Title

Agricultural Land Use Change and Sustainability Challenges in the Sacramento Valley, California

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Agricultural Land Use Change and Sustainability Challenges in the Sacramento Valley, California

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LUKE SALVATO
DISSERTATION

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of the

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Introduction

To address the complex challenges facing agricultural sustainability, there is need for adaptive land management strategies that promote sustainable agricultural practices while adapting to changing environmental conditions. This research presents three possible approaches to managing agricultural sustainability at the landscape scale, utilizing the Sacramento Valley of California as a research template. This region was a native wetland habitat that was reclaimed for agricultural production and is now dominated by rice agriculture. The unique climate, topography, and soils of this region make it important habitat for endangered species as well. The three chapters of this dissertation discuss sustainability challenges and potential solutions for this research: (1) Methylmercury dynamics in the region's water, plants and soil during a summer and winter season; (2) Crop rotation as a solution to managing limited water resources and weed pressure; (3) The drivers and consequences of converting rice fields into perennial tree crops. Each of these three sections is introduced in the following paragraphs.

Methylmercury (MeHg) is an environmental toxin often produced in and exported from flooded soils. Little is known about MeHg in agricultural wetlands of the Sacramento Valley, where irrigation drain water flows into sensitive wetlands downstream. Soil, grain, and surface water (dissolved and particulate) MeHg and total mercury (THg) were monitored in six commercial rice fields across this region throughout a winter fallow season and subsequent

growing season. Both dissolved and particulate mercury fractions were higher in fallow season rice field-water. Total suspended solids and particulate mercury concentrations were positively correlated ($r = 0.99$ and 0.98 for THg and MeHg, respectively), suggesting that soil MeHg was suspended in the water column and potentially exported. Filtered THg and MeHg concentrations were positively correlated with absorbance at 254 nm ($r = 0.47$ and 0.58, respectively) in fallow season field water. In the growing season, fields with higher irrigation water MeHg concentrations (due to recycled water use) also had elevated in-field MeHg ($r = 0.86$, $p < 0.05$) and grain MeHg concentrations ($r = 0.96$, $p < 0.01$). A mass balance analysis shows that soil mercury pools were orders of magnitude larger than surface water or grain mercury pools; however, fallow season drainage and grain harvest were the primary pathways for MeHg export. Based on these findings, efforts to reduce mercury exports in rice field drainage water should focus on reducing discharge turbidity and the build-up of labile carbon pools during the fallow season.

Crop rotation is one strategy for adapting agroecosystems to a framework that balances ecological diversity, sustainability, and food production. The Sacramento Valley, one of the most productive rice growing regions in the US, faces sustainability challenges including increasing herbicide resistant weed pressure and water use restrictions. Increasing crop diversity may help address these challenges, but this region has unique soil attributes including high clay content, salinity, alkalinity, and cemented subsurface layers, and the degree to which these soil properties influence crop rotation decisions remain unclear. The objectives of this study were to quantify the extent of crop rotation in this region, compare soil properties for rotated and continuous rice fields, and assess the potential for expanding rotations based on the geographic coverage of influential soil variables. Using satellite derived land cover data for 2007-2021, our analysis

shows that only ~5,000 ha are in rotation with rice, while 220,000 ha are in continuous rice production. This land cover information is fused with SSURGO soil maps in a spatial random forest model. The modeling approach indicates that fields with soil pH between 6.5 and 8, EC between 0.5 and 2 (ds m^{-1}), and saturated hydraulic conductivity less than 2 (μm s^{-1}) are more likely to be rotated. However, we estimate that only 11% of the continuous rice area has all three of these soil properties combined, suggesting soil limitations are an important constraint. To better understand barriers to agroecological diversification, this research highlights a method for evaluating land use decisions in relation to spatial variability of soil properties.

Broader land use changes in California's Central Valley over the past 20 years have been dominated by shifts from annual to periannual cropping systems. However, the Mediterranean climate of in this region is prone to drought conditions, which are increasing in frequency due to climate change. The northern portion of the Central Valley is dominated by commercial rice production. Periannual tree crops such as almond and walnut are increasing in this area, however large portions of the valley have unique wetland-basin soil attributes that make growing non-flooded crops difficult. We use a remote sensing land cover information and spatial soil information to quantify the land use changes in the region, and to better understand the effect of soil type. Our analysis shows that almond and walnut have increased in the area over the past 15 years, but that their area is limited (10% of total area). Crop prices, and revenue per hectare are 3-4 fold higher for almond and walnut compared to rice, which has incentivized some growers to plant these crops. However, our random forest model reveals that continuous rice fields and periannual fields have distinct soil types. Clay is the most important variable in the model, and fields with high clay (>40%) are unlikely to be planted in almond or walnut. Many of the fields with high clay are in the interior basins of the rice growing region, where there are no perennial tree crops. This research provides a framework for evaluating land use decision making to promote sustainable land management.

Chapter 1:

Influence of Irrigation Water and Soil on Annual Mercury Dynamics in Rice Fields

1. Introduction

Methylmercury (MeHg) is a toxic and bioaccumulative form of mercury produced by anaerobic microbes under conditions experienced in flooded soils (gilmour et al., 2013). Rice, a stable crop for most of the world's population, is grown in flooded soils and can create effective habitats for converting inorganic mercury (thg) into mehg (windham-myers et al., 2014a). Mehg can pose risks to wildlife inhabiting rice fields, while mercury exported in drainage water can affect downstream habitats (Ackerman et al., 2009). Furthermore, MeHg that accumulates in rice grain is a potential health risk to humans (chan et al., 2010; horvat et al., 2003).

Rice is grown on approximately 210,000 ha in the Central Valley of California (USDA - NASS, 2018). In the mountains surrounding this valley, natural sources, exacerbated by historic mercury mining and mercury use in gold processing has resulted in widespread mercury contamination (Alpers et al., 2016). These sources have resulted in elevated soil and water mercury concentrations in rice-producing areas including the Sacramento-San Joaquin Delta (hereafter referred to as the "Delta") and the Sacramento Valley (Ackerman et al., 2014; Alpers et al., 2014; Bachand, et al., 2014; Eagles-Smith et al., 2014). While 95% of California's rice production occurs in the Sacramento Valley, relatively few studies have focused on mercury dynamics in the region. Tanner et al. (2017, 2018) studied two rice fields in this region and reported that soil and water mercury concentrations were considerably lower than in the Delta. However, these fields were still potential sources of MeHg to downstream habitats, particularly during the winter fallow—a finding consistent with other studies at sites where background soil mercury concentrations were elevated (Alpers et al., 2014; Eagles-Smith et al., 2014; Tanner et al., 2017).

Sacramento Valley rice fields provide habitat and forage for wildlife and the water drained from these rice fields flows to the Delta, which is an environmentally sensitive region that is rich in biodiversity. Annually, California rice fields experience two flooded periods when MeHg production and export can occur (Tanner et al., 2017, 2018), during the rice growing season, when fields are flooded for rice production, and during the winter fallow season, when fields are flooded to aid in the decomposition of rice straw (Linquist et al., 2006) and provide waterfowl habitat. Tanner et al. (2018) only investigated mercury dynamics in two rice fields with considerably different mercury levels. Understanding the factors affecting mercury dynamics will help develop improved mitigation measures.

One potential factor is the irrigation water mercury concentration. In Sacramento Valley rice fields, fresh irrigation water is typically used during the winter fallow season. However, during the growing season, rice field drainage water may be recycled and reapplied (Marcos et al., 2018). Rice field drainage water has elevated MeHg concentrations (Tanner et al., 2017; Zhao et al., 2016), suggesting that irrigation with elevated MeHg concentrations can indirectly influence in-field MeHg processes by influencing the gradients between MeHg concentrations in the soil and overlying water, which drive in-field MeHg fluxes (Alpers et al., 2014; Bachand et al., 2014a; Bachand et al., 2014b).

The fractionation of mercury forms in the water is another important consideration for developing our understanding of mercy dynamics. Mercury can be broadly grouped into filter-passing (considered dissolved or colloidal) and non-filter-passing which is considered particulate. Each of these fractions has different management implications. For example, dissolved and colloidal mercury have greater potential for further cycling and transport than particulate bound mercury (e.g. Alpers et al., 2014; Hammerschmidt & Fitzgerald, 2004; Zhang et al., 2012). Particulate mercury, on the other hand, may be linked directly to soil mercury suspended in the water column. Previous studies of mercury in this region (Tanner et al., 2017, 2018) only considered whole water mercury (the sum of these fractions).

Here, our objectives were to expand upon the findings of Tanner et al. (2018) in Sacramento Valley rice fields by 1) evaluating the distribution of mercury fractions between the dissolved and particulate in rice field inlets, in-field water, and outlets, throughout a winter fallow season and a growing season; 2) determining the impact of irrigation water and soil mercury concentrations on outlet water and grain mercury concentrations; and 3) quantifying seasonal mercury pools in surface water, soil, and grain in rice fields.

MATERIALS AND METHODS

Site Description

This study was conducted during the 2017/18 fallow and 2018 growing season in six commercial rice fields located in California's Sacramento Valley (Figure 1). All fields were managed by rice growers using standard management practices. Key soil characteristics and the timing of key water management events are provided in Supplemental Table S1. This region has a Mediterranean climate with warm, dry conditions during the growing season (April to

September), and cool, wet conditions during the fallow season (October to March). This region has two main rivers: the Sacramento River and the Feather River (Figure 1) which flow from north to south into the Delta south of Sacramento. Irrigation water is mostly from upstream dams. Canals direct surface irrigation water to fields and tailwater recycled onto the next field downslope. Individual rice fields (up to 80 ha) are divided into checks (sub-fields or basins) using levees and built-in weirs to manage water (Figure 1, inset).

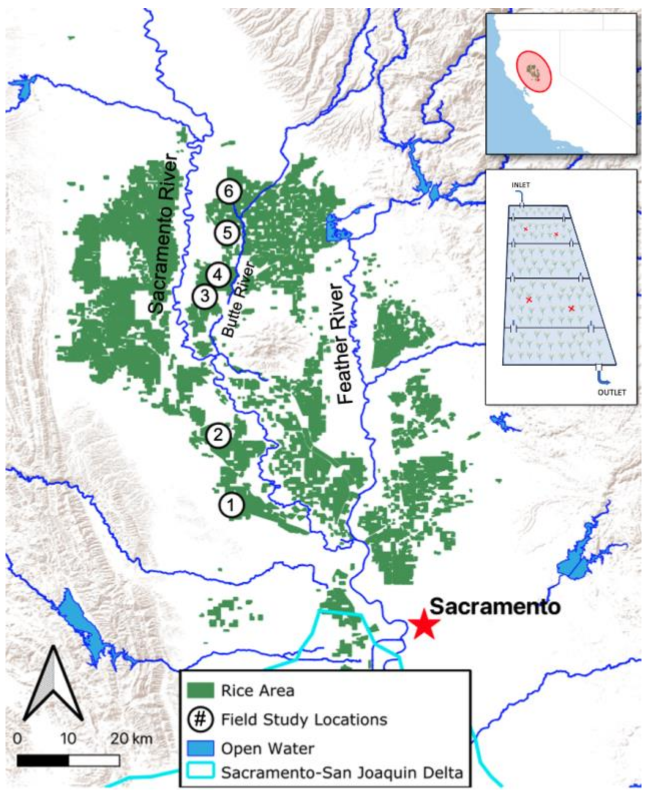

Figure 1. Map showing Sacramento Valley rice rice and the locations of the six fields in the study. The inset drawing shows an example field's inlet and outlet, where water samples were collected, while the red crosses indicate typical in-field sampling sites where water, soil, and grain samples were collected. Sources: ESRI, USGS, USDA, California DWR.

After field preparation in spring, fields are flooded and planted (water-seeding). Water management during the first month of the growing season varies based on weed management practices. From mid-season through drainage for harvest, irrigation inflow is adjusted to maintain a constant level of water in the field, resulting in tailwater water drainage from outlet (referred to as "maintenance flow"). After harvest, rice straw is tilled into the soil, and fields are flooded for the fallow season. During the fallow season, growers supplement winter rains with irrigation to keep the fields full. In both seasons, the three major hydrologic management periods are hereafter referred to as 'flood', 'maintenance flow', and 'drain'.

Water Measurements, Field Samples and Laboratory Analyses

Hydrologic Field Measurements

Irrigation volumes were measured and reported by the irrigation district managing each field. A digital flowmeter (McCrometer, Inc.) in a submerged inlet pipe was used in Fields 1 &2. In Fields 3 to 6, a SonTek FlowTracker™ was used every time inlet flow was adjusted, and every few days between adjustments. Rainfall data were obtained from the nearest weather station (CIMIS, 2018).

