Irrigation revenue loss in Murray–Darling Basin drought: An econometric assessment

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ABSTRACT

This article presents an econometric analysis of irrigation commodity area and revenue responses to varying commodity prices, water availability and climate conditions for the second half of a decade long drought in the Murray–Darling Basin, Australia. We find statistically significant evidence of irrigation area decline with reductions in water allocations and irrigation revenue shrinking with area irrigated. Results also indicate hotter drier weather conditions experienced in the drought effected crops differently: some crop revenues suffered, while higher evapotranspiration and yield potential appeared to support higher revenue outcomes for other crops. Comparison revealed that marginal revenue changes in response to water allocations estimated are much less than those implicit in other economic assessments of water scarcity impacts for the same basin that used different methods. We find that triangulation of results between methods provides confidence in consistent results and reveals possible avenues for future research and methodological development.

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1. Introduction

Irrigation is expected to play a major role in meeting future world food demand (McCarthy et al., 2001). Yet, much of the world's irrigated area is in arid and semi-arid regions where droughts are common, and are anticipated to be more common and severe under future climate change (Schwabe and Connor, 2012; Schwabe et al., 2013). Many irrigated food production regions including parts of Australia and the USA face a compounding challenge as water is increasingly reallocated away from irrigation to in-stream flows for water dependent ecosystems (Garrick et al., 2012).

A number of studies have used mathematical programming models to forecast irrigation sector economic responses to reduced water availability (Iglesias et al., 2003; Calatrava and Garrido, 2005; Peck and Adams, 2010). Specific to our study region, Qureshi et al. (2007) assessed Murray–Darling Basin (MDB) irrigation sector impacts from environmental water reallocation and Connor et al. (2009, 2012) assessed climate change and salinity impacts on southern MDB irrigation. Computable general equilibrium (CGE) modelling is another common approach to economic assessment of drought and water scarcity (Goodman, 2000; Berrittella

et al., 2007). Wittwer and Griffith (2011) used CGE modelling to assess both the impact of drought and water resource reallocation in the MDB. An advantage with mathematical programming and CGE models is that they allow assessment of scenarios that are outside actual experience. For instance, Harou et al. (2010) assess California irrigation sector impacts from a 72-year-long drought that is consistent with geologic records but much longer than any drought in the hydrologic record. One challenge with programming and CGE models is the specification of technical coefficients characterising yield, land use, revenue and cost changes in response to changes in available water. Misspecification, for example under representation of the true range of adaptation options, or the overspecialisation in a single crop, can lead to erroneous conclusions with respect to policy or future climate assessments.

Econometric simulation is an alternative to programming models which has been used to assess factors driving irrigation response to drought and water reallocation at the level of an irrigation district (Lorite et al., 2007), irrigated farm (Rubio-Calvo et al., 2006) or single crop (Quiroga and Iglesias, 2009). A potential advantage with econometric study of drought is that it provides a basis for modelling coefficients that is grounded in revealed responses to actual reductions in water available for irrigation. A challenge that can arise with small sample panel datasets can be statistically estimating significant marginal effects reliably (Hox, 2002, 2010). This is potentially an issue in our case study as the available survey and

census data involves a small unbalanced panel dataset. Another issue with the data are missing explanatory variables including capital and labour inputs to production. Despite these limitations, a strong drought signal and irrigation adaptive response do allow identification of significant marginal impacts of reduced water availability for most MDB irrigated commodities.

In what follows, we describe our case study, the conceptual basis for our regression model, the data sources, prior hypotheses, model specification, testing, and results. We then compare our econometrically estimated responses to those from other recent MDB irrigation sector drought economic impact assessments that used programming or CGE models and discuss reasons for the differences. We end with a discussion about the advantages of comparing different methodologies both in providing evidence for consistent results and where results differ, for future research agendas and method development.

2. Case study

Situated in the south-eastern part of Australia, the MDB covers about 1 million square kilometres or 14 percent of Australia. There are 23 river valleys and climatic zones range from cool temperate rainforests in the northeast to hot dry arid plains in the west and semi-arid plains in the south. Nearly two million people live in the Basin and it provides municipal industrial water to an additional 1.3 million people outside of the Basin (Loch et al., 2012).

