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Assessing the Impacts of Salinity and Nitrate Leaching on Sustainability of Groundwater and
Irrigated Agriculture in the Central Valley

By

FLOYID NICOLAS
DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

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DAVIS

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2024

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To the memory of my father, Phazil Nicolas. To my mother Fernande Coffy and my Siblings.

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ABSTRACT

Salinity and nitrate leaching in California's Central Valley significantly impair agricultural productivity and groundwater sustainability. Through extensive biophysical and agrohydrological modeling and empirical field data, the research quantifies the impacts of these environmental stressors and offers evidence-based strategies for mitigating their effects. A biophysical model that incorporates soil, weather, crop data, water cost, and production costs predicted that salinity levels exceeding 5 dS/m can reduce crop yields by up to 45% for highly sensitive crops like almonds and table grapes. On the other hand, these crops could profit growers more because of their market values. The economic analysis shows that the profitability of agricultural production under different salinity scenarios varies significantly, with potential annual economic losses amounting to hundreds of millions of dollars, underscoring the critical need for tailored salinity management strategies. A salinity decision-support web tool was developed. This tool enables users to input data and predict crop yields and economic outcomes. The tool's application in real-world scenarios has shown that it can effectively assist farmers and policymakers in making informed decisions that optimize economic returns and environmental sustainability.

Concurrently, the dissertation evaluates the effectiveness of various conservation practices, such as cover crops, irrigation nitrogen credits, and high-frequency low fertigation, in reducing nitrate leaching. Utilizing the APEX model, the results demonstrate that these practices can reduce nitrate leaching of the root zone by up to 90%, thereby substantially decreasing the risk of groundwater contamination. This study also evaluated an integrated AMRS model to assess and manage nitrate nitrogen ($\text{NO}_3\text{-N}$) leaching into groundwater at a field scale. The model was evaluated at the deep vadose zone and shallow groundwater and showed that conservation practices such as HFLC can mitigate groundwater $\text{NO}_3\text{-N}$ contamination. This part

of the research highlights the practical benefits of integrating agronomic and environmental conservation practices into farming operations to enhance the sustainability of water resources.

Overall, this dissertation provides a comprehensive framework for understanding and addressing the dual challenges of salinity and nitrate leaching in irrigated agriculture. By offering detailed insights into the mechanisms underlying these challenges and developing practical tools for stakeholders, the research contributes to the sustainable management of natural resources in agricultural regions facing similar environmental pressures.

CHAPTER 1 INTRODUCTION

Problem Statement

California's flourishing agricultural economy has not occurred without environmental consequences that continue exacerbating undesirable effects across the state. Intensive irrigated agricultural and industrial activities coupled with population growth have resulted in significant increases of salts in soils, surface waters, and groundwater and dramatic nitrate accumulation in groundwater (Harter et al., 2017; Kondash et al., 2020; Rosenstock et al., 2014; Schoups et al., 2005). Over 4.5 million acres of irrigated cropland in Central Valley (CV) have been adversely affected by either saline irrigation water or saline soils, thereby putting tens of thousands of productive agricultural acres at risk (Central Valley Salinity Alternatives for Long-Term Sustainability [CV-SALTS], 2023). Salt accumulation caused about 250,000 acres to be removed from agricultural production, and another 1.5 million acres were considered damaged by salinity (Hanak et al., 2019). The annual salinity-related losses in the Central Valley are expected to surpass \$3 billion (CV-SALTS, 2023). Over the last several decades, nitrate nitrogen ($\text{NO}_3\text{-N}$) levels in public supply wells have increased at an average rate of 2.5 mg/L per decade in several regions of the Central Valley, and numerous wells exceed the required maximum contaminant level (10 mg/L $\text{NO}_3\text{-N}$) fixed by the California Department of Public Health (Boyle et al., 2012; Ransom et al., 2016). Nonpoint source $\text{NO}_3\text{-N}$ loading in the Central Valley groundwater has led to over 163 Gg N/year (Rosenstock et al., 2014). The California State Water Resources Control Board, charged with the responsibility of safeguarding, improving, and rehabilitating the condition of California's water resources, has implemented the Central Valley-wide Salt and Nitrate Management Plan (SNMP) in response to mitigate the accumulation of salt and nitrate in groundwater throughout the Central Valley. The goal of this research was to develop modeling

frameworks, groundwater protection formulas, and decision-support tools to improve sustainable management of salinity and nitrate in the Central Valley of California.

Background and Motivation

The Central Valley of California is a prime example of agricultural efficiency and productivity, playing a pivotal role in feeding the United States and contributing significantly to global food supplies. This region, covering about 52,000 km² through the heart of California, is known for its diverse and abundant agricultural output (Bittman, 2012; California Department of Food and Agriculture, 2023; Faunt et al., 2016). The Central Valley is unmatched in producing a wide range of crops, which include fruits, vegetables, and nuts. The diversity of crops grown in the Valley is a testament to the ability of the region to meet various market demands (California Department of Food and Agriculture, 2023).

The climatic conditions of the Central Valley play a significant role in its agricultural success. Characterized by a Mediterranean climate, the region experiences hot, dry summers and mild, wet winters. However, this climate varies between the northern and southern parts of the Valley, influencing the types of crops grown and the agricultural practices employed (Pathak et al., 2018). The southern part of the Valley, being warmer and drier, faces more significant challenges and relies more heavily on irrigation. Irrigation is the backbone of agriculture in the Central Valley. The region's sophisticated network of reservoirs, canals, and aqueducts, including the Central Valley Project and the California State Water Project, is essential for transporting water from various sources to the agricultural fields (Johnson and Cody, 2015). Groundwater also plays a vital role in irrigation, especially during drought when surface water supplies are limited (Levy et al., 2019).

However, the reliance on irrigation has led to significant environmental challenges. Inadequate management practices have triggered soil salinization and nitrate leaching to water

resources (Scanlon et al., 2012). Soil salinity, in particular, threatens the sustainability of agriculture in the region by degrading soil quality, reducing crop yields, and eventually rendering the land unsuitable for agriculture (Nicolas et al., 2023; Singh, 2015). Additionally, the widespread use of nitrogen fertilizers to boost crop productivity has contributed to nitrate leaching, affecting groundwater quality and posing public health risks (Ward et al., 2018). For decades, obstacles to sustainable agricultural production have included increasing salinity caused by soluble salt deposition in the crop root zone and water resources contamination from nutrient leaching due to inefficient conservation practices.

Salinity in environmental contexts is broadly categorized into primary and secondary. Primary salinity is attributed to natural processes that gradually accumulate salts in soils and groundwater over long periods, often spanning centuries. Secondary salinity, however, is a consequence of human activities that disrupt the natural hydrologic balance of soils (Parihar et al., 2015). The soil of the west side of the Central Valley was originally sedimentary and alluvial, formed in the uplifted seabed. Water distribution and transportation through a network of channels from the Delta to the Valley has led to a gradual accumulation of salts that mineralize and leach over time, resulting in rising saline water tables and soil salinization in the Central Valley (Quinn, 2020; Quinn and Oster, 2021). The salinity problem in the Central Valley has been exacerbated mainly because of agricultural practices, which have greatly affected crop productivity and agricultural sustainability (Hansen et al., 2018; Nicolas et al., 2023). Current circumstances necessitate well-informed decision-making in order to maximize agronomic measures that mitigate economic loss due to salinity and enhance the sustainability of irrigated agriculture in the Central Valley.

In addition to the rising salt levels that threaten drinking water and affect crop production in some areas of the Valley, NO₃-N has accumulated in groundwater to the point that drinking water for rural households and small water systems does not meet safe standards (CV-SALTS, 2023). Agricultural activities are the primary sources of groundwater NO₃-N pollution due to excess nitrogen-based fertilizer application and unbalanced management practices (Boyle et al., 2012; Dubrovsky et al., 2010; Harter et al., 2017). Significant increases in nitrogen fertilizer application rates were observed in Sacramento Valley, San Joaquin Basin, and Tulare Basin of the CV for the period 2002-2012 compared to 1991- 2001 (Harter et al., 2017). More than 740,000 tons of nitrogen fertilizer were applied to roughly 6.7 million acres of irrigated farmland in California. The excess nitrogen fertilizer that leaches into the aquifer has contaminated the groundwater and disturbed the ecological balance (Harter, 2009).

The path to sustainable agriculture in the Central Valley involves a holistic approach that encompasses efficient resource use, environmental stewardship, and economic viability. Achieving sustainability goals requires a concerted effort from farmers, researchers, policymakers, and other stakeholders (Brodt et al., 2006; Marchetti et al., 2020). Factors such as innovations in agricultural technology, policy reforms, and community engagement are essential components of this journey. The future of agriculture in the Central Valley hinges on the balance between meeting current food production needs and preserving the region's natural resources for future generations (Jackson et al., 2011). The challenges of agricultural productivity and water management, such as salinity and nutrient leaching, must be addressed through innovative, integrated, and sustainable approaches to ensure the long-term productivity and environmental sustainability of the Valley.

Statement of research objectives

The main goal of this dissertation is to develop new knowledge, data, modeling frameworks, and decision-support tools to enhance sustainable management of salinity and nitrate-nitrogen in the Central Valley of California. The overarching hypothesis is that conservation practices and decision support tools are capable of reducing the impacts of nitrate leaching and salinity on groundwater quality and crop productivity. Database and Geographic information technologies, web-based programming, process-based agrohydrology models, and data visualization will be used. The primary objectives of this research include:

1. Assess salinity impacts on crop yield and economic returns of selected crops in the California Central Valley and predict yield and revenues considering irrigation water quality and production cost at small and regional scales.
2. Develop a user-friendly web-based decision-making support tool that predicts crop yield and profitability across the Central Valley.
3. Evaluate the effectiveness of conservation practices in reducing nitrate-nitrogen leaching out of the root zone.
4. Develop a field-scale agrohydrologic modeling-based groundwater protection formula for assessing groundwater contamination from nitrate-nitrogen loading.

CHAPTER 2 ASSESSING SALINITY IMPACTS ON CROP YIELD AND ECONOMIC RETURNS IN THE CENTRAL VALLEY IN THE CENTRAL VALLEY

Abstract

Salt accumulation in the root zone can impair crop yields and profitability. The study integrated soil variables, climate conditions, irrigation inputs, and economic information to predict crop yield and profits for the Central Valley. For model simulation, four crops (alfalfa, almonds, table grapes, and processing tomatoes), five different irrigation water salinity levels (from 0.5 to 5.5 dS/m), and daily irrigation water (from 0 to 12 mm) were used. In yield prediction, R^2 were 0.82, 0.77, 0.78, and 0.64, and the RMSE was 9, 8, 23, and 11% for alfalfa, almonds, grapes, and tomatoes, respectively. In profits prediction, R^2 was 0.99 for alfalfa, almonds, and processing tomatoes, and 0.74 for grapes, while the RMSE was 48, 211, 2461, and 68 \$/ha for alfalfa, almonds, grapes, and processing tomatoes, respectively. The spatial component developed for the model indicated that yield and profits would vary based on soil type and water salinity across the Valley. At a daily irrigation rate of 3 mm, no profits were predicted for all crops, while 6 mm/day triggered profits of up to \$1000/ha for alfalfa and processing tomatoes, while more than 8 mm/day was required to predict profits for almonds and grapes. This modeling framework can help policymakers identify areas unsuitable for sustainable and profitable irrigated agriculture and prioritize them for multi-benefit land repurposing to reduce agricultural water demand and achieve groundwater sustainability. The model can also serve as a decision-aid tool to help growers in arid regions anticipate losses from crop yield reduction due to salinity.

Keywords. Yield, Irrigation, Salinity, Modeling, Central Valley

Introduction

High concentrations of soluble salts such as sodium chloride, sulfates, calcium, magnesium, and bicarbonates in soil and water threaten irrigated and rainfed agriculture worldwide (Hopmans et al., 2021). More than 954 million hectares (ha) of land worldwide are salt-affected, and between 25% and 30% of irrigated lands are rendered unproductive due to salinity (Shahid et al., 2018). The increase in the world population is expected to expand salinization further through an array of processes, including an increase in treated wastewater reuse for irrigation (Farid et al., 2020; Ogunmokun and Wallach, 2021; Pedrero et al., 2020; Tanji, 1997), groundwater contamination due to percolated salts from irrigated lands (Foster et al., 2018; Merchán et al., 2020; Quinn, 2020), and an increase in the use of brackish or saline water for irrigation (Baath et al., 2020; L. Wang et al., 2020; Yuan et al., 2019). The consolidative nature of these processes suggests that salinity issues are inherent to crop production and agricultural water management strategies in many water-constrained regions. Methods to quantify and reduce economic losses due to salinity should be incorporated into policies at regional and local scales.

In semi-arid and arid regions like California, where rainfall is insufficient to meet crop water needs, irrigation is necessary. About 40% of global irrigated land is located in arid/semi-arid zones, and irrigation is often associated with salinization (Hopmans et al., 2021; Smedema and Shiati, 2002). Intensive irrigation has allowed the Central Valley of California to become one of the world's most productive farming regions (Olmstead and Rhode, 2017). The long-term sustainability of irrigated agriculture is threatened due to decreased irrigation water quality and increased salt build-up in the soil and groundwater, particularly in the southern part of the Valley (Schoups et al., 2005; Welle and Mauter, 2017). Various factors, such as drought, climate

change, water shortages, and land-use changes, exacerbate salinity problems and severely affect the Central Valley's agricultural productivity and sustainability.

In the San Joaquin Valley (Southern part of the Central Valley), more than 2 million ha of irrigated cropland are salt-affected through saline irrigation water or saline soils, and tens of thousands of ha of arable land were reported to be at high-risk (Letey, 2000). Over 30% of the agricultural salt-affected land is highly saline (Scudiero et al., 2017). Salt build-up caused about 100,000 ha to be taken out of agricultural production, and another 600,000 ha were considered damaged by salinity. In contrast, only 15% of the annual salt load is being addressed by current management activities (CV-SALTS, 2019). The high levels of salt concentrations in the Central Valley can be directly correlated with irrigation using a combination of agricultural, industrial, and municipal water. The amount of salt brought into the Valley has been increased through dams and imported water supplies. More than six million tons of salt are imported and accumulated yearly in the San Joaquin Valley (CV-SALTS, 2019; Quinn, 2020). Using remote sensing methods, (Welle and Mauter, 2017) reported that salinity reduced California's agricultural revenues by \$3.7 billion. Long-term management strategies are needed to address the remaining 85% salt load. Under current conditions, informed predictions about future salt build-up are required to optimize agronomic practices to reduce economic loss due to salinity and improve irrigation sustainability.

California's Central Valley agricultural production relies on surface water imports from a massive network of reservoirs, waterways, and groundwater over-drafted due to irrigation (Quinn, 2020). In recent decades, the Valley has turned to perennial (tree and vine) crops, which has triggered increased water demand amidst a cycle of multiple-year droughts and new regulations on groundwater pumping (Mall and Herman, 2019). Moreover, the Central Valley

faces the challenge of protecting water quality due to inadequate dilution from rainfall. Such conditions, inherent to semi-arid agricultural regions, have led to alternative solutions, including using marginal-quality water such as recycled wastewater and brackish groundwater for irrigation (Gile et al., 2020; Kisekka et al., 2024; Qin and Horvath, 2020). However, such non-conventional irrigation water sources are likely to contain dissolved salts that can accumulate in the root zone, affecting crop productivity and leaching to groundwater and surface water, resulting in severe environmental degradation (Chittick and Srebotnjak, 2017; Foster et al., 2018). The use of water high in salts requires best management practices that entail screening biological-physical system concerns and the production's economics (Kaner et al., 2019). Under constrained soil and water systems protection measures, water management strategies are challenged to maximize productivity. In addition to the evaluation of adverse effects of water containing excess salts on crop yield (relative to crop salt tolerance) and the ecosystems, decisions related to the use of marginal quality irrigation water for crop production can further consider the assessment of economic parameters such as production inputs and potential benefits.

Numerical and analytical modeling approaches to estimate crop yield for a specific soil as a function of saline water and irrigation amounts have been widely described and compared in previous research (Oster et al., 2012; Shani et al., 2009; Skaggs et al., 2014). Integrated models coupling agronomic, hydrological, and environmental aspects of irrigation-salinity water systems to economic models have also been developed and assessed in literature (Booker et al., 2012; Slater et al., 2020). However, coupling robust economic information with biophysical models and their spatial correlation has been limited. (Shani et al., 2007, 2009) evaluated the impact of water stress and irrigation water salinity on crop yield and discussed the potential use of the model as an economic decision decision-support tool. Kaner et al. (2019) later integrated the

model with economic information and implemented it as an agronomic-economic coupled decision support system for irrigation water salinity. However, these model applications were implemented considering one or two soil types without considering the spatial distribution of crop yield and profitability in terms of irrigation water salinity and quantity.

This study aimed to develop a framework that integrates the analytical biophysical model with economic and geospatial data and to assess the impact of irrigation water quality and quantity on crop productivity and economic outcomes for selected crops in the Central Valley of California.

Materials and methods

Biophysical model description

The ANalytical Salt-WatER (ANSWER) model contains crop parameters, hydraulic properties, and a meteorological variable (Shani et al., 2007, 2009). Four assumptions underlie the model. First, ambient conditions in the root zone affecting crop root water uptake and growth are represented by parameters, including electrical conductivity (EC), defined by water content (θ) and soil solution salinity (Schoups and Hopmans, 2002). Second, steady-state conditions of water and salt status (Ben-Gal and Shani, 2003) are assumed. Third, the environmental conditions, including weather, are considered static, so the average seasonal transpiration (T_p) value is considered as potential transpiration for the growth period. Fourth, there is a proportional relationship between the ratio of actual yield to the potential yield and the ratio of transpiration to potential transpiration (Ben-Gal et al., 2008; Shani et al., 1987). The relative yield is expressed in Equation 2-1:

$$Y_r = \frac{Y}{Y_p} = \frac{T}{T_p} = T_r \quad (2-1)$$

where Y is yield or biomass production and T is transpiration. Y_r and Y_p are the relative yield and potential yield, respectively. T_r and T_p represent the relative transpiration and potential transpiration, respectively.

The model combines salt and water balance by calculating the soil moisture of the root-zone and soil hydraulic conductivity according to the soil hydraulic model of Brooks-Corey (Brooks and Corey, 1966) as expressed in Equation 2-2:

$$K(\psi) = \min\{K_s, K_s(\psi_w * \psi^{-1})^\eta\}, \theta(\psi) = \min\{\theta_s, (\theta_s - \theta_r)(\psi_w * \psi^{-1})^\beta + \theta_r\} \quad (2-1)$$

where K is the soil hydraulic conductivity, K_s is the saturated hydraulic conductivity, θ_s is the saturated volumetric soil moisture content, and θ_r represents residual volumetric soil moisture content; ψ is the soil matric head, ψ_w is the air-entry head, and η and β are empirical soil characteristic parameters.

Maas and Hoffman (1977) modeled a piece-wise linear model (Mass-Hoffman model) in which crop salt tolerance is described by a salinity threshold and a slope describing yield loss beyond that threshold. The EC_{e50} designates the EC_e (dS/m) for which the relative yield decreases by 50%, and p is a crop parameter describing the function's steepness. The EC_{e50} values were estimated through the rearranged Equation 2-3 from Maas and Hoffman (1977).

$$EC_{e50} = \frac{(1 - Y)}{S + EC_{eT}} \quad (2-2)$$

where EC_{eT} is the salinity threshold (dS/m), Y is the yield (set to 50%), and S is the slope (% yield decline per dS/m).

The logistic curve characterizes the plant-specific reduction function with an initial plateau followed by a decreasing section (Equation 2-4)

$$f_{EC} = \frac{1}{1 + \left(\frac{EC_e}{EC_{e50}}\right)^p} \quad (2-3)$$

where f_{EC} is the relative yield reduction function due to increasing salt concentration levels and EC_e is the average saturated soil extract of the root zone. The parameter p is responsible for the steepness of the S-shape function. Recent experiments in alfalfa ((Benes et al., 2018) have allowed the update of the threshold and slope for a more accurate EC_{e50} . Table 2-1 provides the salinity threshold, slope, and EC_{e50} for each crop.

Table 2-1: Threshold (dS/m) and slope (%) for almonds, alfalfa, processing tomatoes, and table grape

Crop	Threshold (dS/m)	Slope (%)	ECe50 (dS/m)	p	References
Alfalfa	2	5	12	3	Benes et al. (2018)
Almond	1.5	19	4.13	3	Maas and Grattan (1999); Maas and Hoffman (1977)
Grape	1.5	9.6	6.7	3	
Tomato	2.5	9.9	7.55	3	

(Shani et al., 2007, 2009) developed the transpiration function expressed as Equation 2-5:

$$T = \frac{\min \left\{ T_p, \left[\left(\psi_{root} - \frac{\psi_w}{\left(\frac{I-T}{K_s}\right)^{1/\eta}} \right) (I-T) * b \right] \right\}}{1 + \left(\frac{EC_{iw} * I * \left(\theta_r + (\theta_s - \theta_r) \left(\frac{I-T}{K_s}\right)^{1/\delta} \right)}{EC_{e50} * (I-T)\theta_s} \right)^p} \quad (2-5)$$

where I represent the different irrigation water amounts and EC_{iw} the water salinity levels. The model simulated crop performance under different irrigation management and water quality (salinity levels). Equation 2-5 includes management factors (I and EC_I), physical properties (T_p , K_s , δ , θ_r and θ_s) or biophysical processes (EC_{e50} and ψ_{root}). The physical and biological

parameters are site and plant-specific and are determined independently. The parameter p that governs the steepness of the curve was set to 3 (unitless) (Shani et al., 2007; van Genuchten and Gupta, 1993), and the parameter b , used to characterize the flow length from the soil to the crop roots was set to 10 mm under all likely conditions (Nimah and Hanks, 1973; Shani et al., 2007). Relative yield with the initial soil water content (Y_{r0}) was assumed to be zero for all four crops. Tables 2-1 and 2-2 provide the soil and crop parameters, respectively, for the model.

Model input data

Input parameters included the amount and salinity of the applied water, 50%-yield soil salinity (ECe_{50}) and water stress, and potential evapotranspiration (T_p). Irrigation water amounts ranged from 0.4 to 12 mm/day, and six salinity levels (0.5, 1.5, 2.5, 3.5, 4.5, and 5.5 dS/m) were considered. Historical crop yield and market prices, costs to establish an orchard/farm, and water prices were also used as input for the model. In the spatial component of the model, salinity in irrigation water and diverse soil hydraulic properties were input to simulate spatial crop yield and profits as a function of irrigation water salinity across the Central Valley. Tables 2-2 and 2-3 provide inputs for sandy loam soil and crop biophysical conditions.

Table 2-2. Parameters of a sandy loam soil used to compute the site-specific transpiration. K_S is the saturated hydraulic conductivity; θ_s is the saturated soil water content; θ_r is residual soil water content; ψ_w is air entry head; η , β and δ are soil physical parameters of the Brooks-Correy soil hydraulic model.

Parameters	Values ^a
K_S (mm/day)	3600
δ	4.91
β	0.55
η	2.7
θ_s (cm ³ /cm ³)	0.41
θ_r (cm ³ /cm ³)	0.06
ψ_w (mm)	-200

^a (<http://app.agri.gov.il/answerapp/>)

Table 2-3. Crop parameters considered in the study.

Crop	T_p (mm/day) ^b	Ψ_{root} (mm) ^c
Alfalfa	5.5	-6000
Almond	8	-8000
Grape	6.5	-6000
Tomato	5.5	-6000

^c(Šimůnek and van Genuchten, 2002)

^b<https://openetdata.org/>

Assessing biophysical model performance

A systematic review was conducted to collect experimental yield data from previous research to assess the model's performance. The criteria for selecting the studies were irrigation water salinity, crop yield, soil type, and weather data. The framework Protocol, Search, Appraisal, Synthesis, Analysis, and Reporting (PSALSAR) was applied to select the articles that fit the criteria related to the model. Details related to the PSALSAR framework are provided by (Mengist et al., 2020). The searching string was “((Salinity OR saline water) AND (crop yield OR yield)) AND (almonds OR alfalfa OR tomatoes OR grapes).” The search was done for each crop separately. Databases Web of Science and CAB-Abstracts were the primary search engines considered in this study.

The R package “metagear”(Lajeunesse, 2016) was used to screen the abstracts, retrieve the articles, and delegate tasks. The package, coupled with a GUI, was also used to extract data from the figures of the selected papers. A total of 996 articles were downloaded from the databases, and 15 were selected after screening and full-text assessment (Figure 2-1). R^2 and RMSE (Equations 2-6 and 2-7) were calculated to assess the model performance in predicting crop yield in different biophysical environments, such as soil type, irrigation regime, and other management practices.

$$R^2 = 1 - \frac{\sum(O_i - S_i)^2}{\sum(O_i - \bar{O}_i)^2} \quad (2-4)$$

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n (S_i - O_i)^2 \right]^{\frac{1}{2}} \quad (2-5)$$

where S_i and O_i are the predicted and observed variables, respectively; \bar{O}_i is the observed mean value, and i is each observation.

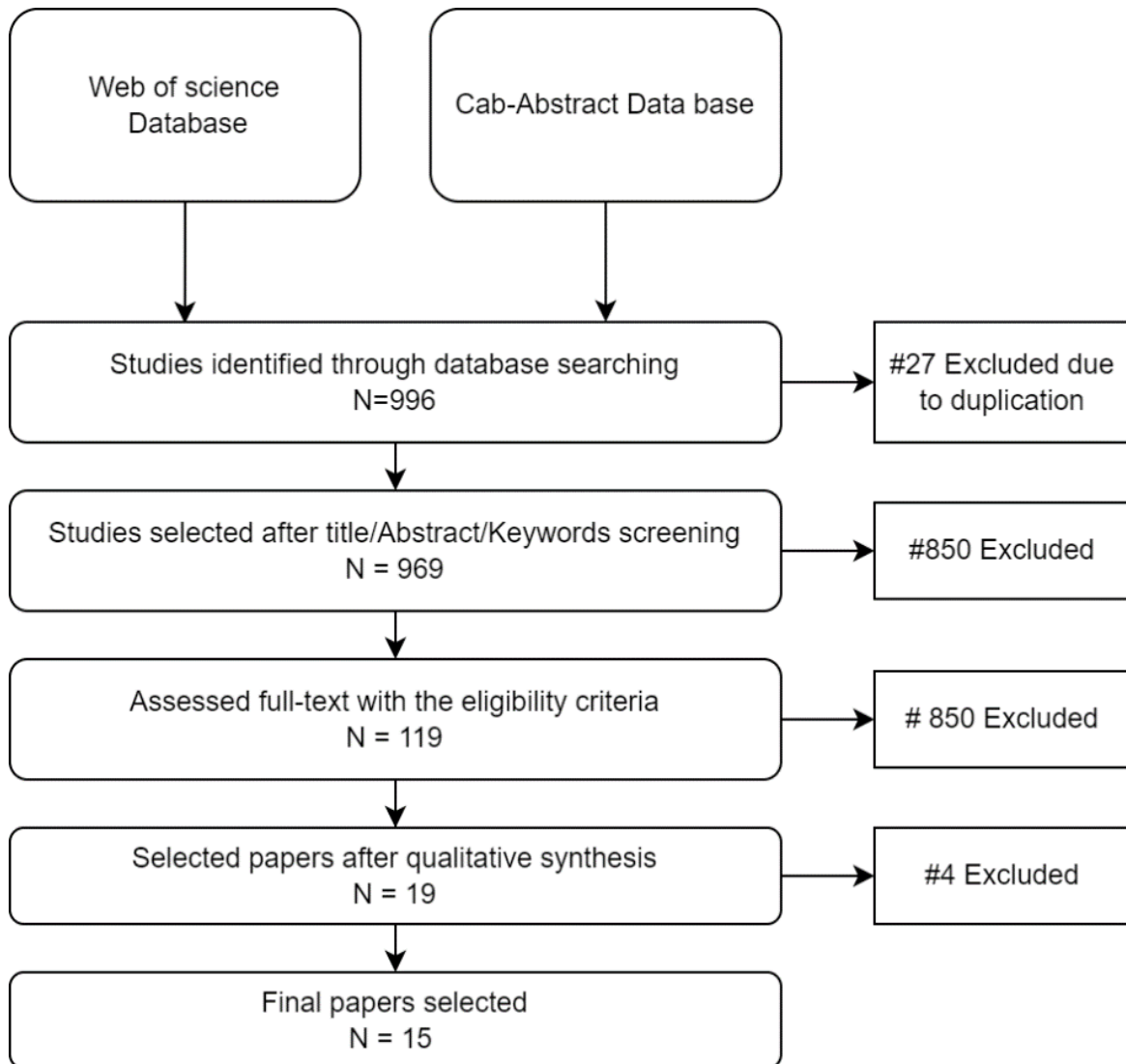


Figure 2-1. Systematic literature review framework used for identification, screening, eligibility, and selection of final papers fitting the established criteria of salinity impacts on crop yield.

Table 2-4. Final selected papers from literature review after PSALSAR method application.

EC _{iw} (dS/m)	Crop	References
0.1 – 16.5	Alfalfa	(Al-Farsi et al., 2020; Ayars et al., 2009; Díaz et al., 2018; Hussain et al., 1995; Lunin et al., 1964; Qiu et al., 2021; Shani and Dudley, 2001)
1 – 4	Almond	(Sanden et al., 2014)
1.5 – 4.8	Grappe	(Ben-Asher et al., 2006; Hepaksoy et al., 2006; Stevens and Partington, 2013)
1 – 10.2	Tomato	(Kamaluldeen et al., 2014; Prazeres et al., 2016; Wang et al., 2020)

Economic considerations

Five economic variables, including revenue per ton (\$/ton), return per ha (\$/ha), yield-dependent costs (\$/ha), fixed cost (\$/ha), and maximum yield (ton/ha) were used to compute the potential profits (Equation 2-8). All investments, including overhead and establishment costs (including the cost of old orchard removal and machinery), were incorporated into fixed costs. The fixed costs were assumed to encompass all costs of owning a field or establishing a farm (alfalfa, almond, grape, and tomato), including production, harvesting, and packaging costs. The fixed costs include operating, cash, and non-cash overhead. The irrigation water cost (water price) was considered an independent variable of interest to simulate different profits. The maximum yield was averaged over five years of historical market prices for each crop/tree considered in this study.

