

# Simulated Crop Yields Response to Irrigation Water and Economic Analysis: Increasing Irrigated Water Use Efficiency in the Indian Punjab

S. K. Jalota, A. Sood, J. D. Vitale,\* and R. Srinivasan

## ABSTRACT

The Indian Punjab has been heralded for its technical achievements but increasingly criticized for leveraging its success on the environment. Irrigation has been one of the main pillars of the Punjab's Green Revolution. The availability of water has pushed rice and wheat productivity to new heights. Cheap water policies have enabled farmers to exploit groundwater. Water tables are shrinking in some areas, while water logging poses a major problem in other parts of the Indian Punjab. This article investigates the potential for reducing irrigation water use through policies that align irrigation water prices with their true social cost. This includes charging Punjabi farmers for irrigation water and introducing alternative, more water efficient crops. Results indicate that alternative crops, cotton (*Gossypium hirsutum* L.) and soybean [*Glycine max* (L.) Merr.], would enter cropping patterns provided that irrigation water prices moved to about 25% of the price charged by municipal water authorities. Shifting cropping patterns toward more water-efficient enterprises would decrease irrigation water use on a typical paddy by nearly 66%. Future policy considerations are required to offset the declines in producer welfare that would accompany the irrigation water pricing.

THE Indian Punjab has witnessed a rapid growth in rice (*Oryza sativa* L.) and wheat (*Triticum aestivum* L.) production that has virtually defined the Green Revolution in Asia. During the past three decades, the Indian Punjab has transformed its agriculture through the introduction of new technology whose documentation is legion. Highlighted by high-yielding cultivars, increased fertilization, and irrigation, rice and wheat yields have more than doubled since the dawning of the Green Revolution (Punjab Ministry of Agriculture, 2005). Rice and wheat have also received market support from the Indian government through minimum support price (MSP) and procurement policies that provide assured markets. The remunerative nature of rice and wheat has resulted in a dramatic area expansion in the Indian Punjab: a total of 2.6 million ha of paddy rice and 3.4 million ha of wheat are now under cultivation (Punjab Ministry of Agriculture, 2005).

The economic benefits have been leveraged in large measure through water irrigation. Rainfall in an average year is insufficient to provide paddies with adequate

S.K. Jalota, Dep. of Soils, Punjab Agric. Univ., Lab-125, Ludhiana, Punjab 141 004, India; A. Sood, Punjab Remote Sensing Centre, Ludhiana, India; J.D. Vitale, Dep. of Agricultural Economics, Oklahoma State Univ., Stillwater, OK 74078; and R. Srinivasan, Spatial Sciences Lab., Texas A&M Univ., College Station, TX. Received 18 Feb. 2006. \*Corresponding author (jeffrey.vitale@okstate.edu).

Published in Agron. J. 99:1073–1084 (2007).

Economic Analysis

doi:10.2134/agronj2006.0054

© American Society of Agronomy  
677 S. Segoe Rd., Madison, WI 53711 USA



soil moisture throughout the growing season,<sup>1</sup> particularly for the water intensive rice and wheat crops that dominate the cropping patterns in the summer and winter. Punjabi farmers are able to supplement their water requirements in dry periods using irrigation. An intensive network of canals and groundwater systems has been developed during the past three decades that provides irrigation to 94% of the cultivated land within the Indian Punjab (Sondhi and Khapar, 1995).

The Indian Punjab's agricultural performance has been impressive, but evidence suggests that groundwater is being exploited to the detriment of the environment (Shiva, 1991; Raul, 2001). Unlike in the past when Punjabi farmers often experienced drought conditions, farmers now appear to have unfettered access to water. The rampant use of irrigation water is encouraged by both cheap water policies and subsidies that provide low cost, often free, electricity for pumping irrigated water. This trend has led to an excessive use of groundwater as the primary means of irrigation. In the year 2000, nearly 75% of the irrigated land within the Punjab was serviced by groundwater, with canals providing only 25% (Government of India, 2002). As a result, production systems have overworked groundwater sources and have strained the environment. Watershed health is deteriorating. Water tables are on the decline in some areas while water logging persists in others (Directorate of Water Resources, 2002). In 2005, for instance, the groundwater table declined by an average of 0.74 m in the Indian Punjab region.

To help prevent pending environmental "disasters," more water-efficient crops have been suggested as an alternative to rice and wheat (Johl and Ray, 2002; Jalota, 2004; and Hira et al., 2004). Existing conditions are unlikely to provide incentives for introducing more water-efficient crops: alternative crops lack assured markets and are less productive than rice and wheat. These issues pose a challenge to policymakers. Farmers will only diversify their crop portfolio if it is in their economic interest to do so (Tanaka et al., 2002). Policies will need to strike an adequate balance between decreasing water usage for the betterment of society while assuring that farmers can still make a profit.

A policy under consideration is the removal of irrigated water subsidies (von Braun et al., 2005). Moving farmers' irrigation costs closer to prevailing market prices

<sup>1</sup>Paddy refers to the fields where rice is grown. More generally, paddies can be used for other crops; for instance wheat is grown in paddies during the winter growing season.

**Abbreviations:** MSP, minimum support price; OLS, ordinary least square; PA, precision agriculture; PAU, Punjab Agricultural University; QP, quadratic programming.

would generate incentives to encourage more efficient use of irrigation water. Innovative cost structures would include graduated rates that reflect how social costs increase as larger volumes of groundwater are pumped onto the rice paddies. This process could include making “green payments” to farmers who reduce irrigation water usage and provide subsidies only for farmers who grow water-efficient crops in their paddy fields.

This article studies the impacts of agricultural policies that promote more socially desirable use of irrigation water in the Indian Punjab. The policies include the introduction of an irrigation water pricing structure and the promotion of more water-efficient crops. An integrated economic–biophysical model is used to analyze the impacts from each of the policies. The biophysical module uses meta equations, which describe how crop yields respond to irrigation water, to assess changes in productivity. The economic module embeds the yield meta equations within a farm household decision-making model. The response of a representative Punjabi farmer to the alternative policy instruments is predicted by the economic model.

The article begins with a background section describing the Indian Punjab study region. This section is followed by a methods section that describes how the

biophysical simulations were conducted. An economic model is then presented that considers the sequential nature of irrigation water strategies through both recourse of water applications and risk. Next the economic model results are presented that indicate how producers would respond to a schedule of irrigation water prices. The article ends with conclusions outlining policy implications and recommendations.

## BACKGROUND

The study area is the Indian Punjab (Fig. 1). As discussed above, the Green Revolution transformed Punjabi agriculture from traditional, rain-fed farming systems to modern, irrigated ones. Cropping patterns were shifted from traditional crops, primarily maize (*Zea mays* L.), to high yielding varieties of rice and wheat. Both rice and wheat have responded well to the higher levels of water and nutrient inputs. During the last 30 yr, the Indian Punjab has witnessed a rapid growth in rice and wheat production. Today the Indian Punjab has the unique distinction as being both the rice bowl and the bread basket for India’s food demands. Occupying only 1.5% of the geographical area of the country, the Punjab contributes to 65% of India’s food grain requirements.

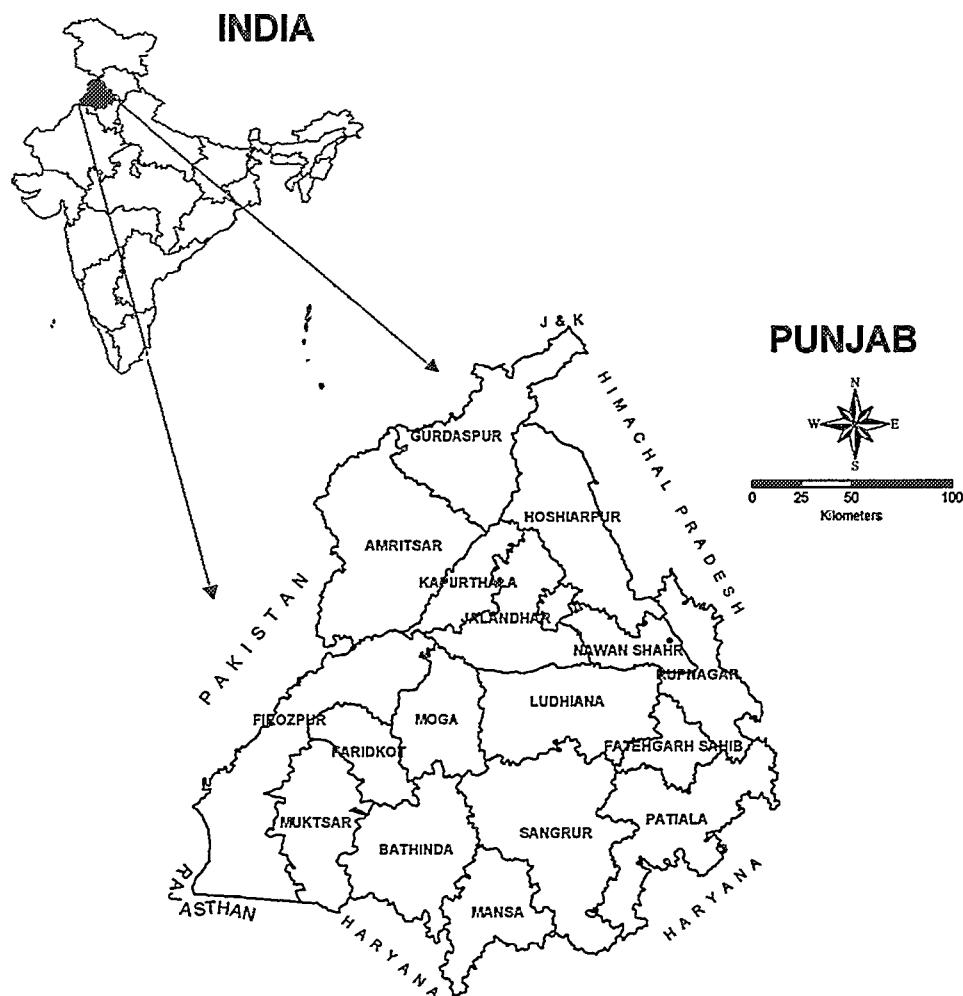


Fig. 1. The Indian Punjab study region.