Outflow was determined by measuring the head over the outlet weir using pressure transducers (Global Water Instrumentation, Model WL16) as described by Aydin et al. (2011) and Tanner et al. (2018). In a few cases, fields were drained rapidly using multiple outlets. In these cases, the volume of water exported was calculated as the change in field water height multiplied by the field area.

Surface Water Sampling

HOBO salinity loggers (Bourne, Mass., USA) were installed at the inlet of each field to measure the electrical conductivity (EC) of the irrigation water. Four in-field sampling sites were established randomly in each field (Figure 1, inset). During both seasons, inlet, in-field, and outlet water was sampled during the three major hydrologic management periods described above. Water was only sampled at the inlets or outlets if water was flowing. During the fallow season, there was no inflow after the initial flood period as rain was used to maintain flooded conditions. During the growing season, Fields 1 and 2 were drained three days after planting and reflooded three days later to promote even stand establishment (Williams et al., 1990). In Fields 3-6, there was no outflow during the first 30 days, but water levels were maintained. In-field samples (500 mL) were collected from the four designated locations and composited into one representative 2-L sample.

All water samples were collected using trace-clean sampling techniques (USEPA, 1996). New polyethylene terephthalate glycol (PETG) 1-L plastic bottles were double-bagged in the laboratory prior to water sample collection. Prior to collecting the sample, sample bottles were triple rinsed with collection site water. Samples were stored on ice in a cooler and transported to the lab for processing within 48 hours. Samples were vacuum-filtered through a pre-weighed 0.3-µm, pre-combusted, glass-fiber filter, with the filtrate collected into a new 125-mL PETG bottle. A portion of the filtered sample was put in a 20-mL glass scintillation vial for absorbance measurements and the remaining water sample was acidified with 0.5% solution of trace-metal-clean HCl. The particulate sample collected on the glass-fiber filters was immediately stored on dry ice in a cooler then stored at -80° C until further analysis.

Laboratory Analysis

Filter-passing (THg_f and $MeHg_f$ - referred to as "dissolved") and non-filter-passing ($MeHg_p$ and THg_p – referred to as "particulate") mercury were analyzed as described by Marvin-DiPasquale et al. (2011). $MeHg_p$ and THg_p, expressed as a volumetric concentration, was calculated using the mass of MeHg and THg on the filter and the volume of water filtered. THg_w and $MeHg_w$ refer to 'whole-water' mercury concentrations (sum of dissolved and particulate). For quality assurance, field blanks and field duplicates were collected and analyzed; and laboratory duplicates were analyzed for quality assurance of water sample filtration and averaged for data analyses. Method detection and reporting limits for all analyses are in Table S2. All sediment and grain samples were above the reporting limits. For water samples less than the method detection limit, estimated values based on instrument readings were used in statistical analysis.

Water partitioning coefficients (Kd) were calculated as the ratio of a sample's particulate mercury concentration (ng kg^{-1}) to its dissolved concentration (ng L^{-1}) and expressed as L kg^{-1}. Total suspended solids concentration (TSS) was calculated as the total mass of the non-filter-passing material after filtering a defined volume of sample water through the 0.3-µm filters and drying to constant weight at 105°C. Water absorbance (A_{254}), an indicator of dissolved organic matter (DOM) concentration (Dittman et al., 2009), was determined in filtered, non-acidified water samples in a Shimadzu UV-1280 spectrophotometer.

Soil Sampling and Analysis

Soil samples were collected at the in-field water sampling sites. For baseline soil characteristics, dry soil samples (~ 0-15 cm) were collected at the beginning of the study (Nov 2017) following post-harvest tillage. Four scoops (each ~125 cm^3) per site were collected from all four in-field locations and combined. Flooded soil samples were taken in both seasons, approximately two weeks after flooding from the four in-field sampling sites by taking three cores (5-cm-diameter) per site to a depth of 5 cm and compositing into one representative field sample.

All soil samples were placed on dry ice for transport, then stored at -80° C until analysis. Soil samples were analyzed for THg, MeHg, and bulk density (Marvin-DiPasquale et al., 2011). For THg, samples were digested with aqua regia overnight and a treatment of heated oxidation with BrCl (USEPA, 2002). THg concentration was quantified on a Tekran 2600 THg analyzer with a method detection limit of 0.2 ng g^{-1} dry weight. For MeHg, samples were extracted with 25% KOH in methanol for 4 hours at 60°C and then distilled and ethylated (De Wild et al., 2002). MeHg concentration was quantified on an automated MeHg analyzer (Brooks Rand, MERX unit). For quality assurance, analysis of certified reference materials, laboratory duplicates, and matrix spikes for MeHg and THg were conducted.

Rice Grain Sampling and Analysis

Rice grain samples were collected during the 2018 harvest from the four in-field sampling locations and composited into one representative field sample. Samples were transported on dry ice and then stored at -80°C. Unmilled rice grains were lyophilized, ground to a fine powder using a coffee grinder cleaned with ethanol between samples (Drennan-Harris et al., 2013), then analyzed for MeHg using the same method as for soil (Marvin-DiPasquale et al., 2014). For THg analysis, the samples were digested with concentrated HNO_3 (Kleckner, Kakouros, & Robin Stewart, 2017) and then quantified following BrCl addition (Marvin-DiPasquale et al., 2011).

Mercury Load Calculations

Loads were computed for mercury in irrigation water imports and drainage exports by integrating the products of mercury fraction concentration and flow rate data, then normalized to field area. Net loads were calculated as the difference between irrigation imports and drainage exports.

Mercury pools in grain and soil were calculated as the product of the substrate mass and its mercury concentration. Soil pool sizes were calculated based on the mass of soil (0-5 cm depth) and the average annual soil bulk density of each field. The grain yield was provided by the farmer.

Statistical Analyses

Flooded soil data were analyzed to examine differences in soil THg and MeHg between the fallow and growing seasons. Water data were analyzed to compare seasons, hydrologic management regimes (flood, maintenance flow, drain), and sampling locations (inlet, in-field, outlet). To account for potential autocorrelation of repeated sampling, data were analyzed using linear mixed effects regression modeling where 'field' was included in the model as a random intercept. To compute relevant comparisons within each model, orthogonal contrasts were used. To compare mercury pools, paired t-tests were used.

Statistical analyses were conducted using R Studio (version 2022.7.1.554; R Studio Team, 2022). Tests with $p < 0.05$ were considered significant. Model assumptions of normalcy and homogeneity of variance were checked using standard diagnostic plots and, where appropriate, natural log transformations of response variables were used. R packages 'lme4' (Bates et al., 2015), 'lmerTest' (Kuznetsova et al., 2017), and 'effects' (Fox & Weisberg, 2018) were used to fit and test linear mixed effects regressions and to calculate model parameters. R packages 'emmeans' (Searle et al., 2022) was used to compute orthogonal contrasts using model means. R package 'stats' (R Core Team, 2019) was used for paired t-tests.

During both seasons, $MeHg_f$, $MeHg_w$, THg_f, and THg_w, % MeHg, and TSS were similar between in-field and outlet samples (Table S3); therefore, in-field and outlet samples were grouped into a new category called 'field-water' for analysis.

Pearson correlation analysis was used to determine the relationships among grain, soil, inlet water and in-field water THg and MeHg (seasonal average) using R libraries corrplot (Wei and Simko, 2021) and caret (Kuhn, 2022). To directly compare water and grain mercury concentrations within fields, “in-field” water mercury rather than “field-water mercury” was used for the correlation analysis.

RESULTS

Surface Water Mercury

Inlet THg_f and THg_w were similar between seasons, averaging 0.40 and 1.39 ng L^{-1}, respectively (Figure 2). During the fallow season, mean field-water THg_f and THg_w were higher than inlet concentrations and were 3- and 8-fold higher, respectively, than during the growing season. During the flood period (Figure 3) and fallow season (Figure S1), field-water THg_f was 4-fold and 7-fold higher, respectively, than its respective inlet samples.

Mean inlet $MeHg_f$ and $MeHg_w$ were similar between seasons (Figure 2). However, during the growing season, inlet $MeHg_f$ and $\%MeHg_f$ were 1.67 and 2.40-fold higher, respectively, during maintenance flow than flood periods (Figure 3). Field-water $MeHg_f$ and $MeHg_w$ were 6- and 7-fold higher in the fallow season than in the growing season, respectively.

Overall, in-field water mercury was more highly correlated with inlet mercury than soil mercury (Table 1) in both seasons. Furthermore, grain mercury fractions were also more strongly correlated with in-field water $MeHg_w$ than soil mercury.

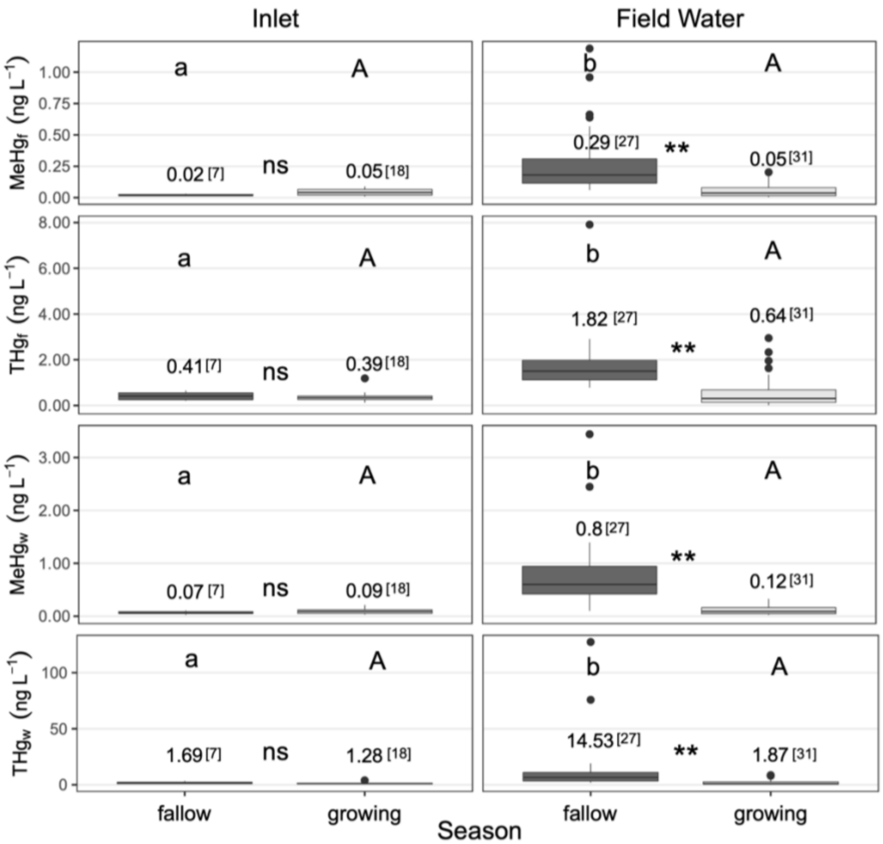

Figure 2. Seasonal average water Hg concentrations of rice field inlets (left) and field water (right; average of in-field and outlet samples) for the following: $MeHg_f$, THg_f, $MeHg_w$, and THg_w. Different letters above each box denote a significant difference ($p < 0.05$) between sites during each season (lower case letters are used for comparison of fallow season sites, and upper-case letters for the growing season). Asterisks denote significant differences across seasons at each site (* indicates $p < 0.1$, ** indicates $p < 0.05$). Middle lines indicate median values, lower and upper hinges correspond to first and third quartiles, the whiskers extend no further than 1.5 times the interquartile range, and dots are outliers. Mean values and number of observations, in brackets, are reported above each box.

