Murray Darling Basin Irrigation Adaptation to Drought: A Statistical Evaluation

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Contributed paper prepared for presentation at the 56th AARES annual conference, Fremantle, Western Australia, February7-10, 2012

Introduction

This document describes a statistical evaluation of irrigation sector response to drought in the Murray Darling Basin. It forms the basis for an economic simulation model of the Murray Darling Basin irrigation sector that is used in an integrated hydrology and economic model (Kirby et al, 2012a) and applied to several scenario evaluations (Kirby et al., 2012). Methodologically, the economics underpinning the integrated model is an econometric simulation. In a first step, the subject of this paper, land area, water use per hectare and gross value of irrigated agricultural production changes observed during the drought are estimated as functions of observed price and climatic condition (rainfall and ET), water allocation levels for irrigation.

The approach of statistically relating observed agricultural adaption and economic impacts to observed changes in climate controlling for other factors such as commodity prices is known in the climate change agricultural economic impact literature as “Ricardian” economics (Mendelsohn, Nordhaus, and Shaw, 1994). The original idea was that shifts in climate that impact agricultural production possibilities should effect agricultural land values in ways that can be observed and used to estimated land value changes as a function of observable climate change. Over time the literature along these lines has evolved from solely estimating changes in land value in response to observable climatic variation to estimating underlying agricultural adjustment such as crop and livestock species choices (Seo and Mendelsohn, 2007) and resultant economic impacts. Similar statistical simulation approaches can be found elsewhere in the agricultural economics literature; notably in a body of US literature characterising allocation of land to farming versus conservation land uses (Antle and Capalbo, 2001).

The last decade, 2000 to 2010 was a period in which water available for irrigation declined steadily, from near full entitlement in the 2000/01 irrigation season to only about one third of full entitlement available in 2007/08 and 2008/09. In some regions allocation levels in late years of the decade were much less than the Basin average. For example, in the NSW Murray, 2007/08 allocations were just 6% of entitlement. During this time there was also variation in crop prices with notable rises in wheat and dairy prices in some drought years, and climatic variation that influenced crop evapo-transpiration and yield potential. This significant variation and the resultant irrigation sector adaptation represents an opportunity to better understand economic impact of water scarcity and to calibrate response coefficients used in simulation modelling to actual experience.

This document is organised as follows. The next section (2) describes the conceptual model and its basis in economic theory. Section 3 describes the model statistical specification of land allocation, water use and gross value equations by major commodities and NRM regions for the MDB. Section 4-6 describe statistical estimation results for land area, water use per hectare and GVIAP regressions respectively and compares the implied responsiveness of these variable with responsiveness estimates from several other published models. Section 7 summarises and concludes the paper.

Conceptual model

Our conceptual model follows the tradition in statistical evaluation of the agricultural sector of economic impacts of climate initiated by (Mendelsohn et al., 1994). In their original work, Mendelsohn et al. (1994) used returns to land as measured by observed land rental price as the dependent variable in regression. The objective was to isolate the partial impact of climatic variables such as change in temperature or rain on land rental price. In many studies following Mehdelsohn et al. (1994), rental price of land was not readily observable and regressions were instead on returns to agriculture (Gbetibouo and Hassan, 2005; Kumar and Parikh, 1998). Seo and Mendelsohn (2008) have also generalised the framework to estimate not only profits by also estimate production and environmental determinants of output level of livestock.

A common micro-economic conceptual model underlies all of these approaches. Irrigators are assumed to have an objective of maximising profit as in equation 1, where profit, $\prod$, is a function of product prices, *p*, a vector of the market or shadow prices of inputs, *r* (e.g. prices of fertiliser, and irrigation water), a vector, y, of inputs to production that are fixed in the short run, within a growing season (e.g. capital, and land in perennial crops) and a vector, *z*, of exogenously determined and stochastic environmental effects (e.g. rainfall, temperature). In the standard micro-economic framework, output, *q* (equation 2) and variable inputs, *x* (equation 3), are assumed to be the profit maximizing levels of outputs and inputs chosen in response to prices, *p*, *r*, environmental conditions, *z* and fixed inputs, *y*.

In translating from the conceptual to a statistical framework, economists realise that some of the factors influencing production are observable, others are not. The impact of these omitted variables is expressed as an error term or unexplained variance in returns, supply and demand, the *e* term in equations 1 – 3.

$$\max \Pi = p * q(x \mid z, y) - r * x + e \ldots (1)$$

$$q^{*} = q(p, r \mid y, z) + e \ldots (2)$$

$$x* = x(p, r \mid y, z) + e \ldots (3)$$

In pragmatic terms, without original survey work, the data available dictates the form of observations of inputs, outputs and returns used in estimating economic responses. For example, Mendelsohn et al (1994) had observations of county level land rental value observations while Seo and Mendelsohn (2008) had farm level returns and livestock stocking level observations. In this case study we have data reported in annual surveys by regions within the Murray-Darling Basin. This includes observations of revenues from production for 10 major commodities. From a micro-economics theory perspective, the revenue or gross value regressions, *g* can be thought of as price times the profit maximising output quantity given fixed factors y and stochastic environmental impacts z (equation 4)

$$g^{*} = p * q(x \mid z, y) + e \ldots (4)$$

Observations of land area in production of each of seven major irrigated crops; and observation of irrigation demand expressed as irrigation application for each of seven crops. Both land and water application rate are treated factors of production that are variable across years as in equation 3. Whilst in can be argued that overall land is a fixed asset, amounts allocated to different crops and total area irrigated are varied annually.

Regression Analysis

The model geographic coverage is the entirety of Murray Darling Basin irrigated agriculture. Two separate data sets are used in regression analysis:

Data set 1 – 2005/06 to 2008/09 NRM region data: The data covers four years and is disaggregated into the 17 natural resource management (NRM) regions used by the Australian Bureau of Statistics (ABS) to report on MDB irrigated agriculture (Figure 1). With this data, we estimate determinants of changes in revenues from production for 10 major crop and livestock commodities; and land area and irrigation application rate changes for 7 crop commodities. The temporal coverage is the years with available ABS reporting disaggregated at the NRM region level (2005/2006 to 2008/09).

