Evaluating Efficacy of Fumigation under Weather Uncertainty in Tomato Production

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Abstract

Several alternative fumigants have reached the market since the phase-out of methyl bromide (MBr). However, all of the MBr alternatives tend to provide inconsistent weed control. Weather variability during and immediately following application can result in significantly different efficacy. In this interdisciplinary study, we proposed a modeling framework for analyzing how weather factors affect fumigation efficacy in weed control, tomato yield and the overall economic performance of fumigants. We found that soil temperature reduced the efficacy of all fumigants against nutsedge, while rainfall only reduced the efficacy of a limited number of fumigants. Tomato yield is affected by weather conditions and by weed and other pest pressure under each treatment. We simulated fumigants' economic performance over a range of environmental conditions to identify the fumigant that is most effective under diverse weather conditions. We found that although 1,3-D:Pic:Kpam outperformed MBr over the experiment period, when accounting for weather variability, MBr is still the best treatment. In the post-MBr era, 1,3-D:Pic:Kpam was more effective than the current industry standard, 1,3-D:Pic, and was the best alternative to MBr. The results of this study highlight the impact of environmental conditions on fumigant efficacy. The proposed methodology can be adapted to other pest management problems and other crops to enhance our understanding of the interaction between environmental conditions and pest management, and identify management programs most likely to succeed under variable weather conditions.

Keywords: Fumigation efficacy; Methyl Bromide alternatives; Tobit analysis; Monte Carlo simulation; Weather uncertainty

Highlights

- Fumigant alternatives demonstrate inconsistent weed control over time.
- An econometric model is developed to identify the effect of weather conditions on fumigation efficacy.
- Monte Carlo simulation is used to evaluate economic performance of fumigants under weather variation.
- Among fumigants considered, 1,3-D:Pic:Kpam was the best alternative to MBr.
- When accounting for weather variability, MBr is still the best treatment.

1. Introduction

Fresh tomatoes are an important crop in the US fruit and vegetable industry, with a national farm gate value of $1.2 billion in 2015. US growers historically relied on MBr to control and regulate soil-borne pests including fungi, nematodes, insects, mites, rodents, bacteria and weeds. Fresh tomatoes accounted for 50% of total MBr pre-plant usage in the U.S. before 2000 (Osteen, 2000). It was the most effective, easy to use, odorless, and least expensive fumigant for over five decades (McCook, 2006). However, the Montreal Protocol treaty listed MBr as an ozone-depleting substance in 1992 and the U.S. has since halted production and importation of MBr. To date, exemptions to the phase-out have only allowed for quarantine and pre-shipment, critical use, and chemical feedstock uses. The methyl bromide phase-out resulted in a broad technological shock for the fruit and vegetable industry. There has been an extensive search for alternative fumigants for fruit and vegetable production in the U.S.

The USDA has supported research to develop MBr alternatives but no alternative fumigant with the same broad-spectrum efficacy and consistency as MBr has been identified. Many alternative fumigants have been identified that can be used in combinations, or in sequence (Gilreath et al., 2004; Gilreath et al., 2005; Santos and Gilreath, 2006; Gilreath and Santos, 2004), but it is generally acknowledged that these alternatives tend to provide inconsistent weed control (Freeman et al., 2016). For instance, Gilreath and Santos (2005) found that combination of MBr and chloropicrin (Pic) controlled purple nutsedge more effectively than 1,3-dichloropropene (1,3-D) : Pic in combination with pebulate in the 1997/98 tomato season, while another experiments conducted by Gilreath et al. (2006) in 2000/2001 showed that there was no significant performance difference between them. Weed control with alternative fumigants has been variable with reports of both acceptable and poor control compared to MBr

(Hanson and Shrestha, 2006). Alternatives that have acceptable efficacy under favorable weather may fail in other years when the weather is less favorable. In consecutive field trials, 1,3-D:Pic had excellent performance in three tomato seasons but failed to improve weed control in a subsequent season (Gilreath et al., 2005). Santos et al. (2006) indicated that 1,3-D:Pic in combination with drip-applied sodium azide were consistently equal to MBr:Pic for two out of three seasons.

Previous studies have suggested that variability in fumigation efficacy is due at least in part to soil conditions. An effective fumigant dosage is a combination of a specified concentration over an extended duration. Volatilization or the gaseous loss of fumigant from the soil can limit efficacy by either reducing the concentration in the soil around the pest or shortening the exposure duration or both. Soil moisture and temperature change rapidly in the first 5 cm of field soil in response to changes in the atmosphere (Gilreath et al., 2004). As a result, the rate of chemical conversion, distance moved, and the rate of movement are affected by rainfall or irrigation and temperature. To identify the most efficacious fumigant alternative, it is necessary to examine fumigation efficacy over multiple years with varying rainfall and temperature. Although it is well documented that fumigation efficacy is sensitive to weather conditions, no study has systematically shown how weather conditions affect efficacy. The current study is based on data from a four-year trial in Florida and identifies the effect of weather conditions such as soil temperature and rainfall on fumigant efficacy including MBr, the current industry standard and other promising MBr alternatives. The effects on both weed control and fruit yield are analyzed.