Agricultural production, both irrigated and dryland is a significant economic activity throughout the Basin accounting for 34 per cent of Australia's gross value of agricultural production and 65 percent of Australia's irrigated land (Bryan and Marvanek, 2004). In response to a deepening drought water diverted for irrigation in the Basin declined between 2000 and 2010 (Kirby et al., In Press). Reductions in water allocations (annual water allocations tied to a water entitlement vary with inflow and storage) were more severe in the second half of the drought and severity of reductions varied by region. For example, in the South Australian (SA) Murray irrigation region 2008/09 allocations were just 18 percent of the long term average (Wheeler et al., In Press). During the drought dry, hot conditions affected crop evapotranspiration and yield potential and during this period irrigated commodity prices were highly variable (Kirby et al., In Press). These characteristics make the drought a useful case study to examine observed irrigation sector adaptation with the objective to better understand the economic impacts of water scarcity.

Data gathered for this study for five growing seasons; 2005/06 to 2009/10 was retrieved from publically available databases for 16 Australian Bureau of Statistics (ABS) Natural Resource Management (NRM) regions within the MDB, see Fig. 1. Dependent variable observations are irrigated land area and irrigated revenue for nine major commodities that represent more than 90 percent of the value of Basin irrigated production. These commodities are: beef, dairy, sheep, wine, perennial horticulture (fruit and nuts), cereal (wheat and other broadacre crops such as barley), cotton, and vegetables.

3. Model specification and estimation approach

The conceptual basis for the econometric specification in the modelling is the micro-economic theory of production. Observed output, and variable inputs are assumed to be profit maximizing responses. They are estimated as responses to input and output prices, climatic conditions, and fixed inputs. Other econometric studies of climate impacts on irrigation are also underpinned by this conceptual model (Kumar and Parikh, 2001; Gbetibouo and Hassan, 2005; Seo and Mendelsohn, 2008). The choice of dependent variables is partially determined by the availability of empirical data.

Table 1
Regression dependent and explanatory variables.

Name	Description	Units
Dependent variables		
IRRIGN_AREA	Logits of land area	Logits
IRRIGN_REV	Revenues from irrigated agricultural production	AU$ $\times 10^6$
Explanatory variables		
ALLOCN	Regional irrigation water allocation measured as the reported percentage of full regional entitlement	%
IRRIGN_AREA	Area irrigated	hectares
PRICE	Commodity price	$/t
IRRIGN_D	Variable measuring climatic influence on crop irrigation demand calculated as crop potential evapo-transpiration less crop available rainfall	Mm

Used observations of county level land rental value to assess climate impacts on irrigation value, while Seo and Mendelsohn (2008) used observations of farm level returns and livestock stocking levels. Available data allowed us to estimate demand for irrigated land area (IRRIGN_AREA) with water allocation (ALLOCN), commodity prices (PRICE), and an irrigation water demand proxy (IRRIGN_D, calculated as evaporation minus rainfall) as explanatory variables, see Eq. (1). We also estimate irrigation revenue (IRRIGN_REV) as a function of irrigated land area (IRRIGN_AREA), PRICE and IRRIGN_D, see Eq. (2).

$$A_{i,j,y} = \alpha_i^0 + \alpha_i^{wa} \times wa_{i,j,y} + \alpha_i^p \times p_{i,y} + \alpha_i^c \times c_{i,j,y} + e1_{i,j,y} \qquad (1)$$

$$R_{i,j,y} = \varphi_i^0 + \varphi_i^a \times area_{i,j,y} + \varphi_i^p \times p_{i,y} + \varphi_i^c \times c_{i,j,y} + e2_{i,j,y} \qquad (2)$$

where, subscript i indicates commodity, j indicates region, and y indicates year. Terms α, and φ are regression coefficients with superscript 0 indicating the regression intercepts, a indicating the IRRIGN_AREA coefficients, p indicating the PRICE coefficients, c the IRRIGN_D coefficient, and the terms $e1_{i,j,y}$, and $e2_{i,j,y}$ are the error vectors for the two equations. The explanatory variables are described in Table 1. Note that we have organised the regions into a northern and southern catchments as this has been shown to be relevant in discussion of irrigation responses to drought in the Basin (Kirby et al., In Press). Summary statistics for all variables are reported in Table 2.

Intuitively, it would seem logical to have estimated IRRIGN_REV as a direct function of ALLOCN and other relevant explanatory factors. However, we found that including ALLOCN directly in the IRRIGN_REV regression yielded relatively poorer explanatory power (lower R^2 values and fewer significant marginal effects) than our less direct approach explaining IRRIGN_AREA as a function of water allocations in Eq. (1), and IRRIGN_REV as function of IRRIGN_AREA in Eq. (2). For detailed results of the direct regression of IRRIGN_REV on ALLOCN, PRICE, and IRRIGN_D see Table A1 in the online Support material.