Data set 2 – 2000/01 to 2009/10 Basin aggregate irrigated land use data: This ABS data reports area by each of 8 types of major irrigated commodity. More detailed description of this data and explanatory variables used in regressions are described in the data section below, and data summary statistics are reported appendix 1.

Irrigated area regression model

In estimating land as an input to irrigated crop production, we begin with the conceptual equation 3. Moving from a conceptual to an empirical model we are restricted to variables that can be constructed with data readily available in a consistent way across years (*y*) and MDB regions (*r*). Within theses constraints we are able to construct three explanatory variables: the level of stochastically varying annual water allocation available for irrigation ($wa_{y,r}$) the price of the commodity (p_i) where *i* is an index of commodities, and a metric related to natural contributions to meeting crop irrigation demand, evapotranspiration less rainfall.

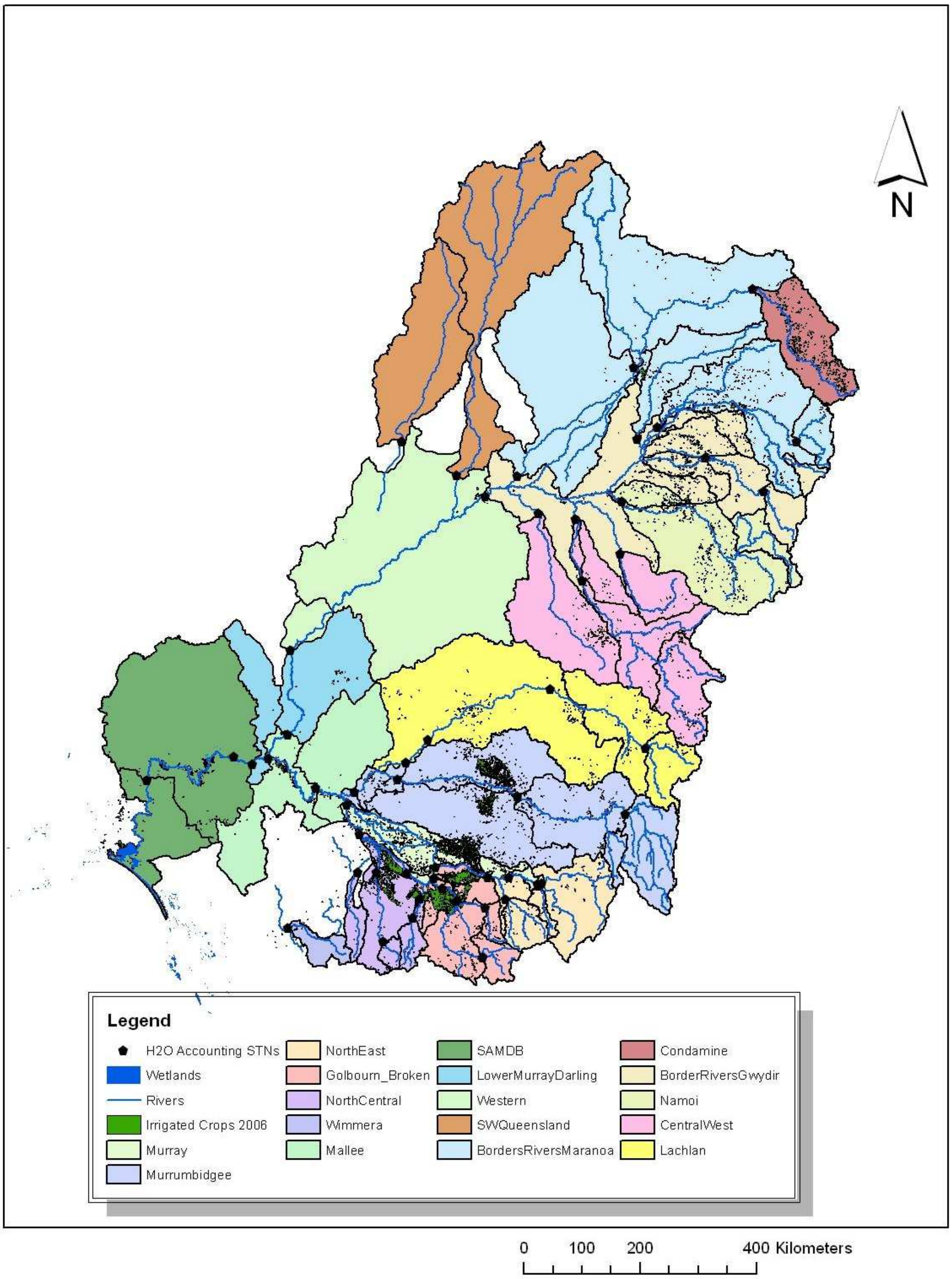
Because the minimum level of land that can be allocated to any crop is 0, a logistical functional form is chosen for the regression analysis. It is assumed that potential area is bounded by zero as a lower bound. For perennial and vegetable crops (for the 2005/06 – 2008/09 NRM region data analysis) we assume that 95% of the maximum area observed between 2005/06 and 2008/09 is an upper bound. For annual crops, the basin record suggests maximum irrigated area can be significantly larger than that observed in our four year time series. In this case the maximum in the 2005/06 to 2008/09 time series is assumed to represent percentile of the water available for diversion in 114 year hydrologic the time series in Kirby et al. (2012).

The logits of the observed area in each year as a proportion of the maximum area for each crop are the dependent variable, A_i in regression (equation 1) where $area_{i,j,y}$ is the area of crop *i* for region *j* observed in year *y*.

$$A_{i,j,y} = \log[\cdots(area_{i,j,y} / \max(area_{i,j,y}))\cdots/\cdots(1/(area_{i,j,y}) / \max(area_{i,j,y})))\cdots]\cdots\cdots(4)$$

One advantage of using proportion of maximum yield by NRM region (equation 4) as a dependent variable is that regional scale differences are eliminated. In a similar way scale differences in dependent variables are eliminated by scaling: allocations in each year are divided by the maximum observed in the recorded data record going back to 1996 for each NRM regions; and net irrigation requirement calculated as region potential crop evapotranspiration less effective rainfall is also scaled by dividing this variable by the average for the time period that estimates exist (1896 to 2009)

Figure 1: Murray Darling Basin Natural Resource Management Regions



Source: Australian Bureau of Statistics

The regression model is presented as equation 5.

$$A_{i,j,y} = \alpha_i^0 + \alpha_i^{wa} * wa_{i,j,y} + \alpha_i^p * p_{i,y} + \alpha_i^c * c_{i,j,y} + \alpha_i^n * n_j + e_{i,j,y} \cdots\cdots (5)$$

Where α_i^0 is the regression intercept coefficient, and α_i^{wa}, α_i^p, and α_i^c are the regression coefficients for the water allocation, price and climate explanatory variables. α_i^c is the regression coefficient for the binary variable n_j included to account for distinct differences influencing land and water allocation and revenues from production in the northern Basin versus the southern basin that are not picked up in the other explanatory variable.

