Risk-Mitigating Crop Choices Under Severe Water Scarcity: The Role of Insurance Provision, Data Aggregation, Asymmetric Returns, and Risk Representation

Abstract

The lack of sufficient irrigation water has forced farmers to reevaluate their planting decisions. In this study, we introduce two risk-efficient crop choice strategies to stabilize returns under water scarcity conditions. The proposed methods are based on portfolio analysis, in which two different risk representations are considered, variance and downside probability. Also, in the absence of farm-level returns needed in the decision-making process, we propose a technique to recover disaggregated yields based on non-symmetric multivariate parametric distributions and observed actuarial information from crop insurance. Crop selection strategies are illustrated in South Texas, where prolonged water shortages have placed significant pressure on local agricultural systems. Empirical results indicate that systematic crop selection can generate efficiencies in resource utilization, especially when combined with crop insurance, resulting in higher returns and lower risks.

Keywords: Downside risk, Farm yields, Mean-Variance, Texas, Value-at-Risk, Yield Protection insurance

JEL codes: Q12, Q15, Q25, C15

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1. Introduction

Water scarcity has become an increasingly recurring and intensifying problem affecting agriculture throughout the United States (Richter et al. 2023; Texas A&M AgriLife Extension Service, 2025). Severe and prolonged drought conditions, coupled with limited irrigation water availability, have forced farmers to rethink their conventional production practices, including their planting decisions (Richter, et al., 2023). New crop choices must adapt to the expected harsh growing environments, as they directly impact the profitability and long-term sustainability of agricultural enterprises (Antle, 2010, OECD, 2029; Berbel and Martinez-Dalmau, 2021). However, finding the optimal crop mix is challenging, as the decision-making process must consider individual objectives and risk preferences, uncertain market conditions, restricted resource availability, and changing environmental factors (He et. al., 2020; Han and Cheng, 2023).

Furthermore, farm management decisions, such as crop choices, often rely on historical farm-level data to estimate yield distributions, risk exposure, and economic outcomes. However, farm-level data are frequently unavailable or incomplete, forcing farm managers and researchers to use aggregated data at the county or regional level (Rudstrom et al. 2002; Finger 2012; Eisgruber and Schuman 1963). Unfortunately,

hierarchical data aggregation can introduce aggregation bias at a more granular level (Finger, 2012; Coble and Barnett, 2008; Cooper et al. 2009). In this case, the aggregation bias of using regional estimates can distort yield variability and misrepresent higher-order moments, leading to suboptimal crop selection decisions (Finger, 2012).

The overall objective of this study is to develop risk-efficient crop choice strategies to stabilize farm income under water scarcity conditions. Proposed methods are based on portfolio analysis to identify the optimal crop mix based on farmers' expected returns, risk preferences, and available production resources. Particularly, the mean-variance (MV) and value-at-Risk (VaR) portfolio optimization methodologies are adapted to the context of crop selection decisions. The resulting systematic crop selection strategies generate efficiencies in resource utilization that translate into higher returns or lower risks. Furthermore, given the lack of farm-level yields needed to make appropriate crop choices, their underlying density functions are derived from the actuarial information on available crop insurance using a functional yield form (Coble, & Dismukes, 2008).

While our decision-making framework can be effectively implemented nationwide, it is exemplified in South Texas, where a combination of reduced rainfall and historically low water reservoir levels has placed significant pressure on the hydrological resources dedicated to the $887 million agricultural sector (Texas A&M AgriLife Extension Service, 2025; Schattenberg, 2024). For instance, the state's only

operating sugar mill closed after more than 50 years due to low sugarcane yields caused by prolonged irrigation water shortages (Tomascik, 2024).

The existing body of literature related to crop selection can be divided into technical studies with limited or no economic considerations and crop choices grounded on economic principles. The former group focuses on maximizing resource use efficiency based on agronomic planting considerations (Gupta et al., 2000; Dury et al. 2012). The economic literature, on the other hand, studies the relationship between risk and returns when identifying the optimal crop combination (Sharpe, 1963; Collins and Barry, 1986). Also, in the economics domain, the problem of crop choice is often posed in terms of symmetrical yields and aggregated data, with variance (or standard deviation) as a recurring measure of risk (Sharpe, 1963; Collins and Barry, 1986). However, the variance of projected returns may not adequately represent the inherent variability and farmers' risk preferences under conditions of asymmetric farm yields (and subsequent returns distributed similarly) and cognitive loss aversion (Antle, 2010; Just and Weninger, 1999; Sherrick et al., 2004). Also, little attention has been paid to assessing the effect of restricting a key factor of production, such as irrigation water, on crop choice and how to mitigate its negative impact through participation in available crop insurance programs (Miranda, 1991; Sherrick et al., 2004).

Compared to previous work, we use portfolio analysis methods to evaluate the trade-off between target returns and the risk associated with crop selection under

limited irrigation water availability. Our proposed crop choice strategies consider two different risk representations. In the MV model, risk is given by the variance of returns, which can be an appropriate measure of risk under symmetry (OECD, 2009; Antle, 2010). Alternatively, in the case of the VaR model, downside risk, given by the probability of the return falling below a given threshold, is used to define risk. Reducing the likelihood of an unfavorable outcome, such as a lower-than-expected return, is aligned with the notion of loss aversion reported among farmers (Han and Cheng, 2023; He, Jin, Kuang et al. 2019). By employing these two risk specifications, we relax the underlying assumption of symmetric returns. Particularly, under symmetrical returns, the crop combination with the minimum variance is also the one with the lowest downside risk. However, MV and VaR strategies differ in their optimal crop selection decisions in the presence of asymmetric returns, since a small variance may be associated with a higher probability of actual returns being lower than their expected value. Moreover, unlike previous studies that used aggregated data, we introduce a multivariate approach to derive the joint density function of farm yields without imposing symmetry. Estimated farm yields are then used to identify optimal crop choices and highlight the role of crop insurance in stabilizing farm income under conditions of limited irrigation water availability.

In the succeeding section, we present our MV and VaR crop selection strategies. Then, we discuss how farm-level yields can be derived from available regional data and

actuarial crop insurance information. This is followed by an application of the proposed methods in South Texas, where we illustrate how appropriate crop selection combined with participation in a crop insurance program can help farmers mitigate the risk associated with worsening water scarcity conditions. We proceed to analyze the expected returns, underlying risk, and optimal crop choice under the current irrigation water availability, from which our conclusions are derived.