Consistent with past econometric studies of land use change, we used a logistical functional form as the dependent variable in the IRRIGN_AREA regressions (Eq. (1)). This form is popular because it precludes the possibility of negative areas by bounding IRRIGN_AREA estimates between zero and 100 per cent of potential irrigation area (Lubowski et al., 2006; Lewis et al., 2011). The explained observations in the IRRIGN_AREA regressions are the logits of irrigated area as a proportion of the maximum area for each crop and region, where the maximum area was assumed to be the maximum extent in the historic data for the region in the period 1997 to 2010.

We tested the explanatory power of our choice of linear functional form for all explanatory variables in both the IRRIGN_AREA and IRRIGN_REV regressions using Ramsay Equation Specification Error Tests (RESET) to determine whether nonlinear combinations
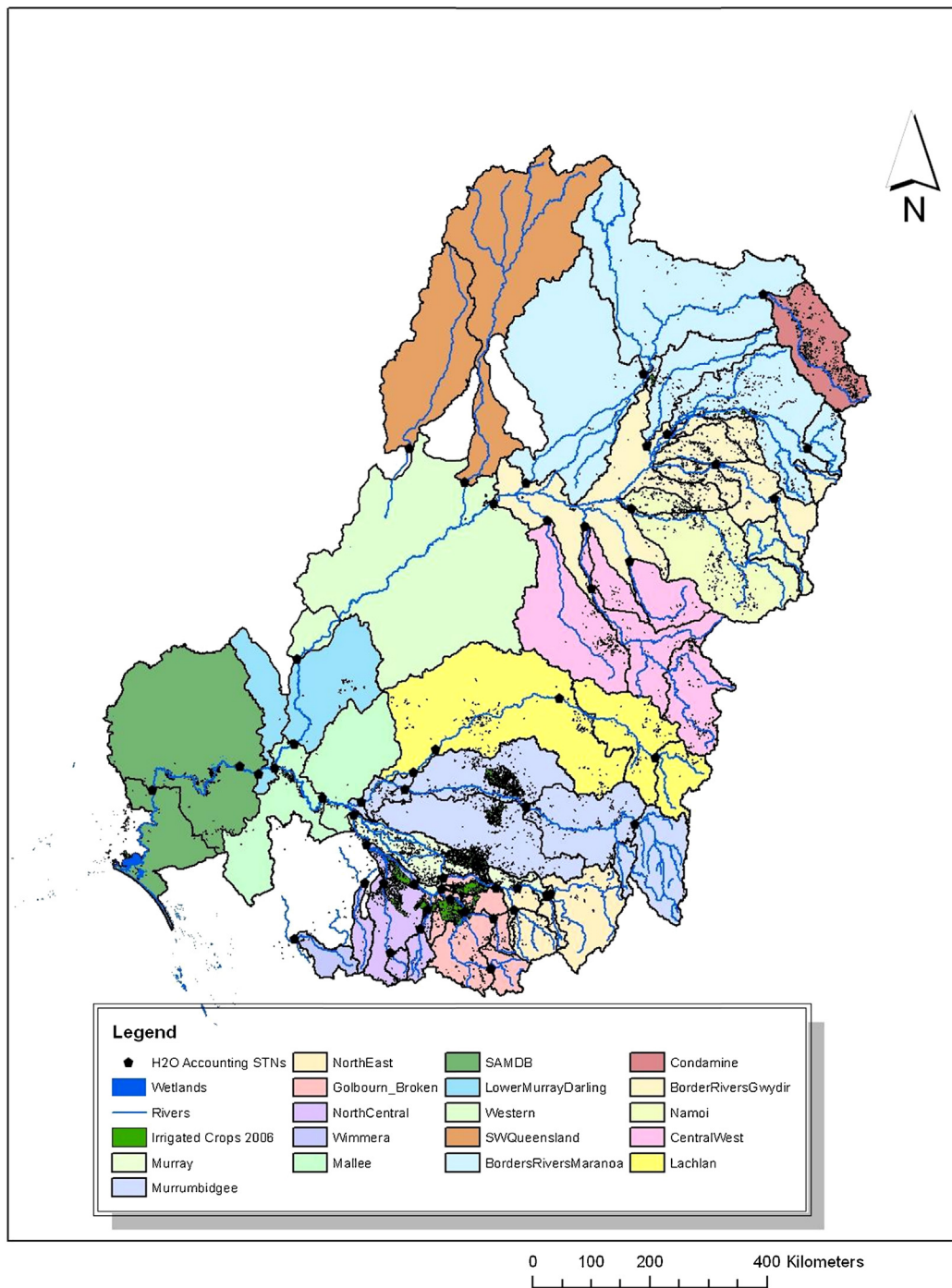
Fig. 1. Murray Darling Basin Natural Resource Management regions.

of the explanatory variables explain variation in independent variable values better than linear regression (Ramsey, 1969). The results showed that the null hypothesis – presence of specification error in our linear specification – was rejected for the OLS versions of all regressions at the one percent level.

