Using a Crop Simulation Model to Understand the Impact of Risk Aversion on Optimal Irrigation Management

R. P. Wibowo, N. P. Hendricks, I. Kisekka, A. Araya

Abstract. *We studied optimal irrigation management by risk-averse farmers with different soil types under limited well capacity. Our modeling framework allowed us to assess the optimal adjustment along the intensive margins (i.e., changes in seasonal irrigation depth) and along the extensive margins (i.e., changes in irrigated area). Our empirical application uses AquaCrop to simulate corn yields with historical weather in southwest Kansas under a large number of potential irrigation strategies. We show that risk aversion significantly increases total water use, especially for low and medium well capacities. While farmers decreased irrigated area due to risk aversion, the increase in water use occurred because it was optimal to increase the seasonal irrigation depth to reduce production risk. The increase in seasonal irrigation depth arises mostly from reduced management allowable depletion (MAD) levels in the initial crop growth stages of corn. Counterintuitively, risk aversion had a smaller impact on water use for a soil with a smaller soil water holding capacity. This result arises because optimal irrigation under risk neutrality is larger for soils with a smaller water holding capacity. Our results highlight the importance of accounting for risk aversion when estimating the optimal irrigation management strategy and show that the impact of risk aversion differs significantly by well capacity and soil type.*

Keywords. *AquaCrop, Irrigation, Risk, Well capacity.*

Irrigation water availability is becoming increasingly limited. One of the major effects of aquifer depletion is limited groundwater availability due to limited well capacities (i.e., the rate of groundwater extraction). Limited well capacity reduces the rate at which water can be extracted and thus may decrease profits from irrigation. The impact on crop production is more severe in dry years because irrigation may not be able to meet crop water demands. For example, a drought in 2011 in southwest Kansas decreased average corn yields to only 9,800 kg ha^{-1} compared to an average of 12,200 kg ha^{-1} in 2010 (NASS, 2016). This weather uncertainty creates risk for irrigation management under limited water availability. The optimal irrigation strategy must consider not only the profits under average conditions but also the risk due to weather uncertainty.

Our study used AquaCrop, a water-driven crop simulation model, to predict corn yields based on historical weather and simulated irrigation water applications. The model was parameterized to correspond with weather and soil conditions in Garden City, Kansas. Garden City is located in southwest Kansas, overlying the High Plains Aquifer, where there has been substantial aquifer depletion. Our model considered irrigation capacity, management allowable depletion (MAD) in each growth stage, and the irrigated area in maximization of certainty equivalent, rather than average returns. Intuitively, a risk-averse farmer prefers a management strategy that provides certain returns over a management strategy that provides uncertain returns, if the two strategies have the same average returns. The certainty equivalent represents the amount of money provided with certainty such that the farmer would be indifferent between the certain money and the management strategy that provides uncertain returns. For a risk-averse farmer, the certainty equivalent is smaller than average returns and provides a metric that can be used to compare alternative strategies with different mean and variance of returns. We show how the optimal irrigation strategy differs depending on the degree of risk aversion with different well capacities and soils.

Many studies have compared irrigation strategies based on profit maximization (e.g., Boggess et al., 1983; Martin et al., 1989; O'Brien et al., 2001; Nair et al., 2013a). Adjustments to limited irrigation can occur either along the intensive margin (i.e., reducing seasonal irrigation depth) or along the extensive margin (i.e., reducing irrigated area) (English, 1990; Wolff and Stein, 1999; Hendricks and Peterson, 2012; Wang and Nair, 2013; Pfeiffer and Lin, 2014). Wang and Nair (2013) showed that the optimal adjustment occurs so that the marginal benefit of increasing the irrigated area

Submitted for review in March 2017 as manuscript number NRES 12320; approved for publication as part of the "Crop Modeling and Decision Support for Optimizing Use of Limited Water" special collection by the Natural Resources & Environmental Systems Community of ASABE in August 2017.

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  ISSN 2151-0032 https://doi.org/10.13031/trans.12320

equals the marginal benefit of increasing the seasonal irrigation depth.

Previous literature is conflicting on whether the optimal adjustment to limited water availability occurs primarily through adjustments at the intensive margin or the extensive margin. Several studies have emphasized the potential of reducing irrigated area as an optimal water allocation strategy with limited water (Martin et al., 1989; O'Brien et al., 1998; Baumhardt et al., 2009; Nair et al., 2013a). Other studies have emphasized the potential to optimize water use adjustment along the intensive margin by applying deficit irrigation (English, 1990; Heeren et al., 2011). Panda et al. (2004) found that there is a minimum MAD level for irrigation schedules that a farmer should attain to avoid severe crop yield loss. Farmers may also focus the available water for irrigation during the most productive growth stages (Heeren et al., 2011; Nair et al., 2013b).

Few studies have evaluated the impact of risk aversion on a farmer's irrigation strategy (Boggess et al., 1983; Bernardo, 1988; Peterson and Ding, 2005; Foster et al., 2014). Peterson and Ding (2005) used a production function approach in which crop yield is related to total annual irrigation water applied or total irrigation within crop growth stages. Furthermore, the economic model of Peterson and Ding (2005) selects optimal irrigation application rather than a soil moisture target so that the farmer applies the same irrigation regardless of the realized weather. In our approach, the farmer selects a MAD level in each growth stage, so the optimal seasonal irrigation depth differs by year depending on the weather.

Irrigation can mitigate the risk associated with weather variability in agricultural production (Wood et al., 2014; Jain et al., 2015). However, irrigation with limited water availability is unable to completely mitigate risk, so the degree of risk aversion has an impact on a farmer's irrigation strategy (Boggess et al., 1983; Bernardo, 1988; Peterson and Ding, 2005; Foster et al., 2014). Deficit irrigation may result in greater variability in crop yield compared to full irrigation, particularly for corn (Kisekka et al., 2015). Therefore, it is likely that more risk-averse farmers respond by reducing the irrigated area (Foster et al., 2014).

Literature on this topic differs on whether risk aversion results in an increase or decrease in total water use. Boggess et al. (1983) found that risk aversion may induce a farmer to irrigate less frequently and use smaller amounts of water compared to the optimal irrigation strategy of a risk-neutral farmer. Similarly, Peterson and Ding (2005) also found that a farmer with risk-averse behavior may choose to use less water when less is available. In particular, a farmer may reduce the water applied during preplant and vegetative growth stages, as their model indicates that more water in these stages increases yield variability. However, Bernardo (1988) found evidence that risk aversion induces farmers to apply more irrigation to reduce the incidence of low yields that create variable net returns.

