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A Rapid Assessment Technique for Identifying Future Water Use and Pesticide Risks Due to Changing Cropping Patterns

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Abstract: Changing weather patterns have already put pressure on cropping systems around the globe. Projected increases in mean temperatures and variance in precipitation will likely affect the profitability of current cropping patterns, leading to shifts in which crops are grown in a given location. The pressure on water resources in a location, in terms of both water quantity and water quality, will also change with the types of crops grown. While the southeastern United States is projected to become warmer under each of the representative concentration pathways, it is also projected to become somewhat wetter. California's Central Valley, where much of the fresh produce in the US is grown, will likely continue to suffer significant and extended droughts. The southeastern US is a prime candidate for expanding fresh produce production in response to reduced yields in the west. This paper explores the consequences on water withdrawals and water quality of shifting from row crop to vegetable production in the southeastern US. The water quality consequences are based on changes in pesticide products and application rates. The water quantity consequences are based on crop water needs. The methodology used here can be applied to other production systems around the world. Identifying the water quality and quantity implications of shifting cropping patterns is critical to the long-term sustainability of water resources.

Keywords: pesticides; agriculture; water; risk; climate change

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1. Introduction

Changes in climatic conditions have potentially profound effects on agricultural systems. The profitability of crops in a particular location can shift dramatically with changes in seasonal temperatures, precipitation, and pest pressures. Around the world, there is the distinct possibility that crops will "migrate" from one region to another in response to climatic changes [1–3]. Those migrations will cause changes in the ecological and environmental pressures associated with agricultural production. The new pressures will reflect changes in water withdrawals and nutrient and pesticide loads.

In the United States, the Central Valley of California accounts for the bulk of fresh and processed vegetable production. The recent increase in the variability of precipitation and the associated vulnerability of surface and groundwater sources have led many to expect a migration of these high-value, water-intensive crops to other parts of the country, especially the relatively wet southeast. If such a migration were to occur, it would represent a shift in the southeast's current row crop-oriented agricultural system.

Figure 1 shows the number of acres planted to the four major row crops (corn, cotton, peanuts, and soybeans) and vegetables in Georgia over time. The data are from the United States Department of Agriculture's Census of Agriculture. The planted acreage is clearly dominated by the row crops, especially cotton and peanuts, although the acreage planted to each does fluctuate; vegetables are planted in the state to a lesser extent. Importantly, the land area suitable for vegetable production in the southeast region (80 million acres) is more than three times greater than that of the western region (22 million acres) [4], and water resources are expected to be significantly less stressed than in the west in the years to come (see Figure 2).

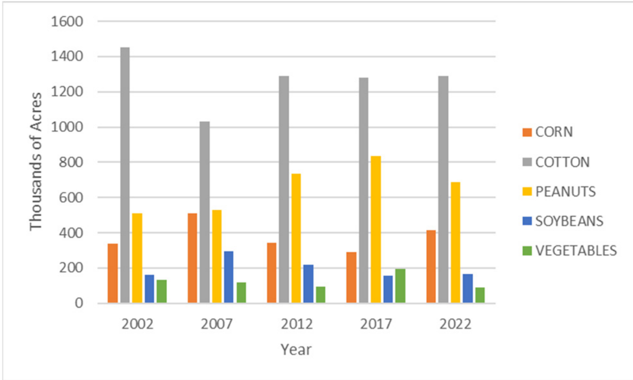

Figure 1. Historic acreage dedicated to major crops in Georgia.

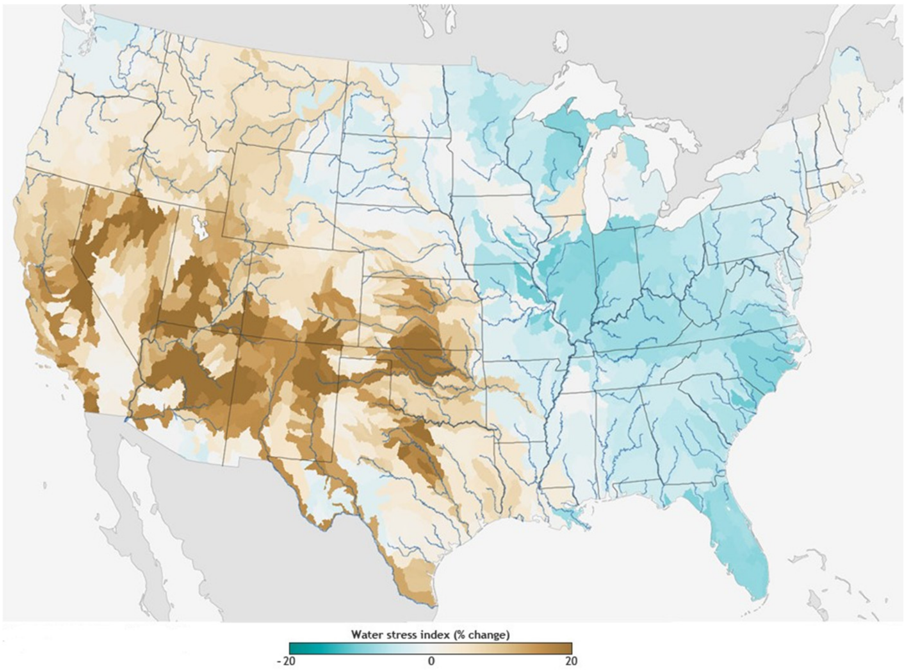

Figure 2. Projected change in water stress by mid-century (2040–2060) Ccompared to 1900–1970 historical conditions (adapted from https://toolkit.climate.gov/image/482, accessed on 20 May 2024).

To assess the costs and benefits of such a migration and develop mitigation strategies, it is important to anticipate how the environmental impacts of agriculture could change. Most agricultural extension services around the world, however, are under-resourced and do not have the expertise or budget to execute assessments that require extensive information and proprietary, pay-for-access models. A relatively cheap, rapid assessment technique that can identify areas of particular concern could be a pragmatic way to prioritize mitigation strategies and efforts.

In this paper, we develop a methodology that uses publicly available pesticide information and free-of-charge modeling software for comparing the profile of relative environmental risk of agricultural production across selected crops. To do this, we examine the relative risks of pesticide active ingredients to eight environmental categories: groundwater, surface water, aquatic species, acute human health, chronic human health, birds, mammals, and non-target arthropods. Additionally, we develop cumulative distribution functions for water withdrawals for each crop based on historical weather data. While the methodology can be used in any setting, we present results for the US state of Georgia to demonstrate its application. It is our belief that illustrating how the risk to communities and the ecosystems they rely on are likely to change as cropping patterns change will facilitate the development of sustainable agricultural policies and practices.