The profits represent the net revenue from crop yield (influenced by soil salinity and irrigation water quality) and crop prices (\$/ton) (Equation 2-8). The actual revenue (\$/ha) is based on the relative yield, the maximum yield, the amounts of land in production, and the revenue per ton per ha (Equation 2-9). The total costs (\$/ha) encompassing fixed costs and irrigation water costs are computed using Equation 2-10.

$$Profits \left(\frac{\$}{ha} \right) = Revenue\ actual \left(\frac{\$}{ha} \right) - Costs \left(\frac{\$}{ha} \right) \quad (2-6)$$

$$\begin{aligned} Revenue\ actual \ (\$/ha) \\ = (Adj\ Y_r * 1\ (ha) * MY(ton/ha) * RpT\ (\$/ton)) / HA(ha) \end{aligned} \quad (2-7)$$

where $AdjY_r$ is the adjusted relative yield (unitless), HA is the hectare amounts (ha), MY is the maximum yield (ton/ha), and RpT is the revenue per ton(\$/ton).

$$\begin{aligned} Costs \left(\frac{\$}{ha} \right) = Water\ cost \left(\frac{\$}{ha} - mm \right) * \left(1ha - \frac{mm}{ha} \right) \\ + Fixed\ costs \left(\frac{\$}{ha} \right) \end{aligned} \quad (2-8)$$

Costs of establishing an orchard/farm (producing, harvesting, and orchard removal) are all incorporated into fixed costs. Expenses of non-cash overhead for an alfalfa farm include costs for establishing the field, amortized over the three-year stand life (Clark et al., 2016; Duncan et al., 2019). The non-cash overhead includes the establishment cost of the almond orchard for the first three years, distributed evenly across the remaining 20 years of the orchard's productive lifespan. An almond orchard's yield usually varies every year before reaching 8 years (Duncan et al., 2019). For grapes, establishment costs reflect three years of investment in planting and maintaining the crop before the start of production. The total cost from the 3 years is divided into an equal cost over the remaining 22 years of the grapes' production lifespan (Fidelibus et al., 2018). The total fixed costs for producing processing tomatoes amounted to \$9,454/ha (Turini et al., 2018). The average maximum seasonal yield was 143 tons/ha. Economic data for alfalfa, almonds, grapes, and processing tomatoes are summarized in Table 2-5.

Table 2-5. Economics variables such as Revenue per ton (\$/ton), Fixed cost (\$/ha), and Maximum yield (ton/ha).

Crops	Revenue per ton (\$/ton)	Fixed cost (\$/ha)	Maximum yield (ton/ha)	References
Alfalfa	250	1,716	24.7	Clark et al. (2016)
Almonds	4,500	5,096	3.7	Duncan et al. (2019)
Grapes	1789.5	21,335	30.6	Fidelibus et al. (2018)
Processing tomatoes	70.5	3,826	143.3	Turini et al. (2018)

Water prices and economic returns

The cost of water is a major factor in the Central Valley’s ability to produce crops. Most regions’ water districts’ prices are still less than \$200 per acre-foot (\$1.62 per ha-mm), while in certain places, it has risen to above \$500 per acre-foot (\$4.1 per ha-mm). Water rates in the northern half of the state are below \$50 per acre-foot (\$0.4 per ha-mm) and, in some districts, are around \$1.00 per acre-foot (0.008 ha-mm). Rates in the southern end of the Central Valley are the highest, ranging from \$1.62 to more than \$4.1 ha-mm in drought years as groundwater pumping is restricted through regulations such as SGMA (<https://aquaoso.com/blog/california-agricultural-water-prices/>). This study considered four different water prices (\$0.41 per ha-mm, \$0.61 per ha-mm, \$0.81 per ha-mm, and \$1.22 per ha-mm) for the model simulations. Historical profits (\$/ha) and crop market prices (\$/tons) reported for 2013 to 2017 were used in the model. Considering a potential increase in the crop market price, the market price in 2017 increased by 150% (Table 2-6).

Table 2-6. Historical prices (\$/tons) for alfalfa, almonds, grapes, and processing tomatoes.

Crop	2013	2014	2015	2016	2017	1.5*(2017)	References
Alfalfa	208	225	160	155	130	195	USDA Agricultural Marketing Service (2023)
Almond	6420	8000	6260	4780	5060	7590	USDA National Agricultural Statistics Service (2023)
Grapes	1617.5	1660	1810	1520	1480	2220	USDA National Agricultural Statistics Service (2023b)
Tomatoes	70.5	83	80	72.5	70.5	105.5	California Tomato Growers Association (2023); USDA Economic Research Service (2023)

Spatial component

Spatial soil hydraulic parameters were collected from the POLARIS soil series (<https://gee-community-catalog.org/projects/polaris/>) (Chaney et al., 2019) and cropland land use from the California Department of Water Resources (<https://data.cnra.ca.gov/dataset/statewide-crop-mapping>). Total dissolved solutes (mg/l) in monitoring and irrigation wells (https://www.waterboards.ca.gov/water_issues/programs/sgma/water-quality-visualization-tool.html) were used as irrigation water salinity (Figure 2-2). Four levels of daily irrigation water, such as 3, 6, 9, and 12 mm, were simulated to evaluate crop response to salinity across the entire Valley. All geospatial processing was performed using the R terra package, google earth engine, and ArcGIS Pro.

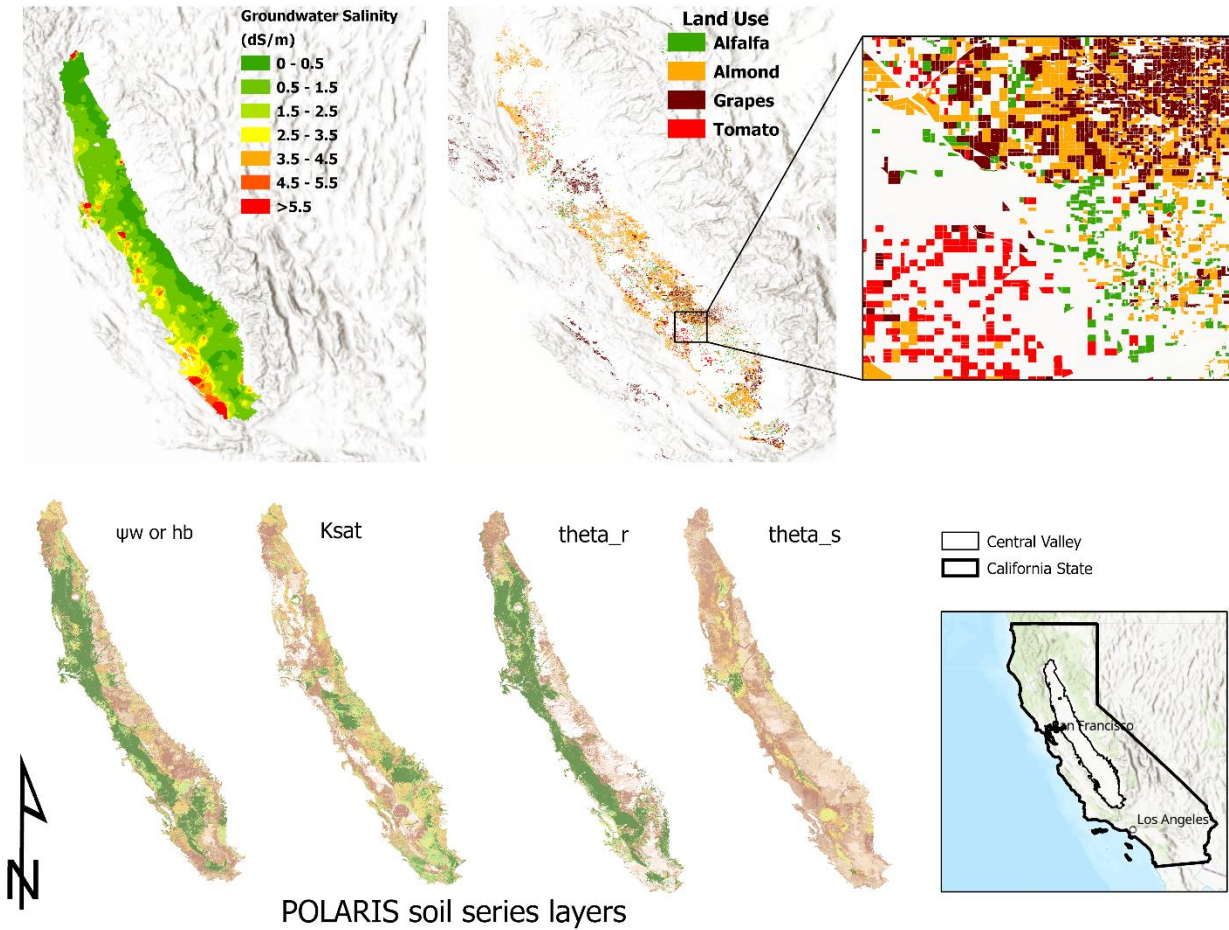


Figure 2-2. Raster inputs for spatial simulation of the model. At the top left, the groundwater salinity map is the spatial distribution of electrical conductivity in water in the groundwater wells. The land use of the four crops used in this study is shown at the top-right. At the bottom left, the raster layers of the soil physical parameters used to predict the spatial yield and profits are represented.

Results

Piece-wise and s-shape salinity function

The EC_{e50} for the four crops was computed using the threshold EC (dS/m) and the slope (% per dS/m) parameters (Table 2-1). Almonds had the lowest EC_{e50} , followed by grapes, processing tomatoes, and alfalfa. Figure 2-3 shows piece-wise and s-shape plots describing the degree of salt tolerance for alfalfa, almonds, grapes, and processing tomatoes, respectively.

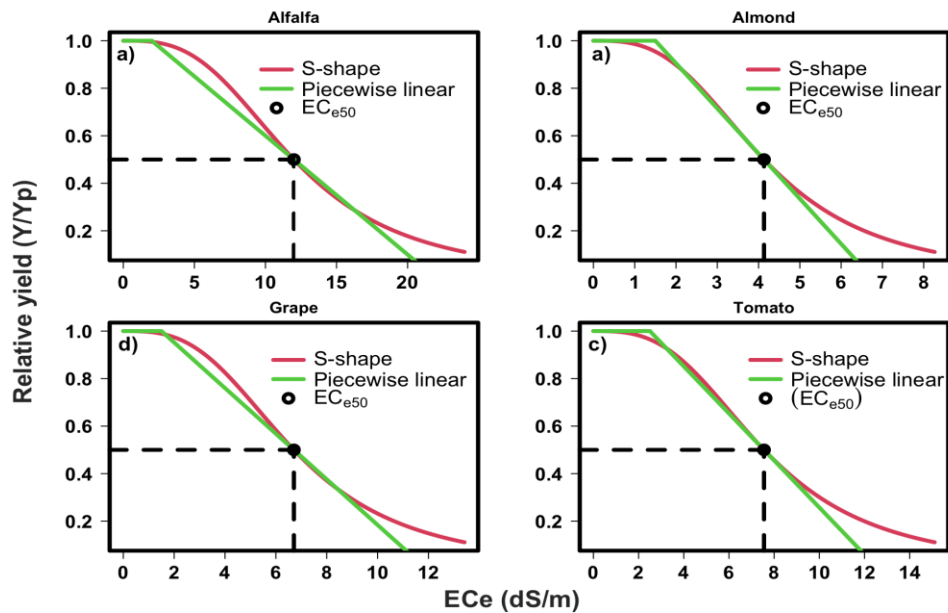


Figure 2-3. S-Shape and piece-wise linear crop salinity response models for a) almonds, b) alfalfa, c) processing tomatoes, and d) table grapes.

Crop yield response to salinity

All four crops were affected by increasing salinity levels in the root zone in a sandy loam soil. The model predicted that an EC_{iw} level of 5.5 dS/m could decrease relative yield by up to 10%, 45%, 18%, and 12% for alfalfa, almonds, grapes, and processing tomatoes, respectively, considering irrigation water application up to 12 mm/day. The model predicted 99% of the relative yield for alfalfa, almond, grape, and processing tomato using 6.5, 8.5, 7, and 5.5 mm/day, respectively, using irrigation water with low salinity level (0.5 dS/m). However, the same daily irrigation amount with an $EC_{iw} = 5.5$ dS/m showed just 76%, 50%, 70%, and 72% of the relative yield is attainable for alfalfa, almond, grape, and processing tomato, respectively (Figure 2-4).

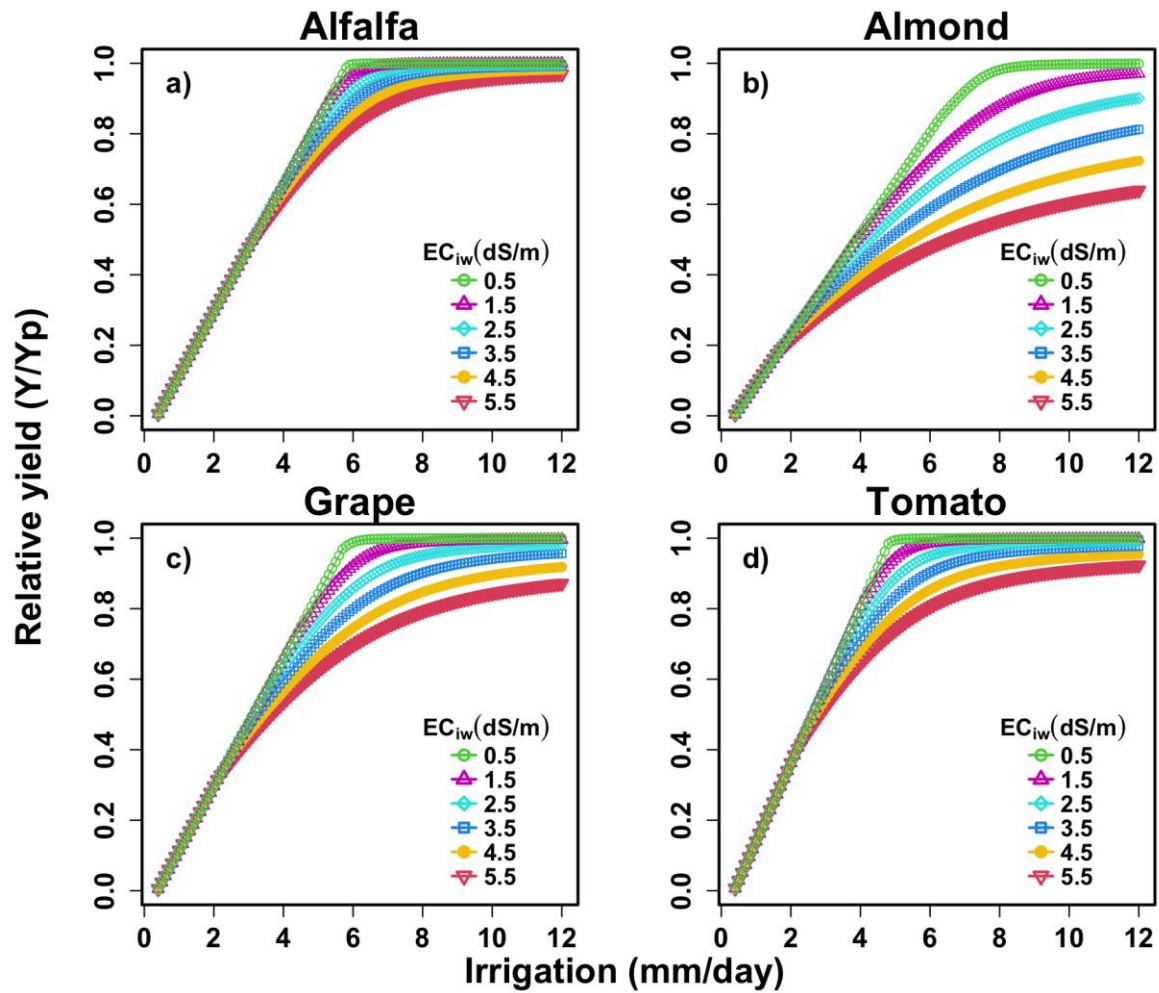


Figure 2-4. Relative yield as a function of daily irrigation amount (mm/day) at different levels of irrigation water salinity EC_{iw} (dS/m) for a) alfalfa, b) almonds, c) grapes, and d) processing tomatoes. Different colors represent different salinity (EC) levels from 0.5 to 5.5 dS/m.

Model performance in predicting yield.

Considering the model's simplicity and the associated estimated parameters (soil properties and EC_{iw}), the model predictions for yield were excellent and within acceptable limits (Figure 2-5). Comparison of experimental data from different studies conducted under different conditions against the model's prediction resulted in an R^2 of 0.82, 0.77, 0.78, and 0.64, and an RMSE of the relative yield of 9, 8, 23, and 11% for alfalfa, almonds, grapes, and tomatoes,

respectively. (Shani et al., 2007) found R^2 of 0.94 and 0.96 for tomatoes and grapevines but did not use RMSE as a performance indicator of the model.

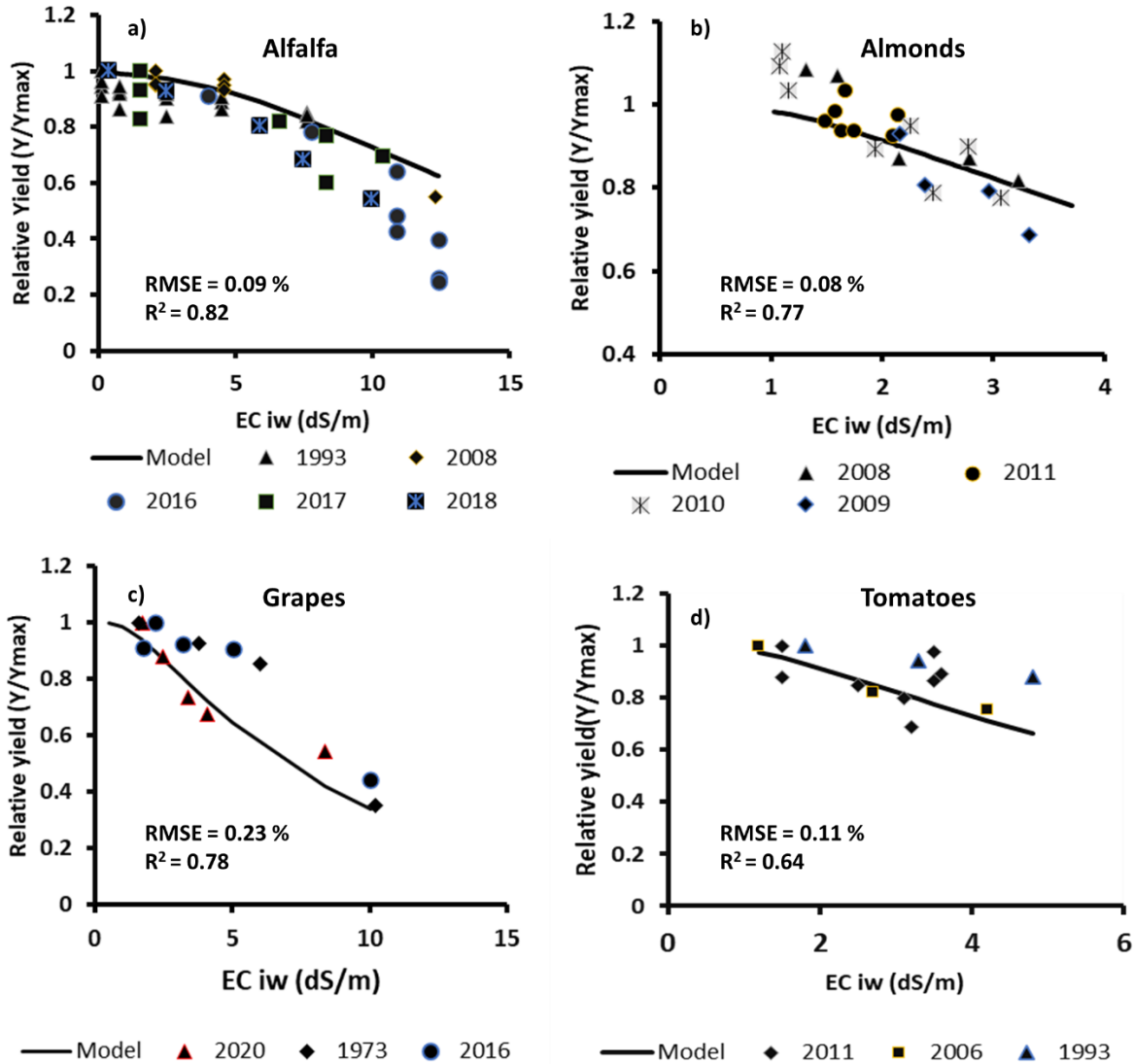


Figure 2-5. Relative yield response to irrigation water salinity (EC_{iw}) for a) alfalfa, b) almonds, c) grapes, and d) tomatoes. The data points are measured yield data collected from selected papers of the systematic literature review.

Salinity impacts on expected profits from crop production

Decreasing yield due to salinity affects expected economic returns. Water cost is critical to profitable crop production in arid and semi-arid climates, where agricultural production relies

heavily on irrigation. At the current water price of \$0.57 per ha-mm, daily irrigation with 7 mm of water ensured profit with Alfalfa, irrespective of the irrigation water salinity (Figure 2-6a). For almond production, profit is only obtained with at least 9 mm/day of irrigation with water with salinity less than 2.5 dS/m (Figure 2-6b). Similarly, grape production was profitable, with at least 8.6 mm/day and EC_{iw} not greater than 2.5 dS/m. As the EC_{iw} increased from 0.5 dS/m for both almonds and grapes, more irrigation is required to maintain profitability. However, above the salinity level of 2.5 dS/m, irrigation with additional water did not generate profit even though it increased yield (Figure 2-6c). Processing tomatoes produced \$186 per ha using 6.4 mm/day of water with EC_{iw} not greater than 0.5 dS/m, and losses occurred beyond EC_{iw} of 1.5 dS/m (Figure 2-6d).

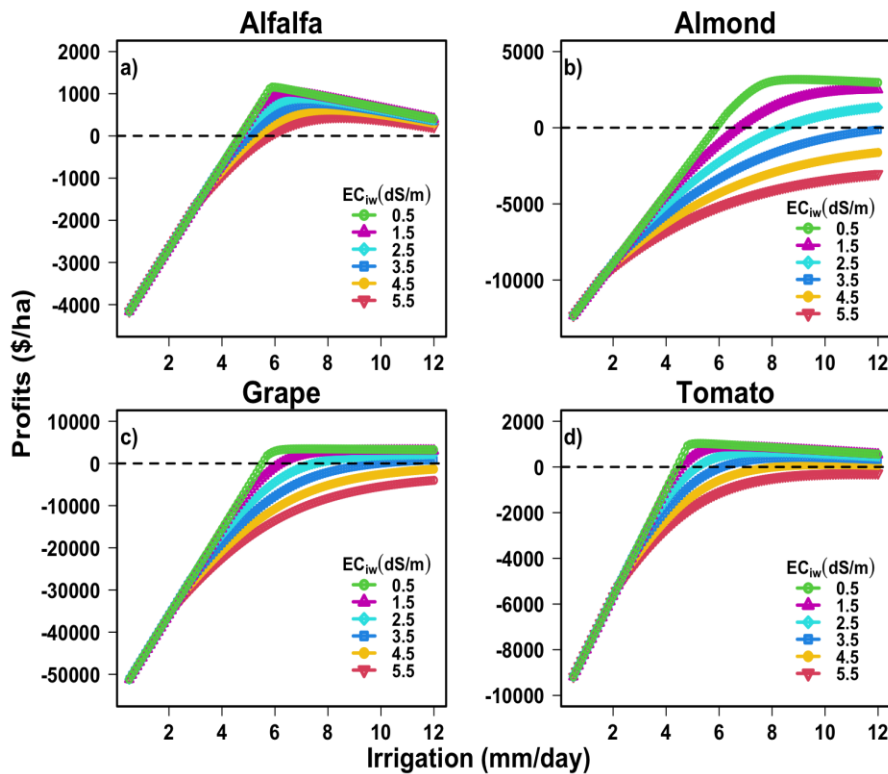


Figure 2-6. Potential profits regarding irrigation water applied and irrigation water salinity (EC_{iw}). The colors represent salinity levels from 0.5 to 5.5 dS/m. An assumed average water cost in California (\$70 per ac-ft \$0.57 per ha-mm) was considered for computing the profits in the graphic.

Crop output depends on water quality and cost. Figure 2-7 shows that alfalfa, almonds, grapes, and processing tomatoes lose profit margins as water prices increase. At \$1.22 per ha-mm, alfalfa and tomatoes become unprofitable. Alfalfa production generated profits (\$1,297-\$356 per ha) irrespective of EC_{iw} values, with the price of water at \$0.41 per ha-mm. However, profits were possible only with EC_{iw} of 0.5 dS/m, at \$1.22 per ha-mm of water (Figure 2-7a). Processing tomato production was only profitable when the EC_{iw} was not above 1.5 dS/m and the water price of \$0.41 per ha-mm. Above \$0.41 per ha-mm, tomato production was barely profitable only when irrigated with EC_{iw} of 0.5 dS/m. At a water price of \$1.22 per ha-mm, tomatoes become unprofitable regardless of the water quality (Figure 2-7d). On the other hand, high-market-value crops like grapes and almonds were still profitable at higher water prices. Provided that the EC_{iw} was not greater than 2.5 dS/m, almond production was still profitable even at \$0.81 per ha-mm water. However, at \$1.22 per ha-mm water, profits were possible only with EC_{iw} not greater than 1.5 dS/m (Figure 2-7b). Similarly, Grape's production was profitable when EC_{iw} levels were not greater than 2.5 dS/m and water prices were less than \$0.41 per ha-mm. At higher water prices, profit was only possible with irrigation water EC_{iw} of 0.5 dS/m (Figure 2-7c).

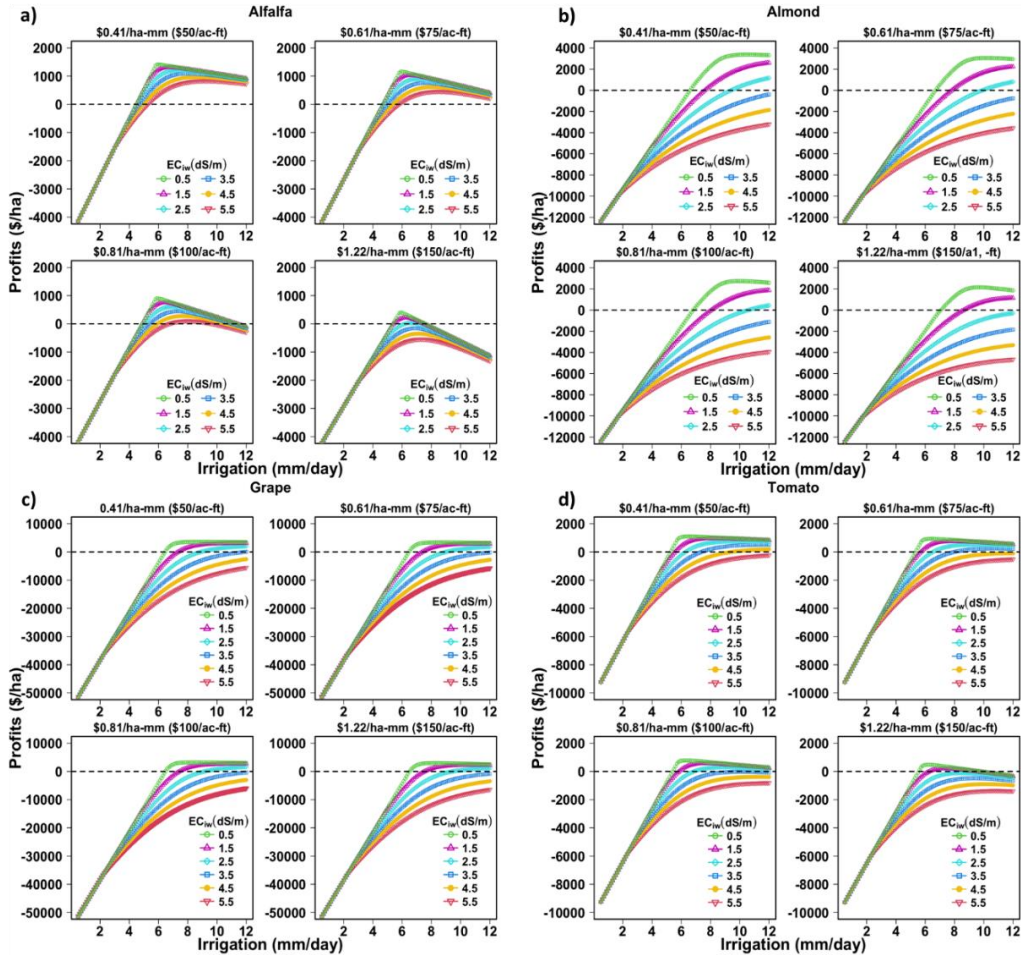


Figure 2-7. Profits (\$/ha) as a function of water amount at different water prices for alfalfa, almonds, grapes, and processing tomatoes. The water prices were \$0.41/ha-mm, 0.61/ha-mm, \$0.81/ha-mm, and 1.22/ha-mm. The colors represent the irrigation water's different electrical conductivity (EC_{iw}) levels from 0.5 to 5.5 dS/m.

Assessing the model performance in predicting profits

According to the R^2 and RMSE obtained from the model predicted crop profit using five years of observed profits versus the reported profits, the model has a very strong goodness-of-fit. The R^2 for alfalfa, almonds, grapes, and processing tomatoes were 0.99, 0.99, 0.74, and 0.99, respectively, while the RMSE for the simulated profits were 48, 211.39, 2461, and 68 \$/ha for alfalfa, almonds, grapes, and processing tomatoes, respectively (Figure 2-8).

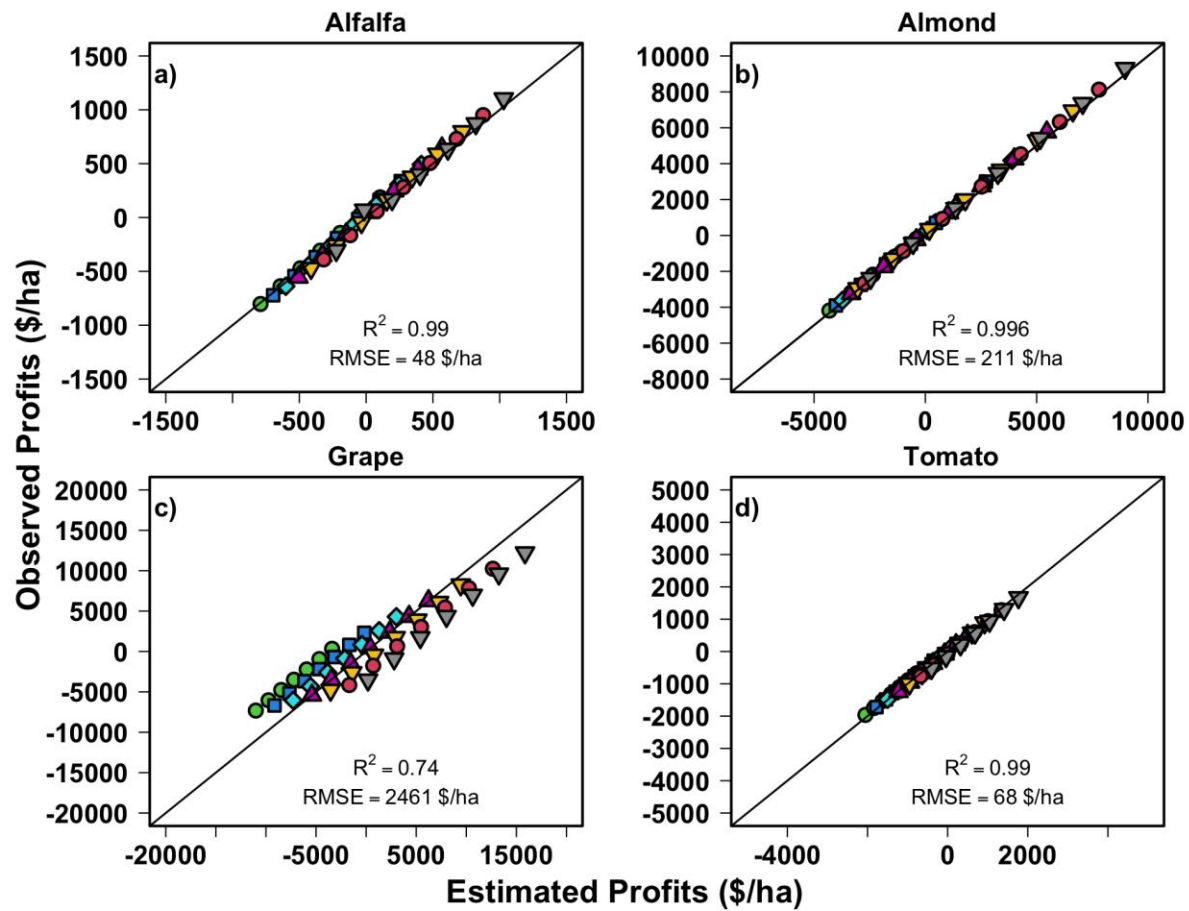


Figure 2-8. Assessing model performance against observed data for a) alfalfa, b) almonds, c) grapes, and d) processing tomatoes.

