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The synergy between water conservation and economic profitability of adopting alternative irrigation systems for cotton production in the Texas High Plains

Yubing Fan[a,*], Sushil K. Himanshu[b], Srinivasulu Ale[c], Paul B. DeLaune[c], Tian Zhang[d], Seong C. Park[e], Paul D. Colaizzi[f], Steven R. Evett[f], R. Louis Baumhardt[f]

[a] State Key Laboratory of Grassland Agro-Ecosystems, College of Pastoral Agriculture Science and Technology, Lanzhou University, Lanzhou, Gansu, China
[b] Department of Food, Agriculture and Bioresources, School of Environment, Resources and Development, Asian Institute of Technology, Pathum Thani, Thailand
[c] Texas A&M AgriLife Research, Vernon, TX, USA
[d] Department of Natural Resource Ecology and Management, Oklahoma State University, Stillwater, OK, USA
[e] School of Agriculture, Tennessee Tech University, Cookeville, TN, USA
[f] USDA Agricultural Research Service, Bushland, TX, USA

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ABSTRACT

Declining water levels of the Ogallala Aquifer challenge economic availability of the groundwater and necessitate adoption of advanced irrigation systems with efficient irrigation strategies. Irrigation methods and application levels affect water productivity and farm profitability. This study evaluated the synergy between water conservation through a deficit irrigation strategy and economic profitability of agricultural production. The economic feasibility of cotton production was compared using field data for mid- and low-elevation spray application (MESA and LESA, respectively), low-energy precision application (LEPA), and subsurface drip irrigation (SDI) systems in the Texas High Plains (THP) region. Treatments included irrigated cotton with water application at 25%, 50%, 75%, and 100% evapotranspiration (ET) replacement levels and near-dryland cotton production. Both field-level data and well-calibrated model simulation data were used to assess cotton profitability at varying risk attitudes of producers. Results showed that more irrigation water consistently increased average net return of cotton production for all irrigation systems, except for SDI, which produced a similar net return at both 75% and 100% ET replacement levels. A larger chance of getting a net return greater than \$380 ha^{-1} was observed for MESA, LESA and LEPA systems with the full irrigation at the 100% ET replacement level as well as for SDI with 75% ET replacement. Economic risk analysis showed that LEPA had a higher net return than other systems at each of the four irrigation levels and it would be preferred by risk-neutral, somewhat risk-averse, and rather risk-averse cotton producers. For each irrigation system, full irrigation was most preferred by risk-neutral producers and only minor differences were observed in the expected returns between 75% and 100% ET replacements as the producers became somewhat or more risk-averse. Groundwater conservation can be achieved with SDI without compromising crop yield or farm income, while government policies and financial incentives can help motivate producers to save irrigation water and maintain a high farm profit under spray and LEPA systems.

1. Introduction

Producers in the Texas High Plains (THP) region are facing challenges to sustain irrigated agriculture due to declining groundwater levels in the underlying Ogallala Aquifer and increasing climate variability (Chaudhuri and Ale, 2014; Modala et al., 2017). Continued water availability in the southern portion of the Ogallala Aquifer is vital to the economy of the THP region where approximately 95% of the pumped groundwater is used for irrigation (Kukal and Irmak, 2020; Lu et al., 2020; TWBD, 2020). Cotton (*Gossypium hirsutum* L.) is a major irrigated cash crop in Texas, with planted acreage of about 2.85 million hectares (about 52% of the total crop acreage in the THP region) and production

* Corresponding author.
E-mail address: fanyubing@126.com (Y. Fan).

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value of approximately $2.14 billion (NASS, 2021; USDA-ERS, 2019), and in this respect it leads all other states in the United States. Full irrigation to meet crop water demands is not guaranteed in this region and crop production needs to be strategized to meet regional water conservation goals (Ale et al., 2020; HPWD, 2015).

Previous studies have focused on crop water productivity (CWP) which refers to crop production per unit of water use, and its increase is a good indicator of improved production efficiency in irrigated agriculture (Araya et al., 2019; Fan et al., 2018; Nair et al., 2013; Zou et al., 2020). Field experiments have been conducted to increase CWP by strategically applying less water than the maximum that crops would use, i.e., regulated deficit irrigation strategies. These strategies have been proposed to maximize yield or net return for a certain amount of water use, rather than maximizing the total yield or gross return (Baumhardt et al., 2009; Garibay et al., 2019; Greaves and Wang, 2017; Himanshu et al., 2019; Hunsaker et al., 2015; Shareef et al., 2018). In the THP region, CWP can be enhanced by either achieving the same crop yield/profit from less water, a higher yield/profit from the same water application (Comas et al., 2019; Pabuayon et al., 2019), or some level of reduced water use that does not greatly decrease crop yield.

Additionally, efficient irrigation systems can promote enhancement of water producivity and economic profitability (Gathala et al., 2020; Levidow et al., 2014). The commonly adopted irrigation systems in the THP region include mid- and low-elevation spray application (MESA and LESA, respectively), low energy precision application (LEPA), and subsurface drip irrigation (SDI) systems[1] (Barnes et al., 2020; Bordovsky and Porter, 2003). Using different irrigation systems along with various irrigation levels have been one focus of farm irrigation management studies (Bordovsky, 2019; Rudnick et al., 2019). Several field studies evaluated agronomic performance of cotton under different irrigation systems and irrigation levels (Colaizzi et al., 2004, 2005, 2010). Many other recent modeling and experimental studies also examined crop yield and CWP (also known as water use efficiency) as affected by different irrigation strategies such as deficit irrigation (Garibay et al., 2019; Witt et al., 2020), variable rate irrigation (O'Shaughnessy et al., 2020b; Yari et al., 2017), ET-based irrigation (Marek et al., 2016), irrigation rate and timing (Bordovsky et al., 2015; Thorp et al., 2020), irrigation scheduling via information communication technologies (Vellidis et al., 2016), or a combination of these strategies (Himanshu et al., 2019; Mahan et al., 2012; O'Shaughnessy et al., 2020a, 2020b).

An economic analysis is needed to better understand profits from producers' investments in improved irrigation systems and more effective irrigation management strategies (Amosson et al., 2011; Guerrero et al., 2016; Reynolds et al., 2020). Partial budget and enterprise budget approaches are mostly used by researchers to calculate the gross margin or net return from different irrigation scenarios (DeLaune et al., 2020; Enciso et al., 2005; Mauget et al., 2013; Segarra et al., 1999). For instance, Bordovsky et al. (2000) found that compared to SDI, a higher net return could be achieved with the LEPA irrigation system when irrigation capacity was more than 2.5 mm d^{-1}. However, the SDI could be a better irrigation option in the THP region if physical and legal constraints limit LEPA application or SDI installation costs become lower. Based on a field experiment conducted in Chillicothe, TX from 2008 to 2010, DeLaune et al. (2012) analyzed the impacts of different irrigation levels (0%, 33%, 66%, 100% and 133% ET replacement) on cotton yield and profits, and they found a maximum net return at the 100% ET level. Additionally, Mitchell-McCallister et al. (2020) compared profits under 27 irrigation treatments using a LEPA irrigation system and found that as compared to lower irrigation levels, a higher gross margin could be achieved at a high irrigation level (6.4 mm d^{-1}) during the maturation stage when growing degree days are greater than 750 °C (baseline temperature of 15.6 °C). Nevertheless, these studies were mostly focused on the comparison of profits without any consideration to uncertainties associated with irrigation amount/timing, rainfall variability, spatial farmland productivity, and input/output price fluctuations that substantially influence crop production, producers' farming decisions, and farm income.

The economic risk analysis approach could be used to incorporate these uncertainties (Anderson and Hardaker, 2003; Hardaker et al., 2015), while the stochastic efficiency with respect to a function (SERF) approach could be used to assess the economic feasibility (Lien et al., 2007; Williams et al., 2012). Producers may have different degrees of risk attitudes towards alternative irrigation systems and water application levels. Relevant research by Bhattarai et al. (2020) examined the profits for two irrigation scheduling methods in Georgia cotton production and they found risk premiums for smart irrigation app and calendar-based checkbook method were \$301-\$341 ha^{-1} and \$306-\$314 ha^{-1}, respectively, relative to dryland production. The authors concluded that the smart irrigation app was the most risk efficient scheduling method which increased the risk-adjusted profits for cotton producers. In addition, SERF has been widely used to compare advanced and innovative farm practices with conventional operations (Archer and Reicosky, 2009; Watkins et al., 2008). In particular, Boyer et al. (2018) investigated the profits of cotton production with no-till and winter cover crops in Tennessee, and they found risk-averse farmers would prefer no-till production without cover crops. Similar studies in Texas concluded that no-till without a cover crop was the most preferred practice by risk-neutral and rather risk-averse growers in dryland cotton production (Fan et al., 2020b), and that no-till with mixed cover crops was most preferred by very risk-averse producers in irrigated cotton systems (Fan et al., 2020a). Therefore, the risk-adjusted profitability analysis can incorporate producers' risk preference and help us better understand their adoption of advanced production systems. To the best of the authors' knowledge, however, no previous study has documented the risk-adjusted farm profitability associated with irrigation strategies.

In the present study, an economic risk analysis was carried out to evaluate the profitability of four irrigation systems (MESA, LESA, LEPA and SDI) at four alternative irrigation levels (25%, 50%, 75%, and 100% ET replacement) in THP cotton production. Yield data were simulated with and tested against a four-year field experiment using a multivariate empirical distribution approach. The net returns were estimated for dryland and irrigated cotton production scenarios using simulated cotton yields and prices. Further, the net return distributions were compared using the SERF procedure, which ranks risky outcomes associated with different irrigation systems and irrigation levels at various risk aversion levels of cotton growers.