For longer, 2000/01 to 2009/10 timeframe, area by crop and at the basin aggregate as opposed to NRM region disaggregated level, was the only readily available ABS data. Thus for each crop only 10 observations were available. This small sample size only allowed univariate regression. For all commodities considered, multiple univariate regressions were performed including regressions of area on water allocation level, commodity price and in the case of perennial crops one year lagged commodity price.

Once the regression was completed, the results were used to predict the area of given crop as a proportion of maximum potential area, PA_i given values of explanatory variable with the transformation,

$$PA_{i,j,y} = \exp(\overline{A}_{i,j,y}) / \exp(1 + \overline{A}_{i,j,y}) \cdots\cdots (6)$$

The variable definitions for all three regressions are summarised in Table 1.

Table 1 – Regression dependent and explanatory variables

Name	**Description**	**Units**
	Dependent variables	
$A_{i,j,y}$	Logits of land area (see equation 4)	Logits
$W_{i,j,y}$	Irrigation application rate per hectare	ML/Ha
$R_{i,j,y}$	Revenues from irrigated agricultural production	AU$*$10^6$
	Explanatory variables	
$wa_{j,y}$	Regional irrigation water allocation measured as the reported percentage of full regional entitlement	%
$p_{i,y}$	Commodity price	$/tonne
$c_{i,j,y}$	Variable measuring climatic influence on crop irrigation requirement calculated as crop potential evapo-transpiration less crop available rainfall	Mm
n_j	Binary indicator variable, equals one for regions in the Darling and Lachlan catchments in the north of the basin and zero for other regions.	Binary
$PA_{i,j,y}$	Predicted land areas – result of regressions in equation 4 – used as an explanatory variable in revenue regressions.	Ha

Prior expectations are that the sign of the coefficient for, $wa_{j,y}$ should be positive as greater levels of water allocated to irrigation should lead to an expansion of irrigated area. It is also expected that the commodity price regression coefficient should also be positive: this follows from the conceptual model with factor demand increasing in output price. The variable $c_{i,j,y}$ is a metric of climatic conditions that influence crop irrigation. It is defined as the estimated potential crop evaporation at maximum yield minus crop available rainfall which is a measure of amount of potential evapo-transpiration that is met by rainfall. The prior expectation is that the coefficient of this variable should be negative, or inversely correlated land area. The logic being that other things equal we would expect irrigators to choice to irrigated smaller areas given hotter and drier conditions with greater irrigation water requirement and less rainfall to help meet this requirement, all other things equal.

It is expected that there are some systematic differences in land allocation, water application and revenues from production in northern versus southern basin regions that will not be fully explained by the other explanatory variables (allocations, net water, and commodity prices). For crops where this is the case, we expect that the coefficient for n_j to be significant indicating a systematic difference in area allocated by crop in the northern and southern basin that is explainable by unobserved factors other than water allocations, commodity prices, and crop potential evapo-transpriation net of crop available rain.

Irrigation area regression can only be applied to crops as opposed to livestock commodities, therefore regressions are run for: cereal (in which we include other broadacre crops such as barley); cotton, rice, pasture and hay (treated as one crop); wine, , fruit and nuts (perennial horticulture); and vegetables. Whilst it would be desirable to disaggregate some crop classifications further, the level of resolution reported in ABS statistics do not allow this.

Irrigation application rate regression model

Water use per hectare equations for each crop i, W_i were estimated with the linear regression model

$$W_{i,j,y} = \beta_i^0 + \beta_i^{wa} * wa_{i,j,y} + \beta_i^p * p_{i,y} + \beta_i^c * c_{i,j,y} + \beta_i^n * n_j + e_{i,j,y} \cdots\cdots (7)$$

The explanatory variables (crop price, allocations available for irrigation, and net irrigation requirement) are as explained in Table 1 and in the land area regression section above; β_i^0 is the regression intercept coefficient, and β_i^{wa}, β_i^p, and β_i^c are the regression coefficients for the water allocation, price and climate explanatory variables. Prior expectations are for the coefficients of the commodity price and allocation and climatic variables are all for positive signs: higher levels of water application are expected with higher commodity prices; higher levels of water availability and with greater potential evapotranspiration less crop available rain, all else equal.

Two alternative forms of equation 7 were estimated for each crop and the form with greatest explanatory power reported: one with the dependent and the explanatory variables normalised as described in the land area regression methods sections above; the other with the dependent variable, water application rate per hectare expressed in non-normalised terms as Ml/Ha.

Water use per hectare regression can only be applied to crops as opposed to livestock commodities, therefore regressions are run for: cereal (in which we include other broadacre crops such as barley); cotton; rice; pasture and hay (treated as one crop); wine, fruit and nuts (perennial horticulture); and vegetables.