Influence of crop market price and salinity on profitability

Crop market price determines the revenue generated from crop production and is critical to the amount of profit that can be generated. Figure 2-9 shows the historical market price and profit for alfalfa, almonds, grapes, and processing tomatoes from 2013 to 2017 and 1.5 times the 2017 market price at various EC_{iw} . Alfalfa’s market value showed a declining trend, with losses recorded from 2015, regardless of the water EC_{iw} . As water prices increased, losses were recorded even with high-quality irrigation water. For almonds, production was profitable irrespective of water price, except in 2016 and 2017, when the market value of almonds was low. Even then, almond cultivation was still profitable, provided that EC_{iw} was not higher than 3.5

dS/m. Profits were possible for grapes with the market price reported in 2015 when the EC_{iw} was not greater than 2.5 dS/m. Regardless of water quality and cost, all other years resulted in net loss, except for the projected market value of 1.5 times the 2017 price. Lastly, the model indicated profit for processing tomatoes when the market value was above \$80/tons (2014, 2015, and 1.5*2017) for salinity levels between 0.5 – 5.5 dS/m, regardless of the water price per ha-mm. The years with poor crop market values (2013, 2016, and 2017) resulted in losses, especially if irrigated with EC_{iw} greater than 1.5 dS/m. Market prices reported in 2013 and 2017 triggered profitability losses with high saline water and water prices.

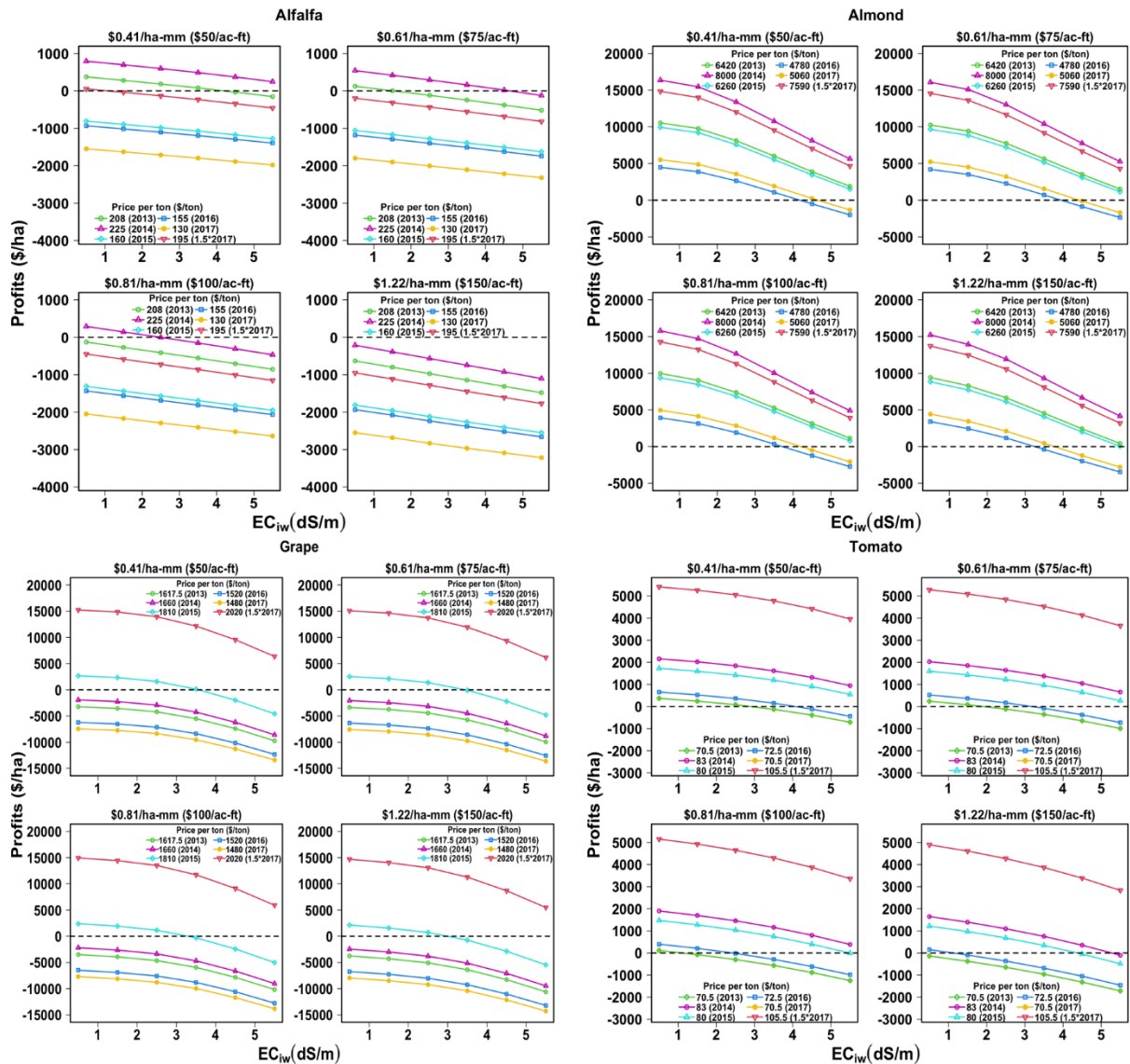


Figure 2-9. Expected profits (\$/ha) as a function of EC_{iw} for alfalfa, almonds, c) grapes, and processing tomatoes under different water prices (\$50 per acre-ft or \$0.41 per ha-mm, \$75 per acre-ft or 0.61 per ha-mm, \$100 per acre-ft or \$0.81 per ha-mm, and \$150 per acre-ft or \$1.22 per ha-mm). The colors represent the different crop prices.

Spatial distribution of predicted yields and profits

Considering groundwater salinity, the model estimated adequate yields in the Central Valley. The relative yields were less impacted in the northern and eastern portions of the Valley compared to the western and southern parts. The relative yield for alfalfa, almonds, grapes, and processing tomatoes with 3 mm of daily irrigation range from 0.20 to 0.54, 0.00 to 0.42, 0.18 to

0.54, and 0.17 to 0.65, respectively. However, with 6 mm/day of irrigation water, the relative yield ranged from 0.24 to 0.99, 0.00 to 0.82, 0.23 to 0.99, and 0.22 to 0.99 for alfalfa, almonds, grapes, and processing tomatoes, respectively. Simulations with daily irrigation amounts of 6 mm allowed alfalfa and processing tomatoes to reach up to 99% of their relative yield, while almonds and grapes required at least 9 mm/day to reach that same yield level (Figure 2-10).

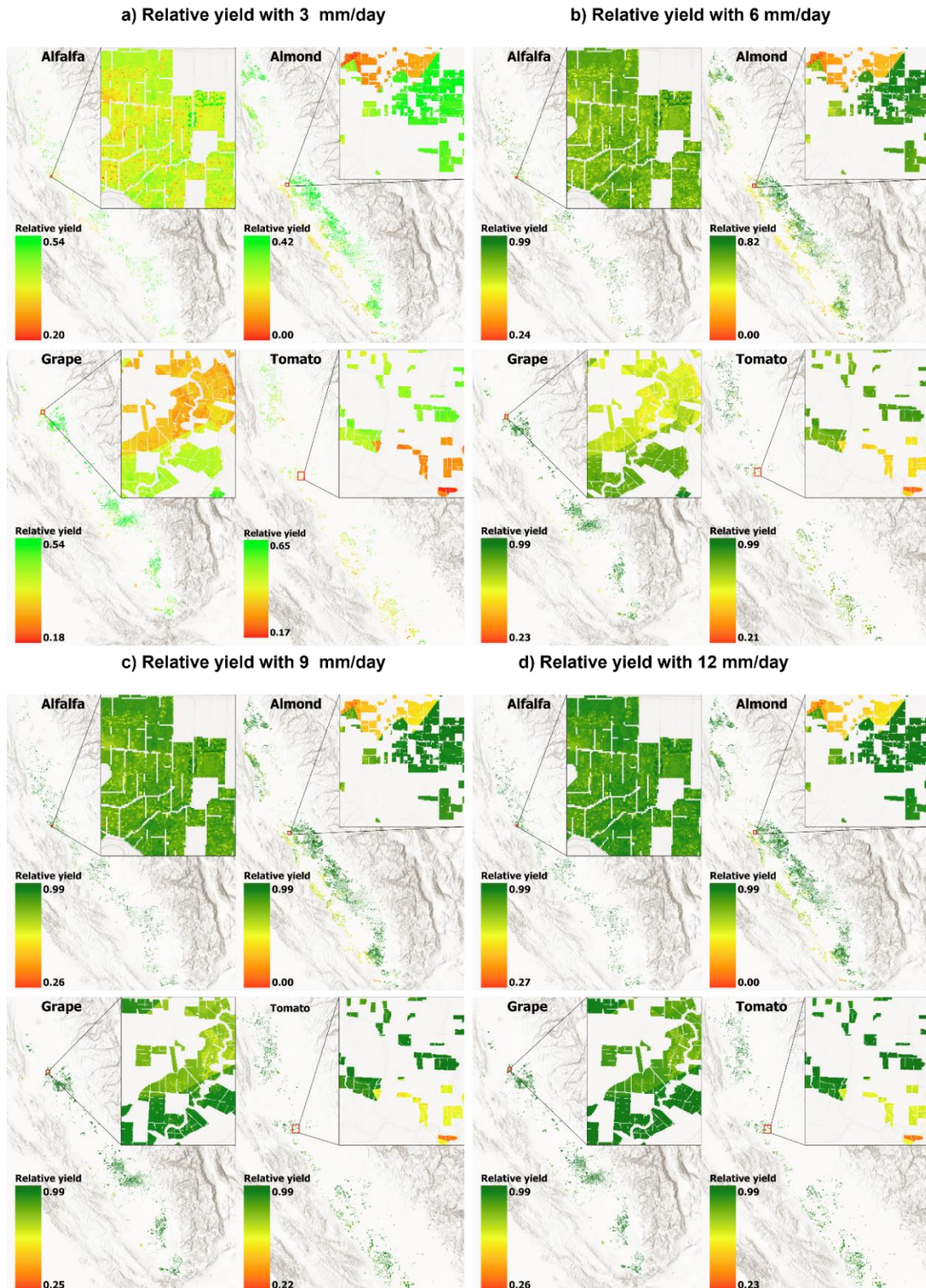


Figure 2-10. Spatial distribution of relative yield across the Central Valley for alfalfa, almond, grape, and processing tomatoes considering groundwater salinity status. a-d represent irrigation amount of 3, 6, 9, and 12 mm/day, respectively.

The model prediction indicated that no profit was possible from all four crops with 3 mm/day irrigation. At 6 mm/day of irrigation, maximum profits were obtained for alfalfa and processing tomatoes. However, at higher irrigation amounts, such as 9 and 12 mm/day, the profits decreased due to the cost of the extra water and the relative yield obtained per mm of water used. Maximum profits with almonds and grapes cultivation were obtained with 9 mm/day irrigation. Similarly, the application of higher amounts of water resulted in a decline in the profit margin (Figure 2-11).

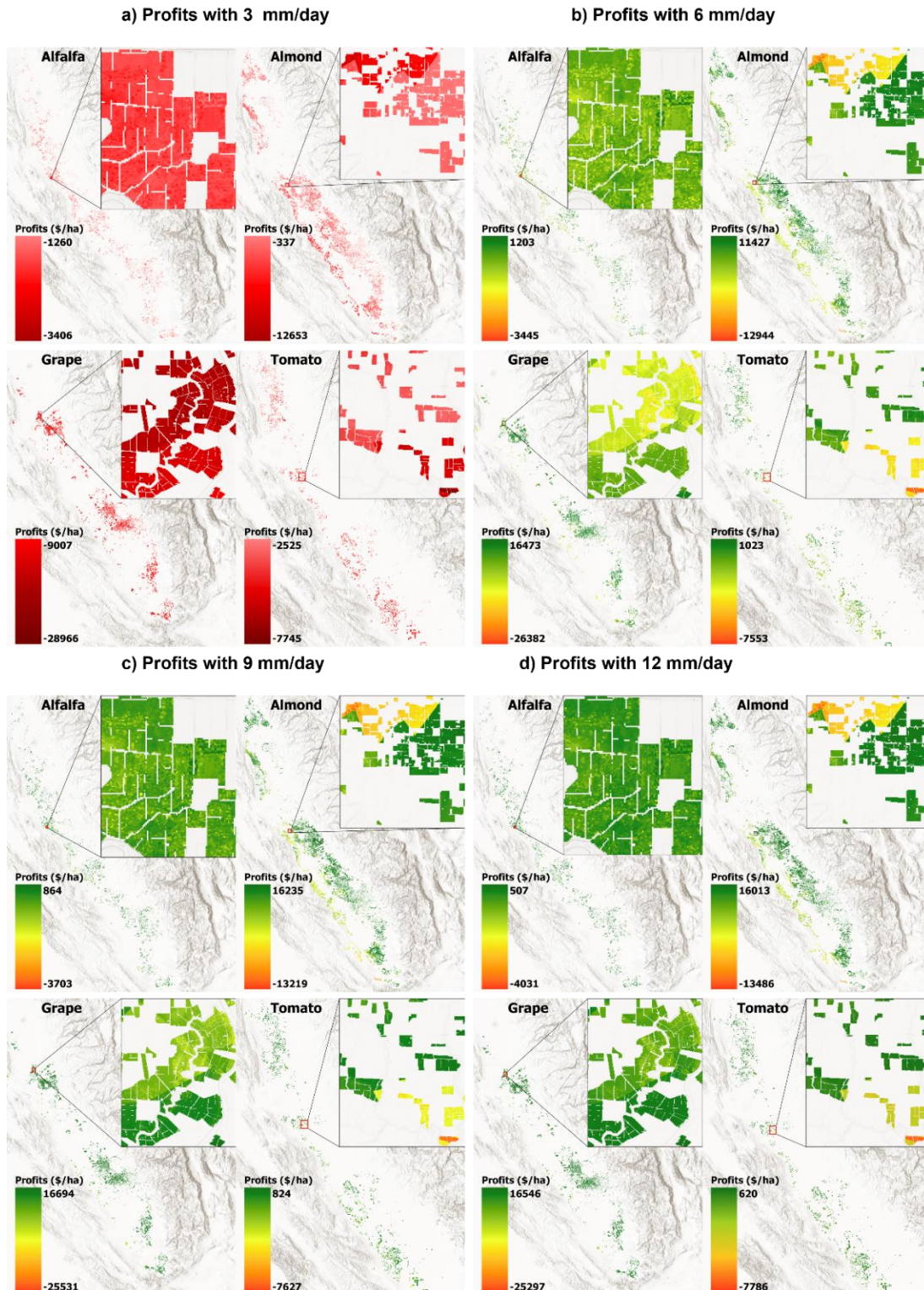


Figure 2-2. Spatial distribution of profits across the Central Valley for alfalfa, almond, grape, and processing tomatoes, considering groundwater salinity status. a-d represent irrigation amount of 3, 6, 9, and 12 mm/day, respectively.

The model forecasted a decrease in relative yield and a reduction in the areas that can generate profits. However, 9 mm/day irrigation is projected to result in sufficient profits across the Valley, although some areas may still experience losses. Figures 1-12 and 1-13 present the stacked data on relative yield and profits for the four crops to better visualize the distribution of salinity impacts on crop production. This allows for a more comprehensive understanding of the impact of salinity on crop production across the Valley. It is important to note that while some areas may still suffer losses, the overall profitability is expected to be satisfactory with 9 mm/day irrigation. This information can be highly valuable for farmers and decision-makers in making informed choices regarding irrigation practices and crop selection. By considering the potential salinity impacts on crop production and the corresponding profit margins, farmers can optimize their yields and minimize losses.

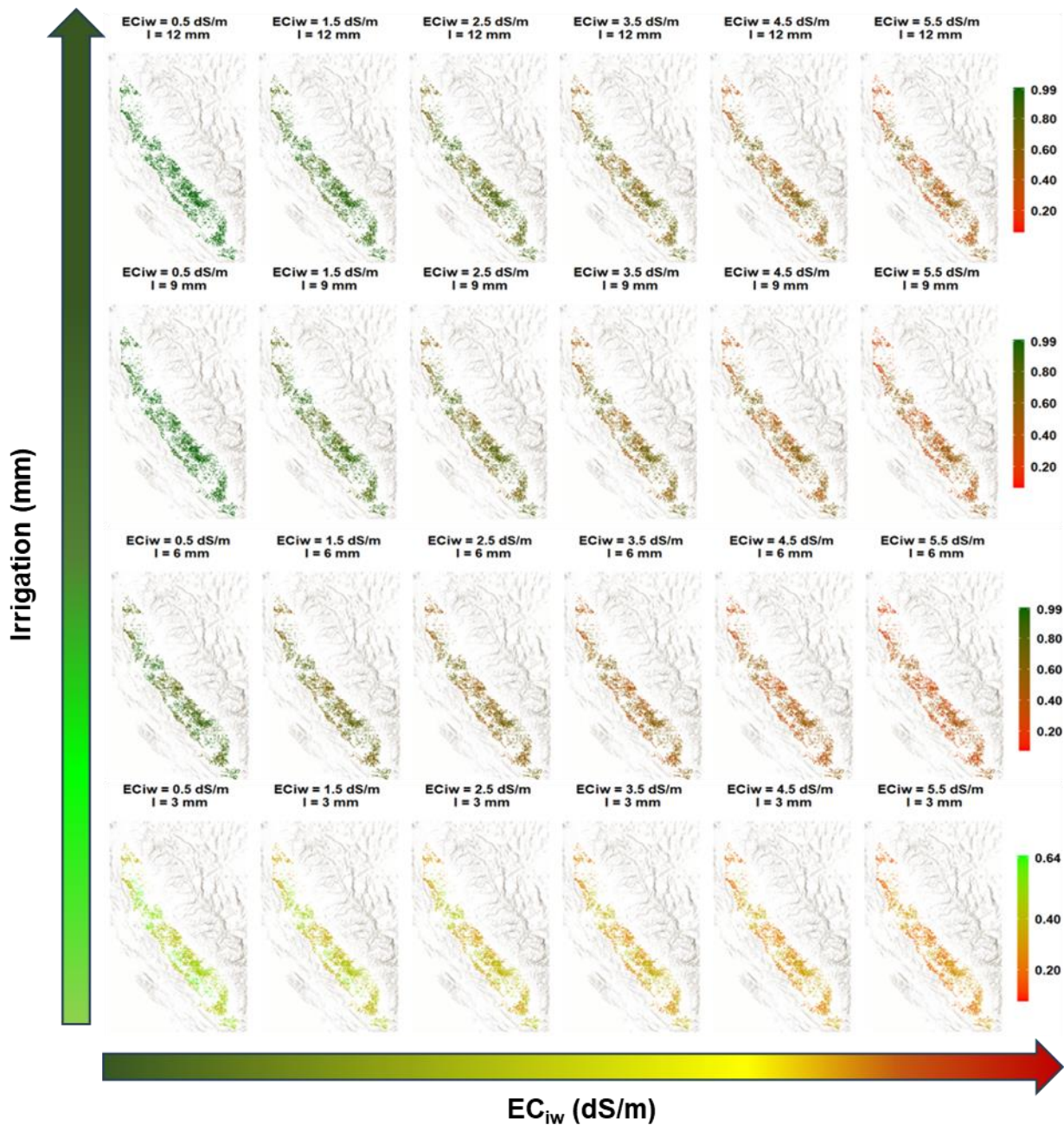


Figure 2-12. Spatial distribution of the relative yield for alfalfa, almond, grape, and processing tomatoes across the Central Valley considering 3, 6, 9, and 12 mm/day irrigation. Water application amounts (from 3 to 12 mm/day) are from top to bottom and increasing EC_{iw} from 0.5 to 5.5 dS/m are from left to right. Crop relative yields are grouped to show the impacts of salinity and irrigation amount on crop yield across the Valley. The color bars, from green to red, illustrate decreasing relative yield as EC_{iw} increases.

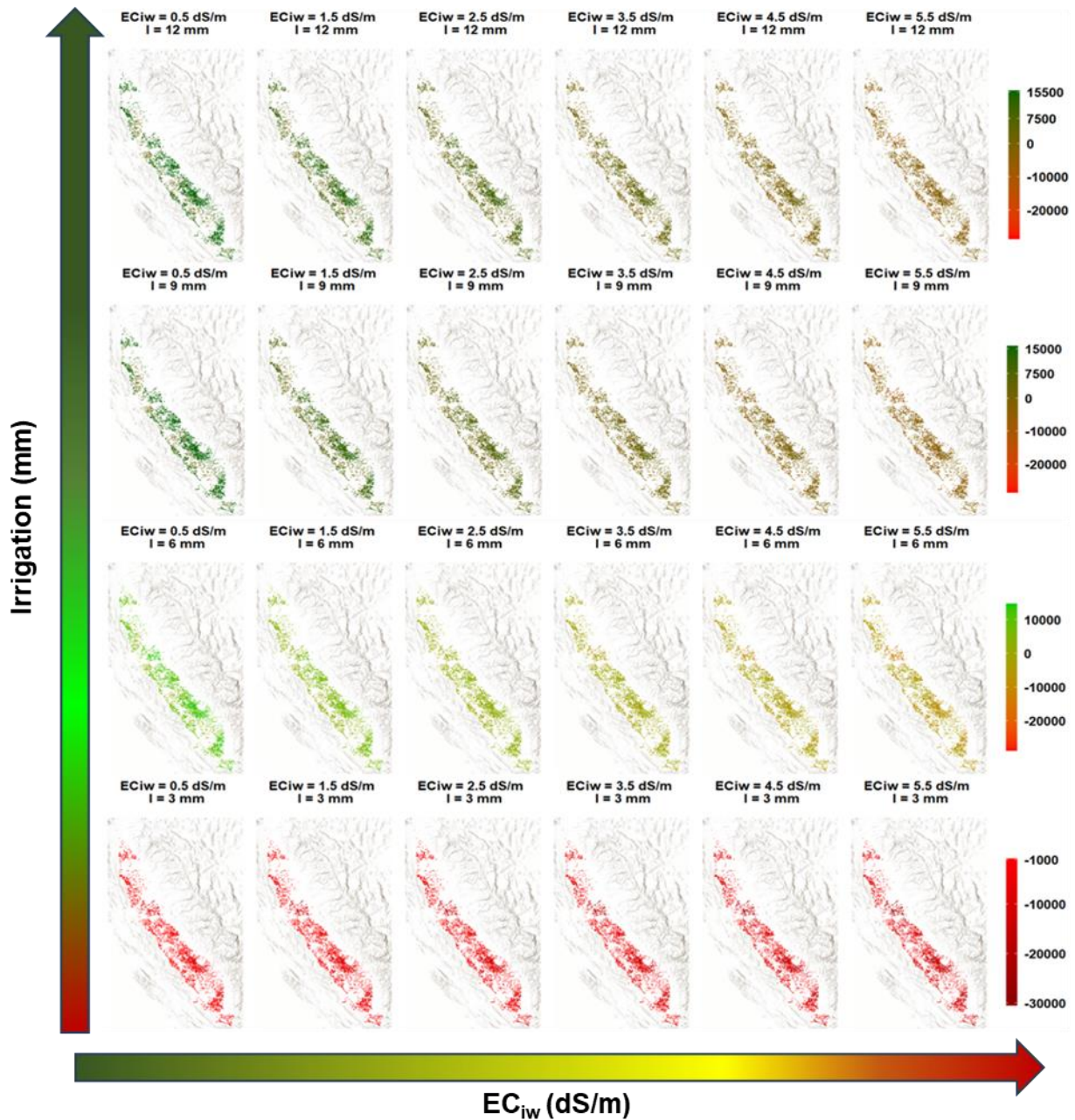


Figure 2-13. Spatial distribution of the relative profits for alfalfa, almond, grape, and processing tomatoes throughout the Central Valley considering 3, 6, 9, and 12 mm/day irrigation. Water application amounts (from 3 to 12 mm/day) are from top to bottom and increasing EC_{iw} from 0.5 to 5.5 dS/m are from left to right. Predicted profits for all four crops are grouped to show the impacts of salinity and irrigation amount on crop production across the Valley. The color bars, from green to red, illustrate decreasing relative yield as EC_{iw} increases.

Discussion

Crop yield response to irrigation water salinity

Crops are tolerant to different salinity levels, and simplistic models have been developed to characterize crop salt response and predict their relative yield as a function of the root zone's average saturated soil extract (EC_e). Woody and vine crops such as almonds and grapes are less tolerant and demonstrate stronger response to salinity than agronomic crops such as alfalfa and tomatoes (Grieve et al., 2012). Crop response to salt can be effectively measured using a threshold value, denoting the maximum tolerable root zone EC_e above which yields decline and with a slope describing the rate of yield decline due to increased soil salinity beyond the threshold (Maas and Hoffman, 1977). The list of crop-specific parameters for the threshold and slopes was updated by (Grieve et al., 2012). Steppuhn et al. (2005) assessed six non-empirical models, including both piece-wise and the discount (S-shape) models, and concluded with similar EC_{e50} values found in the studies. However, some alfalfa varieties are more salt tolerant, and recent experiments showed that a relative yield reduction of 50% can be reached at EC_e from 11 – 14 dS/m (Benes et al., 2018). With this model, we predicted the EC_{e50} to be 12 dS/m by modifying the slope and the threshold. Low salinity tolerance of almonds and grapes has been reported to adversely affect their productivity (Sandhu and Acharya, 2019; Suarez et al., 2019; Zhou-Tsang et al., 2021; Zrig et al., 2011), which is in agreement with the modeling results of this study. Tree crop salinity response can be complicated because of the influence of specific salt constituents (Christie, 1987), and woody perennials can accumulate specific ions in their tissues, leading to specific ion toxicity, e.g., sodium and boron. Semiz and Suarez (2019) found tomato yield loss of up to 50% at 5.7 dS/m, which is very similar to the one calculated by the model in this study ($EC_{e50} = 5.5$ dS/m).

The standard errors pertained to the threshold (EC_{e50}) range from 50 to over 100%, denoting the enormous uncertainty of these values primarily due to a lack of physiological justification (Grieve et al., 2012). The debate about a real threshold value has led to the development of s-shape models (van Genuchten and Gupta, 1993; van Genuchten and Hoffman, 1984) that are more agronomically plausible, although they have found less extensive application as the threshold model due to less intuitive appeal of the s-shape model parameters (van Straten et al., 2019). A more robust and agronomically sound threshold crop salt-tolerance parameter (EC_{e90} : soil salinity that decreases the relative yield up to 90%) was suggested as an alternative to the threshold EC_e (van Straten et al., 2019, 2021).

Alfalfa is classified as moderately sensitive to salinity beyond an EC_e of 2.0 dS/m. A unit increase in salinity beyond this threshold would reduce alfalfa yield by 9.6% (Grieve et al., 2012; Maas and Grattan, 1999; Maas and Hoffman, 1977a). Recent studies such as (Cornacchione and Suarez, 2017) found that alfalfa could produce high biomass (up to 77%) in high saline conditions ($EC_e = 5.8$ dS/m). However, this salinity tolerance might be due to a specific gene, as salinity response varies greatly among alfalfa genotypes (Sandhu et al., 2017). Alfalfa yields using irrigation water with high salinity levels (EC_{iw} of 8-11 dS/m) were found to be economically viable in the Southern part of the Central Valley (21.5 tons/ha) (Putnam et al., 2019). Such findings refute literature values estimating alfalfa yield decline at low root zone salinity ($EC_e = 2$ dS/m).

Almonds are sensitive to salinity, which is reflected by their low threshold EC of the soil saturation extract (EC_e) of 1.5 dS/m and a growth reduction rate of 19% per unit increase in salinity beyond the threshold (Maas and Hoffman, 1977). Several almond orchards are damaged under conditions caused by salinity, even under the published threshold value (Sanden et al.,

2014). Irrigation with high saline water (4.6 dS/m) was reported to decrease almond kernel yield by 46% compared to low saline water (0.8 dS/m) (Franco et al., 2000). Although almonds are drought-resistant, their peak performance is extremely sensitive to irrigation water quality (Prgomet et al., 2020).

Grape is considered moderately sensitive to salinity beyond an EC threshold of 1.5 dS/m and 9.9% of the yield decline rate with a one dS/m EC increase (Grieve et al., 2012; Maas and Grattan, 1999; Maas and Hoffman, 1977). Paranychianakis et al. (2004) reported 50% grape yield loss when irrigated with salty water (EC_{iw} 1.9/m) as compared to freshwater (EC_{iw} 0.6 dS/m). However, long-term studies of grape yield-salinity relationships have shown the pre-eminence of particular rootstocks that allow salinity tolerance (X. Zhang et al., 2002). A confounding issue arises because grapevines can have a catastrophic response to long-term salt exposure as salts build up to threshold levels in woody tissues of the plants, resulting in physiological damages, including vine mortality (Dag et al., 2015; Shani and Ben-Gal, 2005; Simhayov et al., 2023).

Processing tomatoes are considered moderately sensitive to salinity, with a 9.6 % yield decline with one unit of increased salinity beyond the threshold EC of 2.5 dS/m (Grieve et al., 2012; Maas and Grattan, 1999; Maas and Hoffman, 1977). Salinity can significantly affect tomato yield by reducing vegetative growth (Tzortzakis et al., 2022). Tomato yield is reduced at E_{Ce} of 2.5 dS/m or higher, and an increase of 1 dS/m would trigger a yield reduction of up to 10% (Cuartero and Fernández-Muñoz, 1998), similar to our results. However, a salinity level (E_{Ce}) of 4.8 dS/m was found to have no significant impact on tomatoes' fruit yield and improved the quality of the nutrients contained in the fruit (Stamatakis et al., 2003).