The economic performance of fumigants under variable weather conditions is further evaluated. An economic evaluation of fumigants based on limited-year trials is not reliable because fumigation efficacy varies over time. Several studies have examined economic effects of fumigant alternatives on vegetable production in the U.S. using partial budgeting analysis (Sydorovych et al., 2006, 2008) or stochastic dominance analysis (Byrd et al., 2007; Cao et al., 2014). The recommended fumigant alternatives are not necessarily economically sustainable or viable given that experiments were only conducted under fixed or limited variation in weather conditions. Results on economic performance are more reliable when taking into account sufficient variation in weather conditions.

The objective of this study is to identify optimal fumigants that take account into weather impact and variability. To achieve the objective, we developed empirical models to quantify the effects of weather conditions on weed control and tomato yield. Based on the estimated effect and yield response, we simulated tomato yield under diverse weather conditions, and calculated growers' expected utility under diverse weather scenarios to identify optimal fumigants. The information generated from this analysis will illustrate the difference between accounting for weather variation and not accounting for it and will provide an important, economically sustainable perspective for horticulturalists, pest management experts, and growers.

2. Experiment and Data

Tomato field trials were conducted at the University of Florida Gulf Coast Research and Education Center in Balm, Florida, U.S. over a four-year period from the fall of 2008 through the fall of 2011. Treatments were arranged in a randomized complete block design with fumigation as the main plot and herbicide as a non-randomized subplot effect in four field sites. Treatments were assigned to three bed main plots and replicated three times, while each main plot consisted of herbicide and non-herbicide sub-plots. The trial sites and plot location were maintained throughout the length of the study. Fumigant treatments included: a non-fumigated control; MBr:Pic 67:33 at 196 kg · ha^{-1}; dimethyl disulfide plus Pic (DMDS:Pic 79:21) at 561 L· ha^{-1}; 1,3-D at 112 L · ha^{-1} plus Pic (1,3-D:Pic) at 168 kg · ha^{-1}, collectively referred to as the two-way system which is also the current industry standard; and the two-way system followed by metam potassium (Kpam) at 561 L· ha^{-1} (1,3-D:Pic:Kpam), collectively referred to as the three-way system. The 1,3-D was applied below the bed top by using a Yetter® coulter rig, while the remaining fumigants except for Kpam were injected via three shanks using a nitrogen-propelled fumigation rig. These applications occurred in late July to mid-August. Kpam was injected into the bed using drip tapes capable of delivering 950 ml per emitter per hour two weeks after laying the plastic. Tomato plants were transplanted about 40 days after fumigation when fumigant concentration in the bed was safe. During the growing season, the same amount of fertilizer, fungicides, and irrigation were applied to each trial field each year. In year one, the herbicides consisted of imazosulfuron (0.33 kg · ha^{-1}) and napropamide (2.24kg · ha^{-1}). In following years, imazosulfuron was replaced by fomesafen at 0.28 kg · ha^{-1}. The crop was grown using the University of Florida recommended production practices (Freeman et al., 2009).

Weed shoots that escaped the control of the fumigants and/or herbicides were assessed each cropping season. Within each plot, the number of purple and yellow nutsedge (*Cyperus spp.*) seedlings that emerged through the plastic and the number of annual grasses that emerged from the planting holes were counted. The tomato crop was harvested in December and graded according to USDA guidelines (USDA, 1997). To compare the means between fumigation treatments for weeds and yield, we used Tukey's adjusted means comparisons for all pairwise differences. During the four seasons, nutsedge density tended to be higher in the non-fumigated treatment (Table 1). 1,3-D:Pic, the industry standard, did not perform better than the non-fumigated in three of the four seasons whereas 1,3-D:Pic:Kpam provided better control than the non-fumigated and were as effective as MBr:Pic in three of the four seasons. Also, DMDS:Pic and MBr:Pic worked equally well in three of the four seasons. Grass control was relatively more consistent. 1,3-D:Pic:Kpam was as effective as MBr: Pic and tended to provide the best grass control . Finally, all fumigants improved yield. Although 1,3-D:Pic:Kpam tended to be the highest yielding fumigant treatment, the yield difference among fumigant treatments was not always statistically significant. Our data illustrate the season-to-season variability typically observed in fumigant trials (Gilreath et al., 2005;Santos et al., 2006).