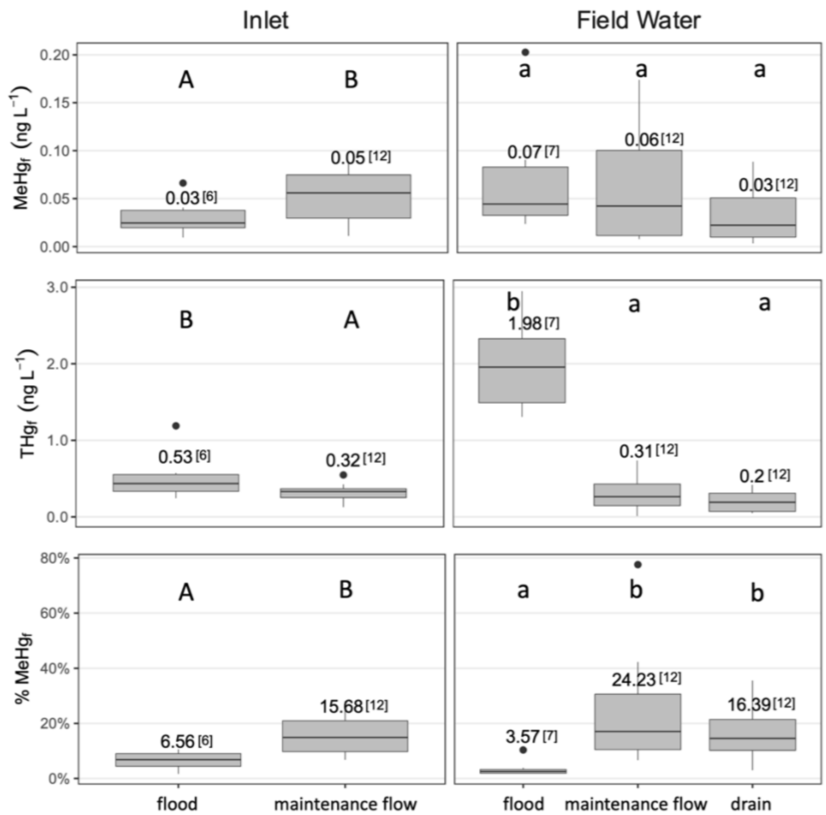

Figure 3. Inlet (left) and field water (right; average of in-field and outlet samples) $MeHg_f$ and THg_f concentrations and % $MeHg_f$ (top to bottom) throughout the 2018 growing season, from flood to drain periods. Different letters indicate significant differences ($p < 0.05$) between management periods at each sampling location, uppercase letters are used for inlets, lower cases for field water. Average growing season inlet and field-water concentrations were not significantly different from each other. Middle lines indicate median values, lower and upper hinges correspond to first and third quartiles, the whiskers extend no further than 1.5 times the interquartile range, and dots are outliers. Mean values and number of observations, in brackets, are reported above each box.

Inlet EC ranged from 2.0 to 430 µS cm^{-1} during the fallow season, and from 3.4 to 760 µS cm^{-1} during the growing season (Figure S2). Fields 1, 2, and 3 had elevated inlet EC (over 190 µS cm^{-1}) before and during maintenance flow, indicating the use of recycled water (Marcos et al., 2018; discussion with irrigation managers). Growing season inlet EC was positively correlated with inlet $MeHg_f$ and $MeHg_w$ (Table S4). Mean inlet $MeHg_w$ was highest during maintenance flows (Figure S3).

TSS was positively correlated with $MeHg_p$ and THg_p in both seasons (Figure 4). The relationship was strongest between TSS and THg_p during the fallow season. Mean TSS was an order of magnitude higher during the fallow season than during the growing season.

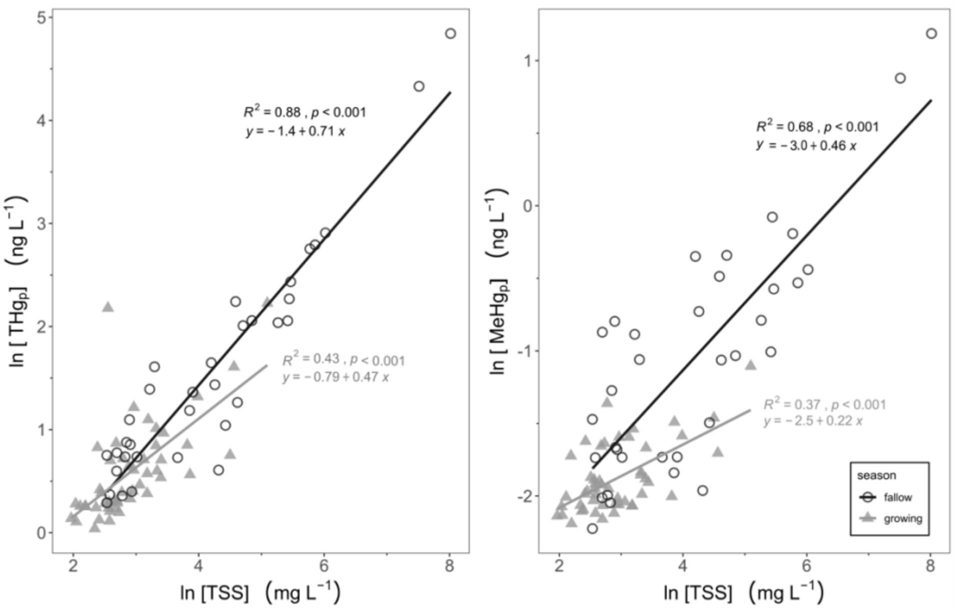

Figure 4. Natural logarithm (ln) transformed TSS and THg_p (left) and $MeHg_p$ (right) concentrations during the fallow (black circles) and growing (grey triangles) seasons for all fields at all sampling locations.

During the fallow season, A_{254} was positively correlated with $MeHg_f$ and THg_f (Figure 5). Field-water A_{254} was about 2.2-fold higher during the fallow season compared to the growing season (Figure S5). Field-water A_{254} was also 7- and 4-fold greater than inlet A_{254} in the fallow and growing seasons, respectively.

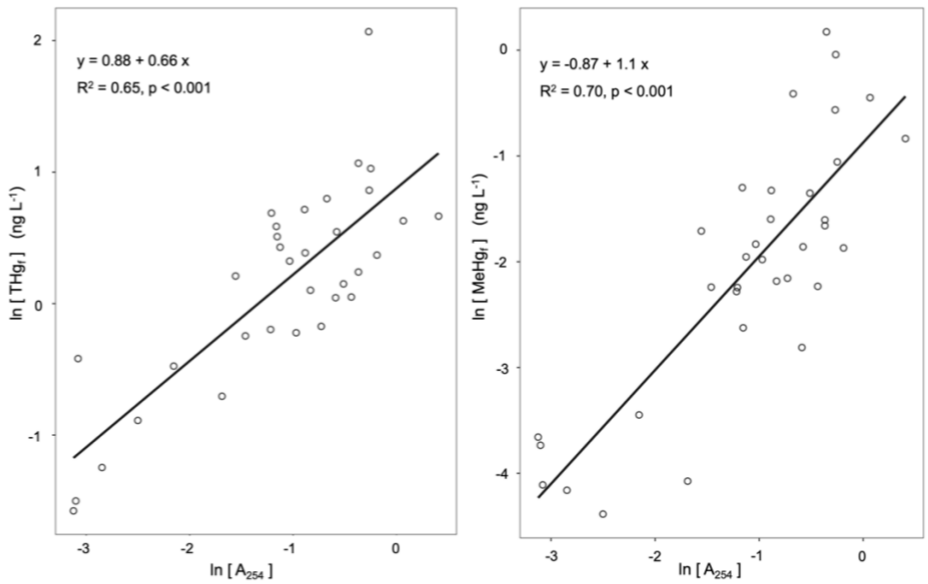

Figure 5. Natural log-transformed absorbance (A_{254}) and THg_f (left) and $MeHg_f$ (right) during the fallow season for all fields at all sampling locations. Tukey t-test results between A_{254} and THg_f and $MeHg_f$ during the growing season were not statistically significant ($p = 0.25$ and 0.21 and $R^2 = 0.028$ and 0.033 for THg_f and $MeHg_f$, respectively), and were not included in this figure.

Inlet Kd was similar across seasons (Figure S6). Field-water Kd_{MeHg} and Kd_{THg} values were significantly lower in the fallow season than in the growing season, indicating relatively more MeHg and THg in the dissolved than in the particulate phase. In the fallow season, Kd_{MeHg} and Kd_{THg} were negatively correlated with A_{254} (Figure S7).

Mercury Pools and Fluxes

Surface Water Mercury Loads

Irrigation imports of $MeHg_w$ and THg_w were 5- and 2-fold greater, respectively, in the growing season than in the fallow season (Table 1). However, drainage exports of $MeHg_w$ and THg_w were 10-fold greater in the fallow season than in the growing season. In the fallow season, all fields acted as THg_w and $MeHg_w$ sources (Table S5). In the growing season, all fields acted as $MeHg_w$ sinks, but were variable with respect to THg_w . Annually, all fields were sources of THg_w, and five of the six fields were sources of $MeHg_w$.

Table 1. Pearson correlation coefficients of field averages for 2018 growing season grain vs. soil and grain vs. in-field water samples; 2017-18 fallow in-field water vs. soil, and in-field water vs. inlet water; 2018 growing season in-field water vs soil, and in-field water vs inlet water samples. The $_f$ and $_w$ subscripts refer to filtered and whole water samples, respectively. Only correlations with $p < 0.05$ are shown (ns = not significant). Coefficient values greater than 0.90 are significant at $p < 0.01$.

	------ Soil -------		-------------- In-field Water --------------			
Grain:	*MeHg*	*THg*	*MeHg$_w$*	*MeHg$_f$*	*THg$_w$*	*THg$_f$*
MeHg	ns	ns	0.86	ns	ns	ns
THg	ns	0.86	0.82	ns	ns	ns

	------ Soil -------		-------------- Inlet Water --------------			
Fallow season in-field water:	*MeHg*	*THg*	*MeHg$_w$*	*MeHg$_f$*	*THg$_w$*	*THg$_f$*
MeHg$_w$	0.91	ns	0.95	ns	0.98	0.82
MeHg$_f$	ns	ns	ns	ns	ns	ns
THg$_w$	0.95	ns	ns	0.82	0.82	ns
THg$_f$	0.86	ns	0.91	0.84	0.92	ns

	------ Soil -------		-------------- Inlet Water --------------			
Growing season in-field water:	*MeHg*	*THg*	*MeHg$_w$*	*MeHg$_f$*	*THg$_w$*	*THg$_f$*
MeHg$_w$	ns	ns	0.96	ns	0.84	0.94
MeHg$_f$	ns	ns	0.92	ns	ns	0.98
THg$_w$	0.94	0.84	ns	ns	ns	ns
THg$_f$	ns	ns	ns	ns	0.83	ns

Rice Grain Mercury

MeHg in rough rice grain ranged from 0.24 to 0.91 ng g^{-1} while THg ranged from 0.90 to 1.66 ng g^{-1} (Table S7. Rice grain harvest resulted in the removal of 750 ng MeHg m^{-2} and 1600 ng THg m^{-2} (Table 2). THg removed in harvested grain was comparable to THg in drain period exports (Tables 2 and 3). However, MeHg removed in harvested grain was 19-fold greater than growing season $MeHg_w$ exports ($P = 0.02$), and about 2-fold greater than gross annual drainage exports of $MeHg_w$ ($p = 0.02$).

Table 2: Area normalized $MeHg_w$ and THg_w (mean ± standard error) seasonal and annual loads across fields (annual $MeHg_w$ and THg_w loads are the sum of growing and fallow seasons).

Surface Water	Parameter	$MeHg_w$ ($ng\ m^{-2}$)	THg_w ($ng\ m^{-2}$)
Fallow Season:	Irrigation imports	22.7 ± 13.0	614 ± 493
	Drainage exports	303 ± 274	6,150 ± 8,730
	Exports – imports	280 ± 266	5,540 ± 8,630
Growing Season:	Irrigation imports	120 ± 114	1,420 ± 1,740
	Drainage exports	39.1 ± 52.0	765 ± 833
	Exports - imports	-83.6 ± 105	-652 ± 1,590
Annual:	Irrigation imports	145 ± 123	2,030 ± 2,160
	Drainage exports	342 ± 305	6,920 ± 9,480
	Exports – imports	197 ± 245	4,890 ± 8,300

Table 3. Average grain (2018 growing season) and soil (0-5cm) MeHg and THg (fallow and growing season) area normalized mass.

	MeHg	THg
Grain ($ng\ m^{-2}$)	750 ± 550	1,660 ± 600
Soil: fallow season ($mg\ m^{-2}$)	0.039 ± 0.023	2.94 ± 0.904
Soil: growing season ($mg\ m^{-2}$)	0.027 ± 0.013	3.07 ± 0.835

Soil Mercury

Flooded soil THg and MeHg ranged from 20.7 to 55.7 ng g^{-1} and 0.07 to 1.1 ng g^{-1}, respectively (Table S7). Mean soil MeHg was 1.5-fold higher in the fallow season than in the growing season, while soil THg was similar in both seasons (Table 3). Mean surface soil %MeHg increased from 0.82% in the fallow season to 1.30% in the growing season.

Area-normalized THg pools (top 5 cm) ranged from 1.67 mg m^{-2} to 4.16 mg m^{-2} across all fields, with no significant differences between seasons (Table S6). Mean MeHg pools were 0.027 mg m^{-2} during the growing season and 0.039 mg m^{-2} during the fallow season (Table 3), a 1.5-fold increase from the growing to the fallow season. Mean MeHg in the fallow season was 110-fold greater than gross annual $MeHg_w$ drainage exports, while mean THg in the fallow season was 420-fold greater than gross annual THg_w drainage exports (Tables 2 and 3).

DISCUSSION

Surface Water Mercury Concentrations Were Highest in the Fallow Season

For field-water, all four mercury fractions were significantly higher in the fallow season than in the growing season (Figure 2), confirming results from previous studies in the Delta and Sacramento Valley (Alpers et al., 2014; Tanner et al., 2017, 2018). Reasons for this include, first, growing season plant transpiration drives dissolved surface water THg and MeHg into the sub-surface where it is taken up by plants or accumulates in the soil (Bachand et al. 2014)while fallow season t transpiration and diffusion of mercury from the soil into water ceases (Rudd et al., 1983; Bachand et al., 2014).