For crop commodities, as opposed to livestock, Eqs. (1) and (2) are estimated simultaneously using a three-stage system of structural equations and Seemingly Unrelated Regression Estimation (SURE) (Zellner, 1962a,b). This method is typically applied where some equations contain explanatory variables that are also dependent variables in other equations in the system. In our case, IRRIGN_AREA is endogenous as it is included as an explanatory variable in the IRRIGN_REV regressions while simultaneously

determined in its own regression. The simultaneous equations approach has an added benefit of increasing the number of observations and therefore degrees of freedom and it accounts for contemporaneous error correlation across equations to create more efficient coefficient estimates. We could not run regressions on IRRIGN_AREA for livestock commodities due to lack of disaggregated observations for land area dedicated specifically to a particular type of livestock. Thus, Eq. (2) was used in single-equation revenue regressions for the three livestock commodities where area of pasture and hay is treated as the IRRIGN_AREA explanatory variable.

Additional statistical testing for common data issues that can lead to biased or inefficient coefficient estimates are briefly described here with detail of all test results provided in the

Table 2
Descriptive statistics for variables aggregated across the seventeen MDB regions.

Commodity	IRRIGN_REV	IRRIGN_AREA	ALLOCN	PRICE	IRRIGN_D
Beef					
Mean	21.22	−0.48	0.59	1.00	1462.53
sd	25.30	1.53	0.31	0.04	529.72
N	47.00	28.00	47.00	47.00	47.00
Dairy					
Mean	92.37	−0.61	0.60	0.98	1362.55
sd	121.57	1.00	0.31	0.14	499.54
N	40.00	24.00	40.00	40.00	40.00
Sheep					
Mean	12.17	−0.55	0.60	1.05	1489.43
sd	11.41	1.03	0.31	0.20	536.00
N	49.00	31.00	49.00	49.00	49.00
Cereal					
Mean	17.62	−1.16	0.62	0.97	1562.70
sd	21.19	1.18	0.30	0.24	531.59
N	59.00	55.00	59.00	59.00	59.00
Cotton					
Mean	60.05	−1.11	0.63	1.00	1497.50
sd	68.34	1.05	0.28	0.07	603.14
N	40.00	26.00	40.00	40.00	40.00
Horticulture					
Mean	96.50	1.56	0.62	1.01	1501.67
sd	93.69	1.03	0.31	0.12	504.68
N	55.00	51.00	55.00	39.00	55.00
Pasture					
Mean	20.42	−0.63	0.58	1.00	1474.51
sd	19.68	1.05	0.31	0.03	522.60
N	49.00	46.00	49.00	33.00	49.00
Vegetables					
Mean	49.81	−0.33	0.63	1.02	1417.90
sd	49.91	1.08	0.30	0.09	538.20
N	41.00	34.00	41.00	41.00	41.00
Wine					
Mean	74.32	1.74	0.62	1.00	1403.36
sd	101.58	0.95	0.30	0.23	539.46
N	53.00	48.00	53.00	37.00	53.00

online Support material (Tables A6–A10). The first issue considered was the potential for multi-collinearity amongst explanatory variables leading to unstable coefficient estimates with small specification changes. Contrary to our expectation that explanatory variables such as ALLOCN and the IRRIGN_D might be highly correlated, we found little evidence of multi-collinearity (Table A7) with the variance inflation factor (VIF) values ranging from around 1 to 2 for all regressions and variables. VIF values greater than ten indicate serious collinearity (Kennedy, 2008). Secondly, Breusch–Pagan tests led to rejection of the hypothesis that regression errors are heteroskedastic for all regressions with greater than 90 percent confidence (Table A5). An exception was the wine IRRIGN_AREA regression where the hypothesis of heteroskedasticity could not be rejected. Finally, we tested for autocorrelation with Durbin–Watson statistics for the single equation regressions and with the Harvey Lagrange Multiplier tests for the SURE regressions (Harvey, 1982, 1990). The hypothesis of autocorrelation was rejected for all regressions with greater than 90 percent confidence with the exception of the sheep IRRIGN_REV regression where the hypothesis could not be rejected (Table A6).

