CDFA-FREP Final Report-February 2019

A. Project Information

Project Title: A Data Driven Nitrate Leaching Hazard Index and BMP Assessment Tool
Grant Number: 14-0452-SA
Project leaders:
Anthony Toby O'Geen
Professor and Soil Resource Specialist in Cooperative Extension
Dept. of Land, Air and Water Resources, University of California, Davis
One Shields Avenue, Davis CA 95616-8627
Phone 530-752-2155; email: atogeen@ucdavis.edu

Jan Hopmans
Professor of Hydrology
Dept. of Land, Air and Water Resources, University of California, Davis
One Shields Avenue, Davis CA 95616-8627
Phone 530- 752 8473; email: jwhopmans@ucdavis.edu

Key Cooperators:
Thomas Harter
Professor and Specialist in Cooperative Extension
Dept. of Land, Air and Water Resources, University of California, Davis
One Shields Avenue, Davis CA 95616-8627

Efstathios Diamantopoulos
Project Scientist
Dept. of Land, Air and Water Resources, University of California, Davis
One Shields Avenue, Davis CA 95616-8627

B. Objectives

The specific objectives of this project are to:
1. Create a state-wide, updated digital database of soil survey information for modeling purposes.
2. Model nitrate leaching using HYDRUS for agricultural soils in California for different crop classes and irrigation types.
3. Develop an online interactive app in Google Maps that enables users to navigate and obtain nitrate leaching hazard ratings for any agricultural soil for major crops and irrigation scenarios.
4. Extend the science and educate the public by linking model outcomes with existing knowledge of best management practices in order to promote practices that limit nitrate loss via leaching.

C. Abstract

The extreme diversity in soils, crops and climate that comprises California agriculture makes it difficult to predict nitrate leaching. The goal of this project was to

develop a data-driven nitrate leaching hazard index for every agricultural soil in California. The index serves as a decision support tool to evaluate nitrate loss beyond the root zone in consideration of soil properties, crop characteristics, irrigation efficiency and climate. The approach links digital soil survey data to HYDRUS, a process-based hydrological model capable of predicting nitrate leaching over infinite scenarios of soil variability. The products of the modeling effort include a first of its kind regional analysis of nitrate leaching potential unique to all agricultural soils, 58 different crops within seven different climatic regions in California. The results were converted into an online interactive map tool that allows users to identify the risk associated with nitrate leaching and evaluate irrigation efficiencies for their soil-climate-crop combination. Nitrate hazard index values that exceed 10 are considered to be of concern for groundwater contamination. This project is positioned for real and immediate impact in light of CA's implementation of the Irrigated Lands Conditional Waiver Program (ILCW), the recent report to the legislature on the sustainability of CA's groundwater resource (Harter and Lund, 2012) and the implementation of the Sustainable Groundwater Management Act (SGMA). The project will directly benefit growers, county planners and watershed coalition groups by linking nitrate leaching hazard, with management strategies and practices and help support Groundwater Quality Assessment Reports linked to SGMA.

D. Introduction

California's agricultural regions have an incredible diversity of soils that encompass a range of properties possibly found in no other agricultural area of similar size in the United States. This soil diversity complicates our understanding of the fate of nitrogen (among other nutrients) in the environment. Spatially explicit information is needed to help growers make informed decisions about nutrient management practices. The Nitrate Groundwater Pollution Hazard Index (HI) http://ciwr.ucanr.edu/Tools/Nitrogen_Hazard_Index/ is a valuable tool used by growers and regulatory agencies to understand the potential for nitrate contamination of groundwater (Wu et al., 2005). The tool rates the relative hazard of nitrate loss as deep percolation for most soil series in agricultural regions of California. There are some shortcomings associated with the index: 1. The index ratings have potential bias as they are based on expert opinion; 2. Not all soils are rated; 3. The experts have passed away and/or moved on to other positions making updates challenging; 4. The index lacks transparency as to what soil conditions influence each rating; 5. The index requires that users know their soil series; 6. There is no mechanism to show ratings spatially in a GIS for watershed scale analysis and planning; and, 7. The index is not linked to management information to improve conditions in areas with undesirable ratings. In light of these limitations, we propose to create a new, data-driven soil nitrate hazard index to guide nitrogen management and deliver information about best management practices in CA.

The overall goal of this project was to simulate nitrate leaching for every agricultural soil in California and convert findings into an interactive geospatial decision support tool to evaluate the likelihood of nitrate loss beyond the soil profile. The tool was developed by linking digital soil survey data to HYDRUS 1-D, a process-based hydrological model capable of predicting nitrate leaching over infinite scenarios of soil variability. The model was run for all agricultural soils, for 58 different crops, three different irrigation efficiencies, across 7 different climatic zones in the State. The modeling results were compiled into an interactive, web-based decision support tool. The tool enables users to select their soil-crop-climate combination from a map-user interface to obtain a nitrate leaching hazard rating, which is also summarized across different irrigation efficiencies, and winter and summer leaching.

E. Work Description

1. *Create a state-wide updated digital database of soil survey information.*

A state-wide coverage of the Soil Survey Geographic Database (SSURGO) was downloaded for the project. The data was integrated into a POSTGIS relational database containing all map unit and soil component properties, the polygon geometries, and spatial locations. We discovered that old survey areas in SSURGO do not populate enough soil property data, and thus, for some locations and some soils we could not directly link this database with the HYDRUS model. The problem was associated with old soil surveys where SSURGO was generalized to fit into an old version of the USDA database. To address this shortcoming, point data was collected and imported from the National Cooperative Soil Survey (NCSS) laboratory. This dataset includes detailed lab characterization of soil properties for representative soil profiles. It serves as the framework from which soil survey was made. Three soil survey datasets were used to populate the HYDRUS model with the soil physical parameters necessary to provide nitrate travel times. The primary dataset consisted of all measured pedons from the National Soil Survey Center pedon database; for soils that were not in the pedon database we used SSURGO data if it represented a more recent soil survey area with fully populated horizon data; and, for the few remaining soils that were not adequately characterized in SSURGO or the pedon database we used the Official Series Description coupled with pedotransfer functions to derive the appropriate data for the model. We linked travel times for each soil series with the dominant component (soil type) of map units in SSURGO to create state-wide maps for all soils (Fig. 1).

Since many soil surveys were conducted over 30 years ago in CA's agricultural regions, the data needed to be updated to account for deep tillage practices. Recent expansion (~last 20 years) from annual crops (or other uses) to perennial tree crops and vines is associated with soil modification practices (deep ripping). This practice destroys layers that otherwise prevent root penetration and deep percolation. Thus, many soils in the SSURGO database are fundamentally different than they were at the time these landscapes were mapped. Our soil survey database was updated to account for this practice by documenting the alteration of all soils with cemented horizons and clay pans by deep tillage. The approach involved: 1. mapping all soils with hydrologically restrictive soil layers; 2. Overlaying this map with areas that have tree crops or vines; and, 3. Accounting for this mixing process by creating a "new" soil via the profile weighted average of soil physical characteristics excluding the limiting layer. The final product is a state-wide map of modified soils and an associated revision of soil properties after modification. To reflect the mixing of soil horizons, the depth weighted arithmetic mean of saturated hydraulic conductivity (K_{sat}) and texture for the entire soil profile was used to reflect the modified soil profile (Fig. 1). However to account for future changes we implemented a function that alters any soil with a restrictive horizon, a choice that the tool user can define. The final database consists of 21136 soil horizons, including cement layers, which correspond to 5685 different soil profiles. Figure 2 shows the percent of sand, silt and clay for all the 21136 soil horizons.

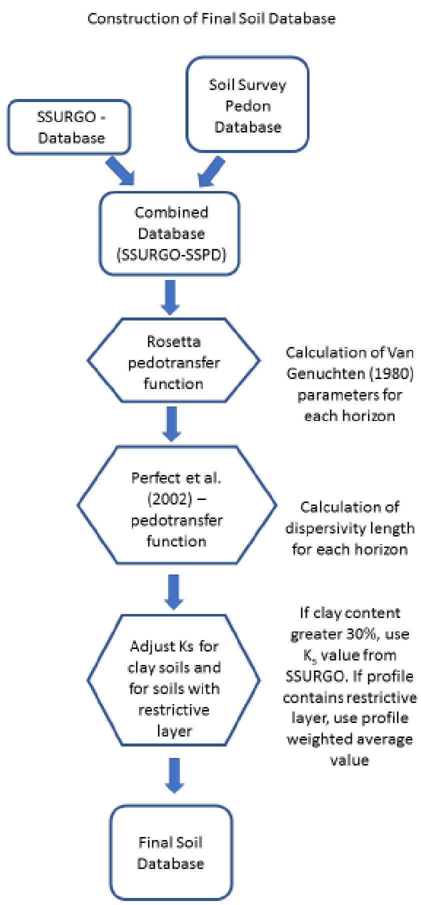

Figure 1. Summary of soil data processing for HYDRUS-1D modeling.