Second, soil MeHg (Table 3) and TSS were higher (Figure 4) in the fallow season than in the growing season. Particulate mercury fractions (THg_p and $MeHg_p$) were positively correlated with TSS (Figure 4). In the fallow season, high TSS caused by wind-driven turbulence across open water likewise suspended mercury exported during drainage.

Third, in-field decomposition of rice straw and production of organic compounds contribute to field-water mercury dynamics. Windham-Myers et al. (2014a) showed that over 86% of the rice straw mercury was released after 28-days in laboratory incubations. Furthermore, field-water A_{254} was elevated compared to inlets in both seasons (Figure S6), but 2-fold higher in the fallow season (Figure 5). Higher A_{254} suggests more in-field production of organic compounds (Krupa et al., 2012) which tend to bind mercury (Weishaar et al., 2003). Filtered mercury was positively correlated with A_{254} during the fallow season but not the growing season (Figure 5). Furthermore, low field-water Kd during the fallow season (Figure S6) indicates that mercury fractions were partitioned more in the dissolved phase. The negative correlation between Kd and

A_{254} (Figure S7) supports previous findings that dissolved aromatic organic structures affect Hg partitioning between the dissolved and particulate phases (Babiarz et al., 1998; Dittman et al., 2009, 2010). Greater concentrations of organic compounds and filtered mercury during the fallow season are likely due to decomposing rice straw in fallow rice fields, decreased photodegradation of DOM, and diffusion of DOM from soil (Ruark et al. 2010; Katoh et al. 2005; Whindam-Myers et al., 2014; Bachand et al., 2014a,b).

Irrigation Source Water Mercury Affects In-Field Water and Grain Mercury

In-field MeHg presents a health risk to organisms that inhabit rice fields (Elphick, 2000; Henery et al., 2010; Holmes et al., 2021), and downstream ecosystems (Alpers et al., 2016; Rudd, 1995). In-field water mercury in both seasons was more strongly correlated with inlet irrigation water mercury than with soil mercury, and these relationships were positive (Table 1). In contrast, studies in the Delta, with higher background soil mercury concentrations, found that irrigation and in-field MeHg were inversely related (Alpers et al., 2014; Bachand et al., 2014ab). They hypothesized that irrigation water, already high in MeHg, reduced the diffusion rate of MeHg from the soil, contributing to the loss of MeHg from the water column via particle settling, advection into the soil via transpiration, MeHg photodegradation, and microbial degradation of MeHg. Our findings, suggest two alternative hypotheses: (1) irrigation water MeHg concentration may directly influence in-field MeHg concentrations; and (2) recycled irrigation water had higher DOC (fields using recycled irrigation water had 1.9-fold higher inlet A_{254}; $P = 0.01$) which facilitates the flux of THg and MeHg from the soil to the in-field water (Bachand et al., 2014).

Mercury in rice grain is also a human health concern, and grain mercury concentrations have been shown to be correlated with soil mercury concentrations (Horvat et al., 2003; Zhang et al., 2010). While they were correlated in this study, grain mercury concentrations were also correlated with in-field water $MeHg_w$ (Table 1). This may be due to the relatively low background soil mercury concentrations in our study.

The main driver of variation in inlet water MeHg concentration in our study was the use of recycled irrigation water, primarily during maintenance periods (Figure 3; Table S4). Fields with elevated inlet EC (indicating recycled water use), had higher inlet MeHg and in-field MeHg. Recycling irrigation water is more common during drought years. With more droughts being forecasted (Mann & Gleick, 2015), increased use of recycled irrigation water is likely to increase MeHg in this system.

System Mercury Pools

The level of mercury in rice grain was among the lowest published values (Rothenberg et al., 2014). Rice grain MeHg concentrations (Table S7) were comparable to those reported by Tanner et al. (2018) for the Sacramento Valley (0.16 to 0.70 ng g^{-1}) but lower than reported for the Delta (4.2 ± 0.6 ng g^{-1}) (Windham-Myers et al., 2014b) or in China near gold mines (> 100 ng g^{-1}) (Qiu et al., 2008).

Plant mercury also represents a significant pool in the system. MeHg in rice grain was double surface water annual $MeHg_w$ exports (Table 2,3). While rice straw mercury was not determined, Tanner et al., (2018) found that rice straw had 62% lower MeHg, but 5- to 8-fold higher THg than grain. Assuming similar values for this study, straw THg and MeHg masses were comparable to the annual drainage exports (Table 2).

Soil THg concentrations (Table S7) were similar to those reported by Tanner et al. (2018), and background soils elsewhere in the US (Obrist et al., 2016) and China (Rothenberg et al., 2014). However, soil THg concentrations were 6- to 15-fold lower than rice fields in the Delta (Marvin-DiPasquale et al., 2014) and orders of magnitude lower than rice growing areas near mercury mines in China (up to 49,000 ng g^{-1}) (Rothenberg et al., 2012).

Surface soils were the largest pool of mercury, consistent with Tanner et al (2018). Soil MeHg pools were 110-fold greater than annual $MeHg_w$ drainage exports and 50-fold greater than grain MeHg pools (Tables 2 & 3).

Fields Are Sources Of Mercury in Fallow Season and Sinks During Growing season

Seasonal mercury surface water loads this study (Table 2) confirm previous findings (Bachand et al., 2014; Tanner et al., 2018) that rice fields are net exporters of mercury during the fallow season and sinks during the growing season. Fields were net sources of mercury during the fallow season because of the combined factors of higher field-water concentrations and more drainage than during the growing season. On an annual basis, rice fields were sources of mercury, although there was variability among fields (Table S5). Similarly, previous studies have reported that some fields were MeHg sinks (Eagles-Smith et al., 2014; Tanner et al., 2018) and others were sources (Bachand et al., 2014; Tanner et al., 2018). These data suggest that rice fields in this region are not likely to become contaminated by accumulating mercury. Efforts to reduce mercury loads from rice fields should focus on the winter flood period.

CONCLUSIONS

Our study is the first to examine mercury dynamics in rice fields across in the Sacramento Valley. We found that rice fields in this region have relatively low soil and grain mercury; and that they are sources of mercury during the fallow season and sinks during the growing season. This finding confirms previous studies and highlights the importance of managing fallow season conditions to reduce the impact of rice systems on downstream ecosystems. Filtered and particulate mercury and their correlations with TSS and A_{254} indicate that wind disturbance and rice straw both contribute to higher mercury in the water column during the fallow season. Finally, irrigation water (specifically recycled irrigation water) drives in-field mercury dynamics and the uptake of mercury by rice.

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Chapter 2

A Geospatial Assessment of Soil Properties to Identify the Potential for Crop Rotation in

1. Introduction

Increased crop rotation is being explored as one potential solution to global challenges in agricultural sustainability (Altieri et al., 2015; Cabell and Oelofse, 2012). Rice (*Oryza sativa* L.), the main staple food for nearly half the world's population, (Awika, 2011; F.A.O., 2019; Yuan et al., 2021) is often grown in continuous cropping systems supporting one to three rice crops per year. Continuous flooded rice production can maintain high productivity due to biological and chemical soil processes unique to flooded agricultural soils (Pampolino et al., 2008; Cassman and Pingali, 1995; Waha et al., 2020; Bronson et al., 1998). However, there are agricultural sustainability challenges for modern continuous rice systems. To support these challenges, diversifying rice-based cropping systems with non-flooded crops is being explored in different contexts (Baste et al., 2021; Cassman and Grassini, 2020; Horton et al., 2021).

In California, rice production is concentrated in the Sacramento Valley, where it is grown on approximately 210,000 ha (*USDA - NASS, 2021*). California is the second largest rice growing state in the US, with some of the highest rice yields in the world (Hill et al., 2006). However, the long-term viability of the California rice industry is threatened by a number of challenges including increasing weed pressure and water scarcity (Hanson et al., 2014; Gebremichael et al., 2021). California rice has the highest number of herbicide resistant weed species of any other crop or region in the U.S. (Hanson et al., 2014). Also, populations of new weed species, such as weedy rice (also known as red rice), are evolving a suite of phenotypic traits that closely resemble cultivated rice, making them particularly difficult to manage (De Leon et al., 2019). Droughts across the Western US have led to severe water shortages, including water restrictions for growers (Hanak et al., 2019; Gebremichael et al., 2021). Gebremichael et al. (2021) found that fallow land across California's Central Valley tripled during drought years due to water use restrictions. In four of the last 10 years, during periods of severe drought, rice acreage declined leading to widespread fallowing throughout the rice growing region (USDA - NASS, 2021). Drought conditions are expected to increase in frequency and severity due to climate change (Cayan et al., 2010), and alternative cropping system strategies are needed to maintain agricultural sustainability.

Diversifying the number of crops grown in the region could be an important component of integrated weed management strategies and has potential benefits for water conservation. Rotations can be part of integrated weed management strategies by allowing for the use of different modes of herbicide action, and cultivation techniques and irrigation systems that are different from those used in typical continuous rice systems and can target different weed species including pervasive aquatic weeds (Kayeke et al., 2017; Beckie et al., 2004; Brim-DeForest et al., 2017). Rice is one of the most water intensive California crops, behind almonds, pistachios, and alfalfa (Cody and Johnson, 2015; Josué Medellín-Azuara et al., 2015). Common alternative irrigated summer annual crops in the region such as processing tomatoes, dry beans, and safflower use 36%, 9.2%, and 3.4% the water that rice uses annually (Cody and Johnson, 2015).

Rotating continuous rice with less water intensive annual crops could help maintain agricultural productivity while meeting water use restrictions.

Despite the potential benefits of crop rotation for weed management and water conservation in rice systems, soil constraints may be a major limitation. Large portions of the Sacramento Valley are reclaimed wetlands that have soil properties that are suitable to flooded rice production but make crop rotation difficult (Hill et al., 2006). Previous studies have reported that more than half of the rice growing region is considered ‘rice only’, where production of other summer or winter crops is, due to properties of the soil, expected to fail due to poor yield and high input costs (Carter et al., 1994; Hill et al., 2006). The remaining half of the region has been described as having limited rotation capability. Soil features such as floodplains, heavy clays, salinity and/or alkalinity, and cemented subsurface layers are widespread in the region and are perceived as major limitations to rotation (LaHue and Linquist, 2021; Rosenberg et al., 2022; Hill et al., 2006). Some rice growers are successfully rotating rice with summer irrigated crops (tomatoes, corn, safflower, and dry beans), vetch and wheat as a winter annual crop, alfalfa, and other forages (Rosenberg et al., 2022), with most rotation occurring in a limited portion the Southern Sacramento Valley (Rosenberg et al., 2022; Carter et al., 1994). However, these evaluations of soil properties were not based on digital USDA-NRCS Soil Survey Maps, which offer the most detailed soil map data for the US (Soil Survey Staff, 2014), and the relative amount of rice area under some form of rotation is poorly quantified. Thus, there is an opportunity to explore the feasibility of rotations based on soil limitations using soil survey maps to determine the relationship between crop rotation decisions and soil properties.

Machine learning methods are one potential approach for assessing the role of soil properties on future land use scenarios to improve natural resource management. Machine learnings models can be used to efficiently examine relationships between multiple, interacting soil parameters and their influence on different land use categories at large spatial scales. For example, these approaches have been used to predict crop rotation in the US Midwest (Socolar et al., 2020), to assess the potential for dryland agriculture in the High Plains region, USA (Deines et al., 2020), to identify floodplains at high resolution across the continental US (Woznicki et al., 2020), to simulate the conversion of grasslands to grain in the great plains (Olimb and Robinson, 2019), and to predict future cropland expansion (Rashford et al., 2013). These studies illustrate the novel insights that can be gained by integrating land use maps with underlying soil properties in a machine learning framework.

The overall goal of this study was to explore the potential for agroecological diversification of rice-based cropping systems based on a geospatial assessment of soil limitations. The method presented here uses land cover data, SSURGO soil data, and a spatial random forest model to identify key soil properties associated with continuous rice fields and rotated rice fields. The specific objectives were to: 1) quantify the total rice area under crop rotation and continuous rice; 2) evaluate differences in soil properties between rotated and continuous rice fields; and 3) estimate the potential continuous rice area that could support a high likelihood of rotations based on the most influential soil variables identified in random forest models. Results will help inform the feasibility of crop rotations as a tool for enhancing the long-term sustainability of California rice systems.

