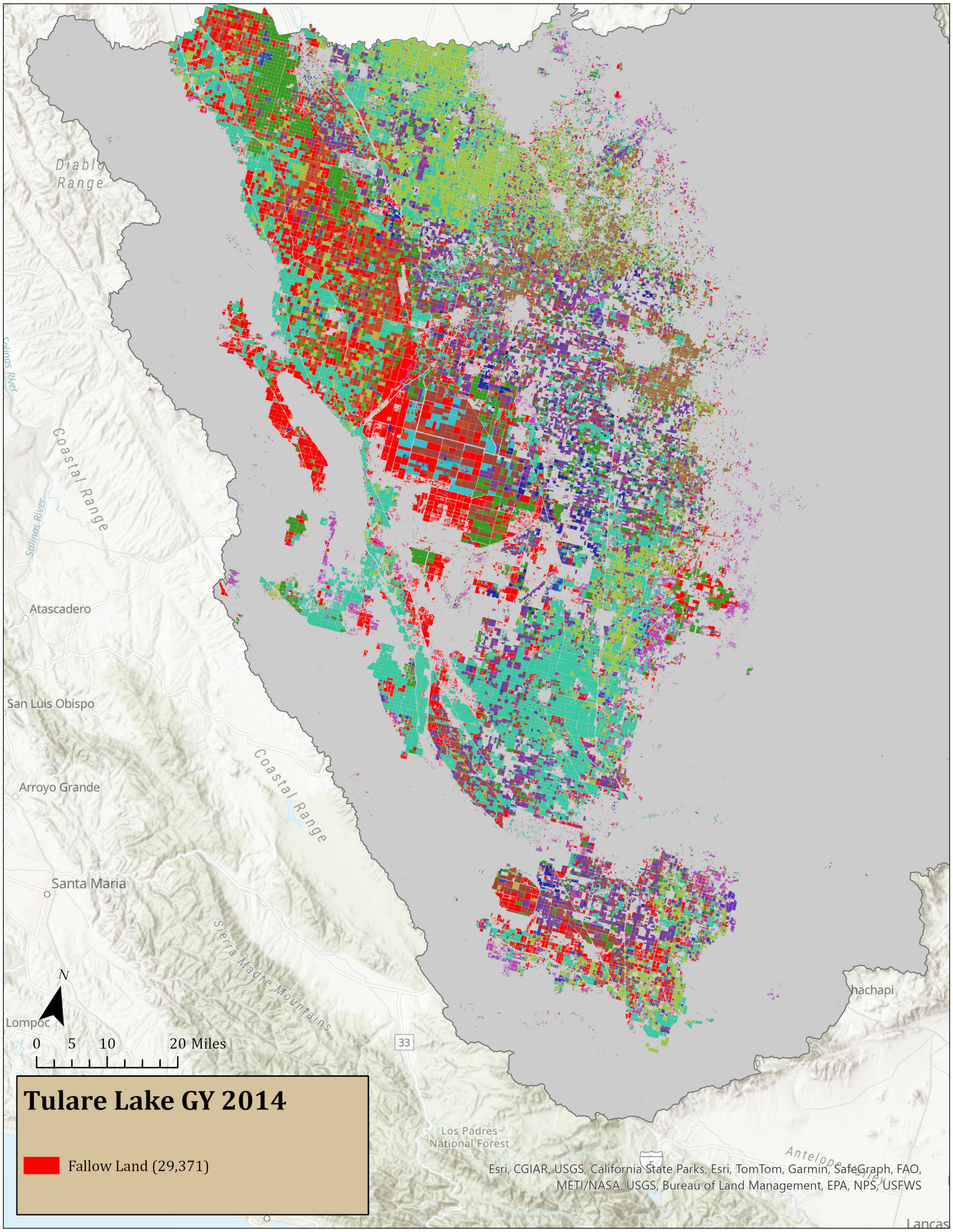


Figure 3d: Fallow land in Tulare Lake HR, growing year 2014. Count of land parcels in parentheses.