As part of the Green Revolution, increased fertilization and irrigation became the pillars of Punjabi farming. The use of chemical fertilizers throughout the Punjab increased sixfold, from 0.19 Tg in 1971 to 1.18 Tg in 2001 (Punjab Ministry of Agriculture, 2005). The total land area under irrigation increased by 81% between 1971 and 2001, starting from 4.24 million ha in 1971 and increasing to 7.68 million ha in 2001. The fertilizer and irrigation area trends enabled dramatic gains in productivity during this period. Rice yields increased by 93% between 1971 and 2001, starting from 2030 kg ha<sup>-1</sup> in 1971 and reaching 3920 kg ha<sup>-1</sup> in 2001. Wheat yields increased by nearly the same amount as did rice yields, 77%, between 1971 and 2001. In 1971, wheat yields were 1 600 kg ha<sup>-1</sup>, and by 2001 wheat yields had increased to 2860 kg ha<sup>-1</sup>.

## MATERIALS AND METHODS

An integrated economic and biophysical modeling approach was developed for this study. This approach is considered appropriate because policies to encourage more socially optimal use of irrigated water cut across both the economic and biophysical disciplines (Brown, 2000). Supporting policy analysis requires simultaneous consideration of biophysical and economic variables. A biophysical module was first constructed to estimate how crop yields would respond to varying levels of irrigated water applications on the paddy fields. A biophysical model, CroPMan, was used to simulate yields for both existing cropping patterns, primarily a rice–wheat system, plus alternative crops that would improve water use efficiency in the Indian Punjab (Gerik et al., 2003). The alternative crops include: maize, cotton, soybean, mustard (*Brassica juncea* L.), and chickpea (*Cicer arietinum* L.). Simulated data was used in this analysis since observed data on the alternative crops was either too limited or nonexistent.

An economic module was then constructed to maintain consistency between farmers' decision-making preferences and the alternative farming strategies analyzed in the biophysical module. The response of crop yields to varying levels of irrigation water was embedded into an economic model of the farm household (Mapp and Eidman, 1976; Vitale and Lee, 2005). The integrated model is then able to predict: (i) the response of Punjabi farmers to alternative irrigation water price structures (whether they would be induced to shift into more water-efficient cropping patterns) and (ii) how Punjabi farmers' welfare (income) would be impacted by the alternative irrigated water cost structures.

### Biophysical Modeling

Simulation-based crop growth models have been gaining acceptance as a practical and cost-effective approach to developing yield response functions (Antle and Capalbo, 2001). Observed data from field surveys may appear to be the preferred approach for gathering yield data, but it is often ill suited to address policy issues. Existing farmers' practices often lie outside of the range of interest to the policy analyst because farmers typically do not use socially optimal levels of inputs, which is true in the Indian Punjab setting. Farmers' irrigation strategies rely excessively on irrigation water. Hence, field surveys will not observe the type of farming techniques that water policy is addressing, (those techniques that make more efficient use of irrigation).

While it is possible to develop such yield observations using experiment station trials (over a wide range of irrigation tim-

ings and application rates data over the required range of input settings), such trials would need to be conducted for a number of years to account for alternative weather patterns. For practical matters, this is both too great of an expense and too inconvenient because such a long time horizon is required.

Biophysical modeling provides analysts with a cost-effective means to generate yield response data under an array of policy scenarios such as alternative irrigation water applications (Ruben and van Ruijven, 2001; Llewelyn and Featherstone, 1997; Mapp and Eidmann, 1976). This approach is flexible and allows analysts to explore a range of farming methods and techniques that extend well beyond what is observable in the field. Simulation yield response data can be generated at a fraction of the cost of observed data, either from farmers' fields or the experiment station. Moreover, crop growth models generate results in a matter of weeks rather than years.

Crop growth models are rooted in a host of well-established biological and biophysical processes. This study used the CroPMan model to simulate crop yields in the Indian Punjab study region (Gerik et al., 2003). CroPMan is a phenologically based simulation model: it updates plant growth on a daily time step using the limiting factor approach. Plant growth is simulated from initial seed germination through grain filling stages. The internal processes of CroPMan have been validated to assure consistency with actual field conditions. Applications of CroPMan across a wide range of settings have shown it to be robust, including the Indian Punjab (Jalota et al., 2006). In this study the primary focus was on developing crop response functions to varying levels of irrigation water.

### Biophysical Simulations: Experimental Design and Input

CroPMan simulations are governed by user defined input files that specify the calendar and intensity of field operations and management practices (Gerik et al., 2003). The field operations in CroPMan include: irrigation water scheduling, field preparation techniques, sowing dates, fertilizer applications, pesticide/herbicide treatments, and harvest date. The field operations used in the CroPMan simulations for rice and wheat were obtained from field surveys conducted by the Punjab Agricultural University (PAU) at two village sites (Mahindra, 2003). For the alternative crops, the field operations used in the CroPMan simulations were derived from recommended practices established by the PAU extension services.

CroPMan includes a detailed treatment of soils, enabling users to model soil profiles with up to four layers. The predominant soil type in the study region is Tulewal, a name local farmers use to describe this sandy-loam soil. Tulewal has a medium texture that contains 71% sand, 12% silt, and 17% clay. The large sand content makes it difficult for the soil to retain irrigation water within its profile. The soil has bulk density of 1.50 Mg m<sup>-3</sup>, saturated hydraulic conductivity of 25 mm h<sup>-1</sup>, pH of 8.2, and EC 5.0 C mol kg<sup>-1</sup>. Soil water contents corresponding to field capacity and permanent wilting point are 0.24 m<sup>3</sup> m<sup>-3</sup> and 0.08 m<sup>3</sup> m<sup>-3</sup>, respectively.

The CroPMan simulations were run under climatic conditions that reflected weather patterns over a 30-yr period from 1971 through 2000. The weather data were recorded at a meteorological observatory at the Punjab Agricultural University in Ludhiana. The weather data were organized into a handful of categories, such as states-of-nature, which distinguished good rainfall years from poor ones (Table 1). This information was deemed necessary because irrigation water applications depend on rainfall, with significantly higher applications in low rainfall years. The rainfall categories are used in the yield meta-equation estimations to account for different

**Table 1.** Rainfall states of nature used in the biophysical modeling experimental design.<sup>†</sup>

| Summer growing season (kharif) |          |                           | Winter growing season (rabi) |          |                           |
|--------------------------------|----------|---------------------------|------------------------------|----------|---------------------------|
| Rainfall state                 | Rainfall | Probability of occurrence | Rainfall state               | Rainfall | Probability of occurrence |
| mm                             |          |                           |                              |          |                           |
| Poor                           | 0–200    | 0.05                      | poor                         | 0–100    | 0.32                      |
| Below average                  | 200–400  | 0.16                      | below average                | 100–200  | 0.38                      |
| Average                        | 400–600  | 0.31                      | average                      | 200–300  | 0.30                      |
| Above average                  | 600–800  | 0.27                      |                              |          |                           |
| Good                           | 800–1200 | 0.21                      |                              |          |                           |

<sup>†</sup>Source: Meteorological Station Data, Punjab Agricultural University, Ludhiana, India.

productivity levels of irrigation water and in the economic analysis to account for risk. Rainfall states of nature were defined for both the summer (rabi) and winter (kari) growing seasons.

Crop yields were simulated by CroPMan using an experimental design that determined optimal irrigation water practices. The experimental design created an array of alternative irrigation strategies that varied the calendar, frequency, and intensity of irrigation water applications. With wheat, for example, the irrigation calendar included four different application dates, generating an array of 15 alternative irrigation water applications (Table 2). From this array, the optimal timing of irrigation was determined by eliminating the inefficient applications.

Yield simulation results for wheat illustrate the critical nature of properly timing irrigation water applications (Fig. 2) because the optimal timing of irrigation activities enables farmers to use irrigated water most efficiently (Table 2). Crop yields can be increased while reducing the number and intensity of irrigation water applications. The efficient frontier for irrigation water identifies the maximum yield that can be obtained for a given quantity of irrigation water (Fig. 2). Within each rainfall group, the efficient yield frontier was determined. As illustrated in Fig. 2, the inefficient irrigation water applications lie beneath the efficient yield frontier. The inefficient irrigation water application timings were omitted from further analysis.