2. Materials and Methods

2.1. Developing a Distribution of Irrigation Water Applications

The Decision Support System for Agrotechnology Transfer (DSSAT) [5–7], available for free download, was used to estimate irrigation water requirements for the row crops. DSSAT is essentially a crop growth simulation model that is widely used to project crop water needs [8–13] and yields under varying climate/weather conditions [14–18], pest pressures [19,20], fertilizer regimes [21], and planting strategies [22,23]. For a given crop and location, parameters related to soil type, weather, planting date, and crop variety may be specified. DSSAT projects daily plant growth and water needs over the course of a season, depending on weather and crop management activities.

We use local weather data from the U.S. National Oceanic and Atmospheric Administration (NOAA) over a 72-year period (1950–2021) to run DSSAT for each year on the four major row crops—corn, cotton, peanuts, and soybeans—grown in the Lower Flint River Basin (LFRB) in the state of Georgia. DSSAT has been calibrated in the study area for each of these crops. The seasonal irrigation water application from DSSAT is then sorted from lowest to highest to sketch a cumulative density function for each crop. While this approach does assume each data year's weather is equally likely to occur, which may not be the case under future climate conditions, the purpose of this study is to provide a general sense of how irrigation water demand could be affected by future shifts in cropping patterns.

The DSSAT model has not been calibrated for vegetable crops in the study area. Instead of running simulations for those crops, we use the results of farmer surveys. The Georgia Cooperative Extension Service (CES) conducted farm surveys in 1992, 1994, 1998, 2000, 2004, and 2008. Those surveys specifically asked farmers how much irrigation water they applied to vegetable crops. The U.S. Department of Agriculture (USDA) also conducted farm surveys in 1998, 2003, 2008, 2013, and 2018 focused on irrigated agriculture, including irrigation water applications on vegetable fields [24]. We use these data in the same manner as the DSSAT results to sketch a cumulative distribution function for irrigation water applications in vegetable production.

2.2. Relative Pesticide Risks

The risks pesticides pose to humans and the general environment depend on a variety of human and non-human factors including but not limited to application rates, application methods, weather factors at the time of application, pesticide handling and storage conditions, and the chemical properties of the pesticide [25]. To compare the relative risk a pesticide poses, we follow the approach developed in [26] and differentiate the environment into eight broad categories: acute human health, chronic human health, groundwater, surface water, aquatic species, birds, mammals, and arthropods. Pesticide active ingredients are assigned a relative risk level (HIGH, MID, LOW) for each environmental category based on the following criteria. This three-tiered classification system allows us to illustrate how pesticide risk profiles vary across different cropping systems.

2.2.1. Groundwater Risk

Gustafson's Groundwater Ubiquity Score (GUS) [27] is used to assign an active ingredient's relative risk level for groundwater. The GUS is a direct function of the soil half-life and soil adsorption index. The data for calculating the GUS for many active ingredients are available at (http://npic.orst.edu/ingred/ppdmove.htm (accessed on 10 December 2023)). We assign a groundwater risk rating of high for active ingredients with a GUS above 2.8; low risk is assigned for GUS below 1.8; and mid risk is assigned for GUS between 1.8 and 2.8.

2.2.2. Surface Water Risk

To assign surface water risks, we use the USDA's Soil Conservation Service (SCS) Surface Water Matrix (SWM) [28]. The matrix classifies active ingredients as high, mid, or low risk. For an active ingredient not included in the SWM, we consider its water solubility, soil adsorption index, and soil half-life, as described in [26].

2.2.3. Acute Human Health Risk

All active ingredients registered for sale in the United States must have a label approved by the U.S. Environmental Protection Agency (EPA). On the label is one of three "signal words" that indicate their relative acute toxicity to humans. In our methodology, active ingredients labeled with the signal word "Caution" are assigned a low acute human health risk; those with the signal word "Warning" are assigned mid risk; and those with the signal word "Danger" or "Danger/Poison" are assigned high risk to acute human health.

2.2.4. Chronic Human Health Risk

Pesticides can impose a wide variety of chronic human health risks. These include risks of cancer, loss of cognitive function, mutagenic reproductive risks, and other impairments. The U.S. EPA uses the following classifications for the results of chronic health effects tests for pesticides: (i) negative; (ii) no evidence; (iii) inconclusive, (iv) data gap; (v) possible; (vi) probable; and (vii) positive. In assigning a relative risk level to an active ingredient, we consider any test that resulted in a positive classification by U.S. EPA to be high risk. If an active ingredient had no positive test but did have any test classified as possible or probable or having a data gap, we consider it to be mid risk. Active ingredients for which all tests were classified negative, no evidence, or inconclusive were assigned low risk.

2.2.5. Aquatic, Mammalian, Avian, and Non-Target Arthropod Species Risk

The relative risk to non-targeted species is based on the toxicity of the active ingredient. For aquatic species, we consider the lethal concentration 50 (LC_{50}) in conjunction with the active ingredient's surface water risk. For non-aquatic species, we consider the lethal dose 50 (LD_{50}). The specific criteria used to assign relative risks to these environmental categories can be found in [26].

2.2.6. Summarizing Pesticide Risks for Each Crop

The core tenet of our methodology with respect to pesticides is "more is worse". With that in mind, after assigning a relative risk level to each active ingredient for each environmental category, we simply add up the expected application rate per acre. While it is true that the fate and transport of pesticides is a function of how they are applied, our methodology sets that component aside and allows us to see how the risk profile changes as a function of crop choice, exclusively.

To identify the pesticides used and their expected application rate for each crop, we use crop production budgets developed by the Georgia CES [29]. These budgets are routinely referenced by farmers to make crop choice and management decisions.

2.3. Fertilizer Loads

Fertilizers, especially nitrogen and phosphorous, are responsible for a significant amount of water quality impairment around the world [30–32]. As with pesticide risks, the manner in which fertilizers are applied has a profound effect on whether they leach into groundwater, run off into surface waters, or remain on the field to which they are applied. Here, again, we simply compare the fertilizer application rates across crops to understand how the risks associated with agricultural production are affected by crop choice. Expected fertilizer application rates also come from Georgia CES crop production budgets.