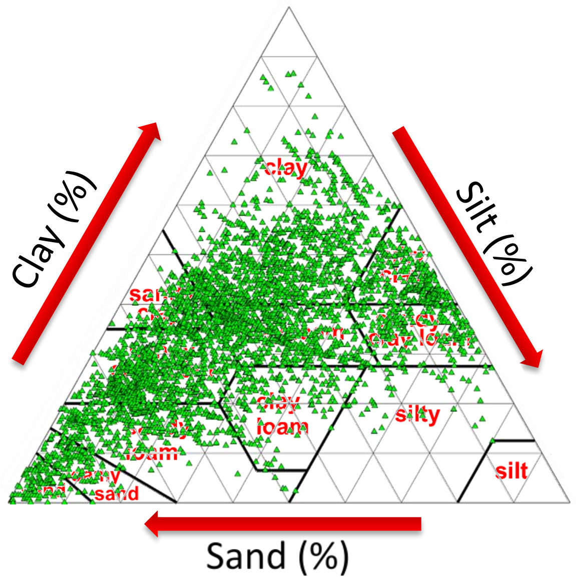

Figure 2. Percent of sand, silt and clay for all the 21136 soil horizons

2. *Parameterize the HYDRUS model with the database of soils, climate, crop characteristics, fertilization practices, and irrigation schemes.*
   In addition to the soil database, a crop database was prepared for major agricultural crops in CA. The database contains all the required information for Hydrus parameterization in terms of root depth, water uptake, crop coefficient (Kc) function and irrigation and fertilization rate (in the year) for each crop. The crop list can be seen in Table 1. The crop database was constructed based on crop list described in (Viers et al., 2012; Harter et al., 2017). Moreover, Viers et al., (2012) provide mean values of nitrogen application rates and nitrogen harvest in Kg/ha/y. Finally, in order to incorporate the effect of climate in our study, we defined 7 climate zones (Fig.3), which are representative of the climate variability along the state of CA for the period of 1/1/1995 until 12/31/2015.

Table 1. *Crop list for the parameterization of Hydrus-1D (*Viers et al., (2012).

Crop	Applied N	Crop	Applied N
	Kg/ha		Kg/ha
Pomegranate	157	Fig	86
Grapefruit	128	Almond	246
Lemon	138	Walnut	196
Orange	146	Pistachio	177
Avocado	125	Field crops	182
Olive	88	Cotton	194
Kiwi	112	Safflower	115
Persimmon	145	Sugar beet	175
Apple	67	Corn	239
Apricots	106	Sorghum	157
Cherry	76	Sudan	246
Peach/nectarine	116	Beans	102
Pear	158	Sunflower	90
Plum	115	Hay/straw	198
Prune	145	Barley	63
Truck crops	215	Wheat	231
Artichoke	193	Oats	69
Asparagus	158	Pasture	0
Green beans	138	Alfalfa	13
Carrot	242	Rice	146
Celery	290	Berries	231
Lettuce	216	Strawberries	215
Melons/squash	165	Peppers	316
Garlic/onions	236	Broccoli	213
Peas	101	Cabbage	195
Potato	202	Cauliflower	267
Sweet potato	168	Brussel sprouts	138
Spinach	157	Grapes	39
Tomato	204		

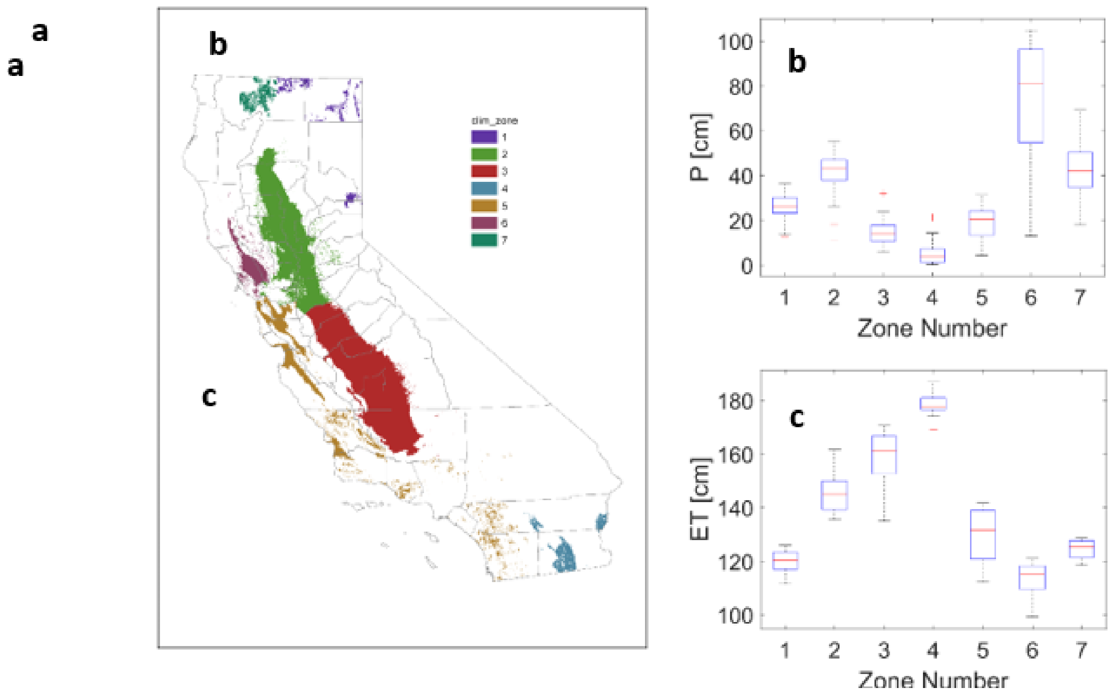

Figure 3. Definition of 7 different climate zones in C; 1- Northeast, 2-Sacramento Valley, 3-San Joaquin Valley, 4-Imperial Valley, 5-Southe and Central Coast, 6-North Coast, 7-North Intermountain (a). Boxplot of yearly precipitation (b) and reference evapotranspiration (c) for a 16 year period (from 1/1/1995 until 12/31/2015).

One dimensional water flow in soils is described by the Richards equation:

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left[K(h)\left(\frac{\partial h}{\partial z} + 1\right)\right] - S \quad \text{(e.1)}$$

where θ [L^3 L^{-3}] is the volumetric water content, t [T] is time, z [L] is the vertical spatial coordinate, positive upward, *h* [L] is the pressure head, *K*(h) [L^2T^{-1}] is the saturated/unsaturated hydraulic conductivity as a function of *h* and *S* is the sink term, representing root water uptake [L^3 $L^{-3}T^{-1}$].

For the numerical solution of equation (e.1), the water retention curve $\theta(h)$ [L^3 L^{-3}] and the hydraulic conductivity curve are required. The two functions are described by the van Genuchten-Mualem (van Genuchten, 1980) model:

$$\theta(h) = \begin{cases} \theta_r + (\theta_s - \theta_r) \cdot (1 + |\alpha h|^n)^{-m} & h < 0 \\ \theta_s & h \geq 0 \end{cases}$$
(e.2)

$$S_e = \frac{\theta(h) - \theta_r}{\theta_s - \theta_r}$$
(e.3)

$$K(S_e) = K_s \cdot {S_e}^l \cdot \left[1 - \left(1 - {S_e}^{1/m}\right)^m\right]^2$$
(e.4)

where θ_s and θ_r $[\mathrm{L^3 L^{-3}}]$ are the saturated and residual water contents, respectively, α $[\mathrm{L^{-1}}]$, n $[-]$, m $[-]$, and l $[-]$ are shape parameters, $m = 1 - \frac{1}{n}, n > 1$, and S_e [-] is the effective saturation.