2. Materials and Methods

2.1 Data sources and processing

2.1.1 Land use Data

Land use maps for the Sacramento Valley were built by integrating the Crop Land Data Layer (CDL) with field boundary data provided by the California Department of Water Resources (DWR). The CDL is a high resolution (30 m) national land cover data set that provides crop-level information on a yearly basis. The CDL is generated from Landsat satellite missions and developed by the United States Department of Agriculture/ National Agricultural Statistics Service (USDA/NASS) CropScape project (*NASS CDL, 2021*). The CDL includes up to 141 land use classes, 117 of which are agricultural. In California, the CDL is currently available from 2007 to 2021, and all years were used in this analysis.

While the CDL is considered the best available crop and land cover information over the United States (National Research Council, 2013), it is still prone to uncertainties that result from land cover classification using satellite remote sensing data. To reduce these errors and improve overall accuracy, the CDL was integrated with a high accuracy land cover and field boundary data set provided by DWR (Lark et al., 2017; Verbeng et al., 2011; Seo et al., 2014). The field boundary data set is prepared by LandIQ, a private mapping company based in Sacramento CA, and provided to the California DWR Regional Office Land Use office (DWR, 2016). The integration approach is as follows. Pixels, or portions of pixels, outside of field boundaries were excluded, managing errors where fields do not align with pixels, and where edge effects can influence acreage estimates (Lark et al., 2017). Within the field boundary, each field was reclassified as the dominant pixel type, mitigating errors where, for example, a few incorrect pixels are scattered across a rice field. Acreage estimates and change detection were performed on this reclassified, field level data set.

After reclassifying all fields within the Sacramento Valley region, we limited the analysis to the rice growing area by selecting all the fields where the dominant class was rice in at least one year of the 15-year data set. In total there were 13,120 fields covering 268,950 hectares. This region has a high diversity of annual and perennial crop types. To simplify our analysis and to increase accuracy (Lark et al., 2017), we grouped CDL crop classes together into eleven dominant groups. These groups are: rice, fallow, summer annual, winter annual, other annual, alfalfa, grasses, walnut, almond, other perennial, and other (See table S1 for a complete list of the CDL classes in each group). We used this data set to examine land use changes in the region including yearly changes in rice area, the acreage under rotation with rice, and the area that has been converted to perennial tree crops such as almonds and walnuts. To assess the accuracy of our custom data set, we compared our county level rice acreage estimates to NASS data (*USDA NASS, 2021*) for the eight major counties in the rice growing region.

2.1.2 Soil data:

Spatial soil information in this region was obtained from the Soil Survey Geographic Database (SSURGO) developed by NRCS (*NRCS Soils, 2021*). SSURGO data was accessed using the FedData package (Bocinsky, 2019), which downloads federal geospatial data directly from the internet and loads it into RStudio. A range of soil variables important to agricultural production were used in the preliminary data analyses including chemical properties (acidity, salinity, sodium adsorption ratio), physical properties (soil texture, saturated hydraulic conductivity, linear extensibility), and general descriptors of soil type (soil order, soil series, irrigated capability class, or the presence of subsurface layers that are restrictive to root growth).

For all numeric soil variables, a depth weighted average was computed across all horizons in the rooting zone (top 30 cm of the soil profile). In this process, horizons that start below 30cm depth are excluded and the thickness of all remaining horizons is computed. A weighted mean for each numeric soil property was calculated by multiplying the soil property value from each horizon by the thickness of the horizon, summing the value for all horizons present, and dividing by the total depth (30cm). This depth weighted average was then applied across the SSURGO map unit area, and field level averages were computed for each field in the study area. This process was conducted using the sf package in R (Pebesma, 2018). Categorical soil variables, such as soil order or irrigated capability class, have only one value per component and do not require a depth weighted average. For this data, the dominant soil component (largest percent composition within the map unit) was selected, and the location of each field's centroid was used to determine the field level value.

2.2 Modelling Process

2.2.1 Data Preparation:

To compare soil properties of continuous rice fields and rotated rice fields, a binomial classification approach was used. For this approach, two classes were determined from the land cover data set: '*continuous rice'* fields and '*rotated rice*' fields. These two groups had strict criteria: Fields that were in rice at least 12 of the 15-year data set and were fallowed in the alternate years (i.e. never planted in a summer annual, winter annual, alfalfa, or grass) were considered '*continuous rice'* fields; Fields that were in rice at least seven years and were rotated with summer annual crops, winter annual crops, alfalfa, or grasses on at least two separate occasions were considered '*rotated rice'* fields. We used these two categories to make a direct comparison between continuous rice fields and fields that are in rice almost half the time but also rotated with other crops. The core objective was to explore the potential for rotation in fields that are currently continuous rice, thus we set a medium requirement of years in rice for rotated fields rather than including fields that were predominantly other crops or not rotated with rice on two separate occasions. As a result, some rice fields were excluded from the model. Fields that were in rice 9 of the 15 years and other land uses the remaining years were placed into a distinct category called '*rice + other*' (15.8% of total area). This includes fields that transitioned out of rice to urban uses, or fields that were fallowed and/or planted with other crops such as alfalfa or annuals only on a few occasions. Fields that were in annual crops (summer annuals, winter annuals, alfalfa, and grasses) 9 of the 15 years were considered '*annual*' (6.3% of total area). Fields that were frequently fallowed (9 of the 15 years) were considered '*fallow*' (1.3% of total area).

2.2.2 Random Forest:

After randomly splitting the data set into training and validation subsets (75% to train and 25% to validate), a random forest classification model (Breiman, 2001) was trained to create a binary prediction for 'continuous rice' and 'rotated rice' based on soil variables. Random forest is an ensemble learning method that has recently become very popular because it combines the interpretability of decision trees with the performance of modern learning algorithms such as artificial neural networks and SVMs. Random forest models use multiple independently constructed decision trees, each with a unique bootstrap sample of the training data set, thus reducing the variance of single trees and improving prediction accuracy (Liaw and Wiener, 2002; Wiener; Prasad et al. 2006). Furthermore, random forest models are efficient, insensitive to overfitting, and are relatively straight forward to implement (Belgiu and Drăgu, 2016).

2.2.3 Model Assessment:

Following model training, model assessment was performed on our remaining validation data set. The primary objective was to correctly classify rotated fields within the rice area. Therefore, we examined classification accuracy using precision (P), recall (R), and F1 score of rotated fields. Precision is how often the classified product (rotated fields) is correct when compared to the source data set (Eq. (1)). Recall, also known as the hit rate, is how often the source dataset is correctly classified by the model (Eq. (2)). F1 measures classification accuracy of rotated fields by combining precision and recall using their harmonic mean (Eq. (3)).

$$P = \frac{T_P}{T_P + F_P} \quad (1)$$

$$R = \frac{T_P}{T_P + F_N} \quad (2)$$

$$F1 = 2\,\frac{P\,x\,R}{P + R} \quad (3)$$

Where T_p is the number of true positives (number of pixels correctly classified as rotated fields), F_p is the number of false positives (number of pixels incorrectly classified as rotated fields), and F_N is the number of false negatives (number of pixels incorrectly classified as continuous rice fields). In our modelling process, the F1 score was used as the primary measure for model evaluation because it balances precision and recall.

2.2.4 Model set up

In spatial data, observations that are relatively close tend to be more related to each other, which means that training and validation data sets are rarely independent, violating an important prerequisite of model building and leading to highly optimistic evaluations of predictive power (Arlot and Celisse, 2010; Ploton et al., 2020). Factors other than soil properties can influence the spatial distribution of crop rotation across a landscape, such as market distance, access to equipment, or economic factors. (Socolar et al., 2020; Rosenberg et al., 2022). One method to deal with spatial heterogeneity in is spatial cross validation. Spatially cross validated models of ecological data can have better performance at predicting error estimates and predicting to new data or predictor space, as well as for selecting causal predictors (Roberts et al., 2006). We used R's 'spatialsample' package (Silge, 2021), to implement spatial cross validation. In summary, our training data was split into ten cross validation groups using k-means clustering of the field's spatial coordinates.

Next, model hyperparameters were defined and tuned. Because the model was assessed primarily with F1, these combinations of hyperparameter values were optimized for F1. F1 was static after a minimum of 150 trees, so 150 trees were used to ensure adequate trees for all models. To define the number of variables randomly selected as candidates at each split (*mtries),* and the minimum number of data points in a node that is required for the node to be split further (*min_n)*, a hyperparameter grid search was performed with values from one to six and 20 to 40, respectively. *Mtries* = 3 and *min_n* = 31 were selected based on the highest F1 score.

Sampling strategy is another model parameter that can require careful calibration, especially when there is substantial class imbalance (Woznicki et al., 2019). In our binomial data set, continuous rice fields were 16-times more prevalent than rotated rice fields. Sampling strategies that adjust the prevalence of either class in the training data can affect precision and recall rates (Chen et al., 2004; Woznicki et al., 2019). Thus, we also optimized for F1 in our model tuning process. The minority class was up sampled randomly and at 10%, 20%, and 50% sampling ratios. The strategy using a 20% sampling ratio had the highest F1 score, so this strategy was used in the final model deployment. Woznicki et al. (2019) used this sampling strategy and similarly found that a 20% sampling regime was optimal because of its higher recall.

2.2.5 Variable Importance

An important task in machine learning interpretation is to understand which predictor variables have the strongest influence on the predicted outcome. To accomplish this, a ranked order of variable importance in the classification model was determined using the permutation method based on AUC. In this method, AUC is computed for each tree after permuting each predictor variable (Greenwell et al. 2018). This method is considered more robust towards instances of class imbalance (Janitza et al. 2013). Variable importance was computed in R's 'vip' package (Greenwell et al. 2020).

To improve interpretability, we pruned our set of predictor variables to reduce model complexity without compromising accuracy. Redundant soil variables were removed if they were highly correlated ($r > 0.8$). Moreover, if model predictions for a variable did not show clear patterns in partial dependence plots (explained below) and omission of this variable in the model did not affect F1 scores when evaluated on the validation data set, variables were removed. This included linear extensibility (%), cation exchange capacity (CEC), drainage class, the presence of a cemented layer, and the soil series name. The remaining set of soil variables used in the modeling process were pH, electrical conductivity (EC), sodium adsorption ratio (SAR), saturated hydraulic conductivity (Ksat), taxonomic soil order (soil order), and irrigated capability class (ICC) (see Table 1 for a complete description of these soil variables).

Throughout our model tuning process, variable importance scores were often tied or closely ranked. To establish a clear order of variable importance, the variable importance computation was executed 200 times across the training data, and the variables were ranked based on their mean effect on the AUC score.

2.2.6 Model Application

Once a subset of the important features was identified, expected target responses were computed while accounting for the average effect of the other predictors in the model. This produces a partial dependence plot (PDP), which is a method of visualizing the effect of each soil variable on the model outcome (yhat) (Hastie et al., 2009). PDPs were built in R's 'DALEXtra' package (Maksymium et al., 2020). PDPs were built for the three most important soil variables from the variable importance plot.

Another primary objective was to estimate the area of continuous rice fields that have the soil features of a rotated rice field based on the three most important soil variables determined by the model. Rather than examining F_p, which can be heavily influenced by sampling schemes (i.e. up sampling or down sampling) (Woznicki et al. 2020), we developed a 'manual approach' using partial dependence data to determine thresholds, i.e. ranges for each of the three important soil variables supporting a higher likelihood of rotation. All continuous rice fields were then examined to determine how many of them met each of these three soil criteria, both individually and combined. For all the fields in each group, we computed the acreage (sum), and median predicted probability that the field is rotated (denoted as $yhat_m$ and shown as a percentage). This manual method allowed us to investigate how soil properties may act as a barrier to crop rotations and to quantify the acreage of continuous rice fields that have some of the properties of a rotated field.

3. Results and Discussion

3.1 Continuous Rice and Rotated Rice

According to our analysis, annual rice production area ranged from 227,000 to 161,000 ha, which is consistent with USDA reported acreage, and represents approximately 95% of California's rice growing area (*USDA -NASS, 2021)*. Across the eight major counties in the growing area, agreement between our data set and USDA NASS acreage was strong ($R^2 = 0.992$) and fell along the 1:1 line (Figure 1).

58% of the study area was in continuous rice production (Figure 2, Table 2). Rotation with rice occurred more in the southern portion of the Sacramento Valley (Colusa, Sutter, and Yolo counties), which is consistent with previous studies(Rosenberg et al. 2022; Carter et al., 1994). While the area under rotation area was considerably smaller than the area under continuous rice, there was high diversity of rotation schemes. Most fields under rotation transitioned from rice to another crop on two to three occasions. A small number of fields in the study area transitioned out of rice up to seven times during the 15-year study period, meaning these fields were planted back to rice every other year. According to our definition of continuous rice and rotated rice, which we used for binomial classification (Table 2), there were 155,640 ha in continuous rice (7,550 fields) and 16,650 ha of rotated rice (470 fields) (Table 2). The other dominant field types in the region are 'rice + other' and 'annuals', which occupy 15.8% and 6.3% of the study area, respectively. Continuous rice production is common due to high prices for rice, consistent high yield, high efficiency of the production system (Hill et al., 2006), as well as farmer experiences or perceptions that these fields are not suitable for rotated crops (Carter et al., 1994; Rosenberg et al., 2021).

