Developing and Validating a Framework for Estimating Pesticide Use in Washington State

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Abstract

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Understanding spatial patterns of pesticide use is critical for environmental monitoring, public health protection, and informed policymaking, particularly in agriculturally intensive regions such as Fresno County, California, and Yakima County, Washington. This study compared two major pesticide data sources—the California Pesticide Information Portal (CalPIP) and the United States Geological Survey (USGS) pesticide use estimates—to assess their agreement and accuracy at the Township Range Section (TRS) scale, which is part of the Public Land Survey System (PLSS) and was created by the United States government in the early 1800s to divide land into rectangular parcels. Focusing on orchard, vineyard, and nut crops, we evaluated pesticide application trends across three key time points (2000, 2010, and 2019/2020) and mapped the distribution of the most commonly used active ingredients, including sulfur, glyphosate, petroleum oil, kaolin, and chlorpyrifos. Our analysis revealed notable differences between the two data sources. CalPIP provided high-resolution, crop-specific pesticide application data, enabling detailed spatial visualizations at a fine resolution. In contrast, USGS

data, which was modeled from county-level crop acreage and average application rates, lacked crop specificity and resulted in more generalized spatial patterns. Despite these differences, both sources highlighted similar high-use regions, indicating that USGS data, although limited, can be used with caution for a more generalized geographic analysis of pesticide use across 49 states outside of California. Validation analysis between USGS and CalPIP grid estimates revealed weak positive correlations, revealing methodological inconsistencies between the two sources, including data suppression, reporting gaps, and the generalized non-specific nature of USGS estimates. These findings highlight the need for improved pesticide use estimation methodologies that can be ground-truthed with satellite imagery and local surveys to improve the accuracy and applicability of pesticide exposure assessments.

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1. Background

Pesticides are widely used in agriculture to protect crops and ensure high yields, but their extensive use raises concerns about environmental contamination and human health risks. Over the last few centuries, the human population has significantly increased. This rise has intensified the demand for food production, with reports from the Food and Agricultural Organization (FAO) of the United Nations estimating a required 70% to meet the demand for the growing population (FAO, n.d.; Wahab, et al., 2022). Consequently, this huge increase in population has resulted in the extensive usage of pesticides due to increasing crop output. Under federal law, pesticides are defined as any substance, or mixture of substances produced to prevent, destroy, repel, mitigate pests, or intended for use as a plant regulator, defoliant, or desiccant (Cech et al., 2023).

Pesticides can be classified into four general categories: insecticides, fungicides, herbicides, and rodenticides, each posing unique health risks due to their chemical nature and usage patterns Pesticides are often associated with farming practices, but they are also widely used in urban areas, especially to mitigate vector borne diseases spread by insects. While pesticide use has increased food production and eliminated pests, pesticides can move away from the application site, and spread through air droplets, soil, water runoff, or wind transport (DPR, n.d.). Key pesticide exposure routes include dermal, inhalation, and ingestion. Pesticide residue can be found in food, and within a human body, it may be metabolized, excreted, stored, or bioaccumulated in body fat, leading to adverse health effects in gastrointestinal, respiratory, dermatological, neurological, and endocrine systems, among many others (Nicolopoulou-Stamati, et al., 2016).

One of the most significant efforts to monitor pesticide-related illnesses is the Sentinel Event Notification System for Occupational Risks (SENSOR)-Pesticides program, which maintains occupational illness and injury surveillance capacity within state health departments (CDC, n.d.). Managed by the National Institute for Occupational Safety and Health (NIOSH), the program started in 1989, but has come to a halt in 2025, limiting current national-level data for pesticide exposure. It supported epidemiological surveillance of pesticide-related illnesses in participating states, including California and Washington (CDC, n.d.). Figure 1 shows a map from the SENSOR-Pesticides program that illustrates the count of acute pesticide-related illnesses by State for all available years (1998-2011). In California, the Pesticide Illness Surveillance Program (PISP) mandates that healthcare providers report pesticide-related illnesses within 24 hours of examination. Reports can be submitted through local health officers, the California Poison Control System (CPCS), or electronically, via the California Reportable Disease Information Exchange (CalREDIE) portal (OEHHA, n.d.). Similarly, in Washington, healthcare providers are also required to report cases of pesticide-related illness to the Washington State Department of Health, which also provides consultations and assistance in lab analysis of pesticide in blood and urine (DOH, n.d.). The state also maintains the Washington Tracking Network, which provides access to acute pesticide illness data (DOH, n.d.). While programs like SENSOR-Pesticides and illness reporting systems can provide crucial data on pesticide-related health outcomes, they are inherently limited in their ability to record broader population-level exposures. Biomonitoring is widely viewed as the best method for quantitative pesticide exposure assessments, but short half-lives of many pesticides and analytical costs can make it a challenge to utilize biological monitoring for understanding population level exposure to pesticides (Hyland et al., 2022). Consequently, Geographic Information Systems (GIS) and remote sensing data have emerged as practical alternative methodologies to assess pesticide use and exposure at larger scales. Due to the effects pesticides can have on the human body, the monitoring of pesticide usage is considered one of the main measures to inform the population about their potential exposure. However, there is no standard in place, and every state measures usage estimates differently, if at all.

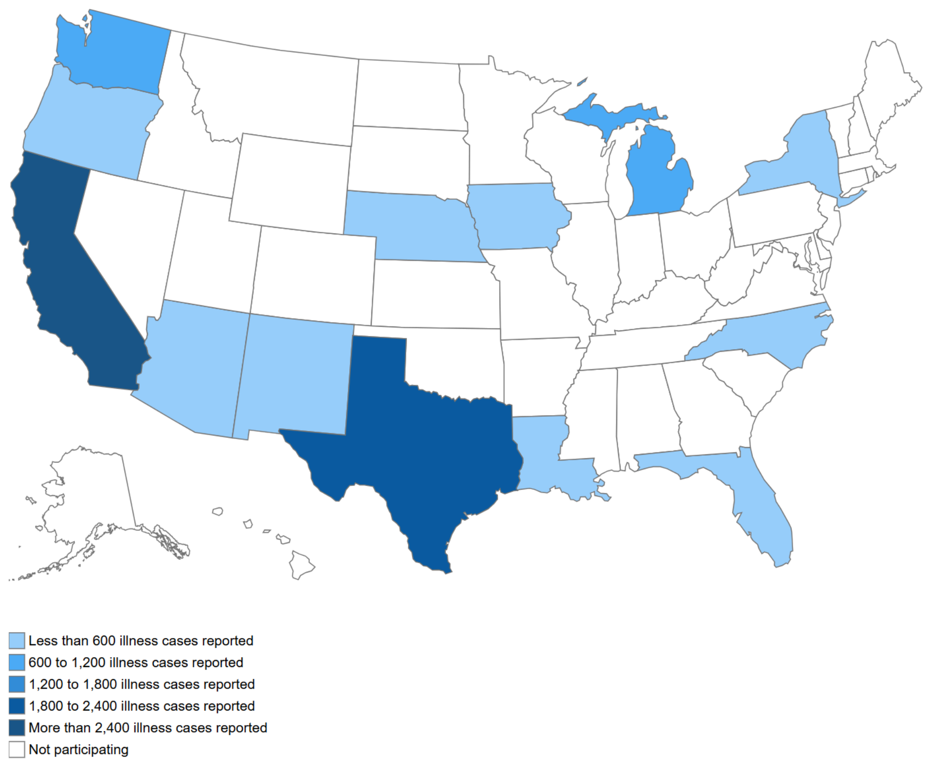

Figure 1: Count of Acute Pesticide-Related Illnesses by State, 1998-2011 via the SENSOR-Pesticides Program (CDC, n.d.)

Despite the need for detailed pesticide use information, most states lack comprehensive reporting systems. The state of California is unique in having a mandatory, statewide pesticide use reporting program that began in 1990, which provides detailed records of all commercial pesticide applications with highly detailed spatial and temporal data. It has been the gold standard for pesticide use monitoring, as it has the most extensive reporting system for agricultural pesticide use in the world, with approximately 2.4 to 2.5 million pesticide application reports per year (Epstein, 2006; DPR, n.d.). The California Department of Pesticide Regulation (DPR) established the Pesticide Use Report (PUR) system, which made it a requirement for commercial agriculture, except livestock, but including postharvest; poultry and fish production; restricted pesticides; pasture, rangeland, parks, golf courses, cemeteries, roadside, and railroad rights-of-way to report pesticide application, made by a pest control operator, including structural applicators, professional landscape gardeners, and aerial and ground agricultural applicators (Epstein, 2006). Any outdoor application with the potential to pollute groundwater must also be reported by the applicator. The PUR system data is stored within the California Pesticide Information Portal (CalPIP).

Washington and the other 48 states do not require full pesticide use reporting, which creates a significant data gap (Donley et al. 2022). Without direct usage reports, agencies and researchers must rely on indirect estimation methods to gauge how much and where pesticides are being applied. Various methods have been developed to estimate pesticide use in regions without mandatory reporting. A common approach is to combine agricultural crop statistics with pesticide application rates sourced from surveys or neighboring regions. County-level pesticide use estimates can be accessed through the United States Geological Survey (USGS) Pesticide National Synthesis Project database. Unlike California's detailed, one square mile pesticide reporting through the Public Land Survey System, the USGS estimates rely on indirect methods due to the absence of mandatory reporting requirements. USGS does not update its databases as frequently as CalPIP, as its most recent finalized and preliminary pesticide use estimates data are from 2017 and 2019, respectively. Although final annual pesticide-use estimates for more recent data are scheduled to be released in 2025, they were not publicly available at the time this thesis was written (USGS, n.d.). Unlike any other state, California uses township data through the Public Land Survey System method to estimate pesticide use in one-by-one square mile grids based on pesticide application record reports to the county and state. Washington, like the other 48 states, relies on harvested-crop acreage data from the US Department of Agriculture's Census of Agriculture to calculate median pesticide by crop use rates in each Crop Reporting District (CRD), which is then applied to the harvested acreage to obtain estimates at a county level (USGS, 2024). County-level estimates can be allocated to agricultural land within each county based on land classifications defined in the National Land Cover Database (Donley et al. 2022).

As shown in Table 1, we selected Fresno County from California and Yakima County from Washington for their comparable fruit and nut productivity and therefore similar occupational and residential exposure pathways. Fresno County is located in the heart of the agriculturally intensive San Joaquin Valley, which has over 1.88 million acres of the world's most productive farmland (County of Fresno, 2023.) and is home to diverse communities (City of Fresno, n.d.). This setting makes Fresno County a critical location to study pesticide use, as it has many implications for public health, given the residential proximity of many agricultural and residential neighborhoods, including schools. Yakima County is the most agriculturally productive county in Washington, especially in terms of fruit cultivation (City of Yakima, n.d.). The cultivation of apples, as well as cherries, peaches, and pears, all require significant pest management efforts. Nearly 188,000 acres of land in Washington have been historical orchard areas subject to application of pesticides, and Yakima, Chelan, Douglas, Okanogan and Benton Counties are among those most affected (County of Chelan, 2021). Yakima County has been identified as a region with several environmental health concerns of contaminated drinking water and air (EPA, 2021).

Table 1: Crop output and pesticide use comparisons between Yakima and Fresno Counties in 2022 (County of Fresno, 2022; USDA, 2022; WSU, n.d.)

Year	2022	
	Yakima, WA	Fresno, CA
Number of farms	2,523	4,427
Land in farms (acres)	1,792,824	1,659,451
Average size of farm (acres)	711	375
Major Fruit Crops	Apples, Pears, Cherries, Grapes	Grapes, Peaches, Mandarins
Major Nut Crops	Walnuts, Chestnuts, Filberts	Almonds, Pistachios
Most Common Pesticides	Herbicides (Glyphosate), Fungicide (Sulfur)	Herbicides (Glyphosate), Fungicide (Sulfur), Insecticide (Petroleum oil)
Total Market Value of Agricultural Products Sold (in thousands of USD) for fruits, tree nuts, and berries	892,016	3,755,350

It is currently impossible to utilize California's method (PUR) to calculate pesticide use in Washington due to the lack of required pesticide use reporting to the state and no publicly available data. We aim to estimate higher resolution pesticide use in Washington State by developing a method to validate nationally-based estimates for the County of Fresno using

USGS and land survey (Township, Range, Section (TRS)) data. TRS displays the smallest unit of the PLSS system, which is a system established to describe land in the United States (National Atlas, 2012). The PLSS divides land into 6-mile-square townships, and townships are subdivided into 36 one–mile-square sections (National Atlas, 2012), as seen in the figure below, and maps to the PUR system in California. In the PUR data, California divides lands into one-square mile grids using the same PLSS system that exists throughout the country, allowing for a within-California comparison of estimates.

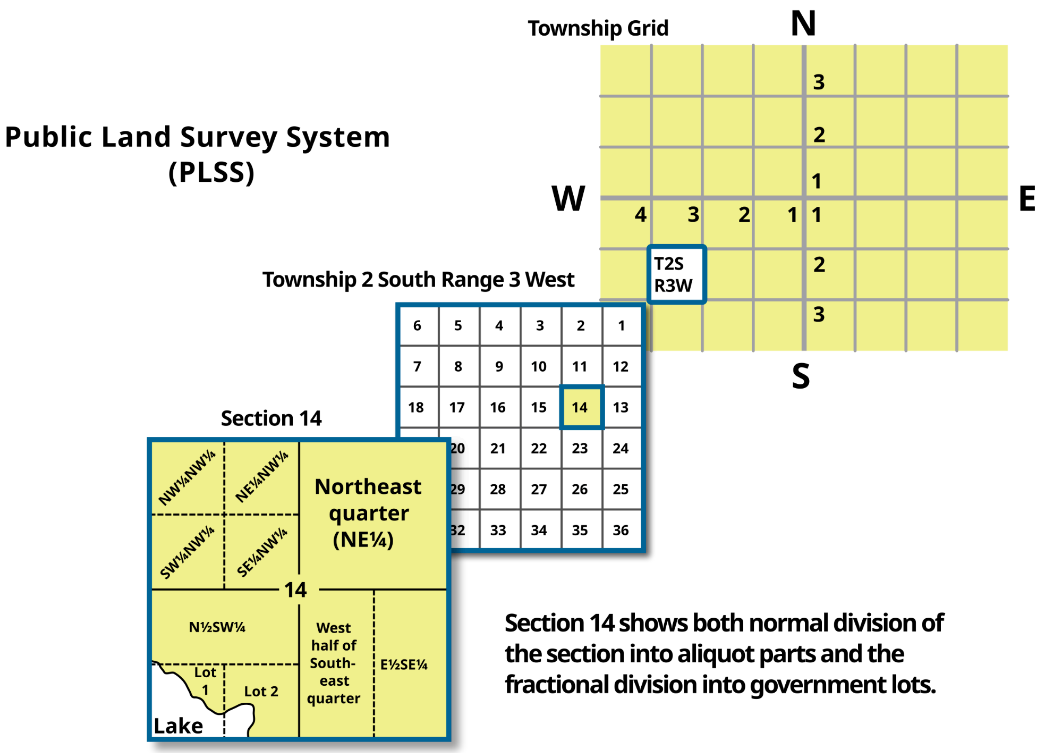

Figure 2: Image showing how PLSS surveys are conducted (National Atlas, 2012).

By creating a prototype that uses current county data from USGS to assign masses of pesticide use in each TRS grid in Fresno and validating this with existing PUR data, we will be able to determine if the proposed method is viable for estimating pesticide use when specialized data like PUR are unavailable. Interest in pesticide exposure has grown in recent years, leading to ongoing research into mapping techniques. This is evident in tools such as the Washington Health Disparities Map published by the Washington State Department of Health (DOH, n.d.). However, there have not been any comparison studies between the different methods of mapping pesticide use estimates. The results of this analysis can be used to provide feedback on current reporting methods in Washington, and to improve future exposure assessment studies employing similar datasets. By leveraging California's extensive pesticide use database and national survey data and applying it to Washington's context, we can generate informed estimates of pesticide use at the county level. Validating these estimates can ensure accuracy and build confidence among stakeholders and policymakers who might use this information for better assessment of pesticide exposure risks and policies in Washington State.

This study aims to develop a robust framework for estimating pesticide use in Washington State by leveraging publicly available data sources, emulating methodologies from California's PUR system, and validating estimates against existing data. A representative county is chosen for each state, Fresno in California and Yakima in Washington.

2. Specific Aims

1. Compare pesticide use patterns between Washington and California for orchard fruit, vineyard, and nut crops by year, mass, and geographic distribution.
    - Select Yakima (WA) and Fresno (CA) Counties as comparable representatives for each state.
    - Identify the top 5 pesticides by frequency and total mass applied annually for fruit and nut crops in Yakima County (2000, 2010, 2019), and Fresno County (2000, 2010, 2020) using USGS and PUR data.

- Create spatial grids for Washington and California pesticides using USGS data. Doing this will allow us to develop grid-based maps for pesticide applications, ensuring reproducibility and utility for policy and research purposes.

2. Develop and validate a grid-based pesticide use estimation framework for Washington using TRS data.
    - Generate TRS-based pesticide use estimates for Yakima, Washington. Adapting methods used in California's PUR system to process TRS data and align it with USGS-derived estimates. This will be done by creating one-by-one-mile grids for the County of Yakima and Fresno and assigning mass estimates to each grid.
    - Validate the TRS-based estimates in Fresno County by comparing them to PUR-reported pesticide use. This will be done using scatterplots made with Microsoft Excel.

3. Methods

A nationally-based estimation method was developed to quantify pesticide use in Washington State at the one square-mile level and then validated against a gold standard set of state-based one-square mile estimates in California. The assumption behind this approach is that, for the same crop, pesticide use per acre in Washington might be comparable to that in California if similar pests and management practices are present. The overall approach involved gathering data on crops and pesticides, implementing the WA-based and CA-based method in two similar agricultural counties, mapping and analyzing pesticide use with GIS tools, and validating the framework through correlation plots.

3.1. Description of CalPIP data

PUR data can be accessed and displayed in three different ways: CalPIP data, which includes updates submitted after the publication of the Pesticide Use Annual Reports; Pesticide Use Annual Reports, which are tables of data totals indexed by chemical or commodity; and Pesticide Use Report Data, which includes the GIS spatial data required to plot pesticide use by township and section (USGS, 2024). The most recent data available for pesticide use estimates for CalPIP is from 2021, and we have decided to use the Pesticide Use Report Data with GIS for this study.

3.2. Selection of Active Ingredients

Pesticide application data for Fresno County were downloaded from the California Department of Pesticide Regulation's PUR database, where annual use totals were extracted and filtered by crop and year. For Yakima County, pesticide use data were obtained from the USGS Pesticide National Synthesis Project, which provides annual high and low estimates by active ingredient for over 340 chemicals. To determine which active ingredients/chemicals to prioritize in this study, the data were first filtered for the cross-county crop groups comparisons that included vineyards, orchards, and tree nuts. While PUR provided a comprehensive list of crop types for each year, the analysis was limited to crops consistently reported across the locations and study years (2000, 2010, and 2019/2020). 2019 was used instead of 2020 for the USGS analysis, as that was the most recent data available. Only agricultural pesticides were accounted for in this study. The selected crops in Fresno County included almond, apple, apricot, cherry, grapefruit, lemon, orange, peach, pistachio, plum, pomegranate, tangerine, walnut, grapes, and grapes (wine). By filtering the data to include only the previously listed crops, we were able to identify the top pesticides used by weight in the county, illustrated in Table 2.

USGS estimates for Fresno and Yakima could not be separated by crop type, limiting the ability to analyze crop-specific pesticide use, though we spatially apportioned the available mass estimates to known crop areas for fruit, orchards, and vineyards, as described in section 3.3 below. Therefore, a more generalized comparison using total annual pesticide use was conducted, with available data limited through the year 2019 instead of 2020. Tables 3 and 4 listed the top 10 active ingredients in Fresno and Yakima Counties, respectively, based on USGS high estimates (EPEST-high). To enhance comparability across regions and focus on similar pesticide exposure scenarios, the list was further narrowed down to include only active ingredients that appeared in the top 10 for both counties. This approach ensured that comparisons were grounded in shared agricultural contexts and exposure routes. The final list of chemicals used in the comparative mapping included: **petroleum oil, sulfur, kaolin, chlorpyrifos, and glyphosate.**

3.3. Data Visualization and Mapping

ArcGIS was used to generate pesticide use maps, enabling spatial visualization and comparison between CalPIP and USGS datasets. This was done twice for Fresno County, using both CalPIP and USGS datasets. First, CalPIP data were joined with TRS grid data provided by the California DPR (DPR, 2022). As both datasets share the same TRS spatial reference system, this allowed for more accurate mapping of each active ingredient by one-by-one-mile grid. In contrast, USGS data do not provide pesticide use by crop or spatial unit. Because of this, we had to approximate grid-level usage, by importing crop distribution data from the California Natural Resources Agency (n.d.) and joining it with the TRS data that was provided by the DPR. For this analysis, the study assumed pesticide use was distributed proportionally to crop area. Grid-level pesticide use was estimated using the formula:

$$Mass\ of\ chemical\ in\ each\ grid\ (lbs)\ =\ Crop\ area\ in\ grid\ (acres)\ \times\ \left(\frac{Total\ county{-}level\ chemical\ use\ in\ 1\ year\ (lbs)}{Total\ crop\ area\ in\ county\ (acres)}\right)$$

Yakima County pesticide use was mapped using a similar method, relying on USGS data and crop distribution from the Washington State Department of Agriculture (WSDA, n.d.).

3.4. Validation of Pesticide Use Estimates

To assess the consistency of the CalPIP and USGS-derived estimates for Fresno County, validation was conducted by aggregating the estimated mass of pesticide use per one-mile grid for each method. Additionally, we filtered for grids with non-zero values in either dataset and were retained for comparison. Using Excel, scatterplots were generated to visualize the relationship between the two datasets and evaluate the strength of correlation between CalPIP and USGS estimates across all active ingredients and study years. Active ingredient-specific estimates were also generated to explore between-chemical patterns.