Combined impacts of salinity, crop market prices, and water prices on economic returns

Water scarcity in California has led to the adoption of high-value crops such as fruits and nuts (Ayars et al., 2015). Under irrigation water with higher salinity values, the model predicted higher profits from crops with high market value, such as almonds and grapes. In contrast, both alfalfa and tomatoes were likely more affected by increased water prices than salinity due to their relatively low market value. The slope of the profits from alfalfa and processing tomatoes decreased slowly with the salinity increase. However, processing tomatoes profits were much more affected than alfalfa at higher salinity levels, such as 5.5 dS/m. The profits from almonds and grapes decreased substantially with the salinity levels. However, water prices and salinity levels affected almond profits less than grapes (Figures 1-9 and 1-10). This might be due to the almond sale prices. Almond's revenue overtook processing tomatoes by providing much more profits in many Counties of the State of California (Smith, 2018). Gebremichael et al. (2021) investigated cropping patterns in California's Central Valley in response to droughts. They concluded that the shift in cropping patterns was probably due to increasing crop prices and changes in pumping costs. These findings agree with our study results predicting higher profits from crops with high market value while predicting lower economic returns from crops with low market values, although with a relatively mild response to salinity.

Similar findings were generated by the same model for a case study evaluating the feasibility of brackish groundwater desalination for irrigation in southern Israel (Kaner et al., 2017). In that study, high-value, salinity-sensitive crops (date palms and table grapes) were found to justify the costs of desalination as an alternative to irrigation with local water high in salts.

The model predicted a decrease in revenues, similar to other studies assessing salinity impacts on economic outcomes in the Central Valley (Medellín-Azuara et al., 2014; Montazar et

al., 2017; Wichelns and Oster, 2006). Integrated biophysical models with soil and irrigation water salinity and economic data can be used as decision-support tools for salinity management. Kaner et al. (2019) implemented a web-based decision support system that returns yield and economic gains from crops considering irrigation water salinity and market price scenarios with environmental considerations. Increases in water prices or salinity were predicted to significantly negatively affect farmers' incomes. Welle and Mauter (2017) estimated that salinity reduced agricultural revenues by \$3.7 billion (in 2014) using a generalizable approach to estimate the agricultural yield losses due to soil salinization. When the Delta water is more saline during dry years, dual export conveyance gives the highest revenue losses, roughly \$4.5 billion annually. Under the future groundwater pumping regulations in the Central Valley, water supplies may not be sufficient to meet water demands and trigger losses by up to 30% of total annual revenues in the Valley (Mall and Herman, 2019). Major crops such as almonds, alfalfa, and grapevine have a significant water footprint in the Central Valley (Fulton et al., 2019), and their economic returns can be severely affected by high water prices in drought periods. The paradox projected declines in water supplies for irrigation in the Central Valley of California would exacerbate salinity problems because there will be less water leaching salts out of the root zone.

Significance and limitations of the model

The success of the model is remarkable, considering its simplicity and dependence on major assumptions. The assumption of steady-state conditions may limit its validity to environments where much of the irrigation season is without significant precipitation and where advanced irrigation scheduling and water are supplied regularly as a constant function of potential evapotranspiration. Pseudo-steady state conditions were found to be the case for date palms grown in lysimeters in Israel (Tripler et al., 2012). The assumption that economic return can be predicted by simulation of vegetative growth (transpiration) is also questionable,

obviously crop-specific, and not always validated in cases where vegetative and reproductive growth are not linearly related. While these may necessitate caution in using the model, its success under advanced irrigated agriculture conditions in Israel and California boosts confidence in its potential as a planning and analysis tool.

Conclusion

The findings of this study shed light on the significant impact of irrigation water salinity on the sustainability of irrigated agriculture, in the form of reduced crop yields and profitability. Salinity is a global problem, with approximately 30% of irrigated lands being salt-affected due to human-induced salinization. In the Central Valley, more than 2 million hectares of irrigated cropland are affected by salinity arising from saline irrigation water or saline soil. The depletion of groundwater resources further exacerbates salinization in certain areas of the Central Valley.

Given the influence of profitability on grower management decisions, it is crucial to establish a comprehensive integrated framework for sustainable management of irrigation water salinity. To address this challenge, the study developed a unique framework that integrates biophysical modeling, economic analysis, and geospatial modeling. This framework enables a comprehensive assessment of the impact of irrigation water salinity on crop yield and profitability.

The framework was applied to evaluate the effects of salinity on major crops cultivated in the Central Valley, including alfalfa, almonds, grapes, and processing tomatoes. A notable feature of the modeling framework was its ability to incorporate site-specific soil and groundwater quality information to assess the impacts on crop yield and profitability. This detailed assessment provided valuable insights into the sustainability of irrigated agriculture in the Central Valley, which is one of the world's most vital agricultural regions.

The study revealed that economic revenue decreases as irrigation water salinity and the cost of water increase. However, even under elevated salinity levels and increased water costs, agricultural activities can remain profitable, particularly when cultivating high-value crops such as almonds and grapes. Moreover, the framework's capability to account for spatial variations in soil properties and groundwater quality enables predictions of regional differences in salinity impacts on crop yield and profitability. Negative impacts were more pronounced on the Westside of the Central Valley.

The spatial predictions derived from the modeling framework can assist in prioritizing lands for potential retirement from irrigated agriculture, especially in regions where groundwater supplies face constraints, as observed under public policies such as the Sustainable Groundwater Management Act (SGMA) in the case of California. While this study focused on the Central Valley, the integrated modeling framework can be applied to any region worldwide grappling with salinity issues and their impact on irrigated agriculture productivity and economic outcomes.

Furthermore, the developed modeling framework, implemented in R, is publicly available and can be utilized by various stakeholders, including policymakers, agricultural consultants, extension professionals, economists, agronomists, engineers, and water managers. Its availability facilitates informed decision-making and the development of sustainable strategies to address salinity-related challenges in irrigated agriculture.

CHAPTER 3 CENTRAL VALLEY IRRIGATION WATER SALINITY DECISION-SUPPORT WEB TOOL

Abstract

The study introduces a novel decision-support web tool designed to assist farmers and policymakers in salinity management in the Central Valley (<https://yieldprofit.ucdavis.edu/>). This tool integrates agronomic, economic, and spatial data to predict crop yield and profitability under varying irrigation water salinity. The resource is intended to assist policymakers and Groundwater Sustainability Agency managers in identifying regions that are unsuitable for profitable crop cultivation and prioritizing these regions for multi-benefit land repurposing, triggering a decrease in agricultural water demand. The tool can also help farmers to predict crop yield and profitability in relation to irrigation water salinity. The decision-aid tool capabilities were evaluated with four major crops (alfalfa, almonds, table grapes, and processing tomatoes) in predicting yield and profits for a range of irrigation water salinity levels across the Central Valley, highlighting the significance of crop-specific responses to salinity. The tool's development, application, and performance underscore the potential of decision-making aid technologies in managing salinity and enhancing the sustainability of irrigated agriculture in arid and semi-arid regions.

Introduction

In California's Central Valley, the increasing reliance on groundwater due to intensive agricultural practices and recent severe droughts has underscored the critical need for sustainable water and salinity management strategies (Faunt et al., 2016; Quinn and Oster, 2021). Innovative solutions, such as the use of recycled wastewater and brackish groundwater for irrigation, have been explored to address these challenges (Kisekka et al., 2024). While offering a potential solution to water scarcity, these alternative water sources contain dissolved salts that can

accumulate in the root zone, potentially impacting crop productivity and leading to environmental degradation through leaching to groundwater and surface water systems (Nicolas et al., 2023). Best management practices are essential to address the biological-physical system concerns and the economics of production under these conditions, highlighting the need for comprehensive strategies to protect soil and water systems while maximizing productivity (Kaner et al., 2019; Shani et al., 2007, 2009). Managing soil salinity and optimizing water use in salt-affected arid regions requires adopting innovative and sustainable agriculture practices (Wichelns and Qadir, 2015). Moreover, integrating soil-water-plant management practices offers a promising approach to using saline waters for crop production, thereby mitigating the adverse impacts on soil and water resources. The development of accurate decision-aid tools and proper irrigation scheduling can significantly support sustainable agriculture in salt-affected arid regions.

Models and decision support systems have been developed to predict relative crop yield for various crops, soil types, and irrigation water salinity (Skaggs et al., 2014). However, maximizing total profit regardless of yield is a critical goal of agricultural production. Shani et al. (2007) developed an analytical model integrating biophysical parameters with economic data to predict crop yield and profitability under various irrigation water salinity levels. Kaner et al. (2019) implemented this biophysical model into a user-friendly decision support web tool, allowing users to predict crop yield and profitability by considering irrigation water salinity and production costs. Both the model and decision support tool did not include a spatial component and, therefore, were limited in site-specific yield and profit prediction. Nicolas et al. (2023) adapted this model for major crops grown in the Central Valley and developed a spatial component to predict crop yield and profitability across the Central Valley.

The objective of this study was to implement the adapted model as a user-friendly decision-making aid web tool that (1) assists growers in predicting yield and profitability as a function of irrigation water salinity and quantity and (2) helps policymakers and Groundwater Sustainability Agency (GSA) managers identify areas unsuitable for sustainable and profitable agriculture and prioritize them for multi-benefit land repurposing to reduce agricultural water demand.

Methods

Agronomic-economic model

The Analytical Salt-WatER model integrates critical aspects of the soil-plant-atmospheric continuum through a one-dimensional, mechanistically-based approach that operates under four foundational assumptions: (a) the root zone's environmental conditions can be abstracted into effective values of key parameters like soil water content and soil salinity; (b) these conditions are considered to be in a steady state, removing the dimension of time; (c) the climate conditions are assumed to be constant and (e) a proportional relationship between relative transpiration and relative yield exists as shown in Equation 3-1:

$$Y_r = \frac{Y}{Y_p} = \frac{T}{T_p} = T_r \quad (3-9)$$

The parameters in Equation 3-1 are Y: yield or biomass production (tons/acre), T: transpiration (mm/day), Y_r : relative yield, Y_p : potential yield (tons/acre), T_r : relative transpiration, T_p : potential transpiration (mm/day).

The behavior of crop transpiration (mm/day) is given in Equation 3-2.

$$T = \frac{\min \left\{ T_p, \left[\left(\psi_{root} - \frac{\psi_w}{\left(\frac{I-T}{K_s} \right)^{1/\eta}} \right) (I-T) * b \right] \right\}}{1 + \left(\frac{EC_{iw} * I * \left(\theta_r + (\theta_s - \theta_r) \left(\frac{I-T}{K_s} \right)^{1/\delta} \right)}{EC_{e50} * (I-T)\theta_s} \right)^p} \quad (3-2)$$

The parameters of Equation 3-2 are I: irrigation (mm/day), EC_{iw} : water salinity levels (dS/m), K_s : saturated hydraulic conductivity (mm/day), θ_s : saturated soil moisture content, θ_r : residual soil moisture content, ψ_{root} : crop sensitivity to available soil moisture (mm), ψ_w : air-entry head (mm), δ and η : empirical soil characteristic parameters, EC_{e50} : soil saturated paste solution EC, reducing yield by 50% (dS/m), p governs the steepness of the curve, and b characterizes the flow length from the soil to the crop roots. The model includes management factors (I and EC_{iw}), physical properties (T_p , K_s , δ , θ_r and θ_s) and biophysical processes (EC_{e50} and ψ_{root}). Shani et al. (2007, 2009) and Nicolas et al. (2023) provide a more detailed description of the model.

Economic considerations and spatial component

The profits are calculated using five economic variables: return per hectare (\$/ha), revenue per ton (\$/ton), yield-dependent costs (\$/ha), fixed cost (\$/ha), and maximal yield (ton/ha). All investments are classified as fixed costs, including farm establishment, production, harvesting, and packaging expenses. The cost of irrigation water (water price) and market price are an independent variable. The spatial component is built using the POLARIS soil gridded data (Chaney et al., 2019), California land use, and groundwater electrical conductivity. Crop yield and profits are predicted across the Central Valley with a 30 m resolution. Validation and

sensitivity of the model, as well as a detailed description of the spatial component development of the model, are provided by Nicolas et al. (2023).

Central Valley Crop Yield and Profitability Response to Salinity Web Tool

The Central Valley Crop Yield and Profitability Response to Salinity Model web tool (<https://yieldprofit.ucdavis.edu/>) was built upon the Analytical Salt-WatER model developed by Shani et al. (2007, 2009). The web tool's home page has three sections. The first section (Figure 3-1(1)) is the model that computes the relative yield and profitability response to irrigation water salinity in either English or Metric units. The second section (Figure 3-1(2)) allows users to explore spatial forecasts of a specific crop's relative yield and profitability for the entire Central Valley. The third section (Figure 3-1(3)) provides data sources and references about the tool.

In the Model (Figure 3-2 and Figure 3-3), users can select a specific crop (Figure 3-2(1)), soil type (Figure 3-2(2)), irrigation water amount (Figure 3-2(3a)), irrigation water electrical conductivity (Figure 2-2(3b)), and water costs (Figure 3-2(1)) to calculate (Figure 3-2(4)) the relative yield and profitability across a range of scenarios. Four crops, including alfalfa, almonds, table grapes, and processed tomatoes (Figure 3-4(1)), and five soil types, including sand, clay, loamy sand, sandy loam, and silt loam (Figure 3-4(2)), are available in the drop-down menu. Any range of irrigation water salinity (EC) (Figure 3-4(3a)) and water quantity (Figure 3-4(3b)) can be specified by the user to calculate yield and profits. The "Calculate" button (Figure 3-2(4)) computes and plots the relative yield. For calculating the profit, users can specify water price (\$/ha-mm or \$/ac-ft) (Figure 3-3(1)), crop area (hectares or acres) (Figure 3-3(2)), irrigation season length (Figure 3-3(3)), and economic parameters (Figure 3-3(4)) such as maximum yield (Figure 3-3(4a)), revenue per ton (Figure 3-3(4b)), and fixed costs (Figure 3-3(4c)). The "Calculate" button (Figure 3-3(5)) computes and plots projected profits. Both relative yield and projected profits can be exported in a table format as a Microsoft Excel .xls download.

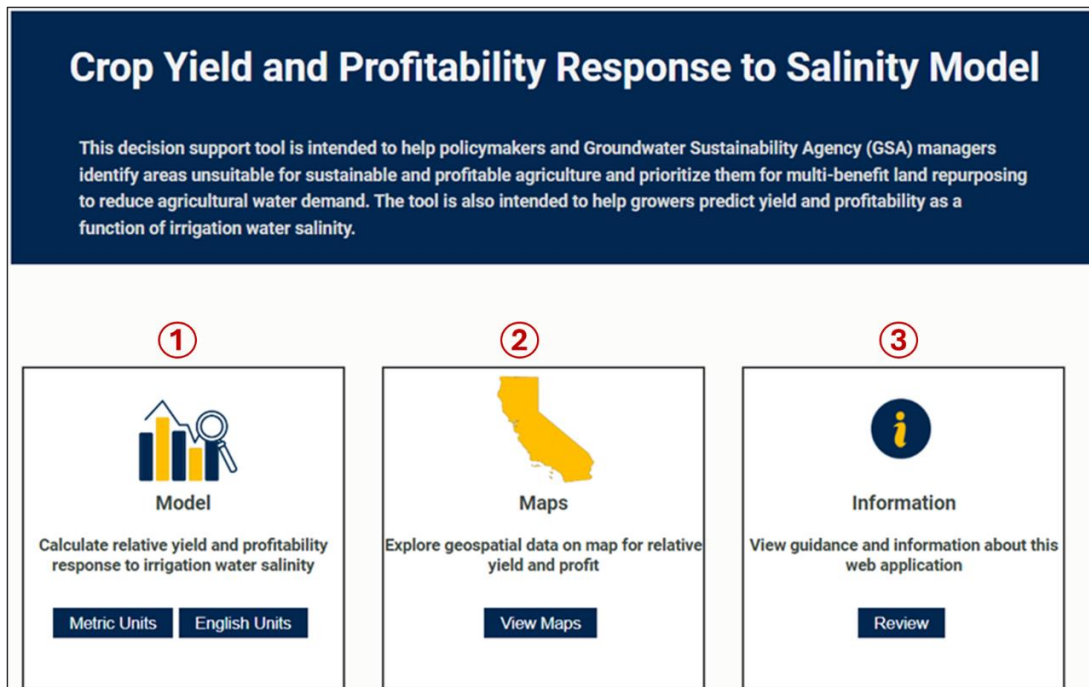


Figure 3-3. Interface of the Crop Yield and Profitability Response to Salinity Decision Support Tool

Figure 3-4. Window of the Decision Support Web Tool for users to choose crop, soil type, irrigation water EC (dS/m), and quantity.

The image shows a web tool interface titled "Profit". It is divided into two main sections. The left section contains three input fields: "Water Price:" with a dropdown menu (labeled 1), "Acre Amount:" with a text input field (labeled 2), and "Season Length:" with a text input field (labeled 3). The right section is titled "Economic Parameters" (labeled 4) and contains three input fields: "Maximum Yield (ton/acre):" (labeled 4a), "Revenue (\$ per ton):" (labeled 4b), and "Fixed Cost (\$ per acre):" (labeled 4c). A "Calculate" button (labeled 5) is located at the bottom right of the interface.

Figure 3-3. Window of the web tool for users to calculate profits by entering water price, acre amount in production, length of the season, maximum yield, price per ton, and costs of production per acre.

To access the spatial component, users can switch from Model/Graph View to Interactive Map View (Figure 3-5). This feature includes six irrigation water salinity levels (0.5, 1.5, 2.5, 3.5, 4.5, and 5.5 dS/m) and four irrigation depths (3, 6, 9, and 12 mm/day) for large-scale yield and profitability forecasts. The forecasted relative crop yield and profits for each 30m area, along with the associated longitude and latitude, can be viewed by clicking on the associated pixel on the interactive map.

1 Crop

select ▼

select

Alfalfa

Almond

Grapes

Tomatos

---Cr...s*---

TP:

EC50: (dS/m)

p: (mm)

Psi Root: (mm)

b: (mm)

Yr0: (mm)

*Do not change crop parameters unless you have experimental data to justify the change.

2 Soil

select ▼

select

Sand

Loamy Sand

Sandy Loam

Silt Loam

Clay

Ks:

Beta: (mm)

Eta: (mm)

Theta_s: (cm³/cm³)

Theta_r: (cm³/cm³)

Psi Water: (mm)

3 Irrigation Water

3a

---Water Salinity [dS/m]---

Min: 0.5

Max: 12

Step: 1.5

3b

---Irrigation [inch/d]---

Min: 0.02

Max: 0.4

Step: 0.05

Figure 3-5. Four crops, five soil types, and different water quantity and salinity (EC) ranges are available in the decision support web tool.

Crop Yield and Profitability Response to Salinity Model

Model/Graph View Interactive Map View

Crop select ▼

Water EC select ▼

Irrigation Depth select ▼

Relative Yield Map

Profit Map

Display Map

Earth Engine Apps

Search places

Map Satellite

United States

Mexico

Guatemala

Seattle

Washington

Montana

North Dakota

Minnesota

Wisconsin

Illinois

Indiana

Ohio

Pennsylvania

New York

Massachusetts

Connecticut

Virginia

North Carolina

South Carolina

Georgia

Florida

Alabama

Mississippi

Arkansas

Tennessee

Kentucky

West Virginia

Missouri

Kansas

Nebraska

Iowa

Colorado

Utah

Nevada

California

Arizona

New Mexico

Oklahoma

Louisiana

Texas

San Francisco

Los Angeles

San Diego

Las Vegas

San Antonio

Houston

Chicago

Toronto

Ottawa

Montreal

Washington

New York

Boston

Miami

Havana

Cuba

Santo Domingo

Puerto Rico

Google

Keyboard shortcuts | Map data ©2024 Google, INEGI | 500 km

Figure 3-6. Six irrigation water salinity levels (0.5, 1.5, 2.5, 3.5, 4.5, and 5.5 dS/m) and four irrigation depths (3, 6, 9, and 12 mm/day) are available for large-scale yield and profitability forecasts using the web tool.

Application of the Central Valley Crop Yield and Profitability Response to Salinity Web Tool

For the demonstration of the graphing tool, relative yield and profits were computed for the four crops currently available, considering eight irrigation water salinity levels (0.5, 2, 3.5, 5, 6.5, 8, 9.5, and 11 dS/m) and water amount from 0.01 to 0.4 inches/day. We considered 100 acres for the area of production and used a maximum yield of 1.5, 12, 12.4, and 58 tons/acre for almonds, alfalfa, table grapes, and processing tomatoes, respectively. We also used default historical revenue (\$) per ton and fixed costs (\$) of production for each crop, as described in Nicolas et al. (2023). The crop yield and profitability prediction for the entire Central Valley was demonstrated with a salinity of 3.5 dS/m and irrigation water depth of 0.35 inches/day (9 mm/day).

Results

Yield response to irrigation water salinity

Distinct trends are observed in predicting the relative yield of alfalfa, almonds, table grapes, and processing tomatoes in relation to irrigation water salinity. Alfalfa exhibits remarkable salinity tolerance, maintaining a high relative yield across all salinity levels, with only a marginal decline at the highest EC 11 dS/m value (Figure 3-6a). Processing tomatoes exhibit a moderate decrease in yield starting at an EC of 6.5 dS/m, suggesting a reasonable resilience to salinity (Figure 3-6d). Table grapes begin to experience a decline in yield at lower EC levels (Figure 3-6c) compared to alfalfa and processing tomatoes, indicating a higher sensitivity to salinity. Almonds show the most significant yield reduction as salinity increases, suggesting a high sensitivity to irrigation water salinity (Figure 3-6b).

Comparatively, alfalfa emerges as the least salt-sensitive crop, suggesting that it can be cultivated successfully under a range of salinity conditions, making it a robust option for areas

with saline irrigation water. Processing tomatoes follows, demonstrating considerable tolerance to salinity, albeit less than alfalfa. Table grapes maintain a higher yield up to a moderate salinity level (EC 5 dS/m), after which the yield decreases more rapidly. Almonds, however, are the most susceptible to salinity among the crops compared, with relative yield decreasing steadily as EC levels rise, underscoring the need for more stringent salinity management to maintain productivity for this crop.

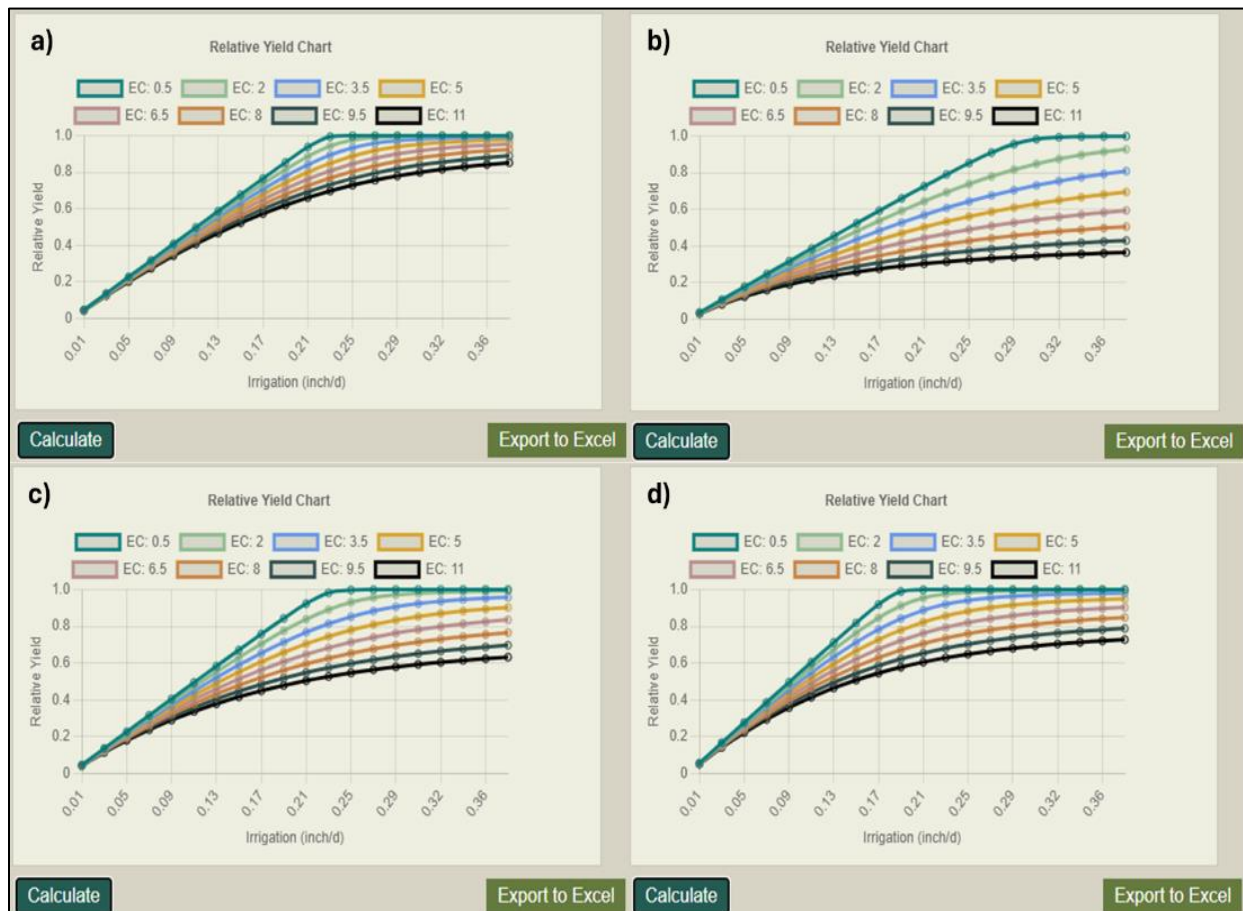


Figure 3-7. Relative yield for a) alfalfa, b) almonds, c) table grapes, and d) processing tomatoes using the web tool. The button “Export to Excel” downloads the graph data.

Profitability response to irrigation water salinity

The profit prediction for the four crops resulted in varying degrees of profitability in response to various salinity levels (EC) of the irrigation water. Alfalfa shows a relatively stable profit across a wide range of EC levels, with a slight peak before profits begin to diminish at the

highest salinity levels. Almonds exhibit a sharp peak in profitability at lower EC levels, suggesting that almonds are highly profitable with low-salinity water. However, beyond this optimal range, profits decline sharply with increased salinity. Table grapes present a more gradual rise to a high-profit plateau, maintaining this level across a range of EC levels (>8 dS/m) before profits start to fall at high salinity levels. Processing tomatoes showed increased profits with more water, with a less pronounced peak, and a decline in profits at higher salinity levels, indicating a reasonable degree of tolerance.

When comparing the economic viability of these crops, almonds present a high but narrow window of profitability contingent on low salinity levels, making them a potentially lucrative but riskier choice in saline-prone areas. Table grapes display the most considerable profit potential across a broader salinity spectrum, making them the most profitable crop under moderate saline conditions. Processing tomatoes also showed significant profit potential, though not as high as table grapes and almonds, but with a broader range of salinity tolerance before profitability decreases. Despite its lower peak profits, Alfalfa offers the most consistent revenue across varying salinity levels, suggesting it is a reliable option for steady income in saline conditions. The varying responses to salinity underscore the importance of choosing crops based on salinity levels to maximize agricultural profitability.

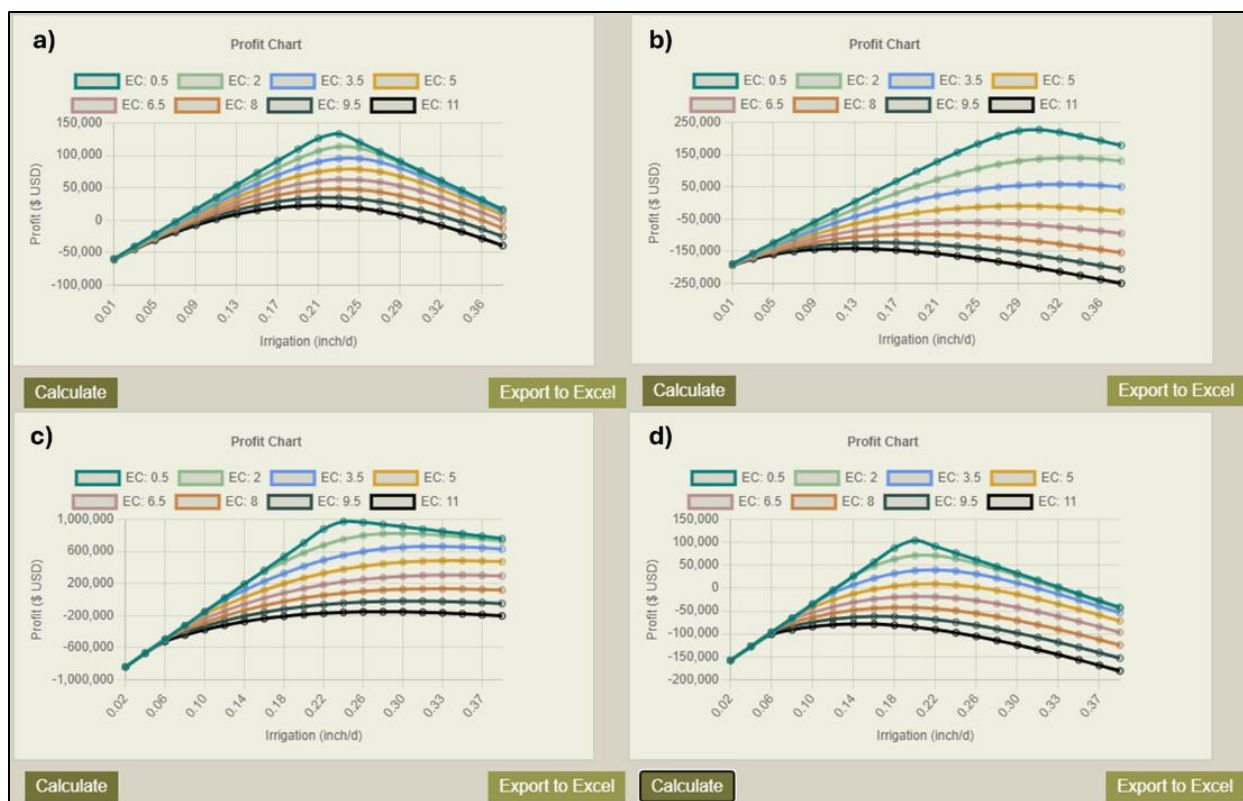


Figure 3-8. Profits for a) alfalfa, b) almonds, c) table grapes, and d) processing tomatoes using the web tool. The “Export to Excel” button downloads the graph data into an Excel spreadsheet.