Our work is most closely related with that of Foster et al. (2014, 2015). Foster et al. (2014) also used AquaCrop to model corn yields under irrigation where a risk-averse farmer selects the optimal MAD and irrigated area. A key difference with our approach is that we allow the optimal MAD to differ by growth stage, whereas Foster et al. (2014) assumed only a single MAD across all growth stages. Because water stress at different growth stages has different effects on crop water productivity (Fereres and Soriano, 2007; Geerts and Raes, 2009; Payero et al., 2009), we argue that it is important to allow the optimal MAD to differ across growth stages. Farmers can optimally manage the soil water depletion in a critical crop growth stage to obtain both a higher yield and better water productivity (Panda et al., 2004). Allowing for non-uniform soil water deficits across crop growth stages could make deficit irrigation more economically appealing. The results we present in this article also provide greater detail than Foster et al. (2014) on how risk aversion affects the optimal irrigation strategy because that earlier study did not focus primarily on the impact of risk aversion.

Our research has three key objectives. First, we estimate how different degrees of risk aversion impact water use. The results from this objective quantify how irrigation water application differs for a risk-averse farmer compared to a risk-neutral farmer (i.e., a farmer who seeks only to maximize average profit). Second, we seek to understand the mechanisms that risk-averse farmers use to adjust their water application compared to risk-neutral farmers. Lastly, our study estimates how the impact of risk aversion on water use varies across different well capacities and soil types.

Model and Methods

Expected Utility Model

Consider a farmer who faces a risky outcome due to some uncertain event (e.g., weather). Our research focuses on the risk arising due to random weather shocks (i.e., positive weather events in some years and negative weather events in other years). In practice, farmers also face risk arising from volatility in prices, but we ignore this price uncertainty. While price uncertainty is likely to be an important consideration for decisions made across growing seasons (e.g., irrigation technology and capital purchases), it is likely to have a small impact on decisions made within a single growing season (e.g., irrigation and chemical purchases). In our model, corn production depends on the irrigation management strategy and random weather shocks.

The risk-averse farmer seeks to maximize expected utility rather than expected profit. Utility is used to represent the satisfaction that a farmer receives from profits. The utility function for risk-averse farmers is concave, implying that risk-averse farmers dislike a random decrease in profits more than they like an increase in profits. Therefore, risk-averse farmers have an incentive to implement practices to reduce the variation in returns. The farmer's subjective probability distribution of the random shocks is generated from information gathered before the growing season begins. The farmer chooses the irrigation management strategy to maximize the expected utility of net returns (Chavas, 2004), as expressed in equation 1:

$$\max EU(\pi, r) \tag{1}$$

where π is net returns with different weather shocks, and r is the absolute risk aversion coefficient (table 1 lists and defines the risk model parameters used throughout this article). The absolute risk aversion coefficient (r) indicates the degree of risk aversion of a farmer; a larger r value indicates a more risk-averse farmer.

Our study assumes that the farmer has constant absolute risk aversion (CARA) preferences, which implies that the absolute risk aversion coefficient (r) is independent of net returns (π). CARA also implies that initial net returns (π) do not influence farmers' willingness to pay to reduce their exposure to risk (Chavas, 2004). Chavas (2004) showed that under the CARA assumption and normality of net returns, maximizing the expected utility is equivalent to maximizing the certainty equivalent. The estimation of certainty equivalent is globally valid with the following (eq. 2) mean-variance maximization (Chavas, 2004):

$$\max E(\pi) - 0.5 \times r \times \mathrm{var}(\pi) \tag{2}$$

where $E(\pi)$ is the expected net returns, and var(π) is the variance of the net returns. The certainty equivalent measures the amount of certain returns the farmer would consider equivalent to the potential uncertain returns.

The risk aversion coefficient (r) is often used in risk and uncertainty models as a parameter to represent the degree of risk aversion. However, the value of the risk aversion coefficient is difficult to interpret without further information (Babcock et al., 1993). Several studies have used empirical methods to elicit the risk aversion coefficient (r) for farmers (Brink and McCarl, 1978; Love and Buccola, 1991; Saha et al., 1994; Chavas and Holt, 1996; Atanu, 1997). Those studies have conflicting results for the value of the risk aversion coefficient. Indeed, varied estimates of the risk aversion coefficient are not surprising because those studies most likely used different samples of farmers. McCarl and Bessler (1989) argued that the use of risk aversion coefficients estimated from other studies is not appropriate because every study uses different utility assumptions and net returns levels.

Table 1. Risk model parameters.

Symbol	Description	Units
π	Net return	\$
r	Absolute risk aversion coefficient	-
ρ	Probability premium	-
σ	Gamble size	-
ω	Risk premium	-
m_d	Management allowable depletion (MAD) in each growth stage	%
l	Irrigation capacity	mm d^{-1}
δ	Irrigated area	ha
φ	Well capacity	m^3 h^{-1}
γ	Maximum duration of extraction per day	h
p	Price of corn	\$ kg^{-1}
$f(\cdot)$	Corn yield function	kg ha^{-1}
τ	Soil characteristics	-
θ_t	Weather conditions	-
w_t	Total seasonal irrigation water	1000 m^3
$c(w_t)$	Cost of energy to extract w_t units of water	\$
n	Costs of production that are proportional to corn yield	\$ kg^{-1} ha^{-1}
IC	Costs of production that are proportional to irrigated area	\$ ha^{-1}
SC	Sunk cost of irrigation technology	\$
k	Cash rental rate of non-irrigated land	\$ ha^{-1}

We use the method proposed by Babcock et al. (1993) to calculate a reasonable range for the risk aversion coefficient (r). Babcock et al. (1993) calculated the risk aversion coefficient by using an assumed risk premium for a particular gamble size, where gamble size (σ) is represented by the standard deviation of the net returns. The probability premium (ρ) is difficult to interpret but represents the degree of risk aversion. The estimation of the risk aversion coefficient (Babcock et al., 1993) is expressed as equation 3:

$$r(\rho,\sigma) = \frac{\ln\left[\frac{1+2\rho}{1-2\rho}\right]}{\sigma} \tag{3}$$

The risk premium (ω) is easier to interpret than the probability premium (ρ) and is represented as a function of the probability premium (Babcock et al., 1993), as shown in equation 4:

$$\omega(\rho) = \frac{\ln\left[\frac{1+4\rho^2}{1-4\rho^2}\right]}{\ln\left[\frac{1+2\rho}{1-2\rho}\right]} \tag{4}$$

The risk premium is defined as the proportion of the gamble size that a farmer is willing to pay in order to avoid all potential losses. For example, a risk premium of 20% indicates that a farmer is willing to pay 20% of the standard deviation of net returns to eliminate all risk. We use equations 3 and 4 to calculate risk aversion coefficients for different risk premiums for each well capacity. Different risk aversion coefficients are generated for each well capacity based on a different gamble size, as represented by the standard deviation of net returns.