3. Effect of Weather Factors

The efficacy of soil fumigation is greatly affected by soil and environmental conditions during and immediately following fumigation application till transplanting. To effectively control weeds, fumigants must penetrate and diffuse into soil pores and be retained in the gas form for a period of time. Many weather factors positively or negatively affect the activity of fumigants. Here we tested the effect of soil temperature and rainfall on fumigant efficacy on weeds. Since a significant fraction of subplots had zero weeds, we adopted a Tobit model to estimate the effect of two factors on controlling nutsedge and grass. The Tobit model is appropriate when the modeled variable is censored below or above a certain value and may have multiple observations at the censoring limit (Wooldridge, 2002). In this case, the weed number has a lower bound of zero with a number of plots of zero weeds. The censored Tobit model of a certain weed W_k is:

$$W_k = \max(0, y), \tag{1a}$$

$$y = c_k + \sum_{i=1}^{5} \beta_{ki} X_i + \sum_{i=1}^{5} \sum_{j=1}^{2} \theta_{kij} X_i Z_j + u_k,\ u_k \sim Normal(0, \sigma_k^2) \tag{1b}$$

where W_k is the weed variable (nutsedge or grass for *k=1,2*), taking values y if y is positive or zero; c is the constant term; X includes five dummy variables representing four fumigants of MBr:Pic, DMDS:Pic, 1,3-D:Pic, 1,3-D:Pic:Kpam (the non-fumigated control is the default and is omitted), and herbicide (X_5); XZ is the interaction terms of dummy variables with two weather factors in Z; β, θ is a vector of unknown coefficients to be estimated; and u_k is an independently distributed error term assumed to be normal with zero mean and variance σ_k^2. Soil temperature after fumigation (TAF) (Z_1) is the average temperature during the plant-back interval, namely, from fumigation till transplanting, while rainfall after fumigation (RAF) (Z_2) is the total precipitation during the same period. Table 2 shows the values of these two variables over the experiment period.

Signs of β and θ determine the direction of change in weed population as the respective explanatory variables change. However, they do not directly give the marginal effects of the independent variables on the dependent variable. For dummy variables, the marginal effects are the difference when the respective dummy takes its two different values 0 and 1, respectively. Therefore, for any fumigant X_i (*i*=1 to 4), its efficacy in controlling weed population is

$$MW_{ki} = E(\,W_k|X_i = 1) - E(\,W_k|X_i = 0),$$

$$= \Phi\left(\frac{c_k+\beta_{ki}+\theta_{ki}Z}{\sigma_k}\right)(c_k + \beta_{ki} + \theta_{ki}Z) + \sigma_k\phi\left(\frac{c_k+\beta_{ki}+\theta_{ki}Z}{\sigma_k}\right) - \Phi\left(\frac{c_k}{\sigma_k}\right)c_k - \sigma_k\phi\left(\frac{c_k}{\sigma_k}\right), \qquad (2)$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the density function and cumulative distribution of a standard normal variable. Subsequently, the effect of any weather factor Z_j(*j*=1, 2) on the efficacy of fumigant X_i can be derived as

$$\frac{\partial MW_{ki}}{\partial Z_j} = \Phi\left(\frac{c_k+\beta_{ki}+\theta_{ki}Z}{\sigma_k}\right)\theta_{kij}, \qquad (3)$$

where $\Phi\left(\frac{c_k+\beta_{ki}+\theta_{ki}Z}{\sigma_k}\right)$ is the probability of observing a positive weed population for fumigant X_i, which is strictly between zero and one. Therefore, the direction of weather factors' effect on fumigant efficacy is determined by θ_{kij}, whereas the magnitude is less than θ_{kij}.

After modeling the treatment and weather effects on weed, we further model tomato yield as a function of weather conditions (temperature and rainfall) and weed and non-weed pressure:

$$Y = \gamma_0 + \sum_{i=1}^{4} \gamma_i X_i + \gamma_5 TAT + \gamma_6 RAT + \sum_{k=1}^{2} \gamma_{k+6} W_k + \varepsilon, \tag{4}$$

where *Y* is the tomato yield; W_k is weed; X_i is dummy variables of fumigants, capturing additional, non-weed pest pressure associated with fumigant use that affects yield, such as nematodes; TAT is soil temperature after transplanting, measured as average soil temperature over the growing period from the middle of September to the beginning of December, while RAT is rainfall after transplanting, measured as the total precipitation over the same period (see Table 2 for values of these two variables); γ is a vector of unknown coefficients, and ε is the error term. Combining equations 2-4, we estimate marginal effect of fumigant $X_i (i = 1, \dots, 4)$ on tomato yield as

$$MY_i = \gamma_i + \sum_{k=1}^{2} \gamma_{k+6} MW_{ki}. \tag{5}$$

The marginal yield effect is a combination of weed impact and non-weed impact associated with the fumigant. Then the effect of weather factor $Z_j (j = 1,2)$ on fumigants' efficacy in tomato yield is

$$\frac{\partial MY_i}{\partial Z_j} = \sum_{k=1}^{2} \gamma_{k+6}\, \theta_{kij}\, \Phi\left(\frac{c_k+\beta_{ki}+\theta_{ki}Z}{\sigma_k}\right). \tag{6}$$