2. Crop Selection Strategies

Mathematical optimization models have a long history of use in agriculture. Since the mid-20th century, starting from the early works of Heady (1954) and King (1953), who used linear programming in farm planning, a wide range of methodological techniques have been developed and applied to agricultural problems. These include linear programming (LP), mixed-integer programming (MIP), and multi-criteria decision-making (MCDM), among other methods (Glen, 1987; Howitt, 1995; Arriaza and Gómez-Limón, 2003). Optimization techniques have been employed to address both technical and socio-economic challenges. On the technical side, models have focused on optimizing production processes, such as maximizing crop yields, improving nutrient and energy use efficiency, optimizing water allocation, reducing pesticide use, and enhancing soil fertility (e.g., Gupta et al., 2000; Dury et al., 2012).

On the socio-economic side, a substantial body of literature has addressed objectives such as profit or gross margin maximization, cost minimization, and optimization of investment and labor costs (e.g., Glen, 1987; Howitt, 1995; Cortignani & Severini, 2009; Moulogianni, 2022). Additionally, economic models can introduce greater realism by incorporating agent behavior and explicit risk measures associated with agricultural activities, and often provide recommendations for mitigating such risks (Coble and Barnett, 2008).

Within this broader literature, a specific family of optimization models integrates risk into agricultural decision-making, building on seminal work in financial economics by Markowitz (1952) and Sharpe (1963) on optimal investment portfolios. In this framework, net returns are treated as random variables, and risk is incorporated via the variance-covariance matrix of returns. The rationale behind the decision-making process is that risk-averse farmers prefer the least risky option among those that generate the same expected return.

More recent contributions to the portfolio optimization literature include multi-objective models, non-stochastic models that do not rely on covariance matrices or prior distributions of returns, and portfolio models that incorporate constraints on natural resource use (Radulescu et al., 2014; Knoke et al., 2015; Miao et al., 2023).

In this study, we advance beyond existing models by presenting a mean-variance portfolio optimization framework for crop selection that incorporates production and

market risks, and a constraint on a fundamental agricultural resource: irrigation water. An additional contribution is the integration of a probabilistic maximum downfall risk that the farmer seeks to minimize within the portfolio optimization framework and the crop choice problem. Moreover, we introduce statistical techniques to estimate the yields of a representative farm using aggregated county-level data and information from agricultural insurance premiums and expected indemnities. Derived farm yields are then used to optimize crop allocation. The proposed methods are detailed in the sections that follow.

2.1. Mean-Variance

In the Mean-Variance (MV) crop selection strategy, the objective is to find the crop mix that generates a desired expected return with the lowest possible variance, subject to meeting all crop and resource allocation restrictions. The total return[1] of a crop selection is a linear combination of the individual returns of each crop:

$$R = \sum_{j=1}^{J} w_j r_j, \quad (1)$$

where w_j is the planted share of the jth crop and r_j is the corresponding return. Note that the total net return is a stochastic variable, whose conditional expected value depends on the allocation of the different crops (i.e., $\boldsymbol{w} = \{w_1, \dots, w_J\}$):

$$E(R|\boldsymbol{w}) = \sum_{j=1}^{J} w_j \bar{r}_j, \quad (2)$$

[1] In this application, returns may refer to the net farm sales (i.e., without insurance compensations) or to the net farm income (i.e., including insurance indemnities).

where $\bar{r}_j = E(r_j)$. Similarly, the conditional variance of R can be represented as:

3) $$V(R|\boldsymbol{w}) = \sum_{j=1}^{J}\sum_{k=1}^{J} w_j w_k \sigma_{jk},$$

where σ_{jk} is the covariance between the returns of the jth and kth crops.

In the MV framework, the crop choice process is formulated as a quadratic programing problem represented as:

4) $$\min_{\boldsymbol{w}} \quad \sum_{j=1}^{J}\sum_{k=1}^{J} w_j w_k \sigma_{jk}$$

$$s.t. \quad \sum_{j=1}^{J} w_j \bar{r}_j = \theta$$

$$\sum_{j=1}^{J} w_j s_{jf} \leq \varphi_f \qquad \forall f$$

$$\sum_{j=1}^{J} w_j = 1$$

$$\sum_{j\in B} w_j \leq \omega_B \qquad \forall B$$

$$0 \leq w_j \leq \ell_j \qquad j = 1, \ldots J$$

where θ is the expected target net return, s_{jf} is the rate of the fth resource used by the jth crop, φ_f is the total amount of the f resource available, $\omega_B \leq 1$ is the maximum proportion allowed for subgroup B of crops, and $\ell_j \leq 1$ is the maximum allowed share for the jth crop.

Note that target expected return (θ) is obtained with the lowest possible variance. Furthermore, crop selection is constrained by available resources (φ_f), which in this case is irrigation water, the limiting resource of interest. The selection process also controls the allocation of different crops. Namely, all crop shares should add up to 1 (equivalent to 100%), the combination of some crops must not exceed a set threshold (ω_B), for

example, the area cultivated with irrigated crops cannot exceed the area suitable for irrigation, and a non-negative quota (ℓ_j) can be assigned to each crop.

2.2. Value-at-Risk

In agricultural decision-making, the role of loss aversion is commonly explored under the lens of prospect theory developed by Kahneman and Tversky (1979, 1991). The concept of loss aversion suggests that people value losses more than equivalent gains, altering preferences for the probabilities of losing and winning, which greatly influences how choices are made. Traditionally, loss aversion is examined from the consumer perspective (Yechiam and Zeif, 2025), but recent studies have shown that farmers also exhibit similar behavior, particularly under uncertain scenarios (Begho and Daubry, 2024). For instance, Krol et al. (2018) evaluated different sustainability indicators across economic, environmental, and social dimensions and found changes in tillage preferences when loss aversion was considered. Also, Han and Cheng (2023) found that farmers reduced their production during the COVID-19 pandemic due to increased uncertainty, compounded by their loss aversion. Namely, farmers preferred to plant less, accepting lower gains, rather than potential losses from overproduction. Similarly, Li and Li (2016) showed that loss aversion significantly affects production quantity decisions under conditions of yield uncertainty. In another study, Zhao and Yue (2020) distinguished between commodity and specialty crop producers and found that sociodemographic factors influence the degree of loss aversion.

In the case of our Value-at-Risk (VaR) strategy, risk is defined by the likelihood of obtaining a total net return below a threshold level (λ). Namely, for a given crop allocation ($\boldsymbol{w}$), the corresponding risk is given by $F_R(\lambda) = P(R \leq \lambda) = \alpha$. The inverse of $F_R(\lambda)$, which is the threshold level λ, is called the Value-at-Risk (VaR_α) (Bersimas et al. 2004; Zapata and Garcia, 2022).