Solute transport for a conservative tracer is described using standard advection-dispersion equation of the form:

$$\frac{\partial \theta c}{\partial t} = \frac{\partial}{\partial z}\left(\theta D \frac{\partial c}{\partial z}\right) - \frac{\partial q c}{\partial z} - S \cdot c \qquad \text{(e.5)}$$

where c [M L^{-3}] is the concentration of solute in the liquid phase, *D* is the dispersion coefficient (L^2 T^{-1}), *q* is the volumetric water flux density (L T^{-1}) evaluated with the flow equation and $S \cdot c$ [M L^{-3} T^{-1}] is the root nutrient uptake for the case of passive uptake. By focusing on hydrodynamic dispersion, *D* is defined as

$$D = \lambda \frac{q}{\theta} \qquad \text{(e.6)}$$

where λ is the dispersivity (cm).

For the numerical solution of equations (e.1) and (e.5), we modified the Hydrus 1D software (Simunek et al., 2016) to account for irrigation based on the water status in the middle of the root zone for a specific period every year. If the pressure head at a specific point (middle of the root zone) in the soil profile is less than a predefined critical pressure head, Hydrus applies a predefined amount of irrigation for a predefined duration of time (Fig. 4). We conducted simulations for 58 different land types (crops), 3880 different soil profiles and 3 irrigation efficiencies (60, 75 and 90%) and seven different climatic zones. The crop names and their area distribution are shown in Table 1. Root water uptake for the six different crops was simulated by assuming a macroscopic root water uptake approach (Feddes et al., 2018). The parameters for equations e.2 and e.4 were estimated using Rosetta pedotransfer function (Schaap et al. 2001). For each soil horizon, dispersivity values (e.6) were calculated by using the pedotransfer function of Perfect et al. (2002).

For an initial condition of equations (e.1) and (e.5), we assumed a uniform distribution of the pressure head and a solute free profile, respectively. At the calculation of the upper boundary condition we used potential values of reference (grass) evapotranspiration (ET_0) and precipitation (P) from the 7 different climate stations (California Irrigation Management Information System (CIMIS)). For each crop, ET_0 values were converted to potential crop evapotranspiration (ET_c) by using the single crop coefficient method (Allen et al., 1998; Fig. 4). Afterwards, these values were used as input daily series in Hydrus 1D. Figure 4, shows ETc, P and irrigation events for a one-year period for a specific simulation. For all crop-soil combinations, we assume three fertilization events per year with the total amount of fertilizer specific to each crop.

An approximate irrigation depth was based on the rooting depth of each crop and the soil type to identify an optimal irrigation amount (Table 2). The net irrigation depth was a based on soil type (table 2) and root depth. This total amount of water applied was scaled by dividing by the irrigation efficiency (60%, 75% or 90%). A midpoint in the root zone was selected to trigger the timing of irrigation when a critical pressure head threshold was exceeded (became more negative) (Table 2).

Table 2. Irrigation considerations

Soil type	Irrigation amount (mm)			Duration of water application	Critical pressure head
	Shallow	Medium	Deep	Days	cm
Sandy	15	30	40	0.5	-200
Loamy	20	40	60	0.75	-600
Clayey	30	50	70	1.0	-1000

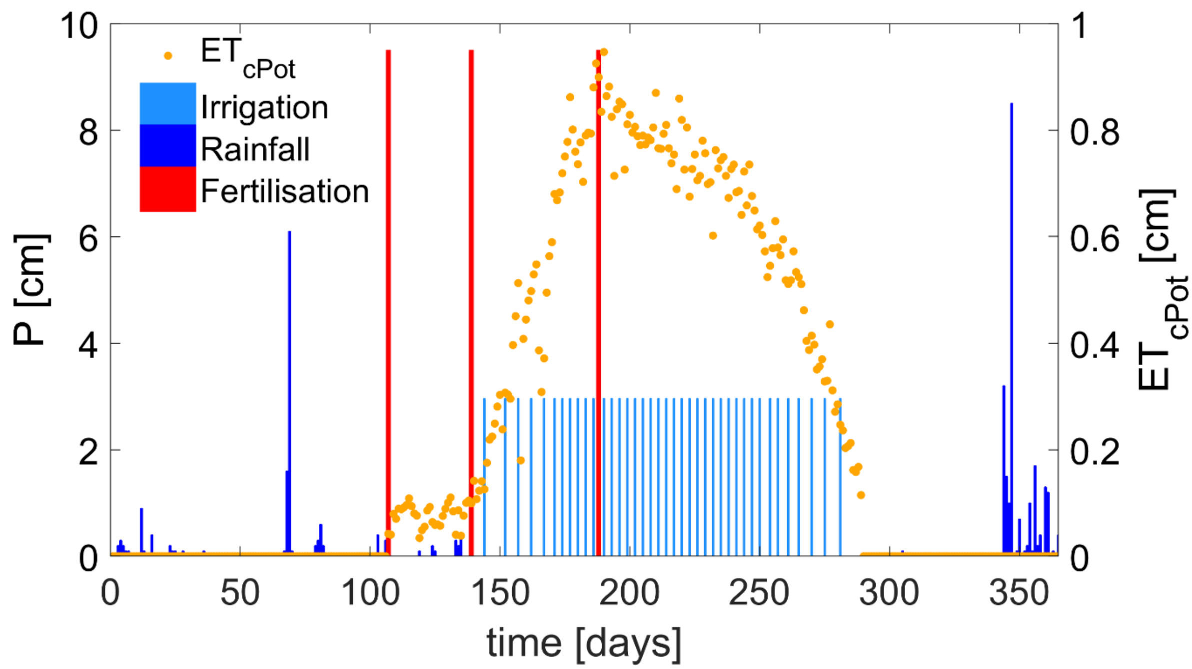

Figure 4. Illustration of daily values of potential crop evapotranspiration in cotton (orange points) used for the description of the upper boundary condition (for a sandy soil). The dark blue bars represent rainfall events and the light blue bars irrigation events. The red bar defines fertilization application of amount equal to 65 Kg/ha (195 Kg/ha/year).

3. *Evaluate the potential to aggregate similar soils to model nitrate leaching in HYDRUS.*

   The potential to aggregate similar soils to model nitrate leaching in Hydrus was evaluated using the following approach. We manipulated the MATLAB script in order to automatically run Hydrus and read the output files for all the simulation scenarios. We ran HYDRUS for a simple scenario. The simulation time was 1 year and we assumed constant rainfall of 1 cm/day and a solute pulse application of 1 Mu/day (Mu: mass unit) for 10 days. Afterwards, we calculated solute travel times from the soil surface to 1.5 m, defined as the time needed for the 95% of the total applied mass to reach the bottom of the profile. The results show that there is the potential to aggregate similar soils for modeling nitrate leaching and we can identify these groups. However, we decided to follow a more computationally intensive approach where the unique properties of all soils are modeled since it is not clear if the groups defined from the simple calculations will hold for more complicated scenarios of irrigation and water/nutrient uptake.

4. *Run the HYDRUS model for each soil (or groups of soils) generating state-wide maps of nitrate leaching across major crop, fertilization and irrigation scenarios.*

   A script was written in MATLAB, which combines information from soil, crop and climate databases and automatically generates required input files for Hydrus (Fig. 5). Moreover, based on meteorological conditions, crop type and the soil profile, the script generates an irrigation and fertilization schedule. The script incorporates different irrigation practices which include a 60, 70 and 90 % irrigation efficiency to simulate flood, sprinkler and drip/pressurized irrigation, respectively. This enables the index to evaluate different BMP's.

   The total number of required simulations is given by the combination of soil profiles (5685), climate zones (7) and different crops (58). This number is over 2.3 million. In order to reduce the number of total simulations and since not all the soil profiles belong to all 7 climate zones, we combined the soil profiles and the climate zones and managed to reduce the number of different soil-climate combinations to 3546. This allowed us to reduce the number of total simulations (without the inclusion of different irrigation efficiencies) to around 200 thousand (Fig. 5).

