

1 Field-scale crop water consumption estimates reveal
2 potential water savings in California agriculture
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Supplementary Information

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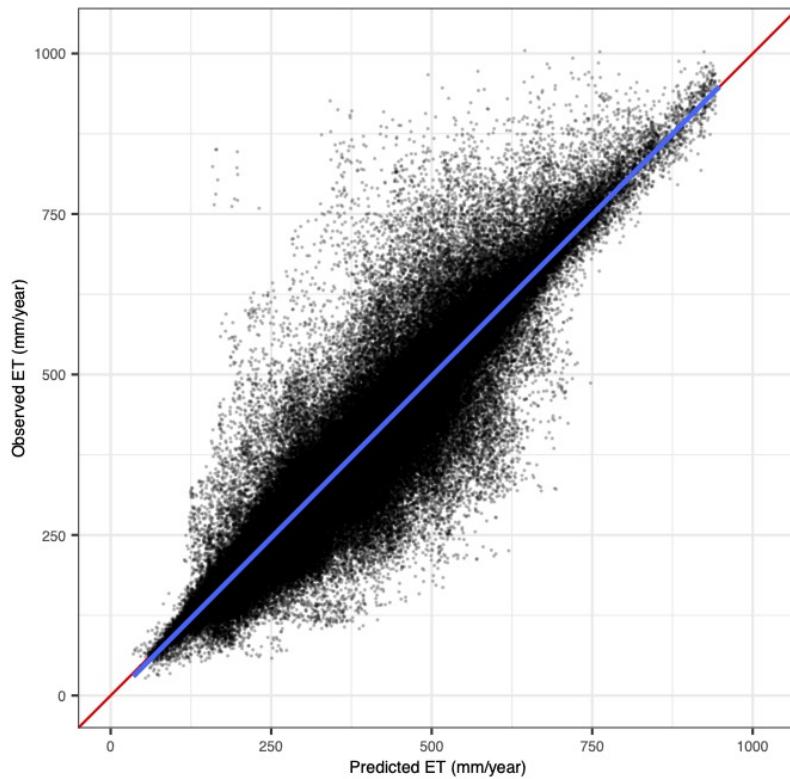
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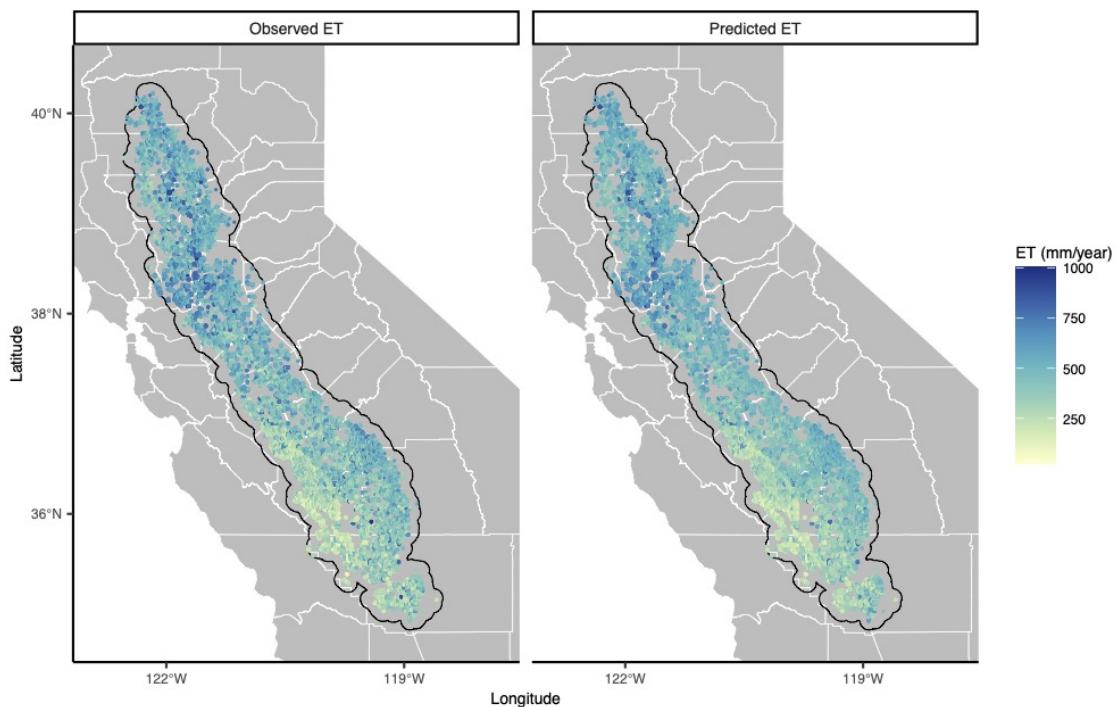
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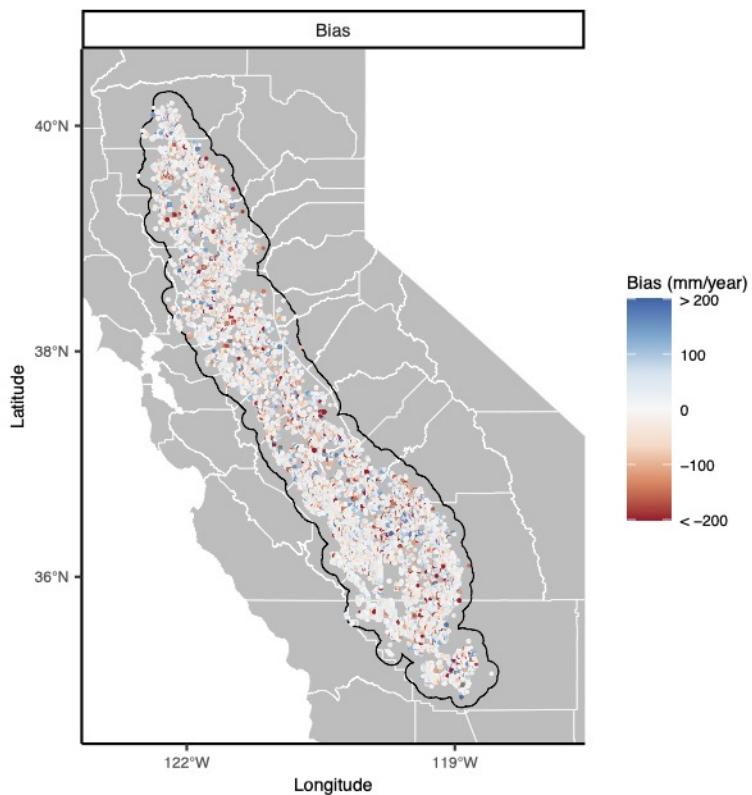
16 madeleine.a.pascolini-campbell@jpl.nasa.gov; john.reager@jpl.nasa.gov;
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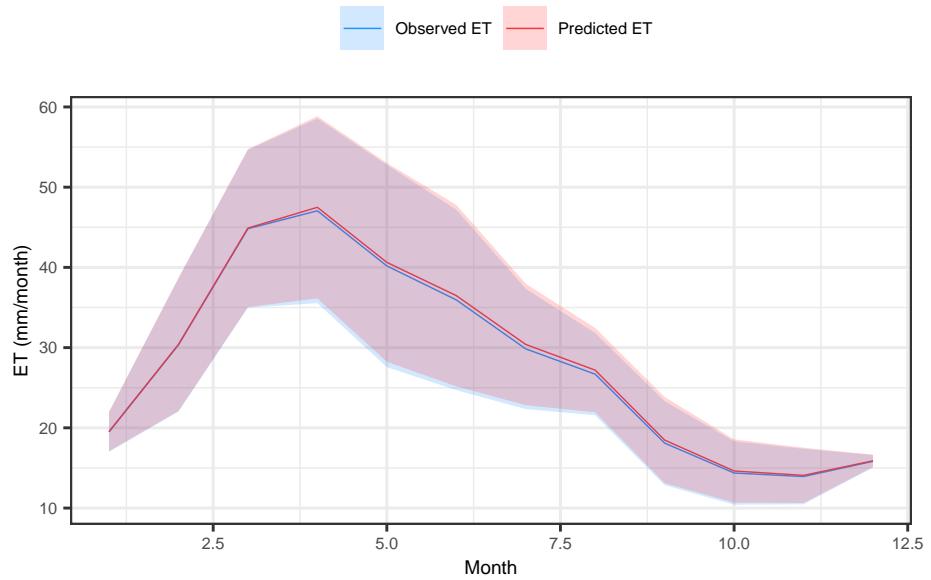
Supplementary Fig. 1 Observed versus predicted naturally-occurring evapotranspiration (ET) over fallow lands. Each point represents one 70m pixel of purely fallow land during 2016, 2018, or 2019. The model is unbiased in its predictions and achieves an R^2 of 0.87 and a MAE of 36 mm per year.