For a given irrigation water application, a range of wheat yields was found. For wheat grown during the winter months, the efficiency frontier indicates that yields of  $5.1 \text{ kg ha}^{-1}$  can be achieved with only three irrigations on 26 January, 2 March, and 30 March, even though conventional practices employ four irrigations on 2 December, 26 January, 2 March, and 30 March (Fig. 2). In doing so, Punjabi farmers would save 75 mm of water with no practical loss in yield. The cost of inefficiency in

the timing of irrigation can be substantial, particularly for the winter (rabi) season crops (Fig. 2). Poorly timed irrigated water on the paddy when wheat is grown, for example, could lead to yield losses up to  $1900 \text{ kg ha}^{-1}$ . Two irrigated water applications of 75 mm, depending on its date, could produce wheat yields anywhere between  $2300$  and  $4200 \text{ kg ha}^{-1}$  (Fig. 2). CroPMan simulations found similar productivity gains from optimal timing in the other crops analyzed as well.

### Crop Yield Meta Equations

Yield response functions to irrigation water were constructed using meta-equation techniques from the CroPMan simulation results (Ruben and van Ruijven, 2001). The meta-equation method simplifies the large quantity of output from CroPMan into a more compact analytical representation (Wu and Babcock, 1999). The biophysical simulation literature has shown that regression techniques can be successfully applied to restructure model output to isolate key relationships among factors being studied. Yield meta equations have, for instance, been developed in various settings including irrigated crops (Llewelyn and Featherstone, 1997).

In this article, ordinary least square (OLS) methods were used for the irrigation water response functions (Greene 1997). Consistent with other studies, quadratic terms were found to be necessary to account for the declining productivity of irrigated water; as more water is applied, the soil-plant system approaches an optimal soil moisture condition beyond which yields fall off (Oweis et al., 1999; Hexem and Heady, 1978; Zhang et al., 1993). The yield meta equation,  $Y_R$ , is given by a quadratic function of total applied irrigation water during the growing season,  $Q_{IW}$ :

$$Y_R = \alpha_0 + \alpha_1 Q_{IW} + \alpha_2 Q_{IW}^2 + \varepsilon \quad [1]$$

**Table 2.** Optimal scheduling of irrigation water applications in the summer and winter growing seasons.

| Irrigation applications<br>no. season <sup>-1</sup> | Alternative irrigation schedule of watering dates (alternative no.) |         |         |         |         |         |         |         |          |
|---|---|---------|---------|---------|---------|---------|---------|---------|----------|
|   | 1   | 2       | 3       | 4       | 5       | 6       | 7       | 8       | 9        |
| Summer growing season (kharif)                      |   |         |         |         |         |         |         |         |          |
| 1   | 22 May  | 12 June | 25 June | 2 July  | 12 July | 5 Aug.  | 14 Aug. | 19 Aug. | 29 Sept. |
| 2   |   | M,C†    | C       | M       | C       | M,S     |         | S       | S        |
| 3   |   | M,C     | M       | C       | M,S     | S       |         | S       | C        |
| 4   |   | M,C     | M,S     | C       | M,S     | M,S     | C       | S       | C        |
| 5   |   | M,C     | M       | C       | M,C     | M       | C       | M       | C        |
| 6   | C   | C       | C       | C       | C       | C       | C       | C       | C        |
| Winter growing season (rabi)                        |   |         |         |         |         |         |         |         |          |
| 1   | 30 Nov.   | 9 Dec.  | 20 Dec. | 30 Dec. | 25 Jan. | 10 Feb. | 20 Feb. | 15 Mar. |          |
| 2   |   |         |         |         | MS      | MS      | W,CH    | W,CH    |          |
| 3   |   |         | CH      |         | W,MS    | MS      | W,CH    | W,CH    |          |
| 4   | MS  | W       |         | MS      | W,MS    | MS      | W       | W       |          |

†The crops are represented by C for cotton, M for maize, S for soybean, W for winter wheat, MS for mustard, and CH for chickpea.

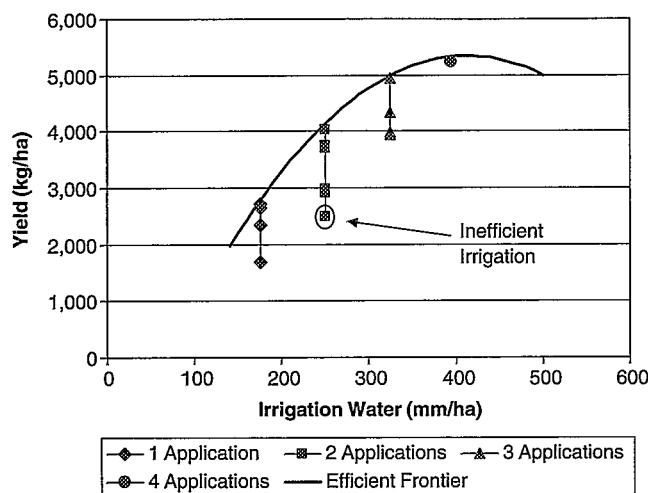


Fig. 2. Effects of optimal irrigation water timing on wheat yields.

where  $\alpha_0$ ,  $\alpha_1$ , and  $\alpha_2$  are regression parameters to be estimated and  $\varepsilon$  is the error term.

Yield meta equations were developed using dummy variables for rainfall states of nature,  $R$ , which represent different categories of precipitation. Rainfall during the wet, summer season was categorized into five states of nature and in the subsequent dry, winter season three states of nature were identified. Dummy variables were used in the meta-equation model because the productivity and yield response of irrigated water can vary across the states of nature. In drier years, a greater presence of evapotranspiration (water stress) exists, with a corresponding increased demand for irrigation water,  $Q_{IW}$ .

The yield meta equations were estimated along the efficient frontier of farm practices that purged inefficient and sub-optimal irrigation strategies from the dataset (Johansson et al., 2004). The efficient frontier contains only the irrigation practices that make optimal use of irrigation water as determined from the biophysical simulations. Hence, the estimated yield functions explain how crop yields respond to irrigation water under best management practices. Rainfall, soil type, fertilizer applications, and other production inputs were included in the yield response functions as fixed effects.

The simulated yield data from CroPMAN were found to be well validated with reported yield data from the Punjab Agricultural University extension services (Table 3). Differences between simulated and reported yields for the five major grain and fiber crops were all below 6%. The average error for these five crops was 2.4%. The simulated pulse crops (soybean, mustard, and chickpea) had more discrepancy with reported values, with errors as high as 27%.

Table 3. Comparison between reported crop yields and those simulated by the CroPMAN crop growth model.

| Crop     | Season of cultivation† | Reported yield      | Simulated yield | Percentage difference |
|----------|------------------------|---------------------|-----------------|-----------------------|
|          |                        | kg ha <sup>-1</sup> | %               |                       |
| Rice     | summer                 | 6.30                | 6.25            | -0.8                  |
| Maize    | summer                 | 5.40                | 5.12            | -5.2                  |
| Cotton   | summer                 | 2.30                | 2.22            | -3.5                  |
| Soybean  | summer                 | 1.80                | 2.15            | 19.4                  |
| Wheat    | winter                 | 5.20                | 5.13            | -1.3                  |
| Mustard  | winter                 | 1.10                | 1.40            | 27.2                  |
| Chickpea | winter                 | 1.60                | 1.79            | 11.8                  |

† Summer growing season begins in May and ends in November; it is known in local language as kharif. Winter growing season begins in November and ends in April; it is known in local language as rabi.

The yield meta equations' estimates provided good statistical fits to the CroPMAN simulation data (Eq. [1]). Econometric results found that the meta equations explained between 87 and 99% of the variation in crop yields using irrigation water and the rainfall groupings (Table 4). The statistical properties of the OLS estimates from Eq. [1] revealed little evidence of hetero-skedasticity, correlation, or nonnormality regarding the explanatory variables and corresponding error terms.