3. Results

3.1. Crop-Level Irrigation Water Distributions

Figure 3 illustrates how expected water use would likely increase if agricultural production in the LFR basin were to shift away from traditional row crops and into vegetable production. Across the row crops, there is a difference in expected water use; the median irrigated withdrawal for corn is about 9 acre-inches/acre, while the median cotton and peanut water withdrawals are about 7 acre-inches/acre, and the median soybean water withdrawals are about 5 acre-inches/acre. The median vegetable water withdrawal is 16 acre-inches/acre, more than double that of cotton and peanuts (the two crops with the largest acreage in the area). Moreover, in years of severe drought (90th percentile), cotton and peanut water withdrawals total around 12 acre-inches/acre, while vegetable production would likely require 28 acre-inches/acre. The median water withdrawal estimates for corn, cotton, peanut, and soybean in Georgia are consistent with previous studies [33], as are the median vegetable water withdrawals [34,35].

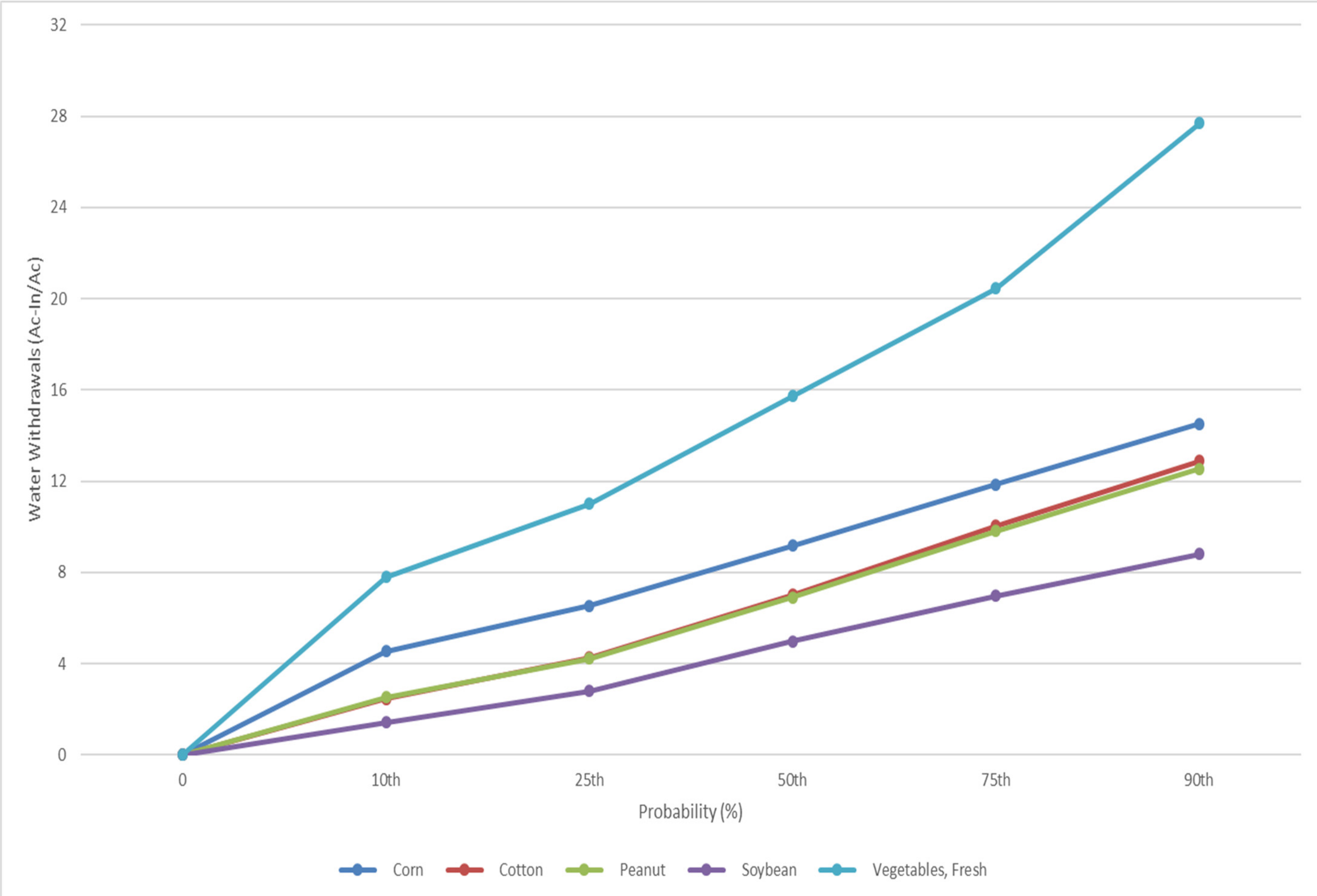

Figure 3. Cumulative density function of irrigation application rates for crops in the Lower Flint River Basin.

3.2. Crop-Level Pesticide Risks

To begin, Figure 4 shows the total pesticide load for each crop considered. The following subsections illustrate how the risk profile of those pesticide loads for each environmental category changes by crop type. Because every pesticide sold in the U.S. must have a label, and every label must have a signal word, all of the active ingredients referred to in the Georgia CES crop budgets can be assigned an acute human health risk. This is not the case with the other seven environmental categories. We were unable to find data for some active ingredients in some of the risk categories. In the graphs below, we include a risk category called "No Data" to illustrate the volume of total pesticide loads in each environmental category to which we could not assign a relative risk category.