2. Methods and data

2.1. Field experiment

Cotton yield simulations and validations were carried out based on the observations from a field experiment at the USDA Conservation and Production Research Laboratory in Bushland, Texas (35.19° N, 102.06° W) (Colaizzi et al., 2004, 2005, 2010). This research site is in a typical semi-arid region of the Texas High Plains. The climate is characterized by low precipitation with an average annual amount of 415 mm, a high class A pan evaporation of 2690 mm per year (NOAA, 2020), and on average, 65% of the evaporative demand and 70% of the precipitation occur from May to October, which represents the growing season of cotton (USDA ARS Conservation & Production Research Laboratory records, 1993–2012). Fig. S1 in the appendix A shows the precipitation

[1] These systems are typically used for farm irrigation in the U.S. Great Plains. MESA and LESA are conventional systems, while LEPA is the most widely adopted irrigation system in this region. Combined with center pivots or linear-move machines, sprinklers discharge water at different pressures, and water application efficiency is lower under MESA as compared to LESA and LEPA (Bordovsky, 2019; Peters et al., 2016). SDI irrigates crops through burried tubes with emitters at regular spacings. This irrigation system is typically used for row crops and its application has rapidly increased in past decades.

during cotton growing and non-growing seasons at a nearby weather station. The predominant soil series at the location is a Pullman clay loam (fine, superactive, mixed, thermic torrertic Paleustoll) (USDA-NRCS, 2020).

Cotton (*Gossypium hirsutum* L., Paymaster 2280 BG RR) was planted during 2003, 2004, 2006, and 2007 growing seasons[2] (Colaizzi et al., 2004, 2005, 2010). The experiment was conducted in a split-block design and the plot design was shown in Fig. S2 of the appendix A. Irrigation was applied using a three-span lateral move system outfitted with zones of three irrigation application methods (MESA, LESA and LEPA) and zones that were not irrigated by the lateral move system but by an SDI system with drip lines laid in the same direction of travel. For the MESA, LESA, and LEPA treatments, irrigation rates were varied in the direction of travel by varying the speed of the lateral move, and irrigation duration was identical for each irrigation method and was typically ~4 h. Further, irrigations by the lateral move were applied only during morning hours to avoid smaller (nighttime) or larger (afternoon) wind and evaporative losses (i.e., when atmospheric demand was average (Howell and Evett, 2005)). For SDI, irrigation rates were varied by emitter flow and spacing along the drip lateral. Irrigation events for SDI were initiated at the same time as the lateral move, but the duration was typically 24 h, which is similar to SDI management used by commercial cotton producers in the region, as observed by the authors. The irrigation methods were randomized within a block and each block consisted of a span of the linear move system with three replications. Each plot was 25 m long and 9 m wide with 12 rows. Each irrigation rate strip was separated by 5 m planted borders. Furrow dikes were installed after crop establishment to control run on and runoff (Schneider and Howell, 2000).

The experiment included a near-dryland treatment (I0, which corresponded to 0% ET replacement) and four irrigated treatments (I25, I50, I75, and I100, which corresponded to 25%, 50%, 75% and 100% ET replacement, respectively) in each growing season. The I100 irrigation rate was determined by soil water content readings using a field-calibrated neutron probe at depths from 0.10 m to 2.3 m in 0.20 m increments (Evett et al., 2008). Irrigation was applied when soil water depletion reached 25 mm in the I100 MESA treatment, and all other irrigation treatments received proportionally less water according to their ET replacement levels (Colaizzi et al., 2005). Irrigations were metered using propeller-type totalizing flow meters (McCrometer, Inc., Hemet, Calif., USA). Rainfall was recorded using a tipping-bucket rain gauge (model TE525, Texas Electronics, Inc., Dallas, Texas, USA) at a micrometeorological station ~50 m south of the experimental field (Porter et al., 2005). In the I0 treatment, sufficient pre-plant irrigation was applied only for crop emergence using MESA. During the four years of the experiment, the average irrigation water applied was 22, 67, 111, 156, and 201 mm for I0, I25, I50, I75, and I100 treatments, respectively (Colaizzi et al., 2010). Seasonal crop evapotranspiration (ETc) was calculated by the soil water balance as irrigation + in-season rainfall + volumetric soil water at planting − volumetric soil water at harvest. Run on and run off were assumed negligible because furrow dikes were installed and the field had a slope of ~0.0025 m m^{-1} (Schneider and Howell, 2000). Deep percolation was controlled by irrigation scheduling based on the neutron probe that avoided overfilling the soil water profile, which was confirmed by the lack of increases in measured volumetric water contents at lower depths (2.1–2.3 m) (Evett et al., 2008).

Similar amounts of pre-plant fertilizer containing nitrogen (N) and phosphorous (P) were applied to the raised beds based on a soil fertility analysis each year (Colaizzi et al., 2005). Additional N was applied with the irrigation water. Compared with the full irrigation treatment, the fertilizer amount was adjusted proportionately in the deficit irrigation treatments.

[2] In 2005, cotton crop was destroyed by hail and the field was replanted with soybeans.

Additional field measurements included plant growth and development, final plant biomass, and lint yield and fiber quality. Plants were measured biweekly and included height, width, number of nodes, and number and location of reproductive organs (i.e., branch number and position). At crop maturity, destructive plant samples were obtained from 10 m^2 areas in the center of each plot. Samples were weighed, ginned, and analyzed for micronaire, strength, color grade, and uniformity at the International Textile Center, Lubbock, Texas, and cotton loan values were determined based on these four fiber quality measurements. Additional details about this field experiment can be found in (Colaizzi et al., 2010).

2.2. Simulation procedures

Crop yields and prices were simulated based on the multivariate empirical (MVE) distribution. The MVE distribution follows the Monte Carlo simulation protocols to account for correlation among the stochastic variables (Richardson et al., 2000). The cotton yields at different irrigation levels may be correlated due to the same soil and climatic conditions, and they can be non-normally distributed because of limited field observations. Cotton yields may be highly variable due to variable weather conditions in the study area (Himanshu et al., 2021), and high variability of cotton prices can also expected due to global supply and demand fluctuations. The MVE simulation, therefore, can capture the variability of variables and provide consistent estimation for farm-level analysis (Richardson et al., 2008).

The MVE simulations were carried out for cotton lint yields at multiple irrigation levels. Field-level data from the four-year experiment (Colaizzi et al., 2004, 2005, 2010) described in the previous section were used to run MVE simulations for lint yields, and the simulations for lint and cottonseed prices were conducted based on the annual prices for Texas upland cotton during 2003–2019 (NASS, 2021). Each MVE simulation was carried out to generate 500 iterations of data points (Richardson et al., 2008). Combining with input use data, these simulated variables were then used to conduct the economic estimation and risk analysis.

As a step-wise process, the MVE model conducts stochastic simulations of random variables (i.e., yield and price). Fig. 1 shows the following simulation procedures adopted in this study as suggested by Richardson et al. (2008).

(1) Estimation of yield range. Given the lint yield data (Colaizzi et al., 2004, 2005, 2010), the mean yield values for all the irrigation treatments were combined with a common variation[3] to determine the range of yield. The upper and lower bounds of the range were determined using Eq. (1):

$$\left\{ \hat{Y}_U = \bar{Y} + z \cdot \frac{\sigma}{\sqrt{n}}, \quad \hat{Y}_L = \bar{Y} - z \cdot \frac{\sigma}{\sqrt{n}} \right\} \tag{1}$$

where $Y_{U/L}$ represents the estimated upper and lower bounds; $\bar{Y}$ is the mean yield in each treatment; z refers to the z-value of a normal distribution; σ is the standard deviation; and n is the number of field observations. The z-value can be specified to generate a certain confidence interval (i.e., 95%). Standard deviation was calculated from the mean and the hypothetical coefficient of variation (c_v) following $\sigma = c_v \cdot \bar{Y}$.

(2) Estimation of yield distribution. The Gray-Richardson-Klose-Schumann (GRKS) model (Richardson et al., 2008) was used to estimate yield distributions from the above estimated ranges. The GRKS approach can generate random variables when little data are available

[3] To be consistent with relevant literature (DeLaune et al., 2020), a coefficient of variation equal to 0.25 was used for all irrigation treatments.

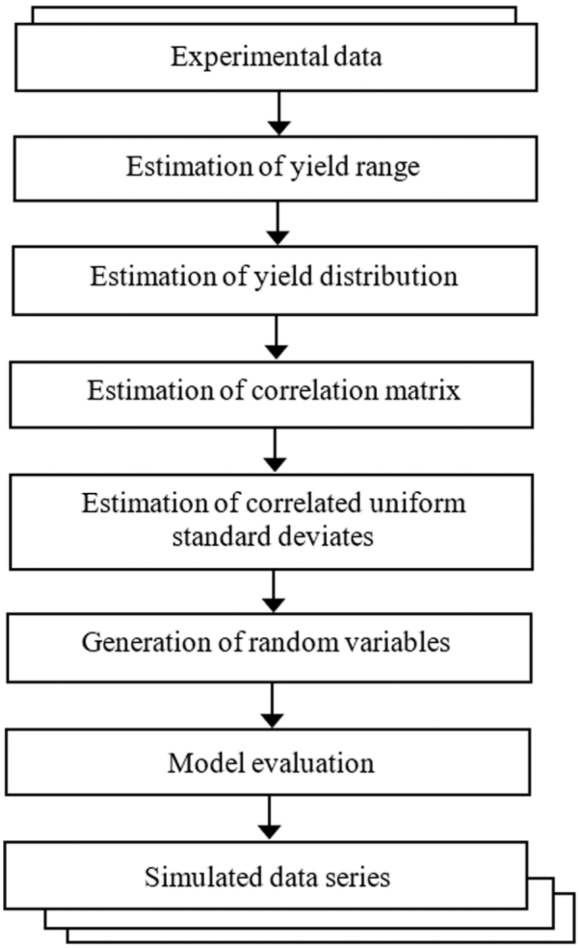

Fig. 1. A flowchart showing the data simulation process.