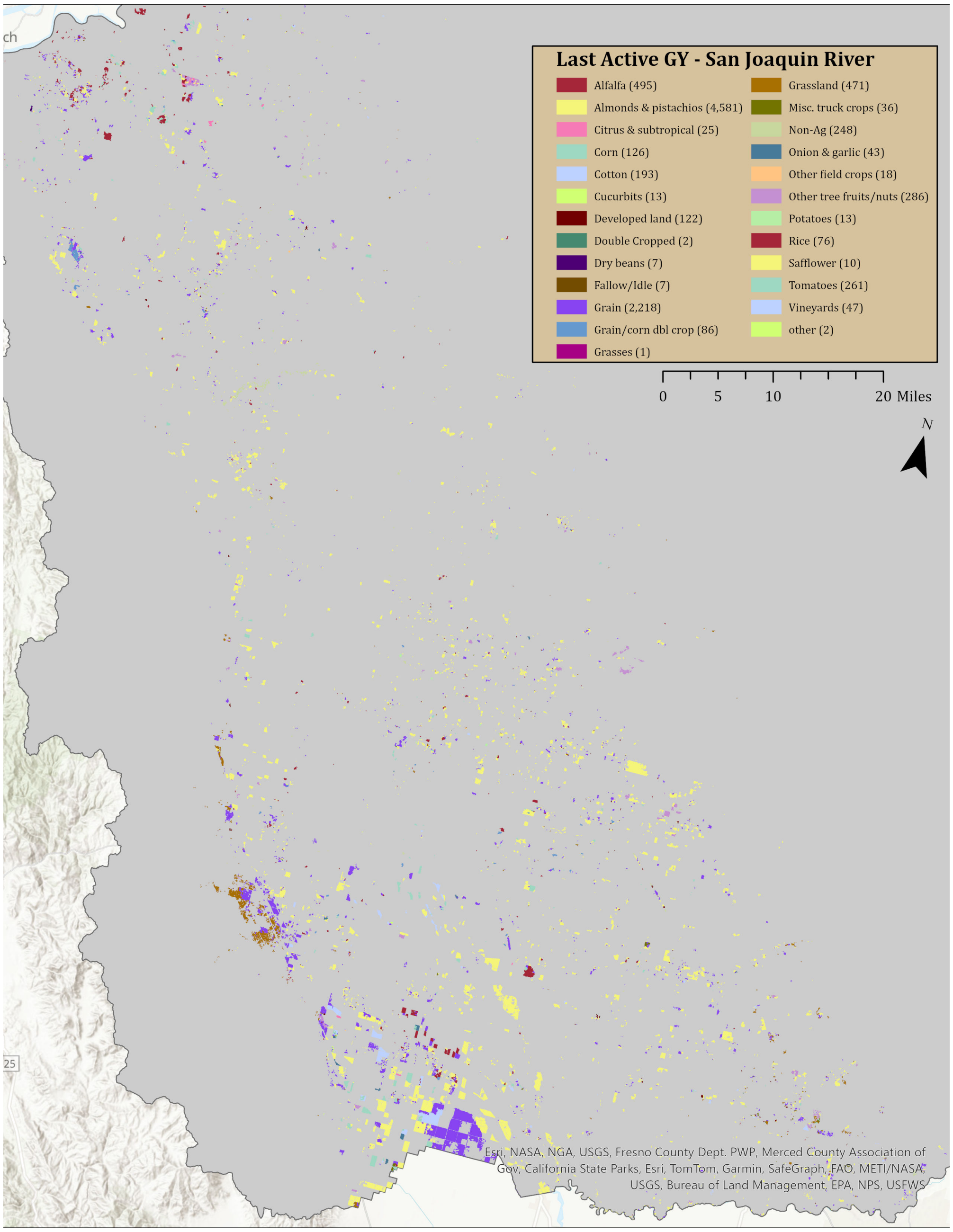
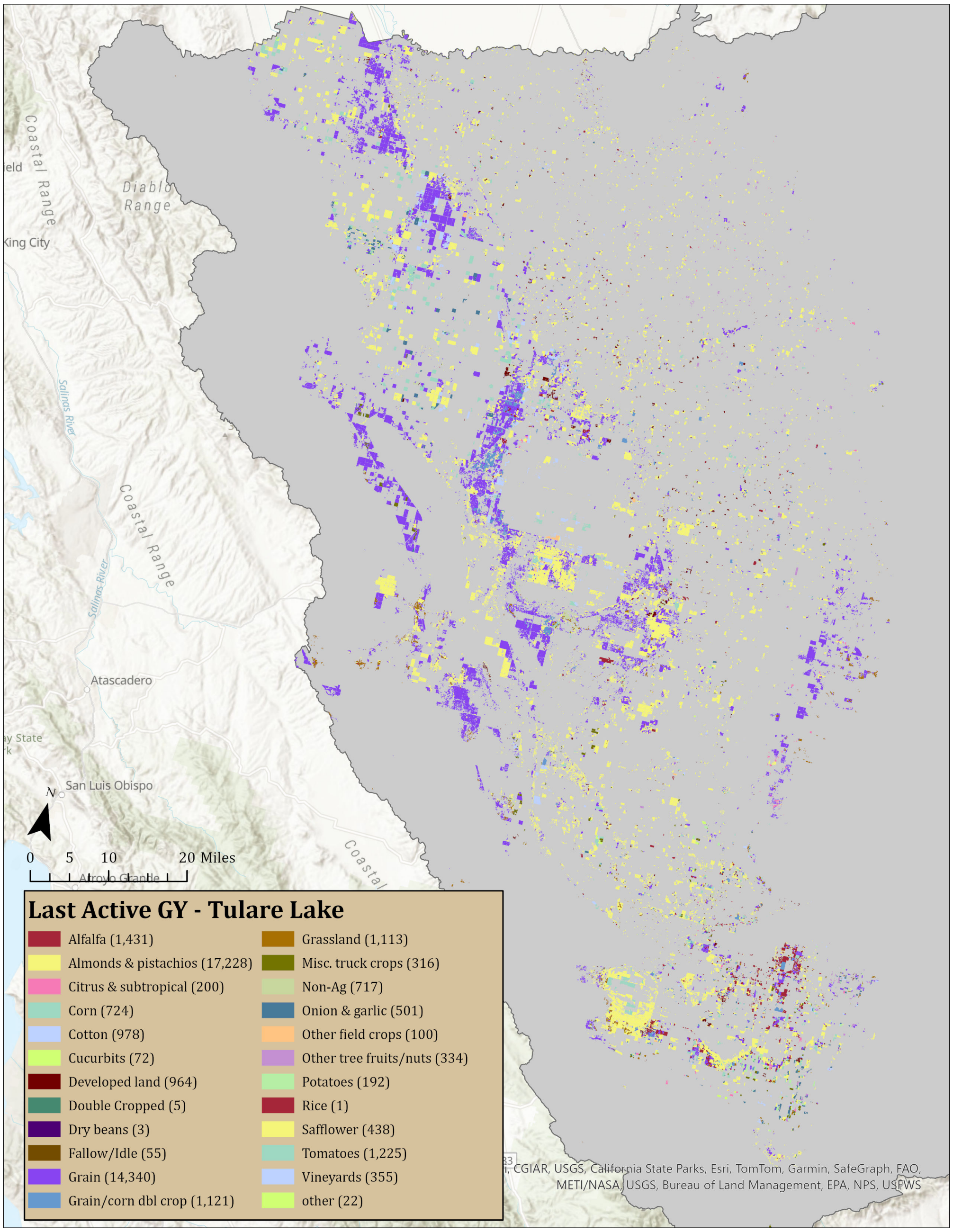


Figure 7: Crop choice in the last active growing season for land that has been fallow in San Joaquin River HR for one or more growing seasons 2016-2023.