4. Estimation Results

Parameter estimates for the Tobit model of nutsedge shoots are presented in Table 3, and marginal effects of all fumigants are presented in Table 5. All parameter estimates of fumigant dummy variables are statistically significant, suggesting that applying fumigants changes nutsedge shoots compared to non-fumigated control. The magnitude of the effect is dependent on weather conditions. With both weather variables (TAF and RAF) held constant at their sample means, 1,3-D:Pic:Kpam reduced nutsedge shoots the most by 7.282 shoots/m^2, followed closely by MBr:Pic with 6.964 shoots/m^2(Table 5). 1,3-D:Pic is the least effective and only reduced 4.159 shoots relative to the non-fumigated. As expected, most interaction terms of fumigants with *weather factors* are significant. Our results suggest that the increased *soil temperature* significantly reduces the efficacy and increases nutsedge shoots in tomato production. MBr:Pic is the least affected, confirming its consistency, while 1,3-D:Pic is affected most, resulting in 3 more shoots/m^2 by one increased degree of soil temperature (Table 5). To maximize fumigant activity, soil temperatures should be at a minimum of 50°F. As soil temperature increases, the rate of fumigant conversion to the gas state increases. High soil temperature speeds the gaseous diffusion, thus shortening the exposure time of nutsedge tubers and resulting in lower efficacy. Rainfall also reduces fumigant efficacy, and its effect is significant for 1,3-D:Pic and 1,3-D:Pic:Kpam. An increase of 2.54 cm (one inch) results in an increase nutsedge density of 0.946 and 0.198/m^2 for 1,3-D:Pic and 1,3-D:Pic:Kpam treatments. Note that fumigants move 10,000 to 30,000 times slower in soil water than in soil air. Water containing the fumigant will move deep into the soil or into the row middles where it will provide little pest control for the bed (MacRae et al., 2010).

The estimates for grass shoots are slightly different. First, 1,3-D:Pic:Kpam led the grass reduction with 0.748 shoots/m^2, followed by MBr:Pic (0.695). DMDS:Pic resulted in higher grass shoots relative to the non-fumigated. Second, few coefficient estimates of interaction terms are statistically significant, suggesting the efficacy of fumigants in controlling grass shoots are less affected by weather condition. Third, in contrast to nutsedge, increasing soil temperature reduces grass shoots for both DMDS:Pic and 1,3-D:Pic treatments. The reason may be that grass seeds are more concentrated on the upper level of the bed and expose to the toxic fumes longer in a high soil temperature condition. Finally, more rainfall increased grass shoots for 1,3-D:Pic.

The estimation results for the tomato yield equation are presented in Table 4. Most estimates of variables in the equation are significant at conventional significance levels, and their signs are consistent with expectations. The positive estimates of fumigant dummy variables imply that applying fumigants would cause a yield increase compared to the non-fumigated. Among them, 1,3-D:Pic:Kpam contributes most to the yield increase. The coefficient estimate of soil temperature after transplanting (TAT) is positive and significant, suggesting a positive correlation with yield. Adams et al. (2001) found that high temperatures increase fruit absolute volume growth rates. The effect of rainfall after transplanting (RAT) on yield is small and insignificant, which is likely associated with the fact that tomato production in the experiment used drip irrigation. Finally, more nutsedge and grass shoots result in lower yield. Increasing nutsedge by 1 shoot/m^2 will lead to a decrease in tomato yield of 0.327 tons/ha, while the effect of an increase of 1 grass shoot/m^2 causes yield a decrease of 1.398 tons/ha.

The aggregated yield effects of fumigants on yield are shown in Table 5. 1,3-D:Pic:Kpam is the leading fumigant in increasing tomato yield, with 10.537 tons/ha. However, the efficacy varies with weather condition after fumigation (TAF and RAF). One degree increase in soil temperature can reduce tomato yield by 0.807 tons/ha while one additional inch of rainfall reduce yield by 0.065tons/ha. The second largest yield increase is from MBr:Pic, with 7.599

tons/ha. It is responsive only to soil temperature and the magnitude is smaller. The least effective and most unstable fumigant is 1,3-D:Pic.

5. Economic Performance Analysis

This section presents results of short-term economic performance of fumigants for each season in the trial period as well as the results of simulated, long-run economic performance, taking into account weather variability.