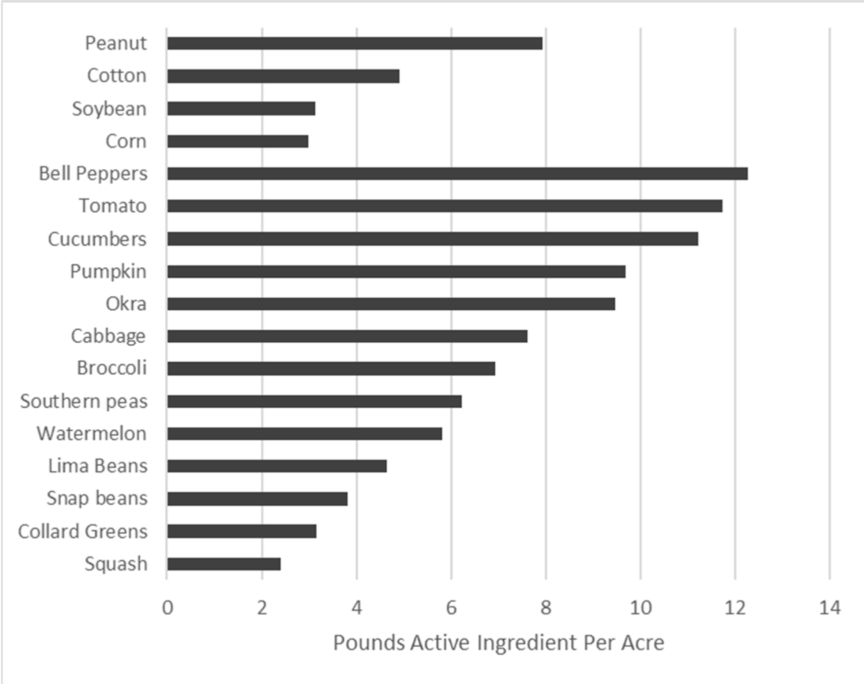

Figure 4. Expected total active ingredients by crop.

3.2.1. Acute Human Health (AHH) Risk

Figure 5 illustrates how the acute human health (AAH) risk profile changes by row crop (corn, cotton, peanut and soybean) and by select vegetable crops. The first thing to notice is that peanut production uses a lot more pesticides than the other row crops. Additionally, importantly, nearly two thirds of the total active ingredients used in peanut production are of high risk to AHH. Soybean production also has a relatively large proportion of an active ingredient that is of high risk to acute human health, but the application rate is less than half that of peanuts.

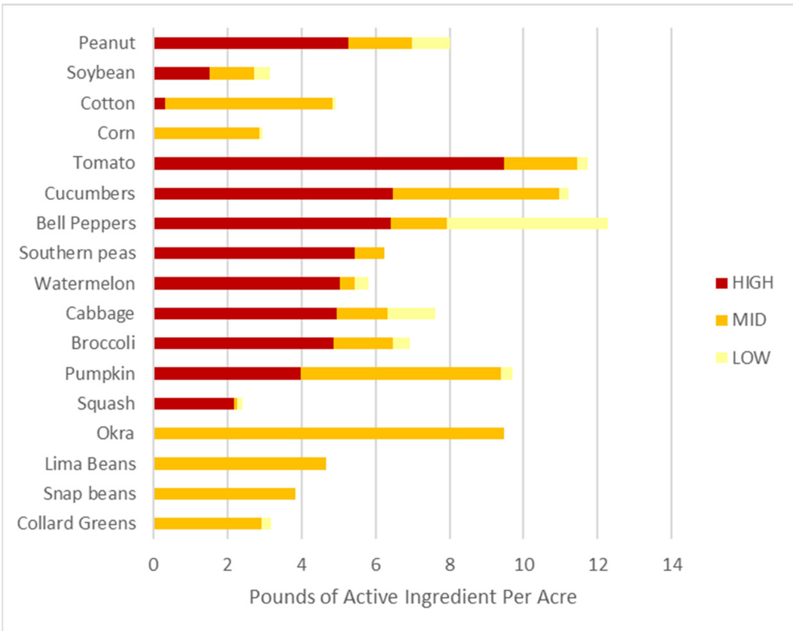

Figure 5. Pesticide loads by acute human health risk and crop.

As shown in Figure 4, there are several vegetable crops—tomato, bell pepper, cucumber, okra, and pumpkin—that have higher total pesticide application rates than all of the row crops. Looking at Figure 5, tomato, bell peppers, and cucumber also use more active ingredients that pose a high risk to acute human health than peanuts. The acute human health risk profiles of cabbage and broccoli are very similar to that of peanuts. Additionally, while southern peas have a lower total pesticide load than peanuts, they use a greater quantity of high-risk AHH active ingredients. It is evident that a shift in crop choice from row crops to toward vegetables, in general, would heighten the need for awareness of these AHH risks in particular.

3.2.2. Chronic Human Health (CHH) Risk

Figure 6 illustrates how the chronic human health (CHH) risk profile changes by row crop and by select vegetable crops. A significant proportion of the cotton, peanut and soybean pesticide load is missing data that can classify the CHH risk. On the other hand, nearly all of the vegetable pesticides could be classified with respect to CHH risk.

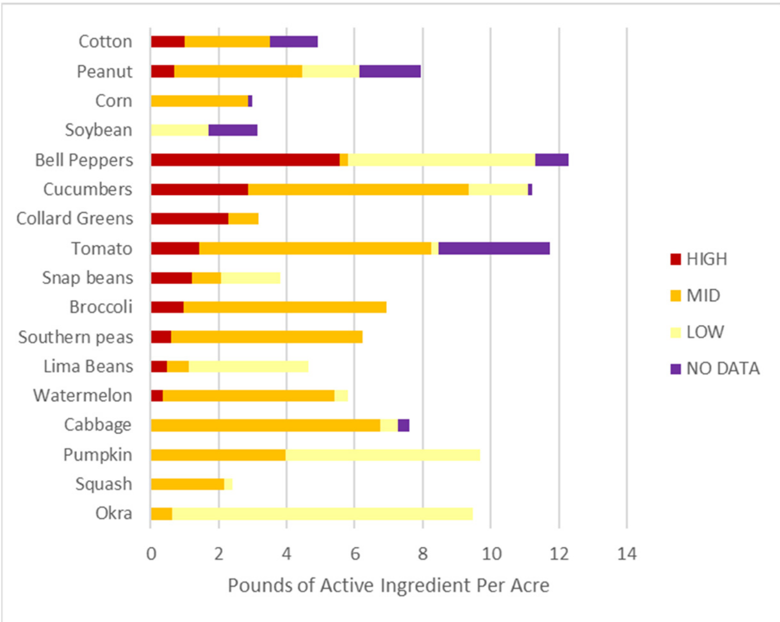

Figure 6. Pesticide loads by chronic human health risk.

As with AHH risk, bell pepper and cucumber production also use a relatively large amount of high-risk CHH active ingredients. Collard greens and snap beans did not have any high-risk AHH active ingredients, but they both use more high-risk CHH than any of the row crops (setting aside the CHH missing data). Tomato production also uses more high-risk CHH active ingredients than the row crops, and as with cotton, peanuts, and soybeans, we were unable to classify about 30% of the tomato pesticide load with respect to CHH risk.