(Richardson et al., 2008). This approach is also preferred for assessing uncertainty because it is flexible to generate distributions for alternative probabilities. The GRKS model can be specified as:

$$\Phi = GRKS(Min,\ \ Middle,\ \ Max) \tag{2}$$

where Φ refers to the simulated distribution which follows a GRKS function with specified minimum, middle, and maximum values. The minimum and maximum values do not necessarily have an equal distance from the middle and the middle value can be mean, median or mode (Richardson, 2010). We trimmed the simulated data by removing the values less than the minimum and greater than the maximum because the GRKS model defines the minimum and maximum as the values that have a probability of 0.02275 and 0.97725 greater than the rest of the distribution, respectively. This gives us the simulated data in a 95% confidence interval (i.e., the distribution with ± 2 standard deviations) which is consistent with the yield range and variation specified in the above step.

(3) Estimation of the correlation matrix. A linear correlation matrix can be specified for the crop yields at a certain irrigation level as well as for the prices of lint and cottonseed. For example, at an irrigation level $i(i = 25,50,75, and 100\%ET)$, the lint yields for the four irrigation methods $j(j = MESA, LESA, LEPA, and\ SDI)$ have a correlation matrix R with correlation r between each pair of the yields:

$$R_{i,j} = \begin{bmatrix} 1 & r_{i,12} & r_{i,13} & r_{i,14} \\ r_{i,21} & 1 & r_{i,23} & r_{i,24} \\ r_{i,31} & r_{i,32} & 1 & r_{i,34} \\ r_{i,41} & r_{i,42} & r_{i,43} & 1 \end{bmatrix} \tag{3}$$

The correlation matrix for the lint and seed prices can be represented by:

$$R_{lint.seed} = \begin{bmatrix} 1 & r_{lint.seed} \\ r_{lint.seed} & 1 \end{bmatrix} \tag{4}$$

Therefore, the price correlation matrix is a 2 × 2 matrix and the yield matrix is a 4 × 4 matrix.[4] The stochastic prices and yields at alternative irrigation levels were simulated using the correlation matrix approach.

(4) Estimation of the correlated uniform standard deviates (CUSDs). As model parameters, CUSDs specify the relationship of the random variables using the correlation matrix and retain the observed stochastic dependency among the variables (i.e., yield and price) in the stochastic simulation. First, we estimated the correlated standard normal deviates by taking the square root of the correlation matrix and multiplying a vector of independent standard normal deviates. Then the CUSDs were obtained by converting the standard normal deviates with an inverse transformation of a standard normal distribution (Richardson et al., 2008). Incorporating the CUSDs in the stochastic simulation avoids under- or over-estimating the mean and variance of yields under different irrigation systems if they are correlated. Given the dimensions of the yields under different irrigation systems and historical prices specified above, the model estimated 19 correlated yield data series and 17 price data series.

(5) Generation of random variables. The random variables were estimated using the MVE model. An empirical distribution function (EMP) was employed using CUSDs in an inverse transformation of the empirical distribution:

$$\tilde{Y}_{i,j} = f\left(\overline{Y_{i,j}}, \sigma_{i,j}, CUSD_{i,j}\right) \text{for} j = 1, 2, 3, 4 \text{at a certain irrigation level} i \tag{5}$$

$$P_{lint.seed} = f(P_{lint.seed}, \sigma_{lint.seed}, CUSD_{lint.seed}) \tag{6}$$

where tilde (~) denotes a stochastic variable; $f(\bullet)$ represents a multivariate empirical function that follows a normal distribution; dash (−) denotes the variable mean of the estimated yield data or historical price data.

Prices and lint yields at alternative ET replacement levels were simulated for 500 iterations to generate stochastic variables using the Latin Hypercube procedure (Richardson et al., 2008). The generated variables followed a uniform distribution with N (500) intervals and each interval has randomly selected at least one value. This ensured that the simulation considered all corresponding areas of the probability distributions.

(6) Model evaluation. The simulated stochastic variables were compared with the model input data. Students' *t*-test determined whether the correlation coefficients of the historical and simulated matrices were statistically different at the 95% confidence level. The Two-Sample Hotelling T^2 test determined whether the mean vectors of the historical and simulated data were equal. The Box's M test determined whether the covariance matrices of the historical and simulated data were equivalent. The Complete Homogeneity test determines whether the mean vectors and covariance matrices are equivalent simultaneously. After the evaluation of the random variables, these simulated data were used to conduct economic analysis. The MVE approach was also employed in previous empirical studies that investigated the economic feasibility of soil and water conservation practices in multiple cropping systems (Adusumilli et al., 2020; Kadigi et al., 2020).

2.3. *Cost and profit estimation*

The profitability of using different irrigation systems and applying

[4] The near-dryland (I0) yield was combined with the yields at I25 to estimate the correlation matrix. Thus, the correlation matrix for I0 and I25 is a 5 × 5 matrix.

Table 1
Validation tests for yield simulations (kg ha^{-1}) under different irrigation strategies.

	I0	I25				I50			
Test Statistics	Near-dryland	MESA	LESA	LEPA	SDI	MESA	LESA	LEPA	SDI
Mean	396	462	494	550	641	557	560	739	800
Std Dev	127	150	161	179	208	178	179	236	255
Min[a]	0	0	0	0	0	26	26	34	37
Max	819	1089	1165	1297	1511	1089	1095	1445	1564
Distribution comparison for individual series									
Two Sample *t*-Test	0.002	-0.011	-0.011	-0.011	-0.011	0.002	0.002	0.002	0.002
p-value	0.999	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
F Test	1.007	1.017	1.017	1.017	1.017	1.002	1.002	1.002	1.002
p-value	0.538	0.509	0.509	0.509	0.509	0.453	0.453	0.453	0.453
Joint distribution of yields at each irrigation level									
Two Sample Hotelling T^2 Test		<0.001				<0.001			
p-value		1.000				1.000			
Complete Homogeneity Test		<0.001				<0.001			
p-value		1.000				1.000			
		I75				I100			
Test Statistics		MESA	LESA	LEPA	SDI	MESA	LESA	LEPA	SDI
Mean (kg ha^{-1})		781	754	870	1020	871	885	992	1065
Std Dev		249	241	278	326	278	283	317	340
Min		36	35	40	47	40	41	45	49
Max		1527	1474	1701	1994	1703	1730	1940	2082
Distribution comparison for individual series									
Two Sample *t*-Test		0.002	0.002	0.002	0.002	1.317	1.888	1.568	0.539
p-value		0.998	0.998	0.998	0.998	0.206	0.077	0.136	0.597
F Test		1.002	1.002	1.002	1.002	1.247	1.381	1.303	1.093
p-value		0.453	0.453	0.453	0.453	0.228	0.146	0.190	0.359
Joint distribution of yields at each irrigation level									
Two Sample Hotelling T^2 Test		< 0.001				< 0.001			
p-value		1.000				1.000			
Complete Homogeneity Test		< 0.001				< 0.001			
p-value		1.000				1.000			

[a] Yield simulations were constrained at 0. I0, I25, I50, I75, and I100 refer to 0, 25%, 50%, 75%, and 100% ET replacement, respectively. MESA, LESA, LEPA, and SDI represent mid- and low-elevation spray application, low-energy precision application, and subsurface drip irrigation systems, respectively.

varying amounts of irrigation water was evaluated by an enterprise budget developed by Texas A&M AgriLife Extension (2020). The production cost was estimated using data on field operations and input use (Colaizzi et al., 2004, 2005, 2010). Input prices were updated to reflect the actual production payment in the region. The total cost for each irrigation system j at a certain irrigation level i was calculated using:

$$TC_{i,j} = VC_{i,j} + FC_{i,j} \tag{7}$$

where TC, VC, and FC refer to the total cost, variable cost, and fixed cost, respectively. Variable costs included expenses on seed, fertilizer, pesticide, herbicide, energy and labor associated with tillage and irrigation, insurance, machinery repairs and maintenance, interest, and harvest costs.[5] Fixed costs included machinery depreciation for tractors, planter, sprayer, irrigation system, etc. These costs were estimated for the Texas Panhandle Extension District 1, and necessary modifications were made for the input and output prices.

Total revenue was estimated using the simulated yield and price data. The cottonseed yield was estimated using a conversion ratio of 1.412 units of seed per unit of lint (Cotton Incorporated, 2018).

$$\tilde{TR}_{i,j} = \tilde{Y}_{i,j}^{lint} \times \tilde{P}^{lint} + \tilde{Y}_{i,j}^{seed} \times \tilde{P}^{seed} \tag{8}$$

where TR refers to total revenue. $\tilde{Y}_{i,j}^{lint}$ is the simulated lint yield in Eq. (5), and $\tilde{Y}_{i,j}^{seed}$ is the estimated seed yield and $\tilde{Y}_{i,j}^{seed} = 1.412 \times \tilde{Y}_{i,j}^{lint}$. $\tilde{P}^{lint}$ and $\tilde{P}^{seed}$ are the simulated lint and seed price in Eq. (6). The net return was finally calculated using Eq. (9):

$$\pi_{i,j} = \tilde{TR}_{i,j} - TC_{i,j} \tag{9}$$

where $\pi_{i,j}$ is the estimated net return for cotton production under each irrigation system j at a certain irrigation level i.