We use risk premiums ranging from 0% to 80%, where a risk premium of 80% represents a farmer with very strong risk-averse behavior. We consider a risk premium between 10% and 20% to be the most plausible values of average risk aversion among farmers. Hudson et al. (2005) estimated that the average risk premium is about 10.5%. Bontems and Thomas (2000) found that the value of information together with risk premium accounted for about 20% of profit per hectare. Babcock and Shogren (1995) estimated a risk premium between 40% and 85%. Other studies have used risk premiums in the range between 0% and 40% to study optimal input usage (Babcock and Hennessy, 1996; Mitchell, 2003).

Model of Optimal Irrigation Management

In this section, we incorporate the previous model of risk aversion into a model of optimal irrigation management. The farmer's objective is to find the irrigation strategy that maximizes certainty equivalent across T potential weather conditions (denoted $t = 1,..., T$) subject to constraints on water availability, as expressed by equations 5 and 6:

$$\max_{\{m_d,l,\delta\}} \frac{1}{T}\sum_{t=1}^{T}\pi_t - 0.5 \times r \times \frac{1}{T}\sum_{t=1}^{T}\left(\pi_t - \frac{1}{T}\sum_{t=1}^{T}\pi_t\right)^2 \tag{5}$$

$$\text{subject to } \; l \times \delta \leq \varphi \times \gamma \tag{6}$$

The farmer's irrigation strategy has three components, consisting of MAD at each growth stage (denoted m_d and measured as % of total available water), irrigation capacity (denoted l and expressed in mm d^{-1}), and irrigated area (denoted δ and measured in hectares). Our study assumes four crop growth stages for corn (denoted $d = 1,..., 4$). The irrigation capacity is the amount of water applied per hectare per day of irrigation. Note that the MAD levels and irrigation capacity together define the total application per irrigated hectare over the entire growing season (i.e., the seasonal irrigation depth). We refer to changes in the MAD at each growth stage and irrigation capacity as adjustments along the intensive margin. Throughout this article, we refer to changes in the irrigated area as adjustments along the extensive margin.

Equation 6 expresses the constraint due to a limited well capacity. In equation 6, the total irrigation each day cannot exceed the maximum water extraction per day. On the left side, total irrigation volume per day is the irrigation capacity (l) times the irrigated area (δ). On the right side, the maximum water extraction per day is the well capacity (φ) times the maximum duration of extraction per day (γ). The well capacity represents the amount of water that can be extracted per hour. Equation 6 implies that a farmer with a particular well capacity may need to decrease the irrigated area in order to increase the irrigation capacity.

The net return for a given weather condition is calculated as equation 7:

$$\begin{aligned} \pi_t = {} & \delta\left[pf\left(m_d, l, \tau, \theta_t\right) - c\left(w_t\right) - n * f(\cdot) - IC\right] \\ & - SC + \left(A - \delta\right)k \end{aligned} \tag{7}$$

where $$w_t = g\left(m_d, l, \theta_t\right) \tag{8}$$

The first terms in equation 7 estimate the net returns from irrigation, and the last term estimates the net returns from the non-irrigated area. The irrigated area is denoted δ, and the total area of the field is A. We consider a 64.74 ha hypothetical field that is divided into a maximum irrigated area of 50.58 ha and a minimum non-irrigated area of 14.16 ha under center-pivot irrigation. This hypothetical field corresponds to the common scenario in our study area of a 160 acre quarter-section field with a center-pivot irrigated circle.

The price of corn is denoted as p. Corn yield is denoted by $f(\cdot)$, which for irrigated area depends on MAD from each growth stage (m_d), irrigation capacity (l), soil characteristics (τ), and weather conditions (θ_t). We simulate crop yield using AquaCrop, as described in the next section. The cost of irrigated production is comprised of several components. The irrigation cost ($c(w_t)$) corresponds to the cost of energy to extract the total water applied per irrigated hectare (w_t) for each weather outcome. Equation 8 shows that the seasonal irrigation depth (w_t) depends on MAD from each growth stage, irrigation capacity, and weather conditions. Variable costs, $n*f(\cdot)$, are assumed to be proportional to crop yield and include fertilizer and machinery harvest charges (i.e., fertilizer costs are assumed smaller for deficit irrigation than full irrigation). The input cost per hectare (IC) is comprised of seed, insecticide/fungicide, herbicide, machinery, crop consulting, non-machinery labor, irrigation labor, interest on non-land cost, and other miscellaneous costs. The annualized sunk cost of the irrigation technology is SC and does not depend on total irrigated area. In other words, we consider the situation in which a farmer already has a center-pivot sprinkler that can irrigate 50.58 ha, so reducing the irrigated area does not reduce the sunk cost of the irrigation technology. The net returns from the non-irrigated area are shown in the last term, where we assume for simplicity that the returns are equal to the cash rental rate of non-irrigated area (denoted k). We use the cash rental rate to reflect the expected returns to non-irrigated land because the rental rate reflects the amount the farmer is willing to pay per year (influenced by expected returns and risk from non-irrigated production) to produce crops on the land. Using the non-irrigated rental rate allows us to avoid using a crop simulation model for the non-irrigated crop production but still accounts for the economic value of the non-irrigated area.

Table 2. Production cost parameters (O'Brien and Ibendahl, 2015).

Input	Cost
Seed[a]	\$9.785 ha^{-1}
Fertilizer[b]	\$0.0671 kg^{-1} ha^{-1}
Herbicide[a]	\$137 ha^{-1}
Insecticide/fungicide[a]	\$320 ha^{-1}
Machinery[a]	\$230 ha^{-1}
Harvest base charge[a]	\$70 ha^{-1}
Harvest extra charge for yields >200 bushels[b]	\$0.025 kg^{-1} ha^{-1}
Harvest hauling[b]	\$0.02 kg^{-1} ha^{-1}
Non-machinery labor[a]	\$40 ha^{-1}
Irrigation labor[a]	\$20 ha^{-1}
Crop consulting[a]	\$16 ha^{-1}
Miscellaneous cost[a]	\$25 ha^{-1}

[a] Variable cost.
[b] Input cost.

The parameters of the cost of production are shown in table 2. Parameters for the cost of production are from farm management guides developed by Kansas State Research and Extension based on a southwest Kansas corn farm given 2015 conditions (O'Brien and Ibendahl, 2015). Therefore, the corn price is assumed at \$0.17 kg^{-1} and the pumping cost is assumed at \$0.051 m^{-3} (O'Brien and Ibendahl, 2015). The sunk cost of the irrigation technology investment came from Lamm et al. (2015). Importantly, we exclude the irrigated cash rent from the cost of production, so the estimated net returns in equation 7 represent the returns to land. The non-irrigated cash rental rate is \$61.6 ha^{-1} (Taylor, 2015).