5.1Whole Farm Budgeting Analysis

The whole farm budgeting summarizes the financial features of the entire farm business (Riggs et. al., 2012). It considers the level of business performance (e.g. profit) after treatment. Besides the costs of fumigation, harvesting and marketing, it also accounts for other expenses, which are unchanged across treatments, including fertilizers, transplants, fixed costs and other costs. Combining the total revenue with total cost information, the average net profit per acre of each treatment is estimated.

First, fumigation costs were estimated, including material, machinery, and labor costs. The market prices of Pic, DMDS, 1,3-D and Kpam and their usage amounts were used to calculate material costs. As with MBr, the original price of MBr before the ban in 1997 was used and adjusted up for inflation. This is because restrictions on MBr production, import, and consumption under the Montreal Protocol have distorted the market and driven the market price of MBr up in the U.S. in recent years. This calculation represents a hypothetical case *if* methyl bromide had not been banned. For all four seasons, we adjusted fumigant prices with the Producer Price Index (PPI) released by the United States Bureau of Labor Statistics and used the average prices over the four seasons to calculate material costs. Fumigation machinery costs included fuel costs, depreciation, and other noncash overhead while labor costs were calculated based on the farm labor rate and working hours of fumigation on an average farm. Two-way and three-way fumigation treatments involve applying fumigants twice and correspondingly incur double labor and machinery costs. In sum, 1,3-D:Pic:Kpam fumigation cost is the highest at $3,480/ha, followed by DMDS:Pic with the expense of $3,033/ha. MBr:Pic is the least expensive fumigation treatment. Second, harvest & marketing costs, which are in direct proportion to tomato yield, include picking, packing, and hauling costs, container cost, selling cost and organization fee. Similarly, costs for four seasons were adjusted for inflation using 1982-based PPI data. Third, other cost categories, which are fixed across treatments, were from production budget for tomato in Southwest Florida (VanSickle, 2009). Finally, the revenue was estimated using tomato market prices and yields. The price was an average of Jan and Feb prices at the Florida shipping point over the four seasons.

Net profits of each treatment over the years are presented in Table 6. The results show that except in 2009, most treatments had negative net profits. This finding is consistent with the reality that the industry is struggling due to both production and market challenges such as the rapidly growing imports from Mexico. The net profits in 2008 for DMDS:Pic and 1,3-D:Pic:Kpam were positive while those of all other treatments were negative. However, the difference was not statistically significant, suggesting no any treatment performs economically better than others. In 2009 all treatments produced positive net profits. MBr:Pic, 1,3-D:Pic, and 1,3-D:Pic:Kpam worked equally well and generated higher net profits than all other treatments. All fumigant treatments resulted in losses in 2010 and worked equally well and outperformed the non-fumigated. The same trend was observed in 2011. It can be concluded that unlike the results for weed control and yield, 1,3-D:Pic:Kpam and 1,3-D:Pic performed as well as MBr:Pic in some years. However, they also performed as poorly as the nonfumiganted for other years. The variation in weather conditions affects fumigation efficacy and increases the variability of their economic performance.

5.2 Expected Utility Simulation Analysis

Means comparison method was not able to provide an unambiguous ranking for all treatments, due in part to the high variability around the treatment means. Even if the outcome of the test indicates a statistically significant difference has been observed, the fumigation treatment that brings in the highest average economic return may not necessarily be the most beneficial treatment for a grower as it might be too risky if the results vary too much across replications or seasons. Therefore, we used the expected utility method, which incorporates risk factors to explicitly account for the variation of net profits of treatments. The expected utility analysis quantified the role of the variation of treatments' net profits in the utility model to determine the economic performance. In a way, the utility model "discounts" the net profits taking into account the variability (risk) as well as growers' risk attitudes (i.e., degree of risk aversion). The role variability plays varies depending on the growers' degree of risk aversion. Generally, net profits are discounted more when the variability is higher, or growers' risk aversion is higher. In this study, we use the power utility function, the most widely used utility function in empirical analysis, to evaluate the treatment under a certain weather condition, that is,

$$U(W_t) = \frac{W_t^{1-r} - 1}{1-r}, \tag{7}$$

where r is the risk-averse coefficient. The range of r is set from 1 to 3, representing "normal risk aversion" to "high risk aversion" (Anderson and Dillon, 1992). When r=1, the power utility function is degenerated to the logarithmic utility function $ln(W_t)$. The grower's end-of-season wealth is random and is the grower's initial wealth (W_0) plus random farm profit from a fumigation treatment, i.e., $W_t = W_0 + P_t$. Utility $U(W_t)$ are random because yield (hence farm profit) follows a random distribution. The grower is assumed to choose the treatment that brings him the highest expected utility $E[U(W_t)]= E\left(\frac{(W_0+P_t)^{1-r}-1}{1-r}\right)$. The expected utility under *N* sets of profit is:

$$E[U(W_{ti})] = \frac{1}{N}\sum_{i=1}^{N}\frac{(W_0+P_{ti})^{1-r}-1}{1-r}, \tag{8}$$

where E(·) is the expectation operator. Following Cao et al. (2014), we assume a representative tomato grower in Florida with 28 ha land and \$3,420,056 farm equity (W_0). We simulate the farm profit from each treatment based Equation (4). Each simulation generates a risky outcome of yield, profit, and utility. The expected utility of *N* replicates under a specific weather scenario *t* could be calculated with Eq. (8).