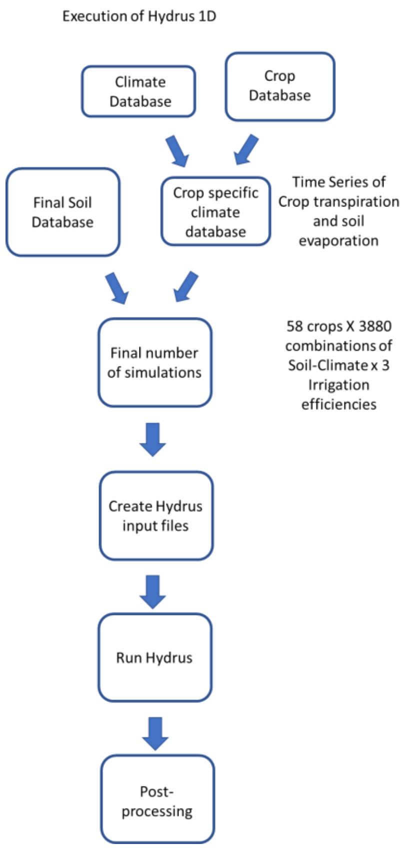

Figure 5. Schematic of HYDRUS 1-D modeling

5. *Develop a rating mechanism that classifies estimates of nitrate leaching loads into a Nitrate Leaching Hazard Index for soils.*
   Nitrate Leaching Hazard index (NHI) values were calculated for all combinations of soil, crop and climate. The NHI was determined with the following equation:

   NHI = (Nitrate mass leached / largest amount Nitrogen applied per year) x 100 (e.7)

   The denominator for this equation was 316 Kg N/Ha/year, for peppers (chili, bell). All nitrate mass leached values are median values based on the 13-year model run

   The scoring system ranges from 0 to 100. Values closer to 100 indicate high risk. Values closer to 0 indicate relatively low risk. Most NHI values did not exceed 50 (Figure 6) because most crops had an applied N rate that was much lower than peppers (e.7). The NHI is calculated from median Nitrate mass leached over the 13-year model timeframe to obtain yearly, summer, winter and monthly index values. We chose to add winter and summer NHI time frames in order to evaluate the influence of climate on irrigation water balance and on winter leaching. This understanding will lead to better management decisions. For example locations with relatively higher winter NHI may want to consider cover crops to scavenge residual N. Locations with relatively high summer NHI may want to consider alternative fertilization strategies or irrigation systems.

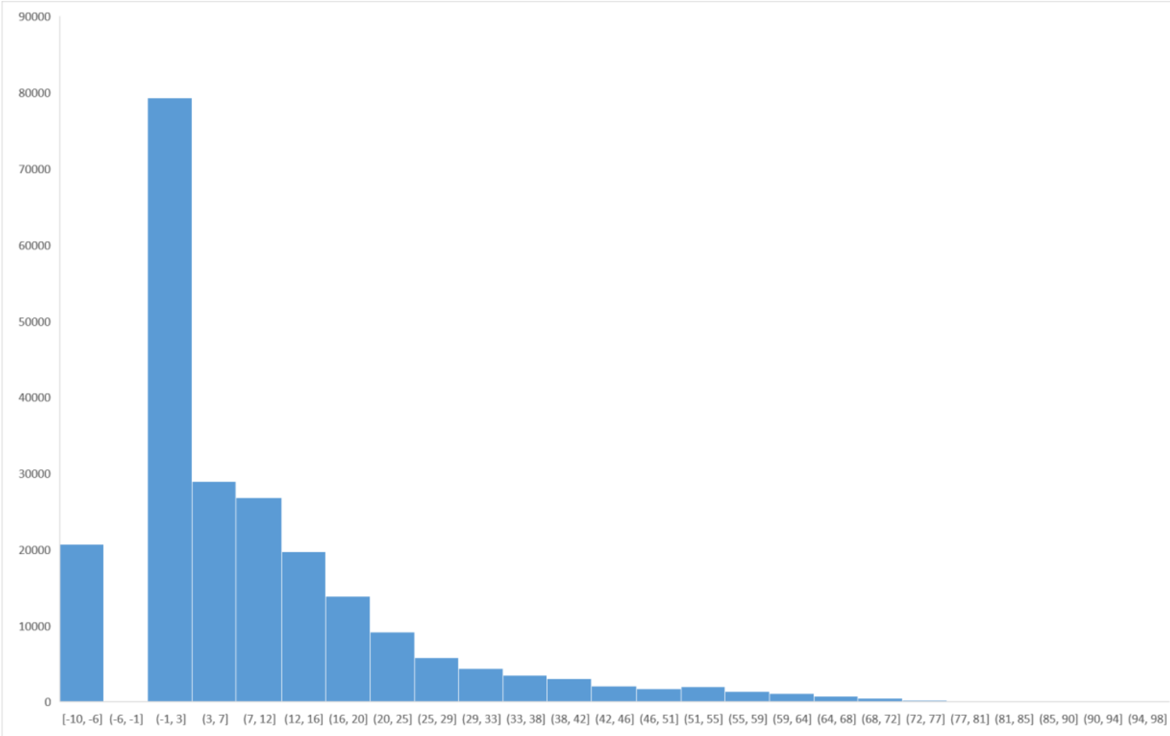

Figure 6. Histogram of yearly NHI using the 75% irrigation efficiency, all soils all crops and all climatic zones. Negative values represent failed simulations.

6. *Develop an online, interactive app that delivers nitrate leaching hazard ratings with relevant BMPs via Google Maps.*
   Currently a beta version of an applications has been completed. The App functions as an interactive map (Fig. 7). The user chooses a crop, an irrigation efficiency and whether or not to include restrictive horizons. The user also has the option to depict NHI calculated year-round, summer or winter. The map automatically displays NHI for all agricultural soils across the different climate regions based on the user selection for any single crop chosen. For now the map does not reflect reality because it only displays NHI for one crop at a time across the state (Fig. 7).

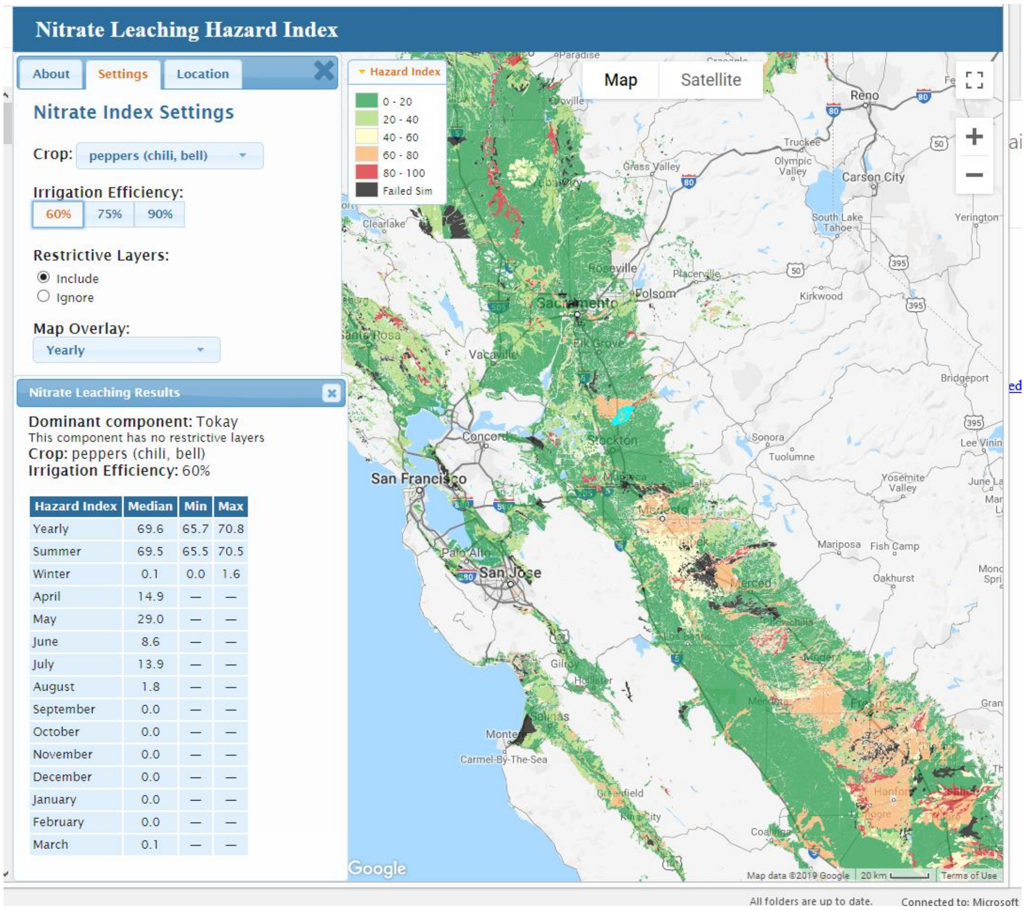

Fig. 7. The official App operates in Google maps to retrieve a summary of NHI. Users can select one of 58 different crops to view output. Other selections include: to ignore or include restrictive layers, Irrigation efficiency.

A future version of the App will be an interactive map that allows users to navigate to a location and query a NHI relative to the soil at that location, the crop that the user chooses, a selected irrigation efficiency and the time of interest.