Spatial yield and profits forecast in the Central Valley

Relative yield data for alfalfa, almonds, table grapes, and processing tomatoes is predicted across the Central Valley considering water electrical conductivity (EC) of 3.5 dS/m and an irrigation depth of 0.35 inch/day. Alfalfa fields exhibit a uniformly high yield, indicated by the predominantly dark green color across the map (Figure 3-8). Almond fields are more heterogeneous, with varying yields, as shown by the interspersed green and yellow areas, suggesting sensitivity to the specified salinity and soil conditions. The table grape areas are dark green with slight variations in some regions in light green, indicating high yield, which implies a moderate tolerance to the salinity level set. Processing tomato fields also show a high yield, though with slight variations in some areas, as indicated by the mix of dark and light green,

denoting overall good but slightly inconsistent yield performance under the given conditions (Figure 3-8).



Figure 3-9. Spatial relative yield for a) alfalfa, b) almonds, c) table grapes, and d) processing tomatoes with 9 mm (0.35 inch) water depth and EC of 3.5 dS/m using the web tool.

The tool generated profit maps for alfalfa, almonds, table grapes, and processing tomatoes under the irrigation water salinity of 3.5 dS/m and 0.35 inch/d of irrigation water depth. In the alfalfa map, profits are shown in varying shades, with some regions indicating potential losses (yellow regions) but many areas showing moderate profits (light green). The almond profit map displays more pronounced variability, with significant losses (yellow regions) scattered extensively across the map, suggesting almonds may not be as profitable under these conditions in some locations. The grape profit map shows a mix of high-profit areas (dark green) with some patches indicating losses or lower profits, implying that grapes have the potential to be highly profitable but may also be susceptible to losses under less-than-ideal conditions. The tomato profit map exhibits a combination of profitable (green) and less profitable areas (yellow), with an

overall indication of moderate profitability and fewer areas of loss compared to almonds, yet not as high profits as seen in the optimal alfalfa and grape regions (Figure 3-9).



Figure 3-10: Spatial profits for a) alfalfa, b) almonds, c) table grapes, and d) processing tomatoes with 9 mm (0.35 inch) water depth and EC of 3.5 dS/m using the web tool.

Discussion

The resilience of alfalfa to salinity (Grieve et al., 2012), with a marginal yield decline at the highest electrical conductivity (EC) values, positions it as a strategic crop for areas prone to high salinity levels. Alfalfa’s consistent profitability across a wide range of EC levels further cements its viability as a reliable agricultural option in saline environments. Conversely, almonds, with significant yield reduction in high salinity conditions (Prgomet et al., 2020) and a narrow window of profitability contingent on low salinity levels, present a higher risk yet potentially high-reward crop choice (Nicolas et al., 2023).

The salinity tolerance exhibited by table grapes and processing tomatoes further exemplifies the diverse adaptive capacities of crops to salinity stress (Grieve et al., 2012). Table grapes showed resilience to increased salinity levels, maintaining profitability even at higher EC

values. This resilience underscores the potential of table grapes as a viable crop in areas with moderately saline irrigation water. On the other hand, processing tomatoes demonstrated significant sensitivity to elevated salinity levels, with yields and profitability sharply decreasing as salinity increased (Nicolas et al., 2023). It is essential to consider the critical balance between biophysical responses and economic considerations in agricultural production under salinity stress (Kaner et al., 2019; Nicolas et al., 2023; Shani et al., 2007).

Shahrokhnia and Wu (2021) developed a web-based soil salinity leaching management model (SALEACH) as an online tool to assist farmers in soil salinity management to sustain agricultural production in irrigated croplands. The tool integrates multiple factors such as water uptake patterns, soil types, and irrigation systems to estimate leaching requirements, predict soil salinity, and determine drainage water salinity, ultimately improving agricultural water management. However, the model is based on a steady-state approach for leaching requirement calculations, which may not capture dynamic changes in soil salinity as water applications increase through the course of the growing season. Also, the model was assessed with other model predictions, which may introduce bias compared to the tool presented in this study that was validated by Nicolas et al. (2023) with observed data.

The decision support tool, developed by adapting and extending the Analytical Salt-WatER model to include a spatial component (Nicolas et al., 2023), offers an innovative solution to the complex challenge of irrigation water salinity management. This tool enables growers and policymakers to make informed decisions regarding crop selection and irrigation practices by predicting yield and profitability as functions of irrigation water salinity and quantity. The spatial yield and profitability forecasts provided by the tool, especially with the introduction of a 30 m resolution mapping across the Central Valley, is a significant advancement in precision water

management, allowing for more targeted salinity management and land repurposing strategies. This approach aligns with the work of Quinn and Oster (2021), who stressed the necessity of utilizing localized measures to address the complex interplay between soil salinity, water use, and agricultural economics.

Conclusion

This study presents the development and implementation of a novel decision support web tool and offers valuable insights into the strategic management of saline irrigation water to optimize agricultural productivity and economic returns. The findings demonstrate that crop-specific responses to salinity levels are critical in guiding irrigation and crop selection decisions. Alfalfa and processing tomatoes, with their higher tolerance to salinity, emerge as viable options for cultivation in areas with saline water resources, offering sustained productivity and profitability. On the other hand, despite the higher profit potential, the sensitivity of almonds and table grapes underscores the necessity for precise salinity management and advanced irrigation strategies to mitigate the adverse effects of salinity.

The decision support tool introduced in this study represents a significant advancement in agricultural technology, providing growers, policymakers, and agricultural stakeholders with a user-friendly platform to make informed decisions based on real-time data and predictive models. By incorporating spatial analysis and yield profitability forecasting, the tool facilitates a more nuanced understanding of salinity's impact across the Central Valley, enabling targeted interventions and the optimization of water resources.

Future research for the refinement and expansion of this decision-support tool is essential. Incorporating additional crops, expanding the database of soil types, and integrating climate change projections can enhance the tool's applicability and accuracy. Moreover, fostering collaboration among researchers, growers, and technology developers will be vital in

ensuring that the tool evolves to meet the changing needs of the agricultural community, particularly in the face of increasing water scarcity and salinity challenges in California. The Central Valley Irrigation Water Salinity Decision Support Application Web Tool offers a promising approach to addressing the complex challenges of salinity management in agriculture. By enabling data-driven decision-making, this tool aids in the sustainable optimization of irrigation practices, contributing to the resilience and profitability of agriculture in salinity-affected regions.

CHAPTER 4
EVALUATING THE EFFECTIVENESS OF CONSERVATION PRACTICES ON REDUCING
NITRATE LEACHING IN PROCESSING TOMATO USING THE APEX MODEL

Abstract

Nitrate contamination from non-point sources significantly threatens groundwater resources in agriculturally intensive regions globally. In response, the State Water Resources Control Board of California implemented the Central Valley-wide Salt and Nitrate Management Plan (CV-SNMP) with the aim of mitigating nitrate leaching into the groundwater. This study employs the Agricultural Policy/Environmental eXtender (APEX) model to evaluate the effectiveness of various conservation practices in a processing tomato field in reducing nitrate leaching below the root zone and to generate a spatial variability map for nitrogen leaching. The conservation practices assessed include the utilization of micro-irrigation technologies, nitrogen credits (NC), winter cover crops, and high-frequency-low concentration (HLFC) fertigation. Calibration results showed R^2 of 0.97, 0.75, 0.84, and 0.62 for yield, evapotranspiration (ET), N uptake, and N leaching, respectively. The RMSE was 1600 kg/ha, 14.8 mm, 38.0 kg/ha, and 35.5 kg/ha for yield, ET, N uptake, and N leaching, respectively. Validation was performed using yield for adjacent counties, and R^2 was 0.85 and 0.60 for Yolo and Solano counties, respectively. The RMSE was 2500 kg/ha and 7070 kg/ha for the two counties, respectively. Polaris grided soil data was successfully integrated into the model to develop variable field N leaching and maps. HLFC was predicted to be the most efficient conservation practice by reducing N leaching by 98%. Drip irrigation reduced N leaching by 90% and more than 95% when combined with cover crops and irrigation NC. Furrow irrigation was predicted as the less effective conservation practice with the highest averaged N leaching but showed improvement with the application of N credits and winter cover crops. APEX model is a potent tool for developing field-scale nitrogen leaching variability maps in row-crop agriculture and identifying

conservation practices that effectively decrease nitrate leaching below the root zone without adversely affecting yield.

Introduction

Nitrogen (N) fertilizer is indispensable in modern agriculture for crop growth, development, and food security. The application of N fertilizer can significantly improve both the yield and quality of agricultural products (E. Liu et al., 2010; Sete et al., 2019). However, overuse and improper management of N fertilizer in agricultural production have triggered the occurrence of excessive levels of nitrates in surface and groundwater (Adelana et al., 2020; Ha et al., 2019; Rosov et al., 2020), which threatens natural resources and human health (Chaudhuri and Ale, 2014; Shaji et al., 2018) and disturb the environmental balance (Gallardo et al., 2020; Harter, 2009). Countries and worldwide institutions have taken measures to reduce nitrate pollution of groundwater. The World Health Organization (WHO) set drinking water's nitrate-nitrogen content at 50 mg/L. The Environmental Protection Agency (EPA) has set the limit of nitrate-nitrogen concentration in groundwater at 10 mg/L (U.S. EPA, 1995). The increasing rate of nitrate levels leaching groundwater in parts of the United States, including the Central Valley of California, poses a significant environmental and health challenge to meet the standards set by the EPA (Boyle et al., 2012; Burow et al., 2012).

Agricultural practices primarily contribute to groundwater contamination, where excess nitrogen-based fertilizers leach out of the root zone and end up in the groundwater (Dubrovsky et al., 2010). Over the past years, the volume of nitrogen fertilizer used in the State has expanded dramatically. Between 1980 and 2001, the annual sales exceeded 600,000 tons of nitrogen in some years (Reid et al., 2005). More than 740,000 tons of nitrogen fertilizer were applied to roughly 6.7 million acres of irrigated farmland in California, and significant increases in nitrogen

fertilizer application rates have been observed in Sacramento Valley, San Joaquin Basin, and Tulare Basin of the CV for the recent decades (Harter et al., 2017). Such over-application has been associated with N leaching out of the root zone, triggering groundwater pollution and various human health concerns (Galloway et al., 2003). More than 50 years of trade-offs of nitrogen fertilizer use and the negative impacts on the environment have been documented in California (Harding et al., 1963; Rosenstock et al., 2014), and regulations have been implemented to mitigate the N leaching and improve groundwater quality while maintaining a prosperous agricultural production (CV-SALTS, 2023). The application of such regulations requires the development of efficient tools, such as models to predict N leaching at field and regional scales and evaluate conservation practices that reduce N leaching in agricultural fields.

Many studies have investigated the impacts of nitrogen leaching in agricultural production systems (Cui et al., 2020; Shrestha and Luo, 2018). Dzurella et al. (2015) mapped the risk of N leaching in irrigated fields in the Central Valley and found that 31% of the analyzed area is at high risk of N leaching loss if not managed carefully. Delgado et al. (2000) highlighted the importance of adapting best management practices (BMPs) to specific crop characteristics for effective nitrogen management on residual soil N for the root zones of crops with varying rooting depths. Management practices such as irrigation systems, crop rotations, and cover crops are pivotal in reducing N leaching depending on the soil conditions, climate, and cropping systems (De Notaris et al., 2018; Dzurella et al., 2015). This suggests the importance of applying conservation practices and the critical need to evaluate their effectiveness in mitigating N leaching. Also, very few studies highlight other conservation practices, such as N credits, and the need to generate field maps of N leaching that can further guide site-specific fertilizer and irrigation water applications.

Various models such as Decision Support System for Agrotechnology Transfer (DSSAT)(Jones et al., 1998), Soil and Water Assessment Tool (SWAT)(Aloui et al., 2023), AqYield-N (Tribouillois et al., 2020) and Agricultural Policy/Environmental eXtender (APEX) (Gassman et al., 2010) been utilized to evaluate the effectiveness of conservation practices in reducing nitrogen leaching in agricultural systems. The models range from field-scale to more extensive watershed-level assessment simulations. SWAT has been widely used to simulate the impacts of different irrigation, cropping, and fertilization practices on total nitrogen loss and assess the ecological and economic impacts of various management practices at large scales (Aloui et al., 2023; Sheikhzeinoddin and Esmaceli, 2017). AqYield-N is a simple model designed to predict nitrate leaching from crop fields over large areas and considers major nitrogen flows in the soil-plant system, including mineralization, plant uptake, and leaching (Tribouillois et al., 2020). DSSAT has been used to simulate the nitrogen cycle in different crop rotations under various conditions, including water supply and fertilization practices, to assess the impact of cover crop rotations on nitrogen leaching and to study the effect of best management practices on irrigation and nitrogen losses (Salmerón et al., 2014). APEX is a multi-field version of EPIC developed for assessing environmental problems associated with various agricultural systems, and it has been used for a variety of environmental assessments, particularly at the farm and small watershed scales (Gassman et al., 2004).

DSSAT focuses more on crop-specific simulations in the field (Liu et al., 2011), while AqYield-N, with its simplicity, is particularly useful for quick estimations of nitrogen leaching under different management practices (Tribouillois et al., 2020). SWAT and APEX are better suited for watershed analyses (Santhi et al., 2014). However, APEX is particularly effective for field-scale simulations, making it ideal for simulating the impacts of different conservation

practices, including those related to sustainability, erosion, economics, water supply and quality, soil health, plant competition, weather, and pests (Gassman et al., 2010; Kim et al., 2020). APEX considers the fields or smaller watersheds as subareas and selects the dominant soil type or crop as unique for the subarea, which limits the model in generating maps showing spatial variability in nitrate leaching or yield.

The objectives of this study were to: (1) integrate the APEX model high-resolution gridded soil data to generate a field-scale N leaching map, and (2) use APEX to simulate the effectiveness of different conservation practices, including Irrigation N credits and high-frequency low-concentration fertigation in reducing N leaching out of the rootzone and (

Method

Site description

The study site is a 34-hectare field crop located in Yolo County, California (Figure 4-1). The soil at the site is classified as Capay silty clay according to the soil series of the National Resources Conservation Service - United States Department of Agriculture (NRCS-USDA). The study site has warm summers with temperatures ranging from 29°C to 38°C and mild winters with temperatures often between 2°C and 7°C. The region receives about 430 to 530 millimeters of rainfall annually, predominantly during winter. Relative humidity in the region varies, usually staying between 30% to 60%. Esparto also benefits from abundant sunlight year-round and experiences mild to moderate wind speeds. Processing tomatoes has been growing since 2016 with rotation with other crops such as triticale and squash. Processing tomatoes are usually irrigated and fertilized below the surface using drip lines. These drip lines are installed 20 cm beneath the soil surface, positioned in the center of the planting beds, with emitters every 30 cm dispensing water at a rate of 0.6 liters per hour.



Figure 4-11: Field site in Esparto, California.

APEX model

The Agricultural Policy/Environmental eXtender (APEX) is a distributed, continuous, and daily time-step model that simulates hydrological and water quality dynamics at field and watershed

scales. The model has several components: weather, hydrology, crop growth, pesticides, nutrient cycles, and management practices (Gassman et al., 2010).

Crop growth

In the APEX model, the dry matter accumulation (DDM) is quantified to simulate how various environmental factors, management practices, and plant characteristics influence crop biomass over the growing season (Equation 4-1). Dry matter accumulation (DDM) in crops is a central aspect of agricultural modeling as it directly relates to the growth and yield of a crop.

$$DDM = 001 * PAR * (RUE - WAVP * X1) \quad (4-1)$$

where DDM is the daily dry matter accumulation (tons/ha), PAR is the photosynthetically active radiation ($MJ \cdot m^{-2} \cdot day^{-1}$) that represents the portion of sunlight ($MJ \cdot m^{-2} \cdot day^{-1}$) that plants use for photosynthesis, RUE is the radiation use efficiency, which reflects the crop's ability to convert absorbed light into biomass, $WAVP$ is a crop parameter that adjusts RUE based on water availability or vapor pressure deficit, reflecting the impact of water stress on the plant's ability to use radiation efficiently, and $X1$ that adjusts RUE further based on environmental stresses, such as temperature extremes or additional water-related stresses. The photosynthetically active radiation (PAR) is described in Equation 4-2.

$$PAR = 0.5 * RA * (1 - e^{(0.65-LAI)}) \quad (4-2)$$

where RA is solar radiation ($MJ \cdot m^{-2} \cdot day^{-1}$) and LAI is leaf area index that represents the total area of leaves per unit area of ground (Equation 4-3).

$$LAI(i) = LAI_0(i) + dHUF(i) * XLAI(i) * \sqrt{REG(i)} * \frac{LAI_0(i)}{TLAI} \quad (4-3)$$

where LAI_0 and LAI are the leaf area index values at the beginning and end of the day, $XLAI$ is the maximum leaf area index, $TLAI$ is the total leaf area of all crops growing at the

beginning of the day, $dHUF$ is the daily change in the heat unit factor, and REG is the value minimum crop stress factor.

Water movement

The model simulates water movement using storage routing, where water flows from a soil layer when the soil water content exceeds field capacity. The flow from one layer to another is described in Equations 4-4 and 4-5:

$$Q = \frac{K_s * A * (h_0 - h_{n+1})}{d} \quad (4-4)$$

where Q is the flow rate ($\text{mm} \cdot \text{day}^{-1}$), K_s is the hydraulic conductivity (mm/hr), A is the cross-sectional area of flow (m^2), d is the distance between layers (m), h_n and h_{n+1} are the hydraulic heads at layers n and $n + 1$, respectively (m). Equation 4-5 describes the change in soil water content (SWC) over time, considering soil field capacity (FC) and the travel time (TT) for water through a soil layer.

$$SWC_1 = (SWC_0 - FC) \exp\left(-\frac{dt}{TT}\right) + FC \quad (4-5)$$

where SWC_1 is the soil water contents at the end of the time interval, SWC_0 is soil water contents at the start of the time interval, FC is field capacity, TT is travel time through the soil layer (hours), and dt is the time steps (e.g., daily).

Nitrate leaching

The leaching of nitrates is modeled considering the nitrate concentration in the soil water and the amount of water percolating past the root zone (Equation 4-6).

$$Q_{NO_3} = Q_{perc} * C_{NO_3} \quad (4-7)$$

where Q_{perc} is the percolation water (mm/day) and C_{NO_3} is the nitrate-nitrogen concentration in the soil water (kg/mm). The amount of nitrate available in the soil influences both leaching and denitrification.

Denitrification

Denitrification is a crucial microbial process in the nitrogen cycle, converting nitrate (NO₃) to gaseous forms of nitrogen, such as nitrogen gas (N₂) and nitrous oxide (N₂O). This process is influenced by various soil factors, including oxygen levels, organic carbon availability, and soil moisture. The APEX model incorporates a process-based method for denitrification, which allows for a detailed representation of how these factors interact to affect nitrogen gas emissions. This method relies on soil temperature, moisture content, and organic matter to simulate the conditions under which denitrification occurs, providing a dynamic and responsive model to predict nitrogen losses in agricultural systems. The denitrification rate (DN) in the APEX model is calculated using the following equation (Equation 4-8):

$$DN = W_{NO_3} * (1 - \exp(-1.4 * T_{FN} * W_{OC})); SWF > 0.95 \quad (4-8)$$

$$DN = 0; SWF < 0.95$$

where DN is the denitrification rate (kg/ha), W_{NO_3} is the NO₃-N content in a soil layer (kg/ha), W_{OC} is the organic carbon content (%), SWF is the soil water factor, and T_{FN} is the nutrient cycling temperature factor, expressed in Equation 4-9:

$$T_{FN} = \frac{STMP}{(STMP + \exp(5.059 - 0.2504 * STMP))} \quad (4-9)$$

where $STMP$ represents the soil temperature in °C at the center of a soil layer. The soil water factor (SWF) is expressed in Equations 4-10 and 4-11.

$$SWF = 0.1 * \left(\frac{ST}{WP}\right)^2; ST < WP \quad (4-10)$$

$$SWF = 0.1 + 0.9 * \sqrt{\frac{ST - WP}{FC - WP}}, \text{ if } ST > WP \quad (4-11)$$

where ST is the soil water content (m/m), WP is the wilting point (m/m), and FC is the field capacity (m/m)

Carbon and nitrogen cycling and transformations.

Litter Allocation and Potential C and N Transformations

Carbon and nitrogen cycling in soil involves complex interactions and transformations that are essential for maintaining soil fertility and ecosystem health. APEX uses the soil organic matter model developed in the Environmental Policy Integrated Climate (EPIC) model to simulate the coupled cycling of carbon (C) and nitrogen (N) in soil (Williams et al., 2015). The EPIC soil organic matter model adopts the methodology of the Century model by dividing the carbon and nitrogen components of organic matter into three distinct categories: microbial (or active), slow, and inert (Izaurrealde et al., 2006). These compartments differ in size, function, and turnover times, ranging from days to centuries. Organic residues that are introduced to the soil can be divided into two categories, metabolic and structural, based on their nitrogen and lignin levels.

In the APEX model, litter allocation and potential carbon (C) and nitrogen (N) transformations are essential for simulating nutrient cycling in soils. Organic residues added to the soil are divided into metabolic (LM) and structural (LS) components, with the fractions of metabolic (LMF) and structural litter (LSF) determined based on the nitrogen and lignin content. All lignin present in the standing dead (STDL) is transferred to the structural litter. The potential transformations of carbon and nitrogen are calculated using substrate-specific rate constants, temperature, and water content, with additional consideration of lignin content and soil texture influencing some transformations. For instance, the calculation of standing dead nitrogen equivalent (STDNE) incorporates the standing dead nitrogen (STDN) and a fraction (S_f) of the

available nitrate (WNO_3) and ammonium (WNH_4), with consideration of the C/N ratio of standing dead crop residue (CNR).

$$STDNE = \begin{cases} STDN + Sf * (WNO_3 + WNH_4) & \text{if } CNR \geq 10 \\ STDN & \text{if } CNR < 10 \end{cases} \quad (4-12)$$

The calculation of the potential transformation of carbon (C) in structural litter (LSCTP) on the surface and subsurface is determined by several factors. These factors include the carbon content in the structural litter (LSC) (Equation 4-13), the rate of potential transformation of structural litter under optimal conditions (LSR), the lignin fraction of the structural litter (XLSLF), and a combined factor (CS) that accounts for the effects of temperature (TFN), soil water content (SWF), oxygen (OX), and tillage (TBP) on biological processes (Izaurrealde et al., 2006; Williams et al., 2015). The combined carbon saturation (CS) factor in the Century model differs from the temperature and water controls on decomposition.

$$LSCTP = LSC * LSR * XLSLF * CS \quad (4-13)$$

$$XLSLF = \exp(-3 * LSLF) \quad (4-14)$$

Actual C and N transformations

The calculations of actual C and N transformations are determined by the nitrogen supply provided by each potential transformation. The demand for nitrogen is determined by the carbon transformation potential of the source compartment and the C/N ratio of the receiving compartment. The nitrogen-to-carbon (N/C) ratios of receiving compartments exhibit variation depending on the substrate and soil conditions. The N/C ratio of biomass generated from surface litter (NCBM) is determined by a linear equation that relates the nitrogen content ($N_f = 100 \times STDNE/STD$) of the degraded material (Williams et al., 2015).

$$\text{NCBM} = \frac{1.0}{(-5.0251 * Nf + 20.05)}; 2.0 \geq Nf \geq 0.01 \quad (4-13)$$

Model construction

The model was set up to represent the management and the characteristics of the land. The ArcAPEX tool (Tuppad et al., 2009) was used through ArcMap software (Esri, V10.7) to delineate a subbasin where the field is located. California land use (California Department of Water Resources, 2022) and soil from the United States Department of Agriculture (USDA) State Soil Geographic (STATSGO) database were used to characterize the most dominant land use and soil type within a subarea. Weather data, including maximum and minimum temperature, precipitation, solar radiation, relative humidity, and wind speed, were obtained from the California Irrigation Management Information System (CIMIS). Following the model setup with ArcAPEX for the subarea, the APEXeditor (Leyton, 2019a) was used to downscale the model and run it for the field (Figure 4-2). The APEXeditor, created with Visual Basic for Applications (VBA) within Excel, provides a user-friendly graphical interface for the APEX model, serving as an alternative to programs like WinAPEX or ArcAPEX that require additional setup or licenses. The APEXeditor allows straightforward editing, composing, and running of the APEX model inputs.

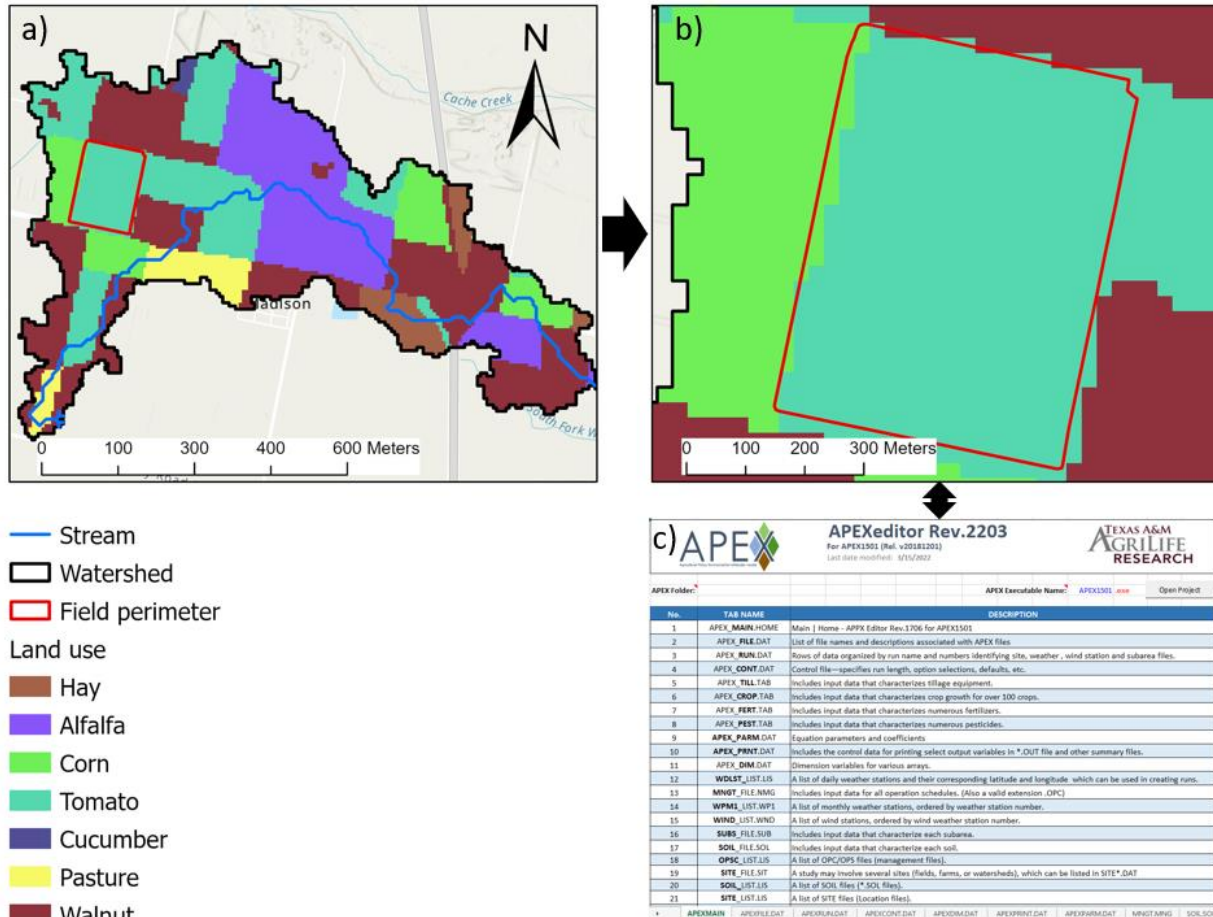


Figure 4-12. Model setup using ArcAPEX and APEXeditor. a) Subarea with land use and stream in the ArcAPEX tool; b) Field study with processing tomatoes; and c) Interface of the APEXeditor used to run the model.

Sensitivity analysis and model performance evaluation

The Sobol method global was used for sensitivity analysis using the auto-calibration and uncertainty estimator (APEX-CUTE) software (Wang et al., 2014; Wang and Jeong, 2016).

Sobol's method is a variance-based sensitivity analysis technique that provides two main types of sensitivity indices: the first-order sensitivity index (S1) and the total sensitivity index (ST).

These indices help quantify the contribution of each input variable to the output variability in a model. The first-order index, S1, measures the direct contribution of each individual input

parameter to the output variance, ignoring interactions with other inputs. This is useful for identifying which parameters are most influential when they act alone.

In contrast, the total sensitivity index, *ST*, accounts for the contribution to the output variance by an input parameter both individually and through its interactions with all other input parameters. This makes *ST* a more comprehensive measure, particularly important in models where interactions between parameters significantly affect the output. The difference between *S1* and *ST* for any given parameter indicates the extent of its interactions with other parameters. Large differences suggest that interactions are significant and should be considered in the model analysis. Implementing Sobol's method involves computational effort, as it requires a number of model simulations based on the formula $N=2*n (P+1)$, where *N* is the total number of model executions, *n* is the sample size per input, and *P* is the number of input factors. For reliable results, Saltelli et al. (2005) recommend using a sample size *n* between 500 and 1000. In this study, *n*=550 was used.

APEX-CUTE, which is part of the APEX model, is designed to simplify the processes of uncertainty estimation and calibration through the use of an intuitive interface. APEX-CUTE compares the model outputs on daily, monthly, or annual scales with field data. However, this study's calibration data consisted of irregular, event-based measurements incompatible with the regular intervals for which APEX-CUTE is designed. Therefore, manual calibration was used instead. The model was calibrated for Yield, N leaching, N uptake, and evapotranspiration using observed data for seasons 2016, 2019, and 2021. N leaching and N uptake came from a mass balance approach. The model was validated using ten years of reported processing tomato yield in Yolo and Solano counties.

Field Scale N leaching variability

Assuming soil type influences N leaching, the Probabilistic Remapping of SSURGO (POLARIS) soil properties with 30*30-meter resolution was used to provide soil input for the models to develop the N leaching maps. Chaney et al. (2019) provide detailed information about the POLARIS soil series. Soil POLARIS was obtained using Google Earth Engine (GEE) and then processed using Python programming script. Soil variables, including hydraulic conductivity, soil texture (clay, sand, and silt), organic carbon, and pH, were extracted from individual raster pixels at each depth during the execution of the script. The extracted data was then stored in a.SOL file, which the model subsequently reads. At the end of each run, the script selects the value of the targeted model output and assigns it to a pixel (respective to the input pixel). Then, all pixels were stitched together based on the gridded soil input to provide the raster pam for the targeted model output value (Figure 4-3).