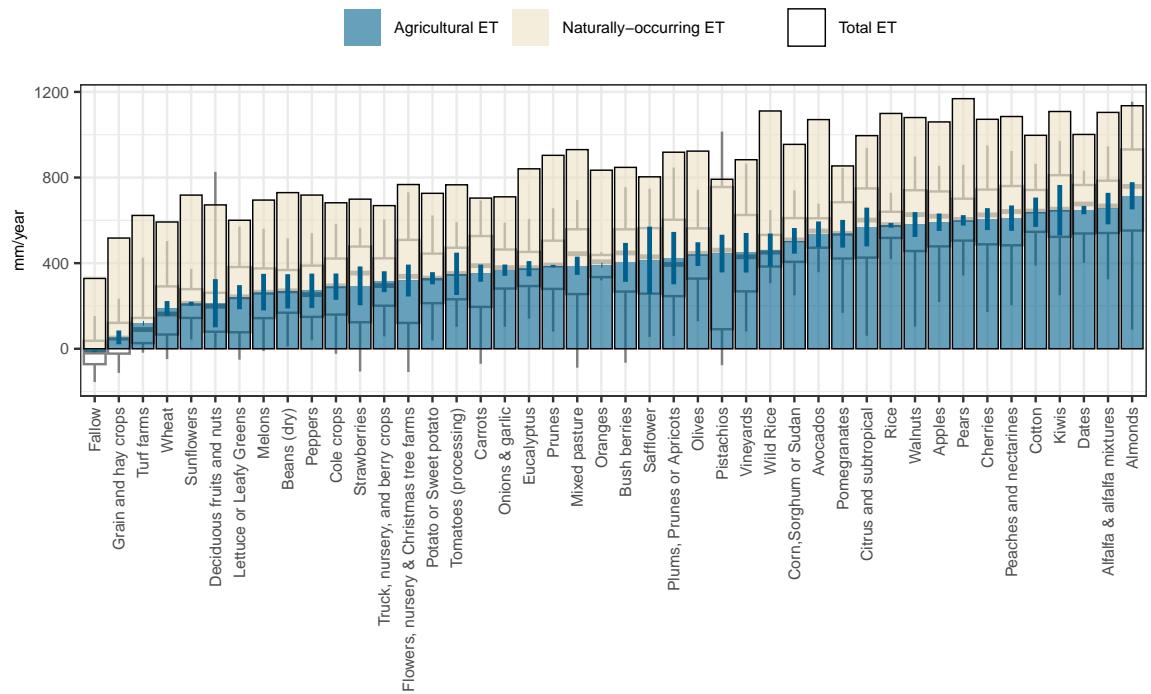
Supplementary Fig. 2 Observed versus predicted naturally-occurring evapotranspiration (ET) over fallow fields in the California Central Valley. The model is able to accurately reconstitute naturally-occurring ET in all regions represented in the test set.



Supplementary Fig. 3 Spatial error structure of naturally-occurring evapotranspiration (ET) predictions over fallow lands. Error, or bias, is calculated by taking the difference between the predicted ET and observed ET. There appears to be no spatial structure to the bias. In other words, the model is not more likely to be positively or negatively biased based on the region it is predicting over.



Supplementary Fig. 4 Temporal error structure of naturally-occurring evapotranspiration (ET) predictions over fallow lands. The average ET observed and predicted over fallow lands are similar throughout the year. In other words, the model is not more likely to be positively or negatively biased based on the month it is predicting over.



Supplementary Fig. 5 Observed, fallow, and agricultural evapotranspiration (ET) by crop type in the Central Valley. Mean agricultural ET by crop type (blue fill and 95% CI) is the average difference between observed ET (black outline) and naturally-occurring ET (cream fill). While we find significant differences in mean agricultural ET across crop types, the gray box plots also show a broad spread in agricultural ET within crop types (box plot shows 0.5, 0.25, 0.5, 0.75, and 0.95 quantiles).

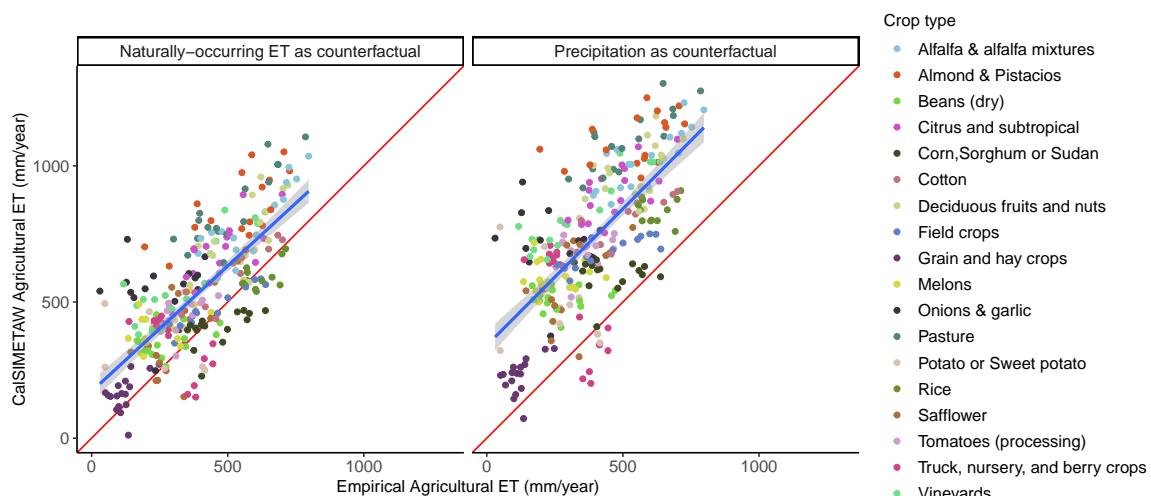
18 Supplementary Note 1: Empirical vs. modeled agricultural ET

19 In the absence of empirical agricultural evapotranspiration (ET) estimates, modeling theoretical crop
 20 water demand can be a useful tool for water management. One popular model developed specifically
 21 for California is CalSIMETAW, a model that estimates crop-specific water demand at the county
 22 level using a combination of crop coefficients which are a measure of crop-specific water intensity,
 23 weather data, and several other variables [1].