4. Results

Spatial analysis of pesticide use revealed distinct patterns in Fresno County and Yakima County. In Fresno, high-use areas were concentrated in the intensive agricultural zones of the San Joaquin Valley, corresponding to large-scale cultivation of fruits, nuts, and other crops. Comparably, Yakima's pesticide use was focused around its orchard regions in the Yakima Valley, reflecting extensive tree fruit agriculture. The fine spatial resolution of CalPIP data allowed identification of local “hotspots” of pesticide application in Fresno, down to specific townships or sections, which would be obscured if only county-level data were available. In Fresno County, total agricultural pesticide use reported by CalPIP matched the USGS estimate for the year 2010, as USGS incorporates California’s Department of Pesticide Regulation data during 2013-2017 (Wieben, 2020), but for the years 2000 and 2019, there may be some disparities between the dataset. Discrepancies were also observed across active ingredients. Our CalPIP vs. USGS analysis suggested that while total annual usage in Yakima is less than in Fresno, the intensity per acre in Yakima’s orchard and vineyard areas may be comparable, something that detailed mapping confirmed.

4.1. Comparison of Pesticide Use Patterns Between Washington and California for Orchard Fruit, Vineyard, and Nut Crops by Year, Mass, and Geographic Distribution

Pesticide use by active ingredient was summarized to identify commonly applied compounds across Fresno and Yakima Counties. Tables 2 and 3 present the top 10 active ingredients used in Fresno, based on CalPIP data and USGS’ high-end estimates for the years 2000, 2010, and 2019 (with USGS) or 2020 (with CalPIP). The following active ingredients appeared in both datasets: petroleum oil, sulfur, glyphosate; petroleum oil, kaolin, glyphosate, sulfur in 2010, and glyphosate in 2020. Similarly, Table 4 presents the top 10 active ingredients used in Yakima for 2000, 2010, and 2019. The following active ingredients appeared across the years for all data: sulfur, glyphosate, petroleum oil, kaolin. Although chlorpyrifos was not among USGS’ top ten for Fresno, it appeared frequently in CalPIP’s list and was also present in USGS’ estimates for Yakima. Given its widespread historical use as an insecticide on fruit and nut trees (EPA, n.d.), chlorpyrifos was included to enhance the depth of the comparative analysis, especially knowing that it was banned for use in California in 2019 and corresponding decrease in use over time

(DPR, 2019). Although mineral oil is among the most used agricultural pesticides in Fresno according to CalPIP, it is not reported in the USGS dataset, leading to its exclusion in this analysis.

Table 2: Top ten active ingredients used by mass for agricultural pesticides in Fresno, filtered by crop type using CalPIP data.

Rank based on year	2000	2010	2020
1	**Petroleum oil, unclassified**	**Petroleum oil, unclassified**	Mineral oil
2	Mineral oil	Mineral oil	1,3 dichloropropene
3	Copper hydroxide	**Kaolin**	**Sulfur**
4	**Sulfur**	**Glyphosate, potassium salt**	**Glyphosate, potassium salt**
5	Petroleum distillates, refined	**Glyphosate, isopropylamine salt**	**Glyphosate, isopropylamine salt**
6	Glyphosate, isopropylamine salt	**Sulfur**	Glufosinate-ammonium
7	Ziram	**Chlorpyrifos**	Copper hydroxide
8	Petroleum distillates	Pendimethalin	**Kaolin**
9	**Chlorpyrifos**	1,3 dichloropropene	Pendimethalin
10	1,3 - dichloropropene	Copper hydroxide	Copper sulfate (basic)

Table 3: Top ten active ingredients used by mass for agricultural pesticides in Fresno, based on high use estimates (EPEST-high) using USGS data.

Rank based on year	2000	2010	2019
1	**Sulfur**	**Sulfur**	**Glyphosate**
2	**Petroleum Oil**	**Petroleum Oil**	Methoxyfenozide
3	Metam	Metam	Imidacloprid
4	Cryolite	Metam Potassium	Metolachlor & Metolachlor - S
5	Copper Hydroxide	**Glyphosate**	Metolachlor - S
6	Sodium Chlorate	Dichloropropene	Azoxystrobin
7	**Glyphosate**	Pendimethalin	Methomyl
8	Petroleum Distillate	**Kaolin Clay**	2,4 - D
9	Sulfcarbamide	Cryolite	Chlorantraniliprole
10	Propargite	Copper Hydroxide	Acephate

Table 4: Top ten active ingredients used by mass for agricultural pesticides in Yakima, based on high use estimates (EPEST-high) using USGS data.

Rank based on year	2000	2010	2019
1	**Petroleum oil**	**Petroleum oil**	**Chlorpyrifos**
2	Methyl Bromide	**Kaolin Clay**	**Glyphosate**
3	**Sulfur**	**Sulfur**	Triclopyr
4	2, 4 - D	**Glyphosate**	2, 4 - D
5	**Glyphosate**	Calcium Polysulfide	Carbaryl
6	Fenbutatin Oxide	Acetochlor	Metolachlor & Metolachlor - S
7	**Chlorpyrifos**	Metam	Metolachlor - S
8	Azinphos-Methyl	**Chlorpyrifos**	Pyraclostrobin
9	MCPA	Sulfuric Acid	Diuron
10	Calcium Polysulfide	Metam Potassium	Acetamiprid

The final set of active ingredients analyzed included the following: **sulfur, glyphosate, petroleum oil, kaolin clay, and chlorpyrifos.**

Mapping the active ingredients revealed clear spatial discrepancies between the two data sources. CalPIP (PUR) data provided detailed, localized application reports at the square mile level, allowing for a more accurate spatial visualization. In contrast, we are only able to model estimates based on crop acreage and annual pesticide use totals using USGS data, offering broader spatial coverage but with less spatial precision. An example of this difference can be seen in Figure 3, which illustrates Sulfur use in Fresno for the year 2000 using CalPIP and USGS, respectively. The CalPIP map shows distinct clusters of application, reflecting actual records, while the USGS presents a more uniform distribution with overestimation west of the known regions for fruit and nut farms. Notably, the USGS data appeared to overrepresent pesticide use in low-application areas, likely due to assumptions tied to crop acreage rather than actual application patterns.

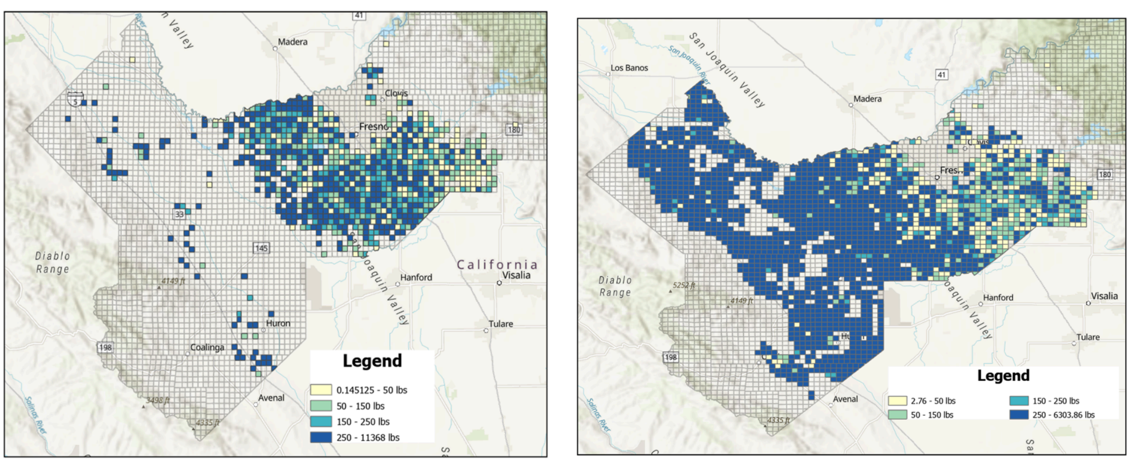

Figure 3: Map of Pounds of Sulfur Applied on Fresno County, CA in 2000, using use estimates from CalPIP (left), and USGS (right)

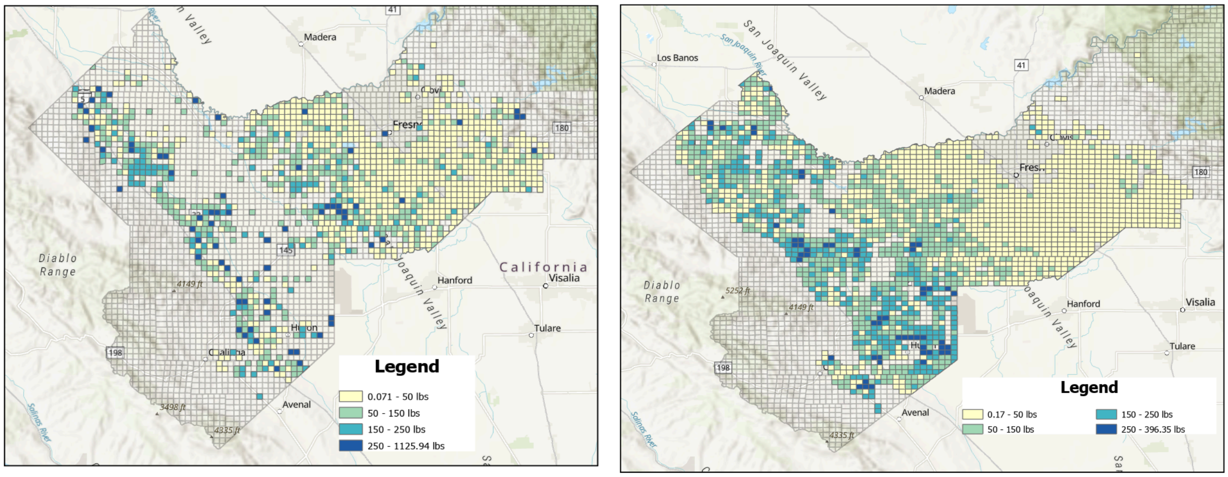

Figure 4: Map of Pounds of Glyphosate Applied on Fresno County, CA in 2010, using use estimates from CalPIP (left) and USGS (right)

Comparing Figure 3 with Figure 4 shows that there seems to be differences in estimation depending on the chemical, and that the USGS estimates for Glyphosate in 2010 showed more similarities to its CalPIP counterpart compared to the previous figure. This suggested that the accuracy of our square-mile gridded approach varied by chemical.

In Yakima County, where CalPIP data were not available, pesticide use was estimated solely using USGS data and mapped using a grid-based modeling framework. Unlike Fresno County, which had specific TRS values for each one-by-one mile grid, Yakima only had published six-by-six mile grids, meaning that to create a comparative one square-mile grid for comparison to Fresno County analysis, we had to utilize ArcGIS' automated grid-making tool. High-use areas were generally aligned with major agricultural zones in the county, particularly in the central and southeastern regions where tree fruit production is concentrated.

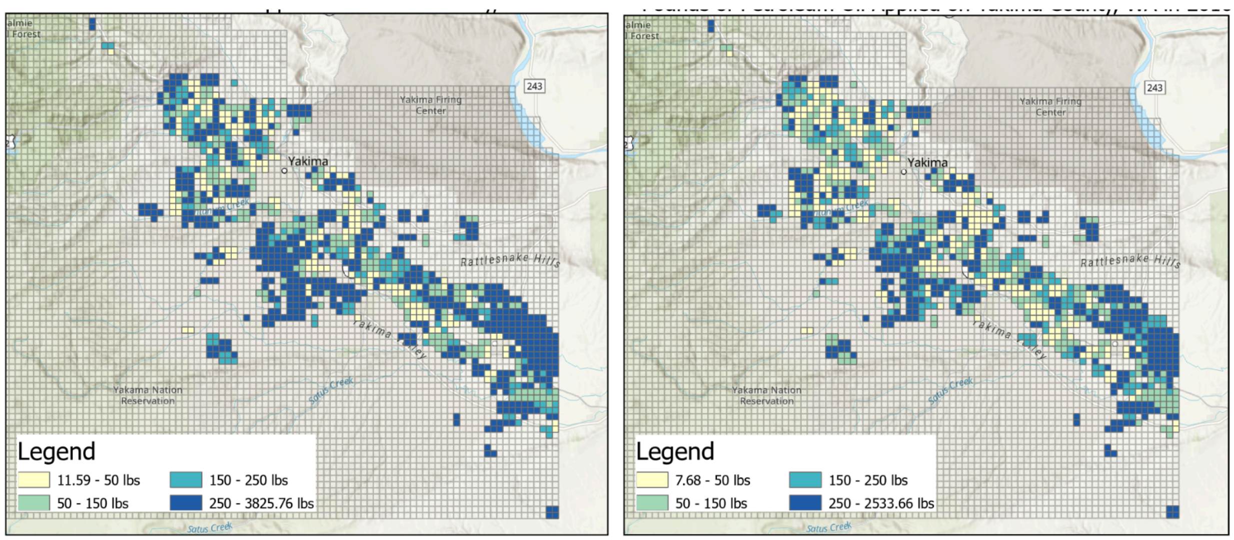

Figure 4: Map of Pounds of Petroleum Oil Applied on Yakima County, WA using USGS data in 2000 (left) and 2010 (right)

Creating maps of Yakima pesticides using the methods created with USGS data allowed us to demonstrate that the data we have now can be utilized for Washington, and most likely other states as well. These maps offer valuable estimates for pesticide use in Yakima and highlight areas where future monitoring or higher-resolution data collection could improve exposure assessment and agricultural research.

4.2. Development and Validation of a Grid-based Pesticide Use Estimation Framework for Washington using TRS data

Pesticide use comparisons across the years 2000, 2010, and 2019/2020 revealed notable differences in reported mass between USGS and CalPIP. For each year, USGS estimates were consistently higher than CalPIP at the grid level. This suggests overestimation may have occurred during USGS data reporting, especially since both high and low estimates were identical, showing limited sensitivity. Regression analyses were conducted to assess the relationship between CalPIP and USGS estimates. Figures 5-7 show the correlation between the datasets for each study year. While weak positive correlations were observed in the graphs for 2000 and 2010, the R^2 values were low (0.068 and 0.0374 respectively), indicating a relatively low agreement between the two sources using this method.

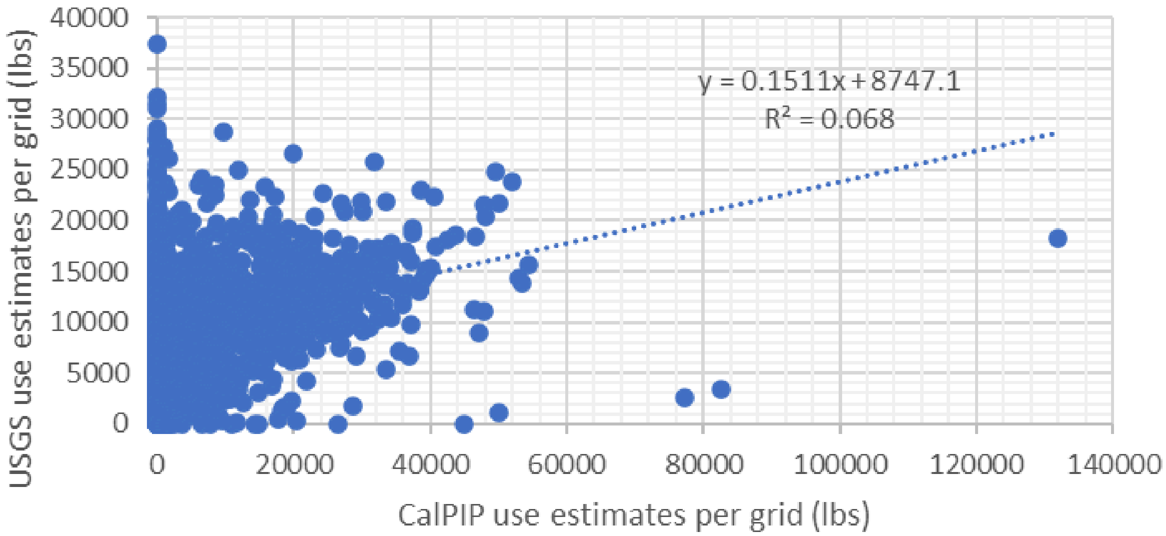

Figure 5: Association between USGS and CalPIP Pesticide Use Estimates on Fresno, California in 2000 for All Chemicals

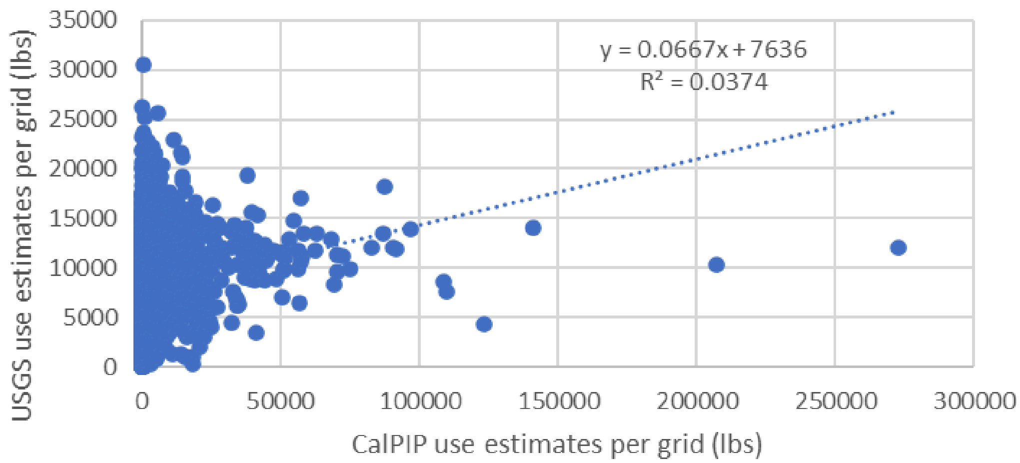

Figure 6: Association between USGS and CalPIP Pesticide Use Estimates on Fresno, California in 2010 for All Chemicals

When all zero-value plots, where either the CalPIP or USGS grid data report zero, are excluded, the graph shows a much higher R^2 value, indicating stronger agreement between the two datasets, as illustrated in Figure 7.

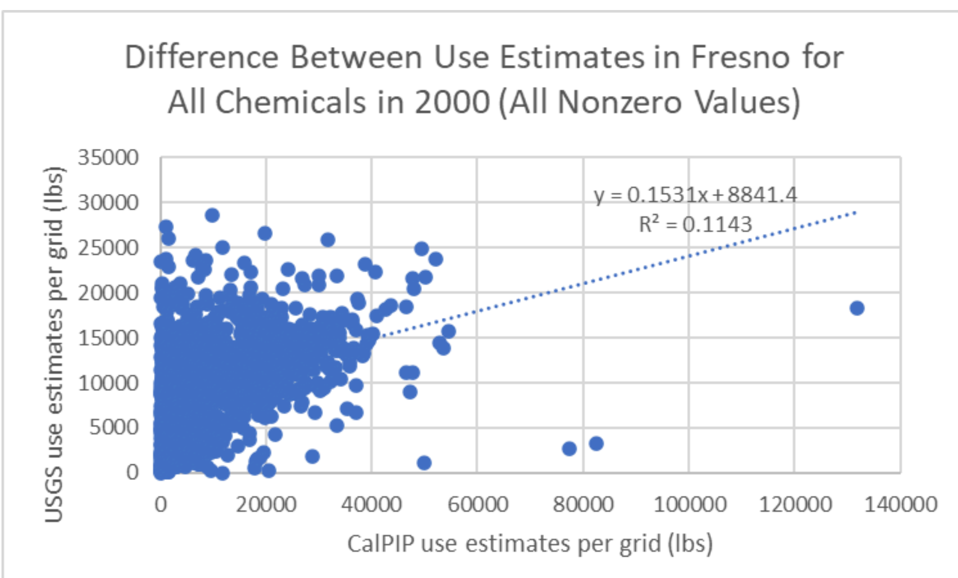

Figure 7: Difference Between Use Estimates on Fresno, California in 2000 for All Chemicals (All Nonzero Values)

Although the plots for all the chemicals display a positive trendline, analyzing individual chemicals reveals that while most graphs follow a positive trendline as well (as seen in Figure 8), others show a negative correlation. This can be seen in Figure 9 below.