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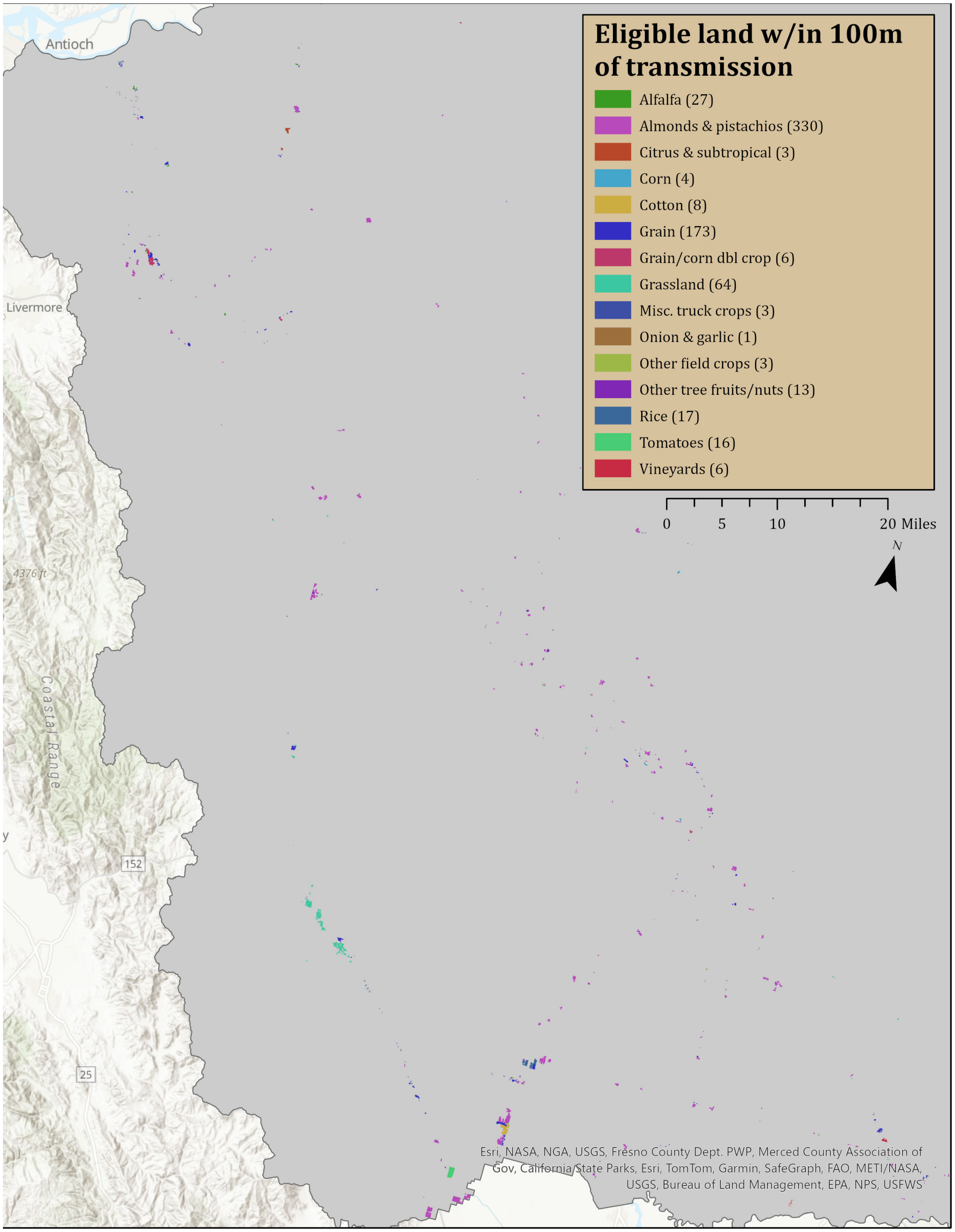


Figure 8a: Land parcels in San Joaquin River colored by crop grown in last active year. Count of parcels is