Irrigated product revenue regression model

The final set of regressions expressed as equation 8 estimate the revenues (gross value of irrigated production, GVIAP in the terminology used by the Australian Bureau of Statistics or ABS who collects statistics on this metric). Data is available for ten irrigation dependent commodities, R_i , as a function of explanatory variables including the area of crop predicted with regressions equation 1, net ET and commodity price, and in some cases a dummy variable for NRM regions in the northern Basin all explained in Table 1 and the section on land area regression. Φ_i^0 is the regression intercept coefficient, and Φ_i^{wa}, Φ_i^p, and Φ_i^c are the regression coefficients for the water allocation, price and climate explanatory variables. Prior expectations for this regression were that revenues should be increasing in land area ($PA_{i,j,y}$) and in commodity price. We did not have a clear prior expectation with regard to the sign of the coefficient on the climate variable Φ_i^c: on the one hand high potential evapotranspiration can be associated with higher yield, on the other hand heat stress leading to reduced yield can result under hotter and drier condition can be correlated with high potential evapo-transpiration.

$$R_{i,j,y} = \phi_i^0 + \phi_i^{wa} * PA_{i,j,y} + \phi_i^p * p_{i,y} + \phi_i^c * c_{i,j,y} + \phi_i^n * n_j + e_{i,j,y} \cdots\cdots (7)$$

In the case of gross value, equations are estimated for the seven crop commodities used in area and water per hectare regressions as well as livestock commodities: beef, sheep, and dairy. For the livestock GVIAP regressions, area of pasture and hay is treated as the area explanatory variable. As with the area regressions, some variables are scaled: allocations in each year are divided by the maximum observed in the recorded data record going back to 1996 for each NRM regions; and in some regressions net irrigation requirement is also scaled by dividing this variable by the average for the time period that estimates exist (1896 to 2009).

Data sources and treatment

Irrigated area and water use per hectare by crop and NRM region data was sourced from the ABS catalogue 46180 series, *Water Use on Australian Farms-* http://www.abs.gov.au/ausstats/abs@.nsf/mf/4618.0; GVIAP data was sourced from catalogue 46100, *Experimental Estimates of the Gross Value of Irrigated Agricultural Production* - http://www.abs.gov.au/ausstats/abs@.nsf/mf/4610.0.55.008. Crop price data was from the ABS series 7501.0 series – Value of Principle Agricultural Commodities Produced - http://www.abs.gov.au/ausstats/abs@.nsf/mf/7501.0.

Time series gridded rainfall and areal potential evapotranspiration (APET) derived from SILO datasets was obtained from Catchment Water Yield Estimation Tools (CWYET) project (Vaze et al. 2011a and 2011b). Under this project daily meteorological data from 1-Jan-1889 to 31-Aug-2009 collected by bureau of meteorology was interpolated at 0.05 x 0.05 degree cell across Australia (Jeffrey et al. 2001). Then daily gridded rainfall and APET was processed to calculate monthly rainfall and spatial average APET for 58 major sub-catchments in the MDB. These sub-catchments are aggregates of the rainfall-runoff sub-catchments used in the Murray-Darling basin.Water allocations data was sourced from the various volumes of *Water Audit Monitoring Report: Report of the Murray Darling Basin Commission on the Cap on Diversions – available from the MDBC prior to 2008/09 http://www2.mdbc.gov.au/__data/page/1782/MDBC_WAM_2006-07.pdf* and from the MDBA from the 2008/09 season - www.mdba.gov.au/water/river_info.

Weather has a significant impact on returns to irrigation. In the regressions presented here Net evapotranspiration calculated as potential crop evapotranspiration less effective rainfall is used to capture main weather impacts. The areal average value of potential crop evapotranpiration and effective rainfall by NRM region was estimated based on the proportion of catchments within a NRM region; crop type and areas; dominant crop calendar and coefficients. These values were initially estimated on monthly time step and then aggregated to calculate seasonal and annual net ET (net irrigation requirements) for economic/crop production function analysis.

Prices were expressed relative to major substitute commodities in the case of annual crops where crop substitution is a viable short-run adaptation. In the case of pasture crops where a consistently collected price time series was not available, the price of the substitute in production, wheat was used.

1. Irrigated area estimation results

Results of irrigated area by crop regression for the 2005/06 to 2008/09 NRM region disaggregated data are summarised in Table 2. For the annual crops considered (cereal, rice, cotton, pasture), the overall regression fits as expressed by the R^2 statistics (0.34 to 0.92) are reasonably to very good relative to expectations for time series cross section data. In contrast, the explanatory power of the area regressions for perennial and vegetable crops is relatively low with R^2 ranging from 0.10 (horticulture) to 0.22 (vegetables).

The signs of all statistically significant regressions coefficients are consistent with prior expectations (Table 2). The sign on the coefficients for the allocation explanatory variable are positive for all area regressions, as expected, and five of the seven were statistically significant at a p-value of 0.1 or less. The p-value for the allocation coefficient in the vegetable regression is also very close to the 0.1 p-value threshold at 0.104. These results offer strong support for the hypothesis that irrigated area declines with reductions in water allocation and that this is the case for all crops across the Basin. No statistically significant relationships between observed land area and prices and our climatic variable (net ET less rain) could be discerned as indicated by p-values > 0.1 for these two variables in all land area regressions (Table 2). This result is not too surprising given the limited variation prices, ET and rain over the sample and the fact that these variable are somewhat correlate with some of the higher price years also occurring when ET less rainfall values were low relative to the four year sample average.

The results of the area regressions with the basin aggregate 2000/01 to 2009/10 summarised in Table 3, are qualitatively similar to the results of land area regression with 2005/06 to 2008/09 NRM region disaggregate data. In six out of eight area regressions, area is directly related to allocation level as expected and in five of these cases, allocations are a statistically significant determinant. As was the case with the NRM region disaggregate regressions, overall explanatory power of the regression was generally better for annual than perenial crops with R-squares of greater than 0.9 for all annual crops other than cereal (0.45). For wine and horticulture, the area as function of allocation level regression had relatively poor explanatory power with a direction of influence that is opposite of expectation on the statistically insignificant allocation level explanatory variable.

Estimated area response elasticity, percent change in area predicted over percentage change from the sample mean in water allocation level, net ET level and price level are summarised in Table 3: Irrigated area by crop regression results - aggregate basin 2000/01 to 2009/10 data

	allocation	intercept	R-square
Pasture - meat	0.00056	-2.74	0.91
Pasture - dairy	0.00038	-1.367	0.9
Rice	0.0009	-7.24	0.95
cotton	0.00058	-3.72	0.92

cereal	0.00016	-0.193	0.45
Wine^	-0.00015	2.58	0.56
Horticulture^	-0.00016	2.7	0.54
Vegetables	0.00026	-0.595	0.72

Table 4. These calculations, based on the 2005/06 to 2008/09 NRM region regressions, allow comparison with elasticity estimates that are inferred from two widely reported alternative MDB irrigation economics models. We estimate elasticities for these studies with the standard arc elasticity formula, $(y_0 – y_1)/y_0]/[(x_1 – x_0)/x_0]$ where y_0 is the base case predicted level of the dependent variable, y_1 is the dependent variable predicted level for treatment 1, x_1 is treatment level of explanatory variable and x_0 is base case explanatory variable level.