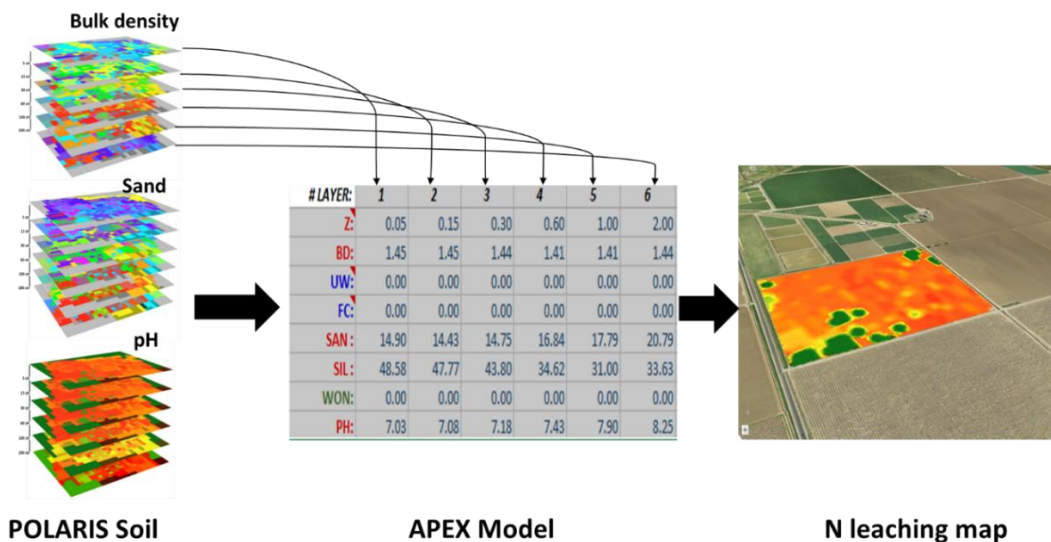


Figure 4-13. Diagram showing the workflow of integrating the gridded soil data in the APEX model to generate field scale N leaching variability.

Conservation practices simulation

In California, the fertilization strategy for processing tomatoes varies between furrow-irrigated and drip-irrigated fields, particularly in applying nitrogen fertilizer. In furrow-irrigated

fields, nitrogen is typically applied once in a side-dressing (Krusekopf et al., 2002). For drip-irrigated fields, multiple fertigation applications allow for a higher nitrogen rate, catering to the greater yield potential (Hartz and Bottoms, 2009; Miyao et al., 2020). The seasonal nitrogen (N) application rate by growers typically ranges between 140 to 280 kg of N per hectare. The University of California Extension researcher suggests that maximum tomato yields can be achieved with approximately 110 to 170 kg of N per hectare (Hartz et al., 2008). A seasonal application rate of 170 kg of N per hectare was considered for model simulations with the validated APEX model to evaluate the long-term effects of management practices on nitrate leaching. Conservation practices, such as micro-irrigation technologies, irrigation nitrogen (N) credits, High-Frequency Low Concentration Fertigation (HFLC), and winter cover crops, were simulated over a period of 30 years to identify best conservation practices that reduce nitrate leaching below the root zone.

Micro-irrigation technologies

The APEX model was configured to replicate the agricultural setting of the field, incorporating parameters specific to irrigation systems. Furrow and drip are the main irrigation systems that have been used in California for growing processing tomatoes (Miyao et al., 2020). In the scope of this study, we simulated the influence of the irrigation systems on N leaching out of the root zone with and without N credits consideration. We simulated subsurface drip irrigation considering the drip lines at 25 cm depth.

Irrigation nitrogen credits (NC)

Irrigation Nitrogen Credits is a critical sustainable agricultural practice, particularly in regions like California, where irrigation is the backbone of crop production. This practice involves considering the nitrogen sources already present in the environment, which includes soil residual nitrate, nitrogen mineralized from organic materials (soil organic matter, plant residues,

manure, and compost), and nitrate in irrigation water. Irrigation water, particularly well water, often contains nitrogen in the form of nitrate (*Fertilizer Research and Education Program-FREP*). The N concentrations in irrigation water were removed from the total application rate. For the simulation of irrigation nitrogen (N) credits, we parameterized the model to account for the nitrogen present in the irrigation water, thus allowing us to monitor the use efficiency of nitrogen and its potential leaching into groundwater. In the Central Valley, the NO₃-N concentrations in the irrigation water can exceed 15 ppm. In the study location, the measured NO₃-N concentration was 12 ppm. The irrigation water was set to 500 mm.

Winter cover crops

The use of winter cover crops is an essential conservation practice in sustainable agriculture (Kladivko et al., 2014; Koudahe et al., 2022). Winter cover crops, such as legumes, grasses, or brassicas, during the non-growing season can be beneficial by absorbing residual nitrogen in the soil, preventing it from leaching into groundwater (Dabney et al., 2001). Winter cover crops contribute significantly to soil health, aid in managing water resources, and support biodiversity, making them vital components in the pursuit of sustainable and resilient agricultural systems. In the study site, the grower used to grow triticale after harvesting and processing tomatoes. For model simulations, triticale was used to evaluate the effect of cover crops in reducing N leaching out of the root zone.

High-Frequency Low-Concentration

High-Frequency Low-Concentration (HFLC) Fertigation is an advanced agricultural technique where water and nutrients, particularly nitrogen, are applied more frequently and in lower concentrations compared to traditional fertilization methods (Cui et al., 2020; Lebesse et al., 2014). The fertilizers are administered often – daily or several times a week – which aligns closely with the nutrient uptake patterns of the crop. The ‘low concentration’ aspect involves

maintaining reduced nutrient levels, especially nitrogen, in each application, providing a steady, manageable supply to the plants. The frequent application of nutrients in small amounts aligns better with the plant's natural nutrient uptake rhythm, reducing the chances of excess nitrogen being left in the soil to leach into groundwater, a significant concern in California's agricultural regions. The HFLC practices were replicated by adjusting the irrigation scheduling parameters within APEX to model more frequent but smaller irrigation events, aiming to reduce water runoff and deep percolation.

Results

Sensitivity analysis and model performance

In the Sobol analysis conducted with APEX-CUTE, several key parameters were identified as pivotal influencers in predicted yield, nitrogen, and water balance. For yield, parameters such as the harvest index (HI) and daily leaf area index (DLAI) were identified as the most influential on yield due to their highest total sensitivity indices (SI_Total). The high SI_Total for HI suggests that it is a crucial driver of yield, with its impact being both direct, as evidenced by its significant first-order sensitivity index (SI_First), and through interactions with other factors. DLAI follows in importance, indicating its substantial role, though to a lesser extent than HI, with its influence extending beyond direct effects to include interactions within the system. Other parameters like PARM97, DMLA, and WA also show notable influences on yield, mainly through interactions within the system, suggesting that their impacts are nuanced and involve complex interdependencies with other system variables (Figure 4-4a). In the analysis of N balance, PARM52 was the most critical parameter influencing N balance due to a considerable direct influence of PARM52, as indicated by its high SI_First, alongside its potential interaction effects with other factors. Other parameters like PARM80, PARM104, and

PARM107, though having lower SI_Total values, are still notable, implying their contributions to N balance (Figure 4-4b).

Regarding the water balance, soil evaporation (PARM17) was the most influential parameter, indicating its significant role in the model water balance. The Hargreaves PET equation exponent (PARM34) also shows considerable influence and interactions. They were followed by PARM23 and PARM12, with relatively lower SI_Totals, suggesting a present but more modest impact on water balance, further emphasizing the complex interplay of multiple factors in the model (Figure 4-4c).

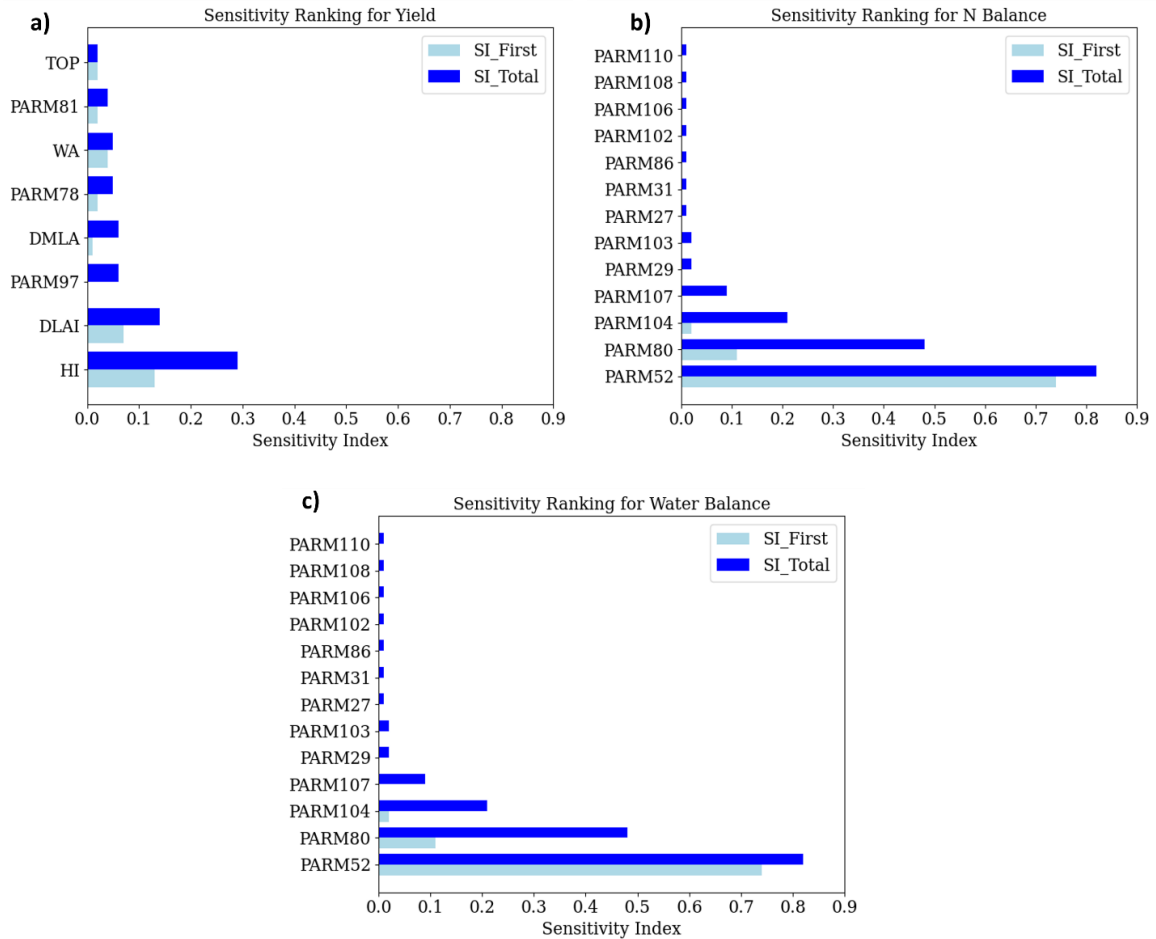


Figure 4-14: Sobol sensitivity analyses for Yield, N balance, and Water Balance. The SA was implemented through APEX-CUTE.

The model, calibrated for yield, evapotranspiration (Eta), nitrogen (N) leaching, and N uptake, demonstrated acceptable performance. This was evidenced by R^2 with values of 0.97 for yield, 0.98 for Eta, 0.99 for N leaching, and 0.88 for N uptake, indicating accurate predictions. Furthermore, the RMSE values were low for all parameters: 1.6 ons/ha for yield, 3.7 mm for Eta, 4.8 kg/ha for N leaching, and 14.1 kg/ha for N uptake, showcasing the model’s precision in estimating these variables. For Yolo County, the model validation showed R^2 and NSE at 0.99, indicating high accuracy, with an RMSE of 0.62 tons/ha, demonstrating precise predictions. For Solano County, R^2 and NSE were 0.93, showing strong accuracy but with a higher RMSE of 2.97 tons/ha, indicating greater prediction errors (Table 4-1).

Model calibration and validation resulted in acceptable performance in predicting yield, evapotranspiration (ET), N leaching, and N uptake. During calibration, the model demonstrated acceptable predictive accuracy, evidenced by R^2 values: 0.97 for yield, 0.75 for Eta, 0.84 for N leaching, and 0.62 for N uptake. The RMSE was 1.6 tons/ha for yield, 14.8 mm for Eta, 38 kg/ha for N leaching, and 35.5 kg/ha for N uptake. The model performed well in Yolo and Solano Counties in the validation phase in predicting yield. For Yolo County, R^2 and NSE were both 0.84 with a low RMSE of 2.55 tons/ha for yield. Conversely, Solano County’s results showed lesser accuracy with R^2 and NSE at 0.60 and a higher RMSE of 7.07 tons/ha (Figure 4-5).

Table 4-4. Model calibration results in the average yield, evapotranspiration, N leaching, and N uptake for three years.

Variables	Observed	Modeled	R^2	RMSE	nRMSE
Yield (ton/ha)	116.1	115.2	0.97	1.6	1.3%
Eta (mm)	546.3	556.6	0.75	14.8	2.7%
N leaching (kg/ha)	173.9	195.3	0.84	38.0	2.8%
N uptake (kg/ha)	168.3	193.5	0.62	35.5	21.1%

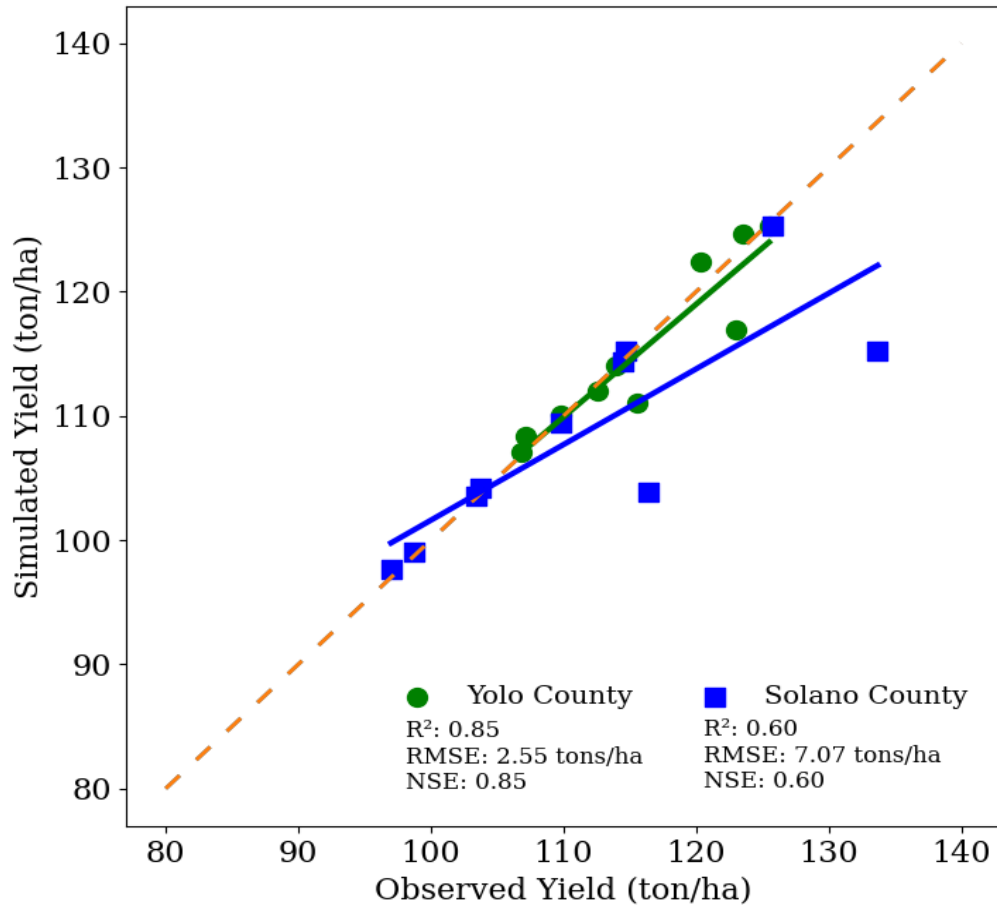


Figure 4-15. Model validation with Yield for Yolo and Solano County. Average county yields for Yolo and Solano Counties from 2011 to 2021 were used to validate the model.

Field-scale N leaching mapping

A field-scale N leaching map was generated with the APEX model, and Figure 4-6 shows the nitrogen leaching variability across the agricultural field. A gradient color scale from green to red indicates the leaching levels of nitrogen, measured in kilograms per hectare (kg/ha). The green areas represent regions with the lowest nitrogen leaching, starting at 80 kg/ha, suggesting potentially better nitrogen retention or uptake by crops. In contrast, the red zones denote areas with the highest nitrogen leaching, peaking at 140 kg/ha, which could be attributed to factors such as over-fertilization, reduced plant uptake, or possibly poorer soil structures.

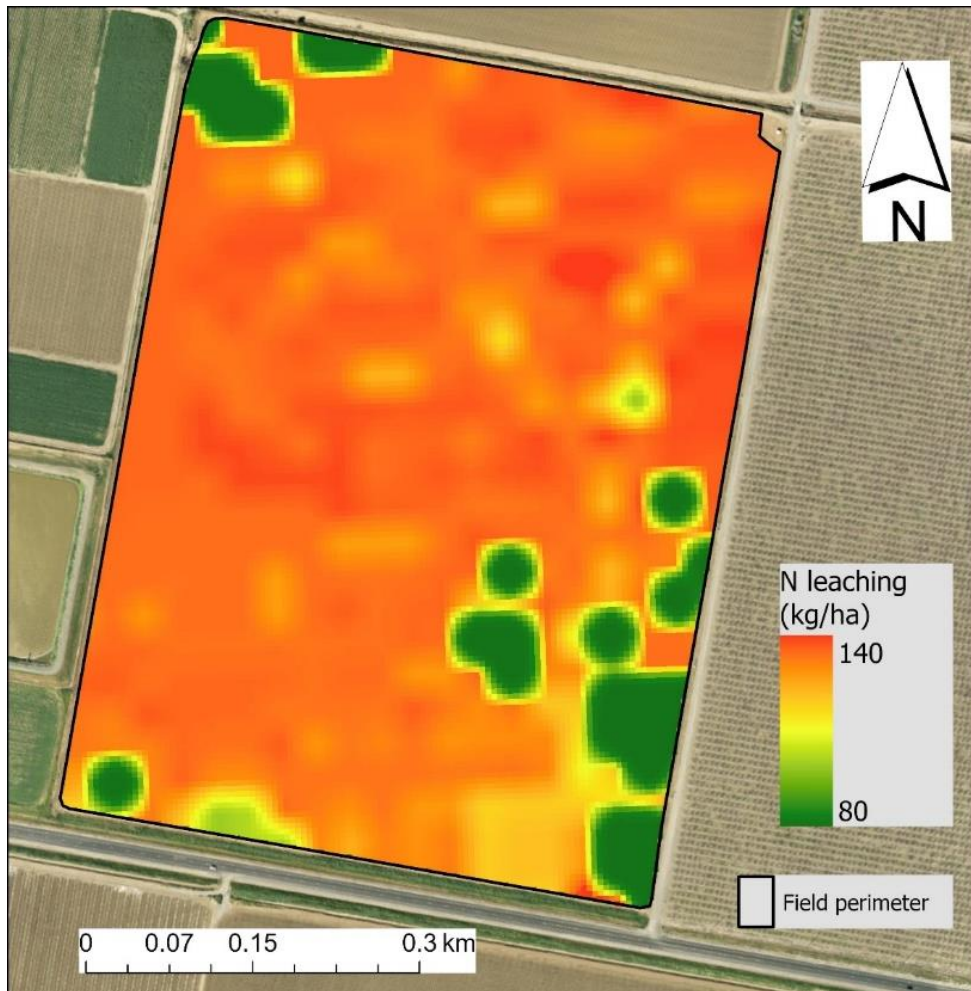


Figure 4-16. Spatial variability N leaching (kg/ha) at field scale. Colors go from green to red. Green colors indicate low N leaching rates, while red indicates high leaching rates.

Conservation practices

The model results in evaluating the efficacy of different conservation practices for reducing nitrogen (N) leaching, which encompasses traditional and modern irrigation methods, alongside N management strategies such as Nitrogen Credits (NC) and winter cover crops (Figure 4-7). The mean N leaching associated with Furrow irrigation was 153.23 kg/ha. Integrating Nitrogen Credits with Furrow irrigation (Furrow + NC) demonstrated improvement, reducing the mean N leaching to 138.96 kg/ha. Conversely, Drip irrigation outperformed Furrow irrigation, with a mean N leaching of 7.83 kg/ha. Adding Nitrogen Credits to Drip irrigation (Drip + NC) further optimized nitrogen utilization, lowering the mean N leaching to 5.71 kg/ha.

Cover crop, a practice widely used due to soil health and nutrient uptake benefits, triggered a lower mean N leaching of 3.53 kg/ha. The addition of crop rotation with nitrogen credits (Cover crop + NC) slightly enhanced the mitigation of N leaching, achieving a mean of 2.75 kg/ha. The most efficient High-Frequency Low-Concentration (HFCL) Irrigation with the lowest mean N leaching (2.32 kg/ha).

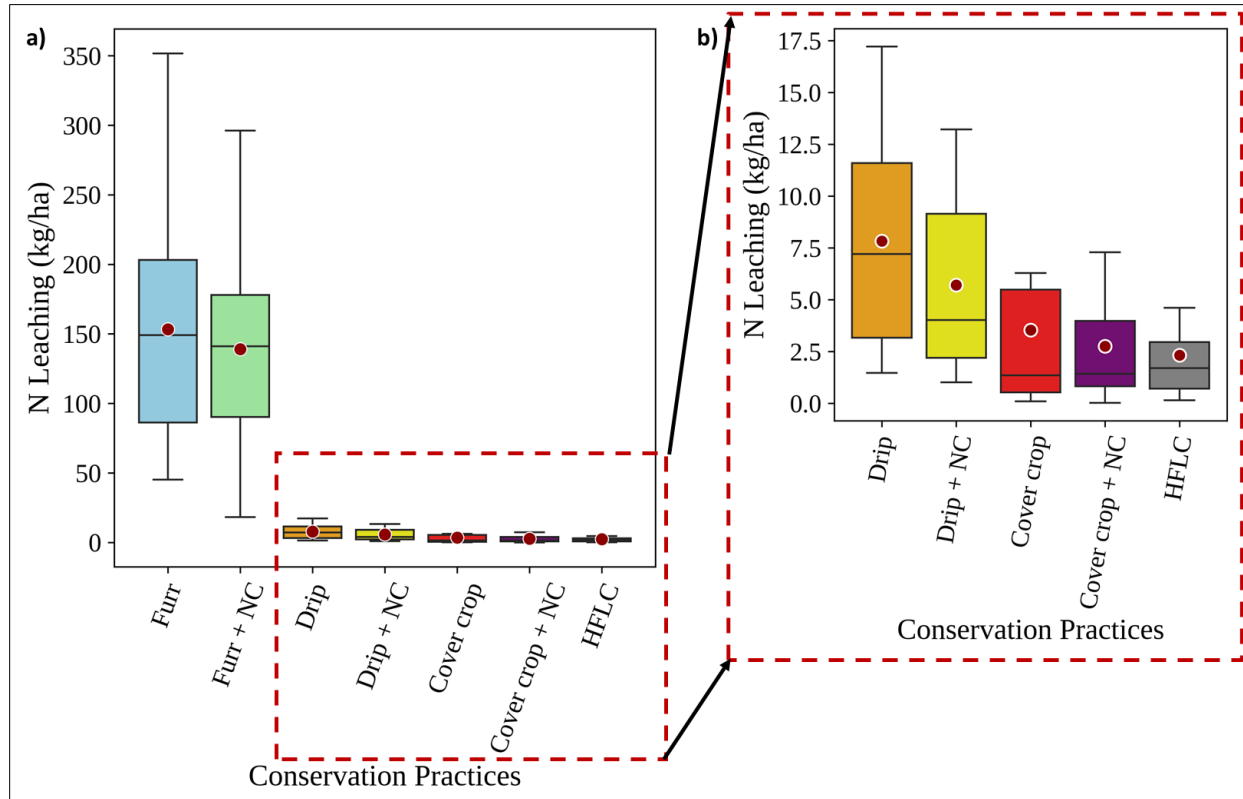


Figure 4-17. Effectiveness of conservation practices in reducing N leaching (kg/ha). A) All simulated conservation practices are plotted together, and b) Drip, Drip + NC, Cover crop, Cover crop +NC, and HFCL are plotted without furrow.

Discussions

Sensitivity analysis

Recent advancements in sensitivity analysis have significantly contributed to the understanding of agricultural systems, highlighting the complex interplay between various parameters affecting yield, nitrogen (N) balance, and water balance (Kim et al., 2021;

Rathnappriya et al., 2022). The impact of the harvest index (HI) and daily leaf area index (DLAI) on yield has been increasingly recognized. An increase in HI is crucial for higher yield (Duan et al., 2018) as HI is an essential determinant of crop productivity, underscoring the potential of genetic improvements to enhance yield (Asefa, 2019). LAI is vital for assessing a plant's capacity for light interception, photosynthesis, and, consequently, its contribution to crop yield. Simulations suggest that maintaining an LAI of 4 m²/m² could lead to a potential yield increase of 4% (Heuvelink et al., 2005). PARM52, identified as the exponential coefficient within the equation that models the impact of tillage on residue decay rate, plays a critical role in N balance simulations by quantitatively expressing how tillage practices influence the rate at which crop residues break down in the soil (Maharjan et al., 2018; Sainju, 2017). The relevance of other parameters like PARM80, PARM104, and PARM107, despite lower SI_Total values. This indicates their subtle yet significant contributions to N balance and the need to understand both major and minor factors in N cycling (Sainju, 2017). Soil evaporation (PARM17) and the Hargreaves PET equation exponent (PARM34) were identified as significant factors in water balance. The significance of soil evaporation and the Hargreaves PET equation exponent in the water balance are critical, as Milly (1994) emphasized the role of these factors in the annual water balance, while Graf et al. (2014) highlighted their influence on the relations between water budget elements and soil water content.

Model performance

The APEX model has been shown to have exceptional predictive accuracy for various variables, including yield, Eta, N leaching, and N uptake, as evidenced by high R² and NSE values and low RMSE (Senaviratne et al., 2013; Talebizadeh et al., 2018; Timlin et al., 2019). These studies have demonstrated the model's stability and applicability across different areas, including the Chesapeake Bay Watershed (Timlin et al., 2019), the upper Bawanghe River

watershed in Inner Mongolia, China (X. Wang et al., 2014), and the claypan region (Senaviratne et al., 2013). The model's performance has been further enhanced through the development of an auto-calibration tool and a simultaneous calibration approach for evapotranspiration and crop yield (Talebizadeh et al., 2018; X. Wang et al., 2014). Other models, such as DSSAT and Hydrus, have shown strength in optimizing resource use and minimizing environmental impacts. Although showing predicting capabilities, the APEX model performance does exhibit variability, particularly in the calibration phase for ETa, N leaching, and N uptake, as well as in different counties during the validation phase. This is important to highlight the relevance of continuous model refinement and adaptation to specific local conditions to enhance predictive reliability in agricultural management practices.

Field-scale N leaching variability

Ignoring spatial variability in nutrient status within agricultural fields can lead to both economic and environmental consequences, including missed opportunities for optimizing yield and unnecessary nutrient losses that can impair soil health as well as groundwater and surface water quality (Ersahin, 2001; Stenger et al., 2002). Site-specific prediction could offer a strategic approach to address these challenges by tailoring soil and crop management practices to the varying conditions found within fields. The APEX model can successfully simulate crop production as well as environmental impacts at both field and watershed scales (Kim et al., 2021; Mason et al., 2020). However, the model assigns the dominant soil or land use to the conserved subarea, which increases uncertainties. The POLARIS soils series (Chaney et al., 2019) provides high-resolution grided soil data at different depths, allowing to overcome this limitation in APEX by coercing the model to use one cell size (30*30) as subarea and simulate agricultural practices. Other studies have investigated spatial variability of nitrate leaching with mechanistic model (Ersahin, 2001), simplified water balance (Bruckler et al., 1997) at plot scale and regional scale

using machine learning approaches (Spijker et al., 2021). Nonetheless, both the mechanistic and the simplified water balance models were limited in simulating a range of conservation practices capable of reducing N leaching. The predictive modeling framework using the Random Forest (RF) algorithm generated a large-scale map of N leaching but was limited in sample size due to the costly procedure for sampling farms (Spijker et al., 2021).

Effectiveness of conservation practices

Micro-irrigation technologies

The transition from traditional to modern irrigation methods, such as from furrow to drip irrigation, offers a significant leap in reducing N leaching by enhancing water and nutrient delivery efficiency directly to plant root zones, thus minimizing losses (Lv et al., 2019; Sun et al., 2013). Drip irrigation was predicted to decrease N leaching by 95% compared to furrow irrigation, similar to the findings of Lv et al. (2019). Drip fertigation can lead to significantly higher yields, water productivity (WP), and nitrogen use efficiency (NUE) compared to traditional irrigation. The extent of such improvement depends highly on crop types and other factors such as climate and management capabilities (Li et al., 2021).

Irrigation nitrogen credits

The addition of Nitrogen Credits (NC) to these irrigation systems further refines improving nitrogen use efficiency (NUE), demonstrating the synergy between precise water application and strategic nitrogen management in substantially lowering N leaching rates (Ferguson, 2015). This is important in light of the increasing regulatory pressure on agricultural regions, notably California agriculture, to improve nitrogen management to protect groundwater quality (Cahn et al., 2017). Agricultural nitrogen pollution requires an integrated society-wide solution, and a comprehensive nitrogen credit system can help address this issue by incentivizing mitigation efforts from multiple parties along the food chain by acknowledging the

responsibilities and limitations of various stakeholders (Gu et al., 2021). Model predictions of this study showed that the application of NC would trigger a decrease in N leaching by more than 25%. Water quality trading, which involves providing financial rewards to farmers for implementing conservation measures on their farms, could be beneficial for treatment plants, agricultural producers, and the environment (Lal et al., 2008).

Winter cover crops

The implementation of winter cover crops stands out for its soil health and nutrient uptake benefits, translating into reduced N leaching (Kladivko et al., 2014). Triticale (as a cover crop), in conjunction with irrigation N credit, was predicted to reduce N leaching by more than 95%. Cover crops have become essential in sustainable agriculture, aiming to protect agroecological systems by reducing chemical application and preserving farm natural resources while remaining profitable (Abdalla et al., 2019). However, the adoption of cover crops is hindered by perceived costs and lack of awareness of their benefit. Research and promotional efforts should concentrate on highlighting possible benefits, quantifying and communicating potential risks, and improving facilitating infrastructure to support the widespread adoption of cover crops (Arbuckle and Roesch-McNally, 2015). DeVincentis et al. (2020) performed a cost-benefit analysis to examine the viability of winter cover crops in specialty crop systems in California. They found that the long-term profitability of winter cover crops in California is contingent upon a multitude of factors, including the cropping system, irrigation conservation, accessibility to financial subsidies, and climate change. The evaluation of the economic and agronomic impacts of winter cover crops is a complex task because benefits and expenses accrue differently over time and with extended planning horizons. Interdisciplinary investigation into the trade-offs and synergies between the economic impacts of agricultural services and cover crop adoption is necessary to increase the adoption of cover crops.