24 County-level, crop-specific water demand estimates calculated using CalSIMETAW are available
 25 for years 2000-2015. To retrieve modeled estimates of agricultural ET from CalSIMETAW's water
 26 demand estimates, we try removing naturally-occurring ET in two different ways: (1) by subtracting
 27 our empirical estimates of naturally-occurring ET or (2) by subtracting precipitation as reported by
 28 CalSIMETAW. In line with how agricultural ET is generally calculated using modeling, we calculate
 29 agricultural ET at a monthly time step and set it to zero if it is negative before aggregating to a
 30 yearly estimate. To compare these to our estimates of agricultural ET, we aggregate our empirical
 31 agricultural ET estimates to corresponding crop categories at the county level, also computed at the
 32 monthly level using the protocol just described.

33 We find a correlation of 0.74 between empirical and modeled county-level, crop-specific agricultural
 34 ET when using our naturally-occurring ET estimates as the counterfactual for the modeled
 35 estimates (Supplementary Fig. 6A). Modeled agricultural ET has a positive bias of 14.1 cm per year
 36 (12.4-15.8 95% CI) as compared to the empirical measurements. Using precipitation as the counter-
 37 factual deteriorates the relationship between empirical and modeled agricultural ET: the correlation
 38 drops to 0.69 and the bias increases to 34.2 cm per year (32.1-36.3 95% CI) (Supplementary Fig. 6B).

39 We note the discrepancy in years used to calculate the modeled (2000-2015) versus empirical
 40 (2016, 2018, 2019) agricultural ET estimates. However, we believe that the biases found are not a
 41 result of this difference: if the climate is different between these sets of years, the more recent years
 42 are those that have been most hot and dry [2]. As a result, one could expect that the bias to be even
 43 larger if the same years were used for the analysis.

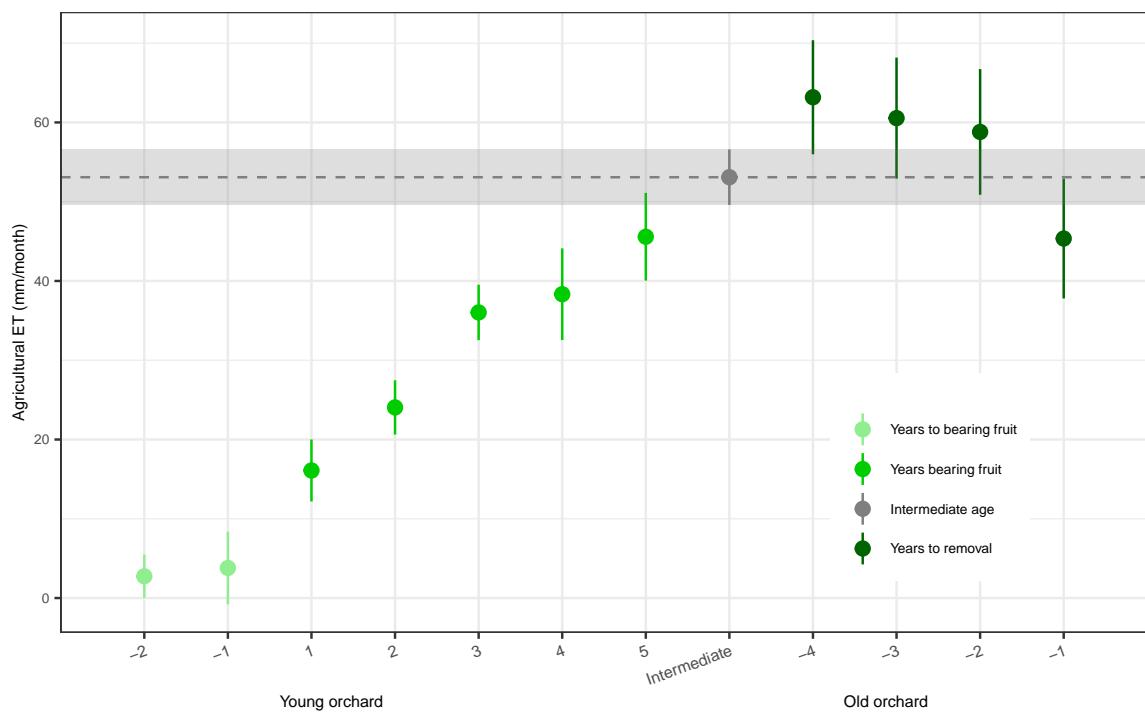


Supplementary Fig. 6 Simulated vs. empirical agricultural evapotranspiration (ET). Simulated agricultural ET is calculated using theoretical crop water demand from the CalSIMETAW model and by subtracting either (A) naturally-occurring ET estimated using machine learning or (B) precipitation. Each point represents the agricultural ET for a crop in a specific county in the California Central Valley.

44 **Supplementary Note 2: The effect of orchard age on**
 45 **agricultural ET**

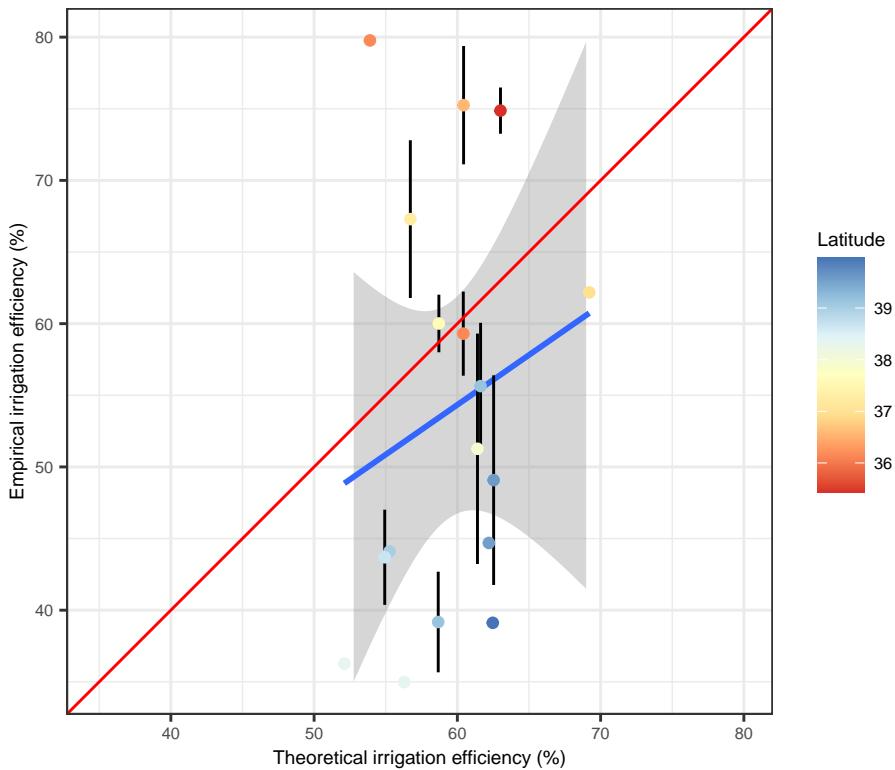
46 Water consumption is known to be affected by orchard age, especially for young orchards [3]. One
 47 advantage of data-driven, field-scale estimates of agricultural ET is that they can capture such
 48 variation.

49 Since information about orchard age is not currently available in California, we use the LandIQ
 50 dataset's transitions from "young perennial" classifications to crop-specific orchard categories as a
 51 proxy for orchard age. "Young perennials" refer to non-fruit-bearing young trees, so their change to
 52 fruit-bearing orchard classifications helps us estimate the age of the orchard. LandIQ crop type data
 53 are available for the years 2014, 2016, 2018, 2019, and 2020. Since we have agricultural ET data for
 54 the years 2016, 2018, and 2019, we can date orchards that have been bearing fruit for up to five years
 55 (i.e. these would be orchards for which we have agricultural ET data in 2019, and were classified
 56 as young perennials for the last time in 2014.) Using this technique, we uncover a clear relationship
 57 between orchard age and agricultural ET (Supplementary Fig. 7).