7. *Conduct in-person and online workshops to obtain preliminary feedback on the tool and to demonstrate the final product.*

Preliminary results were presented at two meetings the CDFA-FREP annual meeting and the Mid Valley Nut Show. Both meetings were held in Modesto, CA and included growers, agency staff, UCCE academics and consultants. After these events we realized that delivering modeled output of nitrate leaching amounts could be misconstrued and misused. We also discovered that the model was irrigating too precisely resulting in no difference among soils. We refocused all our effort into reparametrizing the model to more closely reflect on-the-ground conditions. We also met with CDFA staff to discuss the potential controversy of depicting model output values to the public. We were concerned that these values could be misused. With

CDFA input we decided to construct an app that depicts NHI and not specific modeling output such as mass leached, concentration leached etc.

F. Data/Results

Modeling NHI values produced trends that that strongly reflect the natural variation in soil. A comparison of NHI over different particle size classes shows NHI decreases (risk decreases) as clay content increases (Fig. 8a-c). Coarse textured soils had the highest NHI values indicating greatest risk. The statewide median was around 35 for coarse textured soils for each irrigation efficiency. Median NHI values for loamy textured soils were around 10 for each irrigation efficiency indicating moderate risk. Median NHI values for fine textured soils were all less than 5 indicating low risk.

It is difficult to observe the effect of irrigation efficiency when looking at all soils across all climates and crops. Generally, increasing irrigation efficiency decreased risk of nitrate leaching but the magnitude of this effect was dependent on climate and soil type (Table 2). The largest differences in NHI when comparing 60% and 90% irrigation efficiency were associated with sandy soils, which includes the particle size class Coarse loamy. This average difference between irrigation efficiencies was 16.7 $\pm$ 8.5 (mean +standard deviation) for coarse textured soils and 5.0 $\pm$ 5.6 for loamy textured soils.

Table 2. Comparison of NHI values across different irrigation efficiencies.

		Irrigation Efficiency			Difference
Soil	Particle size Class	60%	75%	90%	60-90%
			NHI		
Tokay	Coarse loamy	69.5	62.5	56.2	13.3
Hanford	Coarse loamy	73.8	67.0	63.0	10.8
Whitney	Fine loamy	21.9	8.4	18.8	3.1
Honcut	Coarse loamy	68.5	59.8	53.4	15.1
Oakdale	Coarse loamy	63.0	52.6	47.7	15.3
Kingdon	Coarse loamy	68.1	58	47.8	20.3
Kimberlina	Coarse loamy	69.6	62.6	59.1	10.5
Indio	Coarse silty	9.5	7.5	3.7	5.8
Atwater	Coarse loamy	63.1	52.4	42.4	20.7
Tujunga	Sandy	43.9	22.8	4.2	39.7
Greenfield	Coarse loamy	72.4	66.5	61.2	11.2
Arroyo Seco	Coarse loamy	70.6	65.2	60.2	10.4
Lockwood	Fine loamy	6.2	6.1	6.2	0
Docas	Fine silty	29.0	20.2	15.6	13.4
Arbuckle	Fine loamy	11.5	6.8	0.8	10.7
Los Gatos	Fine loamy	2.0	1.8	0.8	1.2
Maymen	Loamy	3.0	2.3	1.6	1.4

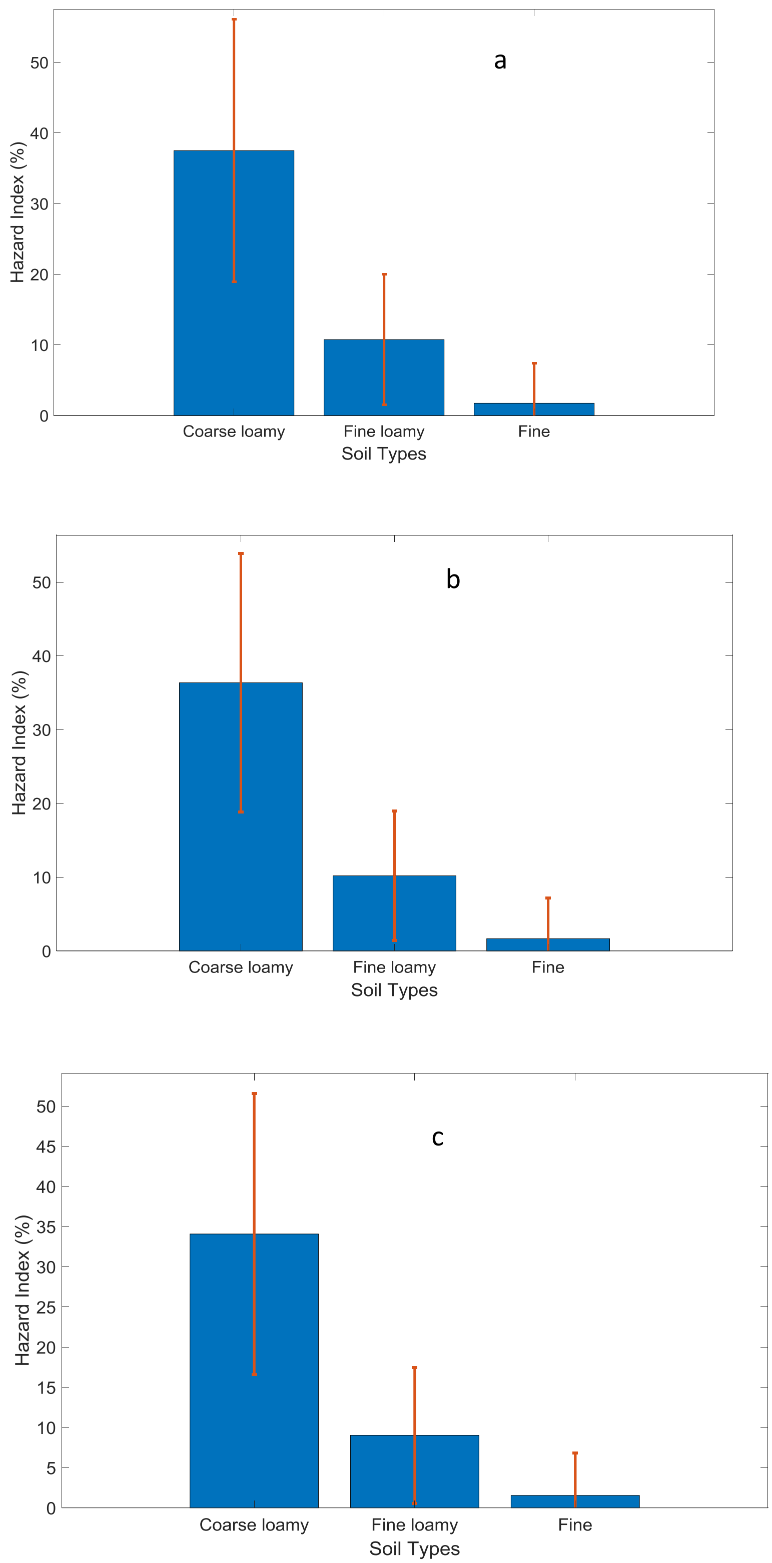

Figure 8. Comparison of NHI across different particle size classes in (a) 60% irrigation efficiency; (b) 75% irrigation efficiency and (c) 90% irrigation efficiency.