High-Frequency Low-Concentration

High-frequency Low-concentration (HFLC) fertigation was predicted as the most efficient conservation practice, reducing N leaching by 98%. HFLC aligns irrigation and fertilization with plant uptake demands to minimize nutrient loss, thus reducing environmental. Research focusing on citrus production in central Florida highlighted the importance of careful irrigation and fertilizer application management. By using fertigation (15 applications per year) and controlled-release fertilizers, $\text{NO}_3\text{-N}$ leaching below the root zone was minimized, demonstrating that appropriate management practices can significantly reduce N leaching risks (Paramasivam et al., 2001). In an almond orchard in California, fertigation frequency and N-source (urea ammonium nitrate vs. calcium nitrate + potassium nitrate) significantly influenced nitrous oxide (N_2O) emissions and nitrate leaching. High-frequency fertigation with nitrogen-based fertilizers reduced N_2O emissions and potentially $\text{NO}_3\text{-N}$ leaching, suggesting the efficacy of high-frequency, low-concentration fertigation in improving nitrogen use efficiency and reducing environmental impacts. (Wolff et al., 2017). A study on drip-irrigated onions demonstrated that fertigation frequency significantly affects $\text{NO}_3\text{-N}$ distribution in the soil profile. High-frequency fertigation led to more uniform $\text{NO}_3\text{-N}$ distribution and minimized leaching risks, supporting the use of HFLC fertigation as a strategy to enhance nutrient use efficiency while mitigating leaching (Rajput and Patel, 2006).

Barriers to adopting conservation practices

Despite the clear advantages of these agricultural conservation practices in enhancing resource efficiency, protecting the environment, and potentially boosting long-term farm profitability, their widespread adoption faces considerable challenges. One of the most daunting hurdles is the initial cost, which can be prohibitive for smallholder farmers operating on narrow profit margins. The required upfront investments for purchasing new equipment, acquiring seeds

for cover crops, or making necessary modifications to existing irrigation systems necessitate external financial incentives or support mechanisms to be feasible. Additionally, the decision of farmers to embrace new practices can be influenced by several factors, including their knowledge base, perceived risks, prevailing cultural norms, and the extent of adoption among their peers.

As the agricultural sector's environmental responsibility, especially concerning water quality and climate change, gains increasing acknowledgment, various forces are propelling the shift towards sustainable practices. These include regulatory pressures, growing consumer demand for sustainably produced goods, and the opportunities for market access or premium pricing for products certified as sustainably produced. In this evolving landscape, extension services, agricultural advisors, and targeted policy instruments are pivotal in narrowing the gap between recognizing the benefits of these practices and actualizing their implementation on farms. Financial incentives, such as subsidies for equipment purchases or compensation for providing ecosystem services, combined with educational initiatives that highlight the long-term advantages and practical viability of these practices, are critical for boosting adoption rates. Moreover, cultivating a community of practice among farmers to exchange insights, achievements, and challenges plays a critical role in alleviating perceived risks and overcoming cultural obstacles to change. This comprehensive approach ensures that conservation practices not only become more accessible but also more appealing to the farming community, fostering a more sustainable and environmentally responsible agricultural landscape.

Conclusions

Our study used the APEX model to simulate the effectiveness of conservation practices in reducing N leaching and generate a field-scale N leaching variability below the root zone. The model was successfully calibrated using collected field experiment data of processing tomatoes

and validated with processing tomato yield data from two adjacent California counties. The integration of high-resolution gridded soil data within the APEX model facilitated the generation of field-scale N leaching maps, providing a better understanding of spatial variability in nitrate leaching. This innovation marks a significant advancement in our ability to predict and manage the environmental footprint of agricultural fields. Simulation results reveal that HFLC and drip irrigation, when combined with nitrogen credits and winter cover crops, can profoundly reduce nitrate leaching, thereby enhancing nitrogen use efficiency and reducing N leaching below the root zone. This research contributes to the ongoing discourse on sustainable agriculture and water resource management, offering evidence-based strategies to balance agricultural productivity with environmental conservation. The demonstrated effectiveness of the explored conservation practices informs agricultural policies and practices and highlights the critical role of precision agriculture in addressing environmental challenges. The study's insights into the APEX model's applicability across varying agricultural contexts underscore the importance of continuous refinement and adaptation of modeling tools. For instance, Bailey et al. (2021) integrated the APEX model with the MODFLOW model because APEX application in groundwater-driven watersheds is limited due to APEX's weak groundwater routines. However, this integrated modeling framework would require high-resolution soil data to be applicable to agricultural fields with no streams. Future research should also focus on encompassing a broader range of crops, climatic conditions, and soil types, as well as on the financial cost and social barriers, thereby enhancing the generalizability and impact of our findings.

Furthermore, engaging with stakeholders across the agricultural sector to facilitate the adoption of proven conservation practices will be crucial in translating these research outcomes into tangible environmental and societal benefits. In essence, our work lays the groundwork for

future endeavors aimed at securing the sustainability of water resources through innovative agricultural practices. By bridging the gap between scientific research and practical application, we can move closer to achieving the vision of a sustainable and resilient agricultural landscape that supports both food security and environmental health.

CHAPTER 5
EVALUATION OF AN INTEGRATED APEX-RT3D-MODFLOW MODEL AS A FIELD-
SCALE GROUNDWATER PROTECTION FORMULA FOR NITROGEN LEACHING INTO
GROUNDWATER

Abstract

Groundwater contamination due to nitrate leaching from agricultural activities poses significant environmental and public health risks. This study evaluates an integrated modeling approach that combines the Agricultural Policy/Environmental eXtender (APEX), Reactive Transport in 3 Dimensions (RT3D), and the Modular Groundwater Flow Model (MODFLOW) to assess and manage nitrate nitrogen ($\text{NO}_3\text{-N}$) leaching into groundwater at a field scale. Applied within a 34-hectare field in California's Central Valley, the model simulates the effects of various conservation practices on nitrate dynamics, incorporating high-resolution spatial data for precise modeling. The model accurately predicted nitrate concentrations and evapotranspiration, achieving a coefficient of determination (R^2) up to 0.95, with Root Mean Square Error (RMSE) values as low as 0.43 mm/month for evapotranspiration and varying RMSE for nitrate concentration predictions across monitoring sleeves, ranging from 10.40 to 13.92 mg/L. The study also demonstrated significant reductions in nitrate leaching when simulating conservation practices such as winter cover crop and high-frequency low fertigation. These results underscore the model's efficacy in providing actionable insights for regulatory compliance and sustainable agricultural practices, aiming to reduce nitrate contamination and enhance water quality. This integrated modeling approach offers a significant advancement in environmental modeling, equipping stakeholders with a detailed framework for understanding and mitigating the impacts of agricultural practices on groundwater quality.

Introduction

Groundwater contamination with nitrate nitrogen ($\text{NO}_3\text{-N}$) leaching remains a pivotal concern for environmental sustainability and public health, especially in agricultural areas where the balance between food production and environmental conservation poses complex challenges (Hansen et al., 2017; Keeney and Follett, 1991). The Central Valley, characterized by its extensive agricultural activities, faces the dual challenge of ensuring water quality while supporting the water needs of one of the world's most productive agricultural regions (Schmid et al., 2021). The intensification of agricultural practices, including the application of synthetic fertilizers and animal manure, has led to the leaching of nitrate-nitrogen ($\text{NO}_3\text{-N}$) into the groundwater, posing risks to drinking water sources and aquatic ecosystems (Harter et al., 2017) and affects human health, including the development of methemoglobinemia in infants and the potential association with stomach cancer in adults (Aghapour et al., 2021; Ward et al., 2018). Consequently, the U.S. Environmental Protection Agency (EPA) has set a maximum contaminant level (MCL) of 10 mg/L of $\text{NO}_3\text{-N}$ in drinking water to safeguard public health (U.S. EPA, 1995). $\text{NO}_3\text{-N}$ is highly mobile in soil and groundwater, exhibiting minimal sorption capacity in the unsaturated zone and moving through the saturated zone by advection-dispersion mechanisms, ultimately reaching streams and rivers through groundwater discharge (Duff and Triska, 2000; Wei et al., 2019). This complex challenge calls for innovative approaches to assess, manage, and mitigate groundwater contamination with $\text{NO}_3\text{-N}$ while supporting agricultural production.

Watershed models are commonly employed to mimic hydrological processes, water yield, and the fate and transport of nutrients, sediments, and other contaminants. (Wei et al., 2019). These processes are simulated to investigate inquiries concerning the water supply of surface water and groundwater resources, the combined use of groundwater and surface water,

the management of nutrients, the control of sediment, the control of pesticides, the loading of pollutants, and how they are influenced by potential management practices and climate change (Bailey et al., 2021). Models such as Soil and Water Assessment Tool (SWAT) and Agricultural Policy/Environmental eXtender (APEX) are prominent for their comprehensive inclusion of processes such as crop growth, nutrient cycling in the soil, and the movement of nutrients to streams via various pathways like surface runoff, soil lateral flow, and groundwater flow, along with in-stream transport (Aloui et al., 2023; Bailey et al., 2016; Gassman et al., 2010; Timlin et al., 2019). While SWAT has traditionally been utilized for basin-scale modeling, APEX has been applied at the field and small watershed scales, attributed to its detailed crop growth routines and nutrient and sediment transport modeling (Kim et al., 2020; Worqlul et al., 2018). However, the groundwater modeling features of both SWAT and APEX are somewhat basic and could be enhanced by integrating more sophisticated methods.

The State Water Resources Control Board of California has implemented groundwater regulations and Nitrate Control Programs to address nitrate contamination in the Central Valley's groundwater by implementing management practices and policies aimed at restoring and protecting groundwater quality and providing safe drinking water (C.A. Water Boards, 2024; CV-SALTS, 2023). These challenges have led to the need to develop a groundwater protection (GWP) formula for regions of the Central Valley affected by high nitrate concentration in the groundwater. Schmid et al. (2021) adapted the SWAT model to develop the Central Valley Soil Water Assessment Tool (CV-SWAT) for generating township GWP formulas and values in the Central Valley. The CV-SWAT adaptation represents a significant advancement in allowing farmers to comply with water board regulations by providing a tool for estimating $\text{NO}_3\text{-N}$ leaching at a broader scale. However, more detailed GWP formulas that operate at the field and

farm levels are needed. This approach would not only offer additional tools for GWP value estimation but would also enhance the accuracy of these estimates, ultimately leading to more effective groundwater protection strategies in areas affected by high $\text{NO}_3\text{-N}$ leaching.

Recent advancements in environmental modeling provide innovative tools to address these issues, combining agricultural and hydrological models to assess the impacts of agricultural practices on groundwater quality (Jeong and Zhang, 2020). Several models for groundwater solute reactive transport, such as Reactive Transport in 3 Dimensions (RT3D) (Clement, 1999) and the Modular 3-D Multi-Species Transport model (MT3DMS) (Zheng and Wang, 1999), have been adapted to incorporate nitrogen chemical kinetics for regional and watershed scale studies (Bailey et al., 2014, 2021; Wei et al., 2019). Furthermore, the Modular Groundwater Flow Model (MODFLOW) and solute transport models were coupled with agricultural systems models such as SWAT (Bailey et al., 2016; Wei et al., 2019), HYDRUS (H. Zhang et al., 2020), and APEX (Bailey et al., 2021) to simulate nitrate transport and fate in coupled surface-subsurface hydrologic systems. However, the APEX model excels in field-level simulation compared to SWAT, making it a prime tool for evaluating the effects of various conservation measures to mitigate N loading to groundwater at field scale (Gassman et al., 2010; Kim et al., 2020). HYDRUS models (1D/2D/3D) have the capability to simulate water and solute fluxes in the deep vadose zone at field-scale. However, they generally require complex model parameterizations and input variables (H. Zhang et al., 2020) and do not have a crop growth algorithm (Šimůnek et al., 2016). Hartmann et al. (2018) implemented a root growth module in HYDRUS to model root growth as a function of environmental stresses, but the model was not validated against independent data, tested under field conditions, nor considered other environmental stresses that may affect root growth.

Bailey et al. (2021) have successfully demonstrated the application of the integrated APEX-RT3D-MODFLOW model in various watersheds across the United States, showcasing the model's ability to accurately simulate hydrological states and fluxes across diverse climatic and hydrological conditions. This integration allows for a comprehensive analysis of how different conservation practices, such as nutrient management, cover cropping, and reduced tillage, influence $\text{NO}_3\text{-N}$ leaching to groundwater, thus providing invaluable insights for developing effective groundwater protection strategies. However, the integrated model is limited in applicability in a single field or a subarea because no MODFLOW grid cell can be generated without multiple subareas and streams (Nicolas et al., 2024).

Therefore, this study adapted the APEX-MODFLOW-RT3D in a single field by incorporating gridded soil data in the integrated model. The objectives were (1) to demonstrate the effectiveness of alternative groundwater protection formulas that quantify the amount of $\text{NO}_3\text{-N}$ that loads to the groundwater from an irrigated parcel of land and (2) to identify conservation practices that effectively reduce groundwater $\text{NO}_3\text{-N}$ pollution at field scale.

Methods

Study site description

The study site is a 34-ha field located in Yolo County, California. The climate of the area is characterized by hot summers, with temperatures typically ranging from 29°C to 38°C, and cool winters, where temperatures generally lie between 2°C and 7°C. The average annual rainfall in this area is between 430 and 530 mm, primarily occurring in the winter months. The region experiences relative humidity levels between 30% and 60%, along with plentiful sunshine throughout the year and light to moderate wind conditions. Eleven monitoring wells were installed around the field's eastern, northern, and western edges. Groundwater flow, determined from elevation data, is northeastward. Groundwater was previously found at 10 meters deep, and

monitoring wells were built at 15 m depth. Crops, such as processing tomatoes, have been grown on this site with rotation of other crops, including triticale, sunflower and squash. A deep vadose zone monitoring system (VMS) with two flexible sleeves (A & B) was installed at the eastern side of the field. Each sleeve was 8.8 meters long and equipped with six time-domain reflectometry (FTDR) moisture sensors and six vadose-zone pore water sampling ports (VSP) (Figure 5-1). Detailed descriptions and applications of the VMS are provided by Dahan et al. (2009) and Turkeltaub et al. (2016).

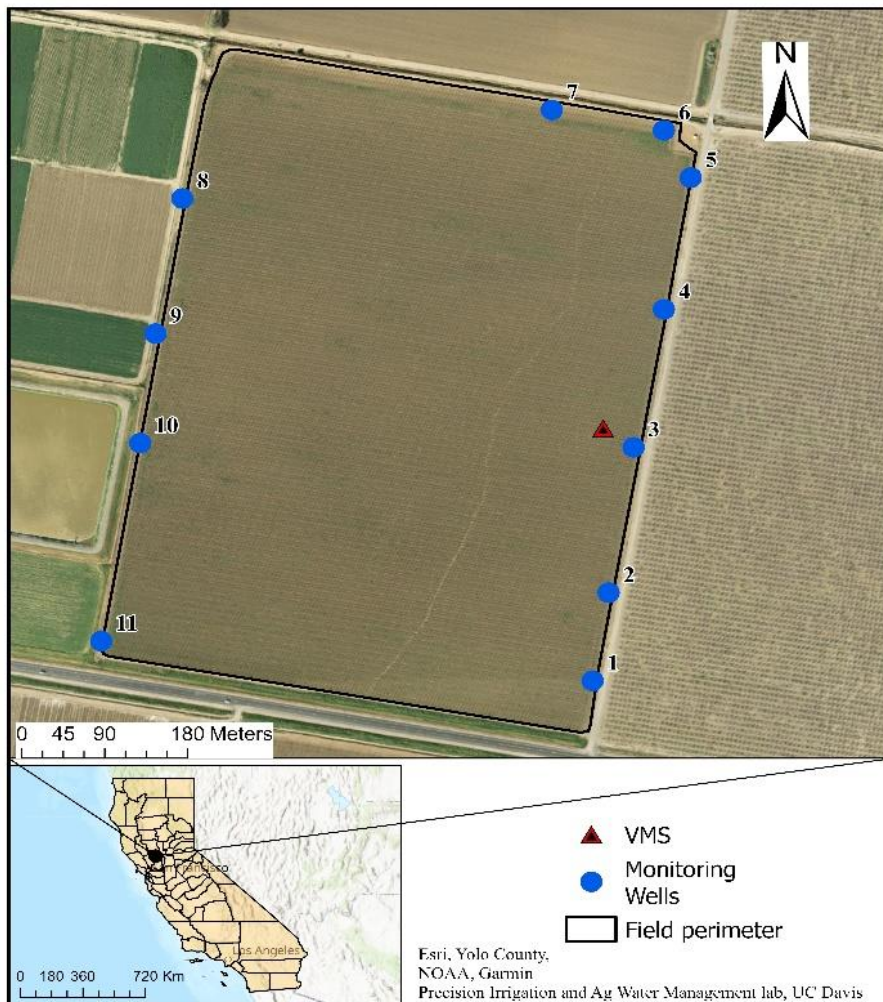


Figure 5-18. Study site located in Esparto, California. The blue dots are the groundwater monitoring wells.

Field monitoring for Model validation

The Vadose Zone Monitoring System (VMS) has a control unit on the ground surface and two sleeves buried in the soil. These sleeves, buried at a vertical depth of 6 meters under the surface, are designed to measure beneath the area affected by drip irrigation and tillage. Each sleeve extends for 8.8 meters and is inclined at a 35° angle, aligning southwest (218°) and northwest (320°) for the first and second sleeves, respectively. The sleeves are outfitted with six time-domain reflectometry sensors and six sampling ports for vadose zone pore water, arranged alternately along their length. NO₃-N samples were collected from April to December 2021 with the VMS at 6-meter depth and from the monitoring wells at 10-meter depth during the processing tomatoes season. The VMS data were used to validate the AMRS model at the deep vadose zone at 6 m depth, and wells data were used to validate the model in predicting NO₃-N concentrations at the shallow groundwater level. An eddy covariance tower was installed to collect daily evapotranspiration (mm) during the season and these ET data were also used to evaluate the model.

The coefficient of determination (R^2), Root Mean Squared Error (RMSE), and Nash-Sutcliffe Efficiency (NSE) were used to assess the model performance in predicting evapotranspiration (mm), NO₃-N concentration (ml/L) at the deep vadose zone and in the shallow groundwater.

$$R^2 = 1 - \frac{\sum(O_i - S_i)^2}{\sum(O_i - \bar{O}_i)^2} \quad (5-1)$$

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n (S_i - O_i)^2 \right]^{\frac{1}{2}} \quad (5-2)$$

$$\text{NSE} = 1 - \frac{\sum(O_i - S_i)^2}{\sum(O_i - \bar{O}_i)^2} \quad (5-3)$$

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (S_i - \bar{O}_i)^2 \quad (5-4)$$

APEX and MODFLOW models overview

APEX Model

The APEX model is a distributed, continuous, daily time-step model that can simulate hydrologic and water quality processes at various scales, ranging from field to watershed. The model has various components such as climate, hydrology, crop growth, nutrient cycling, management practices, soil and plant environment control, economic budgeting, and subarea/watershed routing. Within the APEX system, the watershed is partitioned into smaller subareas. APEX also offers extensive watershed and field management procedures specifically designed for agricultural activity (Gassman et al., 2010; Timlin et al., 2019). However, the groundwater routines in APEX are rather basic and can be enhanced by including more sophisticated methods, such as integration with MODFLOW (Bailey et al., 2021).

MODFLOW Model

MODFLOW is a groundwater model that uses a three-dimensional, physically accurate, distributed finite-difference approach to simulate variably saturated subsurface systems. MODFLOW-NWT, a solver method introduced recently, addresses the issue of complex non-linear drying and rewetting of grid cells in unconfined groundwater systems that existed in prior versions of the model (Niswonger et al., 2011). The model solves the following conservation of mass equations (Equation 5-1) for a representative volume of an unconfined aquifer, considering the mass of groundwater. Equation 5-2 represents the initial condition and Equation 5-3

represents the upper condition considering the water input (recharge) from the APEX model that simulated all the surface processes, including rainfall, irrigation, and management practices.

Equation 5-4 describes the lateral boundary conditions that depend on the hydraulic head in the monitoring wells. The hydraulic head can change over time, reflecting fluctuations due to external influences such as neighboring field activities. Equation 5-5 represents the no-flow boundary condition at the bottom of the aquifer, assuming no vertical flow crossing the lower boundary.

$$F_s S_s \frac{\partial h}{\partial t} + \varphi \frac{\partial F_s}{\partial t} = \frac{\partial}{\partial x} \left(F_s K_{xx} \frac{\partial h}{\partial x} \right) + \frac{\partial}{\partial y} \left(F_s K_{yy} \frac{\partial h}{\partial y} \right) + \frac{\partial}{\partial z} \left(f(F) K_{zz} \frac{\partial h}{\partial z} \right) + W \quad (5-10)$$

$$h(x, y, t = 0) = h_0(x, y) \quad (5-2)$$

$$W(x, y, t) = P_{APEX}(x, y, t) \quad (5-3)$$

$$h(x, y, z, t) = h_{wells}(t) \quad (5-4)$$

$$\frac{\partial h}{\partial z} = 0 \quad (5-5)$$

where x , y , and z represent the three spatial dimensions within the aquifer, h denotes the groundwater head (L), K is the hydraulic conductivity (L/T), and S_s is for specific storage (1/T). The porosity (φ) (L^3/L^3) is considered equivalent to specific yield (S_y) (L^3/L^3), F_s is the fraction of the saturated cell's thickness, and $f(F)$ is a function of F_s , which is set to 1 according to Niswonger et al. (2011). This study concentrates on the interactions between land surface hydrologic processes, as simulated by APEX, and the groundwater in underlying unconfined aquifers. Equation 5-1 encapsulates a water balance for a specific volume of the aquifer, accounting for groundwater movement in and out in the x , y , and z directions, along with sources

and sinks such as recharge, represented by W . Storage changes are included on the equation's right-hand side. P_{APEX} represent the net recharge provided by the APEX model and h_{wells} represents hydraulic heads in the wells. MODFLOW model simulates processes that include groundwater recharge, vadose zone percolation, evapotranspiration, pumping, and discharge to subsurface drains. However, the application of MODFLOW is restricted in simulating the impacts of conservation practices and climate on groundwater and surface water-groundwater and interactions because the model does not simulate surface processes such as land-atmosphere interactions, nutrient cycling and transport, plant growth, management practices in agricultural systems (Bailey et al., 2021).

Reactive Transport in 3 Dimensions (RT3D) model

RT3D is a three-dimensional groundwater contaminant and solute transport model that simulates advection, dispersion, and chemical interactions of dissolved elements in groundwater (Clement et al., 1998). RT3D utilizes groundwater hydraulic head, detailed flow data for each cell across the aquifer domain, and groundwater sources and sinks, such as recharge and exchanges between groundwater and surface water. These inputs are derived from outputs of a linked MODFLOW model to construct the groundwater flow field. The choice of RT3D is primarily due to its capability to model the chemical kinetics involving numerous interacting species. Under conditions of rigid porous media, linear equilibrium sorption, and saturation, the advection-dispersion-reaction (ADR) equations (Equation 5-6) are employed to detail the movement and fate of contaminants for each species, referred to as species k .

$$\phi \frac{\partial C_k}{\partial t} = - \frac{\partial}{\partial x_i} (\phi v_i C_k) + \frac{\partial}{\partial x_i} \left(\phi D_{ij} \frac{\partial C_k}{\partial x_i} \right) + q_s C_{s_k} - \rho_b \frac{\partial \bar{C}_k}{\partial t} + \phi r$$

$k = 1, 2, \dots, m$

(5-6)

where m is the total number of solutes, C_k is the concentration of the k th species [$M_f L_f^{-3}$] with f denoting the fluid phase, D_{ij} is the hydrodynamic dispersion coefficient [$L^2 T^{-1}$], v is the average seepage velocity [$L_b T^{-1}$] with b denoting the bulk phase, ϕ is the soil porosity [$L_f^3 L_b^{-3}$], q_s is the volumetric flux of water representing sources and sinks of the species [$L_f^3 T^{-1} L_b^{-3}$], C_{s_k} is the concentration of the source or sink [$M_f L_f^{-3}$], r represents the rate of all reactions that occur in the aqueous phase for the k th species [$M_f L_f^{-3} T^{-1}$], ρ_b is the bulk density of the porous media [$M_b L_b^{-3}$], and \bar{C}_k is the concentration of the k th species sorbed on solids [$M_f M_b^{-1}$]. The concentration C of each solute is calculated at each grid cell of the aquifer domain, using the same grid as MODFLOW.

The system of Advection-Dispersion-Reaction (ADR) equations, with each equation corresponding to a different chemical species, is solved for the spatially-variable concentration changes using the operator-split (OS) numerical scheme (Yeh and Tripathi, 1989). The identical finite difference grid is utilized in this method as in the accompanying MODFLOW model. The OS method implicitly simulates the concentration variations caused by advection, dispersion, and sources/sinks concurrently by employing linear algebra techniques and an iterative solver. Subsequently, the obtained values are transmitted to the chemical reaction subroutine, which calculates concentration changes caused by chemical reactions using an ordinary differential equation (ODE) solver. The chemical reaction subroutine in the RT3D FORTRAN code can be tailored to incorporate several interacting chemical species, with rate laws for reactions given by first-order chemical kinetics that include Monod terms.

Lee et al. (2006) created a module for RT3D that focused on the conversion of nitrogen, specifically nitrification and denitrification. Similarly, Bailey et al. (2015) developed a nitrogen module that incorporated the complete nitrogen cycle in the crop-soil-water system in

agricultural regions. For instance, Equation 5-7 describes the conservation of mass advection–dispersion-reaction of NO₃ and denitrification. These equations integrate various mechanisms affecting nitrate transport and transformation in subsurface environments. The advection term represents the bulk movement of nitrate with groundwater flow, while the dispersion term accounts for the spreading of nitrate due to variations in flow velocities within the porous medium (Bear, 1972). The reaction term incorporates denitrification, a process typically described by first-order chemical kinetics with Monod terms to account for the dependence on substrate concentration and microbial activity (Monod, 1949). This comprehensive modeling approach ensures that the equations capture the complex interplay between physical transport processes and biochemical reactions, providing a robust framework for predicting nitrate behavior in groundwater systems.

$$\frac{\partial C_{NO_3}}{\partial t} = -\frac{\partial}{\partial x_i}(v_i C_{NO_3}) + \frac{\partial}{\partial x_i}\left(D_{ij} \frac{\partial C_{NO_3}}{\partial x_j}\right) + \frac{q_s}{\phi} C_{sNO_3} - k_{NO_3} C_{NO_3} \left(\frac{C_{NO_3}}{k_{NO_3} + C_{NO_3}}\right) \quad (5-7)$$

$$C_{NO_3}(x, y, t = 0) = C_{NO_3,0}(x, y) \quad (5-8)$$

$$C_{NO_3}(x, y, z, t) = C_{NO_3, APEX\ recharge}(x, y, z, t) \quad (5-9)$$

$$C_{NO_3}(x, y, z, t) = C_{NO_3, wells}(t) \quad (5-10)$$

$$\frac{\partial C_{NO_3}}{\partial z} = 0 \quad (5-11)$$

where Equation 5-8 is the initial condition for nitrate concentration, Equation 5-9 represents the upper boundary condition for nitrate concentration from APEX recharge, and Equation 5-10 is the boundary condition for nitrate concentration at monitoring wells located at the border of the field and Equation 5-11 represents the no-flux boundary condition for nitrate.

Integrated APEX-MODFLOW-RT3D model

The loose coupling of APEX, MODFLOW, and RT3D (Bailey et al., 2021, 2022) facilitates the exchange of data between APEX's simulation of surface phenomena like runoff, evapotranspiration (ET), plant growth, and water and nutrient percolation and MODFLOW's emphasis on underground aspects, such as groundwater storage, water levels, and interactions between groundwater and surface water. Specifically, APEX transfers data on soil percolation from each subarea to corresponding MODFLOW grid cells within those subareas, aiding in the precise modeling of groundwater recharge and movement.

The integrated APEX-MODFLOW-RT3D-Salt (AMRS) was implemented as a Python 3 plugin for Quantum Geographic Information System (QGIS) by Park et al. (2023). The open-source plugin (APEXMOD) simplifies the preparation of input data, allows for the adjustment of simulation settings, and enables the analysis and post-processing of results directly within the QGIS interface. The AMRS model requires specific versions of APEX (v1501) and MODFLOW (either 2005 or NWT) for input. Although RT3D inputs can be generated using alternative software such as GMS, compatibility concerns may develop, especially regarding the absence of salinity data. A detailed description, implementation, and use of the APEXMOD plugin is provided by Park et al. (2023).

Model construction

The ArcAPEX tool (Tuppad et al., 2009) was used with the ArcMap software (Esri, V10.7) to define a subbasin that includes the study field. Data such as land use, Polaris grided soil, and weather, including maximum and minimum temperatures, precipitation, solar radiation, humidity, and wind speeds, were used to set up the APEX model. The APEXeditor (Leyton, 2019b) was used to run the model for the field study. The APEX outputs were then imported into APEXMOD to run the integrated APEX-MODFLOW-RT3D model. The model was linked using

the subareas, a DEM, and the monitoring wells. The field was divided into 479 subareas based on soil types and a false river network was created to facilitate the linkage of the models (Figure 5-2). This APEX model was calibrated and validated in Chapter 2.

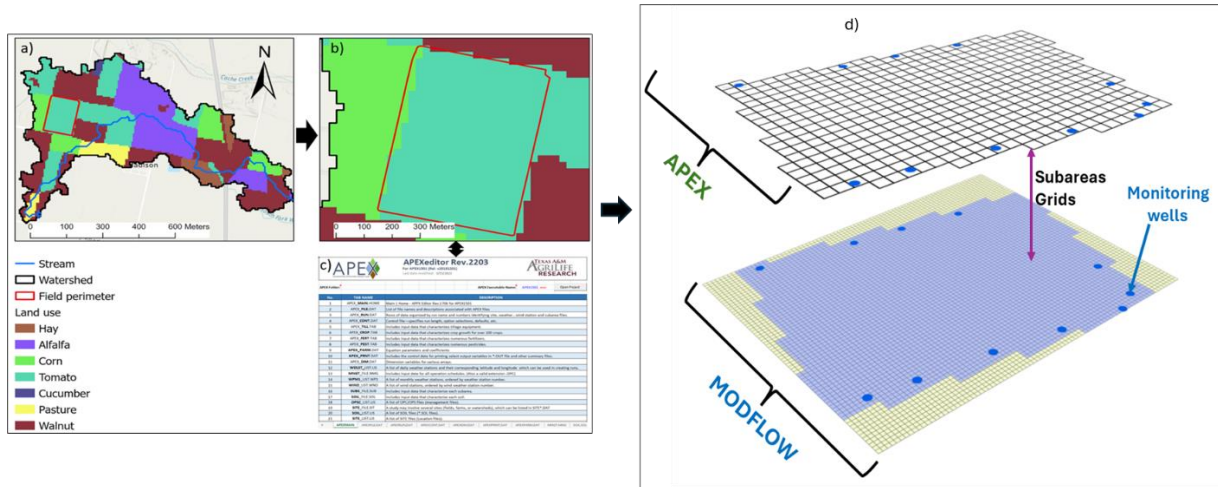


Figure 5-19. Model setup using ArcAPEX, APEXeditor, and APEXMOD. a) Subarea with land use and stream in the ArcAPEX tool; b) Field study with processing tomatoes; c) Interface of the APEXeditor used to run the model; d) Framework of the integrated APEX-MODFLOW-RT3D model.