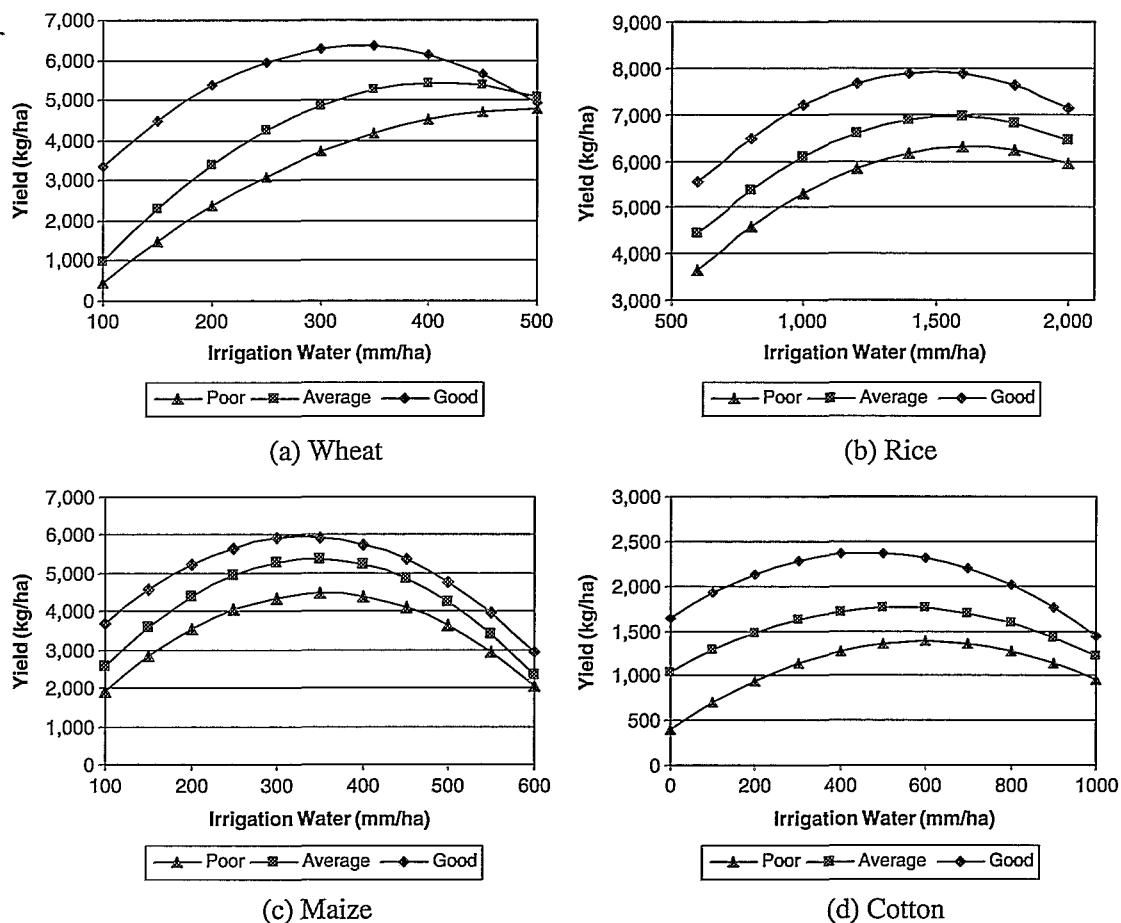
The yield response to irrigation water of wheat, rice, maize, and cotton is illustrated in Fig. 3. The yield responses were found to have fairly similar shapes across the range of rainfall states. The meta-equation results suggest that irrigation water is able to only partially substitute for rainfall since the good years of rainfall were found to have higher crop yields. This result is likely explained by the reduced solar radiation and corresponding lower temperatures, plus less evapotranspiration, that occur in the better rainfall years.

Crop yields' response to irrigation water, given by the coefficient  $\alpha_1$ , varied considerably across the crops (Table 4). Among the rainy season crops, maize yields responded the best to irrigation; each mm of irrigated water would increase maize yield by about 32 kg ha<sup>-1</sup> (Table 4). Wheat responded best to irrigation among the dry season crops; each mm of irrigated water would increase wheat yield by an average of 34 kg ha<sup>-1</sup> (Table 4). The principal summer season crop, rice, had nearly the lowest response to irrigated water. Irrigated water would only increase rice yields at a rate of 8 kg ha<sup>-1</sup>. Of the remaining alternative crops, mustard and chickpea had the best responses to irrigation. Both mustard and chickpea yields would

Table 4. Irrigated water yield meta-equations developed from CroPMAN simulations.

| Crop     | Rainfall state-of-nature | Yield irrigated water meta-equations† |            |            | $R^2$ |
|----------|--------------------------|---------------------------------------|------------|------------|-------|
|          |                          | $\alpha_0$                            | $\alpha_1$ | $\alpha_2$ |       |
| Rice     | poor                     | -347*                                 | 8.15*      | -0.0025*   | 0.95  |
|          | below average            | 57.7*                                 | 8.42*      | -0.0027*   | 0.90  |
|          | average                  | 146*                                  | 8.45       | -0.0027*   | 0.88  |
|          | above average            | 798*                                  | 8.65*      | -0.0028*   | 0.86  |
|          | good                     | 1275*                                 | 8.93*      | -0.0030*   | 0.87  |
| Maize    | poor                     | -482*                                 | 28.02*     | -0.0396*   | 0.97  |
|          | below average            | -399*                                 | 30.94*     | -0.0441*   | 0.94  |
|          | average                  | -178*                                 | 32.29*     | -0.0469*   | 0.85  |
|          | above average            | 510*                                  | 30.58*     | -0.0453*   | 0.84  |
|          | good                     | 1300*                                 | 28.03*     | -0.0422*   | 0.91  |
| Cotton   | poor                     | 400*                                  | 3.26*      | -0.0023*   | 0.94  |
|          | below average            | 690*                                  | 2.93*      | -0.0021*   | 0.95  |
|          | average                  | 1045                                  | 2.68       | -0.0025*   | 0.93  |
|          | above average            | 1345*                                 | 2.44*      | -0.0021*   | 0.91  |
|          | good                     | 1543*                                 | 2.32*      | -0.0019    | 0.90  |
| Soybean  | poor                     | 813*                                  | 5.76*      | -0.0081*   | 0.97  |
|          | below average            | 971*                                  | 5.61*      | -0.0077*   | 0.93  |
|          | average                  | 1882*                                 | 2.18*      | -0.0033*   | 0.91  |
|          | above average            | 1973*                                 | 1.73       | -0.0023    | 0.90  |
|          | good                     | 2141*                                 | 1.42*      | -0.0022*   | 0.96  |
| Wheat    | poor                     | -1994*                                | 27.24*     | -0.0274    | 0.99  |
|          | below average            | -2302*                                | 37.52*     | -0.0454*   | 0.99  |
|          | average                  | 275*                                  | 36.23*     | -0.0539*   | 0.97  |
| Mustard  | poor                     | -771*                                 | 12.83*     | -0.0149*   | 0.98  |
|          | below average            | -466*                                 | 16.38*     | -0.0238*   | 0.99  |
|          | average                  | -237*                                 | 16.38*     | -0.0258*   | 0.96  |
| Chickpea | poor                     | -808*                                 | 10.37      | -0.0097    | 0.99  |
|          | below average            | -1331*                                | 17.85*     | -0.0230*   | 0.99  |
|          | average                  | -743*                                 | 21.04*     | -0.0372*   | 0.99  |

\* Statistically significant at the 95% confidence level.



**Fig. 3. Yield response to irrigation water for wheat, rice, maize, and cotton across poor, average, and good rainfall states of nature.**

increase by about 16 to 18 kg ha<sup>-1</sup> for each mm of irrigation. Cotton and soybean did not respond as well to irrigation. Their yields would increase by only about 2 to 3 kg ha<sup>-1</sup> to irrigation.

The simulation findings that wheat and maize are substantially more water-efficient than rice and the pulse crops are in agreement with empirical results from India and other regions. In the Indian Punjab, wheat and maize have been found to be three times more water-efficient than rice (Ikisan, 2005). Rice demands up to 2000 mm of water compared to only 300 mm of water demanded by wheat and 700 mm of water demanded by maize.

Wheat and maize have been found to provide greater water use efficiency compared with rice, cotton, and pulses across a variety of study areas outside of India. In China, wheat and maize were found to have twice the response of pulse crops to irrigation (Deng et al., 2004). In Australia and the U.S., wheat and maize were found to be between two and three times as water-efficient as soybean, cotton, and rice (Goyne and McIntyre, 2002; Goyne 2002; Neitsch et al., 2002).

## ECONOMIC ANALYSIS

An economic model of a representative Punjabi farm household was constructed in this study. The model uses math programming techniques to simulate the effects of irrigation water policies on the farm household's allocation of resources under risky economic conditions (Cai and Rosegrant, 2004). The model predicts whether the policy incentives would be strong enough to induce

producers to alter their irrigation water demand through adopting water-efficient cropping strategies. The implications of the irrigation water policies on farmers' welfare (changes in income), are also derived from the model's results.

The use of farm programming models is the preferred approach in the ex-ante settings that are associated with policy change (Hazell and Norton, 1986). Econometric approaches (reduced form equations) are not flexible enough to handle the full range of policy alternatives being considered. Field observations on either the alternative crops or on alternative irrigated water strategies applied to existing crop patterns are not available. Farm programming models, however, are able to consider a wide range of policy alternatives and new cropping enterprises. By approximating the decision making tendencies of producers, programming models are able to predict future changes in farming patterns.

## Optimal Irrigation Water Use under Risk

The variable nature of rainfall in the Indian Punjab introduces risk into producers' decision-making processes (Feder, 1980). The sequential nature of plant production requires that farmers make their crop enterprise decisions before they know what the weather conditions will be like during the upcoming growing season. This leaves

farmers with little if any recourse on their planting decisions because once seeds have been sown it's usually too late for farmers to replant. The corresponding cost of making "wrong decisions" in planting, when weather turns adverse, can be significant for producers (Dalton et al., 2004).

Irrigation, however, provides farmers with more flexibility in their decision making. For each crop enterprise, the demand for irrigation water is highly dependent on the quantity of rainfall during the growing season. Farmers can adjust irrigation water applications throughout the growing season according to precipitation levels, providing them with recourse and one means of reducing risk (Harris and Mapp, 1986). In the biophysical analysis, rainfall was explicitly included using states of nature,  $R$ , which accounted for weather patterns based on historical trends. Irrigation water demands for each crop enterprise were then predicted within each rainfall state of nature.

When faced with uncertainty, producers base their crop decisions on both expected (average) income and income variance (Markowitz, 1952). Producers measure risk through income variance, the dispersion of income about its mean, with greater risk associated with higher levels of income variance. The relationship between expected income and income variance is specified by the risk efficiency frontier. This fact establishes that expected income can only be increased by taking on more risk, (through an increase in income variance) (Markowitz, 1952). Similarly, reducing risk can only be achieved through giving up some amount of expected income. Risk preferences, given in terms of a risk coefficient, determines how much a producer is willing to exchange expected income for income variance. Risk-averse producers, for instance, are willing to accept lower expected income to reduce income variance.