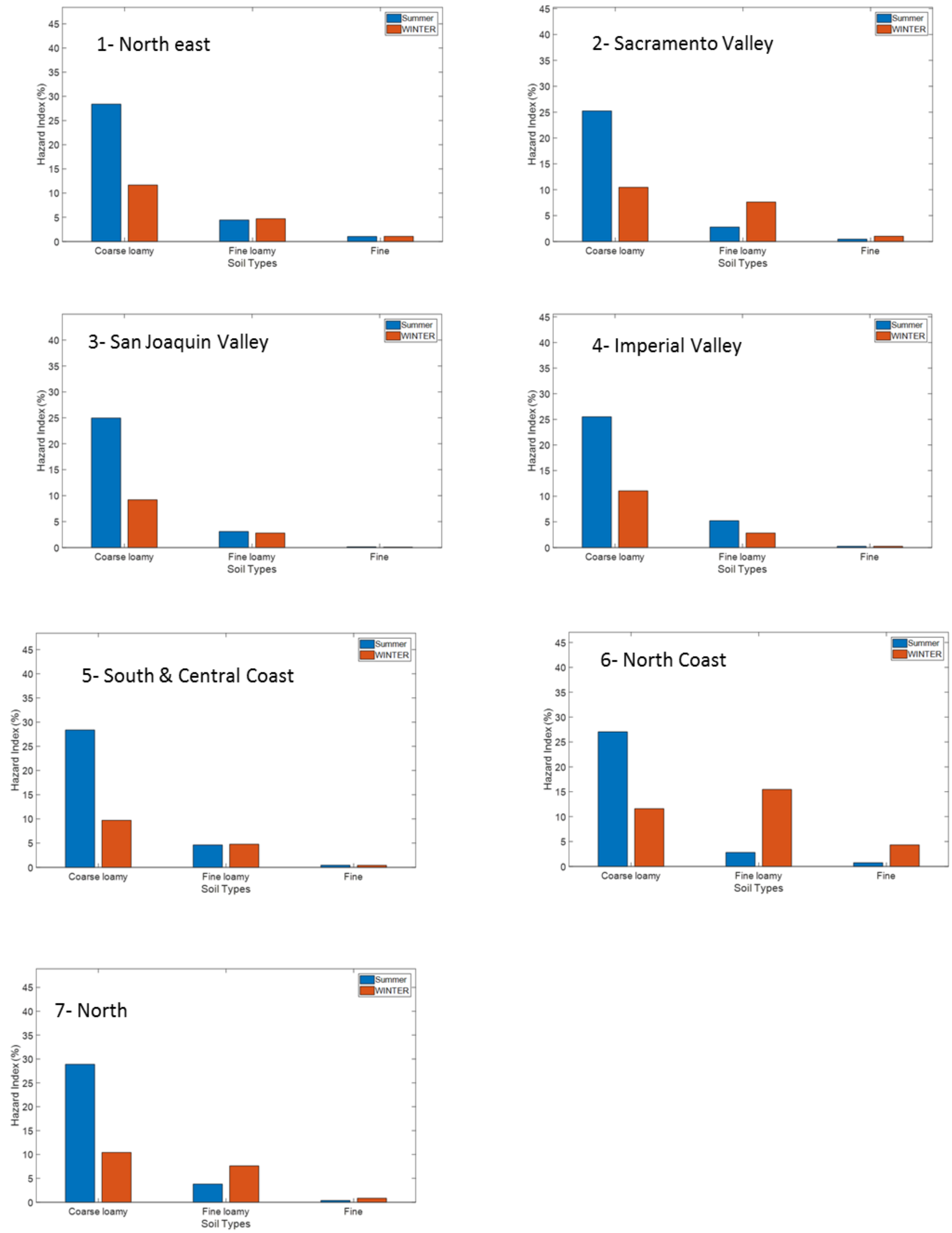

Figure 9. Comparison of median NHI values among the 7 climatic zones. NHI values were aggregated by texture class (coarse loamy, fine loamy and fine).

A comparison of median NHI over the seven climatic zones for all crops and considering three general groupings of soil particle size (coarse loamy, fine loamy and fine showed a modest climatic effect (Fig. 9). For coarse textured soils, median NHI was fairly constant, around 25 in summer and 10 in winter. The main effect of climate zone on NHI appears to be expressed in winter time for the Fine loamy soils, where wet climates such as the north coast and Sacramento Valley had winter NHI values that exceeded summer (Fig. 9). Relationships between soils among climate zones are less clear when grouping all crops. A comparison of select crops in the North Coast and Imperial Valley showed a fairly significant climatic effect where the drier climate of Imperial Valley showed lower NHI compared to wetter North Coast (Fig. 10).

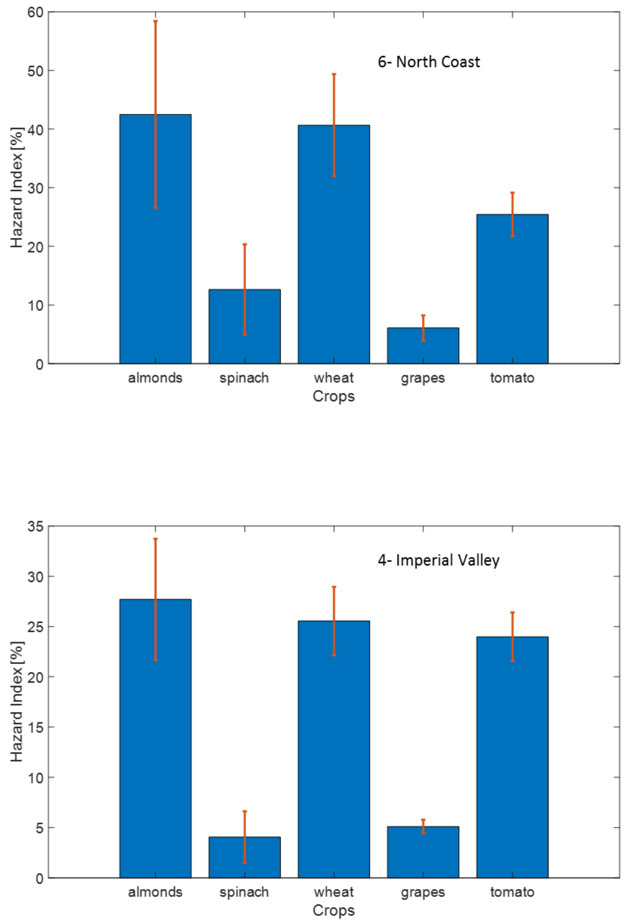

Figure 10. Comparison of crops between two very different climatic zones, the North Coast which is moist and the Imperial valley which is dry. Note differences in scale among the two graphs.

Along with soil type, crop choice had a large effect on NHI values (Fig. 10). Differences in median NHI are primarily a result of nitrogen fertilizer rate and rooting depth. A comparison of select crops (Fig. 10) shows crops with lower N demand such as grapes and to some extent spinach had lower NHI compared to crops with higher N demand such as almonds wheat and tomato. Low NHI associated with spinach suggests that more work is needed to reflect the irrigation needs of leafy green vegetables in the model. It may be that our model underrepresents the irrigation frequency in these crops, and thus, mischaracterizes NHI values lower than they should be.

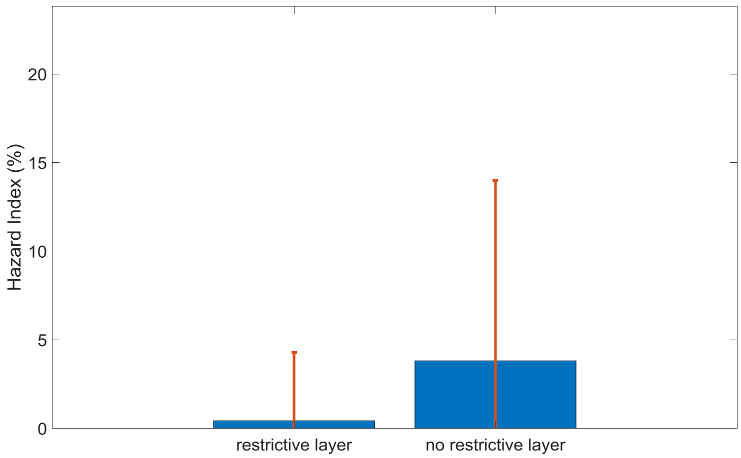

Figure 11. Comparison of the effect of eliminating the restrictive horizon (by deep tillage) on NHI. Note that there is considerable variability in output when the restrictive layer is removed which reflects the range in soil texture of these soils.

Soil survey often does not document activities such as deep tillage that have significantly altered the hydrology of soil profiles. This is because many soil surveys were published prior to significant tree crop expansion in CA. Deep tillage is a standard practice when planting tree crops that improves root penetration and water percolation. We included functionality that accounts for the mixing effects of deep tillage in the model. Figure 11 compares median NHI values in soils with and without restrictive horizons. NHI was low for both conditions, but near zero when the restrictive layer was present. The model does not account for lateral subsurface transport of nitrate which is likely to occur in these soils.

G. Discussion and Conclusions

The modeled NHI revealed a potential to accurately describe the effects of soil, crop, climate and irrigation efficiency on nitrate leaching hazard. Our statewide results suggest that the two major influences on NHI are soil type and crop type. The primary driver of crop type being the amount of nitrogen applied. Climate also had an important effect on NHI values, but the magnitude of that effect can only be seen when comparing specific crops within a climatic zone (Fig. 10). Similarly, when comparing irrigation efficiency across specific soil types big differences were apparent, particularly for coarse textured soils. Risk of leaching was higher in summer compared to winter for coarse textured soils. For finer textured soils there was no clear difference in summer vs winter NHI values, or in some instances (climatic zones) winter NHI was higher (Fig. 9).