To further simulate weather impact on treatment effect, we allow weather conditions to vary, with *T* sets of weather scenarios. Under each set of weather scenario, *N* sets of replications are simulated. To calculate the expected utility, we compute the sample mean on a given set of profits (*N*×*T*), that is,

$$\frac{1}{T}\sum_{t=1}^{T}E[U(W_{ti})] = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{1}{N}\sum_{i=1}^{N}\frac{(W_0+P_{ti})^{1-r}-1}{1-r}\right), \tag{9}$$

where P_{ti} is the net profit of each treatment at replicate *i* in the *t*-th weather scenario (or season). The expected utility of each treatment is then ranked to determine the performance of fumigants.

We first calculated the average expected utility of fumigation treatments with *r = 2* under weather conditions during the trial period (2008-2011), which will demonstrate treatment ranking with limited weather variability observed over 2008-2011. The calculation of the expected utility uses the observed data points for each treatment, which is used to compare the performance of fumigants.

Then, we further calculated the expected utility under *T* sets of simulated weather scenarios. We started with calibration of random variables, which include random shocks in weeds and yields (u_1, u_2, ε), as well as random weather variables (TAF, RAF,TAT, and RAT). The vector of weed shocks $(u_1\ u_2)$ in equation 1 is assumed to be normally distributed with mean zero and variance-covariance matrix estimated in equation 1. The yield shock ε is assumed to be a zero-mean normally distributed random variable with estimated variance in equation 4. Random weather variables (TAF, RAF, TAT, and RAT) are assumed to have a multivariate lognormal distribution, accounting for the covariance between variables, and the levels of uncertainty (variance and covariance) of weather variables employed for the simulation are representative of historical weather risks over 1998-2015 in Florida. Based on the above calibration, we next used the estimated models (equations 1 and 4) to simulate weed and yield. First, one set of weather values are randomly drawn from the above estimated lognormal distribution. Under such predetermined weather condition, shocks to weed populations (u_1 and u_2) are randomly drawn 300 times (N=300) from their respective distributions and placed into equation (1) to generate 300 weed values for each weed (netsedge and grass). Based on equation 1, if the value is negative, the forecast shoot is zero; when it is positive, the forecast shoot is the value itself. Second, yield shocks (ε) are randomly drawn 300 times form its respective distribution and placed together with shoot forecasts into equation (4) to generate 300 yields. The net profit corresponding to each yield is calculated based on tomato market prices and production costs. The procedure is replicated again when a new (*t*-th) set of weather values is drawn. To allow for enough variability of weather, 100 weather scenarios are drawn (T=100).

These 100 sets of weather scenarios and 300 sets of profit under each weather scenario are used to calculate the expected utility with equation 9 for each treatment. In total, 30,000 data points are simulated for each treatment. The treatment with the highest total expected utility values represents the best performance under weather uncertainty. To generate realistic weather scenarios and avoid extreme weather values, we set an upper and lower bound for weather variables and only considered those drawn values within the upper and lower bounds, which are set at 30% higher and lower than the historical highest and lowest values observed over 1998-2015. The 30%-higher upper bound covers approximately 99% of the assumed distribution. In the computation of expected utility, we assumed the farmer' risk attitude (or degree of risk aversion) is represented by $r = 2$. Yet, the magnitude of risk penalty varies with farmers' risk attitude. In order to investigate the robustness of our findings with respect to risk attitude, we re-calculated the total expected utility with two additional risk aversion levels, $r = 1$ and $r = 3$, respectively.

The expected utilities of observed trials and simulated values with weather variation are presented in Table 7. The first column shows the expected utility of the trials over 2008-2011. The ranking results illustrate that the most cost-effective treatment over the trial period is 1,3-D:Pic:Kpam, followed by MBr:Pic and the industry standard, 1,3-D:Pic. DMDS:Pic was the poorest fumigant. However, the ranking is significantly different if accounting for weather variability. First, MBr:Pic outperformed 1,3-D:Pic:Kpam, showing the consistency of MBr:Pic efficacy under diverse weather conditions. Nevertheless, 1,3-D:Pic:Kpam produced a utility closest to MBr:Pic, and is the best alternative to MBr. Second, the industry standard, 1,3-D:Pic, was now worse than DMDS:Pic. Although 1,3-D:Pic generated higher yields than DMDS:Pic, its yield variation is larger across years, so it is less stable under variable weather conditions, resulting in a lower utility ranking for growers. Finally, the corresponding results with different risk aversion levels, reported in the last two columns in Table 7, show that utility increases when growers are less risk averse (r = 1) and decreases when they become more risk averse (r = 3), but the rankings are all unaffected.