3.2.3. Groundwater (GW) Risk

Figure 7 illustrates how the groundwater (GW) risk profile changes with row crops and by select vegetable crops. Corn and cotton production both use a fair amount of high-risk-to-GW active ingredients. Peanut and soybeans use mostly low-risk-to-GW active ingredients; however, a significant proportion of their pesticide load could not yet be classified with respect to GW risk.

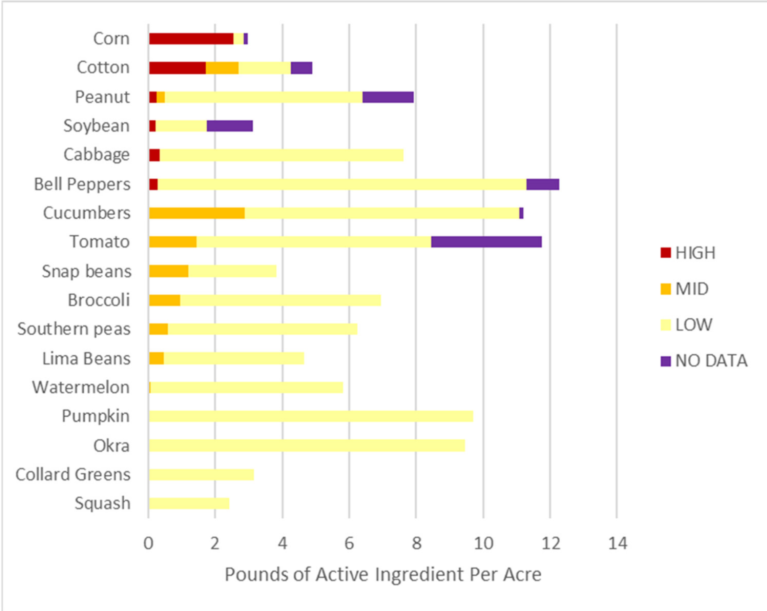

Figure 7. Pesticide loads by groundwater risk.

As shown in Figure 7, the GW risk profile for the vegetables is dominated by low-risk-to-GW active ingredients. The exception again is tomato, nearly 30% of the load of which we could not classify. Because of its sandy soils, pesticide leaching is a concern in the LFR basin. Figure 5 suggests that switching from corn and cotton production to peanut, soybean, and vegetable production would likely alleviate those concerns.

3.2.4. Surface Water (SW) Risk

Figure 8 illustrates how the surface water (SW) risk profile changes by row crop and by select vegetable crops. The SW risk profile for each crop is practically a mirror image of its GW risk profile. We see that peanut and soybean among the row crops utilize a significant proportion of high-risk-to-SW pesticides, while the active ingredients used on corn and cotton primarily pose little risk to surface water.

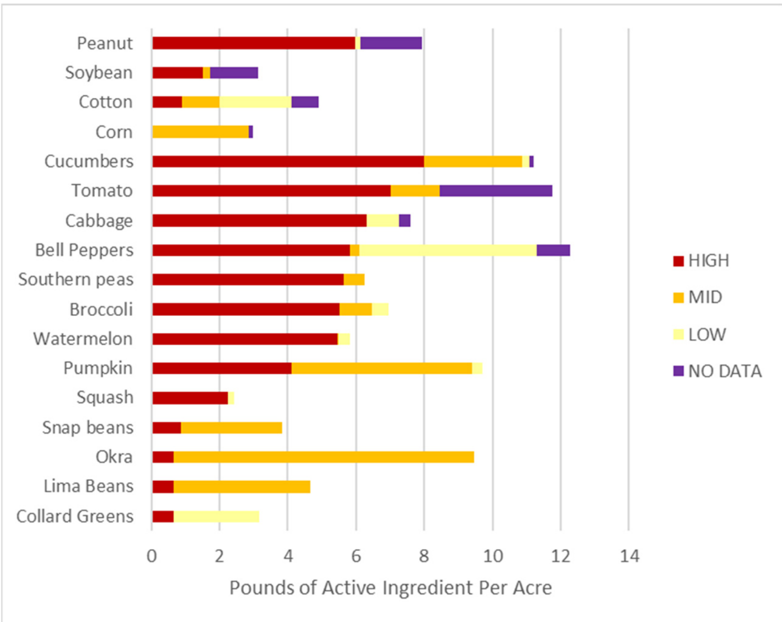

Figure 8. Pesticide loads by surface water risk.

Vegetable crops also are heavily reliant on high-risk-to-SW pesticides. Bell pepper, broccoli, cabbage, cucumber, southern peas, tomato, and watermelon all typically require the application of more than 4 pounds of high-risk-to-SW active ingredient each season. Again, we were unable to locate data to assign a risk classification to about 30% of the pesticide load for tomatoes.

3.2.5. Aquatic Species (AS) Risk

Figure 9 illustrates how the aquatic species (AS) risk profile changes by row crop and by select vegetable crops. As mentioned in Section 2, the AS risk classification for a given active ingredient is calibrated by its surface water risk classification when the SW risk is low, but not when it is mid or high. Bell pepper, collard greens, and cotton are the only crops with significant loads of low-risk-to-SW active ingredients. The pesticide loads for all of the other crops are dominated by high- and mid-SW-risk active ingredients. As such, the toxicity of the active ingredient to aquatic species is the predominant factor in assigning its AS risk class.

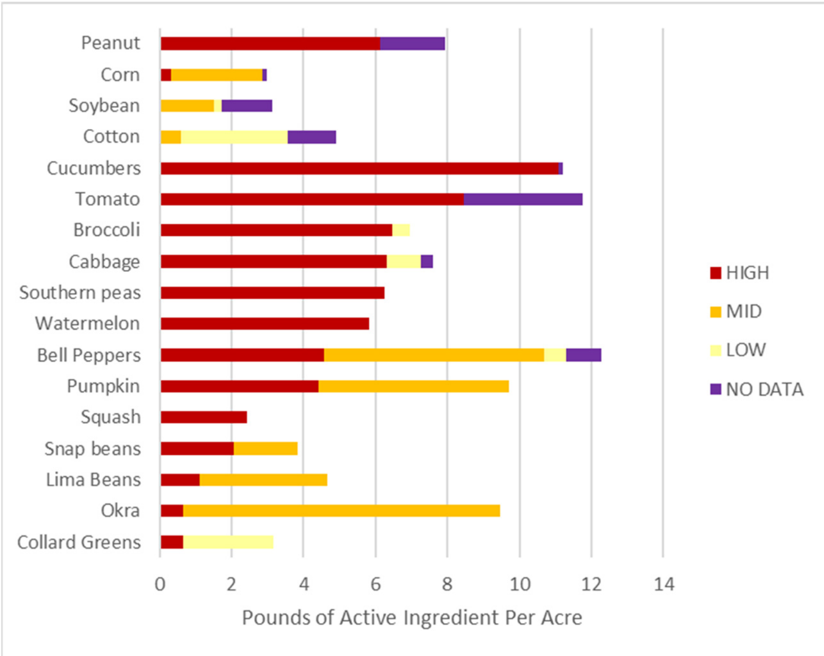

Figure 9. Pesticide loads by risk to aquatic species.

