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From Fields to Photovoltaics: Effects of Agrisolar Co-Location on Food, Energy, Water, and Economic Security

Jacob Stid

stidjaco@msu.edu

Michigan State University https://orcid.org/0000-0003-2428-2340

Siddharth Shukla

Michigan State University

Anthony Kendall

Michigan State University https://orcid.org/0000-0003-3914-9964

Annick Anctil

Michigan State University

David Hyndman

The University of Texas at Dallas https://orcid.org/0000-0001-9464-8403

Jeremy Rapp

Michigan State University

Robert Anex

University of Wisconsin-Madison https://orcid.org/0000-0003-2298-041X

Analysis

Keywords:

Posted Date: November 2nd, 2023

DOI: https://doi.org/10.21203/rs.3.rs-3475091/v1

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Additional Declarations: There is **NO** Competing Interest.

Version of Record: A version of this preprint was published at Nature Sustainability on April 21st, 2025.
See the published version at https://doi.org/10.1038/s41893-025-01546-4.

Main Manuscript Text for

FROM FIELDS TO PHOTOVOLTAICS: EFFECTS OF AGRISOLAR CO-LOCATION ON FOOD, ENERGY, WATER, AND ECONOMIC SECURITY

Jacob T. Stid*[1], Siddharth Shukla[2], Anthony D. Kendall[1], Annick Anctil[2], David W. Hyndman[3], Jeremy Rapp[1], Robert P. Anex[4]

[1]Department of Earth and Environmental Sciences, Michigan State University, East Lansing, MI, 48824, USA, [2]Department of Civil and Environmental Engineering, Michigan State University, East Lansing, MI, 48824, USA, [3]Department of Geosciences, School of Natural Sciences and Mathematics, The University of Texas at Dallas, Richardson, TX, 75080, USA, [4]Biological Systems Engineering, University of Wisconsin-Madison, Madison, WI, 53706, USA

Emails (in authorship order): stidjaco@msu.edu, shuklas7@msu.edu, kendal30@msu.edu, anctilan@msu.edu, hyndman@utdallas.edu, rappjer1@msu.edu, anex@wisc.edu

***Corresponding Author:** Jacob T. Stid, stidjaco@msu.edu

Present Address: Natural Science Building, 288 Farm Lane, Rm 207 East Lansing, MI 48842

Contents: 46 pages including 5 Figures, 12 equations, and References

Abstract

Achieving sustainable net-zero energy production requires understanding how solar PV installations affect the landscape and its critical resources. To enhance this understanding, we investigate *agrisolar* co-location, which is land that is broadly co-managed for agricultural production, solar photovoltaic electricity production, and ecosystem services. We present a food, energy, water, and economic impact analysis of agricultural output offset by agrisolar co-location for 925 arrays (2.53 GW_p covering 39.3 km^2) spanning the California Central Valley. We find that agrisolar co-location displaces a significant amount of food production. However, agrisolar co-location also increases economic security for farmers and likely enhances water sustainability, and thus future agricultural production, by reducing irrigation water use and facilitating the fallowing of irrigated land. Given the unprecedented pace of solar PV expansion globally, these results highlight the need for a deeper understanding of the multifaceted outcomes of agricultural and solar PV co-location decisions.

Main

Climate change significantly threatens our finite food, energy, and water (FEW) resources. As society attempts to mitigate these and other threats, in part by transitioning toward a net-zero carbon emissions energy system (hereafter "net-zero"), new energy installations should be deployed with consideration to the complete FEW nexus. All feasible paths to net-zero involve broad deployment of solar electricity generation[1–3] which shows promise for reducing energy and social costs, along with energy end-use, while producing millions of long-term jobs[3]. While recent research has identified the spatial and temporal extent of solar photovoltaic (PV) installations[4–11], few studies have incorporated long-term FEW and economic effects of agricultural solar co-location[12]. Such interdisciplinary analyses are important as solar capacity in the United States (US) will need to grow more than 10-fold by 2050 to meet net-zero[1]

Solar PV and cropland benefit from similar site characteristics including solar irradiation, topography, and climate, which can lead to land use competition[13]. Recent work suggests that most ground-mounted solar PV facilities in the US, and ~70% in the California Central Valley (CCV)[9], are installed in agricultural settings[6,7]. Yet, regions with high solar-breakthrough like the CCV are often amongst the most valuable and productive agricultural land in the US[14]. The CCV produces more vegetable, fruit, and nut exports than any other US state[15], while claiming 20% of total US consumptive groundwater use[16] on less than 1% of total US farmland.

The competition between solar and agricultural land uses has led researchers to propose various *co-location* methods in which solar PV installations are sited, designed, and managed to optimize landscape productivity across a wide range of ecological and anthropogenic services[17]. This differs from conventional solar PV installations that are often installed and managed strictly for electricity output and reduced maintenance[17]. Emerging concepts like *techno-ecological*

synergies[18] and more recently, *ecovoltaics*[17] encompass a wide variety of co-location strategies enabling renewable energy installations to serve multiple productive agroecosystem purposes. In agricultural settings, crop production and solar PV can be laterally integrated (*agrisolar* co-location)[19], and/or directly share land and photons via vertical integration (*agrivoltaic* co-location)[20,21].

Effective agrivoltaic management can improve agricultural yield, microclimate regulation, soil moisture retention, nutrient cycling[12,22–26], and farmer profitability[24,27,28], while reducing public opposition[29,30]. Aside from installation and management costs concerns[31–33], agrivoltaics have few net-negative consequences[12,21,34–36]. However, techno-economic and political challenges remain for broad deployment of this practice[35,37–39]. While these challenges are being addressed, there have been comparatively few documented installations employing such cultivation methods[40,41]. Although a vast and growing body of literature exists for agrivoltaics[32,35,36], there are fewer efforts on possibly more common practices like ecovoltaics or agrisolar co-location[17]. Given that agrisolar practices are understudied, there is a need to assess regional resource outcomes for most existing solar PV installations.

Herein, we apply a broadened definition of the term *agrisolar* (from that defined in SolarPower Europe[19]), namely: *the integration and co-management of solar photovoltaics, agriculture, and ecosystem services within agroenergy landscapes, explicitly considering the tradeoffs and co-benefits of agricultural, environmental, and socioeconomic objectives*. Thus defined, agrisolar practices are an agriculturally-focused subset of ecovoltaics, including both coincident (i.e., “agrivoltaic”) and adjacent co-location (hereafter, “agrisolar co-location”)[21,33], as illustrated in Fig. 1.