It is difficult if not impossible to validate a statewide model such as this. We used estimates of N in crop harvests as a way to evaluate the model (Fig. 12). Applied nitrogen rates were taken from Viers and others, (2012). In order to calculate N yield, Viers et al., (2012) combined crop production data with a database of crop N and moisture content. They used a four step process to convert the production data listed by crop to harvested N.

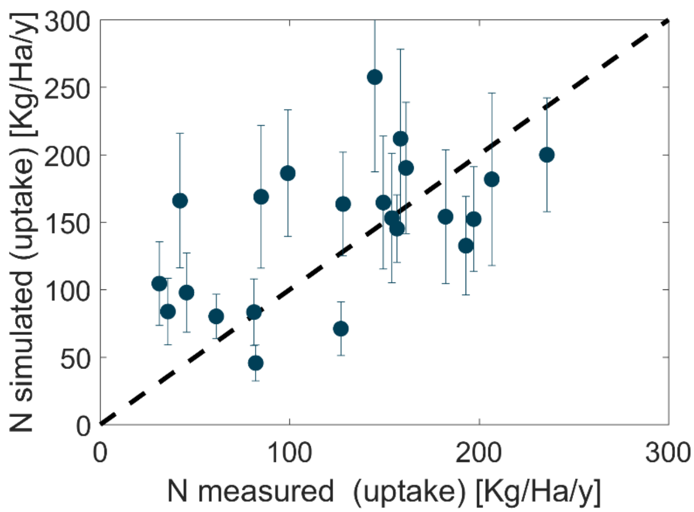

Figure 12. Calculated N harvest (N in yield) in Kg/Ha/y (Viers et al., 2012) vs simulated N uptake by the plant roots in Hydrus for the 58 crops using the 75% irrigation efficiency. Error bars depict the variability associated with soil and climate in the model.

Points located above the one-to-one line indicate an overestimation of nitrogen uptake, thus an underestimation of leaching (Fig. 12). Points located below the on-to-one line identify an over estimation of uptake, and thus, underestimate nitrate leaching. Discrepancies may be a result of N being allocated to other parts of the plant besides the harvest such as leaves and wood. However, discrepancies may also be due to the assumption of passive nitrate uptake in the Hydrus model, which assumes that the root system can take up all available N in the root zone and doesn't reduce its uptake when pore water N is high.

We also compared our NHI values to Nitrate Groundwater Pollution Hazard Index http://ciwr.ucanr.edu/Tools/Nitrogen_Hazard_Index/ (Fig. 13). Overall low risk soils (categories 1 and 2 in fig. 13) corresponded well. Significant discrepancies were evident among moderate and high risk soils (categories 3-5, fig. 13). These discrepancies were expected because the comparison was made on soil ratings from Nitrate Groundwater Pollution Hazard Index that did not account for crop type or climate, which was considered in the NHI rating. There were also some anomalies in our model for some soils that need to be corrected. Figure 13 shows there is no clear trend in NHI in terms of over- or under- predicting risk of nitrate leaching in comparison with the Nitrate Groundwater Pollution Hazard Index for higher risk soils

(3-5). There are also clear discrepancies associated with the Nitrate Groundwater Pollution Hazard Index that make this comparison difficult to interpret.

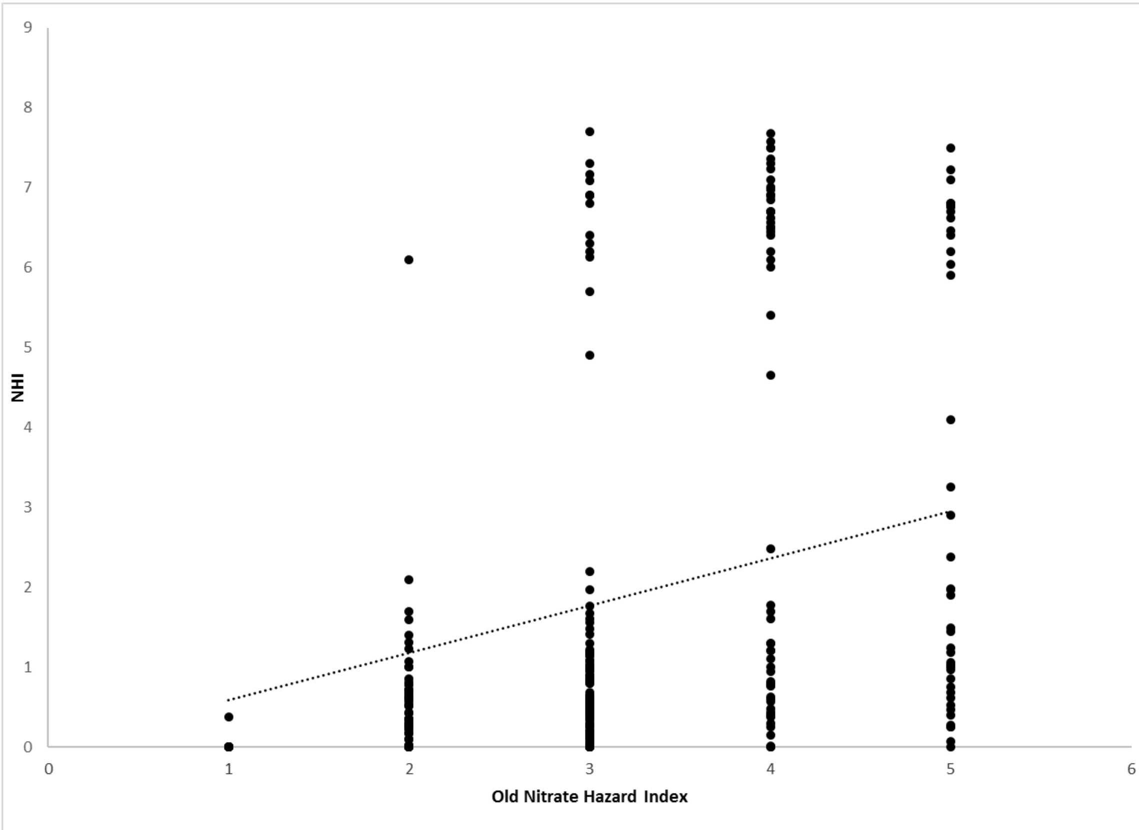

Figure 13. Comparison of Nitrate Groundwater Pollution Hazard Index with modeled NHI. NHI values were normalized by dividing by 10.

Limitations to this approach exist. First, a high degree of uncertainty exists surrounding how much growers irrigate and for each crop. For example it is likely that our model under estimates irrigation frequency and amount in leafy green crops. The model does not simulate actual irrigation methods and these methods give rise to different outcomes e.g. flood irrigation vs sprinkler or drip. The tool does not currently include the flexibility to change when and how fertilizer is applied by crop and the tool does not assume crop rotations or cover crops. The amount of organic nitrogen in soils is not accounted for but we assume that this balances out with denitrification. Similarly organic fertilizers are not considered in this model. Finally, the model assumes passive uptake by crops which makes the assumption that N uptake remains constant and high when N concentration is high which may not represent real conditions.

It is challenging to identify the level of risk associated with NHI values. The computation of NHI is relative to the crop with the highest amount of N applied per year. This amount of N and distribution of crop is not necessarily representative of the major crops in California. Harter et al., 2012 identified 35 kg N/ha/yr as a benchmark leaching value delimitating good vs concerning management. If we apply this benchmark to the calculation of our NHI it shows that any NHI that exceeds a value of 10 would have significant potential for groundwater contamination.

H. Project Impacts

This tool will advance the environmentally safe and sound use of nitrogen fertilizers by helping farmers tailor their nitrogen application to the specific characteristics of soil, climate and crop. This is the first attempt to model nitrate leaching statewide. While we were able to accomplish this huge undertaking, more work is needed to evaluate the results, compare modeling outcomes across soil types, crops and climates. It is impossible to evaluate the impacts of this project at this time. We anticipate growers will find this to be a useful tool once the modeling has been thoroughly evaluated, and necessary adjustments are made.