As a source of model validation, we estimated that the net return for irrigated land for a risk-neutral farmer with Richfield silt loam soil with a well capacity of 161 m^3 h^{-1} is \$274 ha^{-1}, and the net return for a 138 m^3 h^{-1} well capacity is \$254 ha^{-1}. These well capacities are representative of well capacities in the study region. Taylor and Tsoodle (2015) estimated that the cash rental rate for irrigated cropland in Finney County, Kansas, is \$269 ha^{-1}. This comparison with cash rental rate data supports the validity of our model.

AquaCrop and Irrigation Scheduling

Our study used AquaCrop v4.0 (Raes et al., 2009; Hsiao et al., 2009; Steduto et al., 2009) to simulate corn yield under different irrigation schedules. AquaCrop is computer software developed by FAO that simulates crop yield and crop growth based on water availability. The AquaCrop model can be used as an empirical production function for estimating crop yield response to water (Raes et al., 2009). Raes et al. (2009) found that AquaCrop offers better accuracy, simplicity, and robustness than other crop yield simulation models. Moreover, AquaCrop requires fewer parameters and input data to simulate the crop yield response to water (Steduto et al., 2009; Araya et al., 2016).

Using a daily crop simulation model is important because water stress in a short period of the growing season can impact crop yield, and well capacity is a constraint on daily water use. For example, even if average water availability throughout the growing season is sufficient due to large rainfall in the spring, there could still be significant losses in crop yield due to periods of drought in later growth stages. AquaCrop also accounts for the dynamic response of crop production to water availability.

Climate components, soil characteristics, and crop growth parameters are necessary for AquaCrop. We used 30 years (1986-2015) of weather data from Garden City obtained from the Kansas Mesonet (Kansas Mesonet, 2016). Reference evapotranspiration (ET_o) for the AquaCrop production estimation was calculated using the software ET_o calculator (Raes, 2012). We used two types of soils, Richfield silt loam and Valent-Vona loamy fine sand, because of their large difference in soil water holding capacity and because they comprise a large portion of the irrigated area in Finney County (USDA, 1965; NRCS, 2016). The average available water holding capacity for each soil was calculated using the Soil-Plant-Air-Water (SPAW) model (Saxton and Willey, 2005). Using the SPAW model and reference number for the soil texture, we calculated the average available water holding capacity as 159 mm m^{-1} for the Richfield silt loam and 79 mm m^{-1} for the Valent-Vona loamy fine sand.

The crop growth parameters for AquaCrop were calibrated based on actual crop production data under limited irrigation conditions in Garden City (Araya et al., 2017). With regard to the calibration and validation of the crop model, the model was calibrated based on experimental data provided by Klocke et al. (2014) as well as information documented by the original model developers. The principles and guidelines set out in the AquaCrop manuals (Raes et al., 2012; Steduto et al., 2012) and relevant calibration and validation literature from the developers and other contributions (e.g., Heng et al., 2009; Raes et al., 2009; Steduto et al., 2009; Hsiao et al., 2009; Hsiao and Fereres, 2012) were followed.

Briefly, data from the full irrigation treatment for the 2011 cropping season were used for model calibration. All management, soil, crop, and climate characteristics for the experimental site were used in the model. Soil water, evapotranspiration (estimated from soil water balance), leaf area index, yield, and biomass were measured in the field. The canopy cover (one of the most important components) was estimated from leaf area index based on the methodology developed by Heng et al. (2009) and Hsiao et al. (2009). Many of the conservative parameters in the model (which are claimed applicable to a wide range of climate conditions by the original model developers) were found valid for the experimental corn cultivar with only small adjustments. For example, the harvest index of our experimental cultivar was slightly higher than that of the cultivars used for calibrating corn by the model developers. For this reason, slight adjustments were made for water stress effects on harvest index. Adjustment of these parameters was carried out after repeatedly comparing the measured data with the simulated outputs. After adjusting the water stress coefficients, simulated yield, biomass, and ET were in agreement with the measured values. The model was validated based on experimental data measured in 2010 and 2012. Each of these years had six irrigation treatments. The model was able to adequately simulate the ET, yield, and biomass of all the treatments. The goodness-of-fit statistical test between the measured and simulated ET indicated a normalized root mean square of error of 13.8% and an index of agreement of 0.8. Statistics for yield indicated a normalized root mean square of error of 5.1% and an index of agreement of 0.99. Statistics for biomass indicated a normalized root mean square of error of 15.5% and an index of agreement of 0.96. The crop parameters used in AquaCrop are listed in table 3.

There are two components of adjustment at the intensive margin: the irrigation capacity and management allowable depletion (MAD). The irrigation capacity and MAD together define the irrigation schedule. The irrigation capacity is the maximum rate at which water can be applied in one day per hectare of irrigated area (mm d^{-1}). The AquaCrop software simulates daily irrigation amounts based on the irrigation capacity to maintain the soil moisture level by setting MAD for each growth stage. MAD is the maximum amount of total available water (TAW) that can be depleted from the soil before triggering irrigation. Therefore, a smaller MAD level implies that irrigation is used to maintain greater soil water.

The MAD levels were set for four different growth stages: initial (42 days), canopy development (34 days), mid-season (44 days), and late-season (21 days). The growth stages correspond to the FAO-56 stages. The initial stage represents

Table 3. Some of the crop parameters and values used for calibrating the AquaCrop model (Araya et al., 2017).

Parameter	Value
Canopy cover per seedling at 90% emergence	6.5 cm^2
Canopy expansion (CGC)	13.5% d^{-1}
Maximum canopy cover	80%
Canopy decline (CDC)	11.7% d^{-1}
Emergence (days after planting)	20 d
Normalized crop water productivity	33.7 g m^{-2}
Maximum canopy cover (days after planting)	76 d
Start of senescence (days after planting)	120 d
Flowering (days after planting)	80 d
Root depth	2.4 m
Maximum root depth (days after planting)	115 d
Maximum crop evapotranspiration	1.05
Harvest index (HI)	52%
Canopy expansion function	
P-upper	0.1
P-lower	0.45
Shape	2.9
Stomatal closure function	
P-upper	0.65
Shape	6
Early canopy senescence function	
P-upper	0.45
Shape	2.7