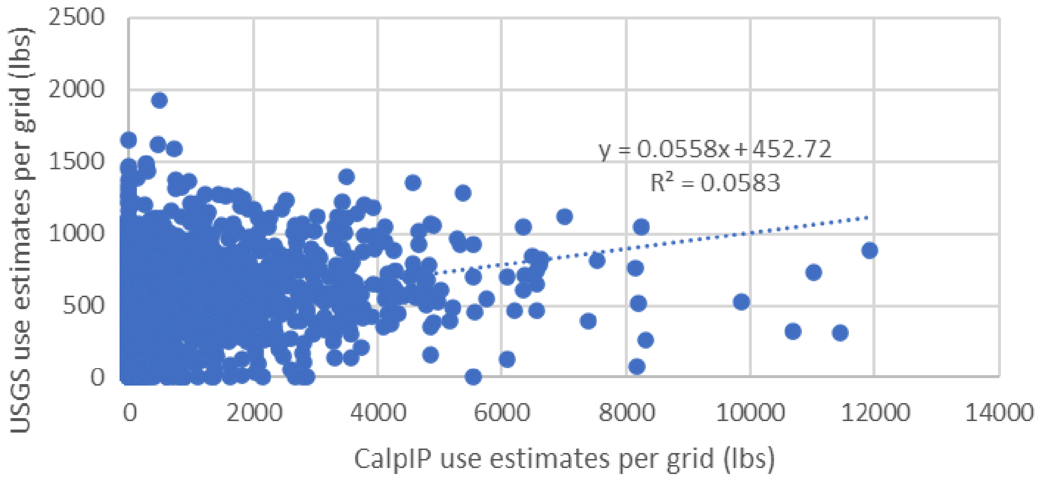

Figure 8: Difference Between Use Estimates in Fresno for Glyphosate in 2010

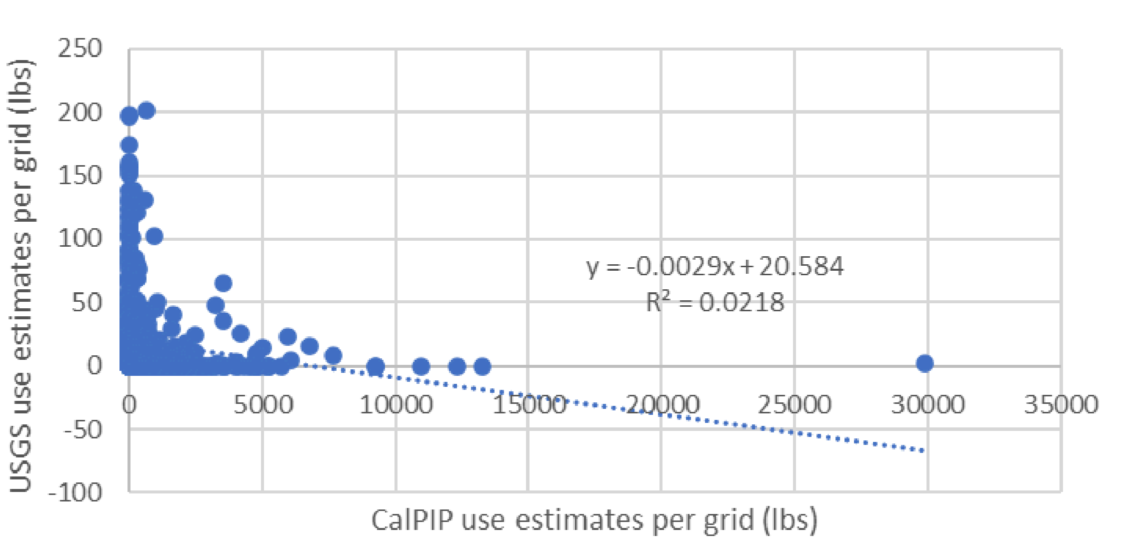

Figure 9: Difference Between Use Estimates in Fresno for Chlorpyrifos in 2010

Using Chlorpyrifos as an example, the negative trendline and downward slope often reflect how this method tends to underestimate use estimates. While the USGS estimates typically show small, nonzero values across many grid cells, CalPIP data frequently reports zero use in many grids, but when it does show usage, the values are often much higher, suggesting more concentrated applications.

5. Discussion

Our framework appears to capture real patterns of pesticide use, even in the absence of a mandatory reporting system. By attempting to validate our approach, we have shown that pesticide use data can be generated for Washington using existing information from national sources, though substantial and unexplained error exists with this approach. At best, 6.8% of the variance in the dependent variable (USGS estimate) was explained by the independent variable (CalPIP estimate) included in the linear models, indicating relatively weak correlation (Figure 5) and that other factors likely have greater influence. The comparative analysis of pesticide use data from California's CalPIP and the USGS national estimates offers insights into both methodological strengths and real-world implications. One key insight is the trade-off between high resolution data and broad coverage. CalPIP's reporting in Fresno County supported the high resolution mapping of pesticide applications and captured even low-use pesticides, which can facilitate targeted exposure assessments. This approach can be useful for environmental health research and practice, as it allows identification of key areas where communities may face elevated exposure, along with the chemicals associated with such exposures. Although the possible timing of chemical exposures is unclear, crop protection guides can be used to identify key timeframes for various pesticide applications and offer ideas for future research. When examining the spatial distribution of pesticide use intensity, the CalPIP data for Fresno enabled mapping within the county scale (e.g. square mile), indicating that relatively small land areas received most of the pesticide applications. This is consistent with findings in other agricultural regions where pesticide use is concentrated in certain areas: for example, a recent nationwide analysis identified a subset of U.S. counties with both high pesticide application rates and high social vulnerability, many of which are in California's Central Valley (Bennett, et al. 2025). Fruit and nut areas in Fresno County were among those identified hotspots and similar trends were observed in agricultural communities in Yakima County Show elevated use in farming communities.

Detailed CalPIP data have been incorporated into GIS-based models to estimate residential pesticide exposure, with some of these models demonstrating strong alignment with biomonitoring results. For instance, one study found that a GIS model using PUR data was able to predict dichlorodiphenyldichloroethylene (DDE) levels in blood with an adjusted R^2 of 0.47, suggesting the model was reasonably effective at identifying and ranking individuals with higher levels of exposure (Ritz and Costello, 2013). On the other hand, the USGS estimation framework provides coverage across the entire country and multiple decades, which is beneficial for regional and temporal comparisons, but it introduces uncertainty at finer scales, as noted by USGS (USGS, n.d.). Despite these challenges, the agreement of CalPIP and USGS data on major trends provides confidence that larger patterns of pesticide use estimates are solid. Adding to the importance of understanding these trends, a recent risk mapping study identified over 140 U.S. counties facing a dual burden of high pesticide use and high social vulnerability (Taiba, et al. 2024). Both Fresno County in California and areas of the Yakima Valley in Washington appeared on that list. The intersection of pesticide intensity and socioeconomic disadvantage raises serious environmental justice concerns, as it suggests that already marginalized communities may bear a disproportionate share of chemical exposure risks. These findings underscore the importance of improving the accuracy of pesticide use estimates to support equitable public health protections.

Understanding pesticide use patterns at a fine spatial scale is critical for environmental monitoring, public health assessments, regulatory decision-making, and as a source of information for farm workers that are routinely exposed to these chemicals, particularly in agriculturally intensive regions like Fresno and Yakima Counties. However, the accuracy and usability of pesticide use data are heavily influenced by differences in data collection methods, reporting requirements, and modeling assumptions. This study addressed these concerns by comparing two major data sources, CalPIP and USGS, to assess their agreement in mapping pesticide use across Fresno County. By highlighting the strengths and limitations of each source, the analysis informs future research and policy decisions that rely on accurate pesticide use information. The USGS estimation framework offers broad national and temporal coverage, making it a valuable tool for regional and long-term comparisons (Thelin and Stone, 2013). However, its reliance on agricultural survey data and county-level crop acreage introduces uncertainty. The modeling process smooths out localized variations, potentially masking areas of intense pesticide use and misallocating chemical loads within a county. USGS has noted that county-level estimates can carry considerable uncertainty, especially when data has to be extrapolated from broader multi-county averages or when input data are incomplete (Thelin and Stone, 2013). For example, in Yakima County, Washington, the absence of detailed pesticide use reporting forces the model to rely on regional assumptions that may not account for real-world variation. Areas within Yakima that are adjacent to large orchards may experience significantly higher pesticide applications than the county average implies, which raises concerns about underestimation of exposure in vulnerable communities. These discrepancies are often only detectable through ground-truthing efforts, such as California's PUR system or biomonitoring programs.

More broadly, the lack of high-resolution pesticide use data is a major hurdle in assessing environmental health risks. This hurdle is not unique to the U.S., however, as similar challenges exist in other regions, such as the European Union, where pesticide usage has historically been estimated based on the number of sales of that product (Gensch, et al. 2024), restricting detailed risk assessments and modeling. Recent efforts to model and map application rates from limited data sources have produced uncertainties as high as an order of magnitude in some areas (Porta, et al. 2025). This mirrors the U.S. situation outside California; without comprehensive reporting, estimates are necessary but come with a great deal of uncertainty.

The findings revealed both consistencies and discrepancies between the two datasets. General spatial patterns of pesticide use were broadly similar, with both sources identifying high-use areas in the western and central parts of Fresno County. However, CalPIP consistently reported higher total pesticide use than USGS. This discrepancy likely arises from their underlying methodologies: CalPIP is based on direct reports from pesticide applicators and permit-holders, while USGS estimates are derived from crop acreage and national-level pesticide use rates. Chemical-specific comparisons further illustrated these differences. For instance, Chlorpyrifos was significantly underrepresented in the USGS dataset compared to CalPIP, potentially due to limitations in USGS modeling for low-use or recently restricted compounds. This underestimation has critical implications for exposure and risk assessments that depend on accurate chemical-specific data. In contrast, for other chemicals such as sulfur, USGS data appeared to overestimate usage compared to CalPIP. Despite the difference in total mass, both datasets revealed similar spatial patterns for sulfur, with heavier usage concentrated in the eastern part of the county. This suggests that while USGS may not always provide accurate volume estimates, it can still reflect relative spatial distribution trends under certain conditions.

The chemical-specific comparisons further emphasized these distinctions. Some of the chemicals that are used in this study, such as Chlorpyrifos, were substantially underrepresented in USGS estimates compared to CalPIP records. An example of this phenomenon is seen in Figure 10.

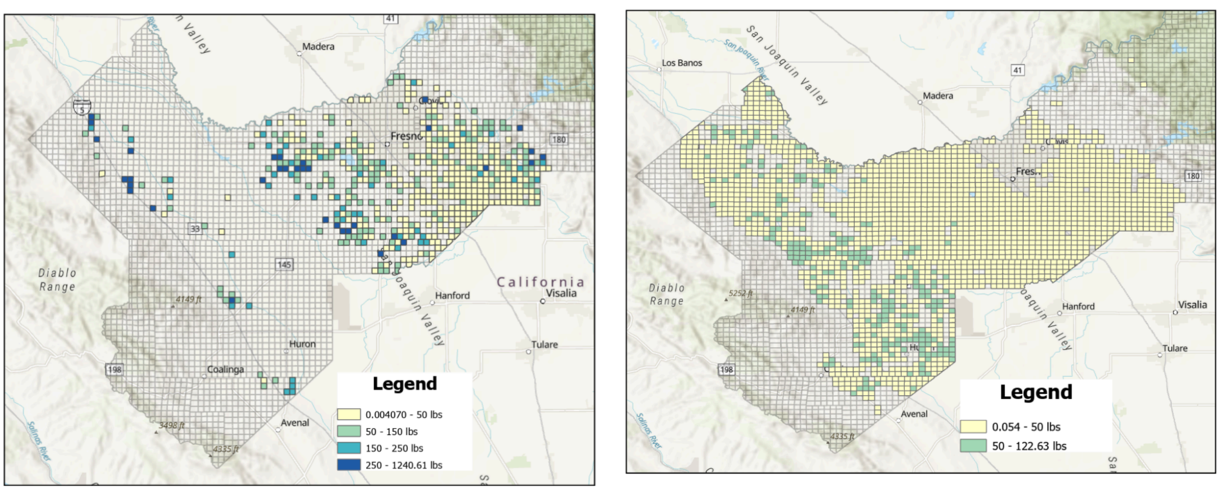

Figure 10: Map of Pounds of Chlorpyrifos Applied on Fresno County, CA in 2000, using use estimates from CalPIP (left), and USGS (right)

While that is true for most chemicals, this does not apply to all of them however, as some chemicals, such as sulfur, seem to be overrepresented with the USGS data. In the case of sulfur, it can be seen that most usage stems from the eastern side of the county. When comparing it with the map created using CalPIP data, it still shows similar usage patterns despite having very different values, with more usage and spacing from the east side, alongside less usage and less spacing on the west side of the county.

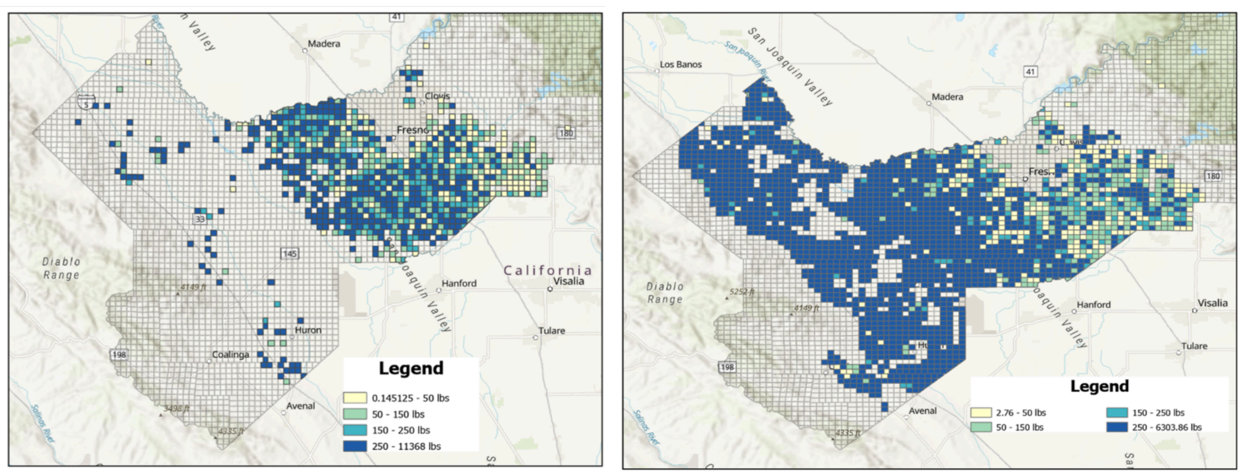

Figure 11: Maps of Pounds of Sulfur Applied on Fresno County, CA in 2000, using estimates from CalPIP (left) and USGS (right)

This overreport/underreport of data may affect risk assessments and epidemiological studies that depend on accurate chemical-specific exposure data, but may also prove useful for offering consistent, long-term trends, especially in areas where CalPIP data may be incomplete or suppressed. The strengths of this study include the integration of two complementary datasets and the application of detailed spatial analysis to evaluate pesticide use at the county level. This is the first study to do so, and by comparing CalPIP and USGS, both major sources of pesticide use reports, the research underscores important considerations for researchers, regulators, and community stakeholders. As noted earlier, tools like the Washington Health Disparities map by the DOH contribute to identifying environmental health disparities, including those related to pesticide exposure. However, their reliance on total mass applied, without accounting for differences in pesticide ingredients or toxicity, is a limitation. In contrast, this method enables analysis by specific pesticide chemical or functional class, even when the national dataset introduces some uncertainty.

The comparison between CalPIP and USGS datasets showed strong overlap for widely used chemicals such as chlorpyrifos but notable discrepancies for niche pesticides or those less frequently reported. CalPIP comprehensively documented specialty chemicals and fumigants used in Fresno and Yakima that were either underrepresented or omitted entirely in the USGS estimates, highlighting differences rooted in their estimation frameworks.

Overall, the results demonstrate that CalPIP's measured data and USGS's modeled data are largely consistent on a broad scale: both indicate Fresno far exceeds Yakima in total pesticide pounds used, and both reflect the dominant chemical classes tied to each region's crop profile. Yet, critical differences emerge when examining the details: CalPIP data show fine spatial heterogeneity and a wider range of chemicals, while the USGS approach provides a national-scale, standardized estimate with recognized uncertainties. These findings reinforce the value of combining multiple data sources to get a complete picture. They also raise important questions addressed in the Discussion, such as how estimation uncertainties and data gaps might affect exposure assessments and what the implications are for community health in these agricultural regions.

To our knowledge, this is the first study to directly compare differences in pesticide use estimates between the USGS and CalPIP's datasets, both of which are widely used in environmental health research. This analysis fills an important gap in the literature by providing insights into the strengths and limitations of each dataset. While direct comparisons are limited, other studies have proposed alternative methods to estimate pesticide use. For instance, a study conducted by Hyland et al. (2024) used proximity to agriculture as a basis to estimate individual-level pesticide exposure. The study calculated the distance from each home to the nearest agricultural field and the total acreage of agricultural fields within a 0.5 km buffer, using this as their ground truth method, and compared it with satellite-derived estimates, which is the method they are evaluating. Similar to the findings in our study, Hyland et al. reported poor to moderate agreement between data sources, particularly noting that satellite-based estimates tended to overrepresent pesticide usage in comparison to more localized data. These results highlight the challenges often seen in modeling pesticide exposure on a finer scale that can have implications for both research and regulation. For instance, exposure estimates inform policies like California's buffer zone requirements, which prohibit pesticide spraying within 60 feet of schools and 300 feet for aerial pesticide applications (DPR, 2014). The USGS pesticide mapping program itself was nearly discontinued in recent years. It was reinstated only after widespread advocacy from scientists and public health experts who emphasized its critical role in supporting hundreds of peer-reviewed studies. Its recent restoration, with plans to update the database annually and include approximately 400 active ingredients, marks a promising step forward (USGS, n.d.; Center for Biological Diversity, 2024) .

5.1. Limitations and Future Research

Although both data sources, CalPIP and USGS, are major pesticide data sources, each comes with limitations that may have impacted the interpretation of results. CalPIP data, although highly granular and based on firsthand reports by applicators, are subject to reporting errors and data suppression for the same reason, particularly in areas with lower pesticide usage, or where privacy concerns may arise. These errors can introduce uncertainties in exposure assessments.

On the other hand, USGS estimates are modeled and not based on real-time application data. A significant limitation of USGS data is its lack of crop-specific reports; estimates are calculated at the county level based on total crop acreage and average national application rates by chemical. As a result, USGS estimates can oversimplify complex agricultural systems, particularly in diverse regions like California's Central Valley, leading to potential over or underestimation of pesticide usage. Additionally, USGS data for 2019 is still in its preliminary stage, meaning that most of the pesticides have not been recorded yet (from over 300 chemicals to only 70), leading to use patterns that might not be true, such as Chlorpyrifos being number one on the Yakima list, despite its usage decreasing over time.

Future Research should focus on harmonizing CalPIP and USGS data more systematically, potentially through the development of models based on ground-truth validation methods or the correction factors tailored to specific crops and/or regions. Incorporating additional datasets, such as satellite imagery for crop identification, remote sensing of land use, and field-based pesticide surveys, may also enhance modeling accuracy. Engagement with state and federal agencies to access unpublished pesticide use data could improve the robustness of USGS-based mapping frameworks. These datasets can then offer a more comprehensive view of agricultural pesticide use patterns, helping inform public health strategies, regulatory decisions, and environmental monitoring. Understanding and addressing uncertainty remains a key issue. Data sources like USGS attempt to capture this by offering both low and high estimates for pesticide use. In practice, this uncertainty tends to be minimal for well-documented pesticides, such as major herbicides, but can be much higher for less commonly used chemicals or in areas with limited survey data. According to Thelin and Stone (2013), around one-third of their crop-pesticide pairings showed significant differences between their EPest and alternative datasets, with no clear pattern. This suggests that some errors in estimation may be random or specific to certain chemicals. In a region like Yakima, this uncertainty means that the actual use of a particular pesticide could differ significantly from what is estimated - an important consideration, especially if the chemicals included in the pesticides are of toxicological concern.

Lastly, our findings highlight the importance of considering cumulative effects. People in agricultural regions are typically exposed not to one pesticide at a time, but to mixtures of dozens. Frameworks like CalEnviroScreen and Washington Tracking Network can be built on a more robust foundation of pesticide use estimation.

6. Conclusion

This study offers one of the first direct comparisons between modeled pesticide use estimates from the USGS and the application-specific data from California's CalPIP's PUR system, using Fresno and Yakima Counties as case studies. While spatial patterns were broadly consistent, CalPIP consistently reported higher localized use than USGS. The limitations of estimating pesticide usage with USGS, such as the lack of crop specificity and the reliance on crop acreage, contrast with CalPIP's report-based system, often considered the gold standard for pesticide surveillance. However, the use of TRS grids allowed for a more structured and replicable approach to estimating use in Washington, where such detailed reporting is unavailable.

By focusing on a subset of commonly used active ingredients, this study makes it easier to draw meaningful comparisons and better understand similar risks, particularly from farmworkers and populations living in agricultural-intensive areas. Findings reinforce the need for improved harmonization between datasets, and future work should explore other validation techniques, such as remote sensing data, and encourage collaboration with authorities in USGS and

California's DPR. Ultimately, by evaluating both strengths and weaknesses of current pesticide data, this research contributes to more informed and effective environmental health protections.