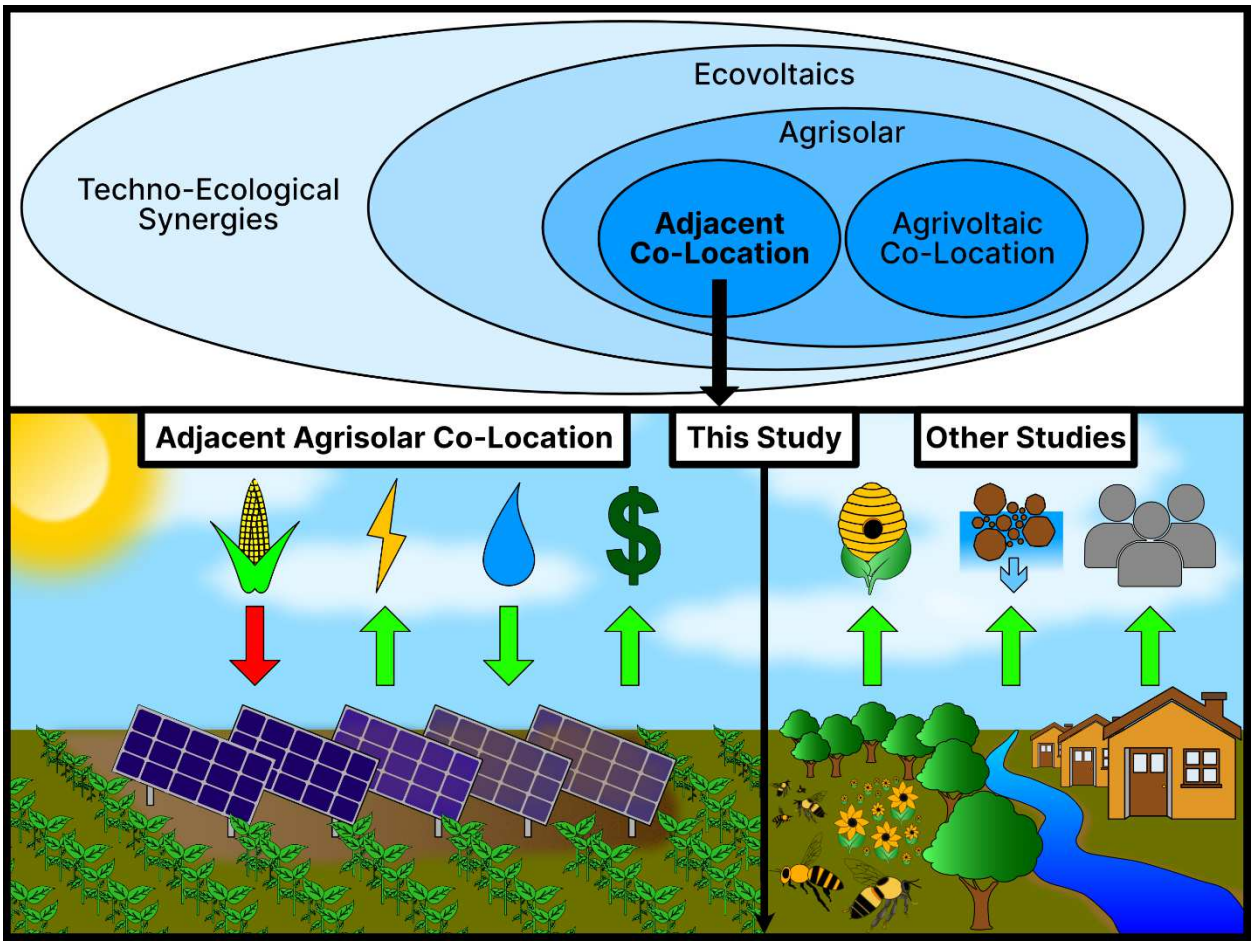


Fig 1. Renewable energy sustainability terminology and adjacent agrisolar co-location diagram. Terminology scales from broad concepts to specific practices. There are many other terms in the literature related to these spheres of influence (see *Supplementary Discussion 4*). This figure (top) was motivated by Figure 1 in McCall et al.[33]. Effects of agrisolar co-location on resources and economics are shown (lower left) and other effects on biodiversity, hydrology, and communities (lower right). The direction of the arrows indicates if a resource is enhanced or decreased (positive: green, negative: red).

Here, we assess the FEW implications of solar PV installations co-located with (installed in) agricultural land across the CCV through 2018 and estimate the economic potential of those arrays throughout a 25-year operational-phase lifespan. We compute landowner cash flow including net energy metering (NEM) for commercial-scale PV installations and land leases for larger utility-scale arrays. All resource and economic effects are referenced to a counterfactual business as usual scenario with no solar PV installation, assuming continued agricultural

production and operation on the same plot of land. This analysis provides the basis to evaluate the FEW impacts of agrisolar co-location, and the economic drivers for the rapid expansion of such solar PV systems over the CCV. We also highlight the need for, and opportunities within, additional research into agrisolar practices.

Results

Commercial- and utility-scale solar PV arrays in CCV

For this study, we assembled the most complete dataset to-date of agriculturally co-located solar PV installations within the CCV. We identified 925 solar PV arrays installed between 2008 and 2018, with an estimated capacity of 2,524 MW_p on 39.3 km^2 of recently converted agricultural land. The estimated solar PV array capacity of each individual individual arrays ranged from 19 kW_p to 97 MW_p. A temporal synthesis of the input solar PV dataset, separated by array scale, is shown in Fig. 2C and 2D. The smaller commercial-scale arrays are roughly twice as common, yet account for one tenth of the installed capacity and converted land area of utility-scale arrays. Note that commercial-scale arrays are predominantly fixed-axis, while utility-scale arrays are more frequently single-axis tracking systems. There are also notable peaks in the number of installations for both array scales in 2016, potentially in response to the NEM 2.0 legislation timeline[42]. While there is some spatial clustering of converted crop types (Fig. 2A), converted crops were widely distributed across CCV.

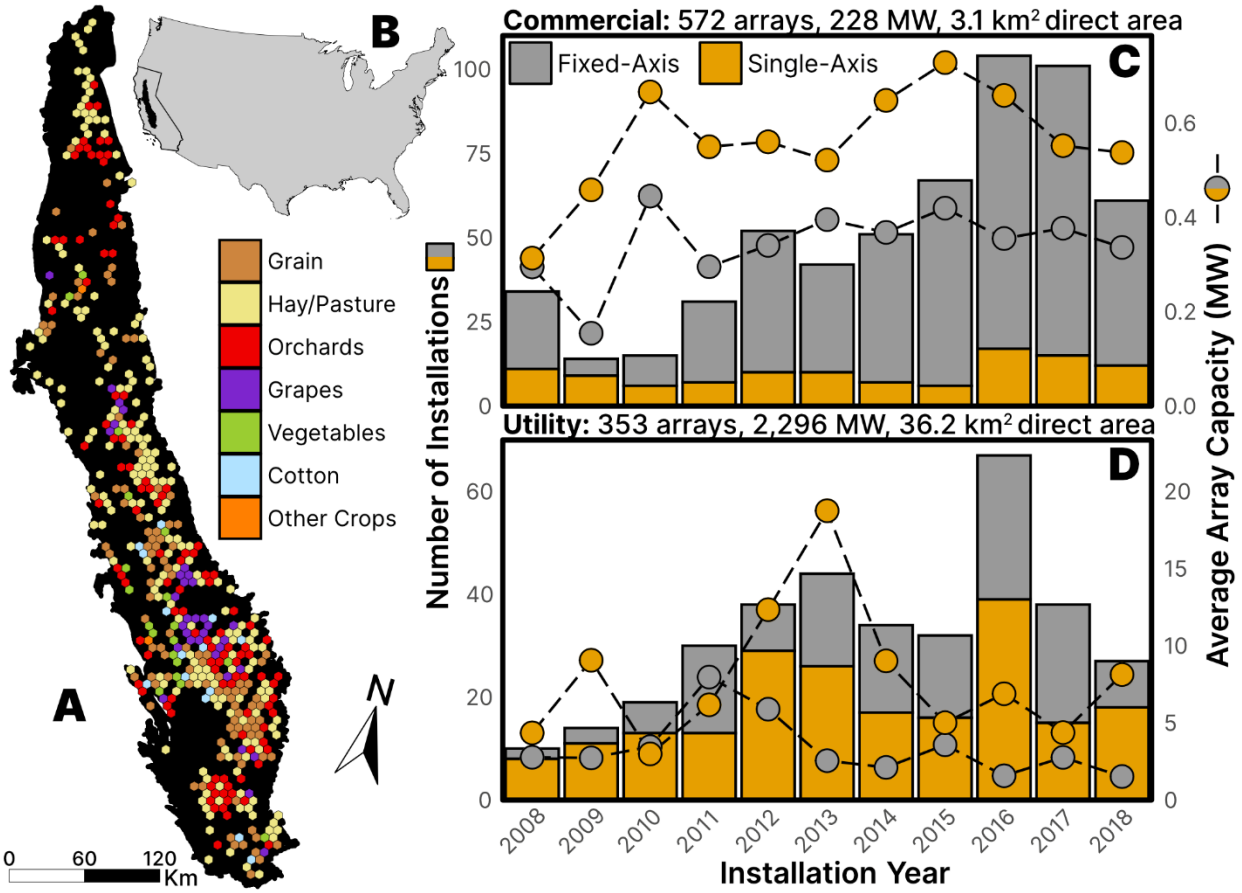


Fig 2. Study area and characterization of ground-mounted solar PV installations. Map of displaced crop groups within the CCV alluvial boundary(Faunt, 2012) (A) based on predominant USDA Farm and Ranch Survey with five-year crop rotation zonally encoded using Uber H3. (B) CONUS map with CCV alluvial boundary. (C) and (D) show the solar PV array installation number, capacity, area, and mount type (fixed-axis or single-axis tracking) by year for the 925 commercial- (C) and utility-scale (D) arrays assessed in this study.