the time from sowing to 10% canopy cover, the development stage ends at 98% canopy cover, the mid-season stage ends at senescence, and the late-season stage ends when the crop reaches maturity (Raes et al., 2010). We considered a range of MAD levels from 0% to 100% in 10% increments. The irrigation capacity was allowed to range from 1 to 16 mm in 1 mm increments. Moreover, the ranges of MAD levels apply to each of the four growth stages separately. The total adjustment at the intensive margin for each well capacity is the combination of MAD and irrigation capacity. There are eleven MAD levels for four different growth stages and 16 different irrigation capacity levels, for a total of 234,256 strategies ($11 \times 11 \times 11 \times 11 \times 16 = 234{,}256$). The irrigation capacity and MAD at each growth stage determine the seasonal irrigation depth, where seasonal irrigation depth is defined as the total amount of irrigation water applied per growing season per irrigated hectare (mm year^{-1}). We assumed that farmers set their irrigation schedules prior to planting, when weather is unknown, but the actual water applied depends on the actual weather in the growing season. This is an important distinction from previous studies that assumed the choice of seasonal irrigation depth was fixed, so farmers were restricted to applying the same amount of water in dry and wet years (Llewelyn and Featherstone, 1997; O'Brien et al., 2001; Peterson and Ding, 2005).

Summary of Model Computation

The computation of the modeling framework described above was implemented as follows. For each irrigation management strategy, AquaCrop was used to predict 30 crop yield and water use outcomes based on 30 different years of historical weather (see the next section for more details). We imposed a constraint on the amount of water that can be applied in a given day as determined by the well capacity (eq. 6) when we performed the simulations using AquaCrop. The yield and water use from AquaCrop were then substituted into equation 7 to calculate the net returns for each year of historical weather. We then calculated the mean and variance of these 30 different net returns estimates and calculated the certainty equivalent for a given irrigation strategy using equation 5.

A total of 234,256 potential combinations of MAD and irrigation capacity were considered. We also considered different sizes of growing area that are feasible given the irrigation capacity. Including the alternatives for growing area generated 27,642,208 total irrigation strategy combinations, from which a farmer can choose the optimal irrigation strategy. The optimal irrigation strategy is the strategy that has the greatest certainty equivalent of all possible strategies that are feasible given the well capacity.

Results and Discussion

Richfield Soil

Panel A of figure 1 shows how the optimal total water application varies by the risk premium for various well capacities for the Richfield silt loam soil. The *x*-axis in panel A varies the risk premium, and the *y*-axis in panel A is the optimal total water application averaged across all historical

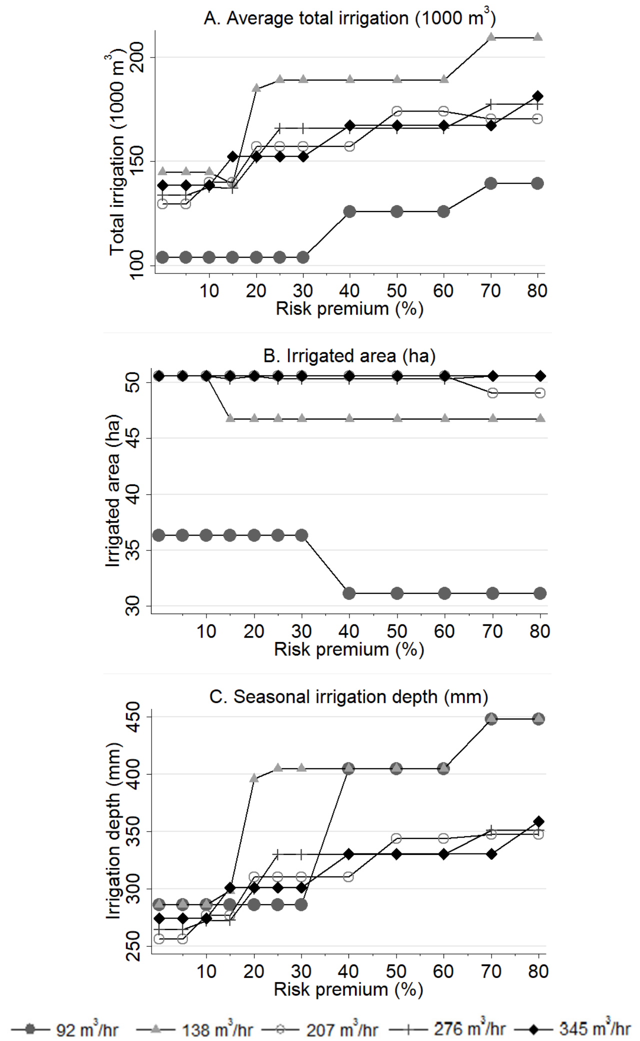

Figure 1. Impact of risk aversion on average total irrigation (1000 m^3), irrigated area (ha), and seasonal irrigation depth (mm) for Richfield silt loam soil.

weather scenarios for a given risk premium. For example, a risk premium of 20% means that a farmer would be willing to pay 20% of the standard deviation of net returns in order to avoid all variation in returns.

The results show that greater risk aversion (i.e., a greater risk premium) results in greater total water use. The changes in the magnitude of water use depend not only on risk-averse behavior but also on well capacity. The increase in water use related with risk aversion is larger for a moderate well capacity of 138 m^3 h^{-1} than for smaller or larger well capacities. The change from risk neutrality to a risk premium of 20% increases the total irrigation by as much as 30% for 138 m^3 h^{-1} wells. A risk premium of 20% increases the total irrigation by 15% for a well capacity of 207 m^3 h^{-1} or larger compared to risk neutrality. These results clearly indicate that risk aversion has a significant impact on water use, and models that ignore risk aversion will underestimate the optimal amount of water use.

Foster et al. (2014) also found that greater risk aversion is associated with greater water use. Our finding that risk aversion has a greater impact on water use for low or medium well capacities (e.g., 92 to 138 $m^3\ h^{-1}$) is in contrast to Foster et al. (2014), who found a greater impact of risk aversion for high well capacities. One reason for the difference could be different risk aversion coefficients. Another potential reason is that our study includes non-uniform MAD across crop growth stages, which enables a risk-averse farmer to focus irrigation applications in more productive growth stages instead of increasing irrigation application in all growth stages.

Another observation from panel A of figure 1 is that total water application is lowest for the smallest well capacity. This is expected because the small well capacity constrains the total amount of water that can be applied during the growing season. Total water application is actually largest for moderate well capacities. Moderate well capacities optimally maintain greater soil moisture because they cannot increase soil moisture as quickly as a large well capacity.