Supplementary Fig. 7 Water consumption by life stage of orchards in California's Central Valley. Prior to bearing fruit, orchards have low agricultural water consumption, or evapotranspiration (ET). Water consumption then increases rapidly during the first 5 years of fruit production, after which it stabilizes.

58 **Supplementary Note 3: Empirical vs. theoretical irrigation**
 59 **efficiency**



Supplementary Fig. 8 Empirical vs. theoretical irrigation efficiency across the counties of the California Central Valley. Empirical irrigation efficiency is calculated using empirical estimates of agricultural ET divided by reports of total water diverted for irrigation. Theoretical irrigation efficiency is calculated based on efficiency estimates and reported irrigation technology used in each county. Theoretical irrigation efficiency underestimates empirical estimates for more southern counties and overestimates it for more northern counties.

60 In the absence of empirical irrigation efficiency measures, irrigation efficiency is often approximated [4, 5] using technology-specific irrigation efficiency estimates drawn from reports [6–8].
 61 Specifically, irrigation efficiency is calculated as the product conveyance efficiency, management effi-
 62 ciency, and application efficiency. Conveyance efficiency captures losses bringing water from its source
 63 to the farm, management efficiency describes losses on the farm, and application efficiency captures
 64 losses during or after application. We calculate county-specific irrigation efficiency by pulling effi-
 65 ciency numbers from the aforementioned reports. We set conveyance efficiency to .85, management
 66 efficiency to .95, and application efficiency to .60 for flood irrigation, .75 for sprinkler irrigation, and
 67 .95 for drip irrigation. The frequency of adoption of different irrigation technologies in each county
 68 is retrieved from the same USGS dataset we obtain reports of water diverted for irrigation from.
 69

70 Our empirical estimates of irrigation efficiency are not significantly different to what theoretical
 71 estimates would predict, though theoretical estimates tend to underestimate efficiency in south-
 72 ern counties and overestimate it in northern counties (Supplementary Fig. 8). It is possible that
 73 theoretical numbers underestimate the irrigation efficiency in the south because they only capture
 74 improvements in irrigation technology, and not any other practices that might increase efficiency. For
 75 example, deficit irrigation can improve irrigation efficiency [9], as well as careful irrigation scheduling
 76 [10] and precision agriculture [11]. Empirical estimates of irrigation efficiency may therefore capture
 77 the effect of additional drivers of irrigation efficiency past the technology being used.

78 **Supplementary Note 4: The effect of OpenET and machine
79 learning model error on agricultural ET estimates**

80 We define agricultural ET as the difference between total ET and naturally-occurring ET, $ET_{ag} =$
 81 $ET_{tot} - ET_{nat}$ (Main text eq. 1), where naturally-occurring ET is the counterfactual ET that would
 82 occur naturally, were the same land fallow. However, we calculate agricultural ET using estimates
 83 of total ET from OpenET and modeled naturally-occurring ET trained on OpenET data (Supple-
 84 mentary eq. 1). Since the OpenET data and the model we use to estimate naturally-occurring ET
 85 have errors associated with them, our estimates of agricultural ET can be described as the true
 86 agricultural ET plus several error terms (Supplementary eq. 4), which we derive as follows:

$$ET_{ag}^* = ET_{tot}^* - ET_{nat}^* \quad (1)$$

87 where ET_{ag}^* denotes our estimate of agricultural ET, ET_{tot}^* is OpenET's estimate of ET_{tot} and ET_{nat}^*
 88 is our estimate of the naturally-occurring ET, predicted by our machine learning (ML) model. The hat
 89 notation indicates estimates inclusive of OpenET error, while the tilde indicates estimates inclusive
 90 of ML model error.

91 Because our naturally-occurring ET ML model is trained on and therefore predicts OpenET
 92 values over fallow lands, we can rewrite the same expression as:

$$ET_{ag}^* = ET_{tot}^* - (ET_{nat}^* + \epsilon_{ML}) \quad (2)$$

93 where ET_{nat}^* is the (naturally-occurring) ET that OpenET would observe if the field were fallow,
 94 and ϵ_{ML} is the error from the ML model in predicting ET_{nat}^* .

95 We can then again reorganize the same equation by separating the error from the OpenET
 96 observations. This reveals the relationship between the true ET_{ag} and our estimate, ET_{ag}^* :

$$ET_{ag}^* = ET_{tot} + \epsilon_{OpenET,ag} - (ET_{nat} + \epsilon_{OpenET,fal} + \epsilon_{ML}) \quad (3)$$

$$= ET_{ag} + \epsilon_{OpenET,ag} - \epsilon_{OpenET,fal} - \epsilon_{ML} \quad (4)$$

97 where ET_{ag} , ET_{tot} , and ET_{nat} are the true (unobservable) agricultural ET, total ET, and naturally-
 98 occurring ET, respectively, $\epsilon_{OpenET,ag}$ is the error associated with the OpenET estimate over the
 99 agricultural field and $\epsilon_{OpenET,fal}$ is the error associated with what the OpenET estimate would be if
 100 the land were fallow.

101 In our study, we seek to estimate mean ET_{ag} , be it over the entire Central Valley, for a certain
 102 crop type, or for a given county, we seek to calculate the expectation of ET_{ag} over a sample of grid
 103 cells. Using Supplementary eq. 5, we can show that our estimate of $E[ET_{ag}^*]$ depends not only on
 104 $E[ET_{ag}]$, but also the expectation of the error terms.

$$E[ET_{ag}^*] = E[ET_{ag}] + E[\epsilon_{OpenET,ag}] - E[\epsilon_{OpenET,fal}] - E[\epsilon_{ML}] \quad (5)$$

105 We show in Supplementary Figures 1-4 that ϵ_{ML} is unbiased, that is, $E[\epsilon_{ML}] = 0$. OpenET has
 106 also been shown to produce unbiased estimates over agricultural lands, so $E[\epsilon_{OpenET,ag}] = 0$ (see
 107 Table 3 on page 6 of the OpenET Intercomparison and Accuracy report) [12]. We can also assume
 108 $\epsilon_{OpenET,fal}$ is unbiased because though OpenET has not specifically been evaluated over fallow fields,
 109 it produces unbiased estimates over natural shrublands and grasslands with ET values of similar
 110 magnitude to fallow fields in the Central Valley [12]. As a result, in expectation our estimates of
 111 agricultural ET are unbiased, and consequently produce unbiased regression coefficients.

$$E[ET_{ag}^*] = E[ET_{ag}] \quad (6)$$

112 While our estimates of agricultural ET are unbiased in expectation, the error terms do add
 113 variance that is not present in the true agricultural ET. Therefore, any analysis that assesses variation

114 across pixels will reflect inflated variance relative to true agricultural ET. For example, this has
115 implications for the farming practices and fallowing scenarios we conduct (Fig. 3). However, here we
116 estimate that error is responsible for only 11% of the variance in our annual estimates of agricultural
117 ET, suggesting its influence over key results is limited. Specifically, if we assume that all error terms
118 are independent, we have:

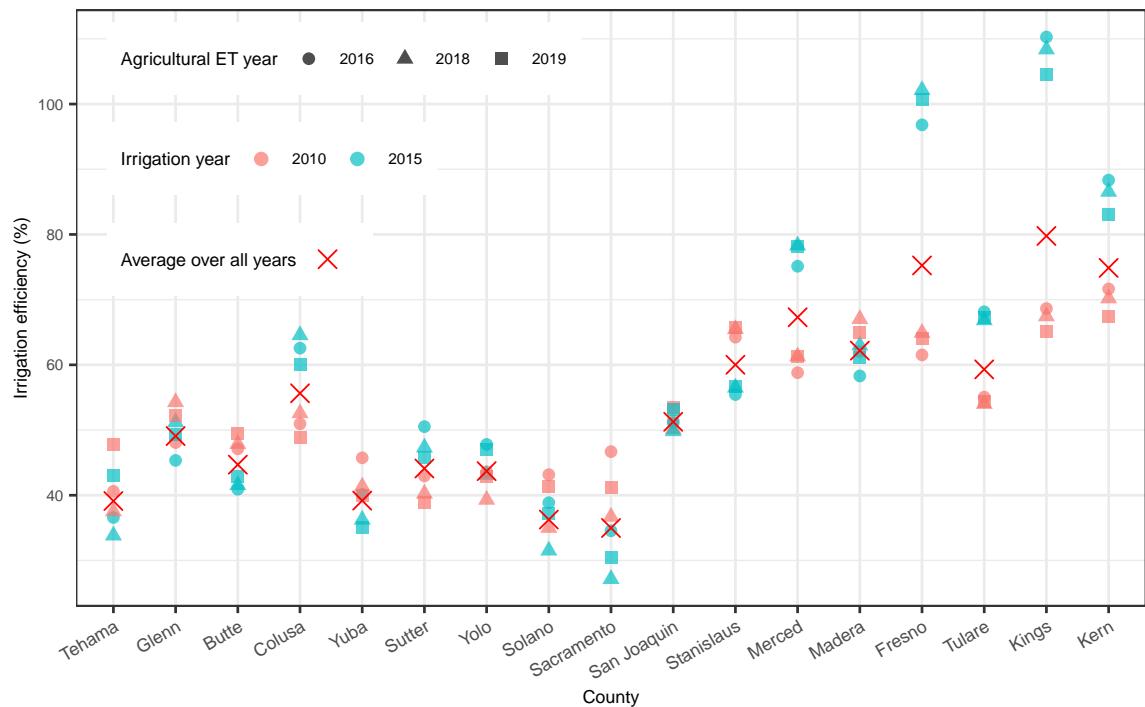
$$\text{var}(\text{ET}_{\text{ag}}^*) = \text{var}(\text{ET}_{\text{ag}}) + \text{var}(\epsilon_{\text{OpenET},\text{ag}}) + \text{var}(\epsilon_{\text{OpenET},\text{fal}}) + \text{var}(\epsilon_{\text{ML}}) \quad (7)$$

119 where $\text{var}(\cdot)$ denotes the variance.

120 Then, because variance is equal to mean squared error (MSE) when bias is 0, we have:

$$\text{var}(\text{ET}_{\text{ag}}^*) = \text{var}(\text{ET}_{\text{ag}}) + \text{MSE}(\epsilon_{\text{OpenET},\text{ag}}) + \text{MSE}(\epsilon_{\text{OpenET},\text{fal}}) + \text{MSE}(\epsilon_{\text{ML}}) \quad (8)$$

121 We calculate the MSE of our machine learning model using our test set, and OpenET provides
122 root MSE values over croplands and shrublands (which we use to approximate error over fallow lands)
123 (again, see Table 3 on page 6 of the OpenET Intercomparison and Accuracy report) [12]. We find
124 that for estimates of yearly ET_{ag}^* , $\text{MSE}(\epsilon_{\text{OpenET},\text{ag}}) + \text{MSE}(\epsilon_{\text{OpenET},\text{fal}}) + \text{MSE}(\epsilon_{\text{ML}})$ represents only
125 11% of $\text{var}(\text{ET}_{\text{ag}}^*)$. This indicates that the vast majority of the variance we uncover is representative
126 of true differences in water consumption across fields, as opposed to variability due to model errors.

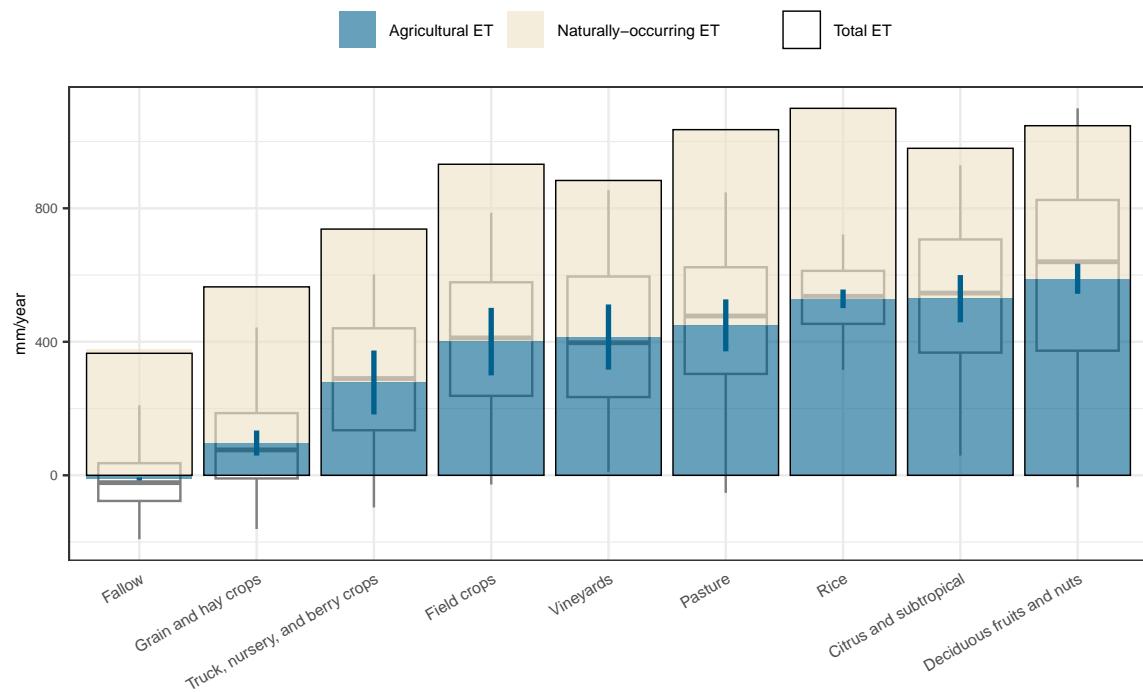


Supplementary Fig. 9 Uncertainty in irrigation efficiency estimates. To calculate irrigation efficiency, we divide agricultural evapotranspiration (ET) by irrigation amount, but the available data do not overlap in years over which they are available. Counties are ordered by latitude, with more northern counties on the left. The average irrigation efficiency is shown as a red x, but we also assess the effect of using different years in the numerator and denominator by combining all different permutations of agricultural ET (shape) and irrigation (color) data. We note that 2016 and 2015 were drought years, while 2018, 2019, and 2010 were wetter. We do find substantial spreads in irrigation efficiency driven by the year of irrigation data, especially in some southern counties. However, most of the spread is driven from combining wet and dry years together, suggesting that an average may successfully decrease much of the variability.