Quadratic programming (QP) is a commonly used approach to incorporate risk into decision making (Freund, 1956). Consistent with how producers formulate decisions under risk, QP includes both expected income and income variance. The QP structure generates a risk-efficient portfolio of crop enterprises, those which minimize income variance at given levels of expected income. Quadratic programming is a flexible approach that makes minimal presumptions on producers risk preferences. The risk coefficient within the QP governs the trade-offs between expected income and income variance; parametric variations in the risk coefficient can encompass a wide range of risk aversion preferences.

The QP formulation is given by the following set of equations:

$$\text{Maximize } EV = E(\Pi) - \varphi \sum_i \sum_k X_i \sigma_{i,k}^2(\Pi) X_k \quad [2]$$

subject to

$$E(\Pi) = \sum_R \Theta_R \Pi_R \quad [3]$$

$$\Pi_R = \sum_i P_i Y_i^R (q_{IW}^R, \mathbf{Z}_i) X_i - P_W Q_{IW}^R - \sum_i \mathbf{C}_i \mathbf{Z}_i X_i \quad [4]$$

$$\sigma_{i,k}^2(\Pi) = \sum_i \sum_k \Theta_R (\Pi_i^R - E(\Pi_i)) (\Pi_k^R - E(\Pi_k)) \quad [5]$$

$$\sum_i^I X_i \leq \text{LAND} \quad [6]$$

$$\sum_r^R \sum_i^I q_{IW}^R = Q_{IW}^R \quad [7]$$

where EV is the objective function;  $E(\Pi)$  is the expected whole-farm profit across the set of  $R$  rainfall states;  $X_i$  is the choice variable for the area grown under the  $i$ th crop enterprise;  $\sigma_{i,k}^2$  is the co-variance matrix;  $Y_i^R$  is the yield of the  $i$ th crop in state of nature  $R$ ;  $q_{IW}^R$  is the choice variable for the quantity of irrigation water applied on the paddy for the  $i$ th crop enterprise in rainfall state  $R$ ;  $\Theta_R$  is the probability that each state,  $R$ , would occur;  $\Pi_R$  is the whole-farm profit earned in rainfall state  $R$ ;  $\Pi_i^R$  is the unit profit that the  $i$ th crop would generate;  $\mathbf{Z}_i$  is a vector containing the production inputs (excluding irrigation water) used in the  $i$ th crop enterprise;  $\mathbf{C}_i$  is the vector of production input costs;  $P_i$  is the selling price of the  $i$ th crop enterprise;  $P_W$  is the price of irrigation water under new policy regime; and LAND is the total land holdings.

The risky objective function of the QP is given by Eq. [2], which performs a trade-off between expected income,  $\Pi$ , and income variance,  $\sigma^2$ . The trade-off is governed by the risk parameter,  $\varphi$ . Risk aversion implies that  $\varphi > 0$  and that the producer discounts variance in their portfolio. Expected income is given by Eq. [3], which is calculated across the range of rainfall outcomes,  $R$ , using the probability of each rainfall state,  $\Theta$ , as the weight. Equation [4] is the whole-farm profit earned in each rainfall state  $R$ . This equation contains recourse as the irrigation water demand,  $q_{IW}^R$ , is chosen according to each rainfall state,  $R$ .

Equation [5] determines the  $i,k$  element of the income co-variance matrix,  $\sigma_{i,k}^2$ . This matrix contains the pairwise collection of variance terms that measure how unit returns from the  $i$ th and  $k$ th crop enterprise vary relative to one another about the expected value of profits. In practical terms, this step is the "risky" portion of the objective function defined in Eq. [2]. The elements of  $\sigma_{i,k}^2$  explain how much each crop enterprise contributes to the overall variance of the crop portfolio, and enable the model to select cropping alternatives that reduce income variance. Equation [6] is a land constraint equation and Eq. [7] is an accounting equation that calculates total irrigation water demand,  $Q_{IW}^R$ .

The basis of the farm programming model is  $X_i$ , a set of crop enterprises (such as farming techniques), which represent the entire range of production alternatives available to the farmer. These include both the crop enterprises that are currently employed by farmers and the alternative crops that could be adopted under changes in irrigation water policy. The crop enterprises are the primary input to the programming model: they populate (quantify) the whole-farm profit function and establish demands on the factors of production (land, labor, capital, and irrigation water). The crop enterprises include a

variable production input, the quantity of irrigation water applied on the paddy,  $Q_{IW}$ . To account for varying levels of irrigation water, the crop–yield production function is embedded explicitly into the whole-farm profit function (Eq. [4]). Because there is recourse in applying irrigation water, the model chooses the quantity of irrigation water for each rainfall state of nature, as indicated by the superscript  $R$  in the irrigation water choice variable,  $q_{IW}^R$ .

All of the other production inputs,  $Z_i$ , are fixed at prescribed levels that correspond to observed farming practices.<sup>2</sup> Defining crop enterprises with fixed input levels is the typical approach taken in simplex based programming models (linear programming models). Hence each crop enterprise,  $X_i$ , can be considered as demanding a discrete package of inputs,  $Z_i$ , that is uniquely bundled (labor, fertilizer, seeds, insecticides, and other inputs.). Production inputs are purchased under competitive conditions at fixed costs as indicated by the vector  $C_i$ .

### Economic Model Data

Crop budgets were established for each of the crop enterprises (Table 5). A crop budget is an itemized list of the production inputs that are used in a particular crop enterprise on a unit (such as per hectare) basis (Kay et al., 2004). By convention, crop budgets use fixed levels of production inputs and uniform costs and are consistent with the programming models. For each input, the budget details the quantity demanded by the enterprise,  $Z_i$ , and its unit cost,  $C_i$ . Input demands and costs for rice, wheat, and the alternative crops were obtained from extension services at the Punjab Agricultural University.

<sup>2</sup> The inputs were developed from Leontief production functions that express crop enterprises using fixed proportions. Crop yields can only be increased by intensifying the use of all inputs by the same amount (in fixed proportions). In the crop response estimations, all of the inputs except for irrigation water were held at fixed levels.

Irrigation water demand was a variable input determined by the farm programming model, so it was not necessary to include it in the crop budgets. The price of irrigated water under existing water policy is \$0.066 ha-mm (Jalota et al., 2006). This cost includes charges only for electricity and the labor required to transport the water from its source to the paddy field; under existing policy the irrigation water itself is available free of charge to Punjabi farmers. Under scenarios that remove subsidies, irrigation water is priced at alternative values. This practice adds an additional component to the \$0.066 ha<sup>-1</sup> mm<sup>-1</sup> cost currently incurred by Punjabi farmers. A water pricing schedule was developed for the economic model analysis. The schedule ranges in value from \$0 to \$60 mL<sup>-1</sup>. Its upper limit of \$60 mL<sup>-1</sup> coincides with the price typically paid by urban consumers in New Delhi for water.

The Punjabi farm programming model is solved using computer-based mathematical programming methods (GAMS). It was calibrated to observed farming conditions in the study region. Household surveys of 30 households in the Punjabi villages of Muktsar and Patiala found that the average land holdings were 2.96 ha, which was rounded to 3.0 ha in the analysis (unpublished data, 2003). The household surveys were also used to estimate labor costs for activities that demand hired labor (such as seed transplanting).

## RESULTS

The economic model's results were found to be well calibrated with the observed mono-cropping in the study region. Under existing cheap-irrigation policies ( $P_w = 0$ ), the cropping patterns are dominated by 3.0 ha of rice in the summer growing season and 3.0 ha of wheat in the winter growing season. Consistent with existing farm practices patterns, none of the alternative crop enterprises were found in the model's optimal

**Table 5. Crop enterprise budgets used in the economic model for rice, wheat, and alternative summer (kharif) and winter (rabi) crops under existing irrigation water prices.**

| Budget item  | Crop enterprise     |        |        |         |        |         |          |
|--|---------------------|--------|--------|---------|--------|---------|----------|
|  | Rice                | Maize  | Cotton | Soybean | Wheat  | Mustard | Chickpea |
|  | Season <sup>‡</sup> |        |        |         |        |         |          |
| Budget item  | S                   | S      | S      | S       | W      | W       | W        |
| <b>Revenue</b>                                     |                     |        |        |         |        |         |          |
| Yield, kg ha <sup>-1</sup>                         | 6960                | 5088   | 2380   | 2193    | 5525   | 2232    | 2108     |
| Price, \$ kg <sup>-1</sup>                         | 0.11                | 0.10   | 0.32   | 0.20    | 0.12   | 0.24    | 0.29     |
| Total revenue, \$ ha <sup>-1</sup>                 | 779.52              | 508.82 | 761.75 | 438.72  | 663.01 | 535.91  | 611.48   |
| <b>Input costs<sup>†</sup>, \$ ha<sup>-1</sup></b> |                     |        |        |         |        |         |          |
| Seeds  | 5.65                | 7.94   | 10.55  | 18.34   | 28.36  | 2.25    | 32.99    |
| Labor  | 162.50              | 119.50 | 250.00 | 92.50   | 36.00  | 88.50   | 114.00   |
| Fertilizer   | 43.47               | 55.14  | 27.72  | 38.02   | 54.10  | 41.80   | 11.02    |
| Insecticide  | 57.50               | 25.00  | 104.38 | 38.75   | 9.35   | 26.98   | 14.50    |
| Mechanization                                      | 52.50               | 52.50  | 35.00  | 35.00   | 61.25  | 61.24   | 43.75    |
| Irrigation (pump)                                  | 89.21               | 23.50  | 31.53  | 19.16   | 26.95  | 23.31   | 26.08    |
| Total unit cost, \$ ha <sup>-1</sup>               | 410.83              | 283.58 | 459.17 | 241.77  | 216.01 | 244.08  | 242.34   |
| <b>Unit profit\$, \$ ha<sup>-1</sup></b>           | 368.69              | 225.24 | 302.58 | 196.96  | 447.00 | 291.83  | 369.14   |
| Irrig. water use, mm                               | 1352                | 356    | 478    | 290     | 408    | 353     | 395      |

<sup>†</sup> Crop budget data was obtained from Punjab Agricultural University Extension Services, 2003.