An empirical distribution function can be used to approximate F_R. For instance, if a sample of n sets of crop returns is observed, $\{r_{1i}, \dots, r_{Ji}\}_{i=1}^{n}$, the corresponding n conditional total returns can be calculated (i.e., $R_i = \sum_{j=i}^{J} w_j r_{ji}$). Therefore, the empirical distribution function of the total net returns can be estimated by:

5) $$\hat{F}_R(\lambda) = \frac{1}{n}\sum_{i=1}^{n} d_i,$$

where d_i equals 1 if $R_i \leq \lambda$, and zero otherwise.

Like the MV rationale, we assume that a risk-averse farmer will prefer the crop allocation associated with the lowest risk (α) among all options that produce the expected target return. However, within the VaR framework, the producer's crop selection decision is formulated as a mixed-integer linear programming problem of the form:

6) $$\min_{\boldsymbol{w},\ \boldsymbol{d}} \quad \frac{1}{n}\sum_{i=1}^{n} d_i$$

$$s.t. \quad \sum_{j=1}^{J} w_j \bar{r}_j = \theta$$

$$\sum_{j=1}^{J} w_j r_{ji} - \lambda + M d_i > 0 \qquad i = 1, \dots, n$$

$$\sum_{j=1}^{J} w_j\, r_{ji} - \lambda + M(d_i - 1) \leq 0 \qquad i = 1, \ldots, n$$

$$\sum_{j=1}^{J} w_j\, s_{jf} \leq \varphi_f \qquad \forall\, f$$

$$\sum_{j=1}^{J} w_j = 1$$

$$\sum_{j \in B} w_j \leq \omega_B \qquad \forall\, B$$

$$0 \leq w_j \leq \ell_j, \qquad j = 1, \ldots J$$

where $\boldsymbol{d}$ is a n-dimensional vector of d_i's and $M > max\{\left|\sum_{j=1}^{J} w_j\, r_{ji} - \lambda\right| : i = 1 \ldots n\}$. The second and third sets of constraints in the VaR formulation serve to create the indicator variables d_i, which are used to empirically compute the downside probability.

We further assumed that deviations below the target total net return (θ) are undesirable and that the objective is to avoid them as much as possible. Therefore, the return threshold level is set to $\lambda = \theta$; however, this is not required and any arbitrary value of λ can be selected to solve the optimization problem.

3. Farm Yield Estimation

Aggregation bias can be a major problem in farm-level management decisions. This bias arises when agricultural economic models for farming decisions use data aggregated at higher levels (e.g., county, regional, or national) rather than collected at the farm level (Rudstrom et al., 2002; Finger, 2012). Aggregated data systematically underestimates the variability and associated risk of agricultural yields, leading to distorted outcomes in farm management analyses, which can result in inappropriate policy recommendations

(Eisgruber and Schuman, 1963). This phenomenon has been extensively studied in the literature, with findings showing that underestimating yield variability negatively affects risk modeling (Rudstrom et al., 2002; Finger, 2012), the formulation of objective functions and constraints in mathematical programming models (Önal and McCarl, 1989; Bechtel and Young, 1999), and the calculation of crop insurance premiums, potentially causing adverse selection or market failure (Cooper et al., 2009; Wang and Zhang, 2002), among other issues.

Additionally, data aggregation can significantly affect higher-order moments of the yield distribution, such as skewness and kurtosis (Finger, 2012). Coble and Barnett (2008) argue that farm-level data are essential for accurately estimating risk levels and producing sound recommendations. Several methodological approaches have been proposed to recover farm-level yields from aggregated data, including the use of conversion factors (Miranda, 1991; Cooper et al., 2009), structural models (Coble and Dismukes, 2008), or maximum entropy techniques (Howitt and Reynaud, 2003). A limitation of some of these approaches is the imposition of restrictive functional forms—typically symmetric yields and univariate densities—on the theoretical distribution of farm-level returns and their relationship to aggregated yields.

There is a large body of research emphasizing the importance of considering asymmetry in crop yield distributions when evaluating agricultural productivity and risk (Antle, 2010). Traditional assumptions of normality in yield data have been

challenged due to observed characteristics such as skewness, kurtosis, and bimodality, in U.S. crop yields (OECD, 2009; Antle, 2010). For example, Day (1965) found that field crop yields (specifically cotton, corn and oats), exhibit non-normality distributions, including skewness and kurtosis. Similarly, Just and Weninger (1999) confirmed that some yields are not normally distributed in specific regions, such as corn in Kansas corn and cotton in West Texas. Subsequent studies have been built on this evidence and support that crop yield distributions can indeed be asymmetric (Ramirez, et al, 2003; Ramirez, 1997; Sherrick et al, 2004). Yield asymmetry influences farm decisions. For instance, Berbel and Martinez-Dalmau (2021) documented how asymmetric yield distributions influence nitrogen application decisions, while Upadhyay and Smith (2005) found yield asymmetry across different management strategies in long-term wheat trials. Perceived risk can also be affected by the distribution of yield and subsequent returns. Therefore, our proposed crop selection strategies relax the assumption of normality (and symmetry) and consider a more flexible representation of risk.

In the absence of disaggregated data, farm-level yields necessary for crop decision-making can be derived from available regional estimates in combination with actuarial information from crop insurance. We extended the univariate approach originally proposed by Coble and Dismukes (2008) and used by Cooper et al. (2009) to recover the density function of unobserved farm yields. Compared to Coble and

Dismukes (2008), we do not assume symmetry and the implicit correlation structure is considered to estimate the joint density of crop yields.

Following the functional form of Miranda (1991), the farm yields of a representative producer are given by:

7) $$y_{ji} = \mu_j + \beta_j\left(y_{ji}^c - \mu_j^c\right) + \varepsilon_{ji},$$

where y_{ji} is the ith yield realization of the jth crop, μ_j is the expected farm yield, β_j measures the responsiveness of farm yield to regional yield deviations, y_{ji}^c is the corresponding and observed aggregated yield (i.e., regional yield), μ_j^c is is the expected aggregated yield, and ε_{ji} is an error term with zero mean and finite variance. Furthermore, the ε_{ji}'s of the different crops are potentially correlated with each other with a correlation structure represented by $\boldsymbol{\rho}$.

Unfortunately, farm yields are generally not observed but their densities could be estimated from the inherent information captured by observed crop insurance premiums. For example, for the Yield Protection crop insurance program (USDA RMA, 2025), the indemnity received is given by:

8) $$\delta_{ji} = \max\left[0, p_j(y_j^{APH}\lambda - y_{ji})\right],$$

where p_j is the projected price for the jth crop, y_j^{APH} is the corresponding historical average farm yield (i.e., Actual Production History yield), and λ is the selected coverage level. Note that a payment is triggered if y_{ji} is below the threshold $y_j^{APH}\lambda$. On the other

hand, the full premium (without subsidy) to participate in the insurance program is equal to:

9) $$\vartheta_j = p_j y_j^{APH} \lambda \tau_j^c,$$

where τ_j^c is the county premium rate for the jth crop, which varies depending on the selected coverage level.