2.4. Economic risk analysis

Income variation can result from the uncertainties associated with input use and crop yield. Farmers' decisions regarding irrigation systems and irrigation levels can greatly influence the sustainability of water resources and agricultural production, and these decisions are further affected by producers' risk attitudes and expected profit (Ribera et al., 2004). Farmers with varying attitudes toward risks may have different preferences for irrigation systems and irrigation levels (Fan et al., 2018; Zhang et al., 2015). Risk-averse producers are more likely to choose the irrigation system and irrigation level that result in a smaller variation in farm profit. Therefore, this study examined cotton farmers' production decisions regarding four irrigation systems and four irrigation levels as mutually exclusive choices to identify the most risk-efficient practices for crop production and groundwater conservation.

Following Anderson and Dillon (1992), the absolute risk aversion coefficient (ARAC, r_a) was used to measure producers' risk attitudes. The ARAC can be expressed by:

$$r_a(w) = \frac{r_r(w)}{w} \tag{10}$$

where $r_r(w)$ is the relative risk-aversion coefficient (RRAC) for a certain amount of farm income, w (Hardaker et al., 2004).

According to Anderson and Hardaker (2003), the RRAC levels include risk-neutral ($r_r = 0$), somewhat risk-averse ($r_r = 1$), rather risk-averse ($r_r = 2$), very risk-averse ($r_r = 3$), and extremely risk-averse ($r_r = 4$). The average farm profit is equal to \$161 ha^{-1} which determines the upper bound of ARAC. Therefore, this study utilized various risk

[5] Land rental was not included in the budget. The application rates of fertilizer, pesticide, and herbicide were assumed the same for the full irrigation level in all four years. The chemical and energy prices, and labor payment were assumed same.

levels including 0 for risk-neutral, 0.0062 for somewhat risk-averse, 0.0124 for rather risk-averse, 0.0186 for very risk-averse, and 0.0248 for extremely risk-averse.

The stochastic efficiency with respect to a function (SERF) approach ranks a set of risky choices based on their certainty equivalents (CEs) across various risk aversion levels. The CE of a risky choice is defined as the guaranteed amount of payment at which a decision maker would be willing to accept instead of taking the risky action:

$$CE(w, \quad r(w)) = U^{-1}(w, \quad r(w)) \tag{11}$$

As determined by the utility function, $U(\cdot)$, and risk aversion level, r, in Eq. (11), a producer is assumed to prefer a risky outcome with a higher CE value (Lien et al., 2007). A specific form of the utility function is required to estimate the CE values. A negative exponential utility function can more efficiently estimate CE with constant absolute risk aversion (Hardaker et al., 2015; Schumann et al., 2004) and this function has been commonly adopted in previous empirical studies (Fan et al., 2020a; Williams et al., 2014).

Subsequently, a utility weighted risk premium (RP) is calculated at a certain risk aversion level of cotton producers. A RP value is the difference in the CEs of adopting a specific irrigation system and an irrigation level relative to a baseline scenario (i.e., near-dryland production). The RP at a certain risk aversion level can be represented by:

$$RP_{ij,dryland} = \quad CE_{ij} - CE_{dryland} \tag{12}$$

The value of RP represents the minimum amount of payment that a producer will have to receive before he/she is willing to shift from dryland to irrigated production at a certain risk aversion level r_a. The value of RP is also considered as the risk-adjusted profit gain from adopting irrigation in crop production. A positive RP suggests a farmer would prefer irrigated production over the dryland production. On the contrary, a negative RP means dryland production is preferred, and the negative value is the expected loss if a producer adopts any irrigation method with a certain irrigation level.

The stochastic simulations and economic risk analysis were conducted by the Simulation and Econometrics to Analyze Risk (Simetar©) software developed by Richardson et al. (2008). The SERF analysis was performed for the net return distributions of cotton production under each of the four irrigation systems and at alternative irrigation levels. The CEs and RPs as well as their rankings are discussed for a range of ARACs representing producers' risk attitudes from risk-neutral to extremely risk-averse.

Table 2
Validation tests for price simulations ($ kg^{-1}).

Test Statistics	Historical Price Lint	Historical Price Cottonseed	Simulated Price Lint	Simulated Price Cottonseed
Mean	1.344	0.195	1.344	0.195
Std Dev	0.268	0.063	0.272	0.063
Min	0.886	0.111	0.625	0.008
Max	1.806	0.319	2.164	0.386
Joint Distribution Comparison				
Two Sample Hotelling T2 Test, p-value			0.000	1.000
Box's M Test, p-value			0.013	1.000
Complete Homogeneity Test, p-value			0.072	1.000
Test Correlation Coefficients (t value)			0.440	
Correlation of Simulated Lint and Seed Prices, p-value		0.573	<0.001	

3. Results and discussion

3.1. Model evaluation

Simulated lint yields were evaluated for both individual series and joint distributions at each irrigation level (Table 1). The average lint yield under near-dryland production was 396 kg ha^{-1}. Similarly, average lint yields for 25% ET replacement irrigation level (I25) treatment were 462, 494, 550, and 641 kg ha^{-1} under MESA, LESA, LEPA, and SDI irrigation methods, respectively. These mean simulated yields were not statistically different from those of the experimental data (i.e., $p > 0.05$). As indicated by the F test, the variance of each simulated yield distribution was not statistically different from that of the field data (i.e., $p > 0.05$). For the joint distribution of yields at the I25 level, the two-sample Hotelling T^2 test showed an insignificant result (i.e., $p > 0.05$), which indicated that the mean vectors of the simulated and experimental lint yields are equal. The complete homogeneity test also showed that the variances of the simulated and experimental yields were not significantly different.

At the I50 level, the lint yields for MESA, LESA, LEPA, and SDI systems were 557, 560, 739, and 800 kg ha^{-1}, respectively (Table 1). As the irrigation water increased to the 75% ET level, the lint yields increased to 781, 754, 870, and 1020 kg ha^{-1} for MESA, LESA, LEPA, and SDI, respectively. Under the full irrigation application, the lint yields were 871, 885, 992, and 1065 kg ha^{-1} for MESA, LESA, LEPA, and SDI, respectively. All the yield values were consistent with the experimental data (Colaizzi et al., 2010) and validated by the statistical tests. Specifically, at each irrigation level, the two-sample *t*-test showed that there was not enough evidence to reject the null hypothesis that the means of simulated and experimental data were equal at the 0.05 significance level (i.e., $p > 0.05$). For the individual data series, the F tests showed that the equal variances of the simulated and experimental data were not rejected at the 0.05 significance level (i.e., $p > 0.05$). Additionally, the joint distribution tests showed the mean vectors and the variance-covariance matrices were not significantly different between the simulated and experimental data at the I50, I75, and I100 irrigation levels, respectively (i.e., $p > 0.05$).

Table 2 shows the results of the validation tests for price simulations. The lint and seed prices considered in this study were $1.344 kg^{-1} and $0.195 kg^{-1}, respectively, which were equal to the means of historical prices during 2003–2019. The joint distribution comparison showed that the simulated means were not statistically different from the historical means (i.e., $p > 0.05$ from the two-sample Hotelling T^2 test), and the variances were also not significantly different (i.e., $p > 0.05$ from the Box's M test). The complete homogeneity test also confirmed that the distributions of the historical and simulated price series were not significantly different. Furthermore, the correlation coefficients test had a t-value of 0.44 which was smaller than the critical value of 1.96 at the 95% confidence level, and therefore, the simulated lint and seed price series were appropriately correlated to the historical data. The correlation coefficient of the simulated lint and seed prices was 0.573, which was significantly different from zero ($p < 0.001$), whereas the correlation of the historical lint and seed prices was 0.557 and it was also significantly different from zero ($p < 0.001$). These results of statistical tests confirmed the validity of using simulated yield and price data in the economic analysis.

3.2. Water use and production costs

Fig. 2 shows the average water use for all the treatments associated with different irrigation systems and irrigation levels. Over the four years of the experiment, irrigation water applications under different irrigation systems were very close at a specific ET replacement level. For example, at the full irrigation level (I100), the seasonal water use (sum of irrigation, precipitation and soil water use) was 589, 588, 592, and 579 mm under MESA, LESA, LEPA, and SDI system, respectively. The

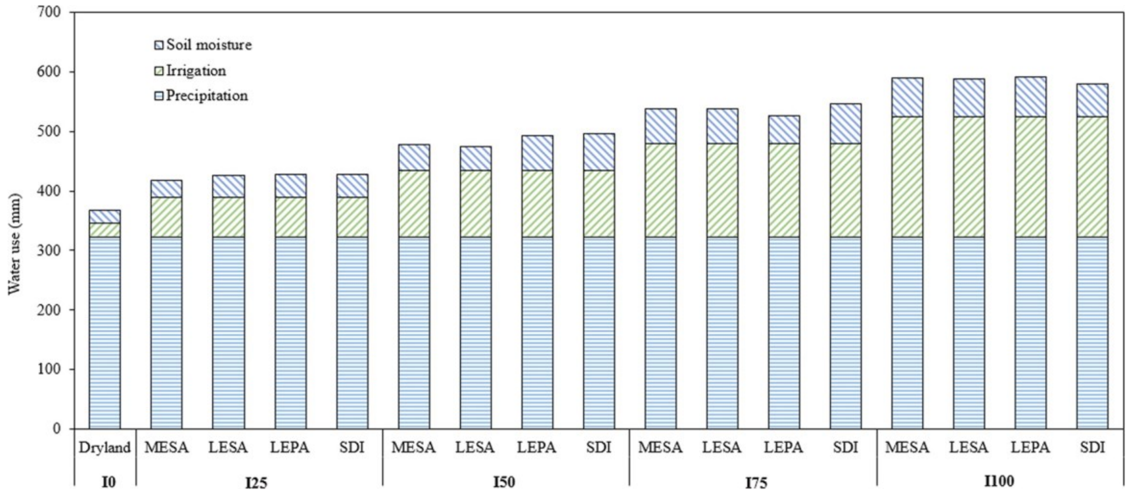

Fig. 2. Four-year average water use for all the treatments with different irrigation systems and irrigation levels. In the near-dryland treatment, minimum irrigation water was applied for crop emergence only, and the average irrigation water amount was 22 mm. Average irrigation amounts were 67, 111, 156, and 201 mm for I25, I50, I75, and I100, respectively. The total water use = precipitation + irrigation water + soil moisture change. Authors' calculation based on data from Colaizzi et al. (2010).