To account for the panel nature of the data a fixed effects specification with regional binary variables was run. The advantage of including time invariant regional fixed effects variables is that it removes bias that may arise from the omission (due to lack of available data) of region specific explanatory variables. These variables are likely to vary across regions in ways that may be correlated with other explanatory variables. Results from statistical tests indicated this was the correct approach for most regressions run (see, Table A8).

3.1. Data sources and treatment

Data on the dependent variables including IRRIGN_REV, IRRIGN_AREA by crop and NRM region was sourced from the Australian Bureau of Statistics (ABS) website. IRRIGN_REV 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. IRRIGN_AREA by crop and NRM region was sourced from the ABS catalogue 46180 series, Water Use on Australian Farms—http://www.abs.gov.au/ausstats/abs@.nsf/mf/4618.0.

Meteorological data obtained from the Bureau of Meteorology was used to calculate an 'irrigation demand proxy' variable (IRRIGN_D) equal to annual evapotranspiration minus rainfall at the weather station closest to each of the MDB irrigation regions. ALLOCN data was sourced from the Water Audit Monitoring Report: Report of the Murray–Darling Basin Commission (MDBC) 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 for the 2008/09 season—www.mdba.gov.au/water/river_info. PRICE data was obtained from the ABS series 7501.0 series—Value of Principle Agricultural Commodities Produced—http://www.abs.gov.au/ausstats/abs@.nsf/mf/7501.0.

4. Regression results

Our objective was to test the hypotheses that: (1) IRRIGN_AREA is: increasing with ALLOCN, increasing with PRICE and decreasing with our IRRIGN_D proxy (implying that less land is irrigated under drier weather conditions; and (2) IRRIGN_REV is: increasing in IRRIGN_AREA, increasing in PRICE and decreasing in IRRIGN_D (implying that irrigated commodity revenue is reduced under drier weather conditions).

4.1. Irrigated area

The explanatory power of the IRRIGN_AREA regressions with fixed regional effects had R^2 values greater than 0.6 for the following regressions: cereals, cotton, and vegetables, see Table 3 (coefficients for regional binary variables are provided in Table A2 - online support material). In the random effects model, without the binary variables for unexplained regional differences, explanatory power was quite limited with R^2 values of less than 0.15 for cereals, cotton, horticulture, and the vegetable IRRIGN_AREA regressions, and with slightly higher values for wine, and for pasture, $R^2 = 0.28$ and 0.37, respectively (detailed random effects regression results are reported in the Supporting online material Tables A9–A15).

Despite somewhat limited ability to identify statistically significant marginal effects, the IRRIGN_AREA regression results confirmed the hypothesis that ALLOCN is a significant determinant of IRRIGN_AREA in five of six IRRIGN_AREA regressions, see Table 3. Contrary to our expectation, the ALLOCN coefficient for the vegetable regression was statistically significant but negative. This may be a result of the aggregation of many commodities in this single category. Alternatively, the estimated sign could be a Type II error in prediction. It has been shown that such errors can arise in fixed effects regressions with small samples (Hox, 2002, 2010). The hypothesis that IRRIGN_AREA is positively related to the IRRIGN_D was supported in one regression only, cotton. Similarly, only one regression, the irrigated cereals area regression, supported the hypothesis that IRRIGN_AREA responded positively to higher PRICE. This may indicate that crop irrigated area decisions are made

Table 3
Irrigated area (IRRIGN_AREA) regression results.

Independent variables	Cereal		Cotton		Horticulture		Pasture		Vegetables		Wine	
	Coef.	$P > |z|$	Coef.	$P > |z|$	Coef.	$P > |z|$	Coef.	$P > |z|$	Coef.	$P > |z|$	Coef.	$P > |z|$
ALLOCN	0.45***	0.05	0.83***	0	0.4***	0.05	0.36**	0.08	−0.45***	0.03	0.39***	0.04
PRICE	1.41***	0	−1.64*	0.09	−0.26	0.66	−0.18	0.62	−1.05	0.2	−0.04	0.91
IRRIGN_D	0.95	0.12	1.82***	0	−0.46	0.25	0.79	0.16	−0.21	0.7	0.48	0.4
Intercept	−5.75	0.26	−1.17	0.79	0.43*	0.12	−7.36	0.52	0.36	0.25	−0.05	0.87
N	41		24		39		33		25		37	
R-square	0.79		0.8		0.96		0.76		0.94		0.99	
RMSE	1.16		0.83		0.09		2.97		0.05		0.13	

* Indicates statistical significance at 0.1 level.
** Indicates statistical significance at 0.05 level.
*** Indicates statistical significance at 0.01 level.

at the start of the season and not when end of season commodity prices are known.