The different crop insurance premiums are actuarily fair if $\vartheta_j = \bar{\delta}_j$, where $\bar{\delta}_j$ is the expected indemnity for the jth crop. Therefore, for a given coverage selection (i.e., p_j and λ), we can find the yield parameters (i.e., μ_j and β_j) and density of ε_{ji} that minimize the absolute value of the expected net indemnity for each crop, $|\vartheta_j - \bar{\delta}_j|$.

In a subsequent step, n' yields are generated for each crop using the previously estimated yield and density functions. A given correlation structure (e.g., $\boldsymbol{\rho}$) can be imposed on this set of independent yields to generate correlated yields with the identified univariate properties. Technically, a sample of correlated yields can be produced by $\boldsymbol{Y}' = \boldsymbol{L}\boldsymbol{Y}$, where $\boldsymbol{L}$ is the Cholesky decomposed lower-triangular of $\boldsymbol{\rho}$ and $\boldsymbol{Y}$ is a $n' \times J$ matrix of uncorrelated yields. The analogous simulation approach described in Richardson et al. (2000) was implemented to generate $\boldsymbol{Y}'$. Note that the individual correlated crop yields, denoted y'_{ji}, are a function of the unknown $\boldsymbol{\rho}$**.** However, the elements of $\boldsymbol{\rho}$ can be derived by finding the correlation structure that minimizes the expected net indemnities across all crops:

10) $$\sum_{j=1}^{J} |\vartheta_j - \bar{\delta}_j|.$$

Alternatively, the yield and density parameters can be jointly estimated using a multivariate density function, but we consider this approach to be computationally intensive.

4. Empirical Application

In order to test the MV and VaR methodologies we have considered the context of water scarcity in South Texas, specifically in the Low Rio Grande Valley (LRGV) region. The Rio Grande Valley is located along the US-Mexico border, and encompasses four counties: Starr, Hidalgo, Willacy and Cameron. Within the region of South Texas, we find two main reservoirs, the Amistad and the Falcon, which supply with water the agriculture, urban and industry uses of the region. However, the RGV suffers a significant water scarcity that frequently stresses the agricultural operations and county water consumption. According to the Texas Parks and Wildlife Development Board (2022), the change in the climate varying from arid in the western portion of the Rio Grande basin to subtropical in the east as the Rio Grande feeds into the Golf of America keeps the drought as a persistent threat against water availability.

The Rio Grande Valley is characterized by producing major field crops such as cotton, grain sorghum, corn and sugarcane, along with some high-value specialty crops like citrus, onions and cabbage. This mix of crops makes the valley highly dependent on irrigation, making them sensitive to the change in water delivery.

Furthermore, the constantly dependency with Mexico to supply water to the USA, exacerbates the water availability problem. The USA and Mexico signed a treaty in 1944 stipulating that Mexico send 1.75 million acre-feet of water to the USA every five years from the Rio Grande, and the U.S will send 1.5 million acre-feet of water to Mexico from the Colorado River each year. The agreement was signed when the water was not a problem. However, in recent years, water levels have been lower than ever at both sites, preventing Mexico from fulfilling its obligations under the agreement (Rao, 2024). The decreasing availability of water led to the closure of Texas' only sugar mill after 51 years of growing and processing (Tomascik, 2024) in 2024. But not only the sugarcane industry has been affected by this water shortage. The region has been suffering an economic impact of losing irrigation water. According to a 2025 report by CNAS, the complete absence of irrigation water for crop production in the RGV would result in an estimated $495.8 million in direct revenue losses, showing that a complete lack of irrigated crop production in the same year, would mean an estimated total loss of nearly $993.2 million, and a $554.8 million reduction in value-added contributions to Texas's gross domestic product (Schattenberg, 2024).

4.1. Production and Market Data

Data for this study was gathered from various sources and underwent several processing steps to produce a comprehensive dataset suitable for modeling. Crop yield data for both irrigated and non-irrigated systems in the Rio Grande Valley (RGV),

covering the years 1981 to 2018, were obtained from the USDA National Agricultural Statistics Service (NASS) (USDA, 2025). Since NASS does not provide data for the most recent years, yields from 2019 to 2023 were collected from the USDA Farm Service Agency (FSA) (USDA FSA, 2025), specifically from the ARC-County Benchmark Yields and Revenue reports. Insurance premium data were sourced from the USDA Risk Management Agency (RMA) using its personalized cost estimator (USDA RMA, 2025). Input costs, including both variable and fixed components, were taken from District 12 Texas Crop and Livestock budgets website developed by Texas A&M AgriLife Extension Services (Texas A&M AgriLife Extension, 2025). Crop price data were retrieved from the 2025 U.S. Agricultural Market Outlook developed by the Food and Agricultural Policy Research Institute (FAPRI) of the University of Missouri (FAPRI-MU, 2025).

In order to build a comprehensive database for the model, several adjustments were necessary. Notably, NASS does not report non-irrigated corn yields separately. To estimate them, we followed the same idea of Ramaswami and Roe (2001) and Miranda (1991), and we derived the general formula that they showed into a two cases formula: $Y_t = \frac{A_i}{A_t} \cdot Y_t + \frac{A_{ni}}{A_t} \cdot Y_{ni}$. Where Y_t is total yield, A_i is irrigated area, A_{ni} is non-irrigated area, A_t is total area and Y_{ni} is total non-irrigated yield. Acreage data were obtained from the FSA (Farm Service Agency, 2025). To generate yield data from 2019 to 2023, which were only available by county, a weighted average was computed based on the cultivated

area of each county in the RGV. Missing values for irrigated corn in years such as 2008, 2009, 2011, 2013, 2014, and 2016 were filled using linear interpolation and average yield data from NASS. Linear interpolation provides a reliable estimation of missing values. It ensures that consistency of the data is preserved while maintaining accurate statistical properties (Bhavsar & Khushbu, 2025).

Cottonseed data from 1981 to 2018 were estimated by multiplying the cotton lint yield by a conversion factor of 1.447 (i.e., each pound of lint corresponds to 1.447 pounds of seed), then divided by 2000 to convert the result into tons. For 2019–2023, FSA yield data included both lint and seed. To isolate the seed yield, we multiplied the total yield by $1/(1 + 1.447)$. Since yields were reported by county and year, seed yields were adjusted using the weighted average of planted area of the corresponding year for both irrigated and non-irrigated, as appropriate. These weighted yields were then summed across counties to compute total production in the RGV. This procedure also was applied to the rest of the crops for the 2019–2023 period.