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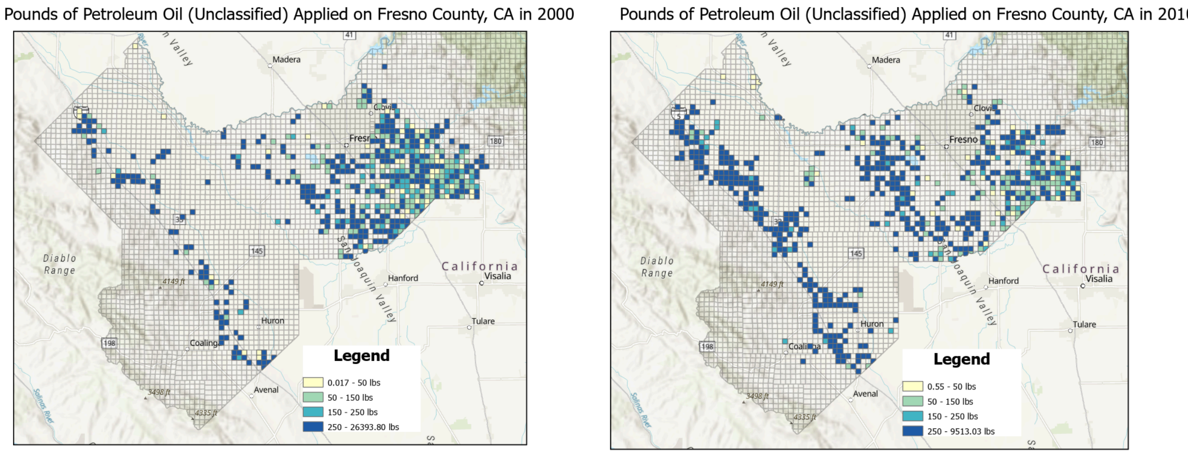
8. Supplemental Materials

No.	2000	2010	2020
1	Glyphosate, isopropylamine salt	Glyphosate, isopropylamine salt	Mineral oil
2	Petroleum oil, unclassified	Glyphosate, potassium salt	Glufosinate-Ammonium
3	Oxyfluorfen	Oxyfluorfen	Glyphosate, potassium salt
4	Copper hydroxide	Mineral oil	Glyphosate, isopropylamine salt
5	Esfenvalerate	Petroleum oil, unclassified	Abamectin
6	Chlorpyrifos	Abamectin	Oxyfluorfen
7	Paraquat dichloride	Propiconazole	Chlorantraniliprole
8	Propiconazole	Iprodione	Methoxyfenozide
9	Iprodione	Pendimethalin	Saflufenacil
10	Spinosad	Esfenvalerate	Rimsulfuron

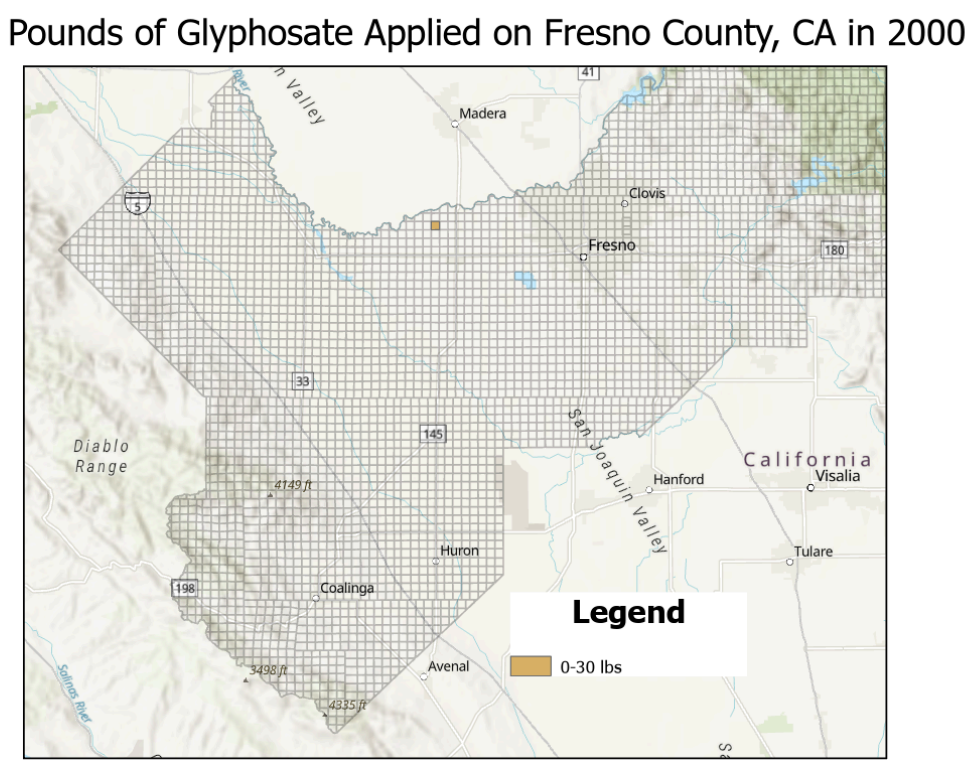
Supplemental Table 1: Top 10 pesticides used in Fresno, CA for orchard fruits and tree nuts based on count of chemical name

Active Ingredient	2000		2010		2020	
	Frequency	Mass (lbs)	Frequency	Mass (lbs)	Frequency	Mass (lbs)
Petroleum oil, unclassified	3134	1794714.345	2753	2481983.855	N/A	N/A
Mineral oil	822	940868.9137	2760	1636636.245	12134	9148810.958
Copper hydroxide	2507	304100.708	1343	133808.5039	2409	276525.3401
Sulfur	1216	217258.8054	1035	270736.3052	1963	1057914.377
Petroleum distillates, refined	498	181447.2748	37	51525.13095	N/A	N/A
Glyphosate, sopropylamine salt	6860	161002.7506	5789	271144.3792	6636	445888.0023
Ziram	925	149134.5048	749	69777.77501	862	76205.97248
Petroleum distillates	282	137796.3526	4	184.2681354	1	0.005149106
Chlorpyrifos	2159	97698.26311	1411	146272.9651	2	16.2872765
1,3 - dichloropropene	27	65474.05553	44	139137.597	177	1126619.465
Kaolin	N/A	N/A	295	292320.2155	289	272676.2533
Glyphosate Potassium salt	N/A	N/A	4346	287519.7443	7849	775994.8902
Pendimethalin	121	11109.63074	1944	142971.7568	2723	243129.9183
Glufosinate - ammonium	N/A	N/A	1467	65420.13059	8847	310038.2642
Copper sulfate (basic)	202	28415.6245	1055	125197.3471	1491	186999.9013

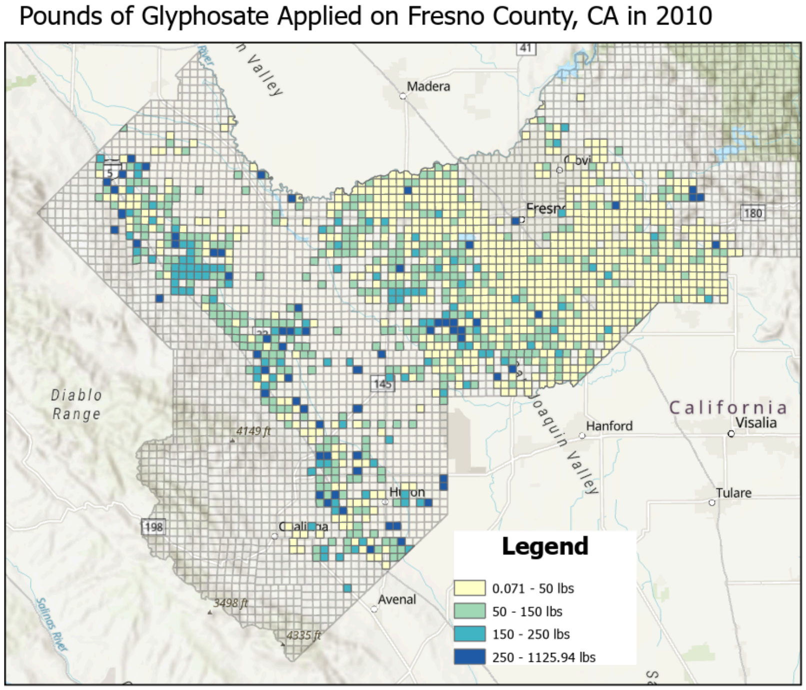
Supplemental Table 2: Table of common chemicals present in Fresno pesticides (mass listed)



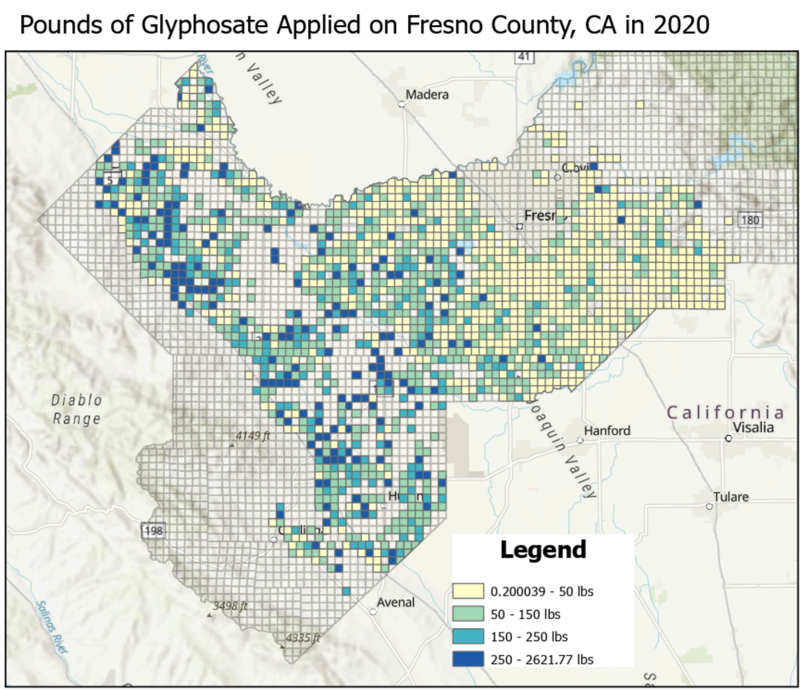
Supplemental Figure 1: Pounds of Petroleum Oil Applied on Fresno County, CA in 2000 and 2010 using CalPIP data



Supplemental Figure 2: Pounds of Glyphosate Applied on Fresno County, CA in 2000 using CalPIP data

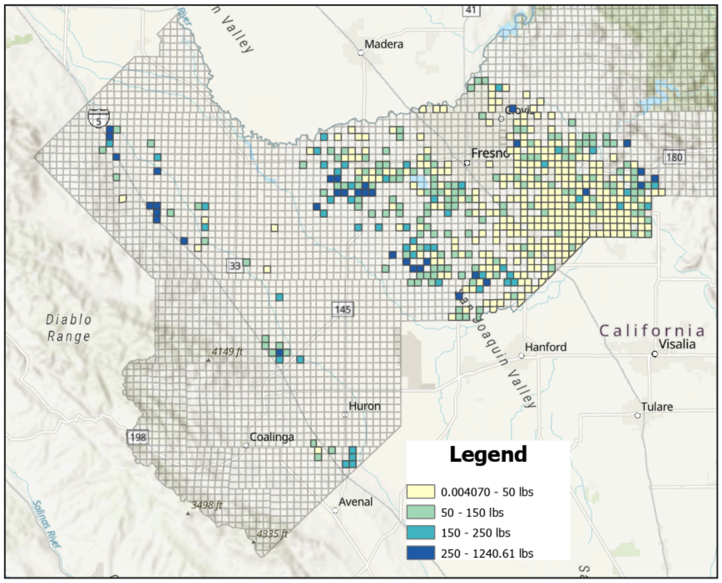


Supplemental Figure 3: Pounds of Glyphosate Applied on Fresno County, CA in 2010 using CalPIP data



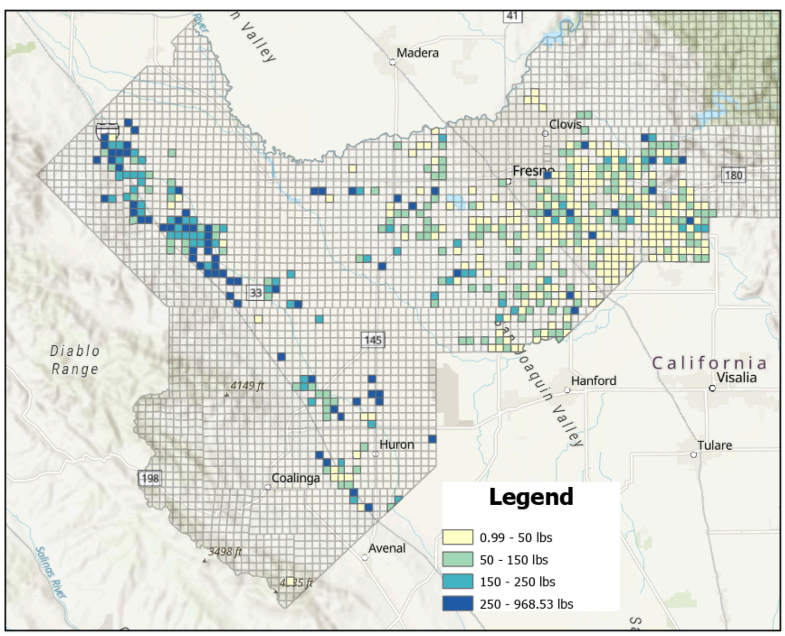
Supplemental Figure 4: Pounds of Glyphosate Applied on Fresno County, CA in 2020 using CalPIP data

Pounds of Chlorpyrifos Applied on Fresno County, CA in 2000

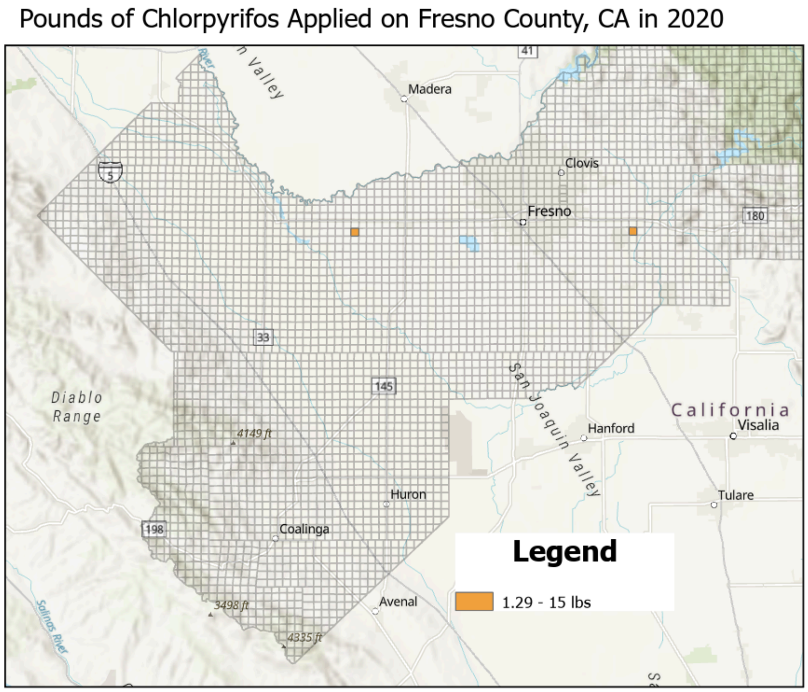


Supplemental Figure 5: Pounds of Chlorpyrifos Applied on Fresno County, CA in 2000 using CalPIP data

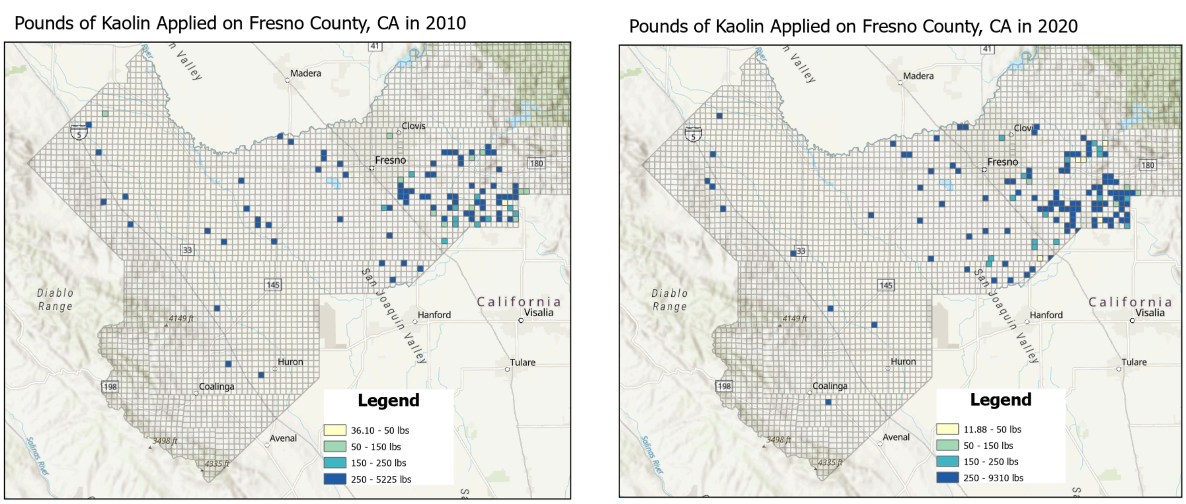
Pounds of Chlorpyrifos Applied on Fresno County, CA in 2010



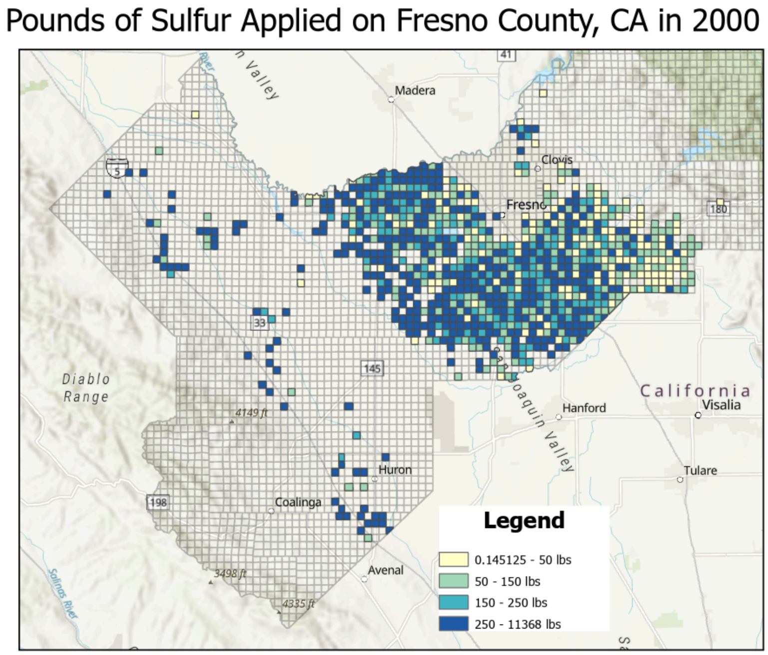
Supplemental Figure 6: Pounds of Chlorpyrifos Applied on Fresno County, CA in 2010 using CalPIP data



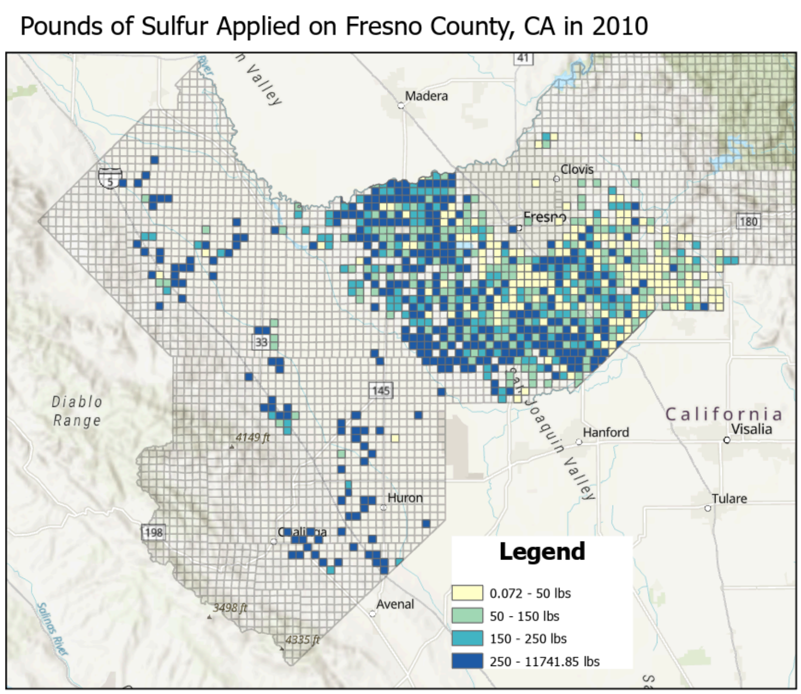
Supplemental Figure 7: Pounds of Chlorpyrifos Applied on Fresno County, CA in 2020 using CalPIP data



Supplemental Figure 8: Pounds of Kaolin Applied on Fresno County, CA in 2010 and 2020 using CalPIP data

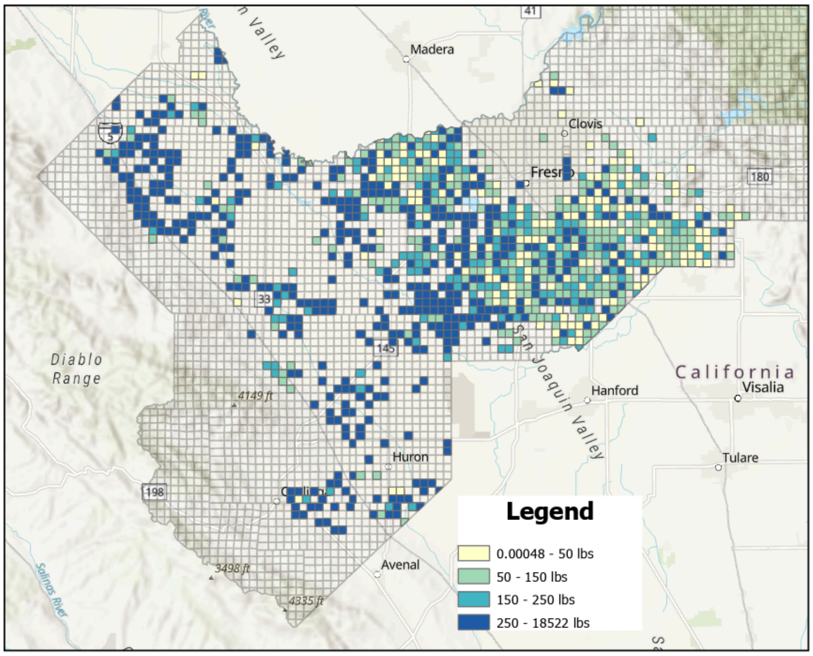


Supplemental Figure 9: Pounds of Sulfur Applied on Fresno County, CA in 2000 using CalPIP data



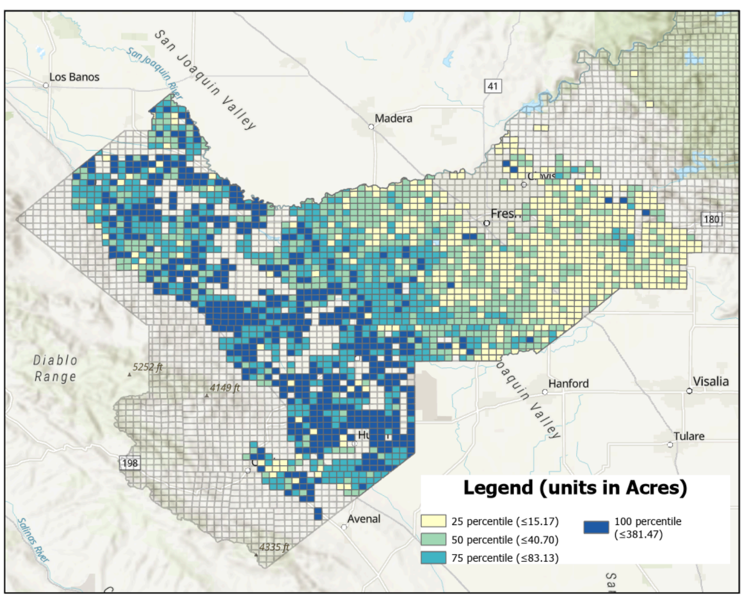
Supplemental Figure 10: Pounds of Sulfur Applied on Fresno County, CA in 2010 using CalPIP data