4.2. Irrigation revenue

The explanatory power of fixed regional effects crop IRRIGN_REV regressions was good with R^2 values ranging from 0.88 to 0.98, see Table 4. R^2 values for livestock regressions ranged from 0.59 to 0.90, see Table 5. A critique of fixed effects regression specifications can be that R^2 values are high but that this is primarily due to the explanatory power of regional binary variables and thus provides little insight into the marginal effects of interest. This was not the case here; even random effects regressions (absent regional binary variables) had high R^2 values and allowed identification of many significant marginal effects (see online Support material Tables A11–A17). In the fixed effects regressions (Tables 4 and 5), IRRIGN_REV was positively related to IRRIGN_AREA for all commodities (crop and livestock) and the relationships were statistically significant in seven of nine revenue regressions. PRICE was a positive and significant determinant of revenue for the cotton, vegetables, beef and dairy models. Positive PRICE and IRRIGN_AREA coefficients may indicate that farmers not only maximise their irrigated area under crops when prices are high but also intensify production through greater use of inputs such as labour, capital and fertiliser when prices are higher. The unexpected, yet significant, negative sign of PRICE_wine coefficient could indicate that viticulturists have little opportunity to influence output in response to annual price variations for wine given that yields are primarily a lagged response to vine establishments that typically take three to four years to produce significant yields.

IRRIGN_D was found to have a statistically significant impact on revenue in five of six crop commodity regressions but was insignificant in all livestock regressions. In horticulture and pasture the sign of this coefficient was negative. For these enterprises, this result may indicate greater potential for heat damage in hot and dry years, and/or reduced ability to provide for crop water requirements. In

contrast IRRIGN_REV for cotton, wine and vegetable crops increased with longer, hotter growing seasons; possibly indicating greater yield potential, so long as adequate irrigation can be provided.

5. Comparing econometric and alternative model irrigation revenue impacts of water scarcity

At the outset, we noted that it may be difficult to capture the full range of irrigator adaptations to water scarcity with programming and CGE models. Response coefficients estimated with econometric models, in contrast, represent results of actual behaviour that includes the full range of irrigator adaptations. To gain a sense of how the responses that we estimated statistically may differ from responses predicted with alternative techniques, we compared our econometrically derived IRRIGN_REV impacts to impacts estimated using two mathematical programming models (Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES), 2011; Adamson et al., 2011) and one CGE model (Wittwer and Griffith, 2011). We chose these three models because they were all used by the Murray–Darling Basin Authority (MDBA) the federal government agency charged with developing a Basin Plan under the Water Act 2007. The MDBA used these three models to assess impacts of the Basin Plan on irrigators and the regional Basin economy. Basin Plan 2012 sets new lower on available irrigation diversions in each catchment in the Basin. A total 2,750 GL will be made available through these programs for environmental flows (see Bark et al., In Press).

Simulation with our model involved first predicting IRRIGN_AREA (Eq. (1)) by crop with and without 10 percent reduction in ALLOCN and holding other data values constant for all observations. The IRRIGN_AREA by commodity predicted in step one was then used as input into the IRRIGN_REV Eq. (2) for each commodity. We express all results in elasticity form as: percent change in IRRIGN_AREA or percent change in IRRIGN_REV divided by the percent change in ALLOCN. We also calculate elasticities for the revenue and irrigated area responses from programming

Table 4
Crop commodity revenues (IRRIGN_REV) regression results.

Independent variables	Cereal		Cotton		Horticulture		Pasture		Vegetables		Wine	
	Coef.	$P > |z|$	Coef.	$P > |z|$	Coef.	$P > |z|$	Coef.	$P > |z|$	Coef.	$P > |z|$	Coef.	$P > |z|$
IRRIGN_AREA	8.88***	0	3.22***	0	22.48	0.64	1.62***	0	107.7***	0.01	48.9	0.23
PRICE	2.44	0.73	103.64***	0	−31.77	0.52	−4.11	0.29	130.94***	0	−101.11***	0.04
IRRIGN_D	−5.13	0.61	44.92***	0	−70.4***	0.03	−17.97***	0	32.37*	0.12	114.32*	0.14
Intercept	11.98	0.66	−157.39***	0	262.07***	0	50.89***	0	−160.03***	0.02	−29.03	0.74
N	41		24		39		33		25		37	
R-square	0.92		0.98		0.91		0.96		0.96		0.88	
RMSE	6.47		10.21		8.73		3.75		10.27		37.04	

* Indicates statistical significance at 0.1 level.
** Indicates statistical significance at 0.05 level.
*** Indicates statistical significance at 0.01 level.