Among the row crops, peanut production uses the most high-risk-to-AS pesticides. Cotton uses the most low-risk-to-AS active ingredient, although to a significant amount of the cotton, peanut, and soybean load, we could not assign an AS risk classification. Cucumbers, tomato, broccoli, cabbage, southern pea, watermelon, and squash production are dominated by active ingredients classified as high risk to aquatic species. With the exception of collard greens, the other vegetable crops use mostly high- and mid-risk active ingredients, with respect to aquatic species. In general, a shift from a row crop production regime to vegetables would constitute a significant shift in the pesticide risk to aquatic species. Peanut production, however, is the row crop outlier in this category.

3.2.6. Mammalian (MA) Risk

Figure 10 illustrates how the mammalian species (MA) risk profile changes by row crop and by select vegetable crops. While there are some data gaps for the row crops, most active ingredients used across all crops are classified as being of low risk to mammals. The same can be said for the vegetable crops, although bell pepper and southern pea production do have high application rates of high-risk-to-MA pesticides. Furthermore, the total amount of active ingredient applied is generally greater for the vegetable crops than the row crops.

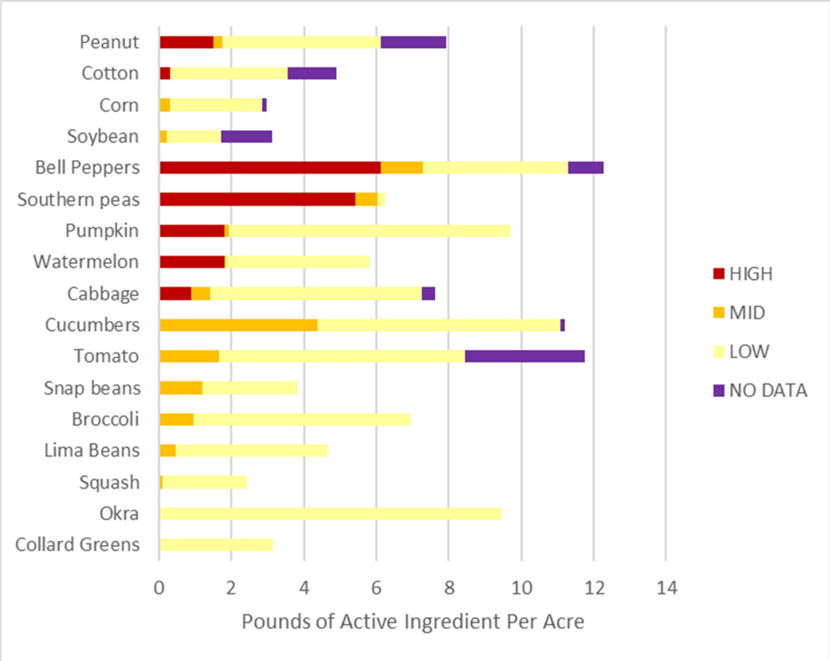

Figure 10. Pesticide loads by risk to mammalian species.

3.2.7. Avian Species (AV) Risk

Figure 11 illustrates how the avian species (AV) risk profile changes by row crop and by select vegetable crops. There are, again, large data gaps for active ingredients used on peanut, cotton, soybean, and tomatoes. Vegetable crops have higher application rates than the row crops, and their risk profiles generally have more active ingredients with high and mid AV risk. As such, a shift to vegetable production would likely increase pesticide risks to avian species.

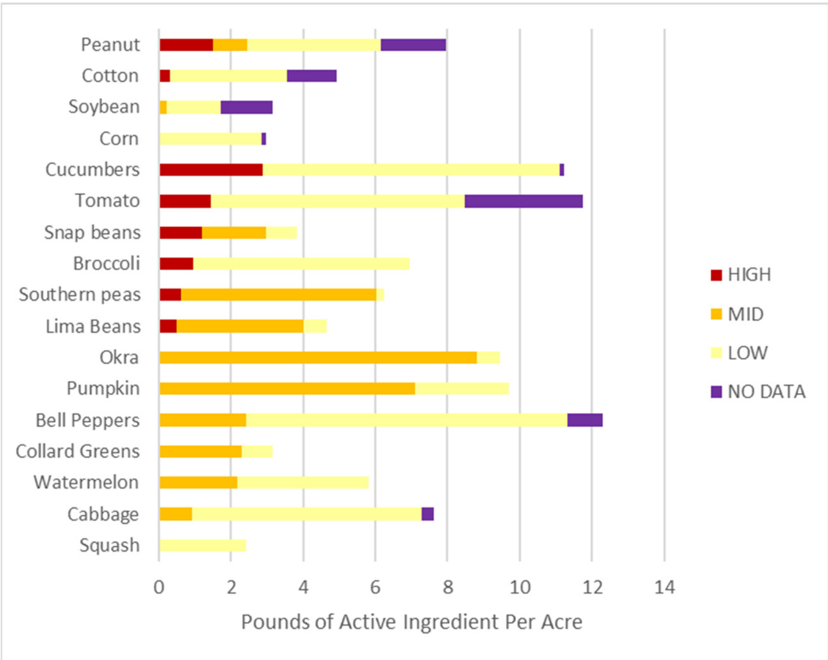

Figure 11. Pesticide loads by risk to avian species.

3.2.8. Non-Target Arthropod (NT) Risk

Figure 12 illustrates how the non-target arthropod species (NT) risk profile changes by row crop and by select vegetable crops. Here, crop selection makes a significant difference in the NT risk profile. Pesticide use for the row crops is oriented mostly toward herbicides, whereas pesticide use in vegetable production mainly involves insecticides. As a result, the active ingredients in row crop production are generally classified as being of low risk to NT, while a significant amount of the pesticide load for several vegetable crops is classified as being of high risk to non-target arthropods. This category is especially important given the need for robust pollinator populations to facilitate the development of most crops.