Pounds of Sulfur Applied on Fresno County, CA in 2020

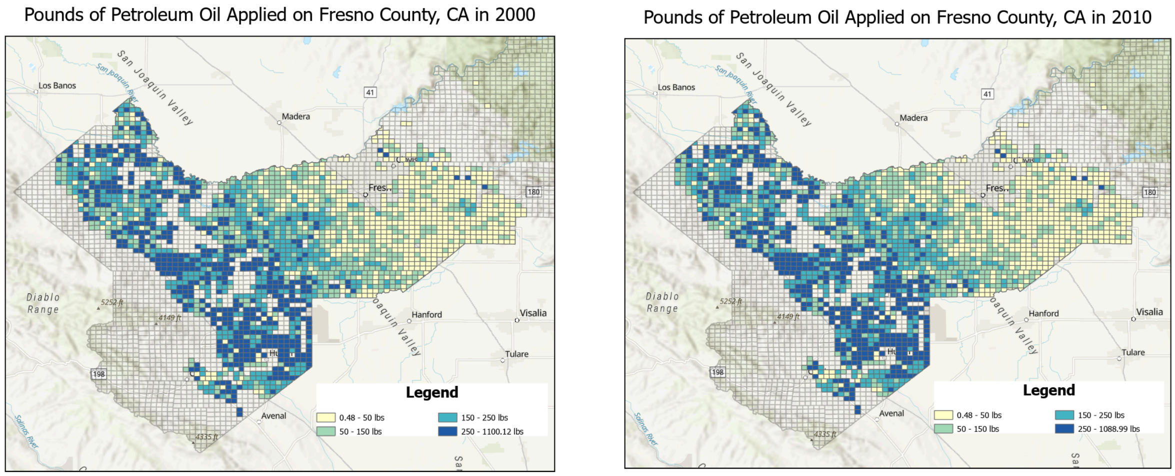


Supplemental Figure 11: Pounds of Sulfur Applied on Fresno County, CA in 2020 using CalPIP data

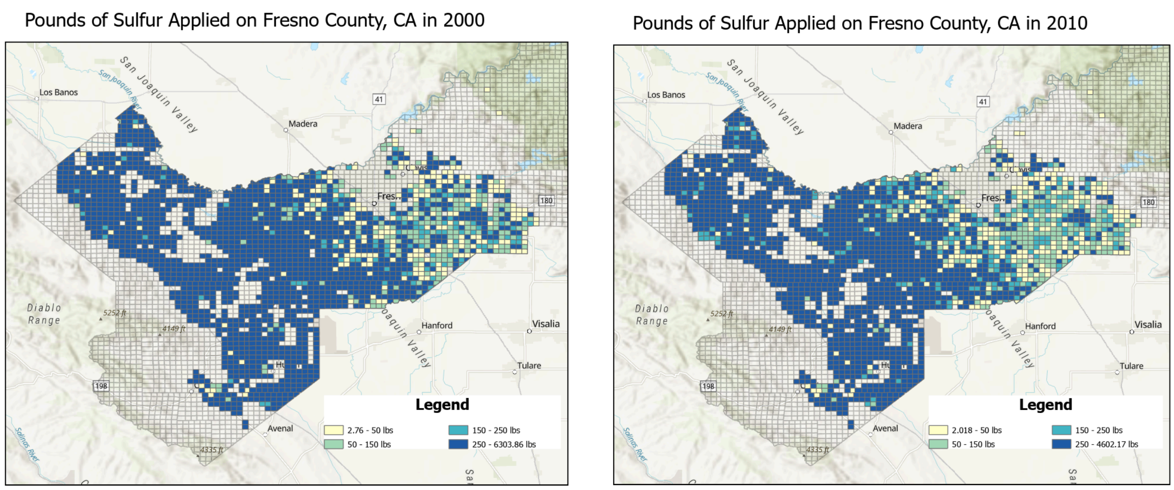
Acres of Orchards, Vineyards, and Tree Nut crops in Fresno



Supplemental Figure 12: Acres of Orchards, Vineyards, and Tree Nut crops in Fresno County, CA in 2023 from California Natural Resources Agency (n.d.)

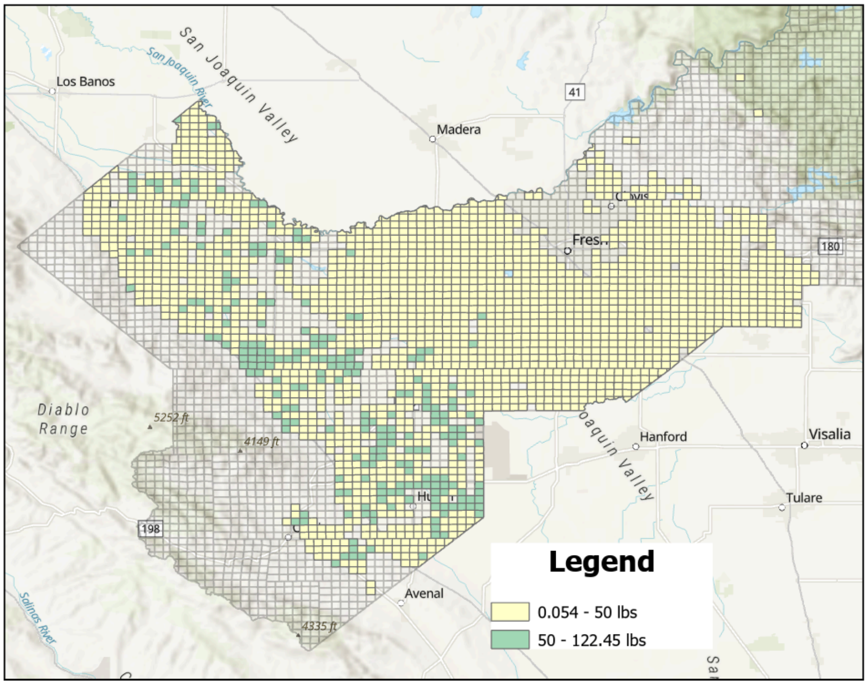


Supplemental Figure 13: Pounds of Petroleum Oil Applied on Fresno County, CA in 2000 and 2010 using USGS data



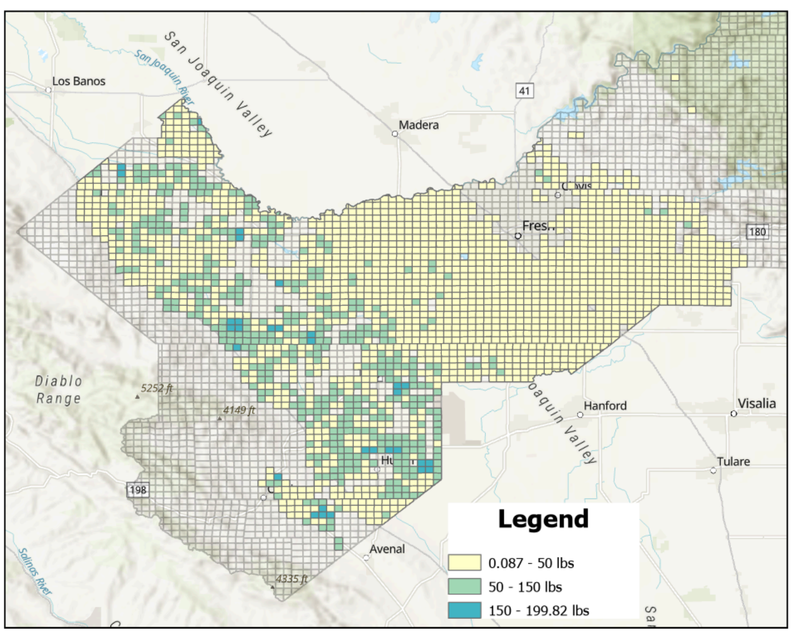
Supplemental Figure 14: Pounds of Sulfur Applied on Fresno County, CA in 2000 and 2010 using USGS data

Pounds of Kaolin Applied on Fresno County, CA in 2010



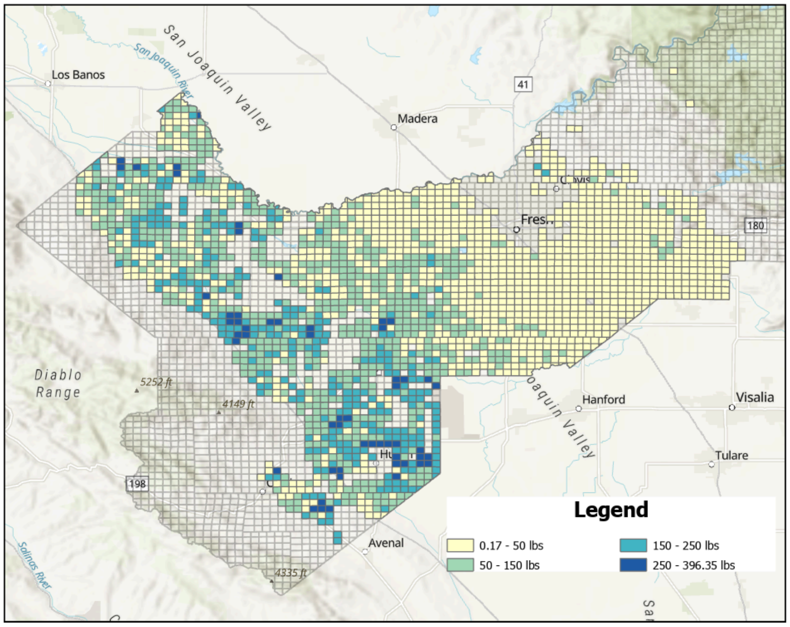
Supplemental Figure 15: Pounds of Kaolin Applied on Fresno County, CA in 2010 using USGS data

Pounds of Glyphosate Applied on Fresno County, CA in 2000



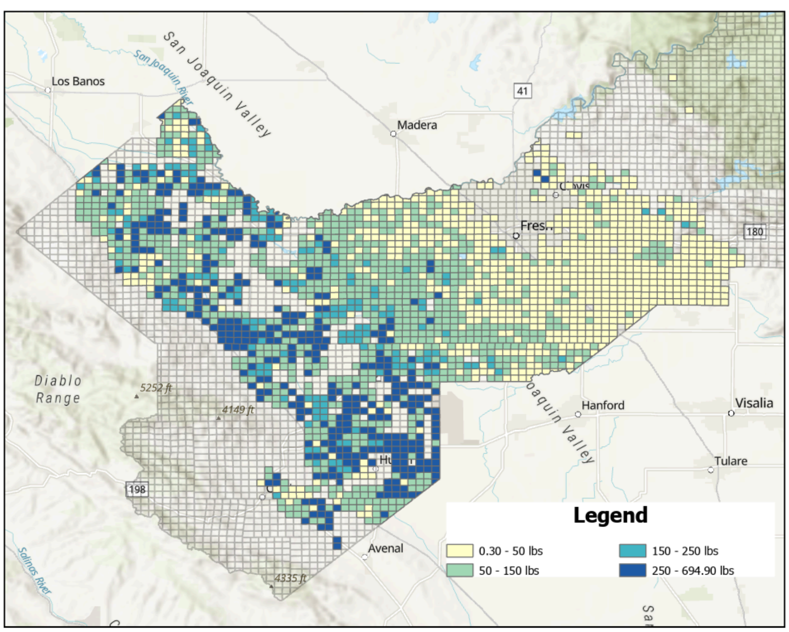
Supplemental Figure 16: Pounds of Glyphosate Applied on Fresno County, CA in 2000 using USGS data

Pounds of Glyphosate Applied on Fresno County, CA in 2010



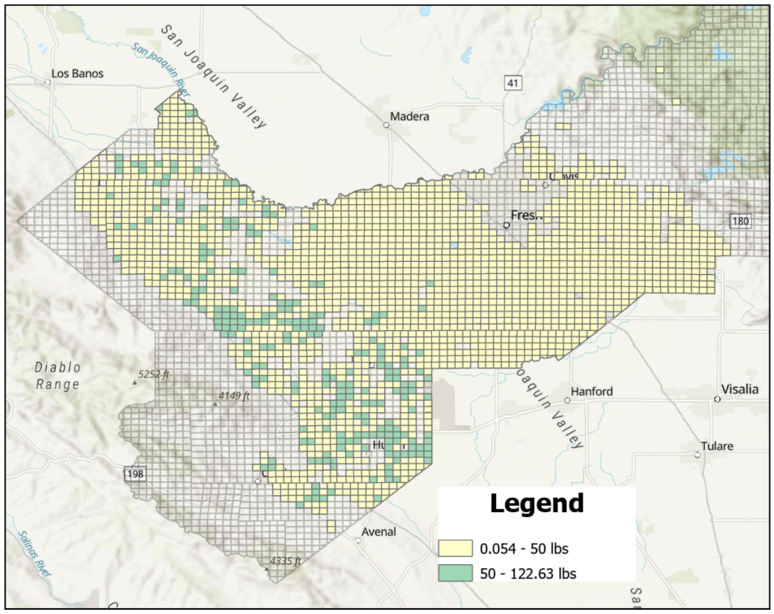
Supplemental Figure 17: Pounds of Glyphosate Applied on Fresno County, CA in 2010 using USGS data

Pounds of Glyphosate Applied on Fresno County, CA in 2019



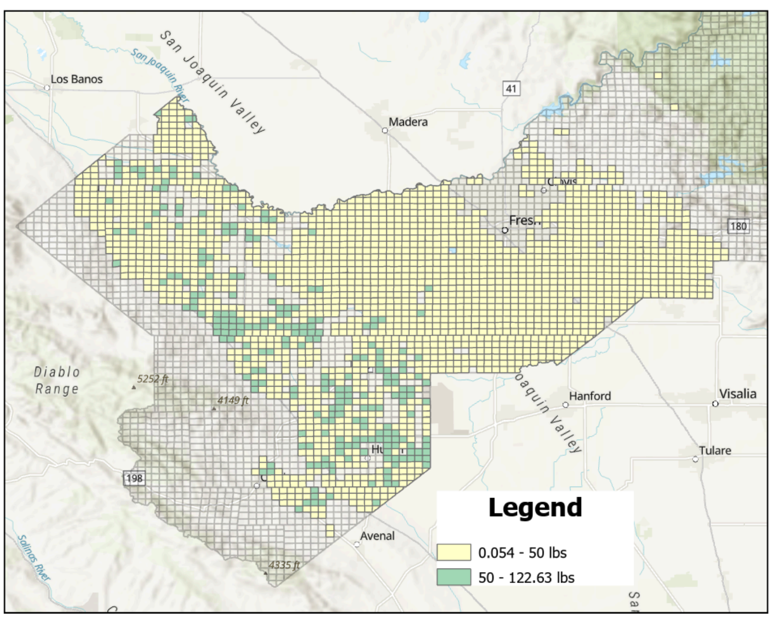
Supplemental Figure 18: Pounds of Glyphosate Applied on Fresno County, CA in 2019 using USGS data

Pounds of Chlorpyrifos Applied on Fresno County, CA in 2000

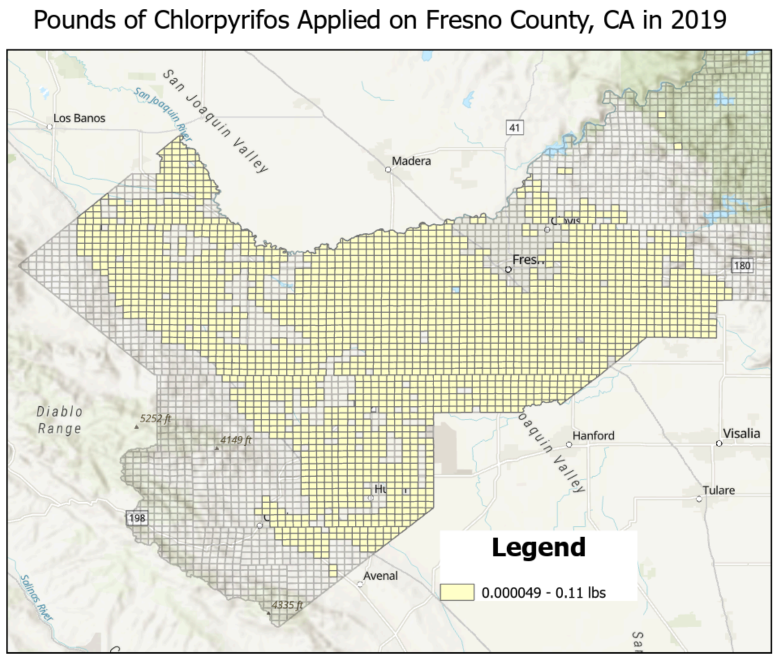


Supplemental Figure 19: Pounds of Chlorpyrifos Applied on Fresno County, CA in 2000 using USGS data

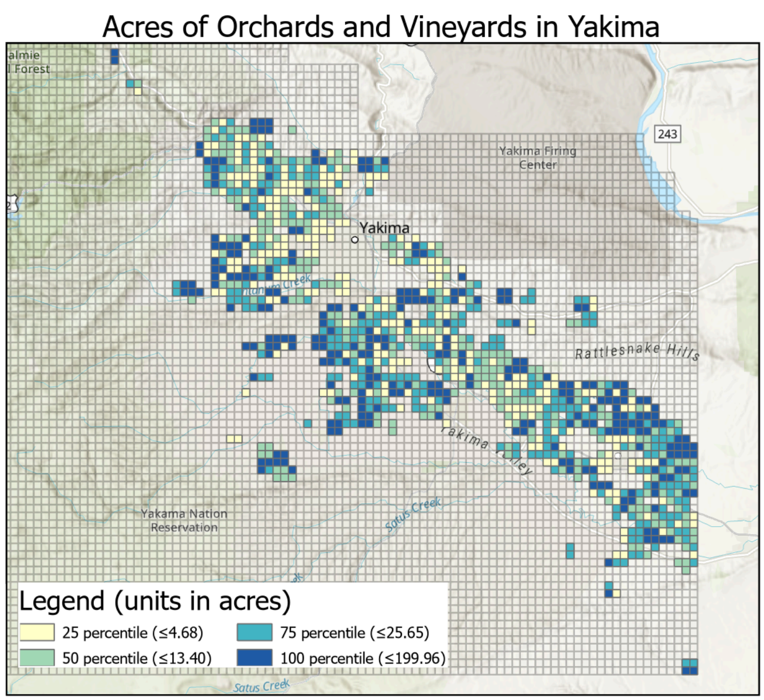
Pounds of Chlorpyrifos Applied on Fresno County, CA in 2010



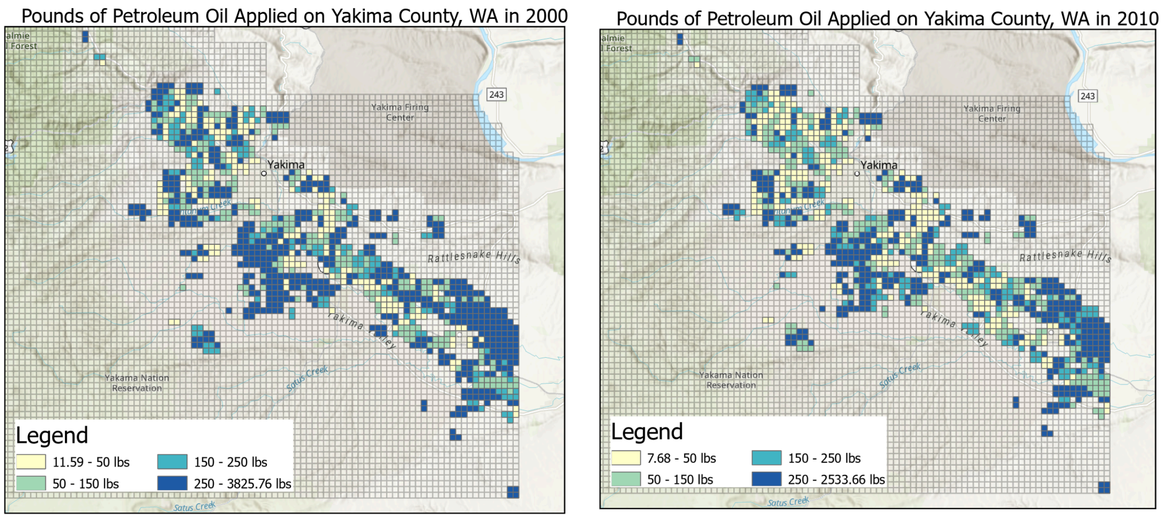
Supplemental Figure 20: Pounds of Chlorpyrifos Applied on Fresno County, CA in 2010 using USGS data



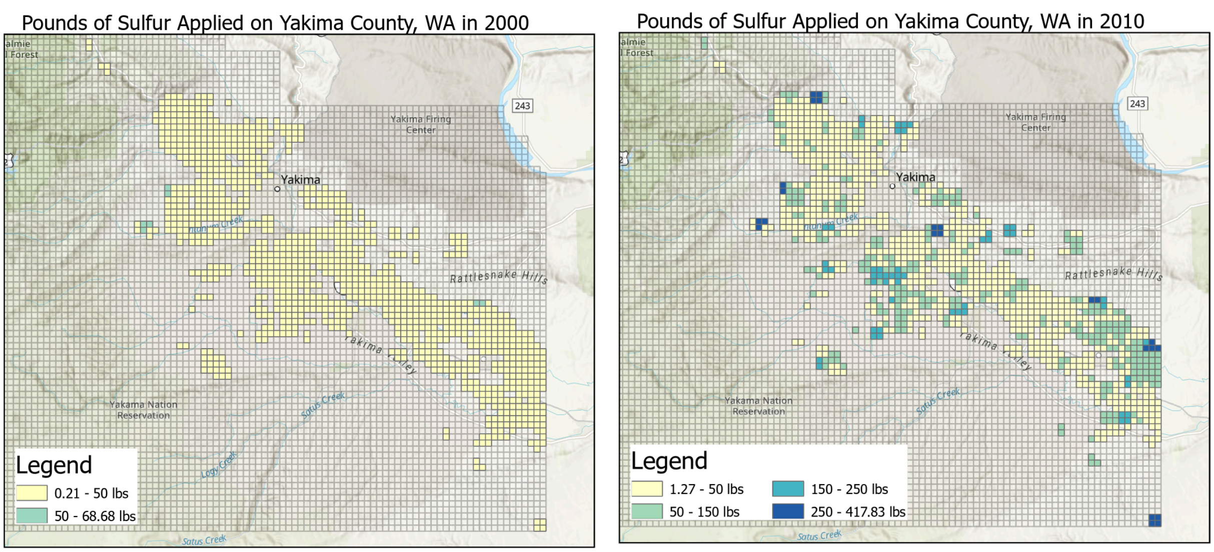
Supplemental Figure 21: Pounds of Chlorpyrifos Applied on Fresno County, CA in 2019 using USGS data



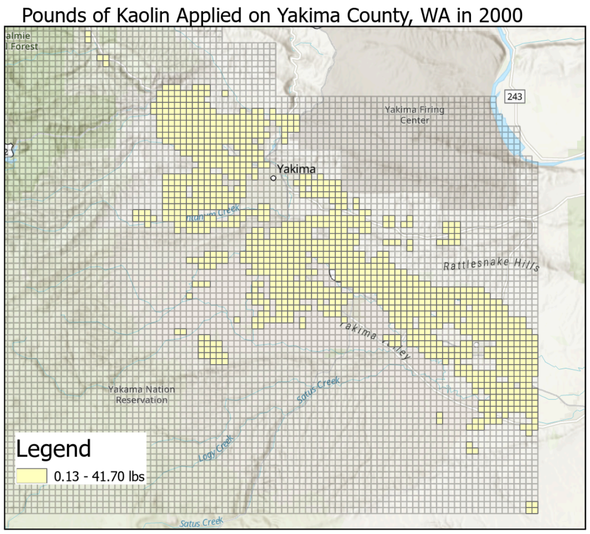
Supplemental Figure 22: Acres of Orchards and Vineyards in Yakima County, CA in 2023 According to WSDA (n.d.)