Colum 1 in Table 3: Irrigated area by crop regression results - aggregate basin 2000/01 to 2009/10 data

	allocation	intercept	R-square
Pasture - meat	0.00056	-2.74	0.91
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Vegetables	0.00026	-0.595	0.72

Table 4 shows our estimates of land area response elasticity to changes in allocation level. Columns 2 and 3 show elasticity estimates inferred from the results of published studies with two other economic models of the MDB irrigation sector. These results show relatively elastic land area contractions with reductions in water allocations for most annual crops including (in order of elasticity magnitude): rice, cereal, pasture. These estimates are also similar to the estimates from other models with the UQ model an outlier in pasture land area elasticity and our estimates of rice area elasticity higher than the others.

In contrast, we estimate very inelastic perennial crop (wine and horticulture) and vegetable crop area response to changes in allocation level. For example our estimated elasticity of area in horticulture is 0.05 about one eight of the elasticity inferred from UQ modeling results. ABARE estimated elasticity responses for these crops are of a similar magnitude but opposite sign. This suggests somewhat implausibly, small expansions in areas of horticulture, wine, and vegetables with reduced allocations all else equal. In contrast, our small but positive elasticity estimates seem consistent with the observed small contraction in areas of these crops with very large allocation reductions during the drought.

Table 2: Irrigated area by crop regression results summary – disaggregate NRM region 2005/06 – 2008/09 data

dependent variable	R-sauare	explanatory variable	coef	std	t-stat	p-value
rice	0.92	ALLOCATION	10.002	2.375	4.211	0.014
		DNET	6.0413	5.972	1.012	0.369
		OWN PRICE	0.51971	1.726	0.3011	0.778
		CONSTANT	-7.7986	3.262	-2.391	0.075
cotton	0.34	ALLOCATION	2.8508	1.141	2.498	0.02
		DNET	0.56296	1.956	0.2878	0.776
		PRICE	2.0169	1.221	1.652	0.112
		CONSTANT	-4.3236	1.145	-3.778	0.001
cereal	0.51	ALLOCATION	3.7457	1.004	3.732	0.001
		DNET	0.12588	1.975	6.37E-02	0.949
		OWN PRICE	0.0021	0.0035	0.5866	0.56
		CONSTANT	-3.3302	1.272	-2.617	0.012
wine	0.14	ALLOCATION	1.1335	0.5324	2.129	0.041
		DNET	0.249	0.5457	0.4558	0.651
		OWN PRICE	-0.19269	0.5964	-0.3231	0.749- 0.056
		CONSTANT	1.6139	0.7149	2.258	0.031
horticulture	0.1	ALLOCATION	0.78932	0.6247	1.264	0.215
		DNET	1.9179	1.229	1.56	0.128
		OWN PRICE	0.21494	1.547	0.1389	0.89
		CONSTANT	1.073	1.716	0.6252	0.536
vegetables	0.22	ALLOCATION	1.3728	0.8196	1.675	0.104
		DNET	-1.9769	1.611	-1.227	0.229
		OWN PRICE	-1.7982	2.008	-0.8956	0.377
		CONSTANT	2.8374	2.224	1.276	0.211
pasture	0.66	ALLOCATION	3.226	0.6483	4.976	0
		DNET	-1.4795	1.272	-1.163	0.254
		SUBSTITUTE PRICE*	-0.0021	0.0020	-1.048	0.303
		CONSTANT	-1.0449	0.8733	-1.197	0.241
		NORTH	-0.109	0.3581	-0.3044	0.763

indicates statistically significant at p-value < 0.10

Table 3: Irrigated area by crop regression results - aggregate basin 2000/01 to 2009/10 data

	allocation	intercept	R-square
Pasture - meat	0.00056	-2.74	0.91
Pasture - dairy	0.00038	-1.367	0.9
Rice	0.0009	-7.24	0.95
cotton	0.00058	-3.72	0.92
cereal	0.00016	-0.193	0.45
Wine^	-0.00015	2.58	0.56
Horticulture^	-0.00016	2.7	0.54
Vegetables	0.00026	-0.595	0.72

Table 4: Estimated land area response elasticity with respect to irrigation allocations

	CSIRO	ABARES	UQ
Pasture	0.82	0.57	1.79
Hay		1.45	
Dairy		-0.1	
Beef		0.14	
Sheep		0.79	
Cereal	1.21	0.93	
Cotton	0.77	0.55	0.61
Rice	3.83	1.07	2.33
Hort	0.05	-0.07	0.43
wine	0.06	-0.09	0
Vegetable	0.11	-0.17	

2. Irrigation application rate regression results

Results of irrigation application rate regressions are summarised in Table 5. Water application rate equations generally had higher explanatory power for perennial (wine, horticulture) and vegetable crops (R-square 0.58 to 0.71) than annual crops(R-square 0.18 to 0.32). The exception is the water per hectare regression for annual crop rice with a very high r-square of 0.91.

Coefficient signs were generally as expected. Overall net irrigation requirement (potential crop evapotranspiration net of effective rainfall) was the most consistently important determinant of water application rates. Hotter and drier (lower rainfall) weather was found to be to positively and statistically significantly related to water application rates per hectare in six of eight regressions. This relationship was particularly strong from perennial (wine and horticulture) and vegetable crops, where the net ET coefficient was significant at the 99% confidence level.

Consistently with prior expectations water application rate per hectare was statistically significant and positively related to allocation levels for rice. However no statistically significant relationship between allocation level and water application rate could be found for the remaining seven regressions. We also found two statistically significant price effects, both consistent with expectation: water applied per hectare is increasing with commodity price for rice decreasing with decreasing in substitute commodity price (wheat) for pasture. However, in general prices effects could not be identified with high levels of statistical confidence in the remaining regressions. One potential explanation for a lack of statistically significant price and allocation level impacts on irrigation water application rates is that these factors may in fact have very little influence. Once irrigators set area to irrigate by crop the marginal economics is driven primarily by the season ET net of rainfall.