To harmonize the full dataset from 1981 to 2023, we employed a ratio-based estimation to impute NASS-equivalent data for the most recent years. The ratio-based estimator was first proposed by Cochran (1940; 1977) and ranged to its usual product estimator by Robson (1957) and Murthy (1964). Lone et. al. (2024), outlined the use of the classical ratio estimator i.e. $y_R = \frac{\sum_1^n y}{\sum_1^j x} X$ as an effective technique for improving estimation accuracy when there is a strong linear relationship. It is well known that

ratio-base estimators are preferred over the mean per unit estimator $\overline{y}$ if the variables y and x are highly positively and highly negatively correlated with each other (Grover & Kaur, 2011). Therefore, we compared two series: NASS data from 2013 to 2018, and FSA data from 2013 to 2023. We calculated the Pearson correlation for each crop to evaluate whether ratio-based estimation was appropriate. A correlation above 0.7 is typically recommended; all crops met this criterion except for irrigated cotton lint, which had a moderate correlation of 0.62. For each crop, we computed the ratio of the sum of NASS values to the sum of FSA values for the mentioned years. This ratio was then applied to the 2019–2023 FSA aggregate yield data to generate consistent estimates. This method assumes that the ratio between actual and predicted values remains relatively stable, allowing us to input missing data using a constant adjustment factor derived from existing data.

4.2. Indemnity Payments

In order to calculate the insurance premium, we used the personalized cost estimator tool from USDA RMA, selecting the most common insurance plan (Yield Protection) for Hidalgo County in 2025 (USDA RMA, 2025), as it is the largest agricultural county in the region. All factors and calculations followed the methodology specified by the USDA RMA estimator tool, and results matched those shown on the website. Indemnity payments were calculated based on the 2025 USDA RMA indemnity template (USDA, 2025). The premiums for each crop are shown in table 1, for instance, for cotton lint

under irrigation has the highest premium among irrigated crops ($48.13), while cottonseed under irrigation has one of the lowest ($10.74). Among non-irrigated crops, cotton lint shows the highest premium ($85.26), followed by corn ($30.58) and sorghum ($15.45).

To ensure comparability across years, we removed the trend from the historic yields from 1981 to 2023, considering as a year base 2025. We aim to separate the influence of long-terms impacts, like changes in technology and management practices. In other words, by doing this detrend process, we isolated the year-to-year variations, and it allows us to analyze yield variability without the influence of long-run improvements. In table 2, we can observe the summary statistics of all the crops adjusted as if they occur in 2025.

In order to calculate the net income of the famers required for the presented model. We compare two scenarios: one where producers are insured and the other one without insurance coverage. The summary statistics of the net returns with insurance are presented in table 3. Likewise, the net returns without insurance are shown in table 4 This comparison allows us to assess the impact of the insurance on the farms' average profit. Same as premiums indemnities are shown in table 1; while premiums are fixed cost, indemnities are variable payments made when yields fall below insured threshold guarantees for each crop.

4.3. Symmetry of Returns

To justify the adoption of a Value-at-Risk (VaR) framework over traditional mean-variance (MV) approaches, we examine the symmetry of the derived farm-level return distributions for each crop. While MV models rely on the assumption of symmetric returns, empirical evidence suggests that agricultural yields—and consequently returns—often exhibit asymmetry (OECD, 2009; Antle, 2010). To formally test this, we apply a diverse set of symmetry tests designed to detect departures from symmetry around an unknown center. These tests differ from normality tests, as they focus exclusively on symmetry and allow for non-normal but symmetric distributions. Following Milošević and Obradović (2019), we implement multiple families of tests—including classic and modified versions of the Wilcoxon signed-rank test, classic and modified Kolmogorov–Smirnov (KS) test, sample skewness test ($\sqrt{b_1}$ test), and Bonferoni-type MGG test (Miao et al., 2006). All tests are applied to the empirical distributions using the sample median as the central location estimator (α-trimmed mean estimator, with α = 1/2), and the confidence intervals were estimated using bootstrapping techniques (Milošević and Obradović, 2019). By employing this broad spectrum of methodologies, we aim to verify the robustness of our findings and provide a rigorous foundation for the use of VaR-based optimization under asymmetric return conditions. The symmetry tests were applied to the farm-level returns for all crops,

irrigated and non-irrigated, considering both the case of insured crops and non-insured crops.

The results, presented in tables 5 and 6, report the p-values (significance levels) associated with each test. A lower p-value indicates stronger evidence against the null hypothesis of symmetry. Using a conventional significance level of 0.05, we find consistent evidence of asymmetry across most crops and test types. For non-insured returns, nearly all tests reject symmetry for corn, sorghum, and cotton (both irrigated and non-irrigated), with the exception of cotton with irrigation, where Wilcoxon and modified Wilcoxon tests yield higher p-values (0.6225 and 0.3300, respectively), suggesting symmetry may not be rejected in this case.

In the insured scenario, the evidence of asymmetry becomes even more pronounced. All tests reject symmetry for corn and sorghum across irrigation types, with p-values uniformly below 0.0002. Cotton under irrigation shows mixed results: while Wilcoxon and modified Wilcoxon tests yield non-significant p-values (0.5796 and 0.5910), the KS and B1 tests suggest asymmetry. For non-irrigated cotton, the results are more varied, with Wilcoxon and modified KS tests showing marginal significance (0.0763 and 0.1610), while other tests strongly reject symmetry. These results can be visually confirmed by inspecting the empirical distributions depicted in figures 1 and 2, which show clear deviations from symmetry in most cases.

Overall, the use of multiple test families enhances the robustness of our conclusions. The convergence of results across different statistical frameworks supports the hypothesis that crop returns are generally asymmetric, particularly under insured conditions. These findings reinforce the rationale for adopting a Value-at-Risk (VaR) framework, which better captures downside risk in the presence of asymmetric return distributions.

4.4. Scenario Evaluated

The proposed MV and VaR crop selection strategies are used to contrast crop allocations under the current water scarcity situation, where the total water available for irrigation has been reduced to 34.54% of the average 2019-2023 allocation (Texas Commission on Environmental Quality, 2025). For reference, the average amount of irrigation water used per acre during this period was 1.11 ac-ft. Furthermore, the net return associated with the average RGV crop allocation during 2019-2023, including sugarcane, along with the expected crop returns for 2025, was estimated to be equal to $32.73/ac

We assess the feasibility of stabilizing farm returns under conditions of severe water scarcity and reduced crop options (no sugarcane). On average, 36.45% of farmland was irrigated (USDA FSA, 2025). This value is set as the maximum share of all crops irrigated in the optimization process. We also considered participating in the Yield Protection crop insurance program. Under this program, failure of irrigation water supply can be an insured cause of loss and can trigger an indemnity payment

(USDA RMA, 2025). Irrigated land left idle is assumed to receive a $208.48/ac indemnity, which corresponds to the preventing planting compensation for cotton. The payment of the "irrigated idle crop" was obtained from the prevented planting calculation using the personalized cost estimator tool from USDA RMA.