Next, we analyzed the source of this change in total irrigation water use. Panel B of figure 1 shows the adjustment along the extensive margin due to different degrees of risk aversion. The points in panel B represent the same irrigation strategies shown in panel A, but panel B shows the irrigated area associated with the optimal irrigation strategy for a given risk premium. Greater risk aversion induces the farmer to reduce the irrigated area when the well capacity is 138 m^3 h^{-1} or lower. However, farmers with larger well capacities show little or no change in irrigated area. Intuitively, adjustment along the extensive margin is greater with smaller well capacities because farmers with small well capacities must reduce irrigated area more to reduce the risk of not meeting crop water demands for a large irrigated area. Our finding is different from that of Foster et al. (2014), who found greater adjustment in irrigated area due to risk aversion when the well capacity is high. Interestingly, we found that risk aversion decreases water use along the extensive margin, even though the overall effect of risk aversion is to increase total water use.

The adjustment at the extensive margin is larger for smaller well capacities due to the limitation on irrigation capacity. In order to meet the crop water demand and reduce the risk in crop production due to dry weather conditions, a farmer with a small well capacity reduces the irrigated area in order to increase the irrigation capacity (figs. 1 and 2). In the case of a small well capacity, increasing the seasonal irrigation depth by only adjusting the MAD without changing the irrigation capacity will not provide sufficient water for crop production, and the farmer will not reduce the exposure to risk.

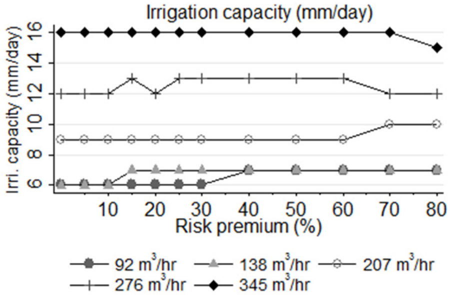

Figure 2. Impact of risk aversion on irrigation capacity (mm d^{-1}) for Richfield silt loam soil.

The increase in total water use due to risk aversion occurs due to adjustment at the intensive margin (panel C of fig. 1). Panel C shows the optimal seasonal irrigation depth associated with each of the optimal management strategies for each risk premium. The risk-neutral farmer with a well capacity of 138 $m^3\ h^{-1}$ has seasonal irrigation depth of 286.4 mm, but the seasonal irrigation depth is 396 mm with a risk premium of 20%. Smaller increases in seasonal irrigation depth are found for higher well capacities. For example, seasonal irrigation depth only increases from 257 to 311 mm if the risk premium increases from 0% to 20% with a 207 $m^3\ h^{-1}$ well capacity. The greater impact of risk aversion on the increase in total seasonal irrigation for low or medium well capacities is due to their limited irrigation capacity. Initially, smaller well capacities have a smaller optimal irrigation capacity (panel C of fig. 1 and fig. 2), and a decrease in irrigated area due to risk aversion permits an increase in irrigation capacity that allows a significantly greater seasonal irrigation depth to increase mean yield and reduce the variation in yield. In contrast, a larger well capacity has greater irrigation capacity initially; thus, the change in irrigation capacity and seasonal irrigation depth due to risk aversion has a smaller impact on the mean yield and yield variability.

We can further understand the change in seasonal irrigation depth by examining how farmers optimally adjust the MAD in each growth stage and the irrigation capacity. The optimal irrigation scheduling is to supply more water (i.e., a lower MAD) during the development stage and mid-season stage (fig. 3). Our results are consistent with those of Heeren et al. (2011).

Greater risk aversion induces the farmer to increase irrigation by decreasing the MAD during the initial stage of crop growth (panel A of fig. 3). Because a farmer with a low well capacity has a lower irrigation capacity (fig. 2), the lower MAD for low well capacities results in more frequent irrigation applications and a larger increase in seasonal irrigation depth compared to large well capacities with a larger irrigation capacity. There are little changes in MAD in the development and mid-season stage (panels B and C of fig. 3), as the optimal MAD is low even with no risk aversion. Small changes in MAD at the late-season stage (panel D of fig. 3) are because additional water in the late-season stage has a small effect on yield. Note that the optimal MAD indicates when irrigation events are triggered but does not necessarily indicate the actual soil moisture deficit of the field. An MAD of 100% indicates that irrigation is essentially never triggered during that growth stage, even though water is available through precipitation and previous soil moisture. An MAD of 0% indicates that irrigation is nearly always triggered during that growth stage. Overall, the results in figure 3 indicate that the main adjustment in seasonal irrigation depth occurs through changes in MAD in the initial growth stage.

Low MAD levels in the initial growth stage do not increase mean yield significantly but primarily reduce the variation in yields. During dry weather conditions, a lower MAD results in a significantly higher yield compared to a higher MAD. However, this is not the case with adequate precipitation, when a lower MAD produces similar yield as a higher MAD. A more risk-averse farmer who sets a lower

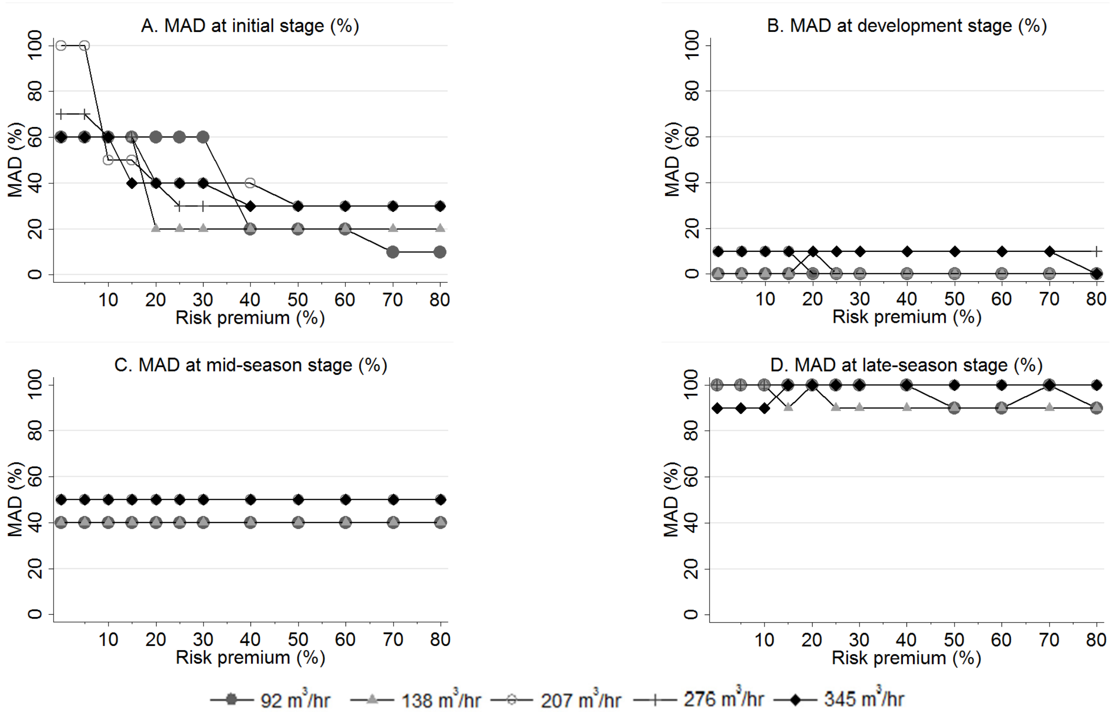

Figure 3. Impact of risk aversion on MAD (%) for Richfield silt loam soil.