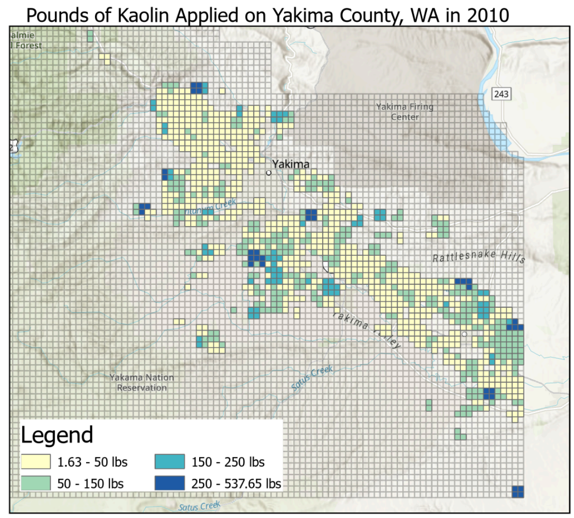


Supplemental Figure 23: Pounds of Petroleum Oil Applied on Yakima County, WA in 2000 and 2010 using USGS data

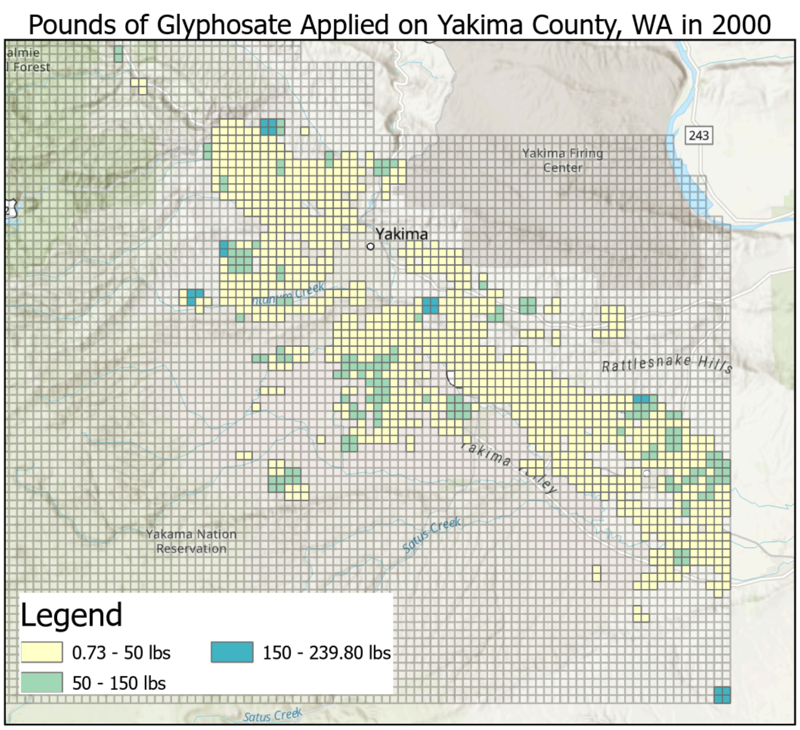


Supplemental Figure 24: Pounds of Sulfur Applied on Yakima County, WA in 2000 and 2010 using USGS data

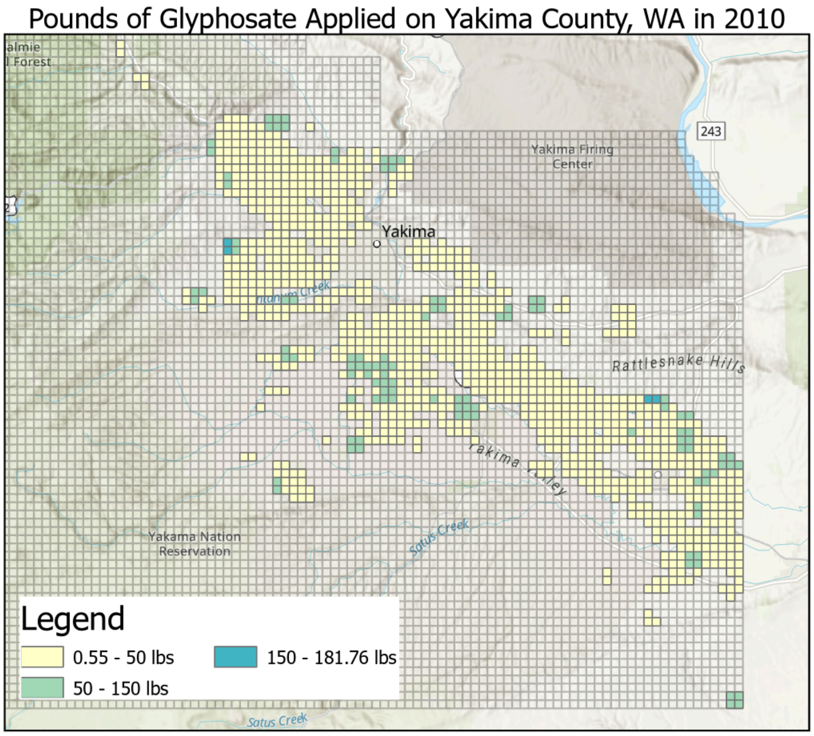




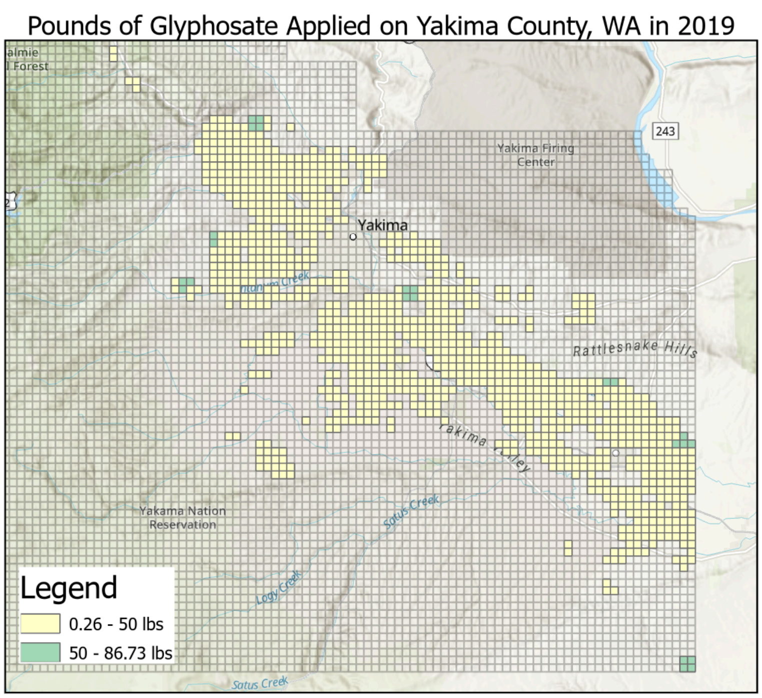
Supplemental Figure 25: Pounds of Kaolin Applied on Yakima County, WA in 2000 and 2010 using USGS data



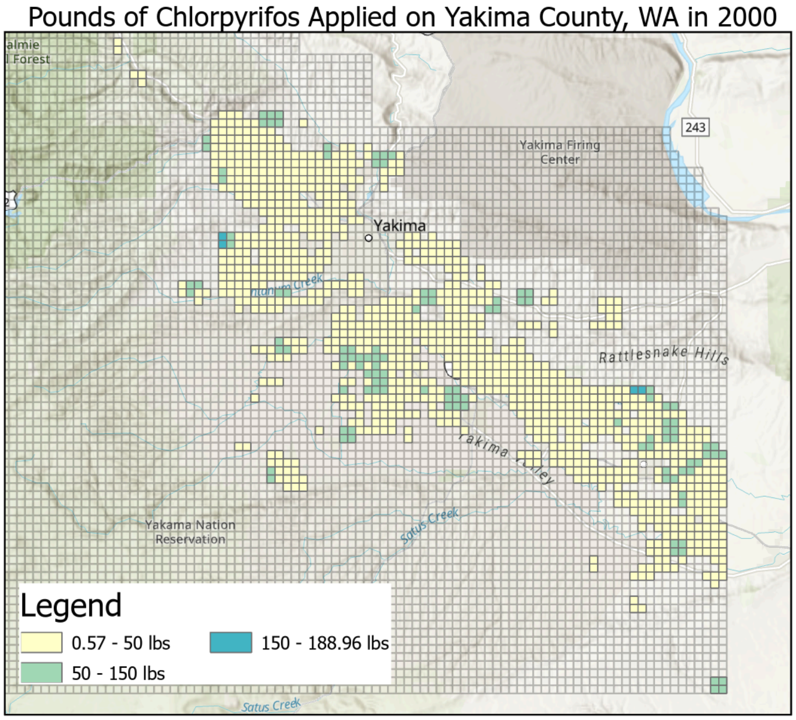
Supplemental Figure 26: Pounds of Glyphosate Applied on Yakima County, WA in 2000 using USGS data



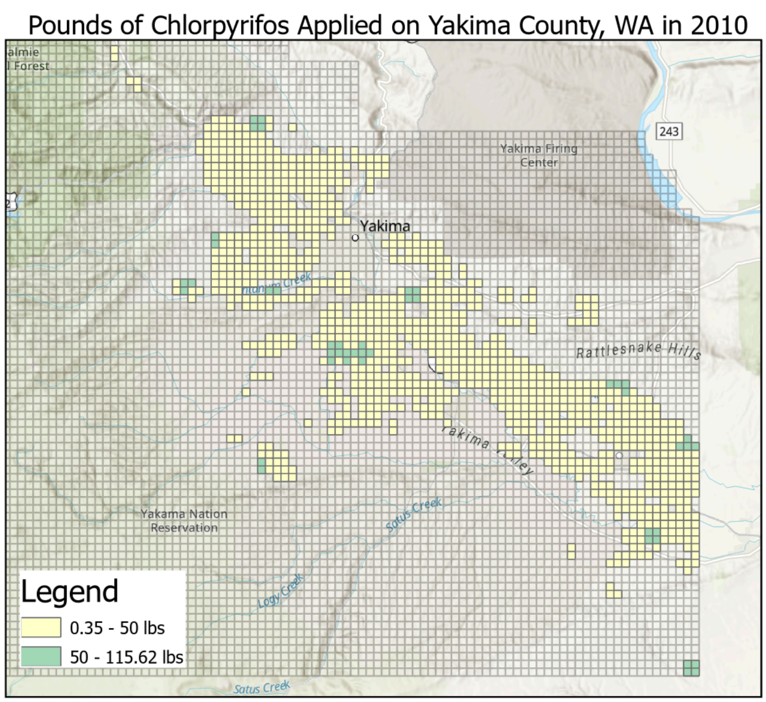
Supplemental Figure 27: Pounds of Glyphosate Applied on Yakima County, WA in 2010 using USGS data



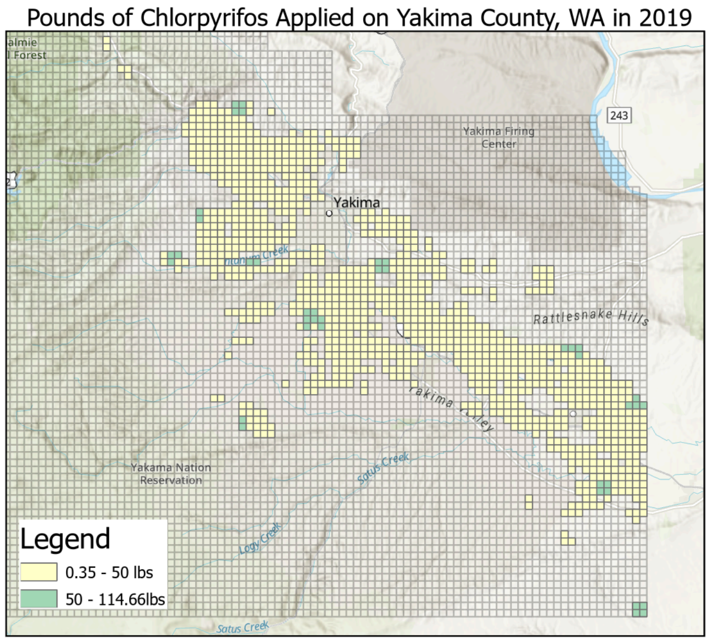
Supplemental Figure 28: Pounds of Glyphosate Applied on Yakima County, WA in 2019 using USGS data



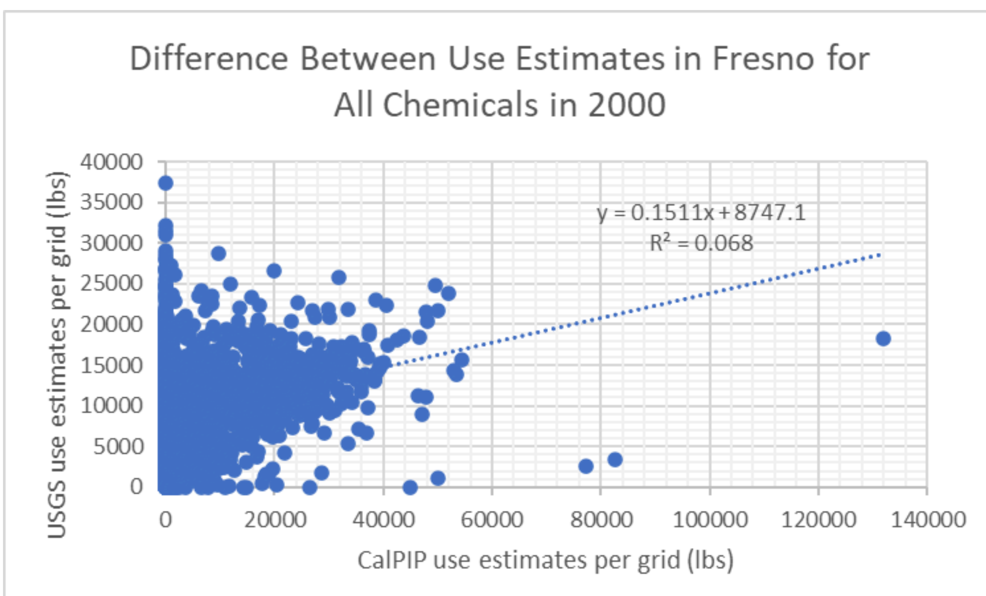
Supplemental Figure 29: Pounds of Chlorpyrifos Applied on Yakima County, WA in 2000 using USGS data



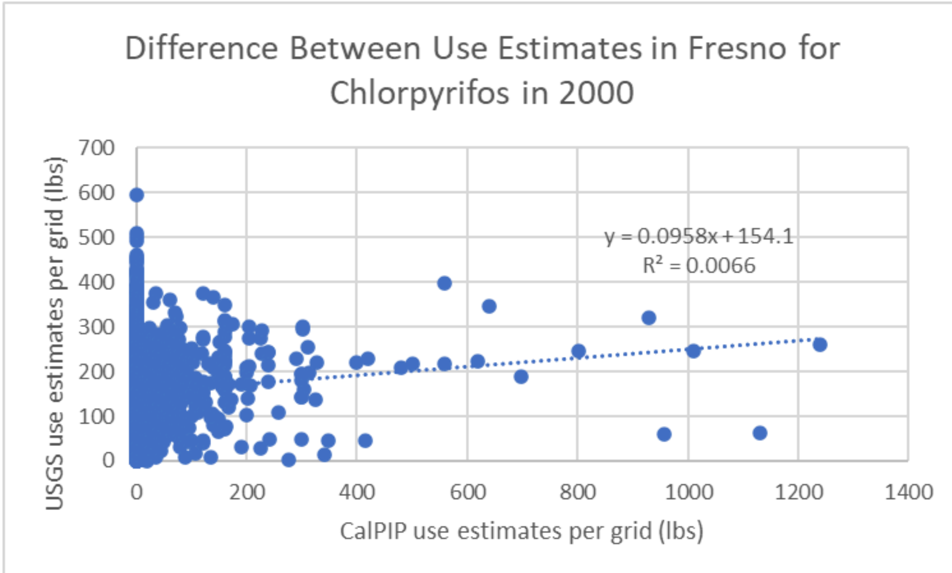
Supplemental Figure 30: Pounds of Chlorpyrifos Applied on Yakima County, WA in 2010 using USGS data



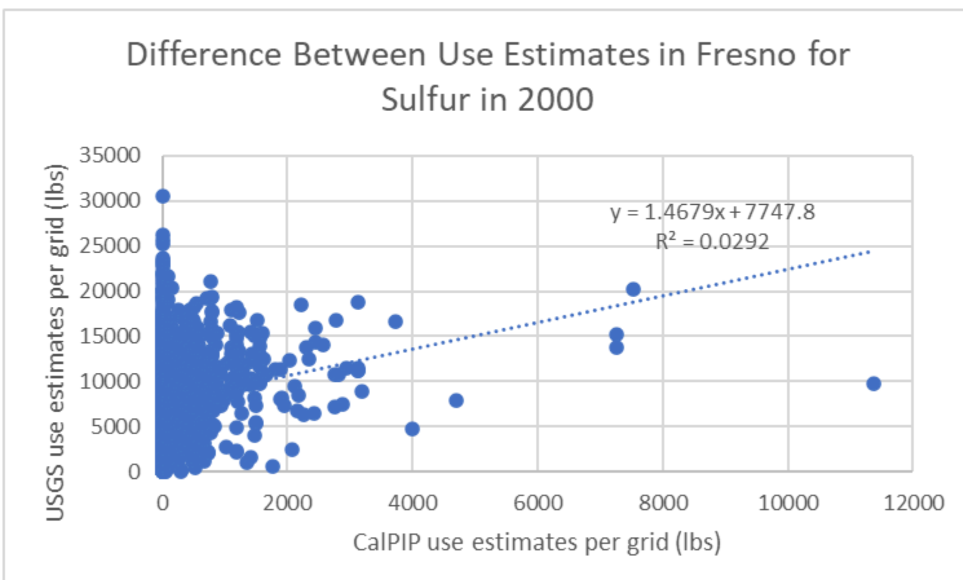
Supplemental Figure 31: Pounds of Chlorpyrifos Applied on Yakima County, WA in 2019 using USGS data



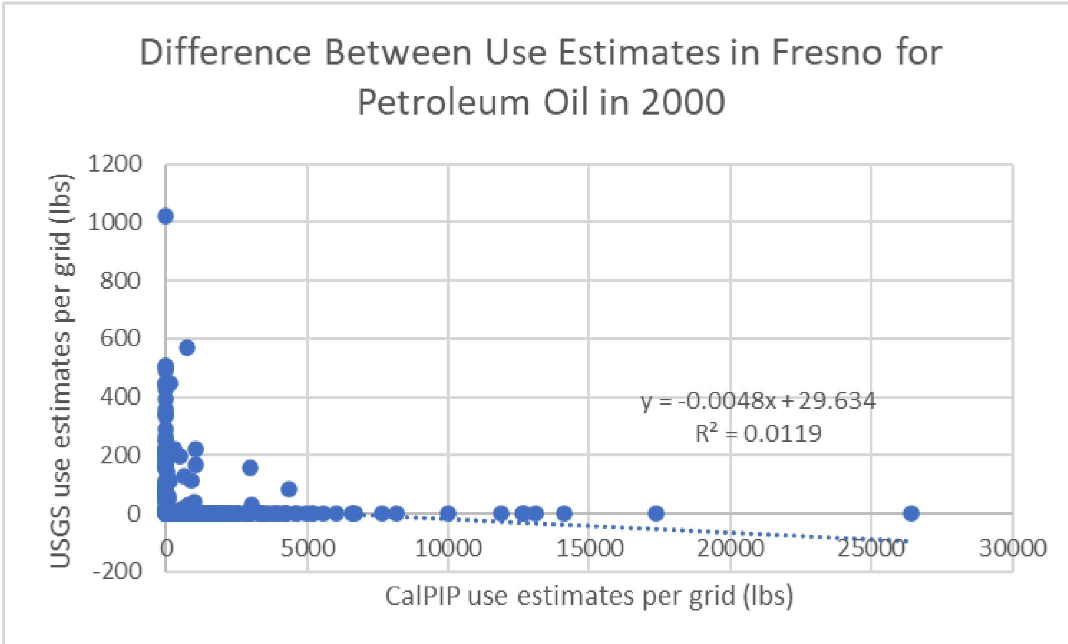
Supplemental Figure 32: Difference Between Use Estimates on Fresno for All Chemicals in 2000