displayed in parentheses by each crop category. Total acreage displayed = 10,457

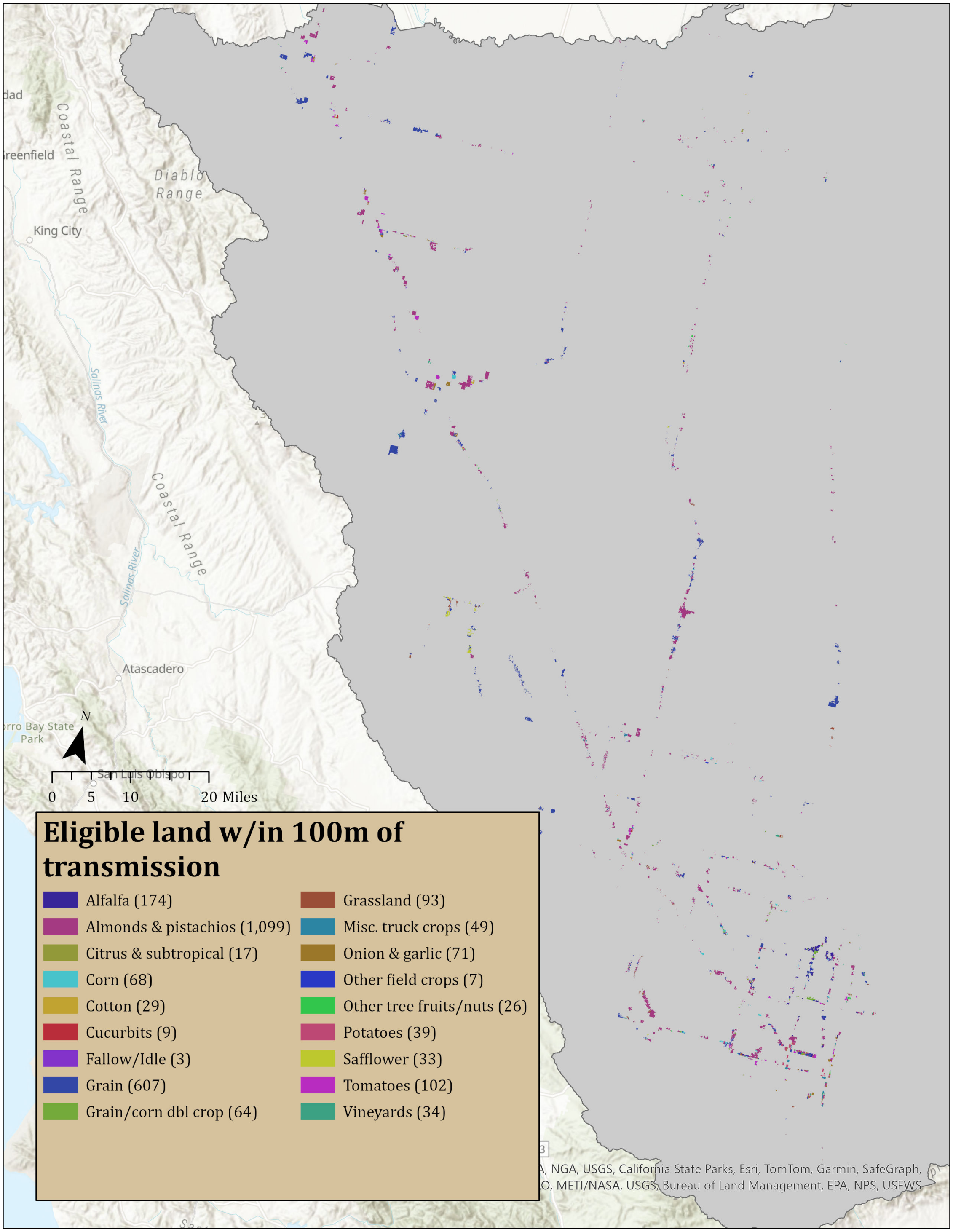
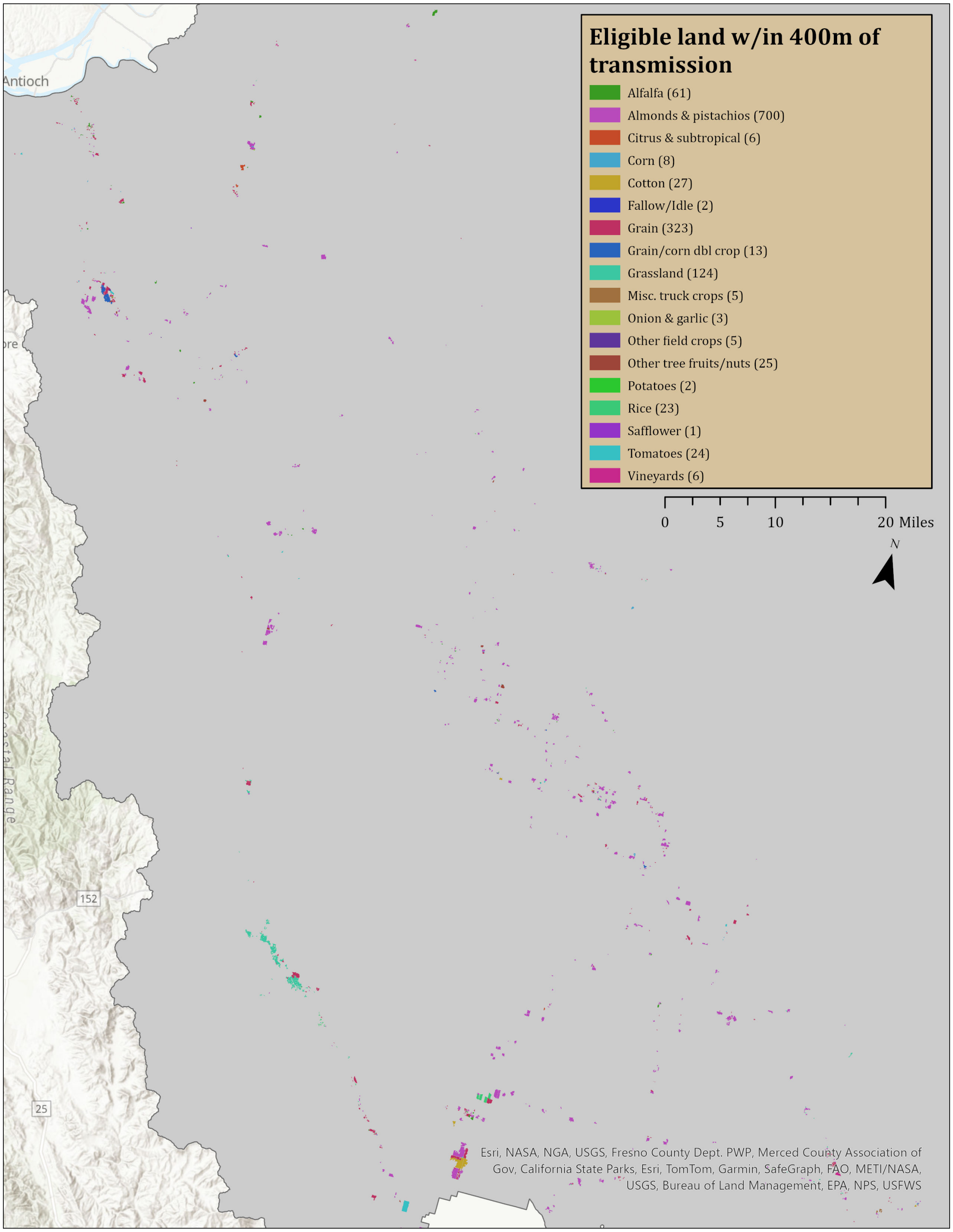


Figure 8b: Land parcels in Tulare Lake colored