Table 5
Irrigated livestock commodity revenues (IRRIGN_REV) regression results.

Independent variables	Beef		Dairy		Sheep	
	Coef.	P > |t|	Coef.	P > |t|	Coef.	P > |t|
IRRIGN_AREA	2.14**	0.07	4.39*	0.12	1.1***	0.01
PRICE	271.11***	0.01	103.56**	0.08	−0.8	0.94
IRRIGN_D	−4.16	0.64	30.95	0.23	3.6	0.48
Intercept	−242.91***	0.01	149.84**	0.07	7.79	0.69
N	38		28		38	
R-square	0.73		0.9		0.59	
RMSE	16.07		41.9		7.14	

* Indicates statistical significance at 0.1 level.
** Indicates statistical significance at 0.05 level.
*** Indicates statistical significance at 0.01 level.

Table 6
Percent change irrigated area (IRRIGN_AREA)/percent change water allocation (ALLOCN).

Commodity	Econometric model	Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (2011)	Adamson et al. (2011)
Cereal	0.29	1.44	
Pasture	0.18		
Cereal and pasture			2.13
Cotton	0.42	0.44	0.09
Wine	0.11		
Horticulture	0.09	0.09	
Sheep	0.18		
Beef	0.18		
Dairy	0.18	0.14	1.13

and CGE models. These are calculated by dividing the modelled percent change irrigated area or revenue estimated by the percent change in water allocations assumed in the models.

Table 6 shows IRRIGN_AREA change per unit reduced ALLOCN estimated with our econometric model and for selected commodities that are reported in Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (2011) and Adamson et al. (2011). Response rates are fairly similar to the ABARES results for most commodities with the exception of cereals where the econometric model predicts IRRIGN_AREA response that is more inelastic than the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (2011) prediction. Table 7 shows IRRIGN_REV change per unit change in ALLOCN predicted from our econometric results and from the alternative models. In our results and the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (2011) results, perennial crops like horticulture are more inelastic compared to lower value broadacre crops like cereals. With the exception of cotton, where the elasticities we calculate are similar to those estimated in Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (2011), our econometric results predict revenue reductions per unit reduction in water allocation aggregated across all commodities that are significantly smaller than both those from Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (2011) and Adamson et al. (2011). The Wittwer and Griffith (2011) CGE modelling results do not provide the level of disaggregate detail that the other models do, however, aggregate elasticities for all irrigated commodity revenue for a unit change in water allocation (0.19) is closer to the elasticity estimated in this study (0.1).

6. Discussion

The advantage of comparing multiple methods is the opportunity to triangulate results with more sources of evidence and in those cases where the results differ, to examine possible explanations for the differences. We found both consistencies and differences between our econometrically-derived results and those from CGE and programming modelling. The consistencies are particularly apparent with the IRRIGN_AREA models and the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (2011) results: this is encouraging and likely reflects in part similar data sources.

One explanation for differences may be data aggregation differences. For example in the econometric modelling we considered uniform water allocation reductions across regions, while the alternative models used detailed water allocation data by region. There is some evidence, at least from programming models, that more aggregate models may estimate slightly smaller marginal effects than less aggregate models (Arriaza and Gomez-Limon, 2003). However, the large magnitude of the difference in estimated impacts seems unlikely to be the result solely of small scenario modelling differences. Less revenue loss per unit reduction in water availability estimated econometrically may also result from less than complete sector adaptive capacity representation in programming and CGE models. As noted by and Qureshi et al. (2013), greater inclusion of options to adjust to water scarcity in programming models tends to lead to smaller estimated income impacts of reduced water supply. While there is not a large body of econometric and programming models of revenue impacts of drought that allow systematic comparison, a meta-analysis by Scheierling et al. (2006) did find that on average programming studies produced less elastic estimates of irrigation water demand response to changing water price than did econometric studies. This may indicate that there are still challenges in fully specifying all adaptation opportunities that implicitly underpin econometric impact estimates. Both Wheeler et al. (In Press) and Kirby et al. (In Press) canvass some of the possible adaptations that may not be fully represented in current programming and CGE models including: a decreasing tendency to leave part of available water unutilised over time; improved efficiency of water use through additional capital, management input over time; increasing yields per hectare over time possibly as result of growing total factor productivity; and a propensity for less productive farms to exit first, leaving more productive farms and thus higher average income per unit water over time.