Table 5: Irrigated water use by crop regression results summary

dependent variable	R-sauare	explanatory variable	coef	std	t-stat	p-value
Rice	0.91	PRICE	0.25923	0.0519	4.993	0.004
		ALLOCATION	0.20022	0.0671	2.982	0.031
		NET	-0.20637	0.2192	-0.9417	0.39
		CONSTANT	0.77737	0.2782	2.795	0.038
						1
Cotton	0.21	PRICE	0.0252	0.2652	0.0949	0.925
		ALLOCATION	-0.0035	0.1095	-0.0324	0.974
		NET	0.34228	0.1727	1.982	0.062
		CONSTANT	0.52341	0.3991	1.311	0.205
wheat south	0.31	PRICE	-0.18664	0.1242	-1.503	0.154
		ALLOCATION	0.11648	0.0792	1.471	0.162
		NET	0.62759	0.2121	2.959	0.01
		CONSTANT	0.39895	0.181	2.204	0.044
						1
wheat north	0.32	PRICE	0.0076	0.0924	0.0826	0.935
		ALLOCATION	-0.18172	0.1424	-1.276	0.217
		NET	-0.55718	0.3315	-1.681	0.109
		CONSTANT	1.5016	0.4278	3.51	0.002
						1
horticulture	0.69	PRICE	-1.4795	1.575	-0.9395	0.354
		ALLOCATION	-0.68831	0.8432	-0.8163	0.42
		NET	4.4054	1.012	4.353	0
		NORTH	-3.6054	0.4666	-7.728	0
		CONSTANT	3.1108	2.05	1.518	0.138
vegetable	0.58	PRICE	0.80156	1.23	0.6515	0.519
		ALLOCATION	-0.31677	0.618	-0.5126	0.611
		NET	4.2242	0.6308	6.697	0
		CONSTANT	0.16238	1.475	0.1101	0.913
		NORTH	-1.9296	0.3444	-5.603	0
Wine	0.71	PRICE	-0.48285	0.4387	-1.101	0.278
		ALLOCATION	0.73344	0.6103	1.202	0.237
		NET	6.0464	0.7076	8.545	0
		CONSTANT	-1.9126	0.6778	-2.822	0.008
		NORTH	-1.9812	0.4323	-4.583	0
pasture	0.18	SUBSTITUTE PRICE	-0.79455	0.439	-1.81	0.076
		ALLOCATION	0.2482	0.5028	0.4936	0.624
		DNET	1.2128	0.5091	2.382	0.021
		NORTH	-0.37585	0.3048	-1.233	0.223
		CONSTANT	3.5938	0.6151	5.842	0

indicates statistically significant at p-value < 0.10

Regression coefficients for the most consistently significant determinant of irrigation rate net ET were converted to elasticity estimates so that there implications could be more easily understood as shown in Table 6. These estimates provide new insight into the process and costs of MDB irrigation sector adaptation of drought. While there is at least one other recent studies that has accounted for what is essentially an ability to substitute rain for irrigation water as an input to production (Whittwer and Dixon, 2011), the study assumed 1 for 1 rain for irrigation application substitutability. Our elasticity estimates suggest that in fact, on average irrigators increase irrigation by nearly two percent for a one percent change in net ET for water stress and heat sensitive wine and wine grapes, and by about 1% for a 1% rise in net ET for horticultural and vegetable crops. In contrast the elasticity of irrigation application for a 1% change in net ET for annual crops is smaller (0.39 for cotton, and 0.42 for pasture, 0.74 for Southern Basin cereals).

Table 6: Estimated irrigation application rate elasticity with respect to net ET

crop	Net ET elasticity
Pasture	0.42
cereal south	0.75
cereal north	NS
Cotton	0.39
Rice	NS
Hort	0.95
wine	1.74
Vegetable	0.97

NS indicates no statistically significant relationship

3. Revenue regression estimation results

A summary of revenue (or GVIAP in ABS language) regression outcomes for crop commodities is shown in Table 7 and for livestock based commodities in Table 8. These regressions generally had good explanatory power (R squares from 0.37 to 0.99). Explanatory power of regressions was generally higher for crop based commodities (R squares from 0.51 to 0.99) than for livestock based commodities and pasture (R squares from 0.37 to 0.62). Whilst the R-square for the rice GVIAP was high (0.99) too few observations and the presence of a high degree of multicolinearity in explanatory variables (correlation amongst these variables) meant that this regression was unable to produce reliable estimates; signs on all coefficients reversed with small changes in specifications, and calculated elasticity numbers were implausible. See section 6 for further discussion.

As expected area was found to be directly related to GVIAP and the relationship was statistically significant in all regressions. We calculated the elasticity of GVIAP with respect to land area and tested whether we could reject the hypothesis that the value was equal to one. We failed to reject this hypothesis in all cases indicating that the data is consistent with an assumption of a one to one relationship between predicted contraction in land area and contraction in GVIAP, all other factors such as crop prices and rain and evapotranspiration equal.

For livestock based commodities estimated elasticities of GVIAP change with respect to changes in land area were less than one (0.31 for beef, 0.44 for sheep and 0.39 for dairy). This indicates that a 1% decline in the area in pasture and hay crops supporting these industries led to a less than 1% (0.31% to 0.44%) decline in the value of output. This is as expected and provides circumstantial evidence that feed was sourced from beyond irrigated production within the Basin for these industries during the drought.

The estimated impacts of commodity prices on GVIAP were also positive as expected for all regressions. The relationship was statistically significant at 90% confidence or better (pvalue < 0.1) for three of these 10 regressions. We calculated the elasticity of GVIAP with respect to commodity prices and tested whether we could reject the hypothesis that the value was equal to one. We failed to reject this hypothesis in all cases indicating that it is consistent with the data to assume a one to one relationship between change in commodity price and change GVIAP, all other factors such as crop prices and rain and evapotranspiration equal.

Kirby et al (2012) reviewed drought experience in the irrigation sector and found that over the drought, irrigated output per hectare of many commodities increased as conditions became hotter and dryer and irrigated land area contracted. It seems reasonable to infer that the net ET coefficient relate to yield impacts on GVIAP pick up this effect, given that price and area impacts are picked up by price and area explanatory variables. As shown in Table 9, we found that net ET does have a positive and significant correlation with GVAIP for beef, dairy and pasture and rice with elasticity of GVIAP with respect to net ET in the (0.16 to 0.85 range). The result may suggest that, irrigators higher potential yields in years of high evapotranspiration may have been realised as irrigators deployed more yield enhancing inputs in the form of water or other inputs that are not captured in regression explanatory variables (e.g. capital or labour inputs that increase irrigation efficiency).