Simulation of conservation practices impacts on Groundwater NO₃-N concentrations

Processing tomato farmers in Central Valley use drip and furrow irrigation systems (Hartz and Bottoms, 2009; Miyao et al., 2020). Growers normally apply nitrogen (N) to their crops at a rate of 140 to 280 kg of N per hectare during the growing season. The APEXMOD model was used to assess the long-term impacts of conservation practices on groundwater nitrate contamination. Management practices such as drip irrigation and furrow irrigation systems were evaluated over a 30-year period.

Results

Model performance

The evapotranspiration (ET) (mm) estimation during the 2021 processing tomato season was performed using the APEXMOD model and compared against measurements obtained via

the Eddy covariance technique. Figure 5-3 illustrates the monthly ET (mm/month). The progression of ET values from April to August displayed an increasing trend, peaking in July before a slight reduction in August at the end of the season. Both the APEXMOD model and the Eddy covariance measurements show a strong correspondence in the pattern of ET throughout the season. The coefficient of determination (R^2) was exceptionally high at 0.95, signifying that the model could explain 95% of the variance in measured ET. The Root Mean Square Error (RMSE) was relatively low at 0.43 mm/month, suggesting minor deviations between the model predictions and the observed data. The Nash-Sutcliffe Efficiency (NSE), a hydrologic model efficiency coefficient, was also high at 0.95, further affirming the model's predictive capability. Mean Absolute Error (MAE) at 0.38 mm/month and the normalized RMSE (nRMSE) at 0.09 underscored the model's consistency and reliability in predicting ET.

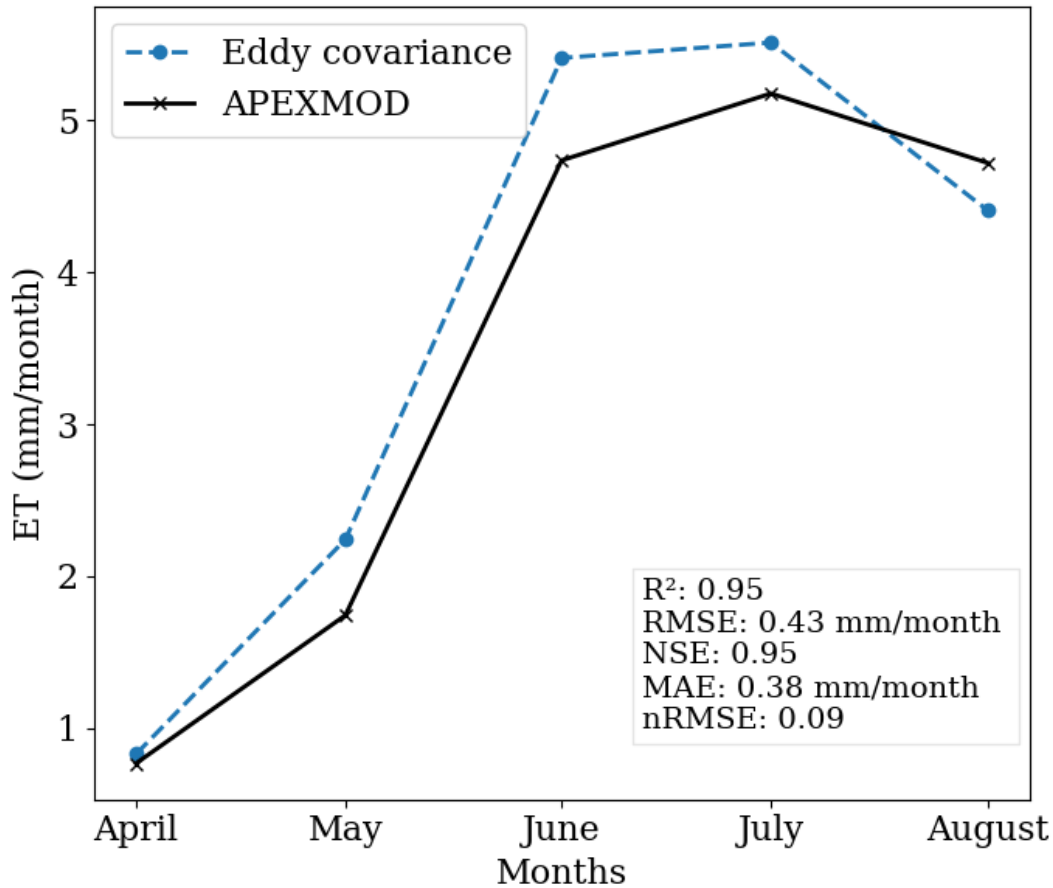


Figure 5-20. Model ET (mm) and Eddy covariance ET (mm) for the processing tomatoes season in 2021.

The temporal distribution of nitrate-nitrogen levels from April to December, shown in Figure 5-3, illustrates the comparison of the APEXMOD model and VMS-measured nitrate concentrations at a 6-meter depth in 2021. The model predictions and observed values from both sleeves exhibit similar trends in nitrate-nitrogen levels throughout the season. Both APEXMOD and VMS sleeves showed an increase in concentrations starting in May, culminating in high concentrations towards the end of the year. However, the observed values from Sleeve B and the averaged data from both sleeves show a more pronounced rise as the year progresses compared to Sleeve A.

The statistical metrics provided in Table 5-1 further elucidate the model performance. The coefficient of determination (R^2) for Sleeve A was moderately low at 0.46, indicating a less

robust correlation between the model predictions and observed values. In contrast, Sleeve B and the combined average of A & B demonstrated higher R^2 values of 0.70 and 0.65, respectively, suggesting a stronger agreement. In terms of the RMSE, Sleeve A recorded the highest value at 13.92 mg/L, while Sleeve B displayed a lower value of 10.40 mg/L, and the RMSE for both sleeves (averaged A & B) was 11.19 mg/L. The Nash-Sutcliffe Efficiency (NSE) mirrored these patterns, with Sleeve A at 0.46, Sleeve B at a higher 0.70, and the average NSE for A & B at 0.65. The Mean Absolute Error (MAE) and normalized RMSE (nRMSE) further supported these results; Sleeve A had an MAE of 11.86 mg/L and an nRMSE of 0.23, whereas Sleeve B and the average A & B reported lower MAE values of 8.40 mg/L and 8.80 mg/L, and lower nRMSE values of 0.17 and 0.18, respectively. These results indicate that the APEXMOD model aligns more closely with the observed values from Sleeve B and the averaged observations than with Sleeve A.

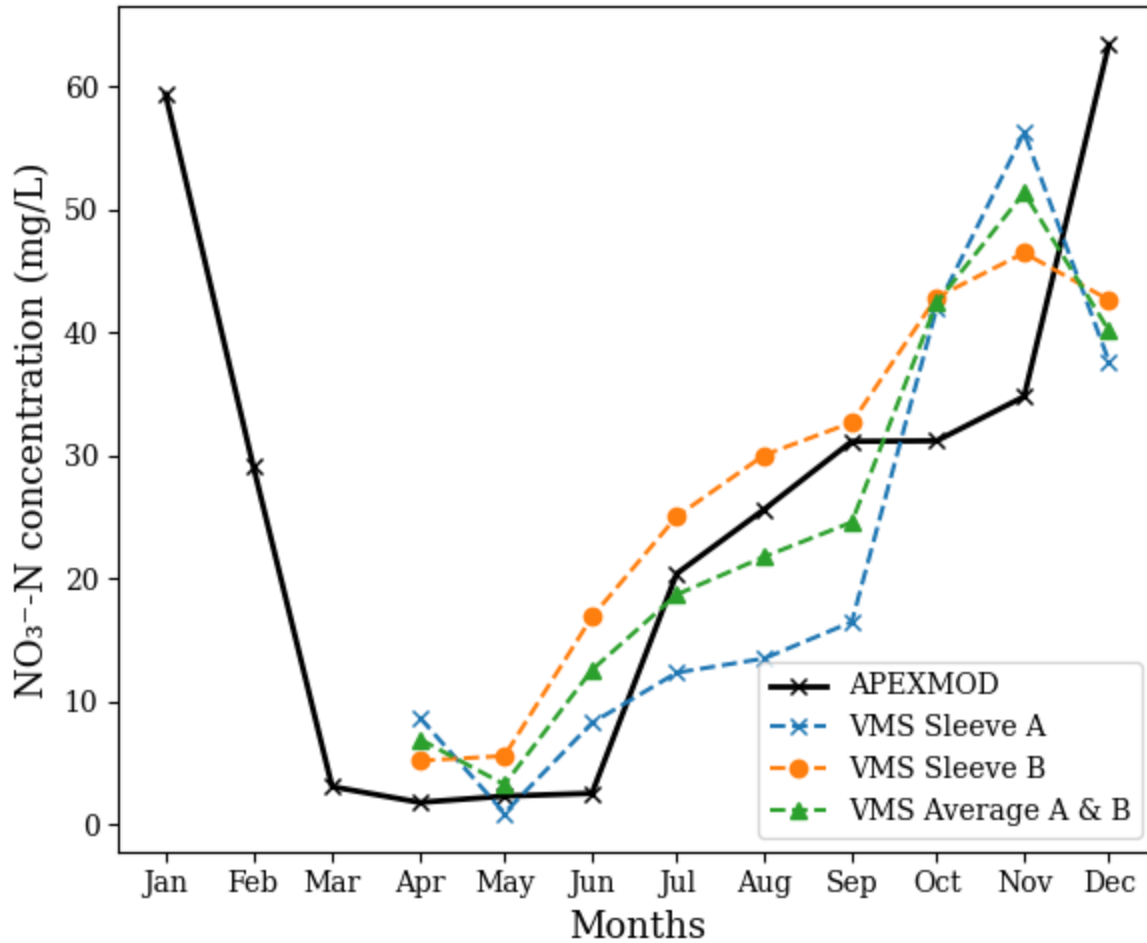


Figure 5-21. Model NO₃-N concentration (mg/L) and VMS measured concentration at 6 meters depth. The measurements were taken from April to December 2021

Table 5-5: Performance of the model in predicting the NO₃-N concentrations at 6 m depth

Metrics	Sleeve A	Sleeve B	Average A & B
R ²	0.46	0.70	0.65
RMSE (mg/L)	13.92	10.40	11.19
NSE	0.46	0.70	0.65
MAE (mg/L)	11.86	8.40	8.80
nRMSE	0.23	0.17	0.18

Nitrate concentrations (mg/L) measured in the wells during 2021 indicated substantial heterogeneity. Some wells exhibited high concentrations, particularly wells 7, 8, and 4.

Conversely, wells 5 and 6 consistently showed the lowest nitrate concentrations throughout the

year. However, there was little change in the concentration levels throughout the year. In addition, the standard deviation suggests a high degree of variability in nitrate concentrations among the wells. The model exhibited an acceptable performance in approximating the average nitrate concentrations across all wells, as depicted by the congruence between the model's forecast line and the monthly average concentration of the year.

Nonetheless, there is a discrepancy between the model's predictions and the observed data towards the latter part of the year, wherein the model tended to underpredict the nitrate levels. The Root Mean Square Error (RMSE) was 1.97 mg/L, and the Mean Absolute Error (MAE) was 1.60 mg/L. suggest the model's predictions moderately agree with the observed average monthly concentrations. Moreover, the normalized RMSE (nRMSE) is 0.22, which, when considered alongside the RMSE and MAE, underscores the model's satisfactory performance in capturing the central tendency of the data across the studied temporal span.

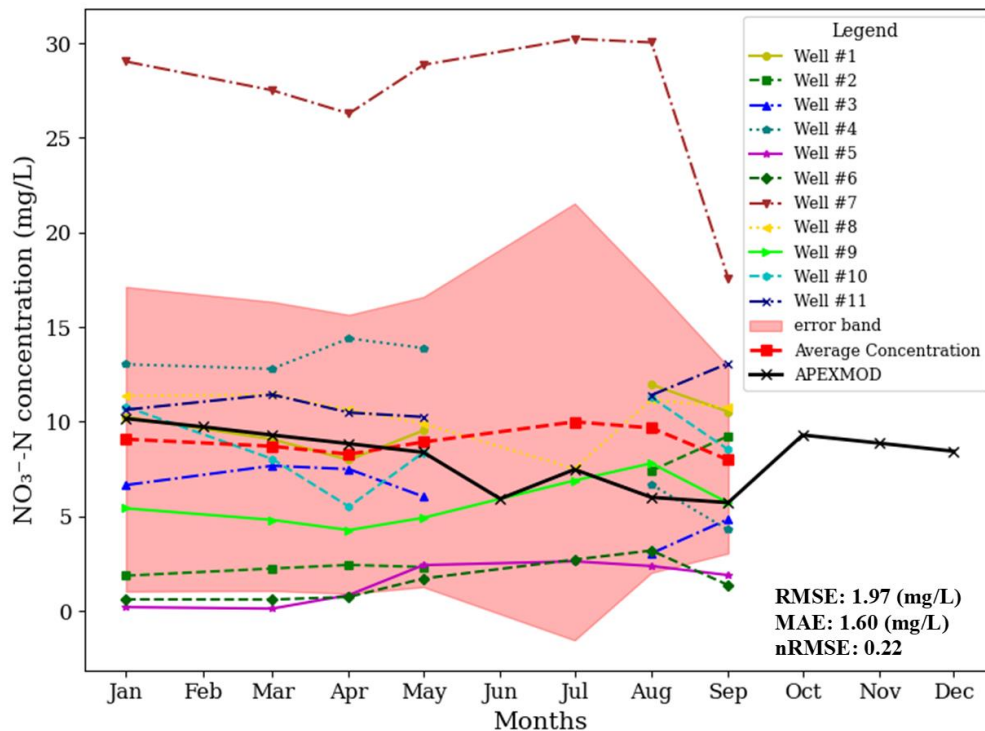


Figure 5-22. NO₃-N concentrations (mg/L) in the 11 wells and APEXMOD NO₃-N predictions in 2021.

Model simulation

The comprehensive analysis of hydrological data has been efficiently translated into a series of maps, elucidating three critical environmental metrics: groundwater recharge rates, nitrate percolation, and nitrogen concentration in groundwater. The first map, delineated by varying shades of blue, signifies the groundwater recharge rates measured in cubic meters per year. A gradation from lighter to darker hues corresponds to an ascending recharge scale, with the most saturated blue pixels indicating regions of maximum aquifer replenishment. Recharge up to 35 cm³ per year occurred in a certain part of the field, mainly in the rainfall season. Furrow irrigation triggered higher range NO₃-N concentration as opposed to drip irrigation, denoting better performance in mitigating groundwater contamination. Part of the groundwater is not impacted by the leaching coming from the management practices due to the denitrification process occurring from the root zone to the deep vadose zone. These visualizations collectively serve as a critical tool for assessing groundwater sustainability and formulating water management policies, highlighting areas of concern where intervention may be required to mitigate contamination and ensure the protection of water resources.

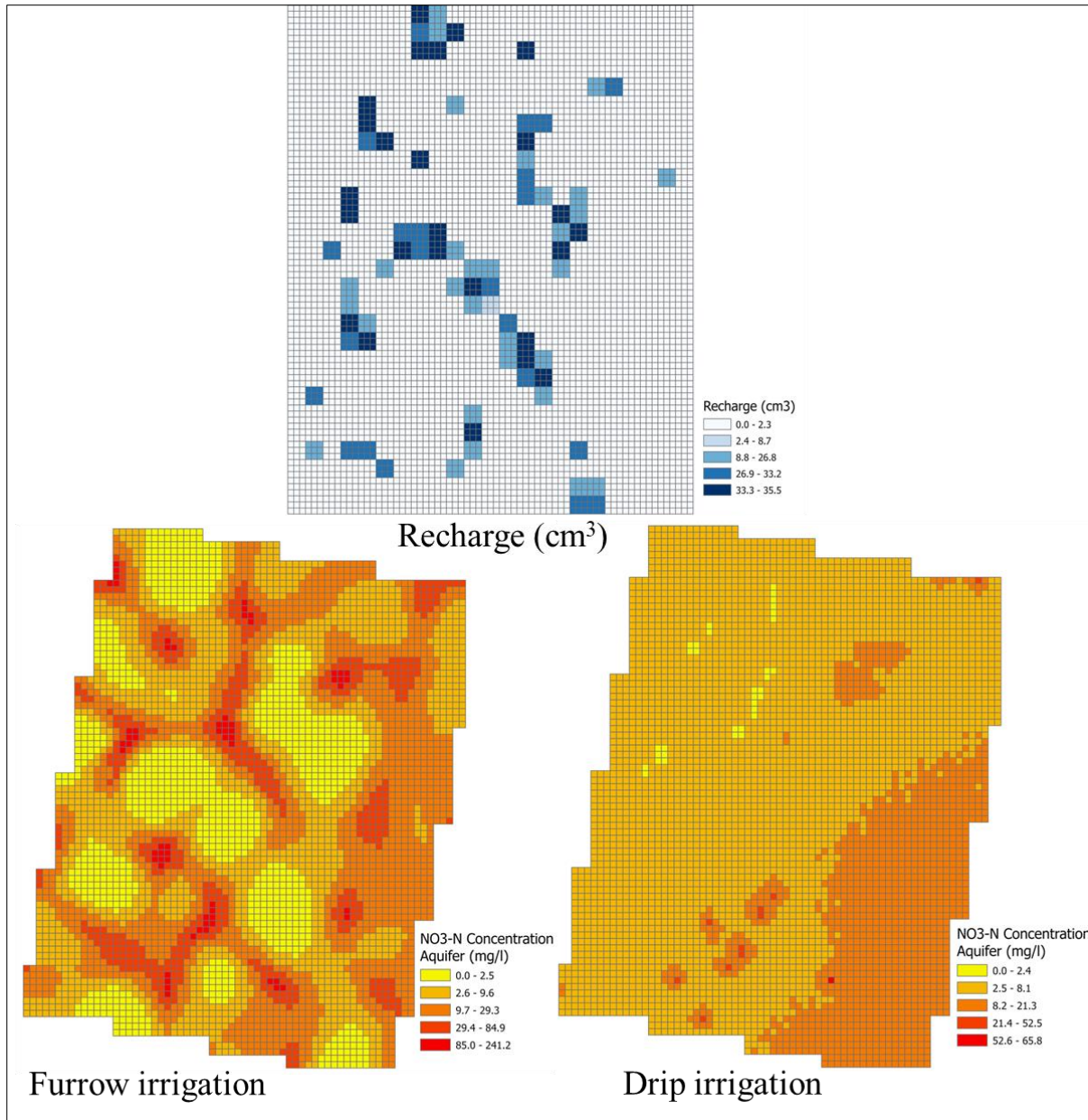


Figure 5-23. Model output with groundwater Recharge, NO₃-N percolation, and Groundwater NO₃-N concentration.

Discussions

The APEXMOD model accurately estimated evapotranspiration (ET) during the 2021 processing tomato season, aligning closely with the Eddy covariance measurements. This substantial agreement, evidenced by a high coefficient of determination ($R^2 = 0.95$) and low RMSE (0.49), underscores the model's capability to simulate ET dynamics in agricultural fields.

ET is a critical component in agrohydrological modeling of water management practices, particularly in water-scarce regions where agriculture consumes significant water resources (Chen et al., 2018; Wanniarachchi and Sarukkalige, 2022).

The estimation of nitrate-nitrogen levels by APEXMOD demonstrates the integrated model's capacity to effectively address agricultural pollution by simulating nutrient dynamics (Wei et al., 2019). The inconsistent performance of the model across different sleeves suggests the likely presence of cracks beyond the model simulation capabilities. This underscores the need for a deeper understanding of soil characteristics and hydrogeological conditions to optimize model predictions (Kim et al., 2021). The seasonal dynamics observed in nitrate levels, with concentrations increasing towards the end of the year, reflect typical agricultural nutrient cycling and leaching patterns influenced by irrigation and precipitation events. Such patterns align with findings from Weber et al. (2020), which discuss the impact of management practices, precipitation, and irrigation on nutrient dynamics in agricultural soils.

The APEXMOD has shown promise in enhancing agricultural water and nutrient management practices (Bailey et al., 2014; Wei et al., 2019). The model exhibits a high level of accuracy in ET estimation and demonstrates a variable but generally reliable performance in nitrate-nitrogen level estimation across different measurement sleeves. This deviation calls attention to potential limitations of the model in capturing the full spectrum of nitrate concentration variability, particularly in the context of individual well data that exhibited higher than average nitrate levels.

The analysis derived from the maps reveals that several areas of the field could trigger higher nitrogen concentrations that surpass the commonly accepted safety threshold of 10 mg/L for drinking water. Such elevated nitrogen levels due to agricultural practices pollute

groundwater resources and pose health risks. In the San Luis Valley, Colorado, nitrate concentrations in the unconfined aquifer have surpassed this threshold (Hudak, 2018). Similar findings have been reported in the Central Valley, Costa Rica, where nitrate contamination of groundwater has been linked to agricultural and urban activities (Harter et al., 2017; Rosenstock et al., 2014)). In the Central Valley, California, excessive loading of fertilizer and manure has been identified as a critical factor in groundwater nitrate contamination (Harter, 2009). However, the high resolution of groundwater contamination in this study highlights the spatial variability of average $\text{NO}_3\text{-N}$ concentration in the field due to factors such as legacy, soil type, management practices, and influence of neighboring fields. These high values can significantly influence the average $\text{NO}_3\text{-N}$ concentration for the entire field and, ultimately, the groundwater protection formula values.

Conclusions

This study has demonstrated the robust capabilities of the integrated APEX-RT3D-MODFLOW model in assessing and managing nitrate leaching into groundwater at a field scale in an agriculturally intensive region. By incorporating detailed, field-level simulations of hydrological and nutrient cycling processes, the model has provided nuanced insights into the dynamics of nitrate nitrogen within the soil and groundwater systems. The empirical validation using data from monitoring wells and the Vadose Zone Monitoring System has confirmed the model's efficacy in accurately simulating nitrate concentrations in the deep vadose zone and shallow groundwater, aligning closely with observed data.

The high-resolution modeling approach allows for a more granular understanding of how different conservation practices, such as cover cropping, reduced tillage, and efficient irrigation and fertilization methods, impact nitrate leaching. This is crucial for devising effective groundwater protection strategies tailored to specific field conditions and agricultural practices.

Moreover, the model's predictive power offers valuable support for regulatory bodies and agricultural managers in making informed decisions to ensure sustainable water use and compliance with environmental standards, thereby safeguarding public health and ecological integrity.

Future work should focus on expanding the model's application to different crops and regions, enhancing its capabilities with more complex hydrological and biochemical parameters, and integrating socio-economic factors to fully capture the trade-offs and synergies in agricultural water management. Additionally, ongoing refinement of the model based on real-world applications and feedback will further improve its accuracy and utility in addressing the challenges of nitrate pollution in agricultural landscapes. Through continued development and application, the integrated APEX-RT3D-MODFLOW model stands as a pivotal tool in balancing agricultural productivity with environmental sustainability, offering a pathway towards more resilient and responsible farming practices in the face of increasing environmental pressures.

CHAPTER 6 SUMMARY AND FINAL REMARKS

Chapter 1

This chapter introduces the critical environmental challenges facing California's Central Valley, primarily focusing on the salinity and nitrate pollution due to intensive agriculture and industrial activities. The Central Valley is described as a crucial agricultural hub, contributing significantly to the US and global food supply, yet grapples with the dual threats of salinization and nitrate accumulation. These issues compromise soil health, crop yields, agricultural productivity, water quality, and the overall sustainability of agriculture in the region. The Central Valley's agricultural success story is overshadowed by the environmental costs of soil salinization and nitrate accumulation in groundwater due to extensive irrigated agriculture and industrial activity. Salinity and nitrate leaching, exacerbated by intensive irrigation, agricultural practices, population growth, and climate change, have led to considerable environmental challenges. These include soil degradation, water quality deterioration, and threats to public health, underscoring the urgent need for sustainable management strategies.

This chapter methodically delineates the research objectives to develop comprehensive modeling frameworks, decision-support tools, and groundwater protection formulas to mitigate the adverse impacts of salinity and nitrate leaching on the Central Valley's agriculture and groundwater sustainability. A multi-faceted approach is proposed to assess the salinity impacts on crop yield and economic returns, develop a web-based decision-support tool for crop yield and profitability prediction across the Central Valley, develop a field-scale groundwater protection formula, and evaluate conservation practices for mitigate nitrate leaching out of the root zone. This ambitious agenda sets the stage for an in-depth analysis of the challenges and potential solutions for managing salinity and nitrate levels, emphasizing the importance of

innovative technologies and sustainable agricultural practices in ensuring the long-term viability of the Central Valley's agricultural sector and the improvement of groundwater quality.

Chapter 2

Chapter 2 delves into the quantitative analysis of salinity impacts on crop yield and economic returns within the Central Valley. In this chapter, a robust modeling framework that integrates soil variables, climate conditions, irrigation inputs, and economic data was developed to offer a comprehensive assessment of how different salinity levels of irrigation water affect crop productivity. This model reveals that increasing salinity significantly diminishes crop yield and profitability, with spatial analyses indicating that these effects are unevenly distributed across the Valley because of many factors such as heterogeneity, water prices, and variability of irrigation water quality. The chapter provides pivotal insights into how salinity management can be optimized for sustainable agricultural practices. Notably, the research identifies critical thresholds of water salinity beyond which crop production becomes economically unviable, underscoring the need for strategic irrigation management and the adoption of salinity-resistant crop varieties. The findings from this chapter can serve to develop targeted interventions to mitigate salinity's adverse effects, thereby contributing to the economic sustainability of agriculture in the region.

The comprehensive modeling framework developed in this chapter analysis extends beyond identifying the problems by offering a predictive means that policymakers and farmers can use to anticipate and mitigate the impacts of salinity on crop productivity. By providing a clear method for evaluating the potential profitability of different crops under varying salinity conditions, the model facilitates informed decision-making that could lead to more sustainable agricultural practices throughout the Central Valley. This chapter underscores the critical need for integrated approaches to water management that consider both the agronomic and economic

dimensions of salinity, paving the way for more resilient agricultural systems. As such, this chapter contributes valuable insights and tools that could be instrumental in the ongoing efforts to address salinity challenges in the Central Valley and similar agricultural contexts globally.

Chapter 3

Chapter 3 introduces a groundbreaking decision-support web tool designed to empower farmers and policymakers in the Central Valley with the ability to make informed decisions regarding salinity management in irrigation practices. The tool integrates agronomic, economic, and spatial data to provide user-friendly access to critical data and the predictive model developed in Chapter 2 to predict crop yield and profitability under various water salinity. The decision-support tool incorporates the complex interactions between soil salinity, crop tolerance, and economic returns, offering a nuanced understanding of how salinity impacts agricultural profitability across different regions of the Central Valley. By providing a user-friendly interface that allows for the customization of variables such as crop type, irrigation water salinity levels, and economic parameters, the tool empowers users to explore a wide range of scenarios. This adaptability ensures the tool's relevance to a broad spectrum of users, from individual farmers making decisions about crop selection and irrigation practices to policymakers developing region-wide strategies for salinity management and agricultural sustainability.

This chapter marks a pivotal contribution to the dissertation's overall aim of enhancing the sustainability of irrigated agriculture in the Central Valley in the face of salinity challenges. The decision-support web tool stands as a testament to the potential of integrating scientific research with technological innovation to create practical solutions for environmental and economic challenges in agriculture. By facilitating informed decision-making, the tool not only aids in the immediate management of salinity issues but also contributes to the broader goals of

sustainable water use and agricultural resilience. By providing a platform for evaluating the effectiveness of various salinity management strategies, the tool contributes to developing more sustainable and resilient agricultural systems. The chapter concludes with reflections on the potential of this technology, such as decision support systems that influence policy decisions, guide resource allocation, and ultimately support the long-term sustainability of agriculture in the Central Valley amidst evolving environmental challenges.

Chapter 4

Chapter 4 explores the effectiveness of various conservation practices in mitigating nitrate leaching in processing tomato cultivation, utilizing the Agricultural Policy Environmental eXtender (APEX) model. This detailed analysis focuses on the environmental and agronomic implications of nitrate leaching, a critical concern in the Central Valley due to its impact on groundwater quality and public health. The chapter methodically examines the implementation of conservation practices such as micro-irrigation technologies, irrigation nitrogen credits, winter cover crops, and high-frequency low-concentration fertigation strategies. Through rigorous modeling and field data analysis, the chapter assesses the potential of these practices to reduce nitrate leaching effectively while maintaining or enhancing crop yield and profitability.

The chapter findings suggest that targeted conservation practices can significantly reduce nitrate leaching, thereby contributing to the protection of groundwater resources and improving the sustainability of agricultural production in the Central Valley. The chapter underscores the importance of adopting a holistic approach to nutrient and water management, incorporating advanced irrigation technologies and sustainable fertilization practices. The chapter calls for increased awareness and adoption of these practices among farmers, supported by policy incentives and educational programs. Moreover, the chapter contributes to the ongoing discourse on sustainable nutrient management, offering a framework for balancing agricultural

productivity with environmental stewardship. Through a meticulous examination of conservation practices and their impacts on nitrate leaching, this chapter advances our collective understanding of sustainable agricultural practices, marking a significant contribution to the quest for more environmentally sustainable farming practices.

Chapter 5

Chapter 5 presents an evaluation of an integrated modeling approach, combining the APEX model with RT3D (Reactive Transport) and MODFLOW (Modular Finite-Difference Ground-Water Flow Model), to assess nitrogen leaching into groundwater at the field scale. This integrative model aims to provide a comprehensive understanding of how agricultural practices influence nitrogen dynamics and groundwater quality. The chapter methodically details the development and calibration of the integrated model, demonstrating its capability to simulate the complex interactions between agricultural land management, nitrogen use, and groundwater systems. The model's effectiveness in identifying risk areas for nitrogen leaching and proposing targeted groundwater protection strategies was applied in a field study located in Esparto. Results showed the potential of the model as a valuable tool for sustainable agricultural and environmental management.

The chapter concludes with the endorsement of the integrated APEX-RT3D-MODFLOW model as an effective field-scale tool for predicting and managing nitrogen leaching into groundwater. It emphasizes the model's significance in informing sustainable agricultural practices, groundwater protection plans, and policy development. By facilitating a detailed understanding of nitrogen transport processes and their impacts on groundwater quality, the model supports the implementation of precise and effective management strategies to mitigate nitrate pollution. The chapter calls for further research and model refinement to enhance its applicability across different agricultural systems and regions, underscoring the importance of

integrating scientific tools in the pursuit of agricultural sustainability and environmental protection.

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