¹²⁷ **Supplementary Note 5: Results without cleaning the training**
¹²⁸ **dataset for the naturally-occurring ET model**

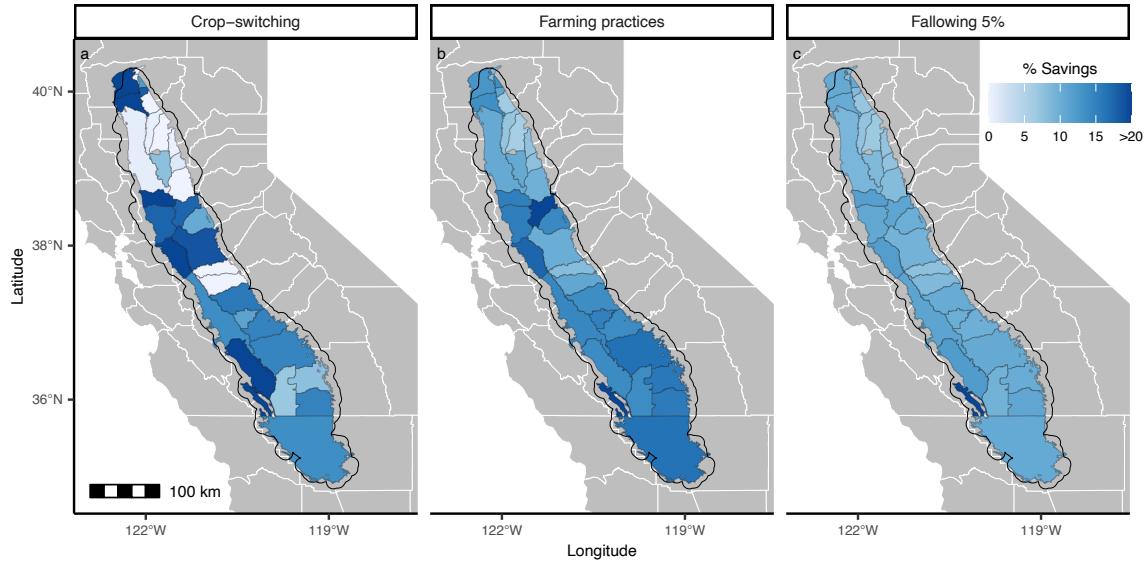
¹²⁹ When training the naturally-occurring ET model, we remove pixels that are within the top 5% ET
¹³⁰ during July-September due to some implausibly high numbers during these months that suggest
¹³¹ mislabeling of an active agricultural pixel as fallow. Here, we evaluate the effect of this step on our
¹³² final results.

¹³³ As one might expect, the agricultural ET estimates recovered without data cleaning are slightly
¹³⁴ lower as opposed to the numbers reported in the main text (Supplementary Fig. 10). Additionally,
¹³⁵ the naturally-occurring ET estimates are more erratic across crop groups (Supplementary Fig. 10).
¹³⁶ Nevertheless, the general trends and conclusions from the main text still hold.



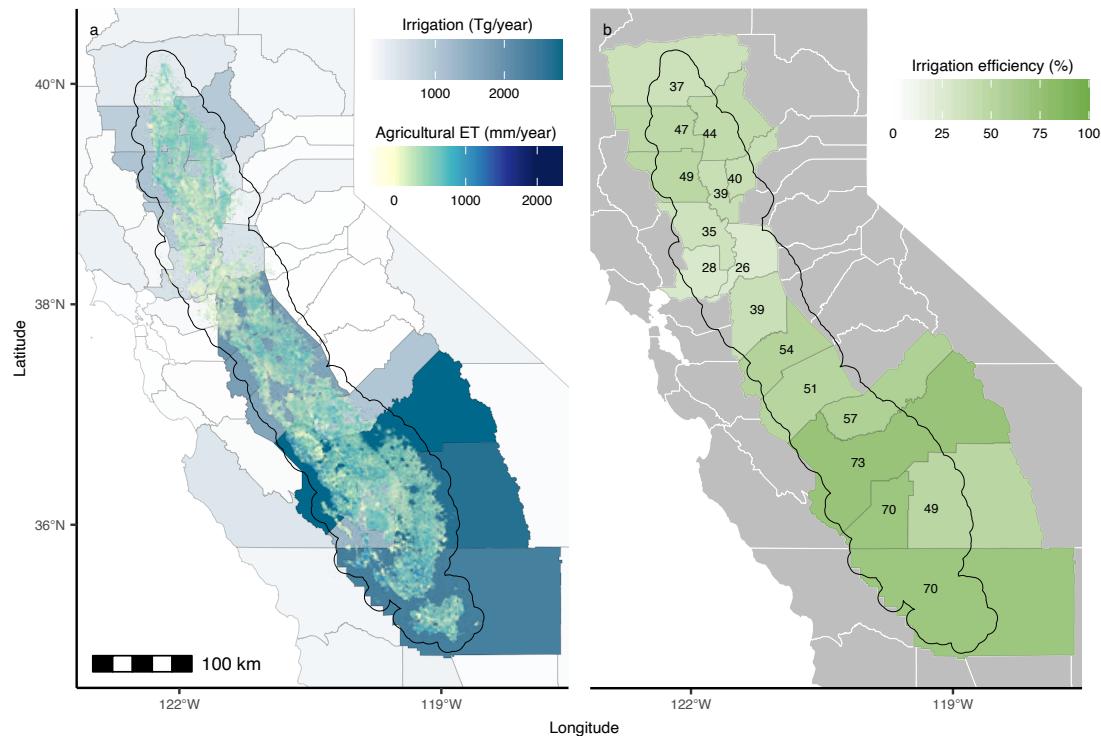
Supplementary Fig. 10 Variations in agricultural evapotranspiration (ET) across and within crop groups without cleaning training data. This is the equivalent of Fig. 2 in the main text, but calculated using a naturally-occurring ET model trained on uncleaned data.

When conducting scenarios, we find that all scenarios are slightly more effective: The crop-switching scenario yields 11.7% savings (95.3% if switching to the minimum-consuming crop), farming practices lead to 13.5% savings, and fallowing 5% of land reduces agricultural ET by 10.0% (Supplementary Fig. 11). All trends are the same as in the main text.



Supplementary Fig. 11 The percent reduction in agricultural evapotranspiration (ET) driven by various management scenarios without cleaning training data. This is the equivalent of Fig. 3 in the main text, but calculated using a naturally-occurring ET model trained on uncleaned data.

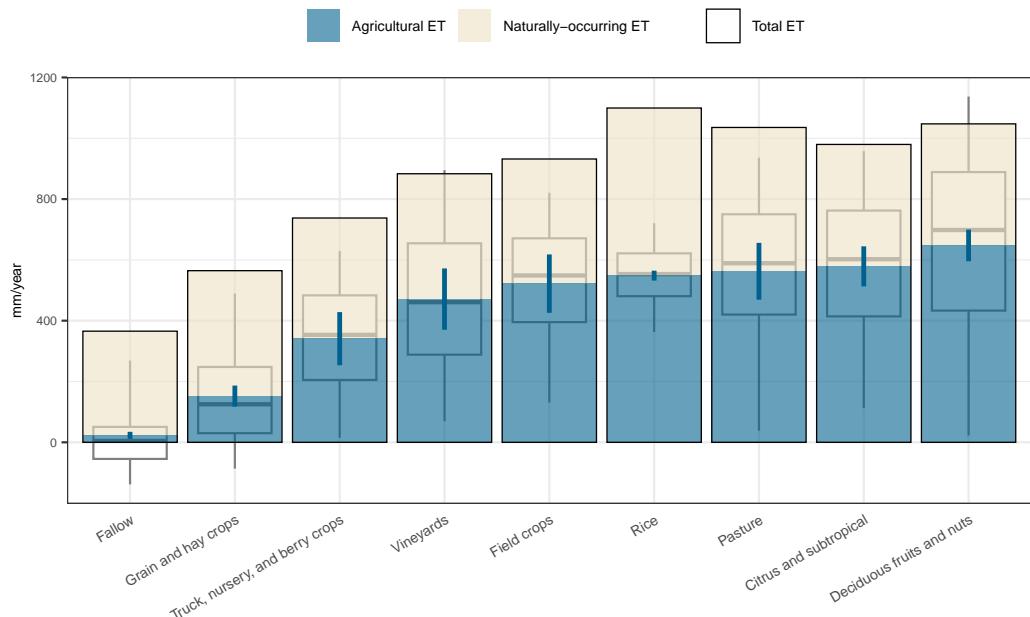
141 As a result of retrieving lower agricultural ET numbers, irrigation efficiency is also generally
142 lower, at 54.6% (46.1, 63.2) on average. However, we still find significantly lower irrigation efficiency
143 in the northern counties (Supplementary Fig. 12).