by crop grown in last active year. Count of parcels is displayed in parentheses by each crop category. Total acreage displayed = 20,001



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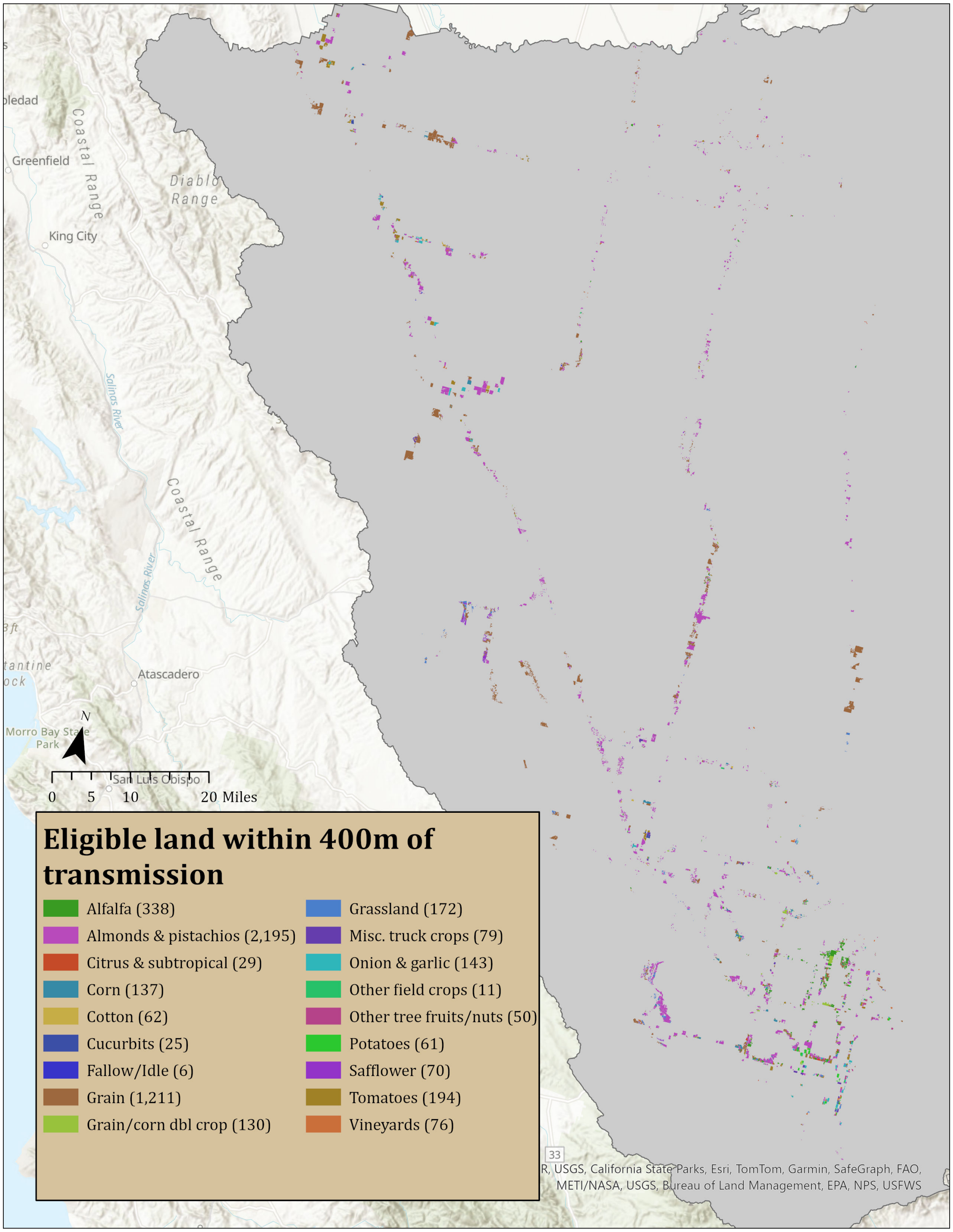

Figure 9b: Land parcels in Tulare Lake colored by crop grown in last active year. Count of parcels is displayed in parentheses by each crop category. Total acreage displayed = 73,500