MAD in the initial stage will use greater seasonal irrigation depth and incur higher irrigation costs. In addition, we examined additional output from AquaCrop (results not reported) and found that a lower MAD in the initial stage results in higher rates of evaporation, surface runoff, and deep percolation. The returns from higher mean yields due to a lower MAD in the initial stage is less than the cost of irrigation, so applying a lower MAD in the initial stage decreases average net returns. However, risk-averse farmers are willing to exchange the higher irrigation cost of using more water with the benefit of less yield variability. Therefore, greater application of water in the initial stage is the primary method that farmers can use to reduce risk from dry conditions with a limited well capacity, even though it decreases average returns.

It is important to note that a decrease in the MAD increases the seasonal irrigation depth more with a smaller irrigation capacity. The reason is that the smaller irrigation capacity results in more frequent irrigation applications. However, more frequent irrigation applications with a small irrigation capacity may be less efficient. The more frequent irrigation applications with a small irrigation capacity result in a higher exposure of wet soil and greater evaporation losses. A larger irrigation capacity has smaller evaporation losses.

Larger well capacities generate benefits to farmers through greater average net returns but also lower variation in net returns. Larger well capacities are able to maintain a larger irrigation capacity, which results in less risk from weather uncertainty. The certainty equivalent measures the amount of certain returns that farmers would consider equivalent to the potential variable returns. For a risk-averse farmer, the certainty equivalent is smaller than the average net returns because the farmer values certain returns over variable returns. For a risk premium of 20%, the average net returns across the entire field (irrigated and non-irrigated) for well capacities of 92, 138, and 207 m^3 h^{-1} are \$21,306, \$31,963, and \$37,452, respectively. The certainty equivalents for the same well capacities are \$18,571, \$28,803, and \$35,281. The relative increase in certainty equivalent is larger than the relative increase in net returns because larger well capacities reduce production risk. Therefore, ignoring risk aversion understates the relative benefit to farmers of larger well capacities.

Valent-Vona Soil

We also investigate the effect of risk aversion on optimal irrigation management with different soil characteristics, which has not been analyzed in previous research, at least to our knowledge. The total production and marginal productivity of water on crop yield are affected by soil texture and soil water holding capacity. Zhao et al. (2007) stated that soil properties have a significant impact on crop biomass productivity, which affects crop growth and crop production. Zhao et al. (2007) also noted that when the difference in soil properties is large between lands, the effect of irrigation on crop productivity varies greatly. Thus, farmers with different soil properties may have different optimal irrigation management strategies. In this section, we compare results for the Valent-Vona soil, with low soil water holding capacity, to the Richfield soil.

Risk aversion has a smaller impact on total irrigation for Valent-Vona soil (panel A of fig. 4) compared to Richfield soil. In fact, there is almost no change in total water use for Valent-Vona soil when the risk premium is less than 30%. The smaller change in total seasonal irrigation with low soil water holding capacity in response to a risk premium is because a risk-neutral farmer uses larger quantities of irrigation

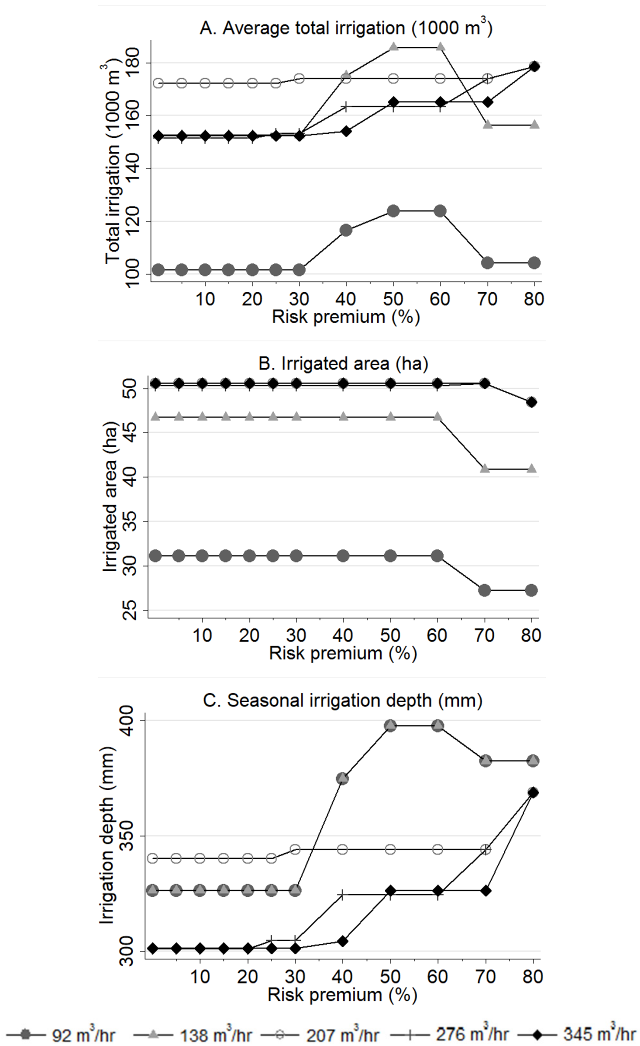

Figure 4. Impact of risk aversion on average total irrigation (1000 m^3), irrigated area (ha), and seasonal irrigation depth (mm) for Valent-Vona loamy fine sand soil.

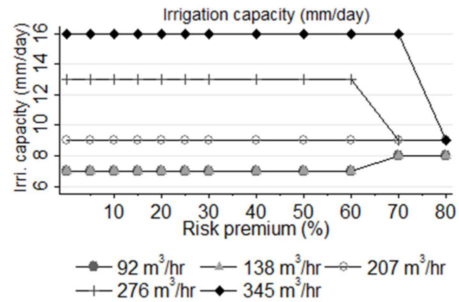

Figure 5. Impact of risk aversion on irrigation capacity (mm d^{-1}) for Valent-Vona loamy fine sand soil.

water, so net returns are less variable for a risk-neutral farmer with Valent-Vona soil. For example, a risk-neutral farmer (i.e., risk premium of 0%) with a well capacity of 138 m^3 h^{-1} optimally applies 152,480 m^3 on Valent-Vona soil but 144,870 m^3 on Richfield soil (roughly 5% less).