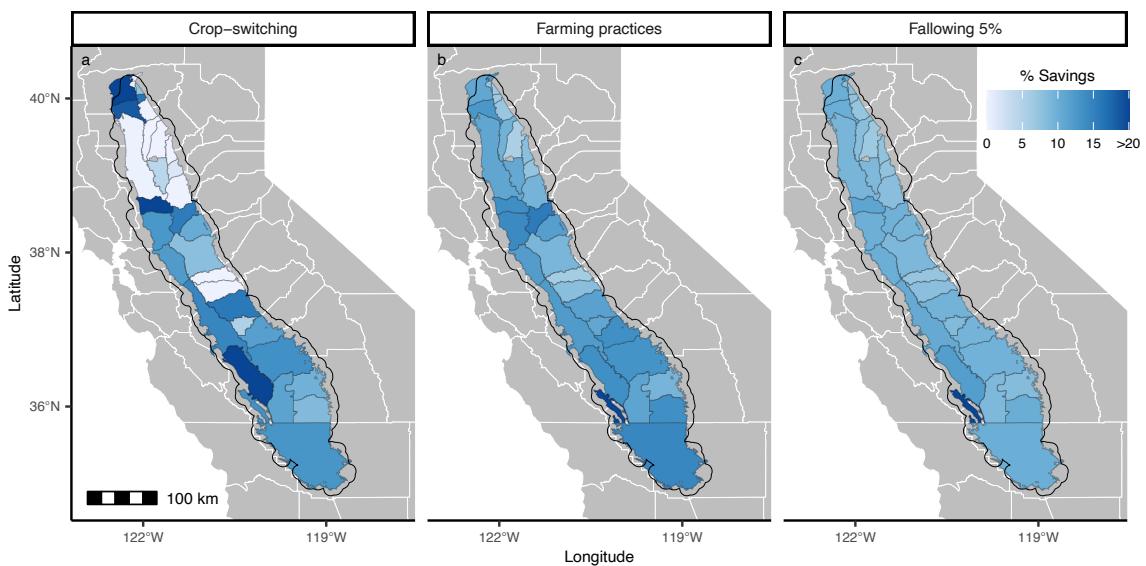
Supplementary Fig. 12 Irrigation efficiency across the counties of the Central Valley without cleaning training data. This is the equivalent of Fig. 4 in the main text, but calculated using a naturally-occurring ET model trained on uncleaned data.

¹⁴⁴ **Supplementary Note 6: Results when using training data also
145 marked fallow by the Cropland Data Layer (CDL)**

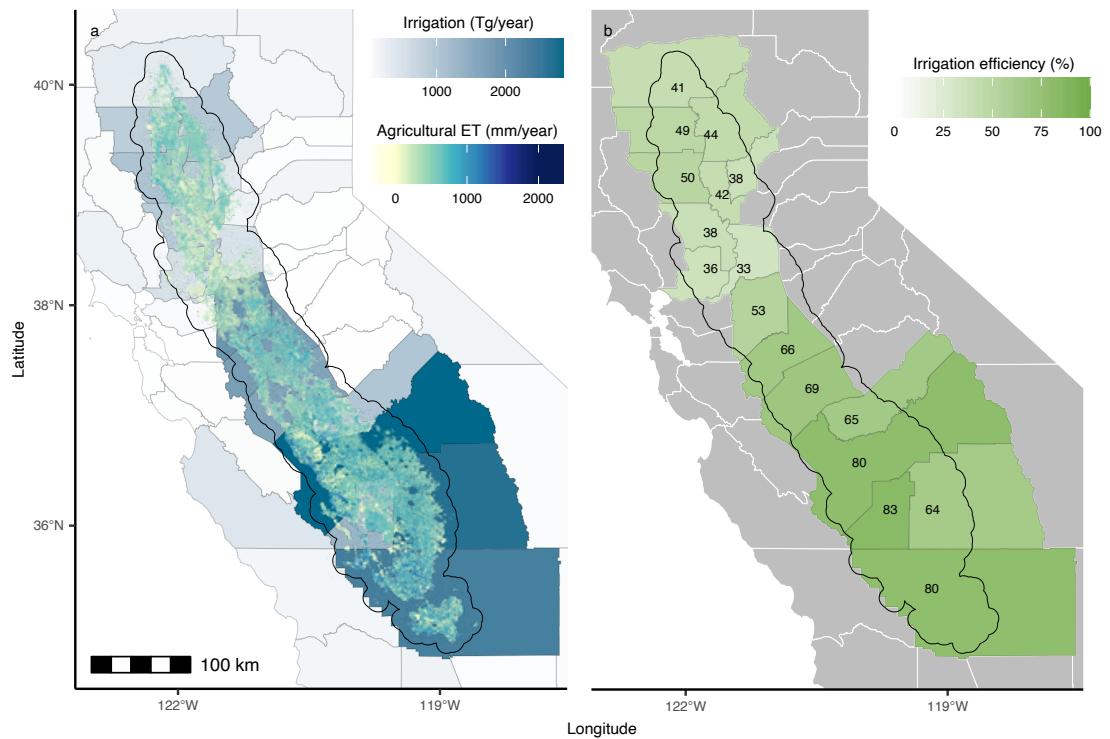
¹⁴⁶ When training the naturally-occurring ET model, we rely on the California Department of Water
147 Resources (DWR) LandIQ crop type dataset due to its high accuracy. Here, we evaluate the effect of
148 instead training the data only on fallow fields that are marked as fallow by both the DWR dataset
149 and the Cropland Data Layer (CDL). Overall, this change does not affect our estimates of naturally-
150 occurring ET: while we estimate 438 mm per year (394.4-481.7 95% CI) in the main text, we estimate
151 423.9 mm per year (369-478.7 95% CI) here. All general trends and conclusions are robust to this
152 change (Supplementary Fig. 13, Fig. 14, Fig. 15).



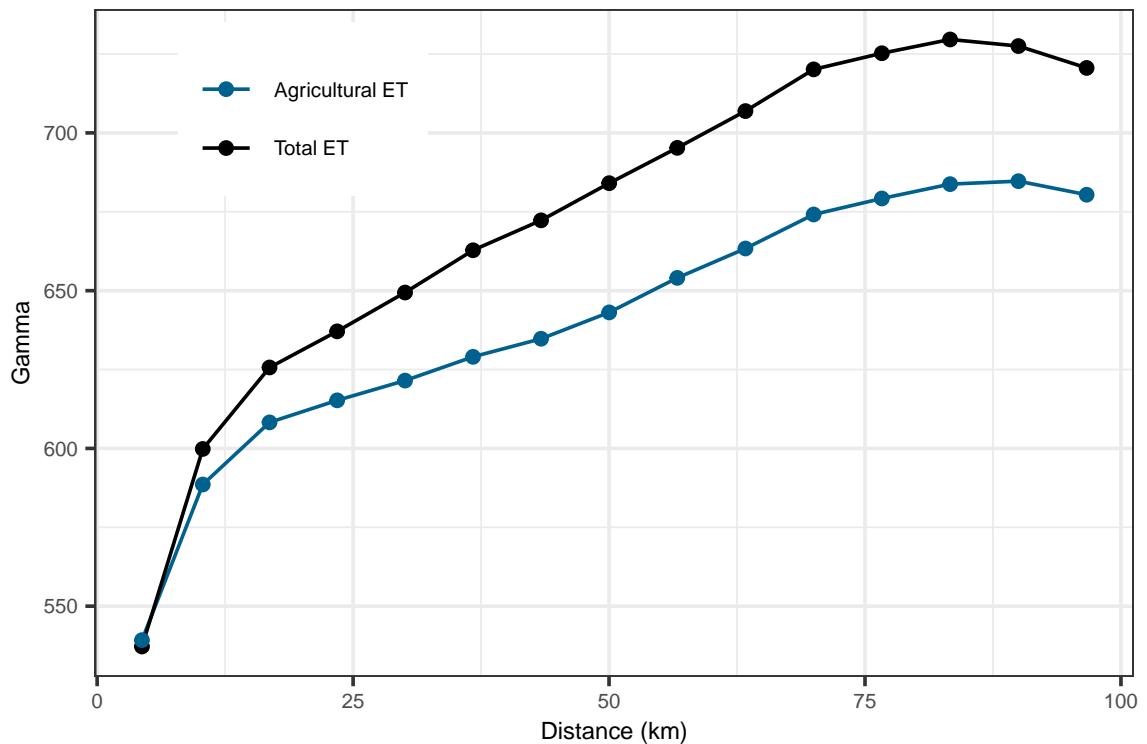
Supplementary Fig. 13 Variations in agricultural evapotranspiration (ET) across and within crop groups using training data also marked fallow by the Cropland Data Layer. This is the equivalent of Fig. 2 in the main text, but calculated using a naturally-occurring ET model trained on data also marked fallow by the Cropland Data Layer.