Approximately 3,000 to 8,000 ha were exchanged annually between rice and other crops including summer annuals, winter annuals, alfalfa, and grasses (Figure 3). This exchange is dominated by summer annuals and winter annuals, on average 3,030 ha and 2,430 ha are exchanged between rice and summer annuals and rice and winter annuals each year, respectively. A smaller portion are rotated with grasses and alfalfa. The area in rotation also decreased throughout the study period ('08-'21) from roughly 8,000 ha to 4,000 ha. This decrease is likely because of specialization of agricultural operations. Interviews with rice farmers suggest that farmers that used to rotate have stopped due to market changes and labor and equipment requirements for alternative crops (Rosenberg et al., 2022). Furthermore, efficient irrigation methods such as subsurface drip are becoming increasingly widespread in non-flooded agricultural systems in the region due to political and economic motivations to maintain or improve production while using less water (Sandoval-Solis et al., 2013). Processing tomatoes, for example, have seen greater than 70% conversion to subsurface drip irrigation due to increased water savings (Ayars et al., 2015). These are semi-permanent crop specific systems that make it difficult to rotate with crops using different spacing or irrigation strategies, such as flooded rice.

Conversion to walnuts and almonds occupied 2.4% and 0.95% of the study area, respectively (Table 2). Conversion to perennial tree crops may be increasing due to increasing walnut and almond crop prices, despite increasing drought conditions (Gebremichael et al., 2021). This represents a shift from annual cropping to a system that is more permanent. Walnut and almond fields have comparable water use to rice (Cody and Johnson, 2015) but they must be watered annually to prevent tree mortality, meaning these fields cannot be fallowed during drought periods without significant economic loss.

3.2 Soil Properties Supporting Crop Rotations

The overall classification accuracy of continuous rice and rotated fields evaluated on the validation data set using random forest models was 93.9%. While our overall accuracy score was high, previous studies have suggested that, when there is class imbalance in the training data, other criteria for model evaluation should also be considered. After hyperparameter tuning and choosing an optimal sampling strategy, an F1 score of 0.62 was possible (precision was 0.52, recall was 0.76) (Table S2). Our F1 score of 0.62 suggests that the model performed well at binomial classification given the severity of class imbalance in the training data. A recall score of 0.76 suggests the model correctly classified 76% of the rotated rice area. This performance indicates that soil properties are a good predictor of crop rotation in the region, but that there may also be other important considerations not observed in this model, such as the economic, cultural, or logistical factors described by Rosenberg et al. (2022). Overall, this performance is consistent with other large-scale land cover modeling efforts using soil predictor variables (Woznicki et al., 2020; Olimb and Robinson, 2020; Sangwan and Merwade, 2015; Wing et al., 2017).

Another objective was to assess the relative importance of soil variables in predicting rotated fields in the rice growing area. Figure 4 shows variable importance plots based on the mean decrease in AUC when each variable is permuted (Greenwell et al. 2018). The red dots show the variable importance score of the initial model execution. EC and Ksat had very similar variable importance scores, so we repeated the model execution 200 times and computed variable importance for each. The box and whisker plot shows the median and interquartile range of the 200 variable importance scores from this approach, while the violin plot shows the distribution of VI scores. Of the six soil properties included in our analysis, pH was the most influential, followed by EC and Ksat. The importance of each of these variables is discussed below. Soil order was the least important variable in the model.

While variable importance plots can help rank the influence of different variables, they do not indicate the behavior (i.e. linear, monotonic, or more complex) or direction (i.e. positive or negative) of the interaction between an input feature and the target response (Hastie et al., 2009). To understand how the three most important variables (pH, EC and Ksat) influenced the likelihood of rotations, we used PDP to predict outcomes across each variable while marginalizing the model output over the distribution of the other features (Figure 5a-c). Including data density curves with each PDP allows us to examine the distribution of values for each soil variable, which aids our interpretation of the PDP.

Soil pH in the study region ranged from five to greater than nine (Figure 5a). The partial dependence data indicates that rotated fields are more likely between 6.5 and 8.0, while fields with pH less than 6.5 or greater than 8.0 are likely to be continuous rice. Annual crops, including rice, have highest productivity in neutral pH ranges (Havlin, 2020). Acidic soils can be managed with limestone, and alkaline soils can be managed with elemental sulfur, but both soil types can be costly and difficult to remediate, particularly alkaline soils (Fernandez and Hoeft, 2021). Soil flooding for rice production, however, results in in the convergence of alkaline or acidic soil pH to neutral, allowing rice growers to maintain high yields without additional inputs (Sahrawat, 2013; Ponnamperuma and Kozlowski, 1984). Furthermore, flooding for rice production improves the availability of nutrients such as ammonium, phosphorous, potassium, and other exchangeable cations, which are mobilized in soil solution (Ponnamperuma 1972; Sahrawat, 2011).

Soil electrical conductivity (EC) is a metric of the salt content (salinity) in the soil, which is both an indicator of mineral nutrients in the soil that can be quickly utilized by plants, and an indicator of salt ions in soil that could limit crop growth (Friedman, 2005). Most of the fields in the study area had relatively low EC (Figure 5b). Fields with EC ranges between 0.5 and 1.5 had a higher likelihood of being rotated, while fields with higher EC were more likely to be in continuous rice. Low EC values could indicate that nutrients needed for plant growth are insufficient (Friedman, 2005), while high salinity has been shown to reduce agricultural productivity by causing reduced water uptake by plants. High salinity can cause reduced osmotic pressure and ion imbalance as plants accumulate salt ions over time (Munns and Tester, 2008). Previous studies have indicated that the salinity threshold for field crops ranges from 1 to 2.5 dS m^{-1} (Ayers and Westcot, 1985; Maas and Grattan, 2015; Grattan et al., 2002; Machado and Serralheiro, 2017). In non-flooded agriculture, salinity can be managed by leaching salts, but in regions where there is also poor drainage this practice often requires installing costly drainage systems (Hanson et al., 2006). In rice production, however, high soil salinity can be managed with flood irrigation. For example, in the growing season, maintaining high water depth and allowing for tailwater drainage early in the season can help manage salinity (Marcos et al., 2018). In the winter season, flooding of rice fields, which is commonly done to decompose rice straw and to promote habitat for waterbirds in this region (Linquist et al., 2006), can lead to diffusion of salts into the water column, where it can potentially be percolated out of the root zone or exported in surface water drainage (Bachand et al., 2014).

Ksat represents how easily water can pass through saturated soil. Fields with low Ksat values will have little water loss to percolation and relatively high-water use efficiency for flooded crops (LaHue and Linquist, 2021). Ksat values in the study ranged from 0 to greater than 50 $\mu m\ s^{-1}$ and most fields in the study area have Ksat values below 15 $\mu m\ s^{-1}$ (Figure 5c). Where Ksat is above 2 $\mu m\ s^{-1}$, fields were increasingly likely to be rotated. Ksat values can vary based on a range of soil and hydrologic factors including soil texture, soil structure, bulk density, field water height, and ground water elevation (Bouman et al., 2007; LaHue and Linquist, 20201). Many fields in the region have low Ksat either because they have very high clay content or because they have a cemented subsurface soil layer. In some parts of Glenn and Colusa counties, clay content was greater than 60%. These clayey soils are used for continuous rice because high clay content can lead to poor tilth, making it difficult to prepare a seed bed, and low water availability and poor aeration in non-flooded soils (Lund 1959). A cemented subsurface soil layer can lead to poor root-ability and poor workability, which is also determinantal to plant growth for non-flooded crops (Dexter, 2004).

While sodium adsorption ratio (SAR) was not one of the three most important variables in the model (Figure 4), some fields in the study area had sodic and saline-sodic soil properties, which likely limits their suitability for rotation. Sodic soils have high pH (> 8.5) and are also high in exchangeable sodium (Na^+) (>15%) (Sumner, 1993). Saline-sodic soils have both high salinity and high Na^+. Sodium toxicity causes dispersion of soil particles leading to soil degradation and poor tilth, making them detrimental to growth of most plants (Qadir and Oster, 2004). Ameliorating sodic soils requires increasing calcium (Ca^{2+}) to replace Na^+ on the exchange, then leaching with excessive irrigation. This process is difficult, costly, and time consuming, especially in soils with low Ksat limiting drainage capacity (Qadir and Oster, 2004). Water management in rice, however, can help the crop tolerate sodic and saline-sodic soil properties with irrigation techniques such as maintaining flooded conditions and excess drainage (Munns and Tester, 2008).

3.3 Feasibility of Expanding Crop Rotations

We used the partial dependence data to determine ranges of the three soil properties (pH, EC, Ksat) that have a higher likelihood of rotation given historical land use decisions in this region (grey shading in Figure 5a-c). Fields with pH between 6.5 and 8, EC values between 0.5 and 1.5 ds m^{-1}, and Ksat values > 2 µm s^{-1} had a higher likelihood of rotation. Most data lay within these ranges for pH and EC, however most of the fields in our study region have low Ksat (Figure 5a-c).

We examined all the continuous rice fields in our study that meet each of these soil criteria to determine the extent and location of similar soil properties associated with rotations (Table 3). Around 69,000 ha (47%) of the continuous rice region has pH values between 6.5 and 8.0. These fields are mostly in the northern and central portions of the study region (Butte, Glen, and Sutter counties) (Figure 6a). Meanwhile 73,000 ha (50% of the continuous rice fields) had EC values between 0.5 and 1.5 dS m^{-1}. These fields are mostly in the center and west of the region (Sutter and Colusa counties) (Figure 6b). Lastly 55,000 ha (37% of the continuous rice area) had Ksat > 2 μm s^{-1}. These fields are in the east (Yuba and Sutter counties) (Figure 6c). For all the continuous rice fields in each group, we computed the median predicted probability of rotation ($yhat_m$). Continuous rice fields that met the pH criteria had a $yhat_m$ value of 32%, while fields meeting EC and Ksat criteria had a median $yhat_m$ of 28% and 21%, respectively.

Combining these thresholds allowed us to examine how multiple soil factors affect the scope for agroecological diversification in this rice-based system (Table 3). A total of 38,720 ha met the combined pH and EC criteria. This accounts for about 26% of the continuous rice fields, and these fields have a 50.7% median predicted probability of rotation. Only 11% (16,710 ha) of the continuous rice area met all three of the combined criteria. These fields have $yhat_m$ of 54.1%. Most of these fields are nearby and to the east of current rotated rice fields, which are in the southern and central portion of the rice growing region (Sutter, Yolo, and southeastern Colusa Counties; Figure 6d), a region known for having a high diversity of agricultural systems including continuous rice (Carter et al., 1994; Rosenberg et al., 2022). The area that meets all three criteria is approximately 12,000 ha larger than the size of the decrease in rotation area over the past ten years (~4,000 ha) (Figure 3). The remaining area under continuous rice production that does not meet the combined pH and EC criteria (74%), or all three combined criteria (89%)

is 115,170 ha and 138,910 ha, respectively. This finding is comparable to the Carter et al. (1994) report on the Sacramento Valley rice area which stated that "on at least [120,000 ha] … it would be very difficult under any circumstances to produce another crop".

While only 11% of the continuous rice area meets all three criteria, incentivizing rotation in this area could help manage weeds concurrently with reduced water use while maintaining agricultural revenue for farmers. In California, pesticide regulations have limited the number of herbicides available to farmers and have limited how the existing herbicides can be applied, leaving limited options for chemical weed management aside from increasing the number of herbicide applications, which has increased herbicide resistance challenges (Hill et al., 2006; Rosenberg et al., 2022). Crop rotation allows for integrated weed management approaches including aerobic irrigation and cultivation techniques and the use of herbicides with different modes of action, which can support weed control and limit herbicide resistance (Beckie et al., 2004; Kayeke et al., 2017; Vencill et al., 2012).

Currently, due to severe drought conditions in the region, many rice farmers are forced to fallow their fields in water districts with limited access to water rights (Pancorbo et al., 2022; Medellin-Azuara et al., 2022). Fallowing, however, is not an ideal solution to water scarcity as fallow fields inherently do not provide a harvestable cash crop or other ecosystem services such as wildlife habitat, and leaving bare soil causes soil erosion and degradation due to wind and water exposure (Pimentel and Burgess, 2013; Kaspar and Singer, 2015; Wendt et al., 1986). Alternative summer annual crops in the region such as processing tomatoes or dry beans use 30% and 5%, respectively, of the annual water requirements for flooded rice (Cody and Johnson, 2015). Winter annual crops such as wheat, oats, and rye, are predominantly rainfed and require little to no irrigation water unless it is a drought year. As droughts increase in severity (Cayan et al., 2017), rotating rice with less water intensive crops, where possible, could help limit agricultural demand for water across the region while maintaining agricultural productivity.