<sup>‡</sup> Season refers to crops grown in the summer season, S, and the winter season, W.

<sup>§</sup> Unit profit is defined as the returns above variable costs. Fixed costs were not factored into the profit calculations.

cropping pattern for either the summer (kharif) or winter (rabi) growing seasons.

Under scenarios where Punjabi farmers would have to pay a fee for irrigation water ( $P_W > 0$ ), alternative crops would enter the cropping pattern during the summer growing season (Table 6). Cotton was found to be the most lucrative of the alternative summer crops. Risk-neutral farmers would replace rice with cotton once irrigation water reached a price of  $\$15 \text{ mL}^{-1}$ . At this irrigation water price, a complete shift into cotton would occur since all 3.0 ha of the paddy would be under cotton production. Cotton would be maintained in the cropping pattern until the irrigation water price reached  $\$40 \text{ mL}^{-1}$ , at which point soybean would become the dominant crop. With water priced at or above the  $\$40 \text{ mL}^{-1}$  level, all of the paddy's 3 ha would be grown in soybean.

Wheat would maintain itself as the economically dominant crop during the winter months (Table 6). Even with higher irrigation water prices ( $P_W > 0$ ), none of the alternative crops were found to enter the optimal crop portfolio. During the winter season, 3.0 ha of wheat would always be grown, irrespective of the irrigation water price. Hence, charging farmers for irrigation water

during the winter months would only serve to reduce farm incomes, without providing any incentives to shift to alternative crops (Table 6).

### Effects of Risk on Crop and Irrigation Choices

Risk-averse producers would shift out of rice and into cotton more quickly than risk-neutral ones (Table 6). Under low irrigation water prices (up to  $P_W = \$5 \text{ mL}^{-1}$ ), the risk-neutral and risk-averse producer would act along similar lines. Both would plant a monoculture consisting of 3 ha of rice. The risk-averse farmer would, however, use more irrigation water than the risk-neutral farmer to stabilize her/his income. Under free irrigation water, crop yields are driven to their physical maximum. But once a charge occurs for irrigation water, producers align their use of irrigation water with its true economic cost. The net effect is a reduction in irrigation water use that increases the variability of both yields and income (Table 6).

The risk-averse producer would use irrigation as a strategy to reduce risk, even though employing more irrigation water on the paddy reduces expected income. The risk-averse producer would trade off about \$5 of

**Table 6. Economic model results for the response of a risk neutral producer to alternative irrigation water prices during the summer growing season (kharif).**

| Item                                    | Irrigation water price, $\$ \text{ mL}^{-1}$ |           |            |              |            |            |            |
|---|--|-----------|------------|--------------|------------|------------|------------|
|   | $P_W = 0$                                    | $P_W = 5$ | $P_W = 10$ | $P_W = 15$   | $P_W = 20$ | $P_W = 40$ | $P_W = 60$ |
| <b>Summer growing season</b>            |  |           |            |              |            |            |            |
| Planted area†, ha                       |  |           |            | risk neutral |            |            |            |
| Rice                                    | 3.0  | 3.0       | 3.0        | 0.0          | 0.0        | 0.0        | 0.0        |
| Cotton                                  | 0.0  | 0.0       | 0.0        | 3.0          | 3.0        | 0.0        | 0.0        |
| Maize                                   | 0.0  | 0.0       | 0.0        | 0.0          | 0.0        | 0.0        | 0.0        |
| Soybean                                 | 0.0  | 0.0       | 0.0        | 0.0          | 0.0        | 3.0        | 3.0        |
| Profit\$, \$                            | 1046   | 884       | 654        | 554          | 516        | 432        | 410        |
| Variance, $\$ 10^3$                     | 376  | 406       | 576        | 1056         | 1338       | 1612       | 2460       |
| $Q_{IW}$ , mm                           | 4170   | 3975      | 3682       | 990          | 923        | 134        | 93         |
| Returns to irrig., $\$ \text{ mm}^{-1}$ | 0.25   | 0.22      | 0.18       | 0.56         | 0.56       | 3.22       | 4.40       |
| Planted area, ha                        |  |           |            | risk averse‡ |            |            |            |
| Rice                                    | 3.0  | 3.0       | 1.63       | 0.0          | 0.0        | 0.0        | 0.0        |
| Cotton                                  | 0.0  | 0.0       | 1.17       | 1.41         | 1.42       | 1.02       | 0.68       |
| Maize                                   | 0.0  | 0.0       | 0.0        | 0.36         | 0.0        | 0.0        | 0.0        |
| Soybean                                 | 0.0  | 0.0       | 0.0        | 1.23         | 1.58       | 1.75       | 1.47       |
| Profit\$, \$                            | 1008   | 838       | 630        | 508          | 492        | 362        | 264        |
| Variance, $\$ 10^3$                     | 145  | 149       | 276        | 350          | 502        | 792        | 862        |
| $Q_{IW}$ , mm                           | 4579   | 4427      | 2465       | 779          | 613        | 335        | 113        |
| Returns to irrig., $\$ \text{ mm}^{-1}$ | 0.22   | 0.19      | 0.26       | 0.65         | 0.80       | 1.08       | 2.34       |
| <b>Winter growing season</b>            |  |           |            |              |            |            |            |
| Planted area, ha                        |  |           |            | risk neutral |            |            |            |
| Wheat                                   | 3.0  | 3.0       | 3.0        | 3.0          | 3.0        | 3.0        | 3.0        |
| Mustard                                 | 0.0  | 0.0       | 0.0        | 0.0          | 0.0        | 0.0        | 0.0        |
| Chickpea                                | 0.0  | 0.0       | 0.0        | 0.0          | 0.0        | 0.0        | 0.0        |
| Profit\$, \$                            | 1332   | 1270      | 1212       | 1152         | 1092       | 866        | 652        |
| Variance, $\$ 10^3$                     | 2820   | 3040      | 3260       | 3480         | 3700       | 4620       | 5520       |
| $Q_{IW}$ , mm                           | 1229   | 1213      | 1197       | 1181         | 1165       | 1101       | 1037       |
| Returns to irrig., $\$ \text{ mm}^{-1}$ | 1.08   | 1.05      | 1.01       | 0.98         | 0.94       | 0.79       | 0.63       |
| Planted area, ha                        |  |           |            | risk averse  |            |            |            |
| Wheat                                   | 3.0  | 3.0       | 3.0        | 3.0          | 3.0        | 3.0        | 3.0        |
| Mustard                                 | 0.0  | 0.0       | 0.0        | 0.0          | 0.0        | 0.0        | 0.0        |
| Chickpea                                | 0.0  | 0.0       | 0.0        | 0.0          | 0.0        | 0.0        | 0.0        |
| Profit\$, \$                            | 1132   | 1060      | 988        | 918          | 850        | 584        | 338        |
| Variance, $\$ 10^3$                     | 146  | 146       | 146        | 146          | 147        | 148        | 150        |
| $Q_{IW}$ , mm                           | 1192   | 957       | 934        | 911          | 889        | 802        | 721        |
| Returns to irrig., $\$ \text{ mm}^{-1}$ | 0.95   | 1.11      | 1.06       | 1.01         | 0.96       | 0.73       | 0.47       |

† Authors' economic model (Eq. [2] through Eq. [7]).

‡ The risk aversion coefficient used in the E-V model was 0.000003, a modest degree of risk aversion.

§ Profit was calculated using returns above variable costs. No fixed costs were included in the calculations.

income to reduce income variance by \$260000 (Table 6). The risk-neutral producer would not respond to the increased yield variance. This type of producer would instead be willing to accept the higher income variance, \$406000, to maintain expected income at \$884.

The effect of risk becomes more apparent when the irrigation water price reaches the (modest) price level of  $\$10 \text{ mL}^{-1}$ . The risk-averse producer would shift into a mixed cropping pattern that includes 1.63 ha of rice and 1.17 ha of cotton (Table 6). Alternatively, the risk-neutral producer would maintain a rice monoculture, with all 3.0 ha grown in rice (Table 6). Cotton enters the risk-averse cropping pattern earlier (at lower water prices) because it enables a more efficient use of irrigation water and enhances income stability. A slight loss in income occurs, \$24, that the risk-averse producer is willing to accept to decrease variance by \$300 thousand (Table 6). By growing over one-third of the paddy in cotton, the overall use of irrigation water on the risk-averse producer's fields is 1217 mm less than that used by the risk-neutral producer, who would maintain all 3.0 ha in rice.