average seasonal water use of the four irrigation systems was 425, 485, 537, and 587 mm for I25, I50, I75, and I100 treatments, respectively. The seasonal water use was 368 mm for I0 production.[6]

The estimated total costs are presented in Table 3. Among the four irrigation systems, the total costs were similar for MESA, LESA, and LEPA, while the total cost associated with SDI was approximately 25% higher. For example, with full irrigation (I100), the total costs were \$1101, \$1075, \$1095, and \$1339 ha^{-1} on average for MESA, LESA, LEPA and SDI, respectively. The high cost for SDI was primarily due to the more expensive subsurface irrigation system and higher harvest cost associated with higher yield. The average cost for the near-dryland cotton was \$553 ha^{-1}, which was about 33% less than the costs under MESA, LESA (\$820 ha^{-1} for both) and LEPA (\$827 ha^{-1}) systems, and about half of that under SDI system (\$1053 ha^{-1}) at the I25 level.

3.3. Crop yield

Fig. 3 compares the simulated lint yields for all the treatments. Across the treatments, the yield range became greater as irrigation water increased. At each irrigation level, the highest lint yield was found with the SDI system, followed by LEPA. In contrast, MESA and LESA systems resulted in a lower cotton yield. These results indicated the highest productivity with the use of SDI systems for cotton production and this was also consistent with the highest irrigation efficiency of the SDI system (Amosson et al., 2009). As expected, the near-dryland production showed the lowest lint yield, which was approximately 56 and 98 kg ha^{-1} less than that under MESA and LESA systems at the I25 level, respectively.

In general, an increase in irrigation water use resulted in a higher cotton yield under each irrigation system. However, the rate of increase in yield slowed down at the higher irrigation levels. For example, the average lint yield using MESA was 464 kg ha^{-1} at the I25 level, and it increased to 557 kg ha^{-1} at the I50 level (i.e., an increase of 93 kg ha^{-1}). The yield increase was 224 kg ha^{-1} from I50 to I75 and 90 kg ha^{-1} from I75 to I100. Similarly, the yield increase for SDI was 159 kg ha^{-1} from I25 to I50, 220 kg ha^{-1} from I50 to I75, and 45 kg ha^{-1} from I75 to I100 (Fig. 3 and Table 1). These results indicated that full irrigation was not always the best strategy to optimize groundwater use in the THP region and that deficit irrigation could provide a higher CWP (Comas et al., 2019; Himanshu et al., 2019; Witt et al., 2020).

3.4. Profit distribution

Fig. 4 plots the cumulative distributions of net returns from cotton production at different irrigation levels. At the I25 level, the profit distribution of LEPA system was further to the right of the rest systems and closely matched with the distribution for the near-dryland cotton system, which indicated that LEPA and near-dryland production systems could provide higher income at very low or no irrigation application (Fig. 4a). In case of I50 and I100 irrigation levels, the net return distribution of LEPA lay to the right of the others, followed by SDI (Fig. 4b, d). This suggested that LEPA could have a higher probability of getting a high income at both full irrigation and half irrigation levels. The distributions of LEPA and SDI were similar at I75 level and they were to the right of the other two systems, except for the levels of net return greater than \$700 ha^{-1} where the distribution for SDI lay to the right of that for LEPA and returns less than \$200 ha^{-1} where the distribution for LEPA lay to the right of that for SDI (Fig. 4c). The net return distributions of MESA and LESA were similar at all irrigation levels. The thick tails of SDI distributions in the four panels indicated that SDI had a larger chance of getting both very low and very high income levels. In addition, a comparison of the four irrigation levels suggested that adopting SDI was as profitable as LEPA at a moderate irrigation level. The LEPA system was most profitable at both half and full irrigation levels, which echoed the wide adoption of LEPA systems in many of the semi-arid areas including the THP region (Amosson et al., 2011; Bordovsky, 2019; Segarra et al., 1999).

To better understand the net return distributions of simulated irrigation strategies, stoplight charts (Fig. 5) were developed, which clearly illustrate the probabilities of net returns being less than a lower target value and greater than an upper target value for all risky alternatives (Richardson, 2010). In this study, the 25th and 75th percentiles of the net returns were used as the lower and upper cut-off values, respectively, for all the treatments. Fig. 5 presents the probabilities of net returns less than -\$140 ha^{-1} and greater than \$380 ha^{-1} for the four irrigation systems and alternative irrigation levels. An overall comparison across all the treatments showed that the higher probability of the high income category (i.e., greater than \$380 ha^{-1}) was generally associated with application of more irrigation water. At the full irrigation level (i.e., I100), LEPA system had the highest chance of getting more than \$380

[6] This included minimum irrigation of 22 mm (mean value for four years) to ensure plant emergence only.

Table 3

Production costs ($ ha^{-1}) of cotton irrigated by different irrigation systems at varying irrigation levels.

Irrigation Level	I0	I25				I50			
Costs	Near-dryland	MESA	LESA	LEPA	SDI	MESA	LESA	LEPA	SDI
Inputs and operation[a]	306	321	321	321	321	336	336	336	336
Repairs and maintenance	38	71	71	71	104	71	71	71	104
Irrigation energy and labor[b]	–	43	36	36	43	86	72	72	86
Insurance	42	42	42	42	42	42	42	42	42
Harvest	99	116	124	138	160	139	140	185	200
Interest[c]	12	15	15	15	16	17	16	16	18
Machinery	56	211	211	204	367	211	211	204	367
Total costs	553	820	820	827	1053	903	889	927	1153
		I75				I100			
		MESA	LESA	LEPA	SDI	MESA	LESA	LEPA	SDI
Inputs and operation		351	351	351	351	366	366	366	366
Repairs and maintenance		71	71	71	104	71	71	71	104
Irrigation energy and labor		129	108	108	129	172	143	143	172
Insurance		42	42	42	42	42	42	42	42
Harvest		195	188	217	255	218	221	248	266
Interest		19	18	18	20	20	19	19	21
Machinery		211	211	204	367	211	211	204	367
Total costs		1019	989	1011	1268	1101	1075	1095	1339

[a] Costs on inputs and operation included expenses on cottonseed, fertilizers, herbicide, custom application, labor and fuel except for irrigation. Similar rates of pre-plant fertilizer were applied in all the treatments each year. Deficit irrigation treatments received proportionately less N in irrigation water (Colaizzi et al., 2005). Other costs were assumed the same for all the treatments.

[b] Near-dryland treatment (I0) received minimum irrigation water to guarantee crop emergence. To be consistent with real dryland cotton production, irrigation costs and irrigation machinery costs were not included in the cost estimation of near-dryland cotton.

[c] The interest rate was assumed as 6.25%.

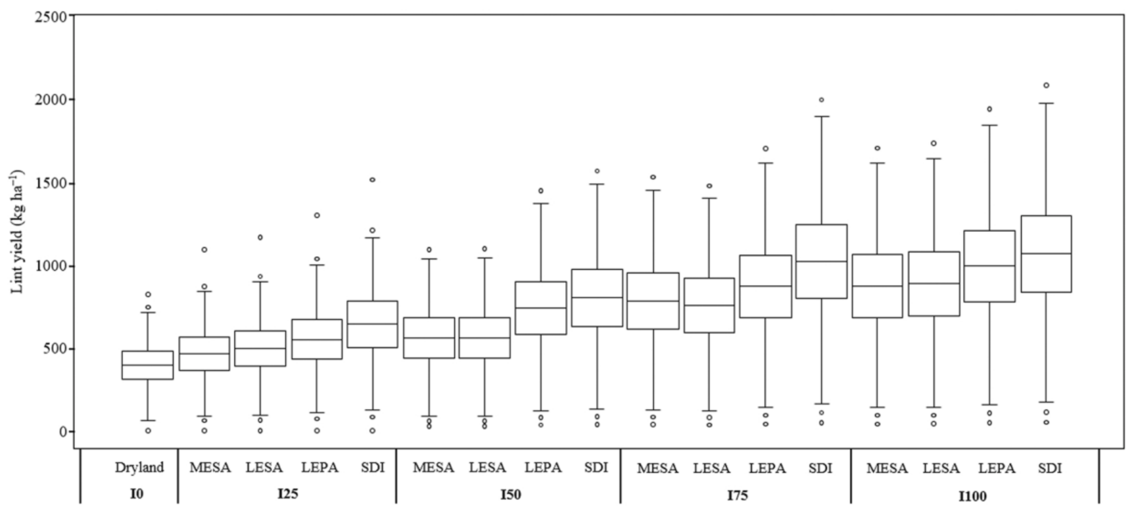

Fig. 3. Box plots of cotton lint yields (kg ha^{-1}) for all the treatments with different irrigation systems and irrigation levels. Number of observations for each treatment was 500. The horizontal line within the box represents the mean. The lower and upper ends of the box represent the 25th and 75th percentiles (Q1 and Q3), respectively. Whiskers that extend from the ends of the box are the "minimum" and "maximum" (Q1−1.5 ×IQR and Q3 +1.5 ×IQR; IQR represents the interquartile range, which equals to Q3−Q1) of the distribution, respectively. Circles below the minimum and above the maximum are the outliers.

ha^{-1} with a probability of 0.56, followed by SDI and LESA systems with probabilities of 0.45 and 0.43, respectively. Under the I75 level, LEPA (0.46) was only slightly better than SDI (0.45) in terms of obtaining a net return of more than $380 ha^{-1}. Additionally, a comparison from low to high irrigation levels showed that the probability of the high net return category (i.e., greater than $380 ha^{-1}) for MESA, LESA and LEPA systems increased continuously, while higher than I75 irrigation would not increase the net return with the SDI system. Therefore, SDI system could potentially save irrigation water when irrigating at the I75 level and achieve the same profit level as the full irrigation level. Producers would more likely need to apply full irrigation to achieve a higher profit under other irrigation systems.