3.4 Limitations of the study

Agricultural systems are coupled human-natural systems that depend on complex food supply chains and international trade (Liu et al., 2007). There are numerous drivers fueling agricultural decision making including soil type, economic variables, socio-cultural factors, government policy, climate change, and distance to networks and terminal markets for agricultural products (Flora et al., 2019; Rosenberg et al., 2022). This study focuses only on the role of soil properties. To do so, this study utilizes soil survey (SSURGO) information, which is only one of multiple options for investigating soil barriers to rotation. SSURGO information in California offers a comprehensive, detailed spatial assessment of soil variables and is an excellent resource for local and regional land use planning. However, SSURGO has a few key limitations. SSURGO does not always integrate land use information and changes to soil management over time, it has variable spatial detail between soil surveys of different vintage, and there are sometimes artificial discontinuities at political boundaries (Zhu and Woodcock, 2001; Li et al., 2011; Gatzke et al., 2011; Subburayalu et al., 2013; Du et al., 2014; Nauman and Thompson, 2014). Results of our study align with Rosenberg et al. (2022) and other's (Hill et al., 2006; Carter et al., 1994); however, SSURGO data does not replace on-the-ground soil sampling or field-based experiments that test the efficacy of planting row crops in unfavorable soils.

4. Conclusions

This research uses satellite-derived land cover information and soil survey data to examine the feasibility of crop rotation in California's Sacramento Valley, a region with a history of continuous rice production and growing sustainability challenges. Our analysis shows that rotation occurs in a limited portion of the region, and that there is a high diversity of rotation schemes including rotation with summer annuals, winter annuals, alfalfa, and grasses. By comparing the soil properties of continuous rice fields to rotated rice fields using a random forest model, our analysis suggests that chemical and physical soil properties such as alkalinity, salinity, and low saturated hydraulic conductivity are key variables that may limit the potential for crop rotations to be easily implemented in the region. This research highlights the importance of including biophysical considerations such as soil properties into broader efforts to diversify modern agricultural systems. Research and extension efforts to implement crop rotation practice in the region should focus on identifying pathways to overcome soil barriers alongside access to markets and equipment for rotated crops. Field scale experiments may be necessary to better understand potential rotated crops that can tolerate the soil conditions in this region while providing water savings, weed management benefits, and economic value.

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Chapter 3:

Change from Annual to Periannual Crop Systems is Driven by Crop Prices and Limited by Soil Type in California’s Rice Growing Region

1. Introduction

Global agricultural sustainability faces numerous challenges including climate change, biodiversity loss, soil degradation, and water scarcity(Ericksen et al., 2009). These challenges are compounded by increasing demand for agricultural products due to population growth, urbanization, and changing dietary preferences (Steffen et al., 2005). To address these complex challenges, there is need for adaptive land management strategies that promote sustainable agricultural practices while adapting to changing environmental conditions (Liu et al., 2009). To develop informed land management strategies, there is need to better understand the drivers and consequences of agricultural land use changes across scales (Burke et al., 2021; Foley et al., 2005).

California's Central Valley is one of the largest and most economically important agricultural regions in the world, producing more than 50% of the fruits, nuts, and vegetables grown in the US (Gebremichael et al., 2021). However, California's Mediterranean climate and reliance on seasonal precipitation and snowpack for water supply make it highly vulnerable to drought conditions (Lund et al., 2015). The state has experienced multiple severe and persistent droughts over the past two decades, which are exacerbated by climate change and increasing water demands due to population growth and agricultural needs (Pathak et al., 2018). These droughts have led to significant environmental, economic, and societal consequences including water shortages, wildfires, crop losses, and heightened competition for water resources among urban, agricultural, and environmental uses. Agriculture accounts for 29-53% of the total water use in California (Mount et al., 2023). As climate models predict a future with warmer temperatures and increasingly precipitation variability, the need for proactive and adaptive agricultural management strategies is paramount.

In recent years, the agricultural landscape of Central Valley has undergone significant land use changes, primarily driven by the convergence of drought conditions and fluctuating crop prices. Most notably, there has been a widespread conversion from annual cropping systems and rangelands to perennial cropping systems across the state (Gebremichael et al., 2021; Cameron et al., 2014). Almond and walnut acreage have experienced the largest increase in cultivated area compared to any other crop (Gebremichael et al., 2021). California is now the world's largest producer and exporter of these crops, bolstered by growing international demand and high market prices (CDFA, 2021). While almonds and walnuts offer a potentially favorable alternative to less profitable crops, they are permanent crops that requiring irrigation during the growing season throughout the crop's life span, exacerbating water resources during drought periods every-year, especially ground water (Scanlon et al., 2012; Lund et al., 2018).

The northern portion of the Central Valley, known as the Sacramento Valley, is dominated by rice production. California is the second largest rice growing state in the US, with some of the highest rice yields in the world (Hill et al., 2006). This agricultural region also provides regional ecosystem services including habitat for endangered migratory waterfowl and for salmon rearing (Holmes et al., 2021). However, commercial rice production is one of the most water intensive crops in the state and the rice growing region faces environmental challenges including water scarcity. During the recent drought periods, water restrictions have led to decreases in rice production and widespread fallowing across the rice growing region (Gebremichael et al., 2021). Meanwhile, almond and walnut cultivation is increasing across the Sacramento Valley (*USDA-NASS, 2020*), providing a profitable alternative to rice (Gebremichael et al., 2021). The degree to which perennial tree crops may replace rice in the Sacramento Valley, however, is poorly understood.

In the rice growing region of California, soil type may play an important limiting factor in land use changes. Large portions of the Sacramento Valley were native wetland habitat before being reclaimed for agricultural production, and they maintain the soil attributes of a basin-wetland ecosystem (Hill et al., 2006). Soil features including high clay content, shrink-swell, salinity, alkalinity, and poor drainage are widespread in this region limiting cropping options (Carter et al., 1994; Salvato et al., 2023). Previous studies have reported that more than half of the rice growing region is considered 'rice only', where production of other summer or winter crops is expected to fail due to properties of the soil (Carter et al., 1994; Hill et al., 2006). These soil attributes may limit the feasibility for alternative crops such as almonds and walnuts to be easily planted in this region. There is a need to better understand the extent to which land use changes are occurring in the region, and the potential role soil properties might play in influencing land use shifts.

The overall objective of this study was to explore the extent of land use shifts in the rice growing region based on an assessment of crop prices, drought, and soil properties using remote sensing and …... The specific objectives were (1) to quantify the timing and location of continuous rice fields, fallowing, and fields that were converted to perennial tree crops using remotely sensed data sources; (2) to evaluate the differences in soil properties between continuous rice fields and fields that have been converted to perennial tree crops using a machine learning framework; and (3) to examine the potential drivers and implications for these land use changes in the region. Results from this study will help inform the likelihood of major land use shifts in this region and provide a framework for science-based land management for other agricultural regions facing sustainability challenges.

2. Materials and Methods

2.1. Sacramento Valley

The Sacramento Valley lies to the north of the Sacramento San Joaquin Delta in the Central Valley of California. It is approximately 450 km long and generally has a flat topography, bordered by the Sierra Nevada to the west and the Coast Range to the east. The climate is typically Mediterranean with hot, dry summers and mild, rainy winters. Two major rivers flow through the region, the Sacramento River and the Feather River. The Sacramento Valley receives most of its rainfall between November and March when > 95% of the rainfall occurs. Irrigation demand is primarily in April to September, and irrigation water is stored in reservoirs in the snowpack of the Sierra Nevada to meet this demand (Mehta et al., 2013).

Land use in the region is dominated by commercial rice production. Rice planting occurs in late April to early May, primarily using water seeding methods. Flooded irrigation is used to maintain water levels throughout the summer to manage weeds and promote even stand establishment. Periodically throughout the summer, water levels are lowered for herbicide application. Harvesting typically begins in late September and extends through October. Following harvest, fields are disked to incorporate straw and flooded with irrigation and rainwater to promote straw decomposition. Some farmers also receive government incentives for winter-flooding to provide beneficial habitat for overwintering waterfowl.

2.2. Data Sources and Processing

Land use maps were built for years 2008 to 2021 by integrating the Crop Land Data Layer (CDL), provided by the United States Department of Agriculture, with field boundary information provided by California Department of Water Resources. This process is described in detail in Salvato et al. (2023). In summary, the 30m raster based CDL is reclassified with DWR field boundaries, excluding pixels outside of the field boundary and mitigating misclassified pixels within the field boundary. Crop area estimates and change detection were performed on the field-level data. To examine land use changes in the rice growing region specifically, we limited the analysis to fields that were in rice at least one year of the 15-year data set, which includes about 268,950 hectares (13,120 fields). The region is home to hundreds of crop types, so to simplify our analysis and improve the accuracy (Lark et al.. 2017), we grouped the CDL classes together into the dominant crop types. This analysis focuses on the five groups that are most important to the historical land use changes across the region: *'rice', 'fallow', 'walnut', 'almond', and 'other perennial'*. *'Other perennial'* contains all the other perennial tree crop classes in the CDL data set (*pistachio, grape , pecan, pears, olive, orange, prune, avocado, pomegranate, nectarine, apricot, cherries, peaches, apples, plums, other citrus and other tree crops*). '*Annual crops'* are also a dominant crop type in this region, but they are outside the scope of this analysis.

Spatial soil data was obtained from the NRCS Soil Survey Geographic Database (SSURGO) (*NRCS Soils, 2021*). The process of selecting soil variables and aggregating them to the field level is described in Salvato et al. (2023).

To examine the role of drought on crop use changes in the region, drought information was obtained from the U.S. Drought Monitor (https://droughtmonitor.unl.edu/). The Drought Monitor is produced by the National Drought Mitigation Center at the University of Nebraska-Lincoln, the United States Department of Agriculture, and the National Oceanic and Atmospheric Administration. Years when California experienced more than 20% extreme drought on an area basis were determined drought years for our analysis. According to this definition, years 2007 to 2009, 2012 to 2016, and 2020 to 2021were determined drought years.

Crop price and crop yield data were obtained for the State from the USDA/NASS Quickstats database (https://quickstats.nass.usda.gov/). Mean annual price data were obtained for years 2000 to 2021 and were adjusted for inflation to 2021 dollars. Crop yield for almonds and walnuts is only available at the state level, so state level yield data was used for this analysis. Crop yield data were obtained for years 2012 to 2021 and 10-year average yields were calculated. 10-year average crop prices were also calculated and multiplied by the average yield value to determine 10-year average price on a per hectare basis.

2.3 Comparing soil properties of rice fields and perennial fields.

2.3.1 Data Preparation

To compare the soil properties of continuous rice fields with fields that were converted to perennial tree crops, a binomial classification modelling approach was used. The two classes were established as follows: '*Rice'* fields were in rice at least 12 of the 15-year data set and were never in perennial crop (n = 8,034; 164,635 hectares), *'perennial'* fields were any field in the data set if almond, walnut, or other perennial was planted during the study period (n = 1,097; 17,996 hectares).

Data from these two classes were randomly split into training and validation subsets (75% to train and 25% to validate), and a random forest (Breiman, 2001) classification model was trained for binomial classification for 'rice' and 'perennial' fields based on soil variables. Random forest is an ensemble learning method that builds independent decision trees each with a unique bootstrap sample of the training data, reducing the variance associated with single trees and improving prediction accuracy (Liaw and Wiener, 2005). For classification purposes used here, output of the model is the class selected by the most trees.

2.3.2 Model Assessment

Model assessment was performed on the remaining validation data set using precision (P), recall (R) and F1 metrics, which we define as:

$$P = \frac{T_P}{T_P + F_P} \quad (1)$$

$$R = \frac{T_P}{T_P + F_N} \quad (2)$$

$$F1 = 2\ \frac{P\ x\ R}{P+R} \quad (3)$$

Where T_P is the number of fields correctly classified as perennial fields, F_P is the number of fields incorrectly classified as perennial fields, and F_N is the number of fields incorrectly classified as rice fields. F1 measures classification accuracy using the harmonic mean of precision and recall.

2.3.2 Model Set Up

We recognize that there may be many unobserved factors that drive the spatial distribution of crop type in this region. To address potential issues of spatial autocorrelation in our modelling process, a spatial cross validation approach was used. In this approach, the training data was split into ten cross validation groups using k-means clustering of the spatial coordinates of the field center. This process was implemented using R's 'spatialsample' package (Silge, 2021). Spatially cross validated models have better performance when predicting to new data or for determining the most important causal predictors for ecological data (Roberts et al., 2017).