Farm yields were derived for a representative farmer in Hidalgo County. Following Miranda (1991) and Coble, & Dismukes (2008), the expected farm yield (μ_j) and β_j parameter in equation (7) were set equal to the average regional yield and one, respectively. A skewed normal distribution function was used to estimate the density of the farm error term (ε_{ji}). For each crop, the expected value of the error was set to zero and the scale and shape parameters were optimized, allowing for possible skewed distributions. Also, a coverage level (λ) of 85% and Actual Production History yields (y_j^{APH}) equal to the average regional value were used in the analysis.

In our crop selection models, all available irrigation water must be used before triggering a preventing planting indemnity (i.e., the resource restriction is set as an equality in the second scenario).

4.5. Results

The results presented in this section and depicted in figure 3 correspond to two scenarios: one with insurance and the other one without insurance. We can observe that these two scenarios are under two frameworks: Mean-Variance and Value-at-Risk. In both methodologies the efficient frontiers with insurance are above the frontiers without

insurance, indicating higher expected net returns for a given level of risk. In the MV model, the insured crop combinations operate with a lower standard deviation range, approximately between $20/ac and $80/ac. The insured crop selections begin at lower risk levels and rise more steeply toward higher returns, while uninsured crop mixes start even with a lower risk, but never reach the same expected net returns, meanwhile insurance expected returns have expected returns about 120 $/ac, unsured crop choices the maximum is $45/ac with a very high risk.

The VaR model shows a similar pattern, i.e., insurance makes farmers increase their return range from about $60/ac to $125/ac while holding a downside risk probability at the same level as the uninsured case. In other words, having insurance shifts the entire frontier upwards without worsening the likelihood of poor outcomes. Therefore, the uninsured frontier goes from slightly above zero to $45 $/ac.

Furthermore, we can observe that under MV, insured crop selections progressively increase the share of non-irrigated corn and, into a lesser extent, non-irrigated sorghum. Without insurance the model allocates even a bigger share of corn non-irrigated, with an increase of cotton non-irrigated share as well, but it is worth saying that there is a slight increase in the share of corn irrigated. Regarding the VaR model, insurance scenario supports a significant share of corn non-irrigated, with a share of irrigated idle and cotton non-irrigated. On the other hand, no-insurance crop choices remain dominated by non-irrigated crops and idle land.

5. Summary and Conclusions

In this study, we present two alternative crop selection strategies to assist farmers mitigate the risk posed by severe irrigation water shortages. In the Mean-Variance (MV) model, risk is given by the variance of returns, and the objective is to find the crop combination that reduces risk for a given target return and available resources. On the other hand, the probability of obtaining a return lower than its expected value is used to define risk in the Value-at-Risk (VaR) strategy. With symmetric returns, both risk specifications are equivalent, but crop choices based on them differ when the symmetry (or normality) assumption is not met.

Optimal crop selection relies on farm-level yields. Unfortunately, these data are often unavailable. Instead, historical farm yields are replaced by aggregated data at the county, regional, or national level, which could lead to aggregation bias. To address this issue, we proposed a simulation approach to recover farm yields observed actuarial based information from crop insurance. Compared to existing methods, we use flexible parametric distributions that allow us to recover the joint density function without imposing symmetry.

The proposed methods are illustrated in South Texas. The region's agricultural sector has suffered significant and prolonged water shortages, to the point where farmers, on average, receive about one-third of their historical water allocation. This situation has forced farmers to reconsider their crop choices. Returns similar to or

greater than those obtained when water was not a significant factor of production can be obtained by using both crop selection strategies. However, the results also demonstrated that systematic crop selection combined with participation in crop insurance programs can further help mitigate potential economic losses and reduce risk.

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Table. 1. Insurance Premiums and Indemnities, n=43

Crop	Premium	Indemnity (Mean)	Std. Dev.	#zeros	Min	Max
Cotton lint irr.	48.128	2.194	13.217	41	0	86.503
Cottonseed irr.	10.739	.059	.384	42	0	2.519
Cottonseed no-irr.	6.658	.412	1.914	41	0	10.341
Cotton lint no-irr.	85.257	5.412	18.225	38	0	86.63
Corn irr.	10.855	1.356	5.932	40	0	34.329
Corn no-irr.	30.575	23.767	34.504	23	0	106.836
Sorghum irr.	15.994	.04	.265	42	0	1.739
Sorghum no-irr.	15.451	14.576	25.768	27	0	97.547

The premium is a fixed cost, the indemnity is a variable, therefore the columns after indemnity (mean), belongs to indemnity results

Table 2. 2025-Adjusted yields, n=43

Crop	Mean	Std. Dev.	Min	Max
Cotton lint irr.	1286.659	173.916	815.069	1739.02
Cottonseed irr.	.931	.126	.59	1.258
Cotton lint no-irr.	746.871	160.234	438.545	1170.105
Cottonseed no-irr.	.54	.116	.317	.847
Corn irr.	103.651	12.052	78.03	136.501
Corn no-irr.	73.751	18.819	43.317	110.62
Sorghum irr.	75.632	6.356	62.823	88.2
Sorghum no-irr.	51.4	12.783	22.772	75.498

Table. 3. Estimated net returns with insurance, n=43

Crop	Mean	Std. Dev.	Min	Max
Corn irr.	55.359	41.817	-9.547	174.562
Corn no-irr.	47.352	44.346	4.837	158.893
Sorghum irr.	16.248	21.283	-25.108	58.451
Sorghum no-irr.	16.55	24.86	-10.726	82.972
Cotton irr.	11.663	79.4	-153.26	229.43
Cotton no-irr.	-85.846	69.751	-174.555	114.183
Idle irr.	208.48	0	208.48	208.48
Idle no-irr.	0	0	0	0

Cotton crop includes both cotton lint and cottonseed.

Table 4 Estimated net returns without insurance, n=43

Variable	Mean	Std. Dev.	Min	Max
Corn irr.	64.858	44.229	-29.172	185.417
Corn no-irr.	54.16	69.066	-57.534	189.468
Sorghum irr.	32.201	21.365	-10.853	74.444
Sorghum no-irr.	17.425	42.968	-78.798	98.422
Cotton irr.	68.276	84.589	-161.097	288.296
Cotton no-irr.	.245	77.935	-149.719	206.098

Cotton crop includes both cotton lint and cottonseed.