3.5. Comparison of irrigation systems

Fig. 6 shows the CEs of cotton production using different irrigation systems at each irrigation level. In each panel, four irrigation systems were ranked as the risk aversion level goes from risk-neutral (ARAC=0) to extremely risk-averse (ARAC=0.0248). At each risk aversion level, the highest CE value presents the most risk efficient irrigation system for cotton producers. Table S1 of Appendix A shows the numeric values of CEs at specific risk-aversion levels.

At each of the four irrigation levels, LEPA performed best among the four systems at risk-neutral, somewhat and rather risk aversion levels. No difference in CE values of MESA, LESA, and LEPA were observed at the very and extremely risk aversion levels. This suggested that risk-neutral or slightly risk-averse producers would prefer LEPA and they are indifferent among MESA, LESA and LEPA when they became more risk-averse. Under I50, I75 and I100, SDI was the second risk preferred for risk-neutral growers, while it became the least preferred among the four irrigation systems for somewhat or even more risk-averse growers. The slope of the curve associated with SDI suggested that SDI was highly

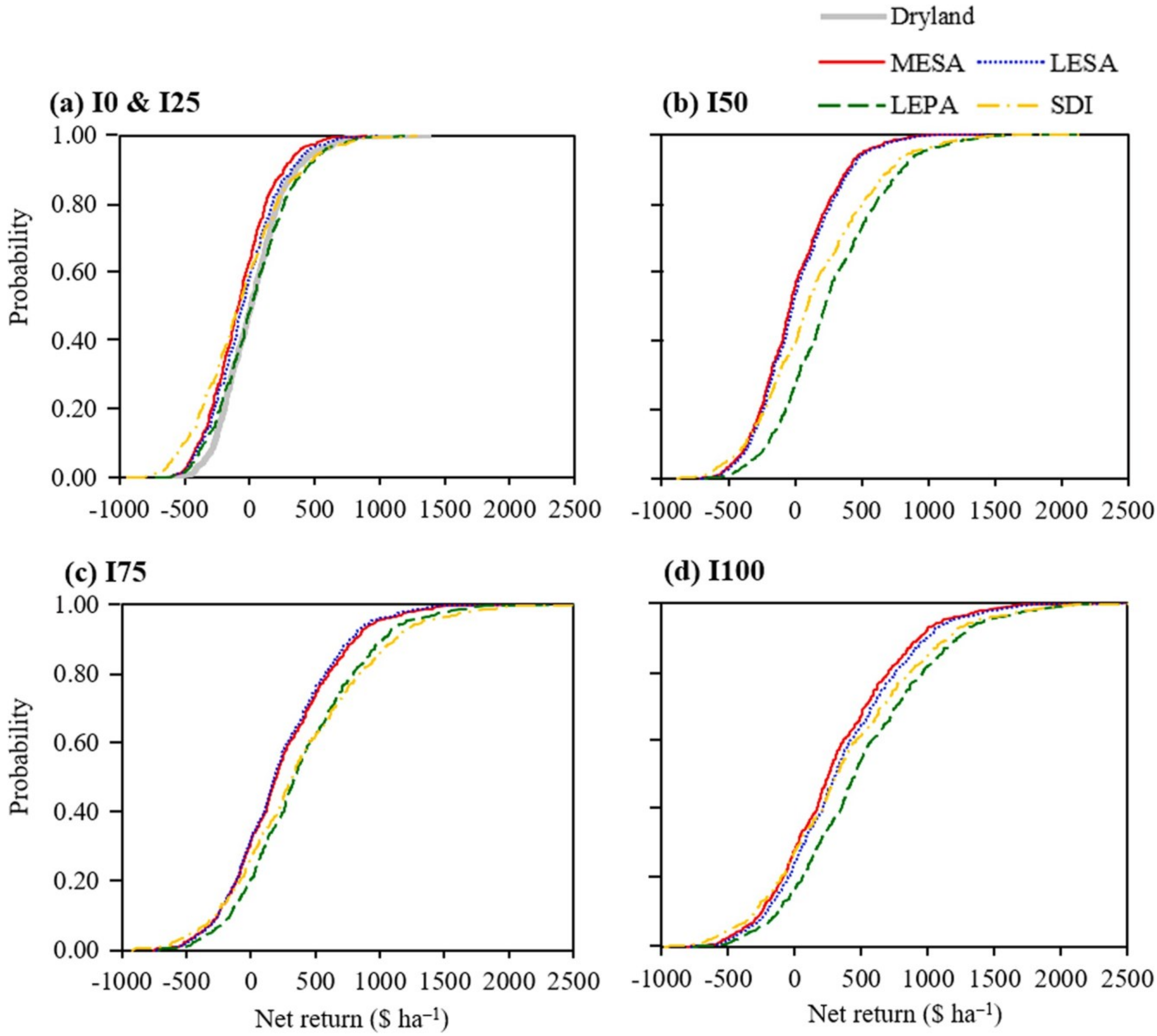

Fig. 4. Cumulative distribution functions of cotton net returns in different irrigation systems at varying irrigation levels.

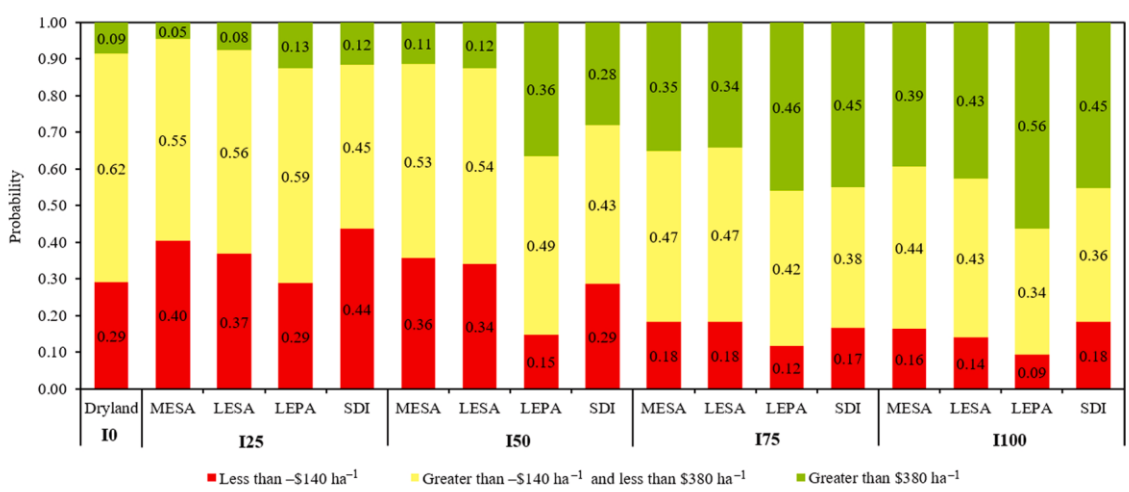

Fig. 5. Stoplight charts for probabilities of achieving net returns less than −$140 ha^{-1} and greater than $380 ha^{-1}.