Offset food and nutritional production

The 925 agriculturally co-located arrays displaced 39.3 km^2 of cropland, which is ~0.10% of the CCV active agricultural land[43]. In the baseline scenario (see *Methods* for scenario details), nutritional loss was 0.16 trillion kcal (Tkcal) and 1.41 Tkcal forgone by commercial- and utility-scale arrays respectively (Fig. 3). The total, 1.57 Tkal (25-million kcal MW_p^{-1} yr^{-1}), is equivalent to the caloric intake of ~86,000 people for 25 years (solar lifespan), assuming a 2,000 kcal day^{-1} diet. The reduction in kcal production from commercial-scale arrays was displaced by

grain (58%), orchard crops (21%), and vegetables (10%). Utility-scale arrays displaced the nutritional value of grain (60%) hay/pasture (16%), and vegetables (10%). Note that for displaced kcal production of hay/pasture, contribution was negligible despite dominating the converted area (Fig. 3D and 3G) due to inefficient caloric conversion to human nutrition for feed and silage crops. Final cumulative resource value estimates are shown in Fig. 3A, B, and C, and reported in *Supplementary Table 1*.

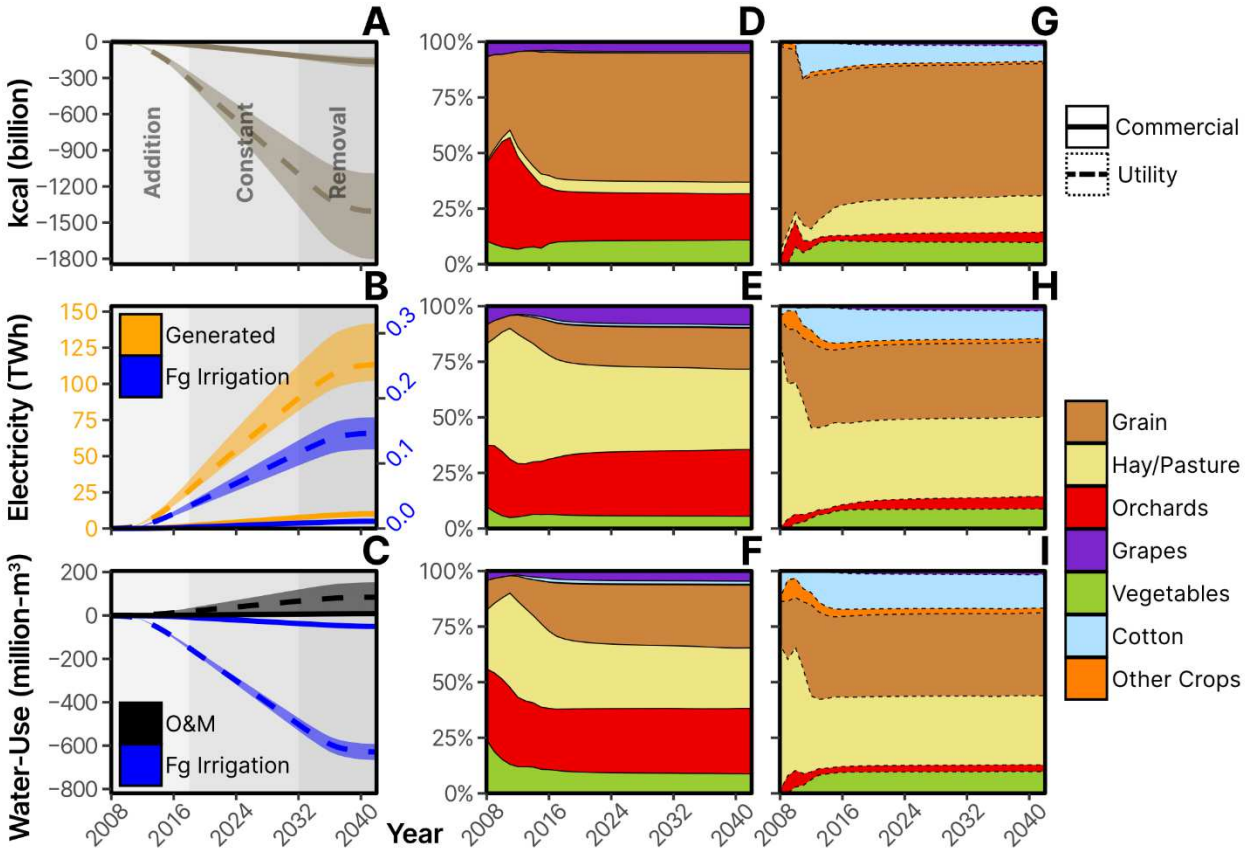


Fig 3. Cumulative food, energy, and water agrisolar co-location effects. Impact analysis for food (A, D, G), electricity (B, E, H), water (C, F, I). Subplots D, E, and F represent commercial-scale crop proportions contributing to final resource effects, while G, H, and I represent the same for utility-scale. The gray panels labeled "Addition", "Constant", and "Removal" represent the three temporal assessment phases described in *Food, Energy, Eater (FEW), and economic effect scenarios: Summary and assumptions*. "Fg Irrigation" indicates forgone irrigation electricity (TWh) and water use (million-m^3), and O&M indicates operation and maintenance water use. In all figures, dashed lines represent utility-scale while solid lines represent commercial-scale arrays.

152 ***Electricity production and consumption***

153 We modeled the annual electricity generation for each array and offset irrigation
154 electricity demand. Total cumulative electricity generation for these identified arrays by 2042
155 was projected to be 10 TWh for commercial-scale arrays and 113 TWh for utility-scale arrays.
156 For reference, the total 123 TWh could power ~466,000 US households (assuming 10.6 MWh
157 yr^{-1} $household^{-1}$) for 25 years. The potential electricity saved by not irrigating converted land
158 was 11 GWh and 146 GWh for commercial- and utility-scale arrays, respectively. Note that this
159 was three orders of magnitude less than the total electricity generation but could still power 600
160 US households for the 25-year solar PV lifespan.

161 ***Changes in water use***

162 A great majority (74%) of co-located solar PV arrays in the CCV replaced irrigated
163 croplands. We computed business as usual irrigation water use on the 33.1 km^2 of array area
164 converting irrigated land. We estimate that crops displaced by commercial- and utility-scale
165 arrays would reduce irrigation water demand by 51 million-m^3 and 629 million-m^3 respectively,
166 over the 25-year period. This could supply ~32 million people with drinking water (assuming 2.4
167 liters $person^{-1}$ day^{-1}), or irrigate 3,400 hectares (ha) of orchards, for 25 years. Irrigated crops that
168 contributed the most to the offset irrigation water use were orchards (29%), hay/pasture (28%),
169 and grain (27%) for commercial-scale installations and grain (37%), hay/pasture (31%), cotton
170 (15%) for utility-scale installations. In contrast, total baseline scenario operation and
171 maintenance (O&M) water use was cumulatively just 8 million-m^3 and 85 million-m^3 for
172 commercial- and utility-scale arrays, respectively, for the same period. Thus, solar PV O&M
173 water use on previously irrigated land was ~8 times less than irrigated cropping—if offset
174 irrigation water were conserved rather than redistributed.

Agricultural landowner cash flow

Adjacent agrisolar co-location is more profitable than the baseline agriculture-only scenario, regardless of how landowners are compensated. For commercial-scale arrays, landowners using NEM experience early losses, assuming installation costs ($Installation$) are paid upfront. However, cash flow from electricity generation (saved from offset load and earned from surplus generation) dominates in later years, with an average economic payback period of just 5.2 years (best- and worst-case payback in 2.9 and 8.9 years respectively, see *Supplementary Fig. 6*). The final cumulative cash flow for agrisolar co-location resulted in 25-times greater returns than lost food revenue (Fig. 4A), or an average \$168 kW_p^{-1} yr^{-1} (2018 US Dollars—USD) across 25-years.

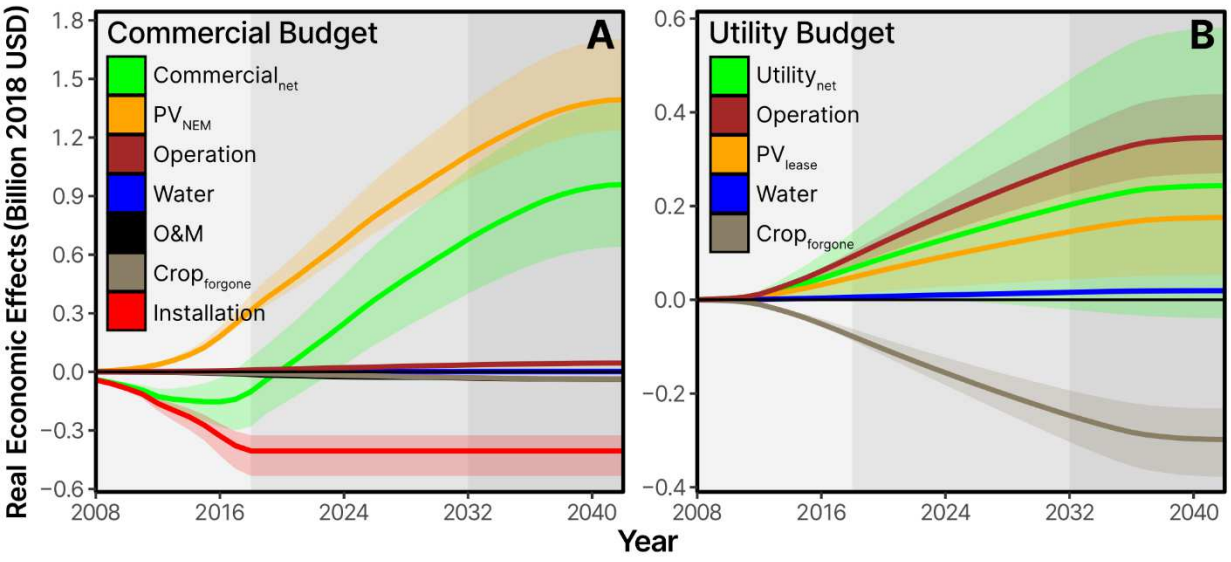


Fig 4. Cumulative discounted cash flow projections for agrisolar co-location. A and B are the commercial- and utility-scale cash flows, respectively (note the different vertical axis scales). Background shading represents the three assessment phases (addition, constant, removal) similar to Fig. 3A. Variables are cumulative net commercial- ($\boldsymbol{Commercial_{net}}$) and utility-scale ($\boldsymbol{Utility_{net}}$) budgets, value of offset load and surplus electricity generation under NEM ($\boldsymbol{PV_{NEM}}$), value of land lease ($\boldsymbol{PV_{lease}}$), value of offset farm operation costs ($\boldsymbol{Operation}$), value of offset irrigation water and electricity use ($\boldsymbol{Water}$), offset crop revenue ($\boldsymbol{Crop_{forgone}}$), and installation costs ($\boldsymbol{Installation}$). See Eq. 9 and 10 in *Discounted cash flow for agrisolar co-location*.

In contrast to commercial-scale arrays, the utility-scale agrisolar budget (assuming land is

leased to a utility) was always positive, as the landowner does not have the up-front installation investment (Fig. 4B). In the baseline scenario for utility-scale arrays, lost food revenue ($298 million) was exceeded by land lease income ($176 million), forgone farm operation costs ($347 million), and reduced water use costs ($20 million) resulting in a total net cash flow of $244 million or $4.25 kW_p^{-1} yr^{-1} over 25 years. Note this is roughly a 40-times smaller economic benefit than commercial-scale co-location. In the worst-case scenario, the total budget was negative (-$39 million), suggesting that some landowners could lose revenue.

In many our estimates, cumulative forgone farm operation costs exceeded forgone food revenue. While this may be affected by reporting differences in agricultural revenue[44] and farm operation cost[45] sources, agricultural margins are known to be small, or negative, for certain croplands (e.g. pastureland), with margins likely to decrease further under future climate change and water availability scenarios[46]. For commercial-scale installations, cutting farm operation costs in half (highly-conservative) resulted in a longer economic payback period of just a month. Cutting offset farm operation costs in half for utility-scale installations did not affect economic payback or the always-positive baseline and best-case budget. Final cumulative economic estimates are shown in Fig. 4 and reported in *Supplementary Table 2*.

Discussion

Agrisolar co-location's effect on agricultural food production

Displacing agricultural land with solar PV results in locally lost production (~1.57 Tkcal or 25-million kcal MW_p^{-1} yr^{-1}), which affects county and state-level food flows and agricultural markets may take time to compensate[47]. California produces 99% of many of the nation's specialty fruit and nut orchard crops (e.g., almonds, walnuts, peaches, olives)[15]. Fields producing these crops were commonly converted to solar PV (270 ha of orchard crops), and it may be

difficult to shift production of these crops to other locations due to their intensive water footprint[48], climate sensitivity, and time to production[49].

Fortunately, at national and global scales, food production occurs within a market where reduced production in one location creates price signals that stimulate production elsewhere. For example, high demand and increased irrigation pumping costs in the CCV have resulted in higher prices received for specialty orchard crops. Thus, farmers that elect to switch from cereal and grain crops to these specialty crops[50] could offset the forgone specialty crop production due to agrisolar replacement. We also show that conversion of feed, silage, and biofuel croplands minimizes nutritional impacts due to the low or non-existent caloric conversion efficiencies of these crops (see Fig. 3D and 3G) while providing high irrigation water use offsets. It is also important to acknowledge that between food waste[51] and a lack of crop-specific nutritional-quality knowledge[52], we cannot evaluate end-point impacts of reported forgone kcal (Calories) on human diets and health.

Global food needs are projected to increase by 60% to 110% over the next 30 years[53–56]. To meet these needs, either food production per unit area must increase and/or the total agricultural land under production must increase. The latter is unlikely in many areas given that 46% of global habitable land is already agricultural[57]. Additionally, arable land area has declined by about a third over the last 40 years due to erosion, soil quality deterioration, aridification, water availability, and other factors[58,59]. The amount of arable land will likely continue to decrease due to strains on water availability under climate change[60], along with urban growth[61] and increasing water use[62]. Given pressures on existing arable land, cropland selection for future solar PV co-location should be assessed at local, regional, national, and international scales to maintain food-specific availability and security. It should also be noted that, solar PV is far more

241 energy dense per unit of land than growing crops to produce biofuels[63]—a practice common
242 across large swaths of agricultural farmland in the US and elsewhere.

243 ***The potential for water sustainability with agrisolar co-location***

244 Here, we show that solar PV installations preferentially displace irrigated land in the
245 CCV (33.1 km^2 and 74% of co-located solar PV). Displacing this irrigated cropland enhances
246 farmer cash flow while likely reducing agricultural irrigation water use by 11,000 to 12,000 m^3
247 MW_p^{-1} yr^{-1} (Fig. 5). The total displaced water use was 8 times the O&M use for those arrays,
248 thus installing solar PV in water scarce regions has significant potential to reduce water use,
249 which bolsters findings from previous studies[63–68]. This analysis does not incorporate the
250 additional hydrologic effects of modifying surface energy and water budgets, including reducing
251 evapotranspiration and the potential for increased groundwater recharge[22,69–74].

252 Given that the cash flow benefits utility-scale agrisolar co-location are relatively small,
253 we evaluated how water use limitations may be a factor in farmland conversion decisions. We
254 hypothesize that fallowing land is largely a consequence of water shortages in the CCV[50,66], thus
255 fallowing land proximal to an array (within 100 meters) may indicate an emergent agrisolar
256 practice: intentional fallowing and irrigation water use offset adjacent to solar PV arrays
257 supported by revenue from the array. Each array was coded by the adjacent crop type prior to-
258 and post-installation of the array. While we cannot know what landowners would have done with
259 the array acreage absent the installation, this analysis provides evidence of broader land use
260 trends that might have been driving decisions. The transition of array acreage from prior- to
261 proximal post-installation land use for utility-scale arrays is displayed in Fig. 5.

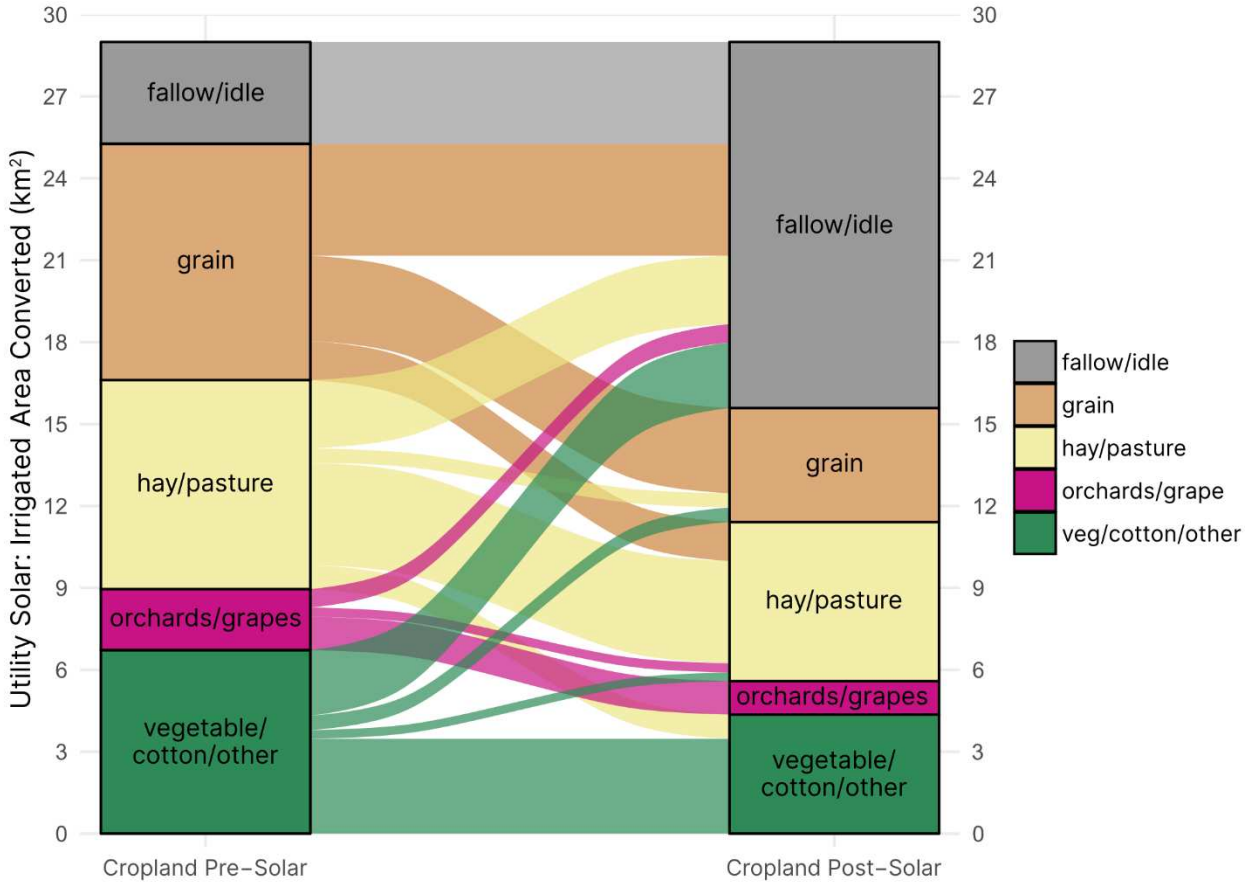


Fig 5. Shift of land use on irrigated cropland proximal to utility-scale solar PV installations in the CCV. Note several crop types have been grouped for simplicity and thus have altered coloring compared to similar groups in other figures. Transitions with total array capacity of < 10 MW_p were omitted for clarity but are shown in *Supplementary Table 13*.

Understanding how economic incentives affect the replacement valuable cropland with solar PV is essential to inform future energy landscape models and policies. Here, we examined the transition to post-solar installation fallowing in adjacent irrigated cropland (Fig. 5). We observed fallowing of adjacent irrigated cropland at 58 utility-scale installations totaling 658 MW_p and 9.7 km^2 (27% of utility-scale area) with 4.1 km^2 of grain, 2.5 km^2 of hay and pasture, 2.4 km^2 of vegetables, cotton, and other crops, and 0.7 km^2 of orchards and grapes. The direct area of these arrays (9.7 km^2) can be linked to a potential irrigation water use offset of 195 million-m^3 over 25-years. The observed fallowing of an additional 140 km^2 of land adjacent to

these 58 arrays could displace 120 million-m^3 of irrigation water use, *each year*, or 3,000 million-m^3 over 25 years (see *Supplementary Methods 3*). Thus, if landowners choose to fallow area proximal to leased land for utility-scale arrays, the water use reductions are greatly amplified. We discuss several important limitations of CDL regarding this analysis in *Supplementary Discussion 5*[75].

Intensely irrigated cropland in the CCV is vulnerable to drought, especially in southern basins that rely heavily on surface-water deliveries due to limited groundwater availability[76]. The California Budget Act of 2021 provides financial support for fallowing to motivate farmers to reduce water use[77]. While fallowing land can help mitigate some hydrological problems, removing production can also result in large-agricultural revenue losses[78]. Converting land with solar electricity production, rather than simply fallowing could reduce risks to farmers while enhancing financial security[64], especially during periods of extreme drought[66]. While this has implications for future installations, we show that farmers already appear to be practicing solar-fallowing, likely resulting in long-term irrigation water use reductions.

We acknowledge the potential issues in assuming that forgone irrigation water use due to solar PV installations was conserved rather than redistributed. However, a portion of this potential offset is likely real given three observations: 1) utility-scale solar PV installations correlate with newly fallowed land (195 million-m^3 to 3,000 million-m^3 potentially offset by 2042), which was not observed for commercial-scale arrays; 2) the 2014 Sustainable Groundwater Management Act (SGMA)[79–81] requires water use reductions by the 2040's, providing an incentive for reduction, and; 3) agriculturally co-located solar PV maintains Williamston Act Status under the Solar-Use Easement, a California tax incentive common in irrigated lands highly-suitable for solar[82]. In our dataset, 46% of utility-scale installations and

58% of commercial-scale installations were completed after SGMA was enacted (Fig. 2C and 2D). Given this potential for water use offset, solar-fallowing for water use reduction presents an opportunity for incentivized solutions that are already of interest to landowning farmers in the region[64]. With suitable solar area in the CCV exceeding projected fallowing acreage to comply with SGMA[82], implementing agrisolar co-location policies and incentives such as these could promote complementary land uses[30].

Owning and leasing solar PV for security

Regardless of scale and related financial benefits, farmers are switching away from cultivating crops to cultivating electricity. This is the first study we are aware of to incorporate farm-specific agricultural dynamics across a region (offset farm operation costs, irrigation costs, and food revenue) into economic considerations for replacing cropland with solar, outside of agrivoltaic literature[32,83]. By including these revenues and costs, this study clearly demonstrates the strong economic incentives to replace cropland with commercial-scale solar PV systems (Fig. 4A). Within just 5.2 years on average, landowners begin to see positive return on investment while simultaneously reducing water use. The resulting total budget (25-times the food revenue) is likely underestimated, because post-lifespan module replacement, resale, or continued use is likely, and property values are likely increased (terminal value) compared to the reference scenario. However, these returns are not unlimited due to NEM capacity limitations (< 1 MW_p) and requirements to size the installation below annual on-farm load[42]. Furthermore, given that commercial-scale arrays generated on average148% of on-farm needs (*see Supplementary Notes 2*), most revenue from these arrays would be conserved even under less generous NEM 3.0 regulations under consideration by California's Public Utility Commission (CPUC). The bottom line is that owning solar PV, offsetting annual on-farm electric load, and selling surplus

electricity back to the utility helps increase economic and energy security for farmers.

While utility-scale land lease rates alone do not offset lost agricultural revenue, including offset farm operation costs results in a substantially lower but still overall profitable landowner budget with no major up-front capital investment (Fig. 4B). In water-scarce regions, particularly where water use reduction is required, the smaller returns from utility-scale agrisolar practices and potentially related fallowing of land may be more attractive than continued cultivation under water supply uncertainty[64].

California's irrigated land has consistently been some of the most valuable in the US, with irrigated cropland real estate values averaging \$35,300 ha^{-1} in 2018[14]. This study empirically affirms that both landowner-focused 'Pro Profit' (NEM) and utility-oriented 'Pro PV/Feasibility' (land lease) incentive structures are viable frameworks for PV deployment[63]. Either way, demonstrated profitability for landowners underlies decisions to replace some of the most valuable farmland in the US with solar PV. Financial security as a motivation to install solar PV will only increase with climate change and decreasing water availability over the coming decades[46] making agrisolar co-location a viable form of risk aversion. Retaining this Pro Profit framework also motivates farmers to select both low-yielding (marginal) agricultural lands and high-yielding solar PV generation land[63] while offsetting irrigation water use. While several studies demonstrated the potential of marginal, abandoned, unused, disturbed, and idle land for broad solar deployment[84–86], the financial benefits to farmers shown here provides an avenue to distribute benefits and energy security across an arable landscape. Importantly, we assumed that all decisions were made by, and returns received by landowning or partial-owning farmers. While we do not have access to land-ownership data for the CCV, nearly 40% of agricultural land in the region is rented or leased[87].

Opportunities for agrisolar research

While funding and incentives for agrivoltaic research and incentives have expanded rapidly in recent years, we advocate extending these to agrisolar co-location. The broadly applied definition of agrivoltaics involves *the direct integration of solar and agriculture* (crops or grazing) *or ecosystem services* (pollinator habitat, native vegetation) *within the boundaries of solar infrastructure*[21]. The earliest technical standardization (Germany) specifies that this can occur *under* or *between* system rows, but not adjacent to, while agricultural yield losses are reduced to less than one-third of reference (no solar PV) yields[20]. Agrisolar co-location, the focus of this study and likely the majority of existing installations would be excluded from the agrivoltaic definition because the enhanced agricultural services are horizontally integrated across the landscape rather than vertically integrated beneath panels. We discuss additional placement and management decisions that fall under the umbrella of agrisolar co-location in *Supplementary Discussion 4*.

Thinking about the agricultural landscape and resource boundaries more broadly could be an effective addition to agrivoltaic research, since the goal of agrivoltaics, to enhance synergistic ecosystem services provided by the co-production of agriculture and energy, is achievable with agrisolar co-location management. Given the ecosystem service benefits reported here, there may be an opportunity to broaden the scope of agrivoltaic research and incentives to include agrisolar co-location practices defined here.

Methods

Identifying agrisolar PV arrays across the California Central Valley (CCV)

We used remote sensing imagery, existing solar PV arrays, and GIS datasets to identify the most complete publicly available dataset of ground-mounted solar PV arrays co-located with

agriculture in the CCV through 2018. We extracted all existing non-residential solar PV arrays from two geospatial datasets (Kruitwagen et al.[7] and Stid et al.[9,88]) within the bounds of the CCV alluvial boundary[89]. We then removed duplicate arrays with preference given to Stid et al.[9] to retain reported panel area and installation year. We then applied the spatial and temporal segmentation methods described in Stid et al.[9] to assign panel area and installation year, and to identify commissions (reported array shapes with no solar PV panels), within the Kruitwagen et al.[7] dataset. We then removed arrays with > 70% overlap with building footprints[90] to ensure that we retained only ground-mounted installations. Finally, overlaying historical CDL crop maps with new array shapes, we also removed arrays with a majority non-agricultural land cover the year prior to installation (see *Supplementary Fig. 5* and *Discussion 5*).

The resulting dataset (925 agriculturally co-located solar PV arrays) included 686 ground-mounted arrays from Stid et al.[9,88] plus 239 from Kruitwagen et al.[7]. For these sites, we calculated solar PV array peak capacity (kW_p) by[91]:

$$Capacity = Panel_{area} * \eta * G_{STC} \quad \textbf{Eq. 1}$$

where $Panel_{area}$ is the total direct area of PV panels in m^2, η is the average efficiency of installed PV modules during the array installation year[92], and G_{STC} is the irradiance at standard test conditions (kW m^{-2}). Arrays were split into "Commercial" (< 1 MW_p) and "Utility" (≥ 1 MW_p) scale arrays following the California Public Utility Commission NEM 1.0 capacity guidelines[93].

Food, energy, water (FEW), and economic effect scenarios: Summary and assumptions

We computed annual FEW resource and economic values for each ground-mounted agrisolar PV array identified across the CCV. For this, we constructed four scenarios: 1)

388 *reference*, business-as-usual with no solar PV installation and continued agricultural production
389 and operation on the same plot of land, 2) *baseline*, agrisolar PV installation with moderate
390 assumptions related to each component of the analysis, 3) *worst-case*, PV installation with high
391 negative and low positive effects for each component, 4) *best-case*, similar but opposite of the
392 worst-case scenario. We compare baseline to reference scenarios to estimate the most likely
393 FEW and economic effects and use the differences between best- and worst-case scenarios to
394 estimate uncertainty. See *Supplementary Table 14-15* for an overview of scenarios for each
395 resource.

396 Identified arrays were installed between 2008 and 2018, and were assumed to have a 25-
397 year lifespan for arrays due to performance, warranties, module degradation, and standards for
398 electrical equipment[94–96]. We assumed that land use change effects ceased following 25 years of
399 operation to simplify assumptions about module replacement, resale, or continued use. We then
400 summarized the FEW and economic effects of all arrays across the CCV and divided our
401 temporal analysis into three phases: 1) *addition* (2008-2018) where arrays were arrays were
402 being installed across the CCV, 2) *constant* (2019-2032) with no array additions but all arrays
403 installed by 2018 are operating and maintained, and 3) *removal* (2032-2042), where arrays are
404 removed after 25-years of operation.

405 California's shifting NEM guidelines could alter the economic benefits suggested here.
406 We discuss these complexities in *Supplementary Discussion 2-3*, and display sensitivity to the
407 commercial- to utility-scale capacity threshold (with a 5 MW_p cut-off) and lifespan (with 15- and
408 50-year lifespans) in *Supplementary Tables 3-8.*

409 ***Displaced crop and food production***

410 Replacing fields (or portions thereof) with solar PV arrays creates two effects vis-à-vis

crop production: 1) lost production of food, fiber, and fuels, and 2) reduced revenue from crop sales. We simplify the complex effects of lost production and include solely the foregone calories, through both direct and indirect human consumption, which is justified because CCV crop production is largely, though not exclusively, oriented toward food crops. We did include lost revenue from cotton production in our economic analysis. Future analyses could evaluate the lost fiber (primarily via cotton) or fuel (via biofuel refining) production.

The economic and food production effects of displaced crops are highly dependent on what crop types were cultivated on the land previously. All crop type information was derived from the USDA NASS Cropland Data Layer (CDL)[43,97] for the array area in both prior- and post-installation years (see *Supplementary Fig. 5* and *Supplementary Methods 3-4* for the adjacent-fallowed land analysis). Each array was assigned a majority previous crop from the spatially-weighted means of crop types within the array area for the five years prior to the installation. We discuss limitations of this assumption in *Supplementary Discussion 5*.

We converted all eligible crop types to kcal (also called Calorie) for human consumption after Heller et al.[52]. Foregone food production ($Food_{Forgone}$ in kcal) following PV installation was then defined for each array as:

$$Food_{Forgone} = kcal_{density} * Yield * Area \quad \textbf{Eq. 2}$$

where $kcal_{density}$ is in kcal kg^{-1}, $Yield$ is in kg m^{-2} and $Area$ of each array in m^2. Crop specific caloric density data (kcal kg^{-1}) were derived from the USDA FoodData Central April 2022 release[98]. FoodData food descriptions and nutrient data were joined and CDL specific crop groupings were made through a workflow described in *Supplementary Fig. 3*. Crop specific yield data (kg m^{-2}) was derived from the USDA NASS Agricultural Yield Surveys[99]. State level (California) yield data were processed similarly, and missing state level crop data were filled

based on national average yields. Annual double crop spatial caloric density was also assumed to be the kcal sum of the two comprising crops. We used caloric conversion efficiencies specific to feed, silage, or oil crop, to account for crop production that humans do not directly consume. See *Supplementary Fig. 2* and *Supplementary Methods 2* for complete caloric density workflow and methods, including best- and worst-case scenario assumptions.

For each array, we calculated annual revenue of forgone crop production in real (inflation adjusted) dollars, calculated by:

$$Crop_{Forgone} = Price_{crop} * Yield * Area \quad \textbf{Eq. 3}$$

where $Price_{crop}$ is in USD kg^{-1}; $Yield$ is in kg m^{-2}, and; $Area$ of each array in m^2. We used the annual "price received" for all crops in the USDA NASS Monthly Agricultural Prices Report for 2008 through 2018[44]. For the baseline case we assumed that food prices will scale directly with electricity prices through 2042 given that they respond to similar inflationary forces[100]. See *Supplementary Methods 2* for best- and worst-case scenario assumptions. Missing CDL crop type prices were grouped based on similarity to other crop types that were present in the data with similar assumptions to the caloric density derivation (*Supplementary Fig. 2*).

Change in irrigation water use and irrigation cost savings

Irrigation water use can only be offset by agrisolar co-location if the prior land use was irrigated. The presence of irrigation was inferred from the Landsat-based Irrigation Dataset (LanID) map for the year prior to installation[101] (see *Supplementary Fig. 5*). If the array shape contained irrigated pixels, then we assumed the cropland area and all respective crops within the rotation were irrigated. Crop-specific irrigation depths were taken from the 2013 USDA Farm and Ranch Survey (FRIS) and 2018 Irrigation and Water Management Survey (IWMS)[102,103] and

logical crop groupings were applied (e.g., almonds, pistachios, pecans, oranges, and peaches were considered orchard crops). As was the case with displaced food, we assumed irrigation water-applied for double crops were the sum of irrigation depths for each crop. Total irrigation needs are dependent on many factors, one of the most important being growing season precipitation[104,105].

We estimated annual crop-specific county-level irrigated depths from survey and climate datasets for each array. For the installation phase (2008 to 2018) these depths varied based on historical climate and survey data, while the projection phases (constant and removal) used a scenario-dependent moderate, wet (worst-case, i.e., least water savings), or dry (best-case, most water savings) year from the historical record (discussed in *Supplementary Methods 4*).

Reported irrigation depths vary depending on the total precipitation in each survey year, the FRIS survey year (2013) was one of the driest years of the study, and 2018 (IWMS year) had average precipitation. We used multi-linear regression to build annual county-level irrigation water use estimates ($IrrigWater_{year}$ in m^3) from five-year USGS water use[106], gridMET growing season average precipitation[107], with year as a dummy variable to incorporate temporal changes in irrigation technologies and practices. We calculated the total forgone irrigation water use ($IrrigWater_{Forgone}$ in m^3) by:

$$IrrigWater_{Forgone} = \frac{IrrigWater_{year}}{IrrigWater_{survey\ year}} * IrrigDepth_{crop} * Area \quad \textbf{Eq. 4}$$

where $IrrigDepth_{crop}$ in m is the crop-specific depth from the USDA FRIS and IWMS surveys, and $IrrigWater_{survey\ year}$ in m^3 is the county-level irrigation water use estimate for the respective FRIS (2013) and IWMS (2018) survey irrigation depths.

Assigning an economic value to water use is difficult and varies based on the temporally

475 changing supply and demand[108]. We calculated the economic value of the change in water use
476 ($Water$ in real USD) to the farmer by:

$$Water = (\Delta Water_{use} * Irrig_{Energy} * Price_{Elec}) + Water_{right} \quad \textbf{Eq. 5}$$

477 where $\Delta Water_{use}$ (m^3) is the offset irrigation water use for the co-located crop minus O&M
478 projected water use; $Irrig_{Energy}$ (MWh m^{-3}) is the irrigation electricity required to irrigate the
479 co-located crop given local depth to water and requirement estimates from McCarthy et al.[109];
480 $Price_{Elec}$ (USD MWh^{-1}) is the utility-specific (commercial-scale) or regional average ($0.17
481 kWh^{-1}—utility-scale) annual price of electricity based on the electricity returns and modeled
482 electricity generation described in *Electricity production, irrigation electricity offset, and*
483 *associated electricity rates* and *Supplementary Methods 3*, and; $Water_{right}$ is a CCV wide
484 average water right contract rate of [110]$32 thousand-$m^{-3}$. Here we assume that water (and thus
485 energy) otherwise used for irrigation was truly forgone and not redistributed elsewhere within or
486 outside the farm. Change in O&M water use was based on Klise et al.[111] reported values,
487 described in *Supplementary Methods 4*.

488 ***Electricity production, irrigation electricity offset, and associated electricity rates***

489 Installing solar PV in agricultural fields produces three primary effects related to
490 electricity: 1) production of electricity by the newly installed array, 2) reduction in energy
491 demand due to reduced water use and field activities, and 3) revenue generation via net energy
492 metering (NEM) or land lease. Here we assume that on-farm electricity demands are dominated
493 by electricity used for irrigation and ignore offset energy (embodied) used for fuel.

494 Electricity generation for each array was modeled using the *pvlib* python module
495 developed from SANDIA National Laboratory[112]. This model accounts for local weather data,

incident irradiance, tilt, efficiency, efficiency degradation, and soiling during the addition period in a simple efficiency model. We also accounted for temporal pre-inverter (DC – wiring, inverter mismatch, shading, and snow loading) and inverter efficiency (AC) losses[31]. Following installation, generation was assumed to decline for each year of the 25-year operational lifespan at an annual -0.75% efficiency degradation rate[113]. Major assumptions about electricity production included: all arrays were connected to the grid during the time of operation, customers were permitted to use generation (load) onsite[42], no arrays were installed before 2008 or after 2018, thus panel and inversion efficiencies for all three scenarios are based on 2008 to 2018 data, arrays are disconnected from the grid after 25-years of service (post-installation year) meaning modules are not replaced or connected for longer than their warranty, and after 25 years, the arrays no longer require maintenance and do not generate any electricity. Our baseline scenario assumes that each array uses PV panels with average efficiency determined by its installation year[92], with best- and worst-case scenarios discussed in *Supplementary Methods 3* and *Supplementary Fig. 6*.

Not only is electricity generated by the solar PV arrays, but electricity consumption is forgone for each array due to not irrigating the array area. The annual electricity effects of the change in the water use ($Electricity_{water\ use}$ in GWh) are calculated by:

$$Electricity_{water\ use} = IrrigElec_{demand} * \Delta Water_{use} \quad \textbf{Eq. 6}$$

where $IrrigElec_{demand}$ is the county level rates for irrigation electricity demand in GWh m^{-3} and $\Delta Water_{use}$ is the change in water use in m^3 from Eq. 5. County-level electricity requirements to irrigate were calculated using irrigation electricity demand methods described in McCarthy et al.[109] modified with a CCV-specific depth to water (piezometric surface) product for the spring (pre-growing season) of 2018[114].

Revenue from electricity generation was calculated separately each array depending on array size and the installation year. Commercial-scale arrays (< 1 MW) were assumed to operate under an NEM 1.0 if installed prior to 2017 and NEM 2.0 if installed later, which allows for interconnection to offset on-farm load and compensation for surplus electricity generation (see *Supplementary Methods 3*). Thus, for commercial-scale arrays, annual cash flow from solar PV (PV_{NEM} in USD) is calculated as:

$$PV_{NEM} = Saved_{offset\ load} + Earned_{surplus} \quad \textbf{Eq. 7}$$

where $Saved_{offset\ load}$ is real USD saved by offsetting annual on-farm electric load and $Earned_{surplus}$ is real USD earned by surplus PV electricity generation sold to the utility under NEM guidelines. For utility-scale arrays (≥ 1 MW), annual revenue from agrisolar co-location (PV_{Lease} in USD) was assumed to be given by:

$$PV_{Lease} = Land_{lease} * Area \quad \textbf{Eq. 8}$$

where $Land_{lease}$ is the economic value estimated to be paid to the farmer by the utility for leasing their land in USD m^{-2}, and $Area$ of each array in m^2. Both $Saved_{offset\ load}$ and $Earned_{surplus}$ are estimated based on *pvlib* modeled electricity generation and valued at the historical utility-specific energy charge retail rates. Historical energy charges were acquired from either publicly available utility reports or the US Utility Rate Database (USURDB) via OpenEI[115]. We considered utility's annual specifications that delineated small and large agricultural customers, summer and winter rates, weekday and weekend rates, and time-of-use (TOU) scheduling rates (for NEM 2.0 customers). For years with missing reports or data, we applied the rate of change in bundled system average rates (SAR)[116] to extrapolate rate changes from years with existing rate data. Utility provider identity for each array was gathered from an

intersection of array centroids with California Electric Utility Service Areas[117]. For more information on utility rates and the utility service providers in the CCV with agriculturally co-located solar PV, see *Supplementary Methods 3* and *Supplementary Table 12*.

We assumed that arrays installed prior to 2017 were grandfathered into NEM 1.0 guidelines for the duration of their lifespan. However, arrays installed in 2017 and 2018 fall under NEM 2.0 guidelines which include a \$0.02 to \$0.03 kWh^{-1} non-bypassable charge (NBC) removed from $Earned_{surplus}$ [42,118–120]. Annual on-farm operational load was estimated and distributed across the year based on reported California agricultural contingency profiles[121] and Census of Agriculture county-level average farm sizes[122–124] (*Supplementary Fig. 1-2* and *Supplementary Methods 3*). With distributed hourly-load estimations and modeled hourly solar PV electricity generation, we delineated electricity and revenue contributing to annual load ($Saved_{offset\ load}$) from surplus electricity and revenue that would have been sold back to the grid and credited via NEM ($Earned_{surplus}$).

Future electricity revenue was projected using 2018 conditions (contribution to annual load, to surplus) and energy charge rates, modeled electricity production described above (includes degradation, pre-inverter, inverter efficiency, and soiling losses) and projected changes in the price of electricity. The Annual Energy Outlook (AEO) report by the EIA provides real electricity price projections annually between 2018 and 2050 for "Commercial End-Use Price"[125]. This annual rate of change was used to estimate projected deviations from 2018 energy charges (2018 USD kWh^{-1}) during the constant and removal phases (2019 - 2042), with projected solar PV generation including discussed losses.

Solar land lease ($Land_{lease}$) contracts are independently negotiated between developers and landowners considering variables including the valued price of the land, solar potential,

proximity to transmission stations, topography, soil properties, and project size. These variables attempt to approach equity for both parties involved[126–129]. While these values are difficult to estimate, several Solar Land Consultants and Industry Report sources indicate that solar land lease rates range from ~\$750 ha^{-1} yr^{-1} to \$4,950 ha^{-1} yr^{-1}, with \$2,450 ha^{-1} yr^{-1} being the average for high value land in the CCV[128,130,131]. Comparable lease rates (~\$1,000 to \$2,950 ha^{-1} yr^{-1}) were used in a solar PV and biomass tradeoff study in Germany[63].

Array installation and operation and maintenance (O&M) costs

Historical installation costs ($Installation$) were taken from the commercial-scale PV installation prices reported in the Annual Tracking the Sun report where reported prices are those paid by the PV system owner prior to incentives[92]. The baseline scenario is the median installation price, while the best- and worst-case scenarios are the 20th percentile and 80th percentile installation costs, respectively. These reported values calculated using NREL's bottom-up cost model and are national averages using average values across all states. Installation cost was not discounted, as this is considered the initial investment for commercial-scale installations at day zero, and all future cash flows, profits, and costs, are compared to initial investments. It is likely that most (if not all) commercial-scale arrays took part in the Solar Investment Tax Credit (ITC) due to wide adoption and incentivization of solar deployment across the US. We have thus included the 30% Solar ITC in the $Installation$ for commercial-scale arrays[132,133]. The system bounds of this impact analysis were installation through the operational or product-use phase. We, therefore, did not assume removal expenses or added property value (terminal value) to remove uncertainty in decision making at the end of the 25-year array lifespan.

Historically reported and modeled $O\&M$ values for years prior to ATB model projections

(2020) range from \$0 kW_p^{-1} yr^{-1} (best-case) to \$40 kW_p^{-1} yr^{-1} (worst-case) with an average (baseline) of [134–136]\$18 kW_p^{-1} yr^{-1}. Projected $O\&M$ costs were based on modeled commercial-scale PV lifetime O&M cost to capital expenditure (CAPEX) cost ratios from historical and industry data that provided scenarios varying on research and development differences (conservative, moderate, advanced). The annual reported values are provided from 2020 to 2050 for fixed O&M (FOM) costs including; asset management, insurance products, site security, cleaning, vegetation removal, and component failure, and are detailed in the Annual Technology Baseline (ATB) report by NREL[135] which are largely derived from the annual NREL Solar PV Cost Benchmark reports.

Farm operation: Economic farm operation costs

Business as usual farm operation costs ($Operation$) were derived from the "Total Operating Costs Per Acre to Produce" reported in UC Davis Agricultural and Resource Economics Cost and Return Studies[45]. We removed operational costs to "Irrigate" from the total because we estimate that as a function of electricity requirements and water rights (described in *Change in irrigation water use and irrigation cost savings*) while retaining "Irrigation Labor" as this was not included in our irrigation cost assessment. Best- and worst-case scenarios for farm operation costs coincided with yield scenarios described in *Displaced crop and food production.* For missing CDL crops, we made similar crop group assumptions described in *Supplementary Fig. 3*.

Discounted cash flow for agrisolar co-location

For each commercial-scale solar PV array across the CCV, we computed the annual real cash flow as:

$$Commercial = PV_{NEM} + Water + Operation - Food - O\&M - Installation \quad \textbf{Eq. 9}$$

and for each utility-scale solar PV array as:

$$Utility = PV_{lease} + Water + Operation - Food \quad \textbf{Eq. 10}$$

where $Commercial$ is the real return in 2018 USD for commercial-arrays (< 1 MW_p) and $Utility$ is the real return in 2018 USD for utility-scale arrays (≥ 1 MW_p). Each of the terms on the right-hand sides of these equations are defined in the sections above.

We then computed real annual discounted cash flow (DCF_{real}) model for each array to estimate the total lifetime value of each array. The DCF_{real} at any given year n is calculated for each array by:

$$DCF_{real} = \sum_{n=1}^{25} \frac{CF_n^{real}}{(1 + r_{real})^n} \quad \textbf{Eq. 11}$$

where CF_n^{real} is the real annual cash flow at year n (either $Commercial$ or $Commercial$ as relevant for each array) and r_{real} is the real discount rate without an expected rate of inflation (i) from the nominal discount rate (r_{nom}) calculated using the Fisher equation(Fisher, 1896):

$$r_{real} = \frac{(1 + r_{nom})}{(1 + i)} - 1 \quad \textbf{Eq. 12}$$

Vartiainen et al.[137] clearly communicates this method in solar PV economic studies, and discusses the importance of discount rate (in their case, weighted average cost of capital) selection. For i, we use 3%, which is roughly the average PPI and CPI (3.4% and 2.4% respectively) between 2000 and 2022, and comparable to other solar PV economic studies[137,138]. We use a 5% r_{nom}[139], and perform a sensitivity analysis using 3%, 7%, and 10% r_{nom} and discuss discount rates used in literature in *Supplementary Tables 9-11* and *Supplementary*

Discussion 3. Separately from the sensitivity analysis for r_{nom}, we also calculated our best-case and worst-case scenarios for each array.

All prices were adjusted to 2018 Dollars for calculation of real cash flow terms in Eq. 11 and 9. We adjusted consumer electricity prices and solar PV installation costs for inflation to real 2018 USD using the US Bureau of Labor Statistics (BLS) Consumer Price Index (CPI) for All Urban Customers[140]. We adjusted all production-based profits and costs (all other resources) using US BLS Producer Price Index (PPI) for All Commodities[141].

Dataset and Code Availability

The code (https://doi.org/10.5281/zenodo.10023281), input data, and baseline outputs (https://doi.org/10.5281/zenodo.10023294) for this study are available through the Zenodo repository, and upon request to the corresponding author.

Acknowledgments

This work is supported by INFEWS grant number 2018-67003-27406 (accession No. 1013707) from the USDA National Institute of Food and Agriculture. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the authors and do not necessarily reflect the views of the USDA.

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