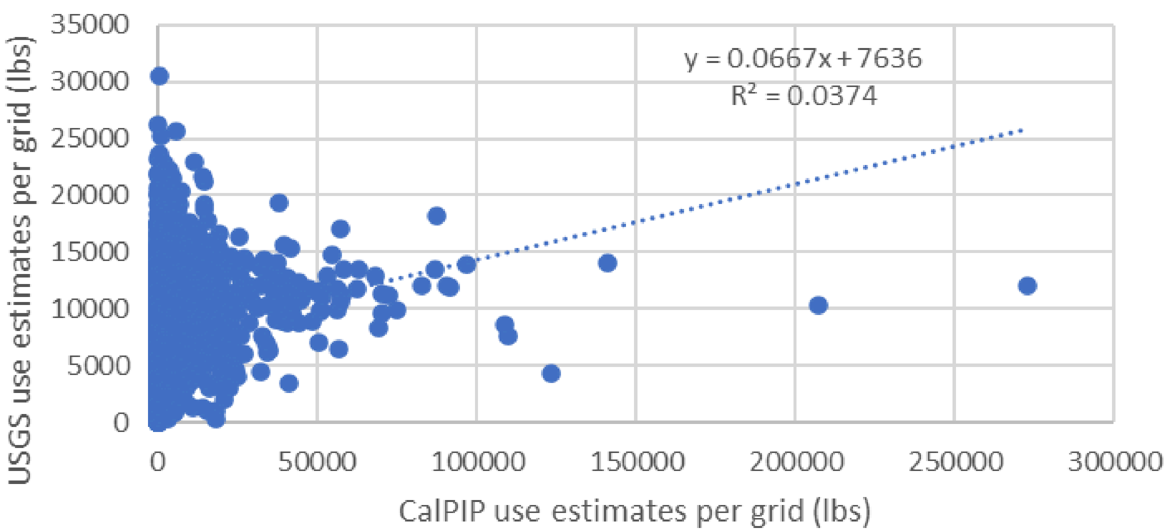
Supplemental Figure 32: Difference Between Use Estimates on Fresno for All Chemicals in 2000



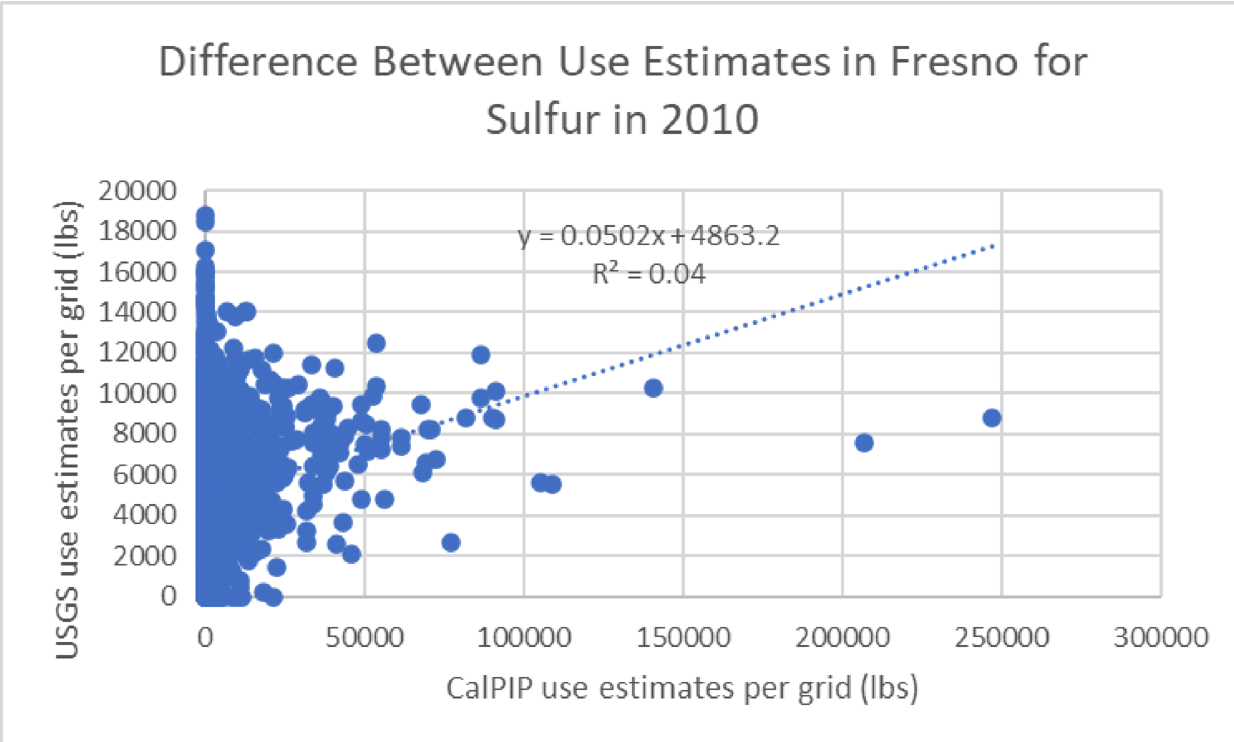
Supplemental Figure 33: Difference Between Use Estimates on Fresno for Sulfur in 2000



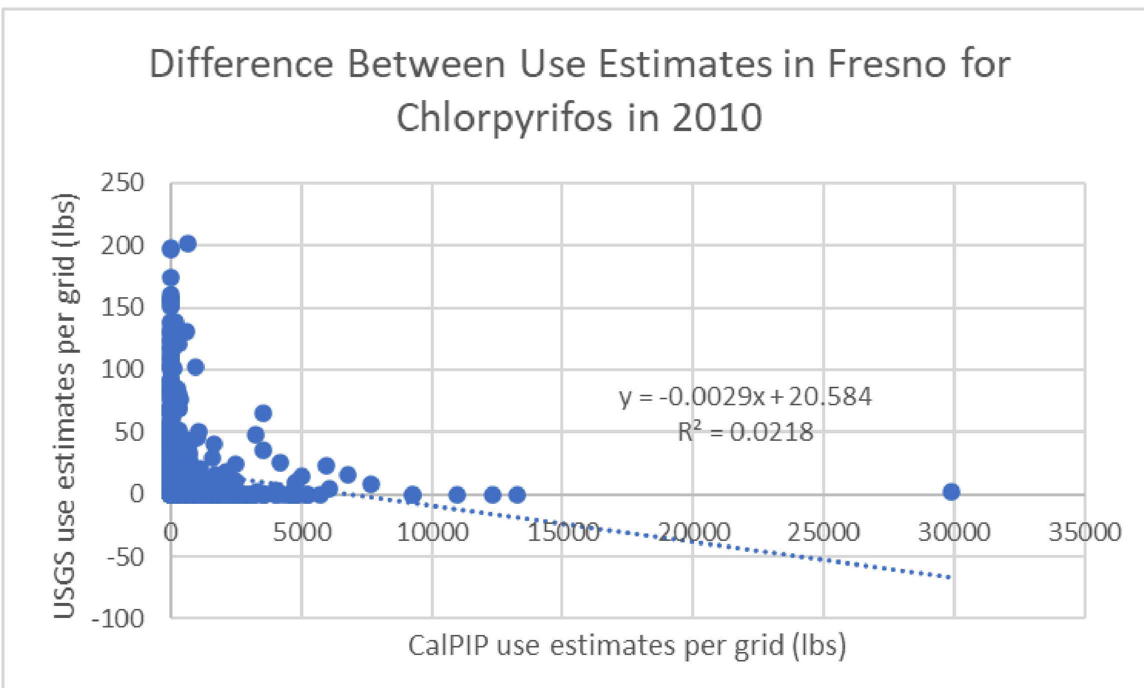
Supplemental Figure 34: Difference Between Use Estimates on Fresno for Petroleum Oil in 2000



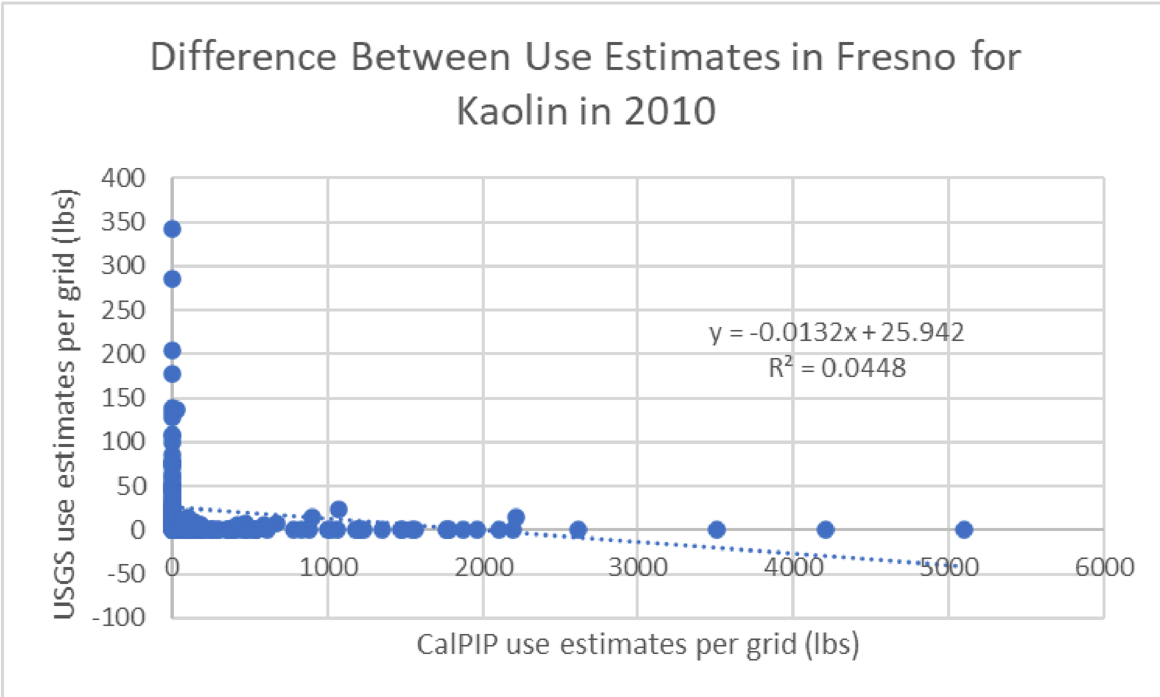
Supplemental Figure 35: Difference Between Use Estimates on Fresno for All Chemicals in 2010



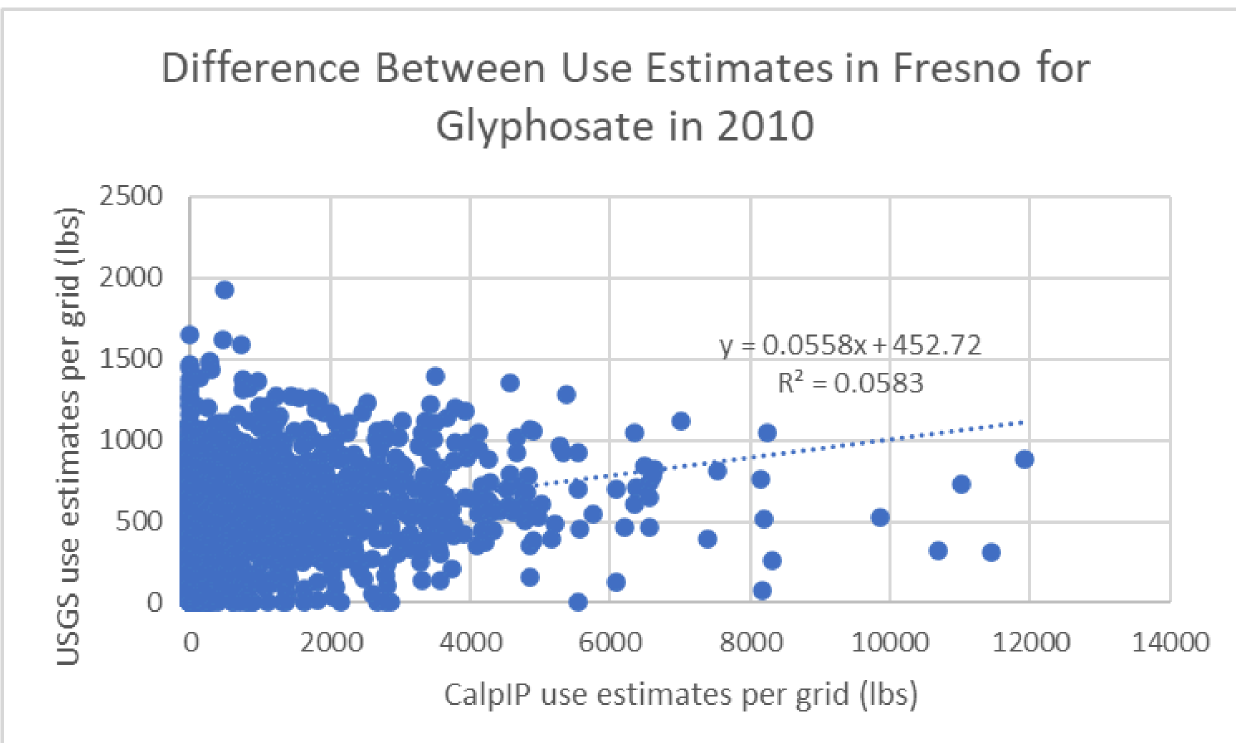
Supplemental Figure 36: Difference Between Use Estimates on Fresno for Sulfur in 2010



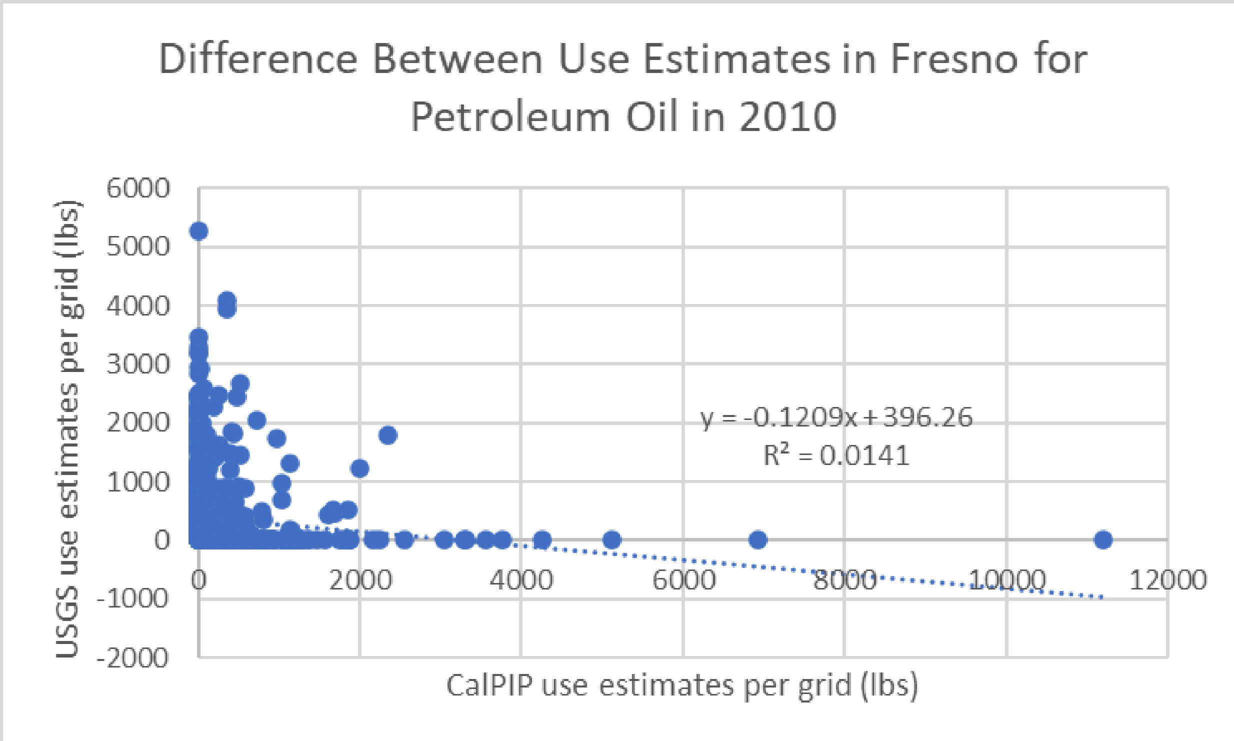
Supplemental Figure 37: Difference Between Use Estimates on Fresno for Chlorpyrifos in 2010



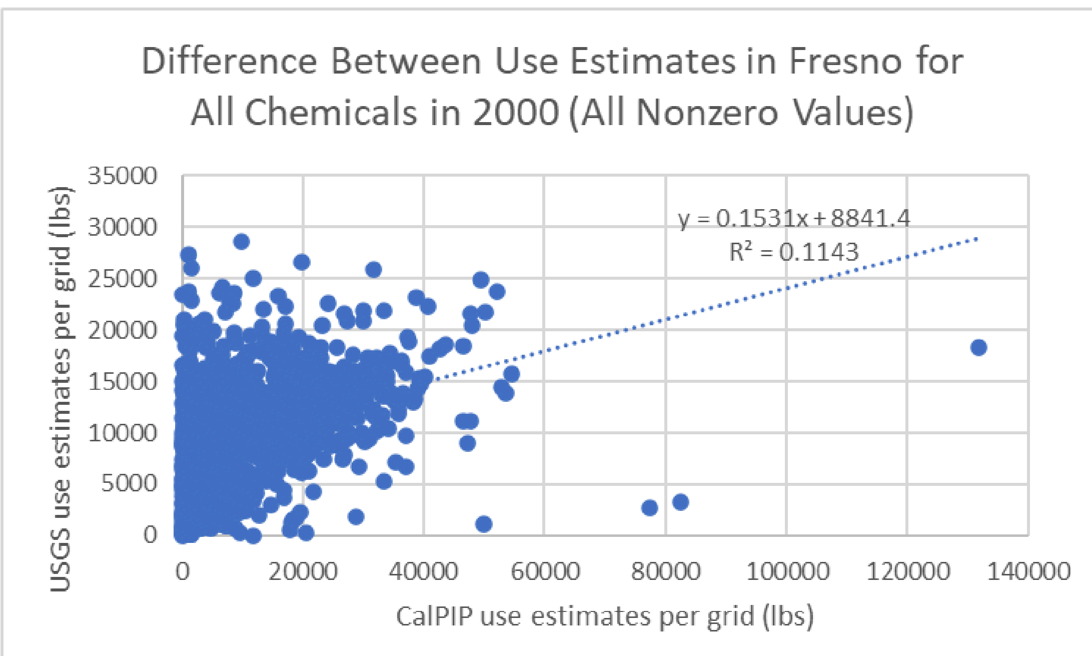
Supplemental Figure 38: Difference Between Use Estimates on Fresno for Kaolin in 2010



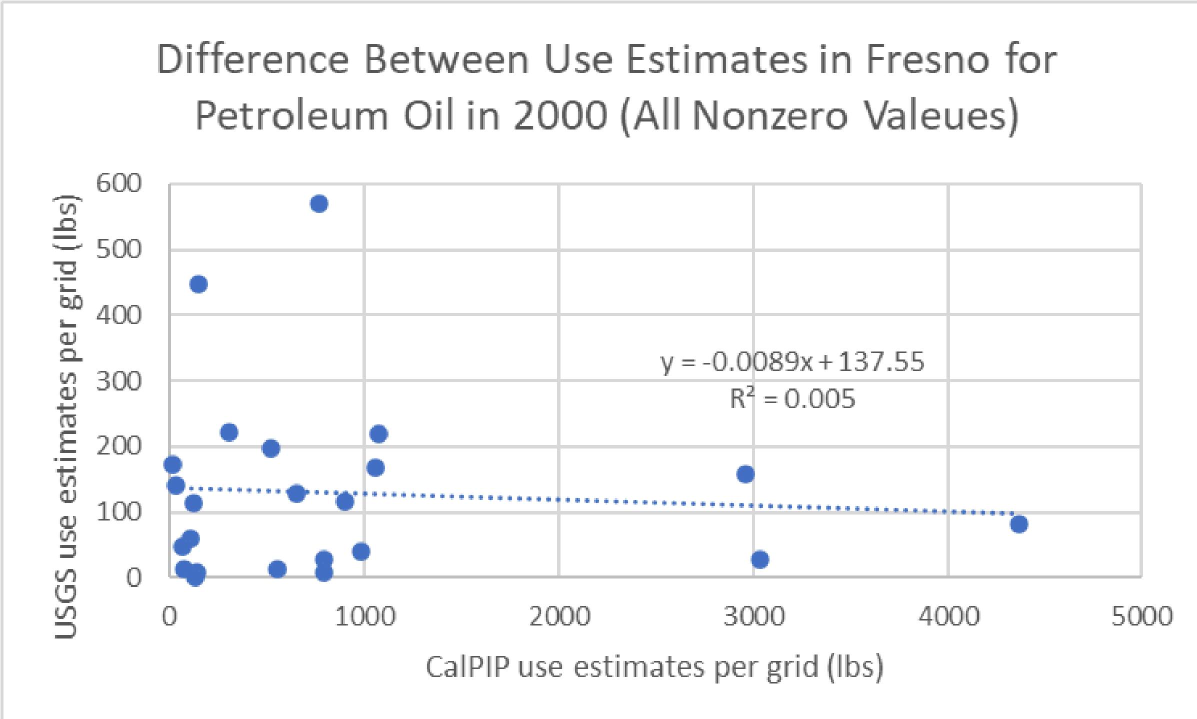
Supplemental Figure 39: Difference Between Use Estimates on Fresno for Glyphosate in 2010