Changes in total water use due to risk aversion occur primarily through changes in seasonal irrigation depth rather than changes in irrigated area (panels B and C of fig. 4). Farmers do not adjust the irrigated area unless the risk premium exceeds 60%. Seasonal irrigation depth increases when the risk premium exceeds 30%. Similar to the results for the Richfield soil, the increase in seasonal irrigation depth due to risk aversion is larger for small well capacities. The increase in seasonal irrigation depth due to risk aversion occurs primarily through adjustments in the MAD in the initial growth stage, similar to the Richfield soil (figs. 5 and 6).

Extremely risk-averse farmers (risk premium greater than 60%) have lower irrigation water use compared to those with risk premiums between 40% and 60% (panel A of fig. 4). This arises because extreme risk aversion decreases irrigated area (panel B of fig. 4) to focus irrigation on a smaller area. Because extremely risk-averse farmers decrease the irrigated area, they are able to increase the irrigation capacity (fig. 5) and decrease the seasonal irrigation depth slightly (panel C of fig. 4).

Similar to the Richfield soil, greater risk aversion induces farmers to increase irrigation by mainly decreasing the MAD during the initial stage of crop growth (panel A of fig. 6). The change in MAD in the initial stage for the Valent-Vona soil is smaller than for the Richfield soil, and the change in seasonal irrigation depth is also smaller. The Valent-Vona soil has a lower water holding capacity, so increasing irrigation applications in the early season has less benefit for crop yield with the Valent-Vona soil. In addition, a small MAD level results in frequent irrigation applications that reduce the water use efficiency.

For a risk premium of 20%, the average net returns across the entire field (irrigated and non-irrigated) for well capacities of 92, 138, and 207 m^3 h^{-1} are $18,550, $30,753, and $36,224, respectively. The certainty equivalents for the same well capacities are $17,568, $29,165, and $35,101. These results indicate that larger well capacities have a slightly larger increase in value to farmers with Valent-Vona soil than with Richfield soil. Overall, the results in this section indicate that models that do not account for the spatial difference in soil characteristics may provide a poor prediction of optimal irrigation strategies and water use.

Conclusion

Risk aversion causes farmers to increase their total irrigation water use significantly compared to the optimal extraction of risk-neutral farmers. These results imply that models that do not account for risk-averse behavior underestimate total water use. Thus, a higher rate of groundwater depletion occurs when farmers are more risk-averse. The increase in total water use occurs through greater seasonal irrigation depth with less irrigated area for farmers with low and medium well capacities. The increase in seasonal irrigation depth reduces the risk faced by the farmer. Meanwhile, farmers with high well capacity increase the seasonal irrigation depth but maintain the irrigated area because they are already constrained by a maximum land area. Overall, the increase in total water use is larger for low and medium well capacities than for high well capacity.

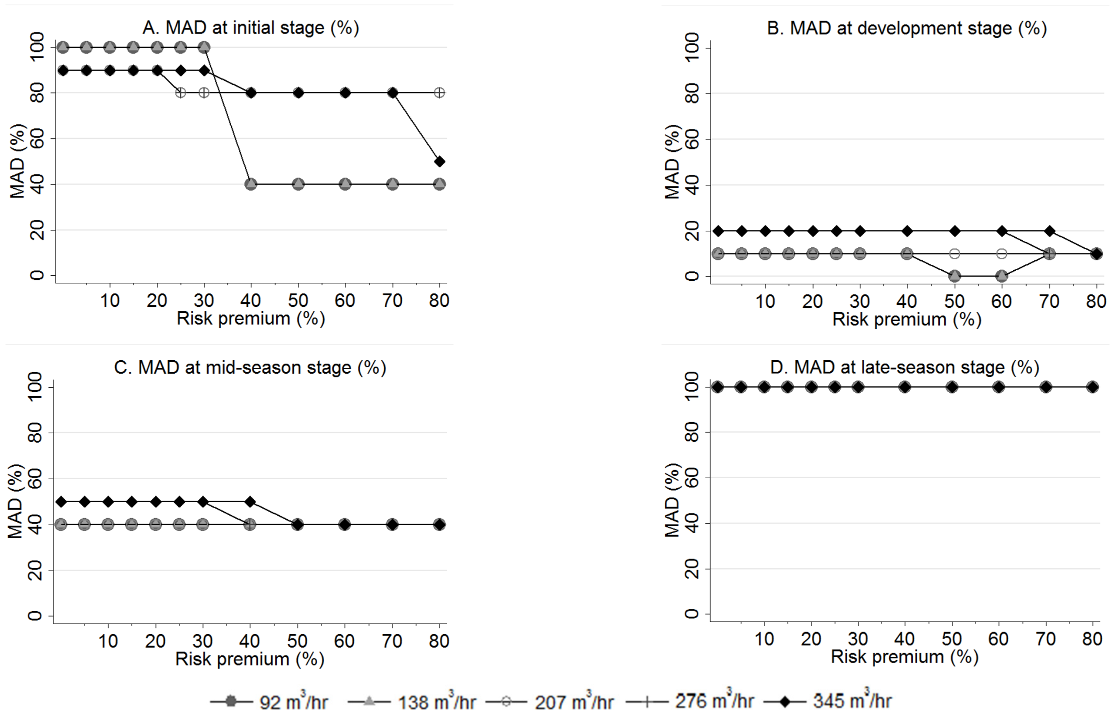

Figure 6. Impact of risk aversion on MAD (%) for Valent-Vona loamy fine sand soil.

Risk-neutral farmers select lower MAD (i.e., more frequent irrigation) at the development and mid-season growth stages than at the initial and late-season stages. Risk aversion induces farmers to reduce MAD primarily in the initial stage, with minimal adjustment in other growth stages. There is little adjustment in the development and mid-season stages because MAD is low in these stages for risk-neutral farmers. There is also little adjustment in the late-season stage because greater water application in this stage has little impact on crop yield.

Results from our modeling study show that risk aversion has a smaller impact on water use for Valent-Vona soil (sandy) than for Richfield soil (silt loam). This is because the optimal total seasonal irrigation is higher for risk-neutral farmers with Valent-Vona soil than with Richfield soil due to the low soil water holding capacity of Valent-Vona soil. The high total seasonal irrigation means there is less variation in corn yield with Valent-Vona soil than with Richfield soil. These results show that the impact of risk aversion on water use varies depending on the soil characteristics. This analysis is also applicable to different crops in regions with limited water for crop production.

Acknowledgements

This research is supported by funding from the Fulbright-Dikti Program. Contribution No. 18-179-J from the Kansas Agricultural Experiment Station.

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