Table 5. Statistical significance levels of symmetry tests to crop returns – non-insured crops

Crop	Wilcoxon	Mod. Wilcoxon	KS	Mod. KS	B1	MGG
Corn irr.	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000
Corn no-irr.	0.0199	0.0140	0.0000	0.0050	0.0000	0.0030
Sorghum irr.	0.0042	0.0000	0.0000	0.0000	0.0000	0.0000
Sorghum no-irr.	0.0547	0.0020	0.0002	0.0090	0.0000	0.0000
Cotton irr.	0.6225	0.3300	0.0012	0.0000	0.0000	0.0010
Cotton no-irr.	0.0063	0.0000	0.0000	0.0170	0.0000	0.0000

*Lower significance levels (p-values) suggest stronger evidence against the null hypothesis of symmetry

Table 6. Statistical significance levels of symmetry tests to crop returns – insured crops

	Wilcoxon	Mod. Wilcoxon	KS	Mod. KS	B1	MGG
Corn irr.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Corn no-irr.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sorghum irr.	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000
Sorghum no-irr.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Cotton irr.	0.5796	0.5910	0.0241	0.0270	0.0000	0.4410
Cotton no-irr.	0.0763	0.9180	0.0000	0.1610	0.0000	0.0000

* Lower significance levels (p-values) suggest stronger evidence against the null hypothesis of symmetry