6. Conclusions

The U.S. tomato industry was significantly impacted by the MBr phase-out. Several alternative fumigants have reached the market which include Pic, DMDS, 1,3-D and Kpam. Although most small fruit and vegetable growers in Florida have settled on them as alternatives to MBr, their reliability in terms of pest management and crop yield is questionable given that all of the MBr alternatives are more prone to adverse weather conditions. This study presents an econometric analysis of the fumigants' efficacy under variable weather conditions. We specified and estimated a Tobit model using data from trials over 2008-2011 to identify the effects of weather conditions on fumigants' efficacy in weed control and tomato yield. We found strong empirical evidence of soil temperature and rainfall influencing fumigation efficacy. First, high soil temperature reduces fumigation efficacy in controlling nutsedge while increases efficacy in controlling grass. Second, the sensitivity of fumigants' efficacy to weather conditions is different across fumigants. All fumigants studied respond to soil temperature, but they are not particularly sensitive to rainfall.

Given the inconsistency of fumigants efficacy under different weather conditions, it is important to take into account weather uncertainty when evaluating the economic performance of fumigants. The study further simulated yields under various weather scenarios randomly drawn from the estimated weather distribution. Monte Carlo simulation in the expected utility model is used to allow risk to be penalized in the analysis. We found that fumigant ranking is significantly different when accounting for weather variability. MBr:Pic performed the best, while 1,3-D:Pic:Kpam was the closest alternative to MBr. In addition, the current industry standard, 1,3-D:Pic was least effective among fumigants studied due to its inconsistency, raising concerns about the industry choice. The discrepancy highlight the critical importance of accounting for weather variability in fumigant performance evaluation, which also presents a challenging request for scientists to implement much longer trials.

The results of this study illustrate the sensitivity of fumigant efficacy and the importance of achieving consistent efficacy to identify long-standing fumigant alternatives. Scientists have been called to address and remediate weather factors causing significant performance inconsistency. Various fumigation application technology, injection depth, mulch type, and application sites and others have been attempted to improve the consistency. This study fills a knowledge gap by quantifying the effect of weather conditions on fumigation efficacy. Together, the econometric model and the expected utility model, along with simulation techniques, form a useful tool that can be practically applied across many areas. One more direct application is to further identifying the effect of weather conditions on fumigant efficacy in controlling other specific pests, such as nematode.

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Table 1

Weed shoots and tomato yields in plots treated with different fumigants

Treatment	2008	2009	2010	2011
Nutsedge Shoots (shoots/m^2)				
Control	0.234 a	4.281 a	11.808 a	7.195 a
MBr:Pic	0.028 ab	0.021 b	1.525 b	1.433 b
DMDS:Pic	0.117 a	0.217 b	2.551 b	5.584 a
1,3-D:Pic	0.100 a	0.178 b	7.489 a	5.247 a
1,3-D:Pic:Kpam	0.004 b	0.013 b	1.009 b	3.748 a
Grass Shoots (shoots/m^2)				
Control	0.305 a	0.847 a	0.158 a	
MBr:Pic	0.015 b	0.012 b	0.013 b	
DMDS:Pic	0.322 a	1.402 a	0.283 a	
1,3-D:Pic	0.028 b	0.314 a	0.087 a	
1,3-D:Pic:Kpam	0.004 b	0.012 b	0.014 b	
Tomato Yields (Tons/ha)				
Control	26.103 a	30.351 a	22.904 a	21.229 a
MBr:Pic	29.882 bc	40.771 bc	28.356 b	28.308 b
DMDS:Pic	32.431 bc	38.042 b	27.654 ab	24.502 a
1,3-D:Pic	29.474 ab	39.466 bc	27.187 ab	27.875 b
1,3-D:Pic:Kpam	33.226 c	42.624 c	31.633 b	30.071 b

Note that the means followed by the same letter are not significantly different based on Tukey adjusted mean comparisons at $p<0.05$.

Table 2

Weather conditions during the experiment period

	2008	2009	2010	2011
TAF	81.239	79.627	81.624	81.849
TAT	72.284	74.772	71.926	73.597
RAF	3.365	9.009	10.977	6.475
RAT	4.765	5.627	2.247	6.544

Note that TAF and TAT are average soil temperatures (°F) after fumigation and transplanting, while RAF and RAT are total rainfalls (inch) after fumigation and transplanting, respectively.