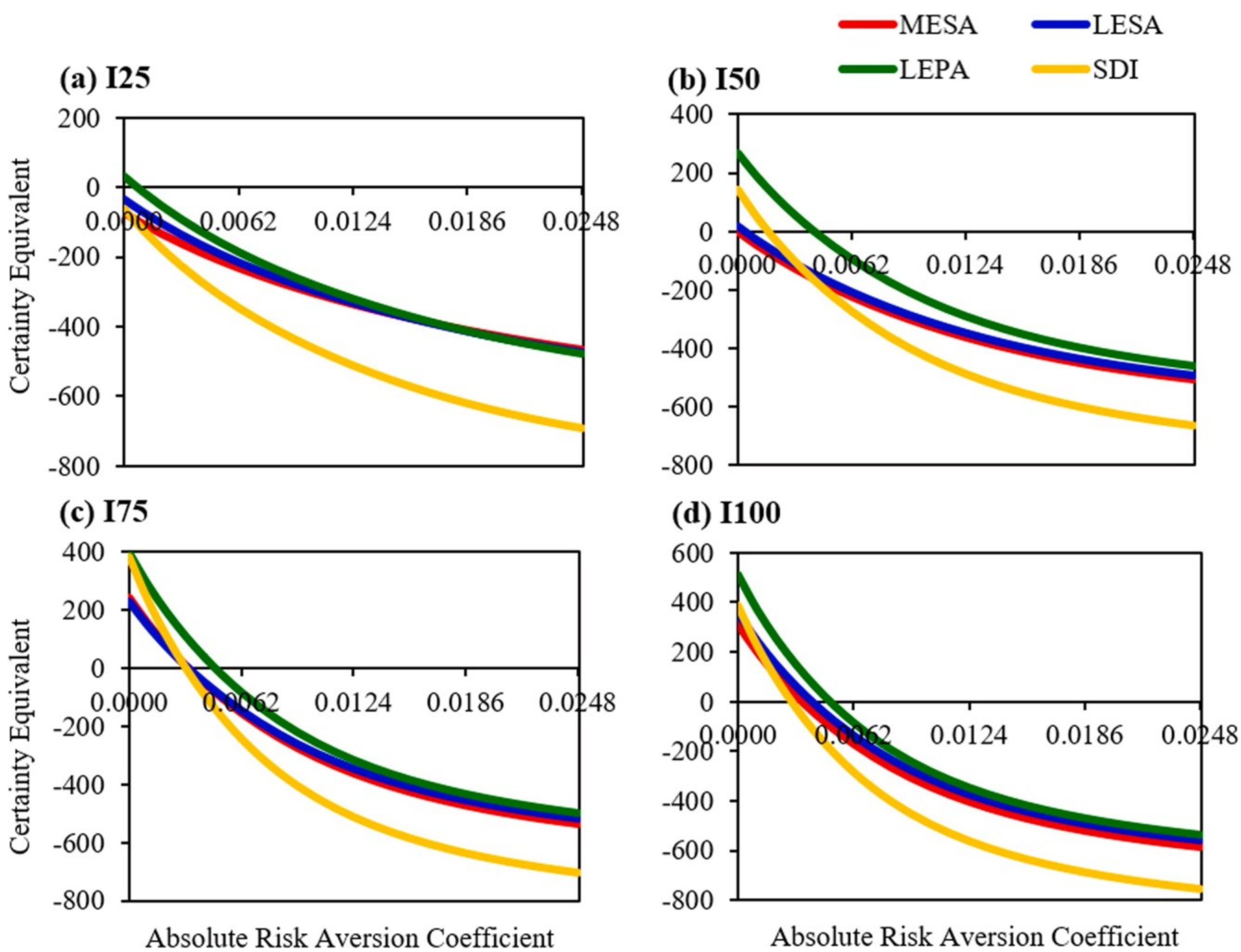

Fig. 6. Certainty equivalents ($ ha^{-1}) of cotton production under different irrigation systems.

sensitive and even a slight increase in the risk aversion level would make it the less preferred system.

To further find the risk-adjusted values for irrigation systems, SERF analysis calculated the risk premiums relative to MESA at each irrigation level. As indicated by RP, Fig. 7 shows the minimum payment amount that a cotton grower has to receive before he/she is willing to switch from MESA to another irrigation system. A positive value could be seen as the profit obtained by a grower from adopting an alternative system, while a negative value could be seen as the loss. Table S1 also shows the numeric values of RPs at specific risk-aversion levels.

Compared to MESA, all RPs of LESA and LEPA were positive across the risk aversion levels, except for very and extremely risk-averse levels under I25 and LESA at the risk-neutral level under I75. Additionally, positive RPs associated with SDI were observed at the risk-neutral and RPs became negative for somewhat and more risk aversion levels. This agreed with the findings of CEs that LEPA was the most risk-preferred system and its performance became less prominent as a producer gets more risk-averse. Bordovsky et al. (2000) also confirmed that LEPA resulted in higher net returns to risks compared to SDI system in cotton production.

3.6. Comparison of irrigation levels

The SERF analysis ranks irrigation scenarios across various risk-aversion levels. The CEs in Fig. 8 suggested that I100 and I75 were the first and second most preferred irrigation levels for risk-neutral producers, while near-dryland production was most preferred as the producers became somewhat or even more risk-averse.[7] The risk premium results showed that I75 and I100 had positive RPs for risk-neutral and somewhat risk-averse growers, and all RP values were negative if producers get more risk-averse. This indicated that full irrigation may not provide the highest farm income, in particular, for at least somewhat risk-averse individuals, and that cotton producers would rather choose irrigation level close to I75 in the THP region.

In addition, Fig. 9 shows the CEs of different irrigation levels for each irrigation system.[8] Consistent findings were observed in the three panels associated with MESA, LESA and LEPA, where full irrigation (i.e., I100) was the most preferred irrigation level for risk-neutral and somewhat risk-averse producers. In each of the three systems, the differences in CE values were minor as producers became even slightly risk-averse.[9] Regarding SDI, the CE values of I75 and I100 were almost the same for risk-neutral and somewhat risk-averse producers, respectively. Nevertheless, near-dryland production was most preferred if a producer becomes more than somewhat risk-averse, regardless of irrigation system.

[7] Fig. S3 shows the stoplight charts of net returns at different irrigation levels.

[8] Fig. S4 shows the cumulative distribution functions of different irrigation levels under each irrigation system.

[9] Fig. S5 shows the risk premiums of different irrigation levels under each irrigation system.

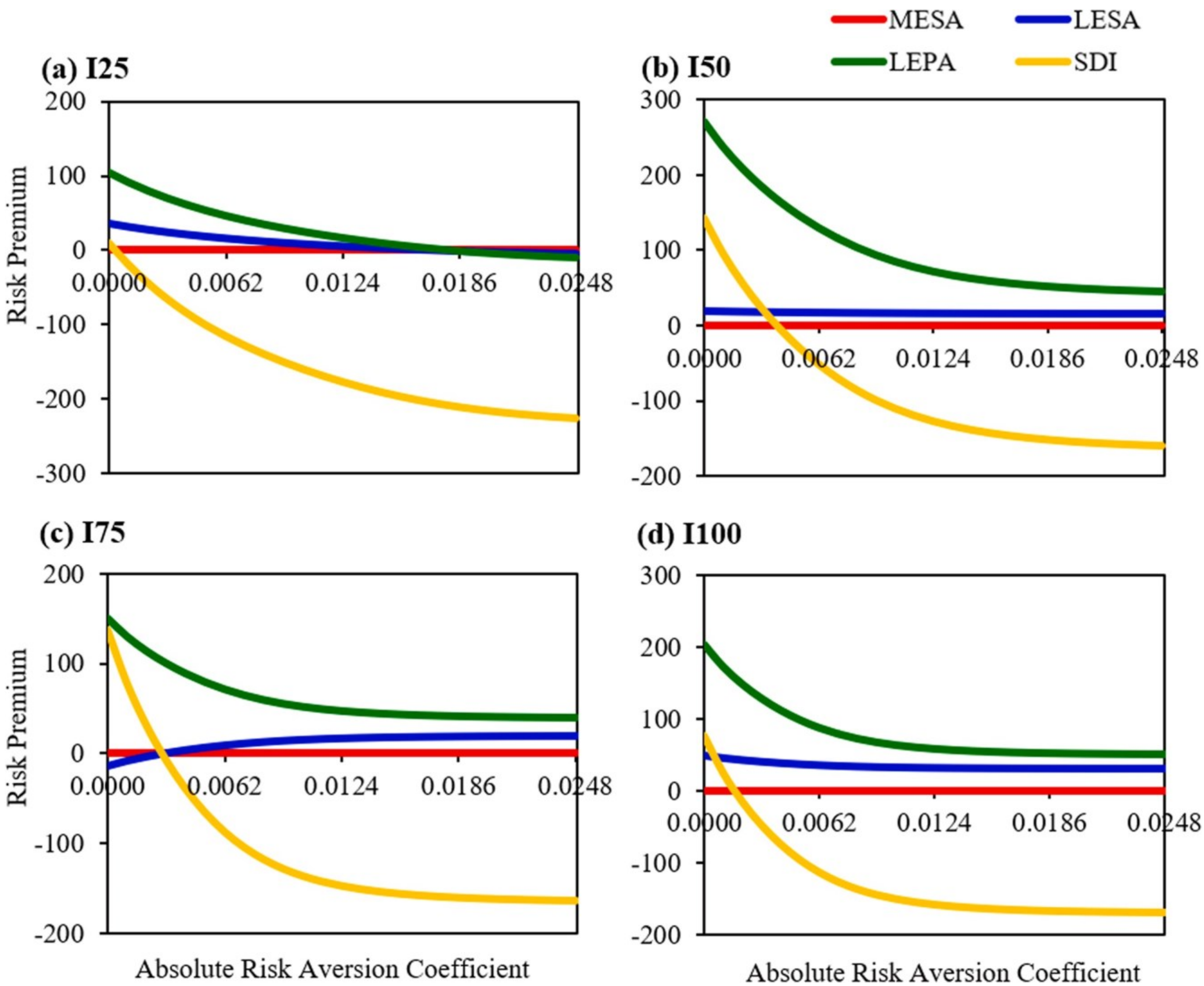

Fig. 7. Risk premiums ($ ha^{-1}) of different irrigation systems relative to the MESA.