We found the opposite effect of greater net ET on irrigation revenues for five crop (wheat, grapes, horticulture, beef, and cotton). Negative coefficients on the net ET variable for these crops are consistent with hotter and dryer conditions leading to decreased yields, though the relationship was only found to be statistically significant for cereals.

Table 7: Irrigated crop commodity GVIAP regression results

dependent variable	R-sauare	explanatory variable	coef	std	t-stat	p-value
wheat	0.86	PRICE	0.0128	0.0180	0.7105	0.481
		AREA	0.0008	0.0001	15.57	0
		DNET	-17.436	10.33	-1.688	0.098
		CONSTANT	-0.93659	5.568	-0.1682	0.867
						1
rice	0.99	PRICE	74.539	6.221	11.98	0.053
		AREA	0.0047	0.0001	39.46	0.016
		DNET	186.4	18.38	10.14	0.063
		CONSTANT	-126.52	10.53	-12.02	0.053
						1
cotton	0.79	PRICE	218.22	190.8	1.144	0.296
		AREA	0.0104	0.0024	4.238	0.005
		NET	-187.86	149.2	-1.259	0.255
		CONSTANT	-24.149	263.1	-0.0918	0.93
						1
pasture	0.63	PRICE	0.0049	0.0209	0.2366	0.815
		AREA	0.0001	0.0000	3.658	0.001
		DNET	52.739	11.77	4.48	0
		NORTH	5.4882	2.564	2.14	0.041
		CONSTANT	-1.3687	6.476	-0.2113	0.834
vegetable	0.75	PRICE	138.06	71.22	1.938	0.066
		AREA	0.0270	0.0046	5.85	0
		DNET	57.458	49.54	1.16	0.259
		CONSTANT	-167	81.99	-2.037	0.054
horticulture	0.51	PRICE	86.768	138.1	0.6282	0.538
		AREA	0.0110	0.0042	2.63	0.017
		NET	-131.63	106.6	-1.235	0.233
		NORTH	-6.6332	38.2	-0.1736	0.864
		CONSTANT	76.128	209.9	0.3627	0.721
grapes	0.9	PRICE	105.26	40.71	2.585	0.023
		AREA	0.0072	0.0008	8.829	0
		DNET	-5.7854	158	-0.0366	0.971
		NORTH	-0.0778	24.49	-0.0032	0.998
		CONSTANT	-111.64	46.13	-2.42	0.031

indicates statistically significant at p-value < 0.10

Table 8: Irrigated livestock commodity GVIAP regression results

dependent variable	R-sauare	explanatory variable	coef	std	t-stat	p-value
beef	0.37	PRICE	194.25	103	1.886	0.073
		AREA	0.00016	0.00009	1.869	0.075
		NET	-47.26	36.19	-1.306	0.205
		CONSTANT	-132.74	95.41	-1.391	0.178
sheep	0.65	PRICE	848.91	1259	0.6745	0.505
		AREA	0.00014	0.00002	6.163	0
		DNET	17.237	9.829	1.754	0.09
		CONSTANT	1.9365	5.022	0.3856	0.703
dairy	0.62	PRICE	102.73	96.19	1.068	0.299
		AREA	0.00094	0.00029	3.213	0.005
		DNET	693.99	132.2	5.248	0
		NORTH	-46.34	35.14	-1.319	0.203
		CONSTANT	-121.44	117.1	-1.037	0.313

[highlighted] indicates statistically significant at p-value < 0.10

Table 9: Estimated GVIAP response elasticity with respect to net ET

crop	Net ET elasticity
Pasture	0.48
Cereal	-0.11
Cotton	NS
Rice	0.58
Hort	NS
wine	NS
Vegetable	NS
Dairy	0.84
Sheep	0.16
Beef	NS

NS indicates no statisitcally significant relationship

4. Statistical issues and their treatment

Error in dependant variable estimates is one statistical issue with our source data. Dependant variables values in the regressions are estimates for an entire NRM region from survey samples and not a census of the entire relevant population. In regions where the commodity in question has a relatively small population of producers, sample sizes are small and as a result standard errors of population inferences from these survey samples is large. The result is potential for errors in measurement of dependent variables used in the regressions. To deal with this issue data was omitted where: the ABS indicated very large standard error in estimation, this was judged to be the case where less than 3 years out of the four possible were available for a variable in a given NRM region and the estimates appeared to vary implausibly from year to year.

Further statistical issues that arose had to do with the nature of errors in regression prediction. In the first instance all equations were estimated with straight forward ordinary least squares regression. We then tested for presence of three potential statistical problems:

1. Heteroscedasticity – this is the tendency for errors in prediction to be systematically correlated with the size of the dependent variable. When errors in regression prediction are heteroscedastic and this is not corrected for with an with an appropriately adjusted weighting in regression, the standard errors of regression coefficients and thus inferences about coefficient significance are inaccurate. The extent of hetroscadasticity was tested with the Gljeser test (Greene, 1990). As summarised in Table 8 hetroscadasticity was identified (a less than a 10% probability of rejecting the hypothesis that errors are heteroskedastic) in seven of twenty four regressions. To ensure meaningful statistical interpretation in these cases, the five equations where hetroscadisticity was identified by not autocorrelation, the equations were re-estimated with a heteroscedasticity adjustment (the hetcov option in Shazam v.10 statistical software which implements the White 1980 correction) to ensure accurate estimates of all regression coefficient standard errors. These heteroscedasticity corrected standard errors and result t-tests of coefficients are what is reported and used in calculation in Tables 2-7.
2. Autocorrelation – this is the tendency for errors in prediction to be related across time periods – rather than being independent (not correlated with one another). When errors in regression prediction are auto-correlated and this is not corrected for with an auto-corellation adjusted weighting in regression, the standard errors of regression coefficients and thus inferences about coefficient significance are inaccurate. An appropriate indicator of the presence of autocorrelation is the Durbin Watson statistic (Greene, 1990). Results of the Durbin Watson test for our regressions are shown in Table 8. Based on these statistics we could not reject the presence of auto-correlated errors (at p-value of 10% or less) for nine of the twenty five regressions. Subsequent analysis by trialling regression models of prediction error on one period lagged error and other lagged models confirmed significant 1st order autocorrelation for all nine case. To ensure meaningful statistical interpretation in these cases and for cases of both autocorrelation and heteroskedasiticity, all nine equations were re-estimated with a first order autocorrelation adjustment using the Shazam statistical software v. 10 (autcov=1 procedure following Greene, 2003, p257) to ensure accurate estimates of all regression coefficient standard errors. These autocorrelation (and

heteroskedasticity where this was also present) corrected standard errors and result t-tests of coefficients are what is reported and used in calculation in Tables 2-7.