Another possible explanation for the much smaller revenue impacts per unit water availability estimated econometrically is that the time period considered in this analysis differs from the time period that the comparison models are calibrated to. There were two distinct periods of irrigation sector adjustment in the recent decade-long drought in the MDB (Kirby et al., In Press). It is possible that the first half of the decade-long drought (2001–2005) saw relatively elastic irrigated area and revenue response; while the second half of the drought (2006–2011) involved more inelastic marginal irrigated area and revenue response to water scarcity. The models

Table 7
Percentage in revenue (IRRIGN_REV)/percent change water allocation (ALLOCN).

Commodity	Econometric model	Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (2011)	Wittwer and Griffith (2011)	Adamson et al. (2011)
Cereal	0.28	1.33		
Cotton	0.4	0.44		
Pasture	0.2	2.19		
Wine		0.69		
Horticulture	0.02	0.30		
Vegetables		0.15		
Sheep	0.043	1.31		
Beef	0.077	0.54		
Dairy	0.04	0.76		
All commodities	0.1	0.49	0.19	0.43

used in the Basin Plan assessment are built on response coefficients calibrated to the data from the first half decade of drought, while estimates reported here are based on data from the second half of the decade. Evidence of rising farm debt during this later period (Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES), 2011) is suggestive that less viable irrigation may have adjusted out of production in the first half of the drought. Remaining farms could have acted consistently with real options theory, quite rationally persisting with production despite losses to maintain the option to resume once conditions improve (Tauer, 2006; Song et al., 2011). Based on surveys of MDB irrigators, Wheeler et al. (In Press) suggest another explanation for limited and delayed income impact of reduced water allocations: large numbers of growers sold water entitlements to the Commonwealth Environmental Water Holder during the second drought half, yet remained in production. With the infusion of liquidity provided, many avoided or delayed exiting farming altogether.

7. Conclusions

In this paper we estimated irrigated area and revenue responses to varying prices, water and climate conditions with readily available data. This enabled us to characterise irrigation economic response to a recent severe drought in the MDB. We found statistically significant evidence to support our hypotheses that: irrigated area contracts with declining water allocation; and that irrigated commodity revenue decreased with declines in irrigated area. Regressions for some commodities also supported the hypothesis that irrigation area increases with higher commodity prices. We also found statistically significant relationships between irrigation revenue and a meteorological irrigation demand variable for most crops considered, though this relationship was both negative in some cases, as postulated, and positive in other cases. This result is consistent with agronomic studies, where there is evidence that some crops may be damaged by hot and dry weather, while such conditions may provide higher evapotranspiration and yield potential for other crops.

The extended drought in the MDB has resulted in a number of studies of irrigation sector response. We compared our estimated marginal irrigated area and revenue responses to reductions in water allocation with those inferred from recent optimisation and CGE model-based assessments of MDB water availability impacts (Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES), 2011; Adamson et al., 2011; Wittwer and Griffith, 2011). Notably, we found consistency for irrigated area results but divergence for irrigated revenue results. Our results show a much smaller marginal revenue decline per unit decline in water allocation. There are a range of possible explanations for the divergent results. One may be that earlier models are calibrated to the data from the first half decade of drought (2001–2005) while our study is based on data from the second half of the decade of

drought (2006–2010). A number of features varied across these two periods including the characteristics of irrigators who remained in production as opposed to those who exited early. Policy settings also varied significantly across the two periods (especially a much larger federal government environmental water purchase program in the second drought half). Productivity growth trends and irrigation efficiency increases that were evident during the drought (but not fully specified in programming and CGE model) could also account for some of the differences.

Triangulation with other methods increases our confidence with results where they are consistent and reveals possible future research agendas. For instance, one avenue of research could be deeper investigation of how elasticities measuring responses to changes in irrigation water availability vary as a drought deepens then breaks. Another possible avenue is research to update specification of induced and autonomous productivity and efficiency trends and responses to water scarcity in modelling studies through use of irrigator-level surveys and econometrics in calibration of programming and CGE models.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agwat.2014.05.003.

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