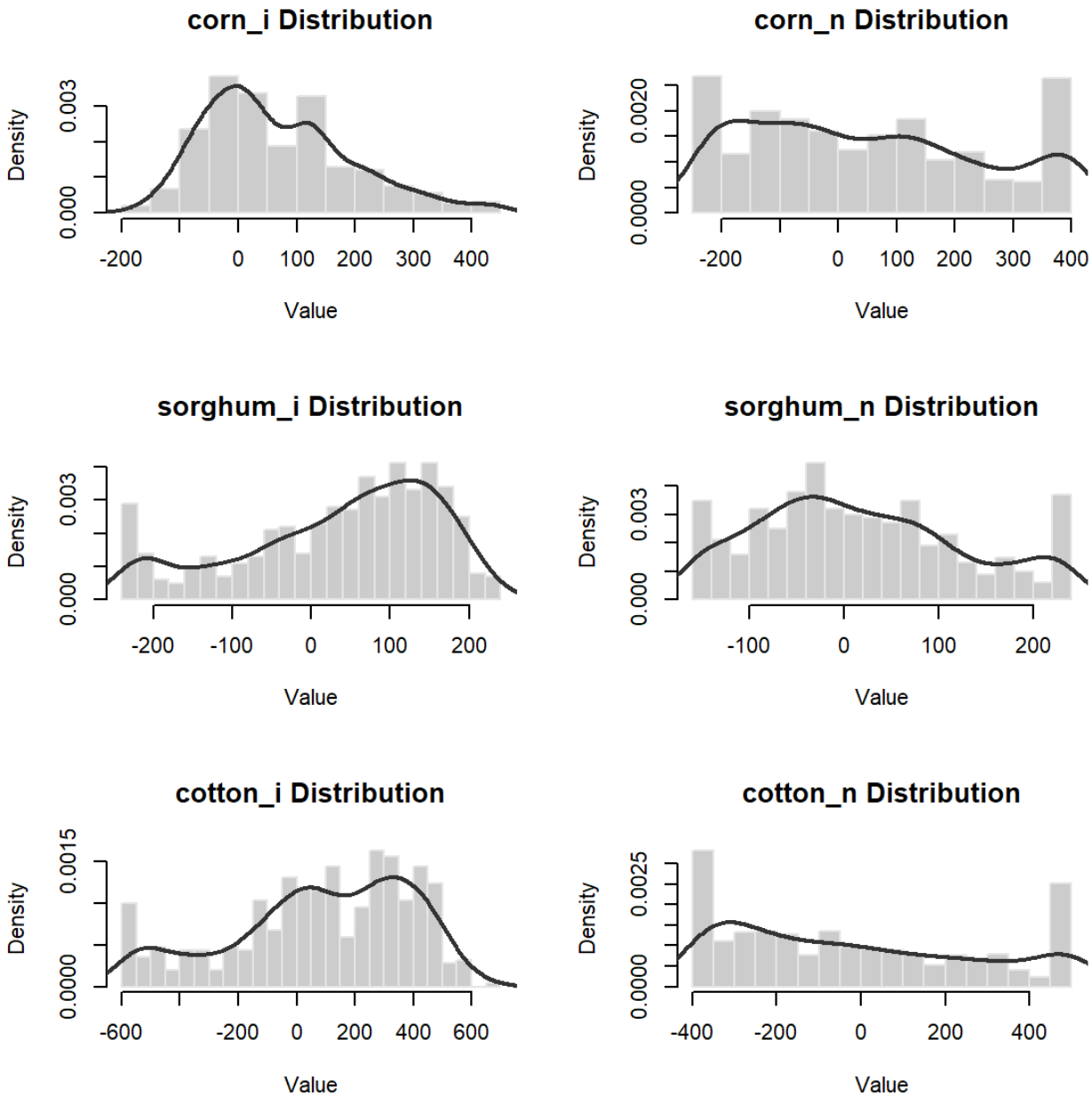


Figure 1. Empirical distributions of crop returns – non-insured crops

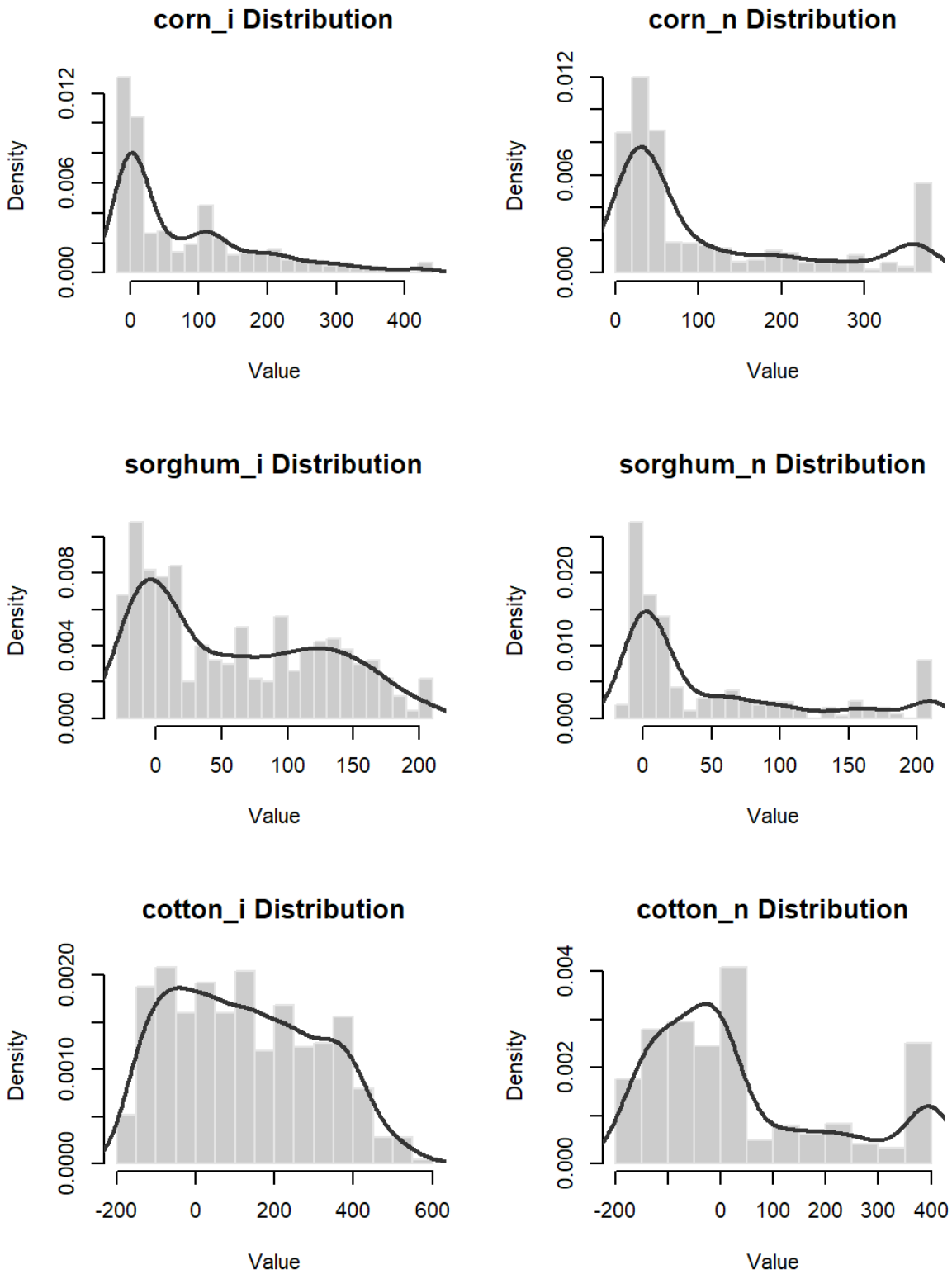


Figure 2. Empirical distributions of crop returns – insured crops

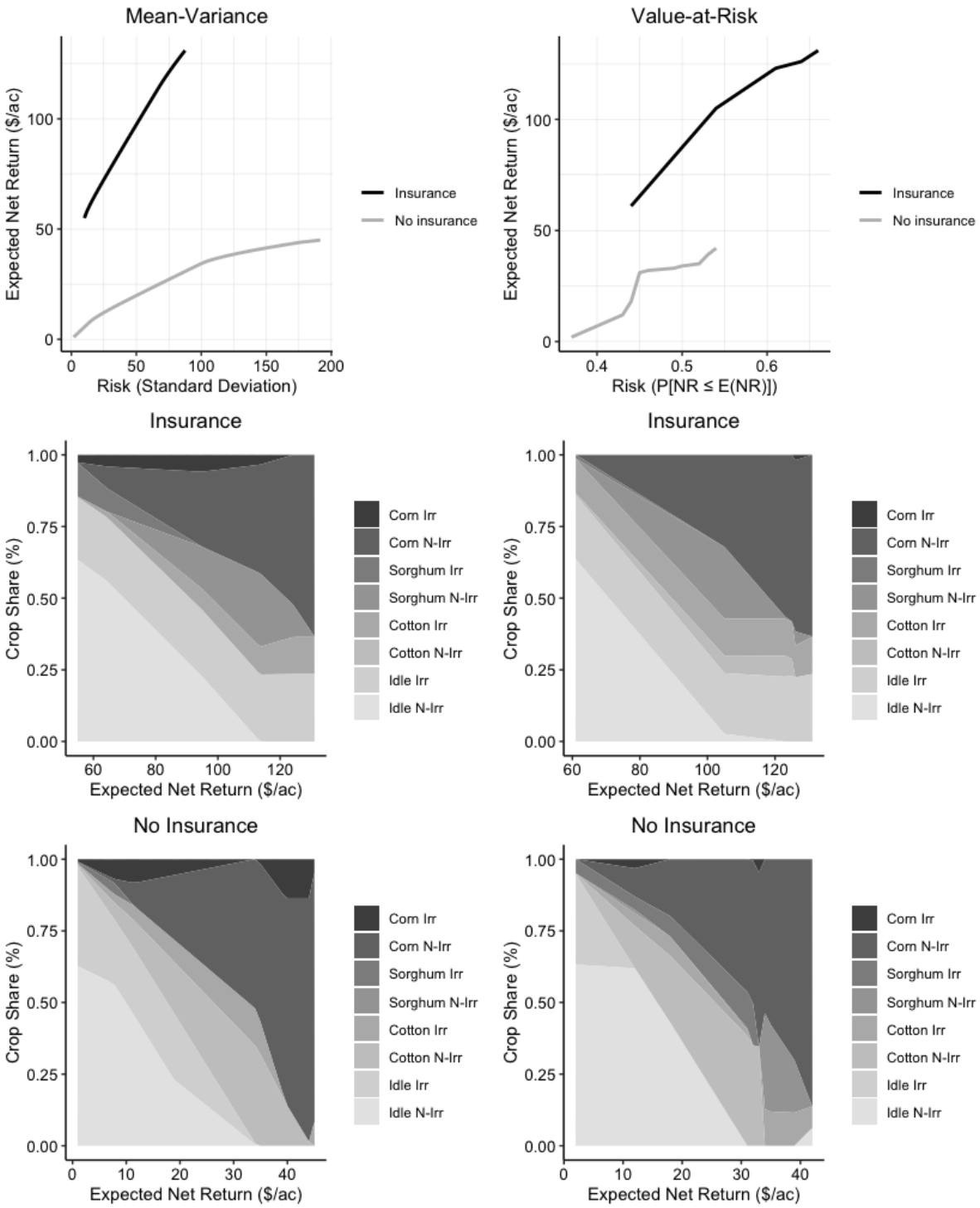


Figure 3. Efficient frontier and crop mix by model and insurance participation.