3. Multicolinearity – is correlation amongst explanatory variables. Its presence can make it difficult to isolate the partial impacts of highly correlated variables and result in statistically insignificant impacts and relatively large changes in coefficient including changes in estimated directions of influence with relatively small changes in regression specification. We tested for multicolinearity by calculating a measure know as the variance inflation factor (VIF); it is a measure of the extent to which each explanatory variable can be predicted as a combination of the other explanatory variables. A VIF value greater than 5 indicates a problematically high level of multicolinearity. Estimated VIF values for all regressions are summarised in table 8. As can be seen none of the estimated VIF values indicated severe multicollinearity in explanatory variables and thus no modifications to regression were pursued to address multicolinearity. The single exception to this is the rice revenue regression. As discussed above

A final potential statistical issue is cross equation correlation in errors – the equations describing land area, water use per hectare, and GVIAP are expected to have correlated errors in prediction as they are explained by many of the same and correlated explanatory variables. Estimating systems of simultaneous equations is possible when this is the case and can result in improved statistical identification of the main determinants of land and water use and GVIAP in irrigated cropping. Such an approach is possible but involves intensive efforts and new specialised software for our case study where the data is what is known in econometrics as “unbalanced panel data” that is it is time series and cross section but with different cross sectional and time series observations for different crops. .

Table 10: Summary of multicollinearity, autocorrelation, and hetroskedasticity testing results

Dependent variable	Variance inflation factor	Probability of rejecting positive auto-correlation	Probability of rejecting negative auto-correlation	Prob. of rejecting hetero-skedasticity	Regression type
Revenue regressions					
Pasture	1.7	0.18	0.82	0.02	Hetcov
Dairy	1.48	0.02	0.98	0.28	Autcov=1
Wine	2.26	0.87	0.13	0.05	Hetcov
Vegetable	1.29	0.01	0.99	0.03	Autcov=1
Horticulture	1.30	0.38	0.62	0.08	Hetcov
Cotton	2.52	0.69	0.31	0.06	Hetcov
Rice	8.82	0.36	0.64	0.81	OLS
Sheep	1.74	0.03	0.97	0.05	Autcov=1
Beef	1.91	0.08	0.92	0.24	Autcov=1
Cereal	1.27	0.11	0.89	0.01	Hetcov
Land area regressions					
Rice	3.45	0.49	0.51	0.76	OLS
Cotton	1.55	0.66	0.34	0.77	OLS
Cereal	1.14	0.02	0.98	0.39	Autcov=1
Cereal south	1.28	0.40	0.60	0.24	OLS
Cereal north	1.43	0.21	0.79	0.59	OLS
Wine	1.41	0.71	0.29	0.43	OLS
Horticulture	1.98	0.69	0.31	0.89	OLS
Vegetable	1.34	0.32	0.68	0.78	OLS
Pasture	1.18	0.68	0.32	0.81	OLS
Water per hectare regressions					
Rice	5.5	0.62	0.38	0.30	OLS
Cotton	1.49	0.82	0.18	0.37	OLS
Cereal	1.57	0.46	0.54	0.12	OLS
Wine	1.40	0.01	0.99	0.53	Autcov=1
Horticulture	1.75	0.01	0.99	0.14	Autcov=1
Vegetable	1.62	0.001	0.999	0.07	Autcov=1
Pasture	1.31	0.04	0.96	0.71	Autcov=1

5. Summary and Conclusions

Key conclusions arising from the crop area regressions are that allocation level was the most consistently statistically significant determinant of crop area. Small but significant area changes in perennials and vegetables could be explained by changes in allocations available to irrigators. Moderate (cotton, pasture, cereal) to large (rice) changes in annual crop are were estimated in response to irrigation allocation changes. Neither price level changes or changes in net ET were found to be statistically significant determinant of some in irrigated crop area.

Key water application rate regression conclusions were that the most statistically significant determinant of irrigation application is the net ET – crop potential ET less crop available rain Statistically significantly greater application rates are correlated with greater ET – rain for 6 of 8 crops. The estimated elasticity of application for a 1% change in irrigation water requirement is estimated to be large for perennials and vegetables, and small for annual crops. Higher prices and higher allocation levels were statistically significantly correlated with higher water application rates for rice.

Key revenue (gross value of irrigated agricultural production) regression conclusions were that the most consistently significant determinant of estimated GVAIP across all commodities considered was estimated area of crop (or pasture for livestock commodities). The hypotheses that GVIAP is in a 1:1 relationship with percentage area and percentage price change could not be rejected for any of the commodities considered. The yield impacts of hotter and drier weather appeared to be positive for some crops and negative for others. Statistically significantly greater GVIAP in years of greater ET – rain was estimated for Sheep, Dairy, Pasture and Rice. Less GVIAP was statistically significantly attributable to hotter and drier weather for wheat. A negative but not statistically relationship was estimated for horticulture, wine, beef, and cotton.

A notable characteristic of both datasets is relatively small sample sizes – for several of the regressions smaller than would commonly be used in regression analysis. From an econometric perspective, larger samples based on micro data from farm level surveys would be more desirable. However, the underlying motivation for this analysis is not the regression analysis itself. Rather, we are motivated to demonstrate an approach to irrigation sector modelling based on precisely, the type of sparse and aggregated data that is readily available in the MDB and likely also to be readily available in other basins where such an approach could also be applied. Connor et al. (2012) describes testing of alternative simulation model specifications for applying these regressions and application of the final model specification to simulating irrigation sector adjustment to alternative price, climate and irrigation water availability scenarios.

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