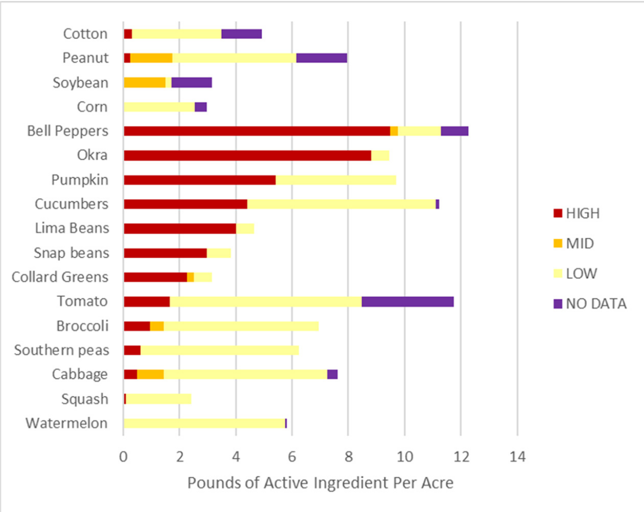

Figure 12. Pesticide loads by risk to non-target arthropods.

3.3. Nitrogen and Phosphorous Fertilizer Loads

Figure 13 illustrates recommended nitrogen and phosphorous application rates for row crops and vegetable crops in Georgia. Peanuts and soybeans are both legumes that do not require nitrogen. Peanuts also do not require phosphorous applications. Corn, on the other hand, has high nitrogen and phosphorous requirements, while cotton has relatively modest nitrogen and phosphorous needs. All of the vegetables, with the exception of lima beans and southern peas, have a nitrogen application rate that exceeds that of cotton, soybeans, and peanuts. Additionally, among the vegetables, only watermelon has a lower phosphorous requirement than cotton, soybeans, and peanuts.

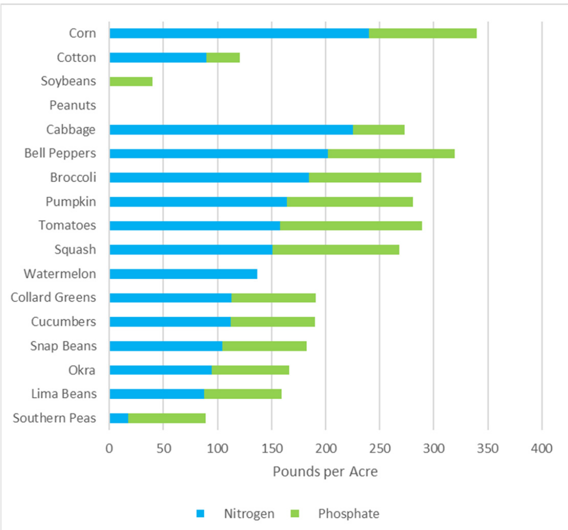

Figure 13. Nitrogen and phosphorous application rates by crop.

3.4. Pesticide Risk and Fertilizer Loads by Cropping System

To gain a better understanding of how changes in cropping systems, as opposed to changes in individual crops, would affect pesticide risk profiles and fertilizer use, we created a representative acre for row crops based on the proportion of acres planted in 2023 to each of those crops in Georgia. We also created a representative acre of vegetable production across which all of the 13 vegetable crops considered above are evenly distributed, i.e., each is planted on 1/13 of an acre. The results are presented in Figures 14 and 15.

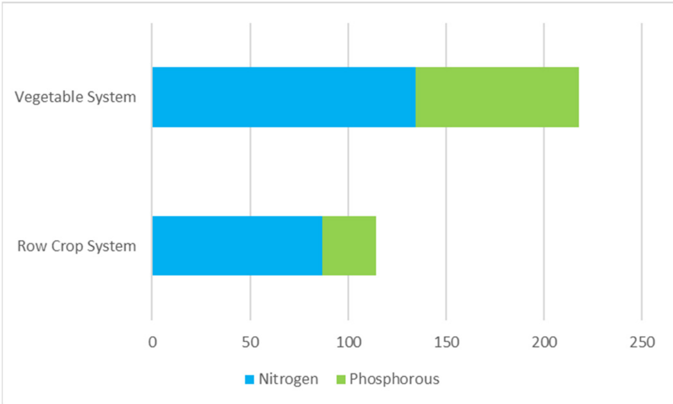

Figure 14. Nitrogen and phosphorous application rates by cropping system.