Next, model parameters were tuned. F1 was static after 150 trees, so 150 trees were used in the modelling process. To define the number of variables randomly selected at each split in a tree (*mtries*), and the number of data points in a node required for the node to be split again (*min_n*), a hyperparameter grid search approach was used, optimizing for F1. *Mtries* = 3 and *min_n* = 27 were selected because that combination yielded the highest F1 score. Finally, because rice fields were 8-fold more prevalent than perennial fields in our training data, the minority class (perennial) was up sampled randomly at a 20% sampling ratio. Woznicki et al., (2019) and Salvato et al., (2023) found that up sampling at 20% was optimal because it led to higher recall.

Soil variables were also pruned using the same approach explained in Salvato et al. (2023). In summary, redundant soil variables were removed if highly correlated ($r > 0.8$), and soil variables that did not improve the F1 score were also removed. The remaining soil variables included in the modeling process were pH, clay content, electrical conductivity (EC), sodium adsorption ratio (SAR), organic matter content (OM), saturated hydraulic conductivity (Ksat), irrigated capability class (ICC), and soil order.

We used variable importance (VI) and partial dependence information to interpret the model results. Variable importance, which can help determine the most important soil variables in the model prediction, was computed using AUC as the metric after permuting each predictor variable (Greenwell et al., 2018). To establish a clear ranking of variable importance, the model was re-executed randomly 200-fold and variable importance was computed for each model repetition. Variables were ranked based on their mean effect on AUC. Partial dependence plots (PDP) were used to visualize the effect of certain soil variables on the model outcome (*yhat)* while accounting for the average effect of other predictors in the model(Hastie et al., 2009). PDPs were built in R's 'DALEXtra' package (Maksymiuk et al., 2020).

3. Results/Discussion

3.1 Trends in Crop Area

Rice is the dominant crop in the study area, varying between 150,000 to 225,000 ha. From 2007 to 2013 rice area was consistently high (~225,000 ha), however during drought periods rice area decreased. During the 2012 to 2016 drought, there were two years when rice area was near 175,000 acres. During the drought period in 2021, rice area decreased to ~160,000 ha. 2017 was not a drought year, however rice area was relatively low (~175,000 ha) due to late spring rain that led to delayed planting or fallowing of many fields (confirmed by conversations with growers). On average, rice area decreased throughout the study period. Mean rice area was 31,500 ha lower in 2013 to 2021 than in 2007 to 2013.

Fallow area varied between 12,000 to 70,000 ha. Fallow area was consistently low until 2013 (less than 25,000 ha) and increased during the 2012 to 2016 drought (up to 70,000 ha). This drought was the most severe drought in recorded history, setting a 12-month average precipitation record (Diffenbaugh et al., 2015) and the lowest snowpack in 500 years (Belmecheri et al., 2016), leading to water use restrictions that likely led to increased fallow land. Rice and fallow area show inverse patterns, decreases in rice area tend to show equivalent increases in fallow area. Fallowing rice fields in the region has led to decreased agricultural revenue but allows flexible water management for the region (Medellín-Azuara et al., 2016). Fallowing also may incentivize the conversion to other crops, as idle land is available for larger-scale field preparation throughout the summer season.

Almonds, walnuts, and other perennial crops combined totaled about 1.2% of the study area until 2013. After 2013, almond and walnut acreage started to increase in the region, while other perennial acreage remained low (Figure 1). In 2021, 2.9 and 3.2 of the region had been converted to almonds and walnuts, respectively (7,800 and 8,600 ha, respectively), while other perennials still occupy less than one percent of the study area. Almond and walnut area started to increase in the study region throughout the 2012 to 2016 drought, the most severe drought on record. This may be because rice farmers were fallowing many rice fields due to water restrictions, which could give them an opportunity to do field prep for almonds or walnuts, which require relatively intensive field-prep due including deep ripping to break up hardpans, site specific leveling to facilitate efficient irrigation, and installing new irrigation systems such as drip or micro-sprinkler. Furthermore, almond and walnut crops have minimal water requirements when the trees are smaller (Egea et al., 2009), which may have been an incentive to convert to these crops during drought in hopes that of higher economic returns once water availability increases.

On average, almonds are the most water intensive crop in California, requiring 340,000 ha-m of water on average (Schauer and Senay, 2019). Walnuts use considerably less water (111,000 ha-m). Rice is somewhere in the middle, utilizing 219,00 ha-m annually. Both almond and walnut growers have relatively inelastic demand for water. They require are 4-6 years of start-up investments that can total $46,500 to $65,000 per hectare (*UCANR Cost Studies).* Recouping these investing's could require three to five years of high yields and high prices. This could be creating an incentive to continue irrigating perennial tree crops such despite water use restrictions, a maladaptation to drought. Across the entire central valley, increases in almond and walnut plantings has led to increased allotment of the state water budget to these crops relative to annual crops including rice, which seen a decrease in planted area during drought (Gebremichael et al., 2021) and an increase in water efficient irrigation techniques leading to water savings per harvested area (Schaeur et al., 2019). Furthermore, increased water demand to maintain perennial tree crops such as almonds has led to increased ground water over drafting in the Southern Central Valley (Gebremichael et al., 2021). While deficit irrigation techniques for almonds or walnuts may be a potential solution (Moldero et al., 2021), feasibility is still poorly understood and is site specific (Goldhamer and Fereres, 2017).

Spatially, almond and walnut plantings in the study area occurred on the perimeter of the rice growing area (Figure 2). Almond plantings are clustered in the North and West of the region, while walnut tend to be in Colusa and Sutter counties, where the Feather and Sacramento Rivers run through the rice growing region. In the interior basins of the Sacramento Valley, there are no almond, walnut, or other perennial plantings.

3.2 The Role of Crop Prices

Statewide prices for rice increased over the past twenty years, however between 2010 and 2021 the price remained consistent (between $300-$400 per metric ton) (Figure 2). Almond and walnut prices peaked in 2014-2015. On a 10-year average basis (Table 1), almond and walnut prices ($ per metric ton) were 14- and 6-fold, respectively, higher than rice. Per hectare, almond and walnut prices were 3.5- and 4.5-fold, respectively, greater than rice. Both almonds and walnuts require substantial startup costs to get orchards established ($16,100 over six years for almonds and $23,100 over seven years for walnuts) (*UCANR Cost Studies).* Almonds and walnuts also have higher maintenance costs per hectare, $5,480/ha for rice, compared to $13,100/ha for almond and $14,300/ha for walnut. However, after excluding startup costs, annual net return above total costs can be up to 10- and 12-fold greater for high yielding almonds and walnuts, respectively, compared to high yielding rice.

Our findings are consistent with other work showing the attractive revenue potential for almonds and walnuts has led to increasing cultivation of these two crops across the entire State, including the Sacramento Valley (Gebremichael et al., 2021). Almond and walnut prices are high because these crops have large international markets and consistent demand due to favorable consumer preferences for nuts and the promotion of dietary benefits by marketing boards, trade associations, and government programs (Ajibade and Saghaian, 2022). Almonds specifically are recognized as one of the most valuable crops not only in California but for the entire US (CDFA, 2020). Walnuts are also known to generate significant revenue in the long run; however, it is possible to observe a drop in revenue some years due to the alternate-bearing characteristics of these crops (CDFA, 2020; UC Davis, 2020). Both almond and walnut prices decreased since 2014, which may be due to increased production and the negative correlation between historical production and price of perennial crops in California (Lobell et al., 2006). Declining prices which may have potential implications for future land use changes. Climate change could lead to yield penalties for perennial tree crops including almonds and walnuts, in some cases up to 40% losses depending on crop variety and the severity of climate change (Lobell et al., 2006). Coupled yield and price decreases could have implications for land use shifts in the near future. Recently, declining walnut prices has led to walnut farmers ripping out productive walnut orchards to look for alternative crops (https://californiaagtoday.com/high-heat-low-demand-hurt-walnut-crop/). This indicates that the relative instability of these markets under a changing can have larger implications for growers who invest in the conversion from annual crop production to perennial tree crop production.

3.3 The Role of Soil Properties

The model examining differences in soil properties of continuous rice fields and rice fields converted to perennials achieved an F1 score of 0.60 after hyperparameter tuning (precision was 0.55, and recall was 0.67) (Table 2). The F1 score indicates that soil properties are meaningful predictors of these two land uses. The recall score of 0.67 indicates that the model correctly classified 67% of the fields in perennial tree crops based on soil characteristics. This performance is consistent with recent efforts using soil variables to predict continuous rice and rotated rice in the region (Salvato et al., 2023), and with other large-scale land use modeling using soil predictor variables. (Socolar et al., 2021; Woznicki et al., 2019). Soil properties are not the only driver of land use decision making in the region (Rosenberg et al., 2022; Salvato et al., 2023), and it is also possible to manage some of the challenging soil properties. These reasons may explain the moderate strength of our F1 score. However, the rice growing region has a high diversity of soil types including challenging soil conditions for successful production of non-flooded crops (Hill et al., 2006; Salvato et al., 2023), and conversations with growers also indicate that soil biogeochemical properties can be a key factor in land use decision making in this region (Rosenberg et al., 2021)

To assess the relative importance of soil variables in predicting where continuous rice fields may be converted to perennial tree crops, we computed the mean decrease in AUC when each soil variable was permuted from the model (Greenwell et al., 2018). This process was repeated 200 times to stabilize the variable importance scores. In figure 4, the violin plot shows the distribution of variable importance scores. The box and whisker plot shows the median and interquartile range of the 200 scores. Clay content (%) was the most important soil variable, followed by ICC. The implications of clay content and ICC on rice or perennial crop production are explained below. Soil pH, EC, and OM were the next most important, and were all closely ranked. Soil order was the least important soil variable included in the model.

The partial dependence plot for clay (Figure 5A) indicates that higher clay content values increase the likelihood of continuous rice. The density plot (Figure 5B) shows that rice may be grown on a wide range of soils with varying amounts of clay. Perennial fields, however, are found where the clay content is less than 40%. High clay content can lead to poor soil tilth (Schjønning et al., 2012), poor workability (Obour et al., 2017), and poor soil drainage (Levy and Van Der Watt, 1988), making production of non-flooded crops difficult. Clays in the Sacramento Valley also have high shrink-swell, meaning they shrink when dry and swell when wet and are difficult to cultivate(Devine et al., 2022). For rice production however, these soil attributes are ameliorated with flooding (Ponnamperuma and Kozlowski, 1984), allowing high productivity without costly management efforts. Furthermore, high clay content impedes drainage, making the fields relatively water efficient for flooded rice production. ICC was the second most important variable in the model (Figure 4). ICC is a land use classification that describes the general suitability of soils for most field crops where irrigation is used (Soil Survey Staff, 2017). ICC includes chemical, physical, and biological soil parameters with the descriptive framework. Soil properties such as EC, pH, and OM, which are also included in the model individually, are factors in ICC. The relative importance of ICC over these parameters individually may indicate that the confluence of multiple soil properties used in ICC are important in land use decision making, while the soil properties individually may be easier to manage.

Spatially, fields with high clay content are in the interior of the rice growing region (Figure 6), where there are also no perennial tree plantings (Figure 2). This is consistent with the region's geography as described by Hill et al. (2006), soils where rice is typically grown were formed from fine sediment deposited by the two major rivers and several tributaries producing clay and silty clay soils. The basin soils have clay content ranging from 40 to 60%, while the older terrace soils on the perimeters tend to have loamy topsoil, expanding the potential range of crop selection. Of the 159,000 ha of continuous rice fields in the model data, 56,200 ha have clay content less than 40%. This indicates that clay content may be a significant limiting factor on the expansion of perennial tree crops into bulk of the rice growing area of California. Soil type factors other than clay influence the distribution and prevalence of non-flooded agriculture in the region, including pH, salinity, and drainage (Salvato et al., 2023, Rosenberg et al., 2022; Hill et al., 2006). Previous studies have indicated that on [120,000 hectares] it would be very difficult to grow any crop other than rice (Hill et al., 2006; Carter et al., 1994). Previous studies have also indicated that walnut rootstock may better tolerate wet and poorly drained conditions than almond rootstock (Ganot and Dahlke, 2021; Vahdati et al., 2021), which may explain why walnuts are more commonly found along the rivers in this region (Figure 2).

4. Conclusions

The rice growing area has demonstrated its utility as a key flexibility in water resource management for the region, as rice area is routinely fallowed during drought periods when water restrictions are tightened. The rice growing region also provides critical habitat for waterfowl and other wetland aquatic species in a region that was formerly a native wetland habitat. A shift in cropping practices toward almond and walnuts in the Sacramento Valley is likely driven by high crop prices despite increasing drought severity. However, our results indicate that soil properties may play a limiting role in this conversion. Water restrictions may also limit the expansion of perennial tree crops into the region, as they have higher overall water use per hectare than rice. Results from this research indicate that both shifts in the size of irrigated land and a change in the relative proportion of crop types are key factors in water resource management. Furthermore, this research highlights the importance of including biophysical considerations such as soil characteristics in ongoing efforts to identify and implement feasible water and land management adaptations to climate change.

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