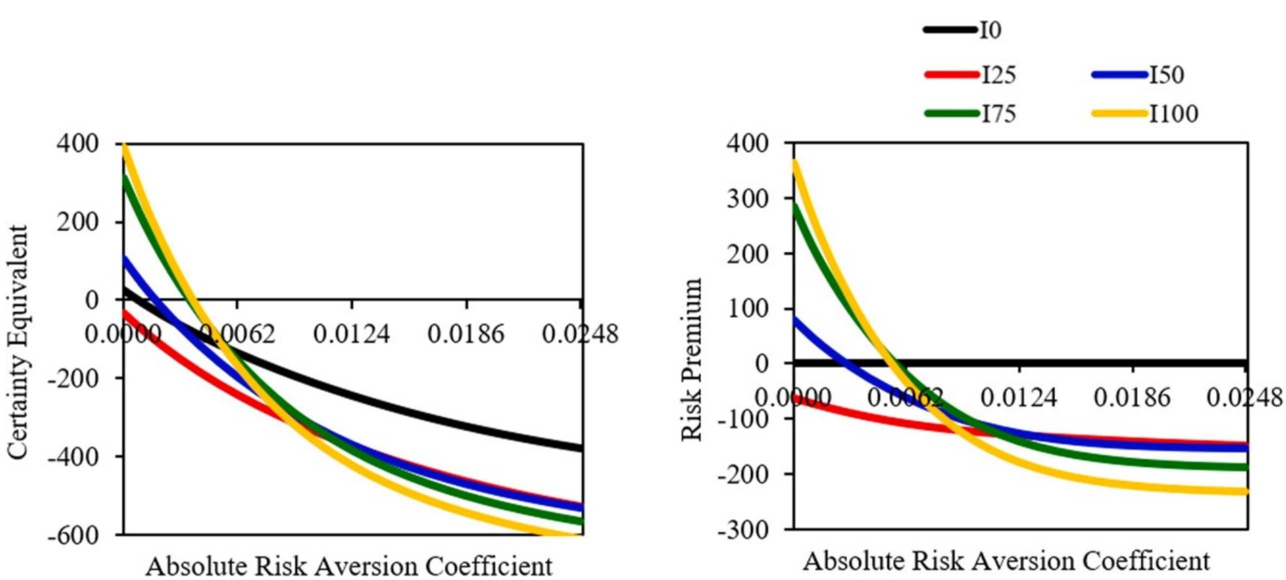

Fig. 8. Certainty equivalents and risk premiums ($ ha^{-1}) relative to the near-dryland production (I0).

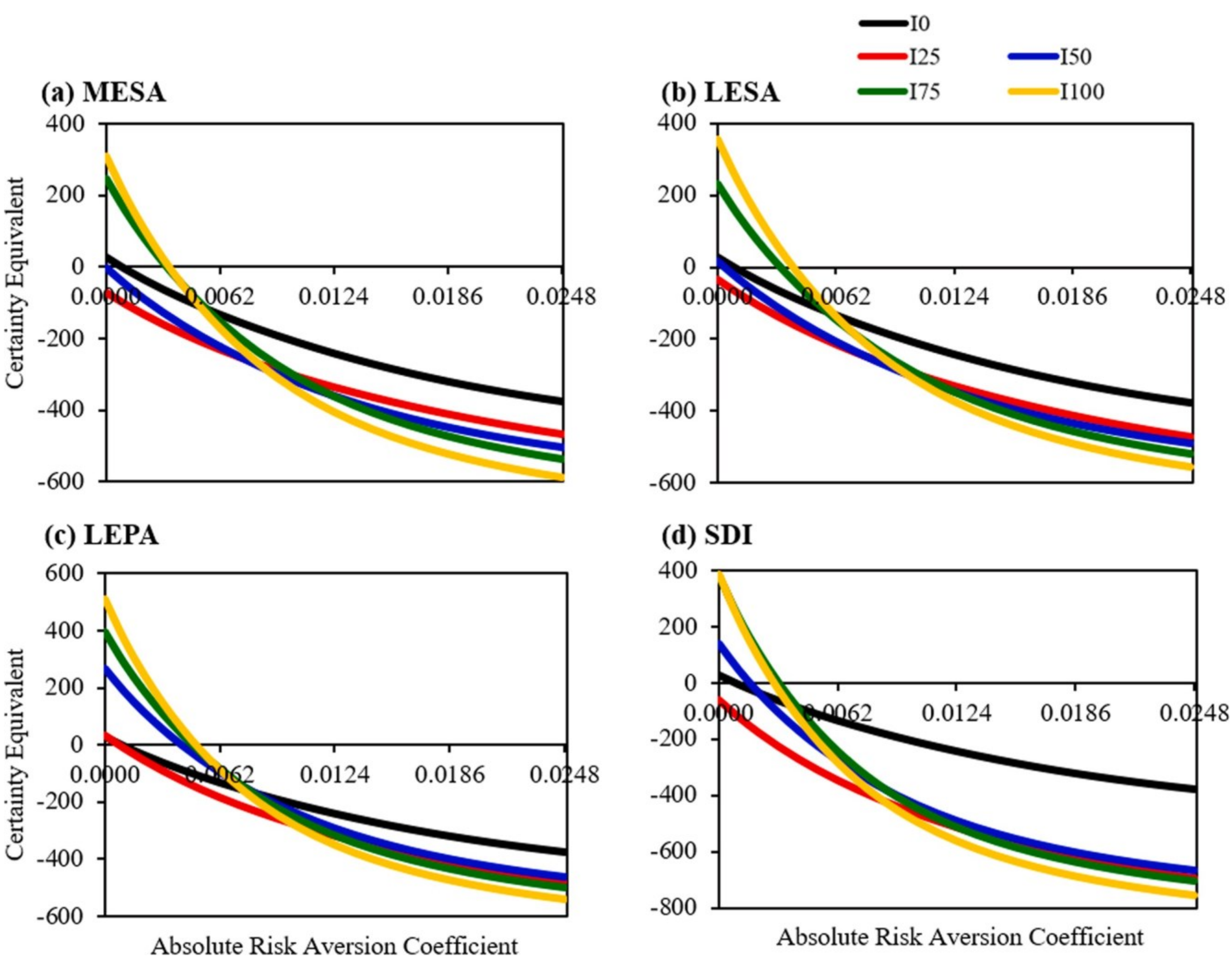

Fig. 9. Certainty equivalents ($ ha^{-1}) of different irrigation systems at varying irrigation levels.

4. Implications and conclusions

This study examined economic profits and their distributions for cotton production with different irrigation applications under MESA, LESA, LEPA, and SDI systems. Cotton yield simulations were based on a four-year field experiment and the net returns of alternative irrigation treatments were estimated using an enterprise budget approach. Economic risk analysis was conducted using the SERF procedure to provide insights for groundwater conservation and profitability of irrigated cotton production in the THP region.

Similar to the results of cotton yields, more irrigation water[10] increased net returns of cotton production under MESA, LESA and LEPA systems, while the profit increase was negligible for SDI when applied irrigation water exceeded 75% ET replacement level. A similar study found no significant difference in cotton yield for 66% and 133% ET replacements, while 100% ET was associated with a higher net return in no-till cotton production (DeLaune et al., 2012). Further, more irrigation increased the variability of cotton yields and net returns under each irrigation system (Fan et al., 2020a; Garibay et al., 2019). More irrigation water application was also associated with a larger chance of getting a higher net return, that is, greater than $380 ha^{-1}, except for SDI. Therefore, full irrigation application was more profitable to producers with MESA, LESA and LEPA systems, while irrigation at the 75% ET replacement was more profitable for SDI. Given that most producers in the region are forced to deficit irrigate by declining water availability (Evett et al., 2020a), this result helps explain why producers have installed so much SDI.

Risk analysis results provided unique insights for irrigated cotton production by incorporating growers' risk attitude. For each of the four irrigation levels, LEPA showed a higher net return than other systems and would be preferred by risk-neutral, somewhat and rather risk-averse producers. The differences in net returns of MESA, LESA and LEPA were minor for very and extremely risk-averse producers at each irrigation level. For producers with a more than somewhat risk-averse attitude, SDI was always the least preferred system. This result when combined with the fact that producers had installed 107,356 ha of SDI by 2013, increasing to 175,000 ha by 2016, in the High Plains Water District alone, occupying 6.6% of the irrigated area by 2018 (Evett et al., 2020a, 2020b), would indicate that producers in the region are willing to take on some risk in expectation of the greater yields associated with SDI. Additional analysis of different irrigation levels showed that full irrigation should be most preferred by risk-neutral producers, and there was only a minor difference in the expected returns of 75% and 100% ET replacement as the producers became somewhat risk-averse. A further analysis associated with different irrigation levels under four systems confirmed that full irrigation should be most preferred for risk-neutral and somewhat risk-averse growers under MESA, LESA, and LEPA systems, while no difference was observed for risk-neutral and somewhat risk-averse growers under SDI.

This research provides economic evidence for ET-based irrigation

[10] That is, increasing from 25% to 100% ET replacement levels, i.e., from I25 to I100.

decisions that fundamentally affect, and are affected by, specific irrigation systems. Both irrigation systems and irrigation levels are of great significance for the sustainable groundwater utilization in the THP region (Ale et al., 2020; Chaudhuri and Ale, 2014). Without undermining the importance of advanced irrigation systems in water conservation, this study comparatively evaluated the economic performance of alternative spray, sprinkler, and subsurface irrigation systems. Their relative performance can be influenced by input and output prices (Fan et al., 2020a). Additionally, farm-level decisions on irrigation system adoption and water application are greatly influenced by input use, investment decisions, and government policies (Fan et al., 2014; Himanshu et al., 2019; Zhang et al., 2015). This study is also limited by the yield bounds observed in the field experiment. Future research can evaluate the economic performance of different cultivars and incorporate cultivar improvement over time. Future research should also incorporate the effects of advanced irrigation decision support system, which are shown to produce improved CWP with regulated deficit irrigation (O'Shaughnessy et al., 2011, 2015; O'Shaughnessy and Evett, 2010). A long-term field evaluation can also help with the validation of the simulation approaches.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2021.107386.

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