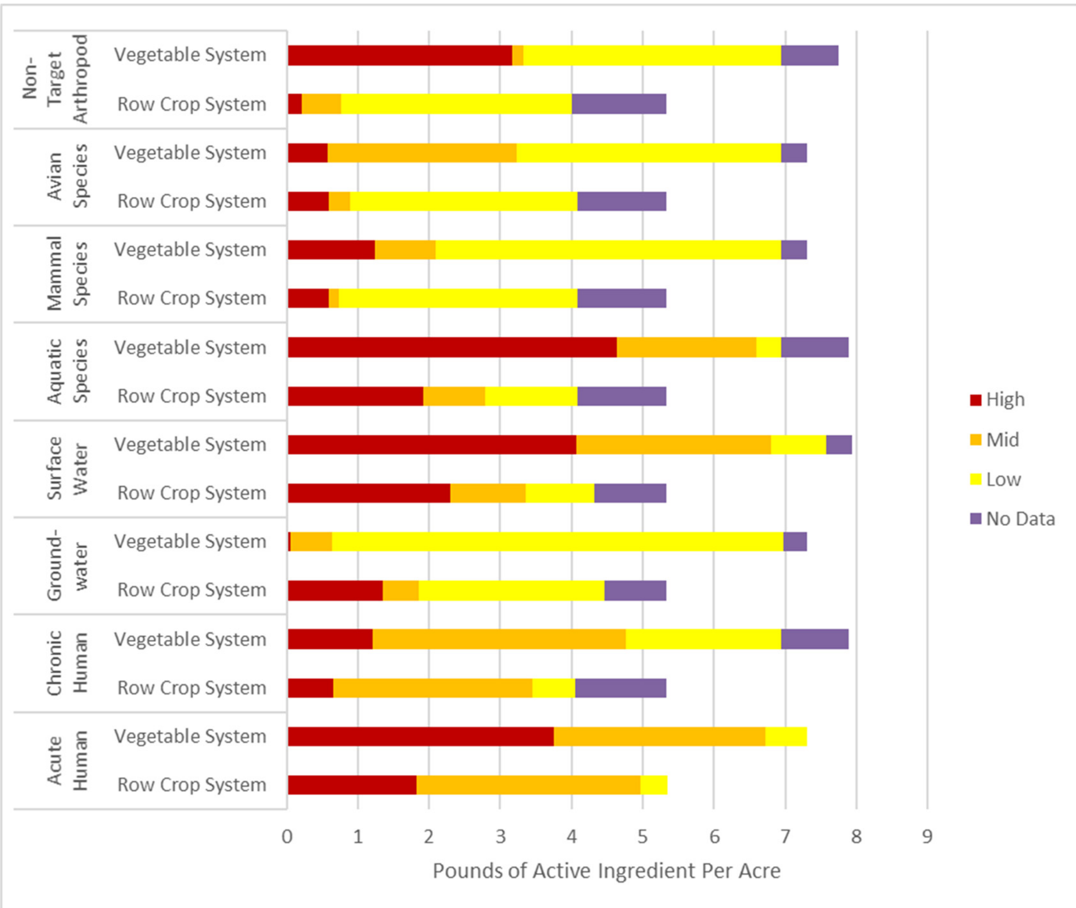

Figure 15. Pesticide risk profiles by environmental category and cropping system.

From Figure 14, we can see that the vegetable cropping system relies on much higher levels of nitrogen and phosphorous applications compared to the row crop system. So, on the whole, shifting from the current cropping patterns in the LFRB to vegetable production would enhance the possibility of nutrient contamination of groundwater and surface water.

From Figure 15, we can see that for all environmental categories except groundwater, the vegetable cropping system would likely require the application of a greater amount of high-risk pesticide active ingredients per acre than the row crop system. In categories, the differential is small (for example, with avian species), and in others, it is large (for example, non-target arthropods, aquatic species, and acute human health). There is not as clear a pattern for the mid-risk and low-risk pesticides between the two cropping systems.

4. Discussion

The concern over deleterious ecological and human health effects from widespread agricultural pesticide use began in earnest 60 years ago with the publication of Rachel Carson's *Silent Spring* [36]. Since then, regulatory efforts have emerged around the globe to mitigate the negative impacts of pesticides while continuing to reap the benefits of their use.

Several numerical indices have been developed to compare the potential negative impacts of various pesticides. These include but are not limited to the Environmental Impact Quotient (EIQ) [37], POCER [38], the Mean Exposure Score [39], and the Pesticide Load Indicator (PLI) [40]. While these indices vary with respect to the level of detail, they each use numerical metrics for different environmental categories and then aggregate those into a single number for an active ingredient. It is important when using these numerical indices to determine when they are inherently ordinal in nature. When strictly ordinal, they are suitable for ranking the overall environmental risks of active ingredients relative to each other, but often, the index values of two active ingredients do not have cardinal properties. For example, the total for EIQ atrazine is 53.55, while the total EIQ for carbosulfan is 126.73 [41]. These total EIQ scores mean that carbosulfan poses a greater risk in general to the environment than atrazine, but it does not mean that carbosulfan is 2.37 times more dangerous, risky, or toxic than atrazine.

Additionally, numerical pesticide risk indices that do not have cardinal properties are not particularly well-suited for comparing the relative risk of growing different crops that use different active ingredients. For example, the sum of the total EIQ across all active ingredients used to grow corn is not directly comparable to the sum of the total EIQ for cotton pesticides, even from an ordinal perspective. This is also true when comparing EIQ scores within an EIQ component: the groundwater (leaching) EIQ score for atrazine = 3 and for carbosulfan = 1, which means, certis paribus, atrazine is more likely to reach groundwater than carbosulfan; it does not mean atrazine is three times more likely to reach groundwater, or that three times as much of it would reach groundwater. As such, the sum of the leaching EIQ score for all of the active ingredients used in corn production is not directly comparable to that of cotton, even in an ordinal sense. When summing strictly ordinal values, 5 + 5 may be greater than, equal to, or less than 3 + 7.

Using categorical bins for pesticide risks (e.g., high, mid, and low) can actually facilitate direct comparison of pesticide risks across crops by establishing cardinal measures within each risk category. For a given environmental component, the methodology presented above adds up the total load of pesticide active ingredient within each risk category, but not across risk categories. As such, the total load of high-risk-to-groundwater pesticides in corn production is directly comparable to that of cotton production, even in a cardinal sense. This allows us to see how the pesticide risk profile changes as crops change. Of course, the thresholds used here for assigning high, mid, and low risk within an environmental component are subjective. We do not argue that these are the only thresholds that should be used; other criteria may be more appropriate depending on one's risk tolerance.

Unlike the EIQ, the POCER score for leaching to groundwater is an example of a cardinal measure used as a risk index. That value is equal to the predicted concentration of an active ingredient in groundwater [37]. That score and the POCER scores for other environmental components are context-specific. They incorporate information like application method, timing, and environmental conditions that the EIQ and our methodology do not. This is an important distinction. POCER scores can give a more precise sense of relative pesticide risks in specific scenarios, but there is an inherent trade-off between precision and cost. Information is expensive, and establishing parameters for POCER scores may be prohibitive when resources are scarce. In comparison, the methodology described above requires information only on the amount of each active ingredient applied per hectare for each crop. This can provide a cheap first-cut to illustrate how pesticide risk profiles change with cropping patterns, thereby facilitating the strategic allocation of scarce extension resources.

5. Conclusions

In the example presented above, we showed that a shift from row crop production to vegetable production in the Lower Flint River Basin of Georgia would lead to higher expected irrigation application rates, placing greater stress on the region's water resources. The change in pesticide risk profile would not be unilaterally toward greater or lesser risk; rather, the change in the pesticide risk profile would vary by crop and environmental component. Nitrogen and phosphorous applications would also vary by crop.

When we look at the row crop system versus the vegetable cropping system, a more definitive pattern emerges concerning fertilizer application rates and high-risk pesticide active ingredient use. In both cases, the row crop system places much less pressure on the environment than the vegetable cropping system.

Pesticides have been critical to the significant increase in agricultural productivity over the last 70 years. The use of pesticides, however, can also generate substantial external costs. Anticipating how pesticide risks will change with climate-induced-shifts in cropping patterns is important for minimizing the negative impacts of their use. Sometimes, taking a relatively cheap and straightforward qualitative approach can provide more actionable insights than information-intensive quantitative measures.

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