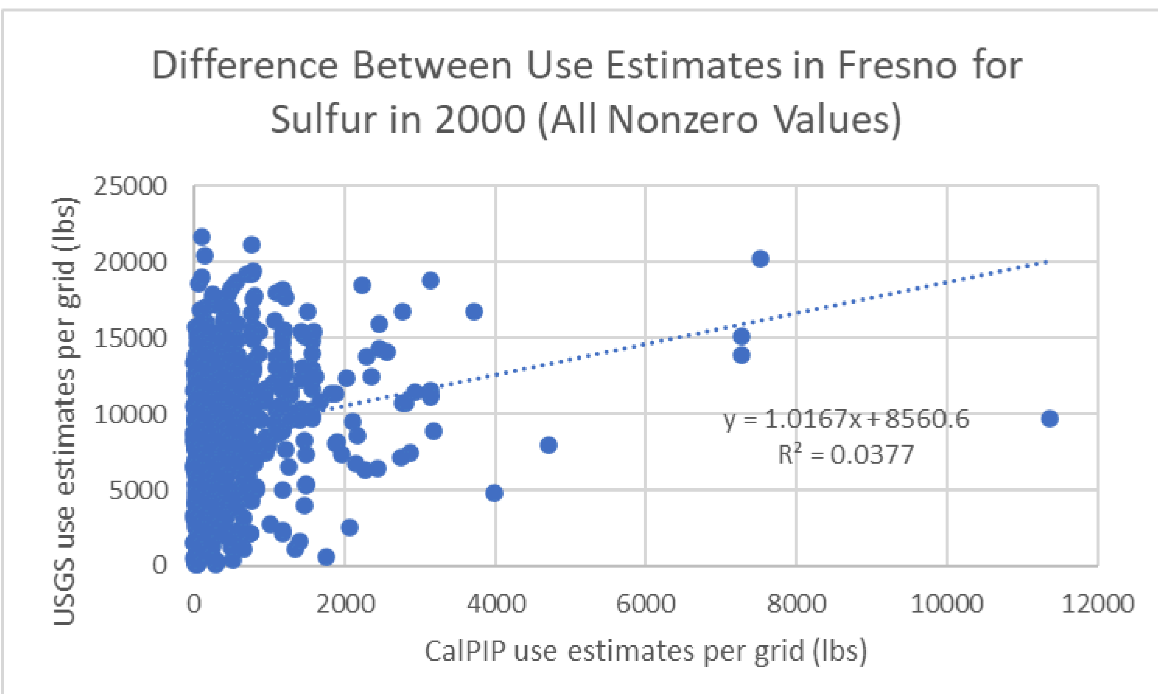
Supplemental Figure 40: Difference Between Use Estimates on Fresno for Petroleum Oil in 2010



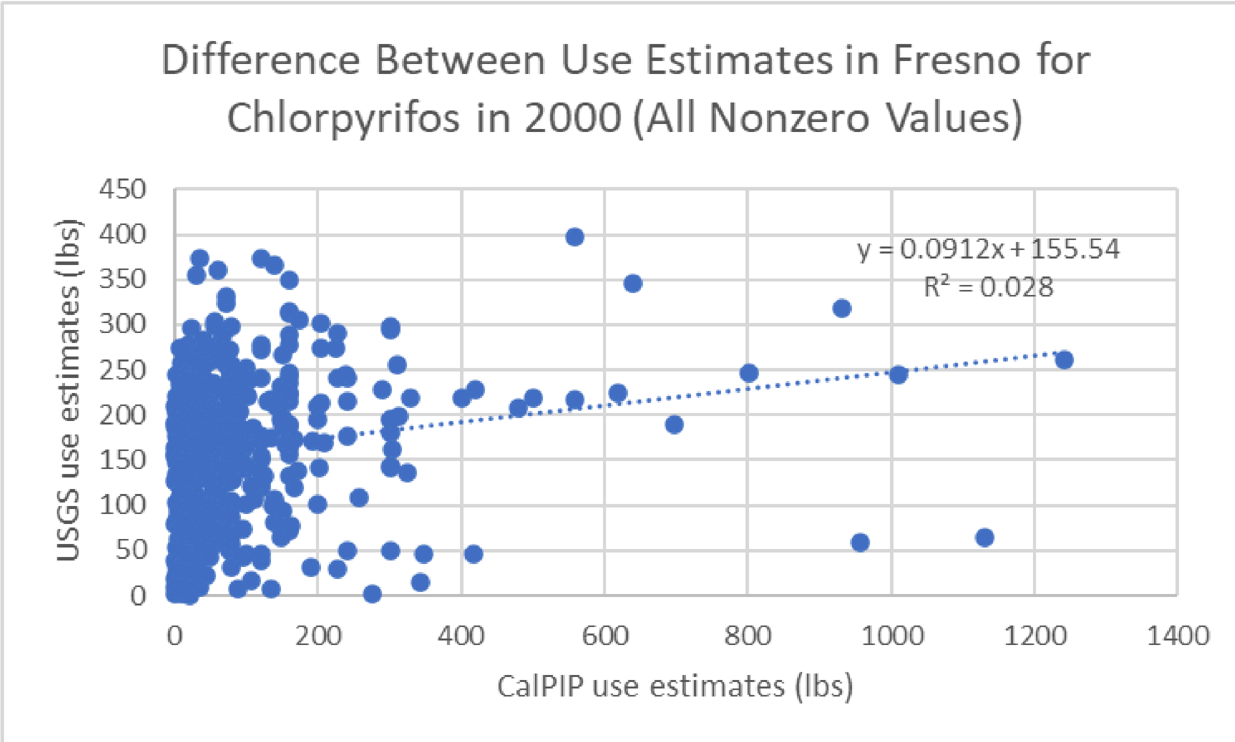
Supplemental Figure 41: Difference Between Use Estimates on Fresno for All Chemicals in 2000 (All Nonzero Values)



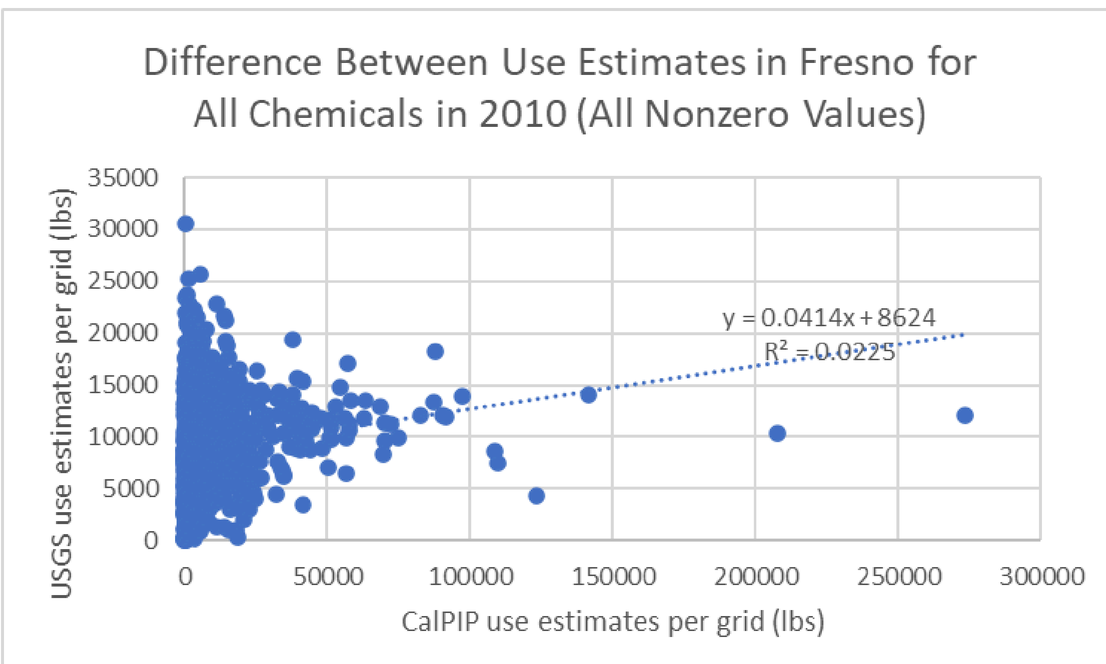
Supplemental Figure 42: Difference Between Use Estimates on Fresno for Petroleum Oil in 2000 (All Nonzero Values)



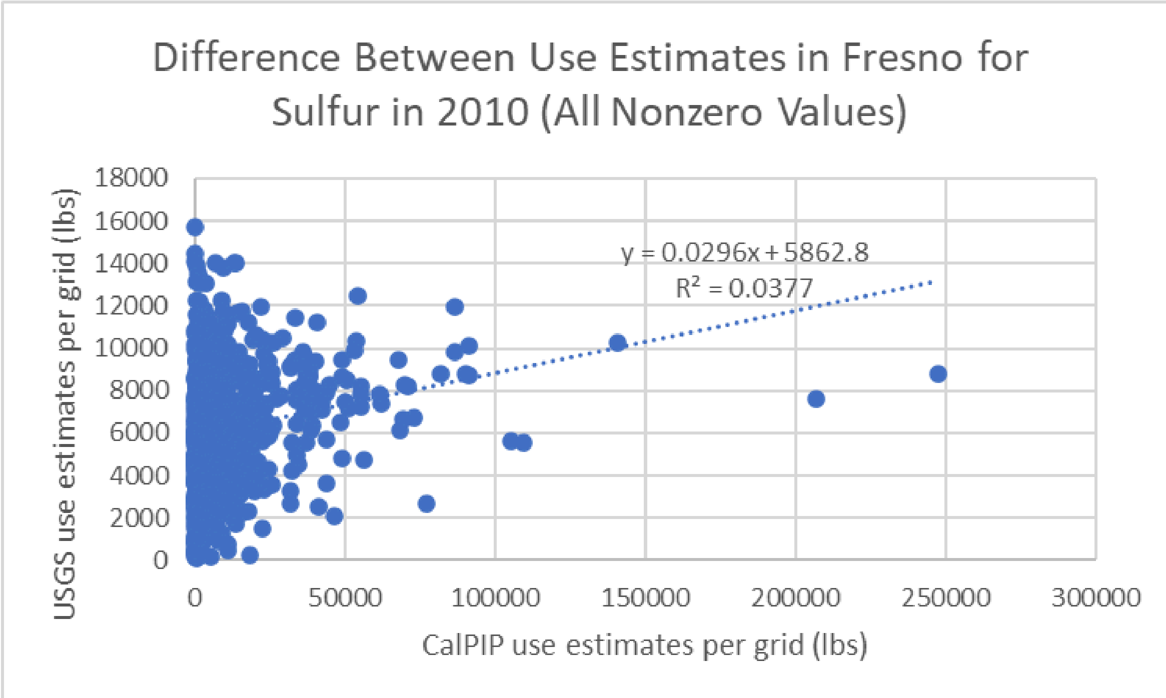
Supplemental Figure 43: Difference Between Use Estimates on Fresno for Sulfur in 2000 (All Nonzero Values)



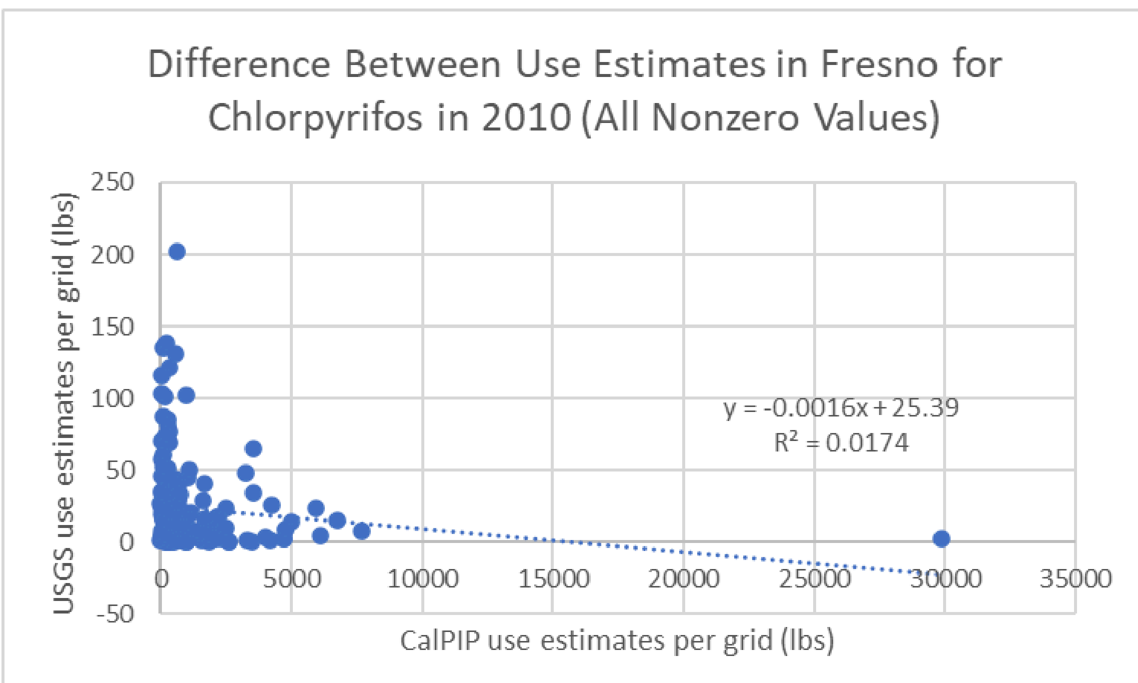
Supplemental Figure 44: Difference Between Use Estimates on Fresno for Chlorpyrifos in 2000 (All Nonzero Values)



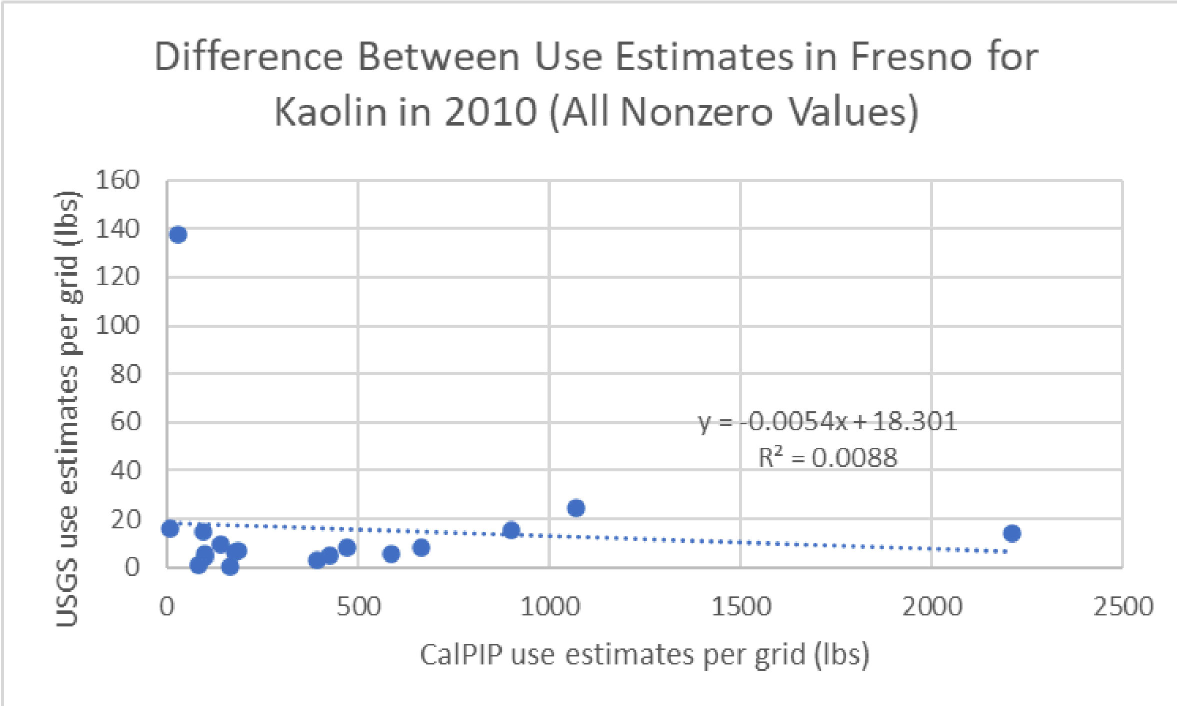
Supplemental Figure 45: Difference Between Use Estimates on Fresno for All Chemicals in 2010 (All Nonzero Values)



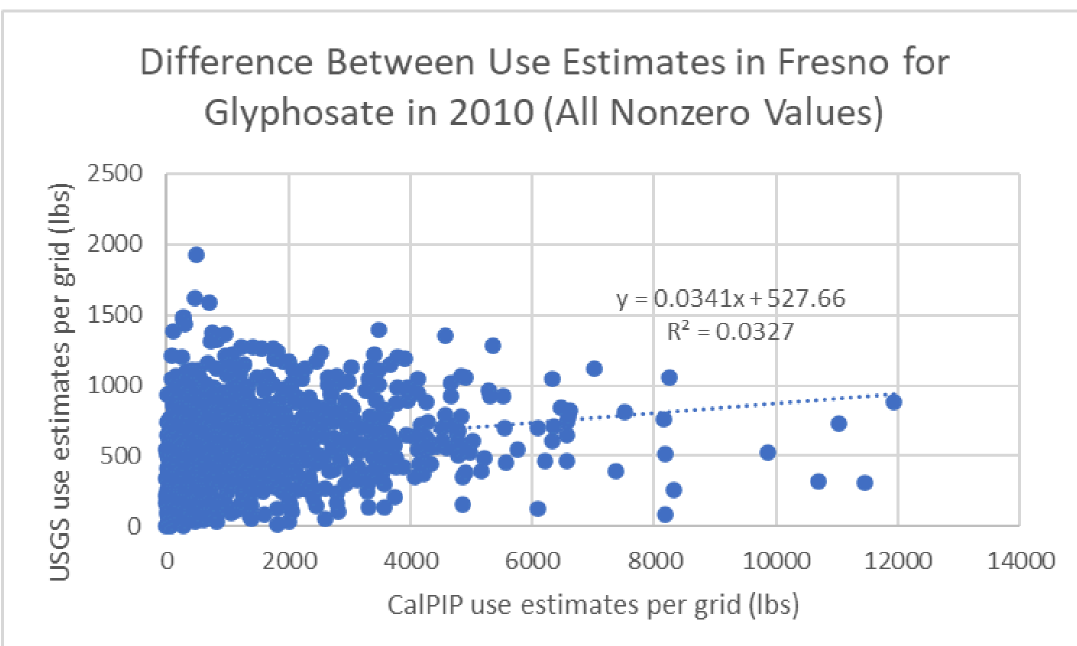
Supplemental Figure 46: Difference Between Use Estimates on Fresno for Sulfur in 2010 (All Nonzero Values)



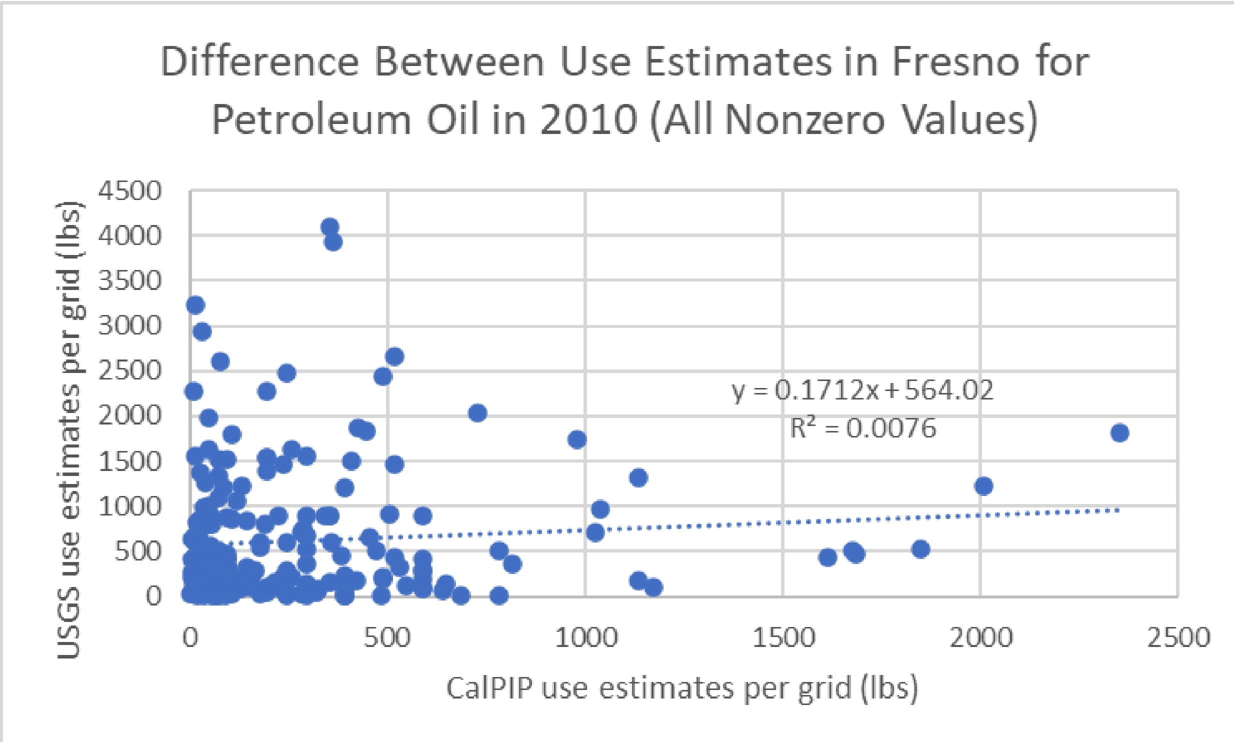
Supplemental Figure 47: Difference Between Use Estimates on Fresno for Chlorpyrifos in 2010 (All Nonzero Values)



Supplemental Figure 48: Difference Between Use Estimates on Fresno for Kaolin in 2010 (All Nonzero Values)



Supplemental Figure 49: Difference Between Use Estimates on Fresno for Glyphosate in 2010 (All Nonzero Values)



Supplemental Figure 50: Difference Between Use Estimates on Petroleum Oil Sulfur in 2010 (All Nonzero Values)