Table 3

Tobit model estimates for nutsedge and grass shoots in tomato

	Nutsedge		Grass			Nutsedge		Grass	
Variables	Coeff.	Std. Err.	Coeff.	Std. Err.	Variables	Coeff.	Std. Err.	Coeff.	Std. Err.
$MeBr$	-263.884***	80.586	-3.661	9.499	$MeBr\_R$	0.296	0.248	-0.001	0.030
$DMDS$	-303.823****	70.690	51.574***	7.204	$DMDS\_R$	0.150	0.228	0.027	0.024
$Twow$	-417.768***	71.133	16.185**	7.417	$Twow\_R$	1.308***	0.246	0.057**	0.027
$Threew$	-454.736***	95.919	5.500	9.325	$Threew\_R$	0.437*	0.261	0.030	0.035
Her	-159.797***	57.145	-8.315	5.751	Her_R	0.006	0.175	0.005	0.020
$MeBr\_T$	3.126***	0.989	0.034	0.117	*Constant*	7.950***	0.643	0.558***	0.079
$DMDS\_T$	3.670***	0.868	-0.638***	0.089					
$Twow\_T$	4.974***	0.872	-0.211**	0.092					
$Threew\_T$	5.462***	1.176	-0.084	0.115					
Her_T	1.899***	0.701	0.098	0.071					

Note that MBr is MBr:Pic, DMDS is DMDS:Pic, Twow is 1,3-D:Pic, Threew is 1,3-D:Pic:Kpam, Her is herbicide; the letters "T" and "R" indicate soil temperature and rainfall after fumigation, respectively; *, **, and *** indicate significance at 0.1, 0.05, and 0.01 levels.

Table 4

Coefficient estimates with standard errors for tomato yield model

Variables	Coeff.	Std. Err.	Variables	Coeff.	Std. Err.
MBr:Pic	4.353***	1.070	*TAT*	3.604***	0.371
DMDS:Pic	5.118***	1.035	*RAT*	-0.519	0.332
1,3-D:Pic	4.248***	1.022	*Nutsedge*	-0.327***	0.061
1,3-D:Pic:Kpam	7.113***	1.074	*Grass*	-1.398**	0.626
Constant	-232.060***	25.906			

Note that *, **, and *** indicate significance at 0.1, 0.05, and 0.01 levels.

Table 5

Marginal effects of fumigants and herbicide on weed population and tomato yield and their variation along with weather variables

Fumigants	*MBr:Pic*	*DMDS:Pic*	*1,3-D:Pic*	*1,3-D:Pic:Kamp*
MW_1	-6.964	-4.531	-4.159	-7.282
$\partial MW_1/\partial Z_1$	1.510	2.554	3.597	2.472
$\partial MW_1/\partial Z_2$	--	--	0.946	0.198
MW_2	-0.695	0.200	-0.359	-0.748
$\partial MW_2/\partial Z_1$	--	-0.580	-0.120	--
$\partial MW_2/\partial Z_2$	--	--	0.032	--
MY	7.599	6.318	6.108	10.537
$MY/\partial Z_1$	-0.493	-0.023	-1.007	-0.807
$MY/\partial Z_2$	--	--	-0.141	-0.065

Note that Z_1, Z_2 are soil temperature and rainfall fumigation (TAF and RAT); $MW_1$is the marginal effect of fumigants on nutesdge control, MW_2 is the marginal effect of fumigants on grass control, MY is the marginal effect of fumigants on tomato yield. Only statistically significant effects are reported.

Table 6

Net profits of treatments through the whole farm budgeting method ($/ha)

Treatments	2008	2009	2010	2011
Control	-1,634	2,252 a	-4,559 a	-6,091 a
MBr:Pic	-297	9,661 b	-1,693 ab	-1,737 b
DMDS:Pic	1,120	6,252 c	-3,247 ab	-6,130 a
1,3-D:Pic	-748	8,390 bc	-2,840 ab	-2,211 b
1,3-D:Pic:Kpam	1,400	9,995 b	-56 b	-1,485 b

Note that means followed by the same letter are not significantly different based on Tukey adjusted mean comparisons at $p<0.05$.

Table 7

Expected utility under different scenarios

Treatments	Trial Period	Simulated Weather Scenarios		
	r=2	$r = 2$	$r = 1$	$r = 3$
Control	0.70075	0.70846	1.23615	0.45723
MBr:Pic	0.71025	0.71384	1.25564	0.45871
DMDS:Pic	0.70525	0.70914	1.23912	0.45737
1,3-D:Pic	0.70975	0.70906	1.23863	0.45736
1,3-D:Pic:Kpam	0.71275	0.71377	1.25561	0.45867