At slightly higher irrigation water prices ( $\$15 \text{ mL}^{-1}$ ), the risk-averse producer would shift into a cropping pattern that includes 1.41 ha of cotton, 0.36 ha of maize, and 1.23 ha of soybean (Table 6). This cropping pattern enables the farmer to reduce income variability from \$1.05 million to \$350 thousand. The shift toward soybean continues as irrigation water prices are increased from  $\$20 \text{ mL}^{-1}$  to  $\$60 \text{ mL}^{-1}$ . At the highest irrigation water price considered ( $\$60 \text{ mL}^{-1}$ ), soybean would dominate the crop portfolio since the risk-averse producer would grow 1.47 ha of soybean and 0.68 ha of cotton. The risk-neutral producer, however, would first shift from a rice to a cotton monoculture at water prices of  $\$15$  and  $\$20 \text{ mL}^{-1}$ , and then shift to a soybean monoculture at the two highest water prices of  $\$40$  and  $\$60 \text{ mL}^{-1}$  (Table 6). Hence, soybean plants generate higher expected income than cotton but soybean plants also have a higher income variance, which discourages risk-averse producers from choosing a soybean monoculture.

Risk was not found to have any effect on the winter season's optimal crop portfolio (Table 6). Both the risk-neutral and the risk-averse producer would grow a wheat monoculture of 3.0 ha across the entire irrigation price schedule from \$0 to  $\$60 \text{ mL}^{-1}$  (Table 6).

## DISCUSSION

Removing irrigation water subsidies would negatively impact Punjabi farmers' welfare. The summer growing season would be most negatively affected. Charging producers at one-third the rate that consumers pay for water, about  $\$20 \text{ mL}^{-1}$ , would reduce farm incomes earned during the summer by nearly one-half. Risk-averse producers would experience slightly more losses than risk-neutral farmers: their incomes would fall from \$1008 to \$492 (Table 6). Risk-neutral producers would experience nearly the same reduction, as their incomes would fall from \$1046 to \$516. Producers would be expected to demand some kind of compensation for their

economic losses. Hence, some type of wealth transfer from the government to the producers would likely be necessary to bring producers' welfare back to its current level.

Irrigation water prices would have less effect on profits generated during the winter growing season. Whole-farm profits would only fall by about 20% during the winter growing season under a  $\$20 \text{ mL}^{-1}$  irrigation water price for either the risk neutral or risk-averse producer (Table 6).

Producers would also have to incur more production risk as pricing irrigation water would increase farm income variability. Producers would be less able to stabilize their income using irrigation water as they currently do now. The distribution of farm income would shift more toward that of rain-fed agriculture where farmers' income varies with weather. Concerns over low income and household welfare in the poor rainfall years could once again surface, which is undesirable since irrigation was initially introduced to help farmers avoid such bad production years.

Charging farmers for irrigation water would induce them to make more (economically) efficient use of the water (Table 6). Overall, the most efficient use of irrigation water was found to be during the winter growing season (rabi). The wheat mono crop was found to have the highest average economic return from irrigation, which would be  $\$1.06 \text{ mm}^{-1}$  under a modest irrigation price of  $\$10 \text{ mL}^{-1}$ .

Rice was found to generate the poorest average economic returns of irrigation water, even though it would generate the highest profit. Rice would provide average economic returns of only  $\$0.26 \text{ mm}^{-1}$  under the modest irrigation water price of  $\$10 \text{ mL}^{-1}$  for the risk averse producer (Table 6). The average economic returns would actually decline over the initial price increases, from \$0 to  $\$5 \text{ mL}^{-1}$ , since profits would fall at a faster rate than would the decline in irrigation water use.

The alternative crops, however, generated much better economic returns from irrigation water once they entered the cropping pattern at higher irrigation water prices. The pure cotton rotation would provide an average economic return of  $\$0.56 \text{ mm}^{-1}$  at an irrigation water price of  $\$20 \text{ mL}^{-1}$  for the risk neutral producer, and an even higher return of  $\$0.80 \text{ mm}^{-1}$  for the risk averse producer (Table 6). The pure soybean rotation would be even more water-efficient, generating an economic return of  $\$3.22 \text{ mm}^{-1}$  at an irrigation water price of  $\$40 \text{ mL}^{-1}$ .

Risk had mixed effects on irrigation water demand and the economic returns to irrigation water. Risk aversion lead to lower irrigation water demand and slightly higher returns at modest water prices (from  $\$10$  to  $\$20 \text{ mL}^{-1}$ ), but higher demand and lower returns elsewhere (Table 6). Demand for irrigation water would decline significantly for both the risk-neutral and risk-averse producer once water charges reached  $\$15 \text{ mL}^{-1}$  (Table 6). On average, the risk-neutral producer would save more than  $3180 \text{ mm ha}^{-1}$  of irrigation water in shifting from rice to cotton once water prices reached  $\$20 \text{ mL}^{-1}$ . Additional savings in irrigation water were

found in the risk-averse case, where  $3966 \text{ mm ha}^{-1}$  of irrigation water would be saved once water charges were  $\$20 \text{ mL}^{-1}$  or higher. The largest difference in economic returns between the risk-neutral and risk-averse cases was found at the two highest water prices of  $\$40$  and  $\$60 \text{ mL}^{-1}$ . At  $\$40 \text{ mL}^{-1}$ , for instance, the risk neutral soybean mono crop had a return of  $\$3.22 \text{ mm}^{-1}$ , where the risk averse mixed cropping pattern with cotton and soybean had a much lower return of  $54.0$  (Table 6).

In the winter growing season, risk was found to reduce irrigation water use. Given the lower productivity of wheat, producers would stabilize their incomes by using less water than the risk-neutral producer (Table 6). This response is opposite from the one the risk-averse producer would take in the summer months where irrigation water would increase (Table 6). The risk-neutral producer would have only a modest reduction in irrigation water use during the winter months. Irrigation water use would only fall by  $64 \text{ mm}$  at the  $\$20 \text{ mL}^{-1}$  price level. The risk-averse producer would reduce her/his irrigation water use by  $303 \text{ mm}$  over that same irrigation water price interval.

## CONCLUSIONS

This study has presented empirical evidence that removing irrigated water subsidies would induce significant changes in Punjab cropping patterns. Promoting policies that bring irrigated water costs in-line with their market value would create more socially desirable outcomes. Irrigated water use would decline and result in a large increase in the economic efficiency of irrigation water use. This policy would be a significant change from the existing "cheap water" policies, under which farmers exploit irrigation water and allocate it inefficiently. Existing water prices are so low that farmers are able to maximize crop yields, ignoring the extremely low productivity of irrigation water that occurs as maximum yields are reached. The model results in this research found that farmers end up pumping much less water onto their fields once they are forced to pay.

Irrigation costs will increase in the Punjab one way or the other over the foreseeable future. Proactively irrigated water can be priced to reflect its true social cost. This procedure will mitigate much of the potential environmental damage and reverse downward trends. Alternatively maintaining existing cheap water policies will lead to much greater environmental costs. While the environmental costs are not necessarily reflected in food prices because of government support programs, they do spill over into other sectors and can create substantial economic damage.

Government procurement programs have maintained rice and wheat prices at favorable levels for producers. The results from this study suggest that similar support should be considered for alternative crops, such as cotton or maize. Charging farmers for irrigation water was found to induce producers to introduce some of the alternative crop enterprises into their crop portfolio. Adding alternative crops to the procurement programs with added price support would achieve the same de-

sired affect as charging farmers for irrigation water. Cotton, in particular, would benefit from greater institutional support, providing cotton farmers with stronger marketing channels and extension services.

Determining a viable price structure for irrigation water would be a challenging task for policymakers. The pricing structure would have to resolve the combined needs of Punjabi farmers, consumers, and society at large. This would require water prices to balance the competing concerns that include mitigating the social costs from environmental degradation, assuring low food prices for consumers, and maintaining Punjabi farm incomes. Most pricing policies seek to apportion the economic damage caused by excessive irrigation to the producers creating the damage. Recent environmental policy has focused on "green payments" and other market based mechanisms to resolve environmental externalities. Hydrologic modeling coupled with GIS can assist policymakers and planners in linking environmental damage to the producers responsible for creating it.

Shifting away from a rice-based monoculture and into a more diversified portfolio with alternative crops would have spill over effects into other markets. In particular with a decline in rice hectareage, significant impacts could be felt on labor markets. Rice production is a major source of rural labor demand. Shifting to alternative crops such as cotton, maize, and soybean would reduce rural labor demand, depress rural wages, and jeopardize the welfare of agricultural labor households. The model results also suggest that cotton and soybean would dominate cropping patterns under even modest irrigation water prices. At the regional level, the shift away from a staple food crop such as rice is likely to put significant upward pressure on food prices, reducing consumer welfare.