I. Outreach Activities Summary

Results of this study were presented at the UC-ANR 2015 Joint Strategic Initiatives Conference http://ucanr.edu/sites/2015jointsiconference/ on October 6th 2015 entitled: *Informing Land-Use Planning with Interactive Soil Survey Apps*. The audience consisted mainly of UCCE advisors and specialists (45 attending), however, some industry leaders and stakeholders were also attending. The intent was to inform potential collaborators and introduce the idea. Given that a majority of the UCCE advisors attended this meeting, it was an impactful event. The talk was accompanied by a poster to attract interest from those who were in joint sessions.

Results of the project were presented in poster format at the annual FREP Conference in Modesto, California (October 26-27, 2016) and in the form of Oral Presentation at the American Geophysical Union Fall Meeting in San Francisco, California (December 12-16,2016).

During this year the study results were presented at two stakeholder meetings, CDFA-FREP Annual Conference in 2017 and the Mid Valley Nut Show. Both meetings were held in Modesto. Members in the audience included growers, UCCE academics, consultants and agency staff. While the information was generally well received, concerns were voiced regarding the potential for this tool to be misused as a regulatory stick rather than a decision support tool.

A brief introduction to the project was also presented on October 21st 2015 at UC Davis-New Zealand joint workshop entitled: "*Repackaging soil survey into interactive decision support tools for agriculture and natural resource management*". Approximately 37 faculty and UCCE advisors were in the audience.

J. Factsheet/Database Template

Project Title: A Data Driven Nitrate Leaching Hazard Index and BMP Assessment Tool
Grant Number: 14-0452-SA

Project leaders: Anthony Toby O'Geen, Efstathios Diamantopoulos, Thomas Harter and Jan Hopmans; Dept. of Land, Air and Water Resources, University of California, Davis
Start Year/End Year: 2016/2019
Location: Statewide
Counties: All agricultural counties
Highlights:

1. This is the first process-based modeling effort to predict nitrate leaching from all agricultural soils and major crops in California.
2. This tool will advance the use of fertilizers helping farmers tailor N applications to specific characteristics of soil, climate and crop.
3. Modeling revealed sandy soils and crops with high N fertilizer application rates are of highest risk for nitrate leaching.
4. Coarse textured soils had higher summer leaching risk compared to winter time.

Introduction:

The overall goal of this project was to simulate nitrate leaching for every agricultural soil in California and convert findings into an interactive geospatial decision support tool to evaluate the likelihood of nitrate loss beyond the soil profile. The tool was developed by linking digital soil survey data to HYDRUS 1-D, a process-based hydrological model capable of predicting nitrate leaching over infinite scenarios of soil variability. The model was run for all agricultural soils, for 58 different crops, three different irrigation efficiencies, across 7 different climatic zones in the state. The modeling results were compiled into an interactive, web-based decision support tool. The tool enables uses to select their soil-crop-climate combination from a map-user interface to obtain a nitrate leaching hazard rating, which is also summarized across different irrigation efficiencies, fertilizer timing and winter and summer leaching.

We created a modified soils database combining SSURGO data with measured soil properties from the Soil Survey Pedon database in order to obtain the best soils input data for every soil type (totaling 5685) in agricultural areas of California. A crop database was prepared for 58 major agricultural crops in CA. The database contains all the required information for Hydrus parameterization in terms of root depth, water uptake, and crop coefficient (Kc) for irrigation of each crop. Finally, in order to incorporate the effect of climate in our study, we defined seven climate zones, which are representative of the climatic variability in the state.

We conducted Hydrus simulations for 58 crops and the thousands of soil-climate combinations. The simulation period was 21 years (1/1/1995 to 12/31/2015). Three irrigation schemes were evaluated based on irrigation efficiencies of 60%, 75% and 90% simulating surface application, sprinkler, and drip respectively.

Model output was integrated into an online interactive decision support tool that depicts nitrate leaching hazard index (NHI). The tool is essentially an interactive map that operates in Google Maps. It allows users to select a location, choose a crop, and returns NHI based on crop-climate-soil combination relative to the scenarios of irrigation. NHI values that exceed 10 are considered to be of potential concern for groundwater contamination.

Modeling NHI values produced trends that that strongly reflect the natural variation in soil. A comparison of NHI over different particle size classes shows NHI decreases (risk decreases) as clay content increases. Coarse textured soils had the highest NHI values indicating greatest risk. The statewide median was around 35 for each irrigation efficiency. Median NHI values for loamy textured soils were around 10 for each irrigation efficiency indicating moderate risk. Median NHI values for fine textured soils were all less than 5 indicating low risk.

Along with soil type, crop choice had a large effect on NHI values. Differences in median NHI are primarily a result of nitrogen fertilizer rate and to a lesser extent rooting depth. A comparison of select crops relative to extreme differences in climate zone (North Coast vas Imperial Valley) shows that median annual NHI is higher in the North Coast for each crop. The dry conditions of the Imperial Valley resulted in less deep percolation, and thus, lower NHI values.

The modeled NHI revealed a potential to accurately describe the effects of soil, crop, climate and irrigation efficiency on nitrate leaching hazard. Our statewide results suggest that the two major influences on NHI are soil type and crop type. The primary driver of crop type being the amount of nitrogen applied. Climate also had an important effect on NHI values but the magnitude of that effect can only be seen when comparing specific crops across climatic zones. Similarly, when comparing irrigation efficiency across specific soil types big differences were apparent, particularly for coarse textured soils. Risk of leaching was higher in summer compared to winter for coarse textured soils. For finer textured soils there was no clear difference in summer vs winter NHI values, or in some instances winter NHI was higher.

References:

Allen R G, Pereira L S, Raes D, and Smith M 1998 *Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements* (Rome: Food and Agriculture Organization).

Feddes, R.A., E. Bresler, and S.P. Neuman, 2018. Field test of a modified numerical model for water uptake by root systems. Water Resources Research 10:1199-1206.

Harter, T., Lund, J.R., Darby, J., Fogg, G.E., Howitt, R., Jessoe, K., Pettygrove, G.S., Quinn, J.F., Viers, J.H., Boyle, D.B., Canada, H.E., DeLaMora, N., Dzurella, K.N., Fryjoff-Hung, A., Hollander, A.D., Honeycutt, K.L., Jenkins, M.W., Jensen, V.B., King, A.M., Kourakos, G., Liptzin, D., Lopez, E.M., Mayzelle, M.M., McNally, A., Medellin-Azuara, J. & Rosenstock, T.S. (2012) Addressing Nitrate in California's Drinking Water with a Focus on Tulare Lake Basin and Salinas Valley Groundwater. Center for Watershed Sciences, University of California, Davis, http://groundwaternitrate.ucdavis.edu

Harter, T., K. Dzurella, G. Kourakos, A. Hollander, A. Bell, N. Santos, Q. Hart, A. King, J. Quinn, G. Lampinen, D. Liptzin, T. Rosenstock, M. Zhang, G.S. Pettygrove, and T. Tomich, 2017. Nitrogen Fertilizer Loading to Groundwater in the Central Valley. Final Report to the Fertilizer Research Education Program, Projects 11-0301 and 15-0454, California Department of Food and Agriculture and University of California Davis, 333p., http://groundwaternitrate.ucdavis.edu

Perfect, E., M.C. Sukop and G.R. Haszler, 2002. Prediction of dispersivity for undisturbed soil columns from water retention parameters. Soil Science Society of America Journal 66:696-701.

Schaap, M.G., F.L. Leij and M.T. van Genuchten, 2001. Rosetta: A computer program for estimating soil hydraulic parameters with hierarchical pedotransfer functions. Journal of Hydrology 251:163-176.

Van Genuchten, M.T. 1980. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils 1. Soil Science Society of America Journal 44:892-898.

Viers, J.H., Liptzin, D., Rosenstock, T.S., Jensen, V.B., Hollander, A.D., McNally, A., King, A.M., Kourakos, G., Lopez, E.M., De La Mora, N., Fryjoff-Hung, A., Dzurella, K.N., Canada, H.E., Laybourne, S., McKenney, C., Darby, J., Quinn, J.F. & Harter, T. (2012) Nitrogen Sources and Loading to Groundwater. Technical Report 2 in Addressing Nitrate in California's Drinking Water with a Focus on Tulare Lake Basin and Salinas Valley Groundwater. Report for the State Water Resources Control Board Report to the Legislature. Center for Watershed Sciences, University of California, Davis. http://groundwaternitrate.ucdavis.edu/files/139110.pdf

Wu, L., Letey, J., French, C., Wood, Y., Bikie, D., 2005. Nitrate leaching hazard index developed for irrigated agriculture. Journal of Soil and Water Conservation 60:90–95