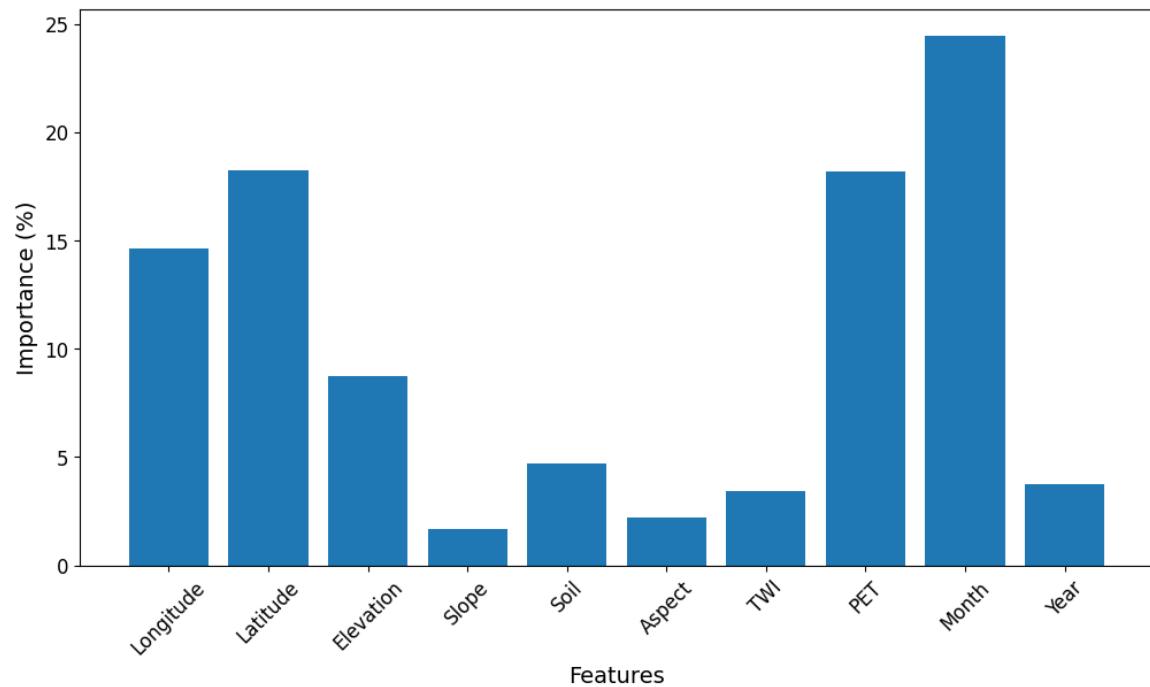
Supplementary Fig. 14 The percent reduction in agricultural evapotranspiration (ET) driven by various management scenarios using training data also marked fallow by the Cropland Data Layer. This is the equivalent of Fig. 3 in the main text, but calculated using a naturally-occurring ET model trained on data also marked fallow by the Cropland Data Layer.



Supplementary Fig. 15 Irrigation efficiency across the counties of the Central Valley using training data also marked fallow by the Cropland Data Layer. This is the equivalent of Fig. 4 in the main text, but calculated using a naturally-occurring ET model trained on data also marked fallow by the Cropland Data Layer.



Supplementary Fig. 16 Variogram representing the spatial relationship of Total evapotranspiration (ET) and agricultural ET between nearby agricultural land. The spatial auto-correlation between pixels levels off around 75km of distance. We therefore use clustered standard errors for areas of 75km x 75km to avoid artificially low standard errors when calculating ET and agricultural ET statistics.



Supplementary Fig. 17 The contribution of each variable included in the gradient boosting model on its predictions of naturally-occurring ET.

¹⁵³ **Supplementary Note 7: Crop groups**

¹⁵⁴ The crop groups used to make Fig. 2 follow the groupings from the Department of Water Resources
¹⁵⁵ LandIQ dataset which we use to designate crop type in our analysis. More information on these
¹⁵⁶ groups can be found in the metadata for these data, and are also described here:

- ¹⁵⁷ 1. Grain and hay crops include barley, wheat, oats, miscellaneous grain and hay, and mixed grain
¹⁵⁸ and hay.
- ¹⁵⁹ 2. Rice includes rice and wild rice.
- ¹⁶⁰ 3. Field crops include cotton, safflower, flax, hops, sugar beets, corn (field & sweet), grain sorghum,
¹⁶¹ sudan, castor beans, beans (dry), miscellaneous field, sunflowers, hybrid sorghum/sudan, millet,
¹⁶² sugar cane, and corn.
- ¹⁶³ 4. Pasture includes alfalfa & alfalfa mixtures, clover, mixed pasture, native pasture, induced high
¹⁶⁴ water table native pasture, miscellaneous grasses, turf farms, bermuda grass, rye grass, and klein
¹⁶⁵ grass.
- ¹⁶⁶ 5. Truck, nursery & berry crops include artichokes, asparagus, beans (green), cole crops, carrots,
¹⁶⁷ celery, lettuce (all types), melons, squash, and cucumbers (all types), onions & garlic, peas, pota-
¹⁶⁸ toes, sweet potatoes, spinach, tomatoes (processing), flowers, nursery & Christmas tree farms,
¹⁶⁹ mixed (four or more), miscellaneous truck, bush berries, strawberries, peppers (chili, bell, etc.),
¹⁷⁰ broccoli, cabbage, cauliflower, brussels sprouts, tomatoes (market), greenhouse, blueberries, Asian
¹⁷¹ leafy vegetables, lettuce or leafy greens, and potato or sweet potato.
- ¹⁷² 6. Deciduous fruits and nuts include apples, apricots, cherries, peaches and nectarines, pears,
¹⁷³ plums, prunes, figs, miscellaneous deciduous, mixed deciduous, almonds, walnuts, pistachios,
¹⁷⁴ pomegranates, and plums, prunes or apricots.
- ¹⁷⁵ 7. Citrus and subtropical include grapefruit, lemons, oranges, dates, avocados, olives, miscellaneous
¹⁷⁶ subtropical fruit, kiwis, jojoba, eucalyptus, and mixed subtropical fruits.
- ¹⁷⁷ 8. Vineyards include table grapes, wine grapes, and raisin grapes.

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