Other policy alternatives are available that could be considered to either complement or substitute for charging producers for irrigation water. Precision agriculture and the use of other high technology can make more efficient use of irrigation water than existing crop technologies used in the Punjab. Drip irrigation, for instance, has been successfully introduced in the western USA to make the most out of literally every drop of water. Precision agriculture (PA) has been used in the past primarily as a means to increase resource efficiency on large farms. Increasingly, however, PA is showing signs that it can be successfully applied on small holder rice farms in Asia. Crop insurance would be another alternative. Punjabi producers use irrigation water as part of their risk management to stabilize incomes across good and bad years. With crop insurance available to them, producers would be likely to reduce irrigation water use since there would be an additional source of income stability. Crop insurance could also be a useful complement to the removal of cheap water policies considered in this article. The results discussed above found that producers would have to take on more risk as irrigation water prices were increased. Crop insurance would provide a means to reduce risk and would likely induce producers to more quickly shift into the alternative crops.

## REFERENCES

- Antle, J., and S. Capalbo. 2001. Econometric-process models for integrated assessment of agricultural production systems. *Am. J. Agric. Econ.* 83:389–401.
- Brown, D.R. 2000. A review of bio-economic models. A paper prepared for the Cornell African Food Security and Natural Resource Management Program. Cornell Univ., Ithaca, New York.
- Cai, X., and M. Rosegrant. 2004. Irrigation technology choices under hydrologic uncertainty: A case study from Maipo River Basin, Chile. *Water Resour. Res.* 40:1–10.
- Dalton, T.J., G.A. Porter, and N. Winslow. 2004. Risk management strategies in humid production regions: A comparison of supplemental irrigation and crop insurance. *Agric. Resour. Econ. Rev.* 33:173–185.
- Deng, X., L. Shan, Z. Heping, and H.C. Turner. 2004. Improving Agricultural Water Use Efficiency in Arid and Semiarid Areas of China. Proc. of the 4th Int. Crop Science Congr., Brisbane, Queensland, Australia. September 2004. Available at [www.cropscience.org.au](http://www.cropscience.org.au) (accessed 26 Jan. 2007; verified 25 Apr. 2007). The Regional Institute Ltd., Australia.
- Directorate of Water Resources. 2002. Statistical abstracts from the Punjab Directorate of Water Resources. Ludhiana, India.
- Feder, G. 1980. Farm size, risk aversion and the adoption of new technology under uncertainty. *Oxford Econ. Pap. New Ser.* 32:263–283.
- Freund, R.J. 1956. The introduction of risk into a programming model. *Econometrica* 24:253–264.
- Gerik, T., M. Harman, M. Magre, E. Steglich, J. Greiner, and L. Francis. 2003. CroPMan (CropProduction and Management model) user's guide: Version 4.0. Available at <http://cropman.brc.tamus.edu> (accessed 26 Jan. 2007; verified 25 Apr. 2007). Blackland Res. and Ext. Ctr., Temple, TX.
- Government of India. 2002. Development of agriculture and allied sectors. Plan Documents prepared by the Government of India.
- Goyne, P.J. 2002. Rural water use efficiency initiative. Milestone 3 Report. Available at [www.nrwd.qld.gov.au](http://www.nrwd.qld.gov.au) (accessed 26 Jan. 2007; verified 25 Apr. 2007). Dep. of Natural Resour. and Water, Queensland, Australia.
- Goyne, P.J., and G.T. McIntyre. 2002. Improving on farm irrigation water use efficiency in the Queensland cotton and grain industries. Available at <http://cotton.crc.org.au/Assets/PDFFiles/Irrigat/RWUE011.pdf> (accessed 1 May 2007; verified 4 May 2007). Australian Cotton Coop. Res. Ctr., Brisbane, Australia.
- Greene, W.H. 1997. Econometric analysis. Prentice Hall, New Jersey.
- Harris, T.R., and H.P. Mapp. 1986. A stochastic dominance comparison of water-conserving irrigation strategies. *Am. J. Agric. Econ.* 68: 298–305.
- Hazell, P.B.R., and R.D. Norton. 1986. Mathematical programming for economic analysis in agriculture. Macmillan, New York.
- Hexem, R., and E. Heady. 1978. Water production functions for irrigated agriculture. Iowa State Univ. Press, Ames.
- Hira, G.S., S.K. Jalota, and V.K. Arora. 2004. Efficient management of water resources to sustain cropping systems in Punjab. Research Bulletin, Dep. of Soils, Punjab Agric. Univ., Ludhiana, India.
- Ikisan. 2005. Irrigation: Water use efficiency. Available at [www.ikisan.com](http://www.ikisan.com) (accessed 26 Jan. 2007; verified 25 Apr. 2007). Ikisan Ltd., Hyderabad, India.
- Johl, S.S., and S.K. Ray. 2002. Future of agriculture in Punjab. Centre for Research in Rural and Industrial Development, Chandigarh, India.
- Jalota, S.K. 2004. Field water budgeting and assessment of water conservation with different water saving technologies. In *Proc. Sustainable Agriculture: Problems and Prospects*, Ludhiana, India. November 2004. Punjab Agric. Univ., Ludhiana, India.
- Jalota, S.K., A. Sood, and W.L. Harman. 2006. Assessing the response of chickpea (*Cicer arietinum* L.) yield to irrigation water on two soils in Punjab (India): A simulation analysis using the CroPMan model. *Agric. Water Manage.* 79:312–320.
- Johansson, R., H. Prasanna, D. Mulla, and B. Dalzell. 2004. Meta-modeling phosphorus best management practices for policy use: A frontier approach. *Agric. Econ.* 30:63–74.
- Kay, R., W. Edwards, and P. Duffy. 2004. Farm management. 5th ed. McGraw-Hill, New York.
- Llewelyn, R.V., and A.M. Featherstone. 1997. A Comparison of crop production functions using simulated data for irrigated corn in western Kansas. *Agric. Syst.* 54:521–538.
- Mahindra, K. 2003. Package of practices for crops of Punjab 2001–2002. Tech. Bull. Punjab Agricultural Univ., Ludhiana, India.
- Mapp, H., and V. Eidmann. 1976. A bioeconomic simulation analysis of regulating groundwater irrigation. *Am. J. Agric. Econ.* 68:391–402.
- Markowitz, H. 1952. Portfolio selection. *J. Fin.* 7:77–91.
- Neitsch, S.L., J.G. Arnold, J.R. Kiniry, J.R. Williams, and K.W. King. 2002. Soil and water assessment tool theoretical documentation. Available at [www.brc.tamus.edu/](http://www.brc.tamus.edu/) (accessed 26 Jan. 2007; verified 25 Apr. 2007). Blackland Res. and Ext. Ctr., Temple, TX.
- Oweis, T., A. Hachum, and J. Kijne. 1999. Water harvesting and supplementary irrigation for improved water use efficiency in dry areas. SWIM Pap. 7. Available at [www.iwmi.cgiar.org/](http://www.iwmi.cgiar.org/) (verified 25 Apr. 2007). Int. Water Manage. Inst., Colombo, Sri Lanka.
- Punjab Ministry of Agriculture. 2005. Statistical abstracts from various years. Available at <http://punjabgovt.nic.in> (verified 25 Apr. 2007). Punjab Ministry of Agriculture, India.
- Raul, C. 2001. Bitter to better harvest: Post Green Revolution. Northern Book Centre, New Delhi, India.
- Ruben, R., and A. van Ruijven. 2001. Technical coefficients for bio-economic farm household models: A meta-modeling approach with applications for Southern Mali. *Ecol. Econ.* 36:427–441.
- Shiva, V. 1991. The Green Revolution in the Punjab. *Ecologist* 21:57–60.
- Sondhi, S.K., and S.D. Khaper. 1995. Water resources development and management for sustainable agricultural production. In *Proc. Water Management Symp.*, Ludhiana, India. May 1995. Punjab Agricultural Univ., Ludhiana, India.
- Tanaka, D., J. Krupinsky, M. Liebig, S. Merrill, R. Ries, J. Hendrickson, H. Johnson, and J. Hanson. 2002. Dynamic cropping systems: An adaptable approach to crop production in the Great Plains. *Agron. J.* 94:957–961.
- Vitale, J., and J. Lee. 2005. Land degradation in the Sahel: An application of biophysical modeling in the optimal control setting. In *Proc. American Agricultural Economics Association Meeting*, Providence, RI. 24–27 July 2005. AAEA, Ames, IA.
- von Braun, J., A. Gulati, P. Hazell, M. Rosegrant, and M. Ruel. 2005. Indian agriculture and rural development strategic issues and reform options. A strategy paper prepared by IFPRI senior management team for consideration by the policymakers of the government of India. Available at [www.ifpri.org](http://www.ifpri.org) (verified 25 Apr. 2007). Int. Food Policy Res. Inst., Washington, DC.
- Wu, J., and B.A. Babcock. 1999. Metamodelling potential nitrate water pollution in the central United States. *J. Environ. Qual.* 28: 1916–1928.
- Zhang, H., X. Liu, and X. Zhang. 1993. Theoretical base for water-saving agriculture. In X. Wang et al. (ed.) *Water-saving agriculture and water-saving technology*. Meteorological Publ. House, Beijing.



#### COPYRIGHT INFORMATION

TITLE: Simulated Crop Yields Response to Irrigation Water and Economic Analysis: Increasing Irrigated Water Use Efficiency in the Indian Punjab

SOURCE: Agron J 99 no4 Jl/Ag 2007

The magazine publisher is the copyright holder of this article and it is reproduced with permission. Further reproduction of this article in violation of the copyright is prohibited. To contact the publisher